A method to calculate heterogeneous evapotranspiration using submeter thermal infrared imagery coupled to a stomatal resistance submodel

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Thermal infrared (TIR) remote sensing of vegetation temperature, combined with surface energy balance modeling, allows efficient estimation of spatially distributed evapotranspiration (ET). Many ET models are sensitive to the parameterization of stomatal control; yet, modelers often employ spatially uniform stomatal resistance values, even in distributed applications. Unfortunately, assuming uniform resistance across a canopy with large temperature variance is physically unrealistic and may produce artifacts in ET magnitude. To account for spatial variations in stomatal control that likely accompany temperature variations, we propose nesting a new submodel within some well-established ET models. The submodel derives, for the canopy patch of interest, a concave-downward relationship between stomatal conductance and temperature, as expected from plant biology. Using the submodel, each pixel’s contribution to the total canopy patch ET is influenced both by its observed temperature and by its location-specific estimated stomatal resistance. The submodel requires only one more parameter than the unmodified ET models, which can be obtained from the literature; it conserves energy between the pixel and image scales, unlike single-valued resistance approaches; it produces realistic ET values at extreme temperature locations; and provides a remote sensing-based way to estimate the in situ canopy stomatal conductance-temperature relationship, which otherwise must be measured under controlled conditions. Since very high-resolution TIR data provide one means to observe large temperature variance, the submodel was tested using data with cm-scale pixels collected over 1.5 m² patches of two vegetation types. The biophysical relationships derived by the submodel were successfully verified against laboratory data.


1. Introduction

Thermal infrared (TIR) remote sensing of land surface temperature enables spatially distributed evapotranspiration rates to be calculated across vegetation canopies at various scales, according to the extent of the remote sensing data. Combination evapotranspiration models in the tradition of Penman–Monteith [Monteith, 1965] and two-source models after Shuttleworth and Wallace [1985] are some of the most prevalent approaches to do so. Applied to remote sensing data, these models solve the surface energy balance and turbulent heat transport equations for each pixel in the TIR image. The TIR pixels often range from submeter scale [Jones et al., 2002; Loheide and Gorelick, 2005; Shimoda and Oikawa, 2008; this study] to subfield scale [e.g., Blonquist et al., 2009] to 60 m for Landsat-7 data [e.g., Anderson et al., 2004], and even larger for other satellite platforms [e.g., Kustas et al., 2004]. Although TIR-based evapotranspiration models are often applied to coarse scale, low-resolution satellite data, the model adjustments proposed by this study will be demonstrated using submeter, high-resolution TIR data. The rationale for examining this fine scale and the potential applicability to coarser scales of general interest are described in due course.

Because one generally cannot measure all evapotranspiration model parameters at the same resolution as the TIR imagery, one typically assumes coarse scale homogeneity in many parameters (e.g., total radiation, ground heat flux, humidity, wind speed, canopy height, and stomatal resistance). Unfortunately, this assumed homogeneity may be contrary to real and important land surface heterogeneity in one or more of these parameters. For example, if TIR data reveal substantial heterogeneity in canopy surface temperature, it is then desirable to account for the likely concurrent heterogeneity in temperature-related components of the surface energy balance.

In practice, spatially distributed TIR-based evapotranspiration estimates are usually based on only one value of stomatal resistance for all TIR pixels in a canopy,
regardless of pixel temperature variations. This practice results in local evapotranspiration rates that vary monotonically with temperature. In some combination models, such as the Penman-Monteith model (Figure 1a [Monteith, 1965]) and the Jarvis-McNaughton/Priestley-Taylor combined model (introduced presently [Priestley and Taylor, 1972; Jarvis and McNaughton, 1986]), evapotranspiration increases monotonically with increasing temperature, all else being equal. This model behavior contrasts with one’s generally correct intuition that higher-surface temperatures should result in higher sensible heat flux and lower evapotranspiration. In other models, such as the Shuttleworth and Wallace [1985] model (also introduced presently), evapotranspiration decreases monotonically with increasing temperature, sometimes achieving anomalously negative evapotranspiration values at high temperatures. In either case, the combination models fail to capture the non-linear relationship between evapotranspiration and temperature expected from plant biophysics when they are evaluated using one value of stomatal resistance to calculate surface evapotranspiration across a range of surface temperatures.

Plant biophysics indicates that stomatal conductance (the inverse of stomatal resistance) and temperature covary in a predictably nonlinear, concave-down manner, with lower stomatal conductance values occurring at high- and low-canopy temperatures (Figure 1c) [Jarvis, 1976; Arndt et al., 1978]. Because canopy temperature is significantly easier to measure than stomatal conductance, determining the shape of this concave-down biophysical relationship from the TIR data alone would usefully inform spatially distributed evapotranspiration calculations: this is the aim of this study. If one accounts for this nonlinearity, leaf temperature and modeled evapotranspiration should covary in a more biophysically realistic manner (Figure 1d).

Conventional evapotranspiration models are highly sensitive to the canopy stomatal resistance parameter [Beven, 1979; Raupach, 1998]. This sensitivity is especially pronounced for the low resistance, moderate leaf temperature conditions characteristic of efficiently functioning leaves (Figure 1b) and when the other resistances to vapor transport, the aerodynamic and boundary layer resistances, are low [Jarvis and McNaughton, 1986]. Under these conditions, given observed spatial variation in canopy temperature, it is especially desirable to account for concurrent spatial variations in stomatal resistance. Unfortunately, stomatal resistance measurement methods are labor-intensive and limited to leaf scale, typically environmentally controlled conditions [LI-COR, 2005; Leinonen et al., 2006; Giuliani et al., 2008], so it is impractical to measure the stomatal resistance of every pixel location using current technology.

Stomatal conductance may covary with many other environmental variables besides leaf temperature and evapotranspiration rate, such as total incident radiation, vapor pressure deficit, soil moisture, ambient CO2 concentration, leaf age and nutrient status, and plant acclimation history. Yet, nonlinear coupling among stomatal resistance, leaf temperature, evapotranspiration, and canopy energy balance is an intrinsic aspect of canopy physiological function [Jarvis, 1976; Farquhar and Sharkey, 1982; Collatz et al., 1991]. Leaf temperature observations integrate all the contributing variables into one final symptom of the local

![Figure 1.](image_url)
canopy energy balance. For example, low midday soil moisture may hydraulically limit the supply of water for transpiration, induce stomatal closure, or both. Such limitations will prevent efficient canopy cooling via transpiration, so leaf temperatures will rise. However, if we know that leaf temperatures are elevated, we know that the leaves are not being adequately cooled, and so we do not need to know precisely how much soil moisture is available to understand that transpiration is reduced. It is in this sense that leaf temperature is a symptom of the surface energy balance that integrates over other contributing factors. Other causes of high apparent leaf temperatures include partial leaf senescence, standing dead plant matter, and elevated canopy positions incurring high radiation loads. However, leaf temperature is known to be more sensitive to conductance than to other variables such as leaf size or absorptivity for both sunlit and shaded leaves [Smith and Nobel, 1977].

[8] The severity of the discrepancies in pixel-level evapotranspiration estimates caused by not accounting for the nonlinear stomatal conductance-temperature relationship are schematically represented at different temperatures by the vertical distance between the solid curve and dashed line in Figure 1d. To reduce these discrepancies, in this study we impose two new constraints on some existing evapotranspiration models. First, stomatal conductance and temperature should vary in a biophysically realistic manner, as in Figure 1c. Second, total evapotranspiration flux (energy) should be conserved across scales: this would be schematically represented by the area under one of the curves in Figure 1f matching the total evapotranspiration calculated by an unmodified, conventional evapotranspiration model for the same canopy area.

