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Multidimensional Disaggregation of Land Surface Temperature Using High-Resolution Red, Near-Infrared, Shortwave-Infrared, and Microwave-L Bands

Olivier Merlin, Frédéric Jacob, Jean-Pierre Wigneron, Jeffrey Walker, and Ghani Chehbouni

Abstract—Land surface temperature data are rarely available at high temporal and spatial resolutions at the same locations. To fill this gap, the low spatial resolution data can be disaggregated at high temporal frequency using empirical relationships between remotely sensed temperature and fractional green (photosynthetically active) and senescent vegetation covers. In this paper, a new disaggregation methodology is developed by physically linking remotely sensed surface temperature to fractional green and senescent vegetation covers using a radiative transfer equation. Moreover, the methodology is implemented with two additional factors related to the energy budget of irrigated areas, being the fraction of open water and soil evaporative efficiency (ratio of actual to potential soil evaporation). The approach is tested over a 5 km by 32 km irrigated agricultural area in Australia using airborne Polarimetric L-band Multibeam Radiometer brightness temperature and spaceborne Advanced Scanning Thermal Emission and Reflection radiometer (ASTER) multispectral data. Fractional green vegetation cover, fractional senescent vegetation cover, fractional open water, and soil evaporative efficiency are derived from red, near-infrared, shortwave-infrared, and microwave-L bands. Low-resolution land surface temperature is simulated by aggregating ASTER land surface temperature to 1-km resolution, and the disaggregated temperature is verified against the high-resolution ASTER temperature data initially used in the aggregation process. The error in disaggregated temperature is successively reduced from 1.65 °C to 1.16 °C by including each of the four parameters. The correlation coefficient and slope between the disaggregated and ASTER temperatures are improved from 0.79 to 0.89 and from 0.63 to 0.88, respectively. Moreover, the radiative transfer equation allows quantification of the impact on disaggregation of the temperature at high resolution for each parameter: fractional green vegetation cover is responsible for 42% of the variability in disaggregated temperature, fractional senescent vegetation cover for 11%, fractional open water for 20%, and soil evaporative efficiency for 27%.

Index Terms—Advanced Scanning Thermal Emission and Reflection radiometer (ASTER), brightness temperature, disaggregation, evaporative efficiency, land surface temperature, Moderate Resolution Imaging Spectroradiometer (MODIS), multispectral, open water, soil moisture, vegetation fraction.

I. INTRODUCTION

Remotely sensed land surface temperature is a signature of the thermodynamic equilibrium state of the surface skin. Consequently, it provides the potential to monitor dynamic information on instantaneous energy and water fluxes at the land-surface–atmosphere interface. Nevertheless, the operational use of thermal remote sensing for hydrological and water resource management studies has been limited to regional scale applications (e.g., [1] and [2]) mainly because the spatial resolution (larger than 1 km) of current high temporal resolution thermal sensors is too coarse to represent the heterogeneity of man-made landscapes. For example, the Moderate Resolution Imaging Spectroradiometer (MODIS) has a revisit frequency of 1 or 2 times per day but a spatial resolution of only 1 km, while the Advanced Scanning Thermal Emission and Reflection radiometer (ASTER) has a spatial resolution of 90 m but a 61 revisit time of only 16 days.

The use of remotely sensed land surface temperature over agricultural areas requires data at both high spatial and temporal resolutions [3]. While there is a lack of high spatial resolution thermal data from satellite with high frequency, there is the potential for land surface temperature derived from kilometre-resolution sensors having high temporal resolution to be disaggregated using high spatial resolution ancillary data. The first disaggregation approach of remotely sensed temperature was developed by [4] using the fractional green vegetation cover derived from red and near-infrared reflectances. Given the high temperature difference between bare soil and a well-watered crop, this approach has proved to be effective over 74 areas with relatively uniform soil and vegetation hydric status. Recently, [5] has extended the approach of [4] to conditions where vegetation hydric status is heterogeneous. This required developing a methodology to estimate the fraction of senescent vegetation cover from a time series of FORMOSAT-2 images.

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The accuracy in disaggregated temperature was improved by taking into account fractional senescent vegetation cover in addition to fractional green vegetation cover.

Fractional green and senescent vegetation covers, however, are not the only factors explaining the spatial variations of land surface temperature, especially over irrigated areas where crop fields may have different moisture status to the surrounds. In particular, the temperature over a flooded crop field may be drastically different from the temperature over a mature crop field. Therefore, the fraction of open water is an important variable to represent the spatial variations of land surface temperature. Over nonwatered land surfaces, the soil evaporative efficiency (ratio of actual to potential soil evaporation) is a signature of the capacity of the soil to evaporate its water content in the near surface and thus to counter an increase of its thermodynamic temperature. Consequently, soil evaporative efficiency is also an essential variable to describe the spatial variations of land surface temperature. Moreover, knowledge of soil evaporative efficiency is needed to decouple the effects of soil and vegetation hydric status on the surface energy budget and hence to better represent the resultant radiative surface temperature. As an example, the crop water stress index (CWSI) [6], [7] can be used to detect plant stress based on the difference between foliage and air temperature. Nevertheless, the application of the CWSI to partially vegetated areas is subjected to large uncertainties because the soil background may have a different temperature to the plants [7] depending on soil evaporative efficiency. Another example is provided by Moran et al. [8] who proposed the vegetation index/temperature (VIT) trapezoid to estimate a most probable range of plant stress over partially vegetated fields. It is a three-step procedure in which the following steps are performed: 1) the temperatures of the four vertices of the VIT trapezoid are estimated using an energy budget model; 2) the minimum and maximum probable vegetation temperatures are estimated from the measured composite land surface temperature, together with the maximum and minimum simulated soil temperatures; and 3) the minimum and maximum probable CWSIs are computed by normalizing the minimum and maximum probable vegetation temperatures from the vegetation temperature extremes simulated by the energy budget model. The point is that this approach does not allow estimating a single CWSI value because the retrieval problem is underdetermined. In particular, Moran et al. [8] noted that “with knowledge of a second point within the hourglass (perhaps soil temperature), it would be possible to infer [the canopy-air temperature] difference and pinpoint the CWSI value.” In the latter case, knowledge of soil temperature is equivalent to knowledge of soil evaporative efficiency, which would remove the underdetermination of the VIT trapezoid.