[9] A heterogeneous TIR image, containing thousands to millions of pixels, will exhibit some variance among its temperature values (e.g., Figure 1e). Because variance naturally increases as resolution increases and more extreme values are resolved rather than averaged out [Journel and Huijbregts, 1978; Isaaks and Srivastava, 1989], we should particularly seek to account for spatial variations in surface conditions when studying the surface energy balance at fine spatial scales. Hence, as a first step in this direction, this study develops a modeling methodology incorporating the above constraints using example data collected at 1-cm pixel resolution over small, 1.5 m² canopy patches of two vegetation types. This demonstration scale also permitted verification of the stomatal conductance-temperature relationships derived by the new method against laboratory data collected at a comparable (cm) scale.

[10] We acknowledge that the coupling of evapotranspiration, stomatal conductance, and leaf temperature can be simulated in great detail by biochemical photosynthetic assimilation-stomatal conductance models [e.g., Farghahar et al., 1980; Collatz et al., 1991]. However, applying biochemical models over large land areas still requires assuming homogeneity in the many parameters used to characterize photosynthetic assimilation rates, many more parameters than are required by combination models or by our method. In this study, our intention is only to improve upon the erroneous assumption of homogenous canopy stomatal resistance in the face of observed canopy temperature variations. Our method provides a hybrid approach between complex biochemical canopy models and more approximate, but generally useful, homogenous-canopy combination models [Raupach and Finnigan, 1988].

2. Method: Spatially Distributed Evapotranspiration Calculations Via Canopy Resistance Mapping

2.1. Overview of Two-Source Model Adaptations

[11] Our distributed canopy resistance and evapotranspiration mapping method is based on the two-source evapotranspiration model by Shuttleworth and Wallace [1985]. We also test an alternative two-source model combining the canopy-airstream decoupling method of Jarvis and McNaughton [1986] and an estimate of soil evaporation [Priestley and Taylor, 1972]. Both two-source models are based on the premise that the transpiring canopy surface does not directly communicate with the above- and below-canopy air masses, i.e., the leaf surface and atmosphere are at least partially decoupled.

[12] In the conventional two-source model designed for application at the bulk canopy scale (Figure 2a) [Shuttleworth and Wallace, 1985], the total transpiration ($E_T$) from a homogenous “big-leaf”-like canopy is coupled to the mean canopy airstream. Transpiration is governed by the gradient between the mean canopy airstream vapor pressure ($e_0$) and the saturated vapor pressure within the canopy “big-leaf” ($e^*$). This gradient is scaled by the sum of the average canopy surface resistance ($r_s^*$, proportional to stomatal resistance) and the in-canopy aerodynamic resistance ($r_a^*$). Soil evaporation ($E_s$) is driven by the gradient between the mean canopy airstream vapor pressure ($e_0$) and the saturated vapor pressure at the soil pore surface ($e_p^*$), scaled by the sum of the soil surface resistance ($r_s^*$) and the below-canopy aerodynamic resistance ($r_a^*$). Solar radiation is partitioned between the mean canopy level and the soil substrate via exponential radiation absorption in the canopy [Shuttleworth and Wallace, 1985]. The mean canopy airstream connects the below-canopy soil fluxes and in-canopy vegetation fluxes to the above-canopy airstream using an aerodynamic resistance model based on Monin-Obukhov similarity theory. The sum of the canopy transpiration and soil evaporation is the bulk canopy evapotranspiration ($E = E_T + E_s$), which is driven by the gradient between the in-canopy airstream vapor pressure ($e_0$) and the ambient airstream ($e_p^*$), scaled by the above-canopy aerodynamic resistance ($r_a^*$). The variables comprising this two-source model framework are listed, for reference, in the notation list.

[13] Our modeling approach maintains the same overall structure as this conventional, canopy-scale, two-source model framework. We add three features in a submodel that represents finer-scale details of the canopy energy balance (Figure 2b), such as may occur at the cm-scale of the TIR canopy surface imagery examined in this study.

[14] 1. Rather than assuming that the canopy functions homogeneously with one average canopy temperature and one canopy stomatal resistance as in conventional models, our submodel considers the heterogeneity exposed by high-resolution thermal imaging. This thermal heterogeneity represents spatial variability in the surface energy balance. The submodel allows for many individual canopy leaf surfaces, represented by the TIR pixels, to simultaneously communicate with the mean canopy airstream. The
The submodel also allows each pixel-sized leaf surface to be represented according to its own local leaf temperature and stomatal conductance (Figure 2b).

2. The submodel maintains continuity with conventional coarser-scale model frameworks by calculating aerodynamic resistances and radiation partitioning at the canopy scale precisely as in the conventional frameworks. These values are then passed to the submodel. We require that the sum of the evapotranspiration fluxes for all TIR pixels calculated by the submodel (the aggregate evapotranspiration) equals the bulk evapotranspiration calculated using the conventional two-source modeling approach applied at the canopy scale. This constraint mathematically conserves energy across scales.

3. The submodel incorporates the nonlinear biophysical control of leaf stomatal aperture into the modeling framework via a simple quadratic relationship of stomatal resistance to temperature. The relationship is not specified a priori: the submodel iteratively derives it. The relationship’s derivation requires only one model parameter beyond those in the conventional two-source models, the temperature of maximum stomatal conductance, which can typically be obtained from the literature. The derived stomatal conductance-temperature relationship then provides each pixel location its own stomatal resistance value that corresponds to the observed temperature variability.

2.2. Submodel Procedure

The five-step submodel procedure is illustrated in Figure 3, in which the circled numbers correspond to the following steps. The variables are collected in the notation list, for reference.

Step 1: Select an evapotranspiration model.

Additional parameter definitions not in section 2.1 or Figure 2 were the radiation available at the canopy surface \( A_c = R_s - R_a \exp (-\kappa \times \text{LAI}_p) \), the radiation available at the soil surface \( A_s = R_s \exp (-\kappa \times \text{LAI}_p) - G \), the total available radiation \( A = R_s - G = A_s + A_c \), the density of air \( \rho_a = (3.486 \times 10^3)/(275 + T_a)/1000 \), the specific heat of air at constant pressure \( c_p = 1005 \ [\text{J/kg/C}] \), and the psychrometric constant \( \gamma = 0.00665 \times \pi \).

[20] The flux resistances \((r)\) were calculated using the approaches of Shuttleworth and Wallace [1985]. Calculation of the available radiation components \((A, \text{LAI}_s, A_s)\) from the net radiation \((R_s)\) was modified from Shuttleworth and Wallace [1985] to include the ground heat flux \((G)\). The vapor pressure deficit \((e' - e_s)\) and parameters \( \rho_a, c_p, \) and \( \gamma \) were calculated based on the approaches of Shuttleworth [1993] and Allen et al. [1998].

[21] The second evapotranspiration model we tested was the “decoupling coefficient” canopy model of Jarvis and McNaughton [1986]. We chose the approach of Jarvis and McNaughton [1986] because of their leaf versus canopy scaling analysis, their recommendation of the model as appropriate across a range of canopy scales, and their model’s strong contrast with the S&W framework. The Jarvis and McNaughton model is very similar to the Penman-Monteith combination equation \([Monteith, 1965]\). The decoupling approach of Jarvis and McNaughton is also amenable to having our canopy surface submodel nested within its broader, canopy-scale model framework. Unlike in the S&W model, the canopy temperature dependence of the Jarvis and McNaughton model occurs via the slope of the saturation vapor pressure curve \((A_s)\) at the specified leaf temperature \((T_l)\) \([Allen \ et \ al., \ 1998]\). The other parameters are as in the S&W model. To enhance comparison of Jarvis and McNaughton’s one-source canopy model with the two-source approach of S&W, we used only the canopy-level available radiation fraction \((A_s)\) in the Jarvis and McNaughton [1986] canopy transpiration model:

\[
E^{(J&M)}_{ij} = A_s \Delta_l + \rho_a c_p (e' - e_s)/r_{ij}. 
\]  

We supplemented the canopy transpiration with additional soil evaporation calculated using the Priestley and Taylor [1972] model for a soil surface at air temperature (subscript “a”):

\[
E^{(J&M)}_{ij} = 1.26 \frac{\Delta_a}{\Delta_0 + \gamma A_s}. 
\]  

The Priestley-Taylor model is appropriate for the largely saturated wetland surface of our study. The support area of our demonstration examples was very similar to that of the lysimeters used by Priestley and Taylor in their original model verification \([Priestley \ and \ Taylor, 1972]\). Other soil evaporation equations could be used in other cases. The combined Jarvis and McNaughton/Priestley and Taylor model is hereafter referred to as J&M.
[22] Step 2: Calculate the bulk evapotranspiration of the canopy using the unmodified, conventional two-source model.

[23] Calculating bulk canopy evapotranspiration \( E_i = E_{\text{bulk}} \) using a conventional two-source model \([e.g., Shuttleworth and Wallace, 1985; Norman et al., 1995]\) uses the bulk radiometric temperature of the canopy \( T_i = T_{\text{bulk}} \) and a representative value of bulk canopy surface resistance provided by the user \( (r_{s1}^s = r_{s1,\text{rep}}^s) \). Our approach trusts that this bulk evapotranspiration value \( E_{\text{bulk}} \) is accurate, as calculated by the unmodified, well-established evapotranspiration models. To calculate the bulk radiometric surface temperature \( T_{\text{bulk}} \) at the canopy scale, one averages the radiances of all the TIR pixels in the selected canopy image area \((\text{pixels } i = 1 \text{ to } N)\) using the fourth-power mean Stefan-Boltzmann law:

\[
T_{\text{bulk}} = \left( \frac{1}{N} \sum_{i=1}^{N} \frac{T_i^4}{s} \right)^{\frac{1}{4}}.
\]

The relationship (6) is similar to that used by Su et al. [1999, equation 32], Anderson et al. [2004, equation 1], and Liu et al. [2006, equation 3b] for flat terrain.

[24] Consistent with the conventional two-source approach, we account for potential canopy layering beneath each TIR-imaged pixel by calculating the representative canopy surface resistance \( r_s^c \) from a representative value of bulk stomatal resistance \( r_{s1,\text{rep}}^c \) and the canopy’s projected leaf area index \((\text{LAI}_p)\) and stomatal ratio \((s)\) \([Shuttleworth and Wallace, 1985]\):

\[
r_s^c = \frac{r_s}{s \times \text{LAI}_p}.
\]

The stomatal ratio is 1 for hypostomatous leaves and 2 for amphistomatous leaves.

[25] Step 3: Calculate the aggregate evapotranspiration of the canopy using the pixel-level submodel.

[26] Step 3a: Initialize the stomatal conductance-temperature relationship.

[27] The submodel estimates a concave-down stomatal conductance-temperature relationship for the observed canopy conditions using as few parameters as possible by assuming a quadratic approximation. The quadratic relationship for the two-sided pixel-level leaf stomatal conductance \( g_{s1,i} \) and its reciprocal, stomatal resistance \( r_{s1,i} \), is

\[
g_{s1,i} = g_{s1,w} - \omega(T_i - T_w)^2 = \frac{1}{r_{s1,i}}.
\]

The unknown parameters in (8) are: the maximum stomatal conductance \( g_{s1,m} \) and the parabola shape parameter \( \omega \). The canopy temperature at each pixel location \( T_i \) is provided by the TIR imagery and the temperature at which stomatal conductance is maximized \( T_m \) is provided by the user from ancillary data or literature. Calculating the parabola shape parameter \( \omega \) is the objective of the submodel. A larger value of the shape parameter results in the more peaked, narrower relationship illustrated by the dashed lines in Figures 1c and 3 (box 3).

[28] The temperature \( T_m \) at which stomatal conductance is maximized \( g_{s1,m} \) is the only parameter required by the submodel, in addition to those in the conventional two-source approach. Since stomatal conductance and photosynthetic carbon assimilation are approximately proportional \([Ball, 1988]\), \( T_m \) is similar to the temperature at which assimilation is maximized. This temperature value is readily obtained for most plant species and land cover classes of interest from assimilation-temperature curves in the literature \([e.g., Antlfinger and Dunn, 1979; Giurgevich and Dunn, 1979; Berry and Björkman, 1980; Pearcy and Ustin, 1984; Sage and Sharkey, 1987; Sellers et al., 1996; Kim and Lieth, 2003; Yamori et al., 2006]\). A representative value of \( T_m \) may also be obtained from laboratory gas flux measurements of the canopy of interest, which was the approach used in our demonstration examples.

[29] The modeler already knows one solution to (8): the bulk stomatal resistance \( r_{s1,\text{rep}} \) and its corresponding temperature \( T_{\text{rep}} \) used to parameterize the conventional bulk flux model \( (\text{see step 2 and box 3 in Figure 3)}\). Although \( T_{\text{rep}} \) was not a parameter explicitly used in the conventional model framework, the \( r_{s1,\text{rep}} \) value selected by the user in step 2 must implicitly have a corresponding \( T_{\text{rep}} \) value: for example, the leaf temperature recorded by a porometer used to measure \( r_{s1,\text{rep}} \). Our approach simply requires that the user explicitly acknowledge this assumed “representative” temperature. Also, in the context of the quadratic model (8), the influence of the one specific \( r_{s1,\text{rep}}, T_{\text{rep}} \) parameter pair supplied by the user is reduced compared to the conventional approach, which is a strength of the new method given likely uncertainty in these values. We substitute the known point \( (r_{s1,\text{rep}}, T_{\text{rep}}) \) into (8) and algebraically solve for the unknown maximum conductance \( g_{s1,m} \). \( T_{\text{rep}} \) must be distinct from \( T_m \). Substituting for \( g_{s1,m} \) in (8), we calculate stomatal resistance \( r_{s1,i} \) values for each pixel:

\[
r_{s1,i} = \left( \frac{1}{r_{s1,\text{rep}}} + \omega(T_{\text{rep}} - T_m)^2 - \omega(T_i - T_m)^2 \right)^{\frac{1}{2}}.
\]

Each stomatal resistance \( r_{s1,i} \) is scaled up to a local, pixel-level surface resistance \( r_{s1}^s \) using (7). Thus, (7) and (9) relate the pixel-scale canopy surface resistances \( r_{s1}^c \) to the TIR pixel surface temperatures \( T_i \) via a shape parameter \( \omega \) and five known scalars \( r_{s1,\text{rep}}, T_{\text{rep}}, T_m, s, \text{and LAI}_p \). The shape parameter \( \omega \) is derived in the next steps of the submodel.


[31] An initial estimate of each pixel’s evapotranspiration \( E_i \) is calculated from the evapotranspiration model \( (\text{equations (1)–(3) or (4) and (5)}) \), using the TIR pixel temperature \( T_i \) and its corresponding canopy resistance value \( r_{s1}^c \) estimated with (7) and (9)). Note that the parameters \( r_{s1}^s, r_{s1}^c, A, A_s, A_{\infty}, P_{\infty}, e_p, \text{and } \gamma \) remain at the bulk canopy scale exactly as in conventional two-source models \([Shuttleworth and Wallace, 1985]\). One applies these parameters uniformly across the whole TIR-imaged canopy to each pixel in the submodel, exactly as in conventional model applications.
[32] Step 3c: Aggregate the pixel scale evapotranspiration values by averaging.