The objective of this paper is to develop a new disaggregation methodology of kilometric land surface temperature using hectometric multivariable ancillary data. The approach is based on a radiative transfer equation that estimates differences in temperature data at hectometric resolution. Specifically, the use of a radiative transfer equation allows the following: 1) including variables other than those used by previous disaggregation approaches and 2) deducing the most pertinent variables. In addition to fractional green and senescent vegetation covers, the new methodology includes the variability at hectometric resolution of fractional open water and soil evaporative efficiency. With respect to other disaggregation algorithms in literature [4], [5], the proposed technique differs in the following four main aspects: 1) it relies on a physically based radiative transfer equation rather than empirical linear regressions; 2) it takes into account the fractional open water derived from shortwave-infrared band as required; 3) it takes into account the soil hydric status via microwave-derived soil evaporative efficiency; and 4) it allows the relative weight of each parameter used for 147 disaggregating temperature to be quantified.

The new disaggregation technique is compared to the existing approaches using data collected during the National Airborne Field Experiment in 2006 (NAFE’06; [9]). The ex-perimental site covers a 5 km by 32 km irrigated agricultural area, which included approximately 5% of flooded rice crops 153 during NAFE’06. Disaggregation algorithms are first tested by 154 aggregating ASTER temperature at 1-km resolution and by 155 comparing the disaggregated temperature to the high-resolution 156 ASTER temperature initially used in the aggregation process. 157 The application to aggregated ASTER data allows evaluating 158 approaches independently of differences between ASTER and MODIS products [5]. Disaggregation algorithms are then applied to MODIS data.

II. Experimental Data

The study area is a 5 km by 32 km area included in the 163 Coleambally Irrigation Area (CIA) located in the flat west-164 ern plains of the Murrumbidgee catchment in southeastern 165 Australia (35° S, 146° E). The principal summer crops grown 166 in the CIA are rice, maize, and soybeans, while winter crops 167 include wheat, barley, oats, and canola. In November, rice crops 168 are flooded under 30 cm height of irrigation water.

The NAFE’06 was conducted from October 31 to 170 November 20, 2006, over a 40 km by 60 km area, with more 171 detailed flights over the 5 km by 32 km focus area studied 172 in this paper. While a full description of the NAFE’06 data 173 set is given in [9], a brief overview of the most pertinent 174 details is provided here. The data used in this paper are 175 comprised of airborne L-band brightness temperature; ASTER 176 red, near-infrared, and shortwave-infrared reflectances; ASTER 177 land surface temperature data (resampled at 250-m resolution); 178 MODIS land surface temperature data; and air temperature data 179 collected by a meteorological station in the NAFE’06 area.

A. PLMR

The Polarimetric L-band Multibeam Radiometer (PLMR) is an airborne instrument that measures both H and V polariza-183 tions using a single receiver with polarization switching at view angles of ±7°, ±21.5°, and ±38.5°. The accuracy of the PLMR is estimated to be better than 2 K and 3 K in the H and V polarization, respectively [10].

During NAFE’06, the PLMR flew on November 14 to collect L-band brightness temperature at 250-m resolution over the 189 5 km by 32 km area in the CIA. PLMR was mounted in the 190 across-track configuration so that each pixel was observed at a 191
given incidence angle (approximately 7°, 21.5°, or 38.5°). Data were processed for incidence angle and beam location on the ground by taking into account aircraft position, attitude, and ground topography.

As the sensitivity to soil moisture is higher for H-polarized brightness temperature than for V-polarized brightness temperature, only the H-polarized brightness temperature TB is used in this paper. Preprocessing of TB consists of the following: 1) resampling H-polarized PLMR data at 250-m resolution on a grid that matches in symmetry to the flight lines over the 5 km by 32 km area and 2) converting the resampled TB to an equivalent value at 21.5° incidence angle. The incidence angle 21.5° is chosen to minimize conversion errors.

The angular conversion involves the brightness temperature collected by inner beams at approximately 7° incidence angle being multiplied by the ratio \( \frac{TB_{MB}}{TB_{OB}} \), with \( TB_{MB} \) and \( TB_{OB} \) being the mean brightness temperatures collected by the middle and inner beams, respectively. Similarly, the brightness temperature collected by the outer beams at approximately 38.5° incidence angle is multiplied by the ratio \( \frac{TB_{OB}}{TB_{DB}} \), with \( TB_{DB} \) being the mean brightness temperature collected by the outer beams. Mean brightness temperatures \( TB_{MB}, TB_{OB}, \) and \( TB_{DB} \) are computed as the average (for all flight lines) of the \( TB \) collected by the beams pointing at \( \pm 7°, \pm 21.5°, \) and \( \pm 38.5° \), respectively. This technique was already used in [11] to generate TB images by assuming that the impact of soil moisture and biomass on the angular dependence of TB is negligible or small. In this paper, a slightly different approach is adopted to take into account the variations in aircraft attitude during data collection, which made the incidence angle \( \theta \) os- cillate around 7°, 21.5°, and 38.5°. The brightness temperature \( TB(\theta) \) observed at the incidence angle \( \theta \) is multiplied by the ratio \( \frac{TB_{MB}}{TB_{interp}(\theta)} \), with \( TB_{interp}(\theta) \) being the mean brightness temperature linearly interpolated at \( \theta \) incidence angle from the mean data collected by the inner, middle, and outer beams.