[33] The initial pixel-level evapotranspiration estimates are aggregated to the canopy (TIR image) level by arithmetic averaging [Raupach, 1995]:

\[ E_{\text{aggregate}} = \text{mean}(E_i). \]  

(10)

[34] Step 4: Reconcile bulk and aggregate evapotranspiration values.

[35] The numerical objective of the submodel is to minimize the difference between the bulk (conventional two-source canopy) and aggregate (fine-scale submodel) evapotranspiration rates by optimizing the \( \omega \)-shape parameter that defines a realistic stomatal conductance-temperature relationship for the canopy of interest for observed conditions.

[36] Step 4a: Subtract bulk and aggregate evapotranspiration values to calculate discrepancy.

[37] The discrepancy (\( \delta \)) between the aggregate evapotranspiration (\( E_{\text{aggregate}} \)) estimated by the submodel in step 3 and the bulk evapotranspiration for the canopy (\( E_{\text{bulk}} \)) known from step 2 is

\[ \delta = E_{\text{bulk}} - E_{\text{aggregate}}. \]  

(11)

To conserve energy (evapotranspiration) across scales, \( \delta \) should be zero.

[38] Step 4b: Minimize aggregate evapotranspiration discrepancy by iteratively adjusting the biophysical relationship in the submodel.

[39] Slight adjustments to the stomatal conductance-temperature relationship (e.g., solid versus dotted curves in Figure 1c) result in notable differences in the aggregate evapotranspiration of the imaged canopy (e.g., integral of solid curve versus integral of dotted curve in Figure 1f). Taking advantage of this sensitivity, the submodel’s biophysical relationship, pixel-level evapotranspiration values, and aggregate evapotranspiration are progressively refined by automated numerical iteration until the aggregate and bulk evapotranspiration values match. Many solution methods could be employed; we used and suggest the Newton method. An initial value of \( \omega \) on the order of \( 10^{-6} \) is suggested, but sensitivity analysis should be conducted for each application and an absolute minimum of \( \delta \) sought.

[40] Step 5: Map evapotranspiration values and canopy resistances at the pixel scale.

[41] Once an optimal solution for \( \omega \) has been obtained by minimizing \( \delta \), the spatially distributed, pixel-scale evapotranspiration values (\( E_i \)) are mapped from the final results of the submodel. The optimized \( \omega \) value provides an estimate of the biophysical stomatal conductance-leaf temperature relationship for the canopy under observed conditions, which is used to convert the remotely sensed temperature field (\( T_i \)) into a high-resolution canopy surface resistance map. If the model separately represents canopy transpiration and soil evaporation components of total evapotranspiration, these variables are also mapped at the scale of the TIR data [e.g., Shuttleworth and Wallace, 1985; Norman et al., 1995].

3. Demonstration Examples

[42] We demonstrate our stomatal resistance-mapping submodel for two different vegetation types using cm-resolution TIR imagery of 1.5 m² canopy patches. Testing the submodel with images at approximately leaf resolution (~cm) made conceptual interpretation in terms of leaf biophysical processes straightforward and permitted validation against laboratory measurements of leaf biophysical function. Although the submodel is, in principle, valid across many scales since the physical requirement of energy (evapotranspiration) conservation is scale independent [Raupach, 1995], the submodel is likely to be most useful in cases of high-canopy surface temperature variance. High-temperature variance may be produced by various circumstances differentially affecting canopy temperature (e.g., heterogeneous stomatal control, soil moisture, leaf nutrient status) and revealed by high-resolution thermal remote sensing. Our cm-resolution, m-extent, demonstration examples follow others’ success in using TIR imagery to better understand fine-scale heterogeneous soil evaporation [Shahraeeni and Or, 2010] and plant transpiration relative to reference surfaces [Leinonen et al., 2006], and are consistent with the informative patch scale analysis of local land-air exchange feedbacks by Raupach [1998].

3.1. Data Collection

[43] The TIR remote sensing imagery was collected in an intertidal salt marsh in southern San Francisco Bay during low tide periods. The surface energy balance of the marsh behaves during low tide as if the marsh were a wet grassland [Moffett et al., 2010]. Repeated TIR images of nearly monospecific and closed canopy surfaces were collected: on 24 September 2008 for the C₄ grass Spartina foliosa (coggrass, Figure 4a) and on 26 September 2008 for the C₃ succulent forb Salicornia virginica (also known as Sarcocornia pacifica, pickleweed, Figure 4b). Imaging was from a ground-based tower using a MobIR M4 thermal camera (8-14 μm; Wuhan Guide Infrared Technology Co., Ltd., Wuhan, China) inside a radiation shield at 3 m height. The camera field of view was 1.05 m × 1.40 m with 120 × 160 pixels, for a pixel size of 0.87 cm × 0.87 cm (rounded to 1 cm in this paper, for convenience). A metal ruler 32 mm wide was included in some images to verify the resolution (Figure 4c). TIR image brightness temperatures were converted to radiometric temperatures by adjusting for the reflected long wave radiation from the sky [Norman and Becker, 1995], as measured by a four-component net radiometer located ~23 m from the imaged marsh locations (CN1, Kipp and Zonen, Delft, Netherlands). Soil heat flux was measured at the same location as net radiation (HF015SC, TCAV, and CS616, from Campbell Scientific, by Hukseflux, Delft, Netherlands) [Moffett et al., 2010]. Meteorological data were collected every 10 min at a weather station 210 m away in an adjacent marsh: wind speed and precipitation at a height of 3 m and air temperature, relative humidity, and barometric pressure at a height of 2 m (HOBO weather station, Onset, Cape Cod, MA, USA).

[44] In principle, the greater the quantity and variance of the TIR data, the better the desired stomatal conductance-temperature relationship can be mathematically constrained using our submodel. To increase the quantity of
3.2 Demonstration Results

The canopy temperatures indicated by the TIR data exhibited diurnal signals (Figure 5). Despite very similar weather and incident radiation on the two measurement days, the temperature range within images of the succulent Salicornia canopy was less than the range within images of the Spartina grass canopy. The bulk evapotranspiration values ($E_{\text{bulk}}$) simulated by the unmodified S&W and J&M flux models responded to these diurnal signals in surface temperature and incident radiation.

The biophysical relationships between stomatal conductance and temperature derived by the submodel were comparable to those estimated from laboratory gas flux chamber measurements of plant leaf stomatal response for each plant species. An individual of each species was taken from the field site with intact roots in August 2008, shortly before the field study. The plants were kept in an outdoor greenhouse under natural light and watered periodically with water from the field site. Prior to measurements, the selected leaves/stems were wiped clean with a damp cloth and allowed to air dry. Leaves were subjected to different air temperatures while photosynthetically active radiation (PAR), influent CO$_2$, and airflow rate were held constant. Measurement conditions for Spartina foliosa were ($\mu \pm 1\sigma$): PAR 1500 ± 1 μmol m$^{-2}$ s$^{-1}$, relative humidity 72% ± 19%, airflow rate 200 μmol s$^{-1}$, and air temperatures 18°C–34°C, resulting in leaf temperatures 21°C–33°C. Measurement conditions for Salicornia virginica were: PAR 1500 ± 1 μmol m$^{-2}$ s$^{-1}$, relative humidity 55% ± 18%, airflow rate 400 μmol s$^{-1}$, and air temperatures 16°C–37°C, resulting in leaf temperatures 19°C – 32°C. Leaf carbon dioxide assimilation and transpiration were recorded using an open-path system (Licor LI-6400) once the fluxes had equilibrated to each change in temperature, after 30–50 min. Stomatal conductance values were calculated from these data [LI-COR, 2005].

Figure 4. Examples of high-resolution radiometric surface temperatures ($T_s$) of: (a) Spartina foliosa and (b) Salicornia virginica. Image dimensions: 160 × 120 pixels with ~ 1 cm pixel size. (c) Example raw TIR image of Spartina foliosa and corresponding digital camera image (taken at 10:34 A.M., shortly before image in Figure 4a). Metal ruler 3.2 cm wide for scale, at temperature 28.3°C to 29.6°C.

[46] The modulation radiometric temperatures ($T_m$) of each canopy was calculated from these data [LI-COR, 2005].

[47] The canopy temperatures indicated by the TIR data exhibited diurnal signals (Figure 5). Despite very similar weather and incident radiation on the two measurement days, the temperature range within images of the succulent Salicornia canopy was less than the range within images of the Spartina grass canopy. The bulk evapotranspiration values ($E_{\text{bulk}}$) simulated by the unmodified S&W and J&M flux models responded to these diurnal signals in surface temperature and incident radiation.

The biophysical relationships between stomatal conductance and temperature derived by the submodel were comparable to those estimated from laboratory gas flux chamber measurements (Figure 6). Scatter in the laboratory data was due to noise among about 600 stomatal conductance values for each plant species, obtained every 30 s. The relationships derived by the submodel were similar for the tall C$_4$ grass canopy (Spartina foliosa) and for the short C$_3$ succulent forb canopy (Salicornia virginica), providing evidence that the methodology is not dependent upon plant morphology or physiology. The submodel converged to nearly identical values of the shape parameter $\omega$, whether run within the S&W or J&M model framework: $\omega \approx 3.15 \times 10^{-6}$ for the Spartina foliosa canopy and $\omega \approx 2.45 \times 10^{-6}$ for the Salicornia virginica canopy (an average of S&W and J&M results).
The derived values were approximately half of those suggested by the quadratic fits to the laboratory data, but the derived curves closely matched the laboratory data over the common leaf temperature range of \(24 \text{C} - 22 \text{C}\) to \(14 \text{C} - 10 \text{C}\). Within this temperature range spanned by the laboratory data, the correlation coefficients between the mean values of each cluster of laboratory data and the modeled stomatal conductance values were \(r = 0.97\) for *Spartina foliosa* \((p = 0.0062)\) and \(r > 0.99\) for *Salicornia virginica* \((p = 0.00036)\).

Table 1. Model Parameters for Demonstration Examples

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Source</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(G)</td>
<td>Soil heat flux (W m(^{-2}))</td>
<td>Empirical regression between (R_n) and (G) measured by a net radiometer and a soil heat flux plate system in the field</td>
<td>(G = 0.26 \times R_n - 64)</td>
</tr>
<tr>
<td>(\kappa)</td>
<td>In-canopy light extinction coefficient</td>
<td>Standard assumption</td>
<td>0.5</td>
</tr>
<tr>
<td>(LAI_p)</td>
<td>Projected leaf area index (LAI/2)</td>
<td>Averages from Zhang et al. [1997]</td>
<td>1.2</td>
</tr>
<tr>
<td>(e_m)</td>
<td>Canopy emissivity (used in sky radiation correction)</td>
<td>Standard assumption</td>
<td>0.98</td>
</tr>
<tr>
<td>(z_u)</td>
<td>Height of wind speed measurements</td>
<td>Field measurement</td>
<td>3 m</td>
</tr>
<tr>
<td>(d)</td>
<td>Roughness dimension of canopy (leaf width)</td>
<td>Average field estimate</td>
<td>0.02 m 0.01 m</td>
</tr>
<tr>
<td>(h_c)</td>
<td>Canopy height</td>
<td>Average field estimate</td>
<td>0.5 m 0.35 m</td>
</tr>
<tr>
<td>(r_b)</td>
<td>Total (two-sided) leaf boundary layer resistance (s m(^{-1}))</td>
<td>Laboratory data</td>
<td>29 s m(^{-1}) 24 s m(^{-1})</td>
</tr>
<tr>
<td>(r_{rep})</td>
<td>Total (two-sided) leaf stomatal resistance at temperature (T_{rep})</td>
<td>Laboratory data</td>
<td>682 s m(^{-1}) 1135 s m(^{-1})</td>
</tr>
<tr>
<td>(s)</td>
<td>Stomatal ratio</td>
<td>[LI-COR, 2005]</td>
<td>1 2</td>
</tr>
<tr>
<td>(T_{rep})</td>
<td>Leaf temperature of “representative” stomatal resistance measurement (r_{rep})</td>
<td>Laboratory data</td>
<td>23.4(\text{C}) 20.0(\text{C})</td>
</tr>
<tr>
<td>(T_m)</td>
<td>Temperature of maximum stomatal conductance</td>
<td>Laboratory data</td>
<td>29.3(\text{C}) 25.0(\text{C})</td>
</tr>
</tbody>
</table>

Figure 5. Diurnal progression of canopy temperatures of (a) *Spartina foliosa* and (b) *Salicornia virginica*. Vertical sets of gray dots mark the centers of 30 histogram bins spanning the range of temperatures in each TIR image; the shades of the dots indicate the relative frequency of temperatures in the bins. Apparent data gaps are because of variable timing between TIR data acquisitions and are inconsequential in this study. Dark line behind dots: average radiometric temperature of whole image \((T_{bulk})\). Meteorological conditions illustrated: net radiation \((R_n/10\), solid line\), air temperature \((T_a\), dashed line\), relative humidity \((RH/10\), dotted line\), and wind speed \((u\), dashed-dotted line\).
fundamental issues with the S&W conceptual model at extreme-temperature locations, not due to the canopy resistance mapping submodel, as discussed presently in section 4.2.

4. Discussion

4.1. Significance of Using Stomatal Resistance Mapping Submodel in Combination Models

The submodel proposed in this study was designed to ensure conservation of energy (evapotranspiration) between the pixel (leaf) and TIR image (canopy) scales and to modulate the evapotranspiration contributions of extreme-temperature pixels via lower stomatal conductance values. But how important were these model revisions? We quantitatively assessed the discrepancies in evapotranspiration estimates incurred by neglecting these considerations via a scaling analysis. We found that the discrepancy in total evapotranspiration that were produced by applying the conventional, uniform-resistance models to high-variance TIR data were more pronounced at finer scales and for TIR images with high-temperature variances. The scaling analysis used the bulk evapotranspiration for each TIR image as the basis for comparison ($E_{\text{bulk}}$), consistent with the expectation that the conventional models perform accurately at the coarser (whole-image) scale. The finest scale of comparison was that of the original TIR data. For this scaling analysis, pixel-level evapotranspiration values were calculated using the same spatially uniform stomatal resistance value as in the bulk model, then averaged over all of the pixels in the canopy image to obtain $E_{\text{aggregate}}$, as in (10). We also recursively divided each TIR image in half to produce comparable data sets at eight intermediate resolutions. We calculated an evapotranspiration flux for each subdivision of each image using average subdivision temperatures, similar to (6), and the same spatially uniform stomatal resistance value as used at the coarse and fine scales. We aggregated the subdivision fluxes for each image at each scale by arithmetic averaging, as in (10).