### B. ASTER

The ASTER instrument was launched in 1999 aboard Terra, a sun synchronous platform with 11:00 UTC descending Equator crossing and a 16-day revisit cycle. An ASTER scene covers an area of approximately 60 km by 60 km and consists of 14 nadir-looking bands and one oblique-looking band to create stereo-based digital elevation models. The three nadir-looking bands in the visible and near infrared have a 15-m resolution. The six bands in the shortwave-infrared have a 30-m resolution. Finally, there are five thermal infrared bands with a 90-m resolution.

The ASTER overpass of the NAFe’06 site was on November 16, 2006. Official ASTER products [12] were used here for surface reflectance (AST_07) and radiometric temperature (AST_08) with accuracies of 5% and 1.5 K, respectively [13]–[19]. They were downloaded from the Earth Observing System Data Gateway (EDG).

ASTER 15-m resolution red (B2) and near-infrared (B3) bands were extracted over the 5 km by 32 km area and resampled at 250-m resolution to match the spatial resolution and extent of PLMR observations. The ASTER 30-m resolution B5 band (1.60–1.70 μm) was extracted over the 5 km by 32 km study area and resampled at 50-m resolution. Fractional open water was estimated using B5 band [20] based on a 250 threshold method. Consequently, B5 data were resampled at a resolution finer than that (250 m) of PLMR data to classify open water pixels at 50-m resolution and to obtain fractional open water at 250-m resolution from the binary classification.

### C. MODIS

The MODIS/Terra data were collected concurrently with ASTER data: MODIS official products consisted of the 928-m resolution surface skin temperature (MOD11-L2) retrieved by the “generalized split window” algorithm [22]–[24] and registered in the sinusoidal projection. The MODIS Reprojection Tool was used to project MOD11-L2 data in UTM WGS 1984 55S with a sampling interval of 1 km.

In this paper, the disaggregation of 1-km MODIS temperature is evaluated using high-resolution ASTER data. To distinguish the errors associated with the disaggregation technique and the errors associated with the discrepancy between MODIS and ASTER temperature products, a comparison is made between ASTER and MODIS data at 1-km resolution over the 5 km by 32 km study area. The ASTER data are aggregated at the MODIS spatial resolution (1 km) by linearly averaging high-resolution temperatures. The root-mean-square difference (RMSD), bias, correlation coefficient, and slope of the linear regression between MODIS and aggregated ASTER data are 2.7 °C, −2.3 °C, 0.75, and 0.52, respectively. The discrepancy regression between MODIS and ASTER data, which is mainly explained here by a significant bias and a relatively low slope of the linear regression, is on the same order of magnitude as the mean difference (about 3 °C) reported in literature [5], [21], [25].

### III. DISAGGREGATION ALGORITHMS

This paper aims to compare different approaches for disaggregating kilometric MODIS land surface temperature data. The study uses aggregated ASTER and real MODIS data and demonstrates the disaggregation at 250-m resolution. The resolution of 250 m is chosen to match with the lowest resolution at which ancillary data composed of red, near-infrared, shortwave-infrared, and microwave-L bands are available. In this case study, the target scale is determined by the resolution (250 m) of airborne microwave data.

As shown in the schematic diagram of Fig. 1, the disaggregation algorithms are noted as \( Di_k \), with \( k \) being the number of factors taken into account in the disaggregation. The new
Using D1, the disaggregated temperature is computed as

$$T^{(1)} = T_{km} + a_1 \times (f_{gv} - \langle f_{gv}\rangle_{km}) \quad (2)$$

with $f_{gv}$ being the fractional green vegetation cover derived at high resolution, $\langle f_{gv}\rangle_{km}$ being the $f_{gv}$ aggregated at kilometric resolution, and $a_1$ being the slope of the linear regression 330 between $T_{km}$ and $\langle f_{gv}\rangle_{km}$. Note that the variables defined at 331 kilometric resolution are noted with the subscript km.

Using D2, the disaggregated temperature is computed as

$$T^{(2)} = T_{km} + a_{1}^{proj} \times (f_{gp}^{proj} - \langle f_{gv}\rangle_{km}) \quad (3)$$

with $f_{gp}^{proj}$ being the projected $f_{gv}$ and $a_{1}^{proj}$ being the slope of the linear regression between $T_{km}$ and the projected $f_{gv}$ estimated at kilometric resolution $f_{gv,km}$. Note that the variables 336 defined at the image scale are written in bold. The notion of 337 a “projected variable” was introduced in [26]. It is a robust 338 tool that strengthens the correlation between two variables by 339 representing the dependence of these variables on other addi- 340 tional variables. In [5], the projection technique was applied 341 to fractional green vegetation cover to artificially improve the 342 spatial correlation between $T$ and $f_{gv}$ by taking into account 343 the dependence of $T$ on $f_{gv}$. The projected fractional green 344 vegetation cover is computed as

$$f_{gp}^{proj} = f_{gv} - \frac{T_{fcsv} - (T_{b,ds} + T_{b,ws})/2}{T_{fcsv} - T_{fgsv}} \times (f_{tv} - \langle f_{tv}\rangle_{km}) \quad (4)$$

with $f_{tv}$ being the fractional total vegetation cover derived at high resolution, $\langle f_{tv}\rangle_{km}$ being the $f_{tv}$ aggregated at kilometric resolution, $T_{b,ws}$ being the temperature of wet bare soil, $T_{b,ds}$ being the temperature of dry bare soil, $T_{fgsv}$ being the temperature of full-cover green vegetation, and $T_{fcsv}$ being the temperature of full-cover senescent vegetation (notations 351 are summarized in Table I). Following the interpretation of 352 the “triangle method” [27], $\langle f_{tv}\rangle_{km}$, $T_{b,ds}$, $T_{b,ws}$, $T_{fgsv}$, and $T_{fcsv}$ 353 correspond to the minimum and maximum soil and vegetation 354 temperatures within the study area, respectively. It is reminded 355 that $f_{tv} = f_{gv} + f_{sv}$, with $f_{gv}$ and $f_{sv}$ being the fractional 356 green and senescent vegetation covers, respectively.

In (4), the projected fractional green vegetation cover esti- 358 mated at kilometric resolution is

$$f_{gp}^{proj} = \langle f_{gv}\rangle_{km} - \frac{T_{fcsv} - (T_{b,ds} + T_{b,ws})/2}{T_{fcsv} - T_{fgsv}} \times (f_{tv} - \langle f_{tv}\rangle_{km}) \quad (5)$$

with $f_{tv}$ being the mean $f_{tv}$ over the whole study area.

The new algorithms D’ use a radiative transfer equation 361 to model the spatial variability of disaggregated temperature 362 within each 1-km resolution pixel, using ancillary data available at high resolution such as $f_{gv}$, $f_{tv}$, $f_{ow}$, and $\beta$. D1’ is 364 a substitute for D1 based on radiative transfer. It expresses 365 disaggregated temperature as

$$T^{(1')} = T_{km} + \Delta T^{(1')} \quad (6)$$
with $\Delta T^{(1)}$ being the difference between the temperature simulated using high-resolution $f_{gv}$, and that aggregated within the 1-km resolution pixel

$$\Delta T^{(1)} = T_{mod} (f_{gv}, f_{tv}, f_{ow}, \langle \beta \rangle_{km}) - \langle T_{mod} (f_{gv}, f_{tv}, f_{ow}, \langle \beta \rangle_{km}) \rangle_{km}. \quad (7)$$

$T_{mod}$ being the land surface temperature simulated by a radiative transfer equation. In (7), fractional total vegetation cover, fractional open water, and soil evaporative efficiency are set to their values aggregated at kilometric resolution. Therefore, only the variability of $f_{gv}$ is taken into account at high resolution.

$D'2$ is a substitute for D2 based on radiative transfer. It expresses the disaggregated temperature as in (6), with the simulated temperature difference $\Delta T^{(2)}$ written as

$$\Delta T^{(2)} = T_{mod} (f_{gv}, f_{tv}, f_{ow}, \langle \beta \rangle_{km}) - \langle T_{mod} (f_{gv}, f_{tv}, f_{ow}, \langle \beta \rangle_{km}) \rangle_{km}. \quad (8)$$

$D'3$ is derived from the same radiative transfer equation and includes the variability of $f_{gv}$, $f_{tv}$, and $f_{ow}$ at high resolution. It determines the disaggregated temperature using (6) but with the simulated temperature difference $\Delta T^{(3)}$ written as

$$\Delta T^{(3)} = T_{mod} (f_{gv}, f_{tv}, f_{ov}, \langle \beta \rangle_{km}) - \langle T_{mod} (f_{gv}, f_{tv}, f_{ow}, \langle \beta \rangle_{km}) \rangle_{km}. \quad (9)$$

$D'4$ is derived from the same radiative transfer equation and includes the variability of $f_{gv}$, $f_{tv}$, $f_{ow}$, and $\beta$ at high resolution. It determines the disaggregated temperature using (6) but with the simulated temperature difference $\Delta T^{(4)}$ written as

$$\Delta T^{(4)} = T_{mod} (f_{gv}, f_{tv}, f_{ow}, \beta) - \langle T_{mod} (f_{gv}, f_{tv}, f_{ow}, \beta) \rangle_{km}. \quad (10)$$

$D'4''$ is an extension of (10) to replace $\beta$ by another formulation of soil evaporative efficiency noted as $\beta'$. The high- to low-resolution simulated temperature difference in (7)–(10) is computed using a linearized radiative transfer equation [5], [28], [29]. Modeled land surface temperature $T_{mod}$ is written as

$$T_{mod} = f_{ow} T_{ow} + (1 - f_{ow}) T_{nw} \quad (11)$$

with $T_{ow}$ being the surface temperature of a water body and $T_{nw}$ being the skin temperature of a nonwatered land surface.

Nonwatered land surface temperature is expressed as

$$T_{nw} = f_{gv} T_{fgv} + (f_{tv} - f_{gw}) T_{fsv} + (1 - f_{tv}) T_{bs} \quad (12)$$

with $T_{fgv}$ and $T_{fsv}$ being the temperature of full-cover green and senescent vegetation, respectively, and $T_{bs}$ being the bare soil temperature. With the soil evaporative efficiency defined [30] as

$$\beta = \frac{T_{b,ds} - T_{bs}}{T_{b,ds} - T_{b,ws}} \quad (13)$$

the bare soil temperature can be expressed as

$$T_{bs} = \beta T_{b,ws} + (1 - \beta) T_{b,ds}. \quad (14)$$

By assuming that water temperature is close to well-watered green vegetation [27], modeled land surface temperature becomes

$$T_{mod} = f_{ow} T_{fgv} + (1 - f_{ow}) T_{nw} \quad (15)$$

with the nonwatered land surface temperature expressed as

$$T_{nw} = f_{gv} T_{fgv} + (f_{tv} - f_{gw}) T_{fsv} + (1 - f_{tv}) \left[ \beta T_{b,ws} + (1 - \beta) T_{b,ds} \right]. \quad (16)$$

The temperature extremes $T_{b,ds}$, $T_{b,ws}$, $T_{fgv}$, and $T_{fsv}$ are extrapolated (according to Section V) from low-resolution land surface temperatures using high-resolution ancillary data [5].

### IV. Derivation of Biophysical Variables

The four variables used by the disaggregation methodology are the following: fractional green vegetation cover $f_{gw}$, fractional total (green plus senescent) vegetation cover $f_{tv}$, fractional open water $f_{ow}$, and soil evaporative efficiency $\beta$. All of these variables are estimated from ASTER red, near-infrared, and shortwave-infrared reflectance products and from the PLMR H-polarized brightness temperature converted at an incidence angle of 21.5°.