![Figure 6. Leaf stomatal conductance–temperature relationships. Quadratic relationships between leaf stomatal conductance and leaf temperature are derived from laboratory measurements (solid lines, solid symbols) and from the remote sensing method (dashed lines; combined Jarvis and McNaughton [J&M] and Shuttleworth and Wallace [S&W] model results nearly identical and plot together). Parameter values used in the method ($T_{\text{rep}}, r_{\text{st,rep}}, T_m$) indicated by open symbols.](image)

$g_{st} = 1/r_{st}$

Stomatal Conductance ($g_{st} = 1/r_{st}$)

(m/s)

18 22 26 30 34

Leaf Temperature (°C)

*Spartina foliosa:*
- lab. data points
- lab. quadratic relationship
- known point ($T_{\text{rep}}, 1/r_{\text{st,rep}}$)
- optimum temperature ($T_m$)
- J&M-derived relationship
- S&W-derived relationship

*Salicornia virginica:*
- lab. data points
- lab. quadratic relationship
- known point ($T_{\text{rep}}, 1/r_{\text{st,rep}}$)
- optimum temperature ($T_m$)
- J&M-derived relationship
- S&W-derived relationship

[50] The scaling analysis used the bulk evapotranspiration for each TIR image as the basis for comparison ($E_{\text{bulk}}$), consistent with the expectation that the conventional models perform accurately at the coarser (whole-image) scale. The finest scale of comparison was that of the original TIR data. For this scaling analysis, pixel-level evapotranspiration values were calculated using the same spatially uniform stomatal resistance value as in the bulk model, then averaged over all of the pixels in the canopy image to obtain $E_{\text{aggregate}}$, as in (10). We also recursively divided each TIR image in half to produce comparable data sets at eight intermediate resolutions. We calculated an evapotranspiration flux for each subdivision of each image using average subdivision temperatures, similar to (6), and the same spatially uniform stomatal resistance value as was used at the coarse and fine scales. We aggregated the subdivision fluxes for each image at each scale by arithmetic averaging, as in (10).
images taken around mid-day (Figure 9). The sign difference between the S& W and J&M models suggested that, as the resolution and variance of TIR data are increased, the aggregate evapotranspiration calculated from a J&M-like model may appear to increase but the aggregate evapotranspiration calculated from a S&W-like model may appear to decrease under the same conditions. In either case, the change in the evapotranspiration rates with changing resolution (when

![Figure 7](image_url). Spatial variability in estimated canopy surface resistance ($r_s$) among (a, c) *Spartina foliosa* and (b, d) *Salicornia virginica*, derived by the submodel from the temperature fields in Figures 4a and 4b. Higher simulated $r_s$ corresponded with comparatively extreme (warm or cool) canopy temperatures (compare with Figure 4) as expected. Color scales differ between species to adequately illustrate $r_s$ variations.

![Figure 8](image_url). Evapotranspiration fields for *Spartina* and *Salicornia* canopies calculated using the spatially variable canopy surface resistances from the submodel in Figure 7 and temperature fields in Figures 4a and 4b. Pixel-level variables are: total evapotranspiration ($E_i$), canopy transpiration ($E_{ci}$), and soil evaporation ($E_{si}$). Color scales differ to adequately illustrate variations. Soil $E_{si}$ is single-valued in the J&M model due to the single-valued modeling approach after Priestley and Taylor [1972]. Causes of very large and very small (negative) values calculated using the S&W model are assessed in section 4.2.
calculated using the same uniform resistance value) violated the conservation of energy across scales.

[52] The scale-dependency of these discrepancies in aggregate evapotranspiration was caused by the increasing inconsistency at finer scales between the single resistance value used and the more pronounced heterogeneity of finer-scale temperature fields. This conclusion was evidenced by the strict proportionality between the aggregate evapotranspiration discrepancy and the surface temperature variance of each TIR image at different levels of subdivision (Figure 10). The reduction in temperature variance at coarser resolutions scaled with the subdivision averaging dimension (inversely with $n$) as expected from regularization of random values [Journel and Huijbregts, 1978; Isaaks and Srivastava, 1989].

[53] The spatially variable stomatal resistance values derived by the submodel reduced the overall variance of the modeled evapotranspiration field, especially for the J&M model. This variance reduction effect was mostly due to the suppression of anomalously extreme evapotranspiration values by lower conductance values imposed at warm temperatures (see Figure 1d). High-variance evapotranspiration fields produced by the S&W model were partially due to anomalous negative values, not due to the submodel. (See section 4.2 regarding difficulties with applying the S&W model to high-variance temperature fields.) Since evapotranspiration should be relatively low when sensible heat flux is high, such as at locations with surface temperatures greatly elevated above air temperature, we deemed the smaller evapotranspiration values calculated by the submodel at such locations more realistic than the extreme evapotranspiration values calculated by the conventional approach. The ranges of evapotranspiration values calculated using the new submodel compared favorably with the ranges of latent heat flux measurements made at a nearby eddy covariance station on the same days [Moffett et al., 2010], although the great difference in support areas and measurement methods precluded direct comparison. The evapotranspiration variance compression produced by our submodel within the J&M framework was also consistent with the rapid, fine-scale regulation of water loss described by stomatal optimization theory [Katul et al., 2010] in that such regulation among a small, relatively homogeneous canopy patch may be expected to homogenize water loss rates.

Figure 9. Scale dependence of aggregate evapotranspiration values for each model ((a, b) J&M model and (c, d) S&W model) and each plant species (Spartina (Figures 9a and 9c) and Salicornia (Figure 9b and 9d)). The magnitude of the discrepancy ($\delta$) in the aggregate evapotranspiration increased as the dimension of the scaled TIR input data decreased (i.e., resolution of the TIR pixels increased). Each line traces the trend in $\delta$ for one TIR image across 10 scales. The lines are color-coded by image time of day. Y-axes differ to maximize display.
4.2. Additional Model Considerations: Problems With a Common Two-Source Surface Energy Balance Model at Extreme Temperatures, High Resolutions

According to our results, the two-source model framework of Shuttleworth and Wallace [1985] results in anomalously extreme evapotranspiration estimates when applied to high-variance canopy temperature fields. Although one of the most widely applied frameworks for remote sensing-based surface energy balance calculations [Kustas and Anderson, 2009; Overgaard et al., 2006], we identify two features of its mathematical implementation that are poorly suited for analysis of especially warm or cool land surfaces. The two difficulties are intrinsic to the mathematical model structure, and so do not depend on the scale of TIR imagery, only on the presence of especially cool or warm pixels among the data. The difficulties were features of the unmodified S&W model, not the result of our submodel.

The first difficulty with the S&W model was its estimation of negative evapotranspiration (condensation) at warm canopy locations. This phenomenon has been noted previously and has been overcome by reassigning negative fluxes a value of zero [Anderson et al., 2008; Norman et al., 1995], justified by the idea that very warm surfaces are likely dry and so evaporation and transpiration are negligible. However, this justification was not applicable in our study of nearly saturated wetland soils and nonwater-limited vegetation. The model itself provides a mathematical explanation for the negative simulated evapotranspiration values. Very-high canopy-surface temperatures \(T_j\) applied in the second term of (1) may easily drive the evapotranspiration to negative values, given typical values of other parameters. Even if high observed temperatures do indicate dry surfaces, for example, if there were partially senesced or dead portions of the imaged canopy, the concave-down stomatal conductance-temperature relationship imposed by our submodel provides a new means to tune evapotranspiration at warm canopy locations toward zero, as an alternative to ad hoc assignments of zero values.