#### A. Fractional Green Vegetation Cover

Fractional green vegetation cover can be estimated from the Normalized Difference Vegetation Index (NDVI) as in [31]

$$f_{gv} = \frac{\text{NDVI} - \text{NDVI}_{bs}}{\text{NDVI}_{fgv} - \text{NDVI}_{bs}} \quad (17)$$

<table>
<thead>
<tr>
<th>Vertex</th>
<th>Surface type</th>
<th>Near-surface soil hydric status</th>
<th>Abbreviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Bare soil</td>
<td>Dry</td>
<td>b,ds</td>
</tr>
<tr>
<td>B</td>
<td>Bare soil</td>
<td>Wet</td>
<td>b,ws</td>
</tr>
<tr>
<td>C</td>
<td>Full-cover green vegetation</td>
<td>Wet or dry</td>
<td>fegv</td>
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<td>C'</td>
<td>Full-cover green vegetation</td>
<td>Wet</td>
<td>fegv,ws</td>
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<td>C''</td>
<td>Full-cover green vegetation</td>
<td>Dry</td>
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<tr>
<td>D</td>
<td>Full-cover senescent vegetation</td>
<td>Wet or dry</td>
<td>fesv</td>
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<tr>
<td>D'</td>
<td>Full-cover senescent vegetation</td>
<td>Dry</td>
<td>fesv,ds</td>
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</tbody>
</table>
Fractional Total (Green Plus Senescent) Vegetation Cover

Fractional total vegetation cover is estimated by correlating $f_{tv}$ with surface albedo for green vegetation and by setting $f_{tv}$ to the maximum $f_{gv}$ for senescent vegetation. This methodology is based on two assumptions, which are generally met in agricultural areas: 1) soil albedo is generally lower than green vegetation albedo, and 2) green vegetation albedo is lower than senescent vegetation albedo. Although a time series of red and near-infrared data would be required to estimate soil albedo and green vegetation albedo on a pixel-by-pixel basis [5], only one ASTER scene is available for this study period. Therefore, an alternate approach is adopted. Surface albedo is modeled as a linear mixing of vegetation and soil components (e.g., [32] and [33])

$$\alpha = (1 - f_{tv})\alpha_{bs} + f_{gv}\alpha_{fgv} + (f_{tv} - f_{gv})\alpha_{fsv} \quad (18)$$

with $\alpha_{bs}$, $\alpha_{fgv}$, and $\alpha_{fsv}$ being the albedo for bare soil, full-cover green vegetation, and full-cover senescent vegetation, respectively, and with the end-members $\alpha_{bs}$, $\alpha_{fgv}$, and $\alpha_{fsv}$ estimated in Section V.

By inverting (18), fractional vegetation cover is expressed as

$$f_{tv} = \frac{\alpha - \alpha_{fs} + f_{gv}(\alpha_{fsv} - \alpha_{fgv})}{\alpha_{fsv} - \alpha_{bs}} \quad (19)$$

with $\alpha$ being the surface albedo estimated as a weighted sum of red and near-infrared reflectances using the coefficients given in [445] and validated in [45–38]. As stated previously, our case study does not allow calibrating $\alpha_{bs}$, $\alpha_{fgv}$, and $\alpha_{fsv}$ on a 447 pixel-by-pixel basis. Consequently, the value of $f_{tv}$ computed from (19) may, on some occasions, be lower than $f_{gv}$ or larger than 1. To avoid nonphysical values, $f_{tv}$ is set to $f_{gv}$ and 1 in the former and latter case, respectively.

The spatial variation of fractional senescent vegetation cover $(f_{sv} = f_{tv} - f_{gv})$ over the study area is shown in Fig. 2. Note that NAFE’06 was undertaken at the beginning of the summer agricultural season so that all irrigated crops were green and healthy.

C. Fractional Open Water

The fraction of open water within each 250-m resolution pixel is estimated using 50-m resolution resampled ASTER B5 reflectance product. Various studies have indicated that the 460 shortwave-infrared band centered at around 1 $\mu$m is highly sensitive to the presence of open water [20], [39], [40]. In this 462 paper, a simple threshold method is applied to classify at 50-m 463 resolution the 5 km by 32 km area in two classes: water and nonwatered surface. The threshold value is estimated as 0.170 from one flooded crop field in the south of the study area. The 466 spatial variation of fractional open water over the study area is shown in Fig. 2. Open water represents 5% of the study area and is attributed to rice cropping.

D. Soil Evaporative Efficiency

Soil evaporative efficiency $\beta$ is defined as the ratio of actual 471 potential soil evaporation. In this paper, $\beta$ is estimated from 472 PLMR brightness temperatures. Two different formulations are used to evaluate the coupling effects of near-surface soil moisture, $f_{sv}$, and $f_{sv}$ on microwave-derived soil evaporative efficiency.

By assuming that brightness temperature is mainly sensitive 477 to surface soil moisture [41] and that soil evaporative efficiency is 478 mainly driven by surface soil moisture [42], [43], soil evaporative efficiency can be estimated as

$$\beta = 1 - \frac{TB - TB_{b,ws}}{TB_{fsv,ds} - TB_{b,ws}} \quad (20)$$

with $TB_{b,ws}$ and $TB_{fsv,ds}$ being the minimum and maximum brightness temperatures observed over the study area, respectively. As brightness temperature generally decreases 483 with surface soil moisture and increases with vegetation cover 484 [44], $TB_{b,ws}$ and $TB_{fsv,ds}$ are interpreted as the brightness 485 temperatures over wet bare soil and full-cover senescent vege- 486 tion with dry soil, respectively. The spatial variation of $\beta$ over 487 the study area is shown in Fig. 2.

Since brightness temperature also depends on biomass (e.g., 489 [45]), a second formulation of soil evaporative efficiency $\beta'$ is 490...
491 derived in order to decouple the effects of soil moisture, \( f_{sv} \), and \( f_{sv} \) on \( T_B \). As in [46], the assumption is that, for a given 492 vegetated pixel, if vegetation is partially stressed (i.e., \( f_{sv} > 0 \) 493 or \( f_{sv} > f_{sv} \)), then near-surface soil moisture availability is 494 zero (i.e., \( \alpha = 0 \)). Alternatively, if that pixel does not contain 495 senescent vegetation (i.e., \( f_{sv} = 0 \) or \( f_{sv} = f_{sv} \)), then \( \beta \) is 496 computed as the ratio of the measured “dry soil” brightness 497 temperature difference to the “dry soil”–“wet soil” brightness 498 temperature difference. Formally, one writes

\[
\beta' = 0 \quad \text{if} \quad T_B > T_{B_{ds}} \\
\beta' = 1 - \frac{T_B - T_{B_{ws}}}{T_{B_{ds}} - T_{B_{ws}}} \quad \text{if} \quad T_B \leq T_{B_{ds}}
\]

500 with \( T_{B_{ds}} \) and \( T_{B_{ws}} \) being the “dry soil” and “wet soil” 501 brightness temperatures, respectively, both being estimated for 502 \( f_{sv} = 0 \). Since green vegetation is partially transparent to mi- 503 crowaves, the “dry soil” brightness temperature is computed as 504 a weighted sum of the brightness temperature over dry bare soil 505 (noted as \( T_{B_{b,ds}} \)) and the brightness temperature over full- 506 cover green vegetation with dry soil (noted as \( T_{B_{fgv,ds}} \))

\[
T_{B_{ds}} = f_{sv} T_{B_{fgv,ds}} + (1 - f_{sv}) T_{B_{b,ds}}.
\]

507 Similarly, the “wet soil” brightness temperature is computed as 508 a weighted sum of the brightness temperature over wet bare soil 509 (noted as \( T_{B_{b,ws}} \)) and the brightness temperature over full- 510 cover green vegetation with wet soil (noted as \( T_{B_{fgv,ws}} \))

\[
T_{B_{ws}} = f_{sv} T_{B_{fgv,ws}} + (1 - f_{sv}) T_{B_{b,ws}}.
\]

511 The spatial variation of \( \beta' \) over the study area is shown in Fig. 2.

### V. Estimating End-Members

513 A key step in the disaggregation procedure is estimating 514 the 14 end-members from ASTER and PLMR data. They 515 are composed of the following: \( NDVI_{bs} \), \( NDVI_{fgv} \), \( \alpha_{bs} \), 516 \( \alpha_{fgv} \), \( \alpha_{fgs} \), \( T_{b,ws} \), \( T_{b,ds} \), \( T_{fgv} \), \( T_{fgs} \), \( T_{bs,ws} \), \( T_{bs,ds} \), 517 \( T_{fgv,ws} \), \( T_{fgv,ds} \), and \( T_{fgs,ds} \). For the convenience 518 of the reader, the unit is degree Celsius for radiometric tempera- 519 ture and kelvin for brightness temperature.

#### A. NDVI

521 NDVI end-members are estimated as the minimum and maxi- 522 mum values of NDVI observed over the 5 km by 32 km area for 523 bare soil and full-cover green vegetation, respectively. Values 524 for \( NDVI_{bs} \) and \( NDVI_{fgv} \) are reported in Table II.

<table>
<thead>
<tr>
<th>End-member</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>( NDVI_{bs} )</td>
<td>0.15</td>
<td>-</td>
</tr>
<tr>
<td>( NDVI_{fgv} )</td>
<td>0.65</td>
<td>-</td>
</tr>
<tr>
<td>( \alpha_{bs} )</td>
<td>0.17</td>
<td>-</td>
</tr>
<tr>
<td>( \alpha_{fgv} )</td>
<td>0.22</td>
<td>-</td>
</tr>
<tr>
<td>( \alpha_{fgs} )</td>
<td>0.31</td>
<td>-</td>
</tr>
</tbody>
</table>

#### B. Albedo

536 Fig. 3 shows the space defined by surface albedo \( \alpha \) and 537 fractional green vegetation cover \( f_{sv} \). Pixels including open 538 water are removed from the scatterplot. The soil albedo \( \alpha_{bs} \) 539 is defined as the minimum ASTER surface albedo observed 540 within the study area by assuming that the dependence of 541 \( \alpha_{bs} \) on soil moisture is small compared to the dependence of 542 \( \alpha \) on vegetation cover. The green vegetation albedo \( \alpha_{fgv} \) is 543 estimated as the surface albedo corresponding to maximum 544 fractional green vegetation cover. The senescent vegetation 545 albedo \( \alpha_{fgs} \) is estimated as the maximum surface albedo 546 observed within the study area. Values for \( \alpha_{bs} \), \( \alpha_{fgv} \), and 547 \( \alpha_{fgs} \) are reported in Table II.

#### C. Land Surface Temperature

549 As the range of surface conditions varies with spatial res- 550 olution, two different procedures are developed to estimate 551 temperature end-members.

1) When estimating temperature end-members from 250-m resolution data, one pixel is identified as fully covered 554 green vegetation, one pixel as fully covered senescent 555 vegetation, one pixel as bare dry soil, and one pixel as 556 bare wet soil. In this case, it is assumed that all extreme 557 conditions are included at high resolution within the study 558 domain.

In this paper, the study domain included extreme conditions 525 in terms of vegetation cover so that NDVI end-members could 526 be estimated from the red and near-infrared reflectances ac- 527 quired over the area on a single date. In the case where extreme 528 conditions are not encountered in the application domain, a 529 different approach should be adopted, such as the use of a time 530 series of NDVI data (instead of a single snapshot image) that 531 would capture the phenological stages of agricultural crops. 532 Also, the determination of reflectance end-members could 533 be further constrained by the use of ancillary spectral data 534 sets [47].

553

Fig. 3. ASTER surface albedo \( \alpha \) plotted against ASTER fractional green vegetation cover \( f_{sv} \). Three particular values of \( \alpha \) are identified: the soil albedo \( \alpha_{bs} \) estimated as the minimum surface albedo, the green vegetation albedo \( \alpha_{fgv} \) estimated as the albedo corresponding to the largest \( f_{sv} \), and the senescent vegetation albedo \( \alpha_{fgs} \) estimated as the maximum surface albedo.