We suggest that this potentially problematic model behavior has not hindered the successful application of S&W-like models in previous studies because such studies...
are mostly based on coarse-scale satellite TIR imagery. Coarse-scale observation captures less surface temperature variance by naturally averaging out extreme values, making observation of extremely warm surface temperatures at coarse scales relatively rare. However, this difficulty appears to render this type of two-source surface-energy balance calculation unsuitable for applications in which very warm surface temperatures are resolved in the TIR data. Problematically warm surface temperatures may be particularly likely among fine-scale TIR imagery such as explored in this study. The specific limits of applicability of the S&W modeling framework are an open question, especially the threshold conditions combining specific temperature extremes and concurrent meteorological and boundary layer influences.

[57] The second difficulty that we observed with the S&W model framework was that it can produce very large soil evaporation values beneath especially cool portions of the canopy. This occurs in the model because the evapotranspiration calculation can easily be dominated by the canopy-air temperature difference \((T_c - T_a)\) in the second term of (1), which is magnified by a combination of resistances, rather than by the canopy-air vapor pressure gradient \((e^* - e_a)\) in the third term of (1). Since the canopy transpiration fraction \((2)\) is largely set by the vapor pressure gradient \((e^* - e_a)\), the soil evaporation fraction \((3)\) can remain strongly dominated by the canopy-air temperature difference, leading to extremely large soil evaporation values being calculated for especially cool canopy locations. This model result is problematic because the canopy is likely to be cool either due to a small supply of radiant energy or because the incident radiation is very effectively dissipated by latent and sensible heat fluxes from the canopy; in either case, there would seem to be little energy available to drive exceptionally large soil evaporation. This difficulty is implicit in the model’s design, as if an electrical circuit of two joined loops. Analysis of the circuit analog reveals that, for fixed resistance and vapor pressure values, if the canopy transpiration \((E_c)\) becomes small, the soil evaporation \((E_s)\) must increase to satisfy Ohm’s Law and Kirchhoff’s Voltage Law. Soil evaporation may truly increase as indicated by the model if the canopy transpiration concurrently tends toward zero due to canopy senescence (reduced LAI) or another exogenous factor, but there was no evidence for such conditions in our demonstration examples. We conclude that, irrespective of the scale of analysis, if simulated canopy transpiration is small due to a small vapor pressure gradient between the canopy and the air \((e^* - e_a)\), conceptual models similar to S&W may produce erroneously high values of soil evaporation at especially cool canopy locations, for some input parameter combinations.

4.3. Discussion of the Stomatal Resistance Mapping Submodel

[58] The evapotranspiration submodel developed in this study produced three results not previously available from TIR image analysis: pixel-level maps of evapotranspiration downscaled from coarse-scale bulk values while conserving energy across scales, biophysically realistic estimates of heterogeneous canopy surface resistance, and an estimate of the stomatal conductance-temperature relationship of the canopy for observed conditions. The conservation of energy across scales and the derivation of this biophysical relationship are the major differences between this method and other methods that have derived high-resolution canopy resistances from TIR data [Boegh et al., 2002]. Notably, the new submodel derives the canopy stomatal conductance-temperature relationship for in situ conditions and does not require one to assume that the in situ canopy behaves identically to leaves observed in the laboratory. A quadratic function was used in this study for simplicity, but a cubic or quartic relationship (e.g., after Tenhunen and Westrin [1979] or Farquhar et al. [1980], respectively) could be used with simple adjustments to the numerical solution scheme: either by supplying one or two additional pieces of information to the relationship, or by optimizing the model (minimizing \(\delta\)) to fit two or three parameters controlling the shape of the stomatal conductance-temperature relationship.

[59] The overall accuracy and generality of the stomatal conductance-temperature relationship derived by the submodel will depend on the soil moisture conditions and plant hydraulic maintenance strategy at the time of imaging. Soil moisture can influence evapotranspiration and leaf temperature and there are multiple plant strategies for managing water pressure and stomatal aperture [Jones, 1998; Franks et al., 2007]. Anisohydric plants maintain low stomatal resistances, regardless of soil water potential and meteorological conditions, until near plant hydraulic death. Isohydric plants maintain constant internal water pressure by dynamically adjusting stomata in response to atmospheric and soil moisture changes. In both cases, however, elevated leaf temperature will be symptomatic of locally inefficient heat dissipation by sensible heat flux and transpiration. In this study, we assumed that observed spatial variability in leaf temperature at the cm scale of our TIR data was more likely to be due to patchy stomatal control, which can vary at leaf-to-subleaf scales [Mott and Buckley, 2000], than to be due to spatial variations in soil moisture. This assumption is justified for wet soil conditions, such as in our examples. However, heterogeneous or water-limited soil conditions may provide additional, nonstomatal controls on transpiration and leaf temperature [Turner et al., 1985; McDowell et al., 2008]. Under these conditions, the submodel would effectively combine soil moisture and stomatal controls into the derived “biophysical” relationship, reducing the validity of the relationship’s interpretation in strictly botanical terms. The stomatal conductance-temperature relationship derived using the submodel thus represents an effective relationship appropriate for the radiation and moisture patterns experienced by the canopy during the observation period. However, we believe it will also include the effects of longer-term plant acclimation [Berry and Björkman, 1980; Matthews and Boyer, 1984], which we consider a useful feature of the method.

[60] The principle source of uncertainty in the submodel is the degree of variability in the TIR canopy surface temperature field. Greater observed temperature variance will more tightly constrain the submodel’s numerical optimization. Relatively scarce extreme temperature values in our TIR images likely account for some of the difference between the biophysical relationships derived in our demonstration examples and those from laboratory data, especially at high and low temperatures (Figure 6). Without
increasing the TIR resolution, greater variance may be obtained by increasing the quantity of data: by time-lapse imaging, as in our examples, or by the combination of regions of the same land cover or canopy type from different images. Combining images from different times of day in the same analysis has the potential advantage of capturing some of the variations in canopy temperature that are due to the three-dimensional canopy structure, but which may only be visible to the TIR sensor at certain solar angles. Of course, this same phenomenon of canopy structure, solar angle, and occlusion or shading is also a source of potential evapotranspiration errors for any analysis of high-resolution TIR data, which is no more mitigated by our approach than by existing methods. In combining data from more than one time or region, separate bulk evapotranspiration values should be calculated using the appropriate meteorological data for each contributing time or spatial region, then one stomatal conductance-temperature relationship may be sought that best matches all of the aggregate and bulk evapotranspiration values of each of the contributing data blocks.

[61] In principle, we believe the submodel is not restricted to the submeter scale of our demonstration examples. The demonstrations presented here are an initial proof-of-concept for the methodology at a scale permitting validation against laboratory data and straightforward conceptual interpretation of the derived conductance-temperature relationship. Large temperature variance was imparted to our examples by high-imagery resolution, but we expect the results would be mathematically equivalent at any resolution given the same temperature field. Our scaling analysis showed that discrepancies in evapotranspiration estimates are proportional to temperature variance across a range of scales (Figure 10). We expect that application of the method at coarser scales could result in a pseudo-biophysical relationship of effective, coarse-scale canopy surface resistance versus coarse-scale radiometric temperature for the land cover of interest, but might also require attention to possible spatial variations in variables such as soil moisture and leaf-area index. Such coarse-scale tests of the submodel are the subjects of ongoing research.