535
TABLE III
LAND SURFACE TEMPERATURE AND L-BAND BRIGHTNESS TEMPERATURE END-MEMBERS THAT ARE ESTIMATED FROM HIGH-RESOLUTION ASTER TEMPERATURE DATA, EXTRAPOLATED FROM AGGREGATED ASTER TEMPERATURE DATA, AND EXTRAPOLATED FROM MODIS TEMPERATURE DATA. FOR THE CONVENIENCE OF THE READER, THE UNIT IS DEGREE CELSIUS FOR RADIOMETRIC TEMPERATURE AND KELVIN FOR BRIGHTNESS TEMPERATURE

<table>
<thead>
<tr>
<th>End-member</th>
<th>High-resolution</th>
<th>Aggregated ASTER</th>
<th>MODIS</th>
</tr>
</thead>
<tbody>
<tr>
<td>(T_{b,bs})</td>
<td>38</td>
<td>40.2</td>
<td>38.9</td>
</tr>
<tr>
<td>(T_{b,ws})</td>
<td>25</td>
<td>27.6</td>
<td>26.2</td>
</tr>
<tr>
<td>(T_{fcgv})</td>
<td>21</td>
<td>21.0</td>
<td>21.0</td>
</tr>
<tr>
<td>(T_{fesv})</td>
<td>34</td>
<td>32.0</td>
<td>28.7</td>
</tr>
<tr>
<td>(T_{b,ds})</td>
<td>240</td>
<td>246</td>
<td>241</td>
</tr>
<tr>
<td>(T_{b,ws})</td>
<td>190</td>
<td>193</td>
<td>193</td>
</tr>
<tr>
<td>(T_{b,gs,ws})</td>
<td>205</td>
<td>205</td>
<td>205</td>
</tr>
<tr>
<td>(T_{b,gs,ds})</td>
<td>240</td>
<td>240</td>
<td>240</td>
</tr>
<tr>
<td>(T_{fesv,ds})</td>
<td>280</td>
<td>280</td>
<td>280</td>
</tr>
</tbody>
</table>

2) When estimating temperature end-members from 1-km resolution data (as in the operational scenario), none of the pixels are identified as representative of any extreme condition. Temperature end-members are extrapolated from 1-km temperature data using ancillary data composed of air temperature, soil albedo, green vegetation albedo, and senescent vegetation albedo as described in the following.

End-members \(T_{b,ws}\), \(T_{b,ds}\), \(T_{fcgv}\), and \(T_{fesv}\) are determined by analyzing the consistency of the diagrams in Fig. 4. Fig. 4(a) shows the space defined by ASTER land surface temperature and ASTER fractional green vegetation cover. The three edges of the triangle \(T - f_{gv}\) are interpreted [27] as “bare soil” between A and B, “wet surface” between B and C, and “dry soil” between C and A. Fig. 4(b) shows the space defined by ASTER land surface temperature and ASTER surface albedo. An interpretation of the polygon \(T - \alpha\) is provided in [5], which is consistent with the triangle method. The four edges are interpreted as “bare soil” between A and B, “wet surface” between B and C, “full cover” between C and D, and “dry surface” between D and A. The notation for polygon vertices A, B, C, and D is summarized in Table I, and the corresponding temperature values \(T_{b,ds}\), \(T_{b,ws}\), \(T_{fcgv}\), and \(T_{fesv}\) are reported in Table III.

In this paper, high-resolution temperature \(T\) is assumed to be unavailable. Consequently, the extreme temperatures \(T_{b,ds}\), \(T_{b,ws}\), \(T_{fcgv}\), and \(T_{fesv}\) are extrapolated from the spaces \(T_{km} - f_{gv,km}\) and \(T_{km} - \alpha_{km}\) defined at kilometric resolution (see Fig. 4(c) and (d) for aggregated ASTER temperature and Fig. 4(e) and (f) for MODIS temperature). An approach similar to [5] is used as follows.

1) Vertex C corresponds to full-cover green vegetation and is located at \((1, T_{fcgv})\) in Fig. 4(c) (Fig. 4(e) for MODIS temperature) and at \((\alpha_{fcgv}, T_{fcgv})\) in Fig. 4(d) [Fig. 4(f)]. In this paper, \(T_{fcgv}\) is set to the air temperature \(T_{a}\) measured at the time of ASTER overpass. Vertex C is thus placed at \((1, T_{a})\) in Fig. 4(c) [Fig. 4(e)] and at \((\alpha_{fcgv}, T_{a})\) in Fig. 4(d) [Fig. 4(f)].

2) Vertex B corresponds to wet bare soil and is located at \((0, T_{b,ws})\) in Fig. 4(e) [Fig. 4(e)] and at \((\alpha_{bs}, T_{b,ws})\) in Fig. 4(d) [Fig. 4(f)]. It is placed in Fig. 4(c) [Fig. 4(e)] 606 at the intersection between (BC) and the vertical line \(f_{gv,km} = 0\). The slope of \(BC\) is computed as the slope 602 of the linear regression of the data points corresponding to the “wet surface” edge of the triangle \(T_{km} - f_{gv,km}\). 604 The off-set of \(BC\) is determined from C.

3) Vertex A corresponds to dry bare soil and is located at \((0, T_{b,ds})\) in Fig. 4(c) [Fig. 4(e)] and at \((\alpha_{bs}, T_{b,ds})\) in Fig. 4(d) [Fig. 4(f)]. It is placed in Fig. 4(c) [Fig. 4(e)] 608 at the intersection between (AC) and the vertical line \(f_{gv,km} = 0\). The slope of \(AC\) is computed as the slope 610 of the linear regression of the data points corresponding 611 to the “dry soil” edge of the triangle \(T_{km} - f_{gv,km}\). 612 The off-set of \(AC\) is determined from C.