[62] We have emphasized that our nested modeling approach maintains continuity with well-established two-source surface energy balance models designed for application at the canopy scale or coarser levels, while accounting for pixel-level spatial variations in surface temperature and stomatal conductance. One might suggest that a further departure from conventional model frameworks that also accounts for spatial variations in radiation and meteorological variables would be desirable; however, it is not necessarily clear how each variable should be accounted for, if not already included in conventional two-source model frameworks. Observed canopy surface temperatures are symptoms of the balance of the dissipation of energy by sensible and latent heat fluxes and the total absorbed radiation, not just the shortwave photosynthetically active radiation [Pieruschka et al., 2010]. The total radiation within a vegetation canopy may differ significantly from the illumination by photosynthetically active radiation, especially when one accounts for reradiation of thermal energy among leaves within the canopy (e.g., see data by Teal and Kanwisher [1970] for the Spartina genus of this study) and for radiation feedback on the canopy energy balance [Raupach, 1998]. Considering canopy structure, deeper layers may experience lower radiation loads, causing the models examined in this study to overestimate evapotranspiration. However, deeper layers may also experience lower air temperatures and wind speeds, causing the models to overestimate sensible heat flux and underestimate evapotranspiration. To the degree that these opposing systematic errors may cancel, uncertainties due to assumptions of uniform meteorological conditions within the canopy may be reduced.

[63] Some uncertainty may also be contributed to the submodel approach by the assumption that the bulk evapotranspiration value ($E_{\text{bulk}}$) used to constrain the submodel was calculated accurately by the unmodified, conventional model. If $E_{\text{bulk}}$ were uncertain because of insufficient confidence in the coarse scale model, it could instead be provided by measurements. If $E_{\text{bulk}}$ were uncertain because of a poorly defined representative value of coarse-scale stomatal resistance ($r_{s, \text{rep}}$), this uncertainty could be mitigated by adding to the submodeling approach an iteration loop at the coarse scale. The additional loop would draw a new $r_{s, \text{rep}}$ value from the current state of the submodel and use this value to re-estimate the $E_{\text{bulk}}$ value used in the successive coarse-scale model iteration.

5. Conclusion

[64] In this study, we proposed that it is physically unrealistic to assume a uniform stomatal resistance throughout a canopy that exhibits large temperature variance and that this assumption may compromise TIR-based evapotranspiration calculations. We developed a submodel to estimate the spatial variations in stomatal control that are likely to accompany observed temperature variations. We nested this submodel within two well-established evapotranspiration models designed for use at the coarse canopy scale. Applying both the unmodified models and the new nested submodel to two different vegetation types imaged at cm resolution over 1.5 m² canopy areas, we showed that the unmodified, single-valued resistance approach failed to conserve energy between the pixel and image scales. In contrast, the mathematical objective of the new submodel was to conserve energy between scales, which it achieved successfully in the demonstration examples. The modified models, which included the variable-resistance submodel, produced more moderate, physically realistic pixel-scale evapotranspiration values at locations of extreme temperature than the unmodified models. The submodel also provided a new remote sensing-based means to estimate the in situ canopy stomatal conductance-temperature biophysical relationship, which otherwise must be measured under controlled experimental conditions. As thermal infrared remote sensing is now being applied at submeter resolutions [Jones, 1999; Jones et al., 2002; Jones and Leinonen, 2003; Leinonen and Jones, 2004; Loheide and Gorelick, 2005; Shimoda and Oikawa, 2008] and TIR imaging technologies tend toward higher resolutions in the future, the availability of high-variance temperature data is likely to increase. Given such data, the utility of methods, such as the submodel proposed in this paper, may also increase to address the additional complexity introduced into evapotranspiration
calculations by the large thermal variance of imaged vegetation canopies.

Notation

Variables defining the two-source evapotranspiration model framework (see Figure 2a):

\[ E \] total canopy evapotranspiration from area of interest
\[ T_a \] ambient above-canopy air temperature
\[ e_a \] ambient above-canopy airstream vapor pressure
\[ u \] ambient above-canopy airstream wind speed
\[ r'_a \] above-canopy aerodynamic resistance
\[ T_0 \] mean canopy airstream temperature
\[ e_0 \] mean canopy airstream vapor pressure
\[ r'_e \] in-canopy aerodynamic resistance
\[ E_s \] total soil evaporation from area of interest
\[ r'_s \] below-canopy aerodynamic resistance
\[ T_s \] soil surface temperature
\[ e_s \] vapor pressure at soil surface
\[ r'_s \] soil surface resistance
\[ e'_s \] saturated vapor pressure at soil pore surface
\[ E_c \] total canopy transpiration from area of interest
\[ r'_c \] average canopy surface resistance
\[ T_c \] canopy (leaf) surface temperature
\[ e'_c \] saturated vapor pressure at stomatal pore surface

\[ A \] total available radiation
\[ A_c \] radiation available at mean canopy level
\[ A_s \] radiation available at soil surface
\[ h_c \] mean canopy height
\[ R_n \] net incident radiation
\[ \kappa \] in-canopy light extinction coefficient
\[ \text{LAI}_p \] projected leaf area index
\[ s \] stomatal ratio (1 for hypostomatous leaves, 2 for amphistomatous leaves)
\[ P \] ambient atmospheric pressure
\[ G \] soil heat flux
\[ \rho_o \] density of air (at \( T_o \) and \( P \))
\[ c_p \] specific heat of water at constant pressure
\[ R_H \] relative humidity
\[ \Delta \] slope of the saturation vapor pressure curve at \( T_o \)
\[ \gamma \] psychrometric Constant

Model variables calculated at a specific scale (\( j \)). Except in scaling analysis, the scale is either the bulk canopy level (whole TIR image) of conventional models (\( j = \text{bulk} \)) or the TIR pixel scale (\( j = i \)).

\[ E_j \] evapotranspiration, from bulk (\( E_{\text{bulk}} \)) or pixel (\( E_i \)) scale
\[ E_{ij} \] canopy transpiration, from bulk (\( E_{c,\text{bulk}} \)) or pixel (\( E_{c,i} \)) scale
\[ E_{sj} \] soil evaporation, from bulk (\( E_{s,\text{bulk}} \)) or pixel (\( E_{s,i} \)) scale
\[ r'_{sj} \] local canopy surface resistance, at bulk (\( r'_{s,\text{bulk}} \)) or pixel (\( r'_{s,i} \)) scale
\[ T_j \] local canopy surface temperature, at bulk (\( T_{\text{bulk}} \)) or pixel (\( T_i \)) scale
\[ e'_{j} \] saturated vapor pressure at stomatal pore surface (at \( T_j \))
\[ \Delta_j \] slope of the saturation vapor pressure curve at \( T_j \)

Variables defined for the submodel:

\[ r_{st,rep} \] any representative value of stomatal resistance (e.g., from porometer measurements or literature)
\[ T_{rep} \] leaf temperature corresponding to \( r_{st,rep} \)
\[ r'_{rep} \] canopy surface resistance corresponding to \( r_{st,rep} \) (see (7))
\[ g_{st,i} \] stomatal conductance at pixel location \( i \)
\[ r_{st,i} \] stomatal resistance at pixel location \( i \)
\[ T_i \] canopy temperature at pixel location \( i \) (from TIR imagery)
\[ g_{st,m} \] maximum stomatal conductance of canopy of interest (not required by submodel)
\[ T_m \] temperature of maximum stomatal conductance of canopy of interest (similar to temperature of maximum assimilation; typically available from the literature)
\[ \omega \] shape parameter defining with of \( g_{st}(T) \) parabola (see (8)), derived by submodel
\[ E_{\text{aggregate}} \] total (mean) evapotranspiration from all \( i = 1:N \) pixels (see (10))
\[ \delta \] the discrepancy between the total evapotranspiration values calculated at the bulk (\( E_{\text{bulk}} \)) and pixel (\( E_{\text{aggregate}} \)) scales (see (11)): to conserve energy between the pixel and bulk scales, \( \delta \) should be zero

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References


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