4) Vertex D corresponds to full-cover senescent vegetation and is located at \((\alpha_{fesv}, T_{fesv})\) in Fig. 4(d) [Fig. 4(f)]. It is placed in Fig. 4(d) [Fig. 4(f)] at the intersection 616 between (AD) and the vertical line \(f_{gv,km} = \alpha_{fesv}\). The 617 line (AD) is considered as being parallel to (BC)[5]. 618 Consequently, the slope of (AD) is determined from 619
vegetation and soil conditions is summarized in Table I.

The counterclockwise direction, and the correspondence with diative transfer models. Vertices are presented successively in five values are estimated from a generalized version \([5], [9]\) of TB

Fig. 4(f). Data [please compare Fig. 4(c) with Fig. 4(e), and Fig. 4(d) with resolution MODIS data in relation to 1-km aggregated ASTER and/or 2) the smaller range of (spatial dynamics) of 1-km mean difference of data. In the latter case, the significant underestimation (5.3◦C) of TB can be explained by the following: 1) the negative mean difference (−2.3◦C) between MODIS and ASTER data and/or 2) the smaller range of (spatial dynamics) of 1-km resolution MODIS data in relation to 1-km aggregated ASTER data [please compare Fig. 4(c) with Fig. 4(e), and Fig. 4(d) with Fig. 4(f)].

**D. Brightness Temperature**

To estimate soil evaporative efficiency \(\beta\) in (20) and \(\beta'\) in (22), five brightness temperature values corresponding to extreme surface conditions are required: \(TB_{b,ds}\), \(TB_{b,ws}\), \(TB_{fcgv,ws}\), \(TB_{fcgv,ds}\), and \(TB_{fcsv,ds}\). In this paper, those five values are estimated from a generalized version \([5], [9]\) of the classical “triangle method” \([27]\).

Fig. 5(a) shows the space defined by PLMR brightness temperature and ASTER land surface temperature. In the following, an original interpretation of the five vertices visible in Fig. 5(a) is provided, which is consistent with both the classical “triangle method” and the state-of-the-art L-band radiative transfer models. Vertices are presented successively in the counterclockwise direction, and the correspondence with vegetation and soil conditions is summarized in Table I.

1. **Vertex at minimum brightness temperature**: L-band radiative transfer models predict an increase of brightness temperature with biomass and a decrease of brightness temperature with surface soil moisture (e.g., \([48]\) and \([49]\)). Therefore, the point at minimum brightness temperature corresponds to wet bare soil. This vertex is noted as B in Fig. 5(a), which is consistent with Fig. 4.

2. **Vertex at maximum land surface temperature**: the triangle method predicts a decrease of land surface temperature with both vegetation cover and surface soil moisture. Therefore, the point at maximum land surface temperature corresponds to dry bare soil. This vertex is noted as A in Fig. 5(a), which is consistent with Fig. 4.

3. **Vertex at maximum brightness temperature**: being consistent with an increase of vegetation emission with biomass and a decrease of soil emission with surface soil moisture, the point at maximum brightness temperature corresponds to full-cover vegetation with dry soil. It could correspond to full-cover green vegetation. However, the associated land surface temperature in Fig. 5(a) is much larger than that over full-cover green vegetation \(21^\circ\mathrm{C}\) and rather close to the temperature over full-cover senescent vegetation \(34^\circ\mathrm{C}\). Therefore, the point 682 at maximum brightness temperature corresponds to full-cover senescent vegetation with dry soil. This vertex 684 is noted as D′ in Fig. 5(a), which is consistent with Fig. 4. A prime mark indicates that D′ corresponds to a dry soil, whereas D does not specify soil hydric status. Note that D′ does not necessarily correspond to dry soil senescent vegetation since wet senescent vegetation can lead to large values of brightness temperature \([50]\). In our case study, however, no rainfall occurred during the 691 four days preceding the ASTER overpass, which means 692 that senescent vegetation was completely dry. In terms of 693 radiative transfer modeling, the effect of dry biomass on 694 brightness temperature can be represented by large values 695 of roughness parameter \([51]\).

4. **Vertices at minimum land surface temperature**: two more vertices are apparent in the counterclockwise direction. Being consistent with a decrease of land surface temperature with green vegetation, both points correspond to full-cover green vegetation. As vegetation is partially transparent to the L-band emission from the soil, each 702 point corresponds to a different soil hydric status. The 703 vertex with a larger \(TB\) [noted as C′ in Fig. 5(a)] 704 corresponds to full-cover green vegetation with dry soil, 705 and the point with a lower \(TB\) [noted as C′ in Fig. 5(a)] 706 corresponds to full-cover green vegetation with wet soil. 707

As high-resolution temperature is assumed to be unavailable in this paper, brightness temperature end-members are not estimated from the polygon \(TB – T\) in Fig. 5(a) but from 710 the polygon \(TB – f_{gy}\) shown in Fig. 5(b). The following is an interpretation of the polygon in Fig. 5(b), based on the 712 consistency with the polygon in Fig. 5(a). In particular, the five 713 vertices in Fig. 5(a) can be located in Fig. 5(b) as follows.

1. **Vertex B** corresponds to wet bare soil. It is located at 715 the minimum value of brightness temperature such that \(f_{gy} = 0\).

2. **Vertex A** corresponds to bare dry soil. It is not apparent 718 in Fig. 5(b) because fractional green vegetation is not 719 sufficient information to distinguish between bare soil and senescent vegetation.

3. **Vertex D′** corresponds to full-cover senescent vegetation with dry soil. It is located at the maximum value of brightness temperature.

4. **Vertex C′** corresponds to full-cover green vegetation with dry soil. It is located at the maximum value of brightness temperature such that \(f_{gy} = 1\).

5. **Vertex C′** corresponds to full-cover green vegetation with wet soil. It is located at the minimum value of brightness temperature such that \(f_{gy} = 1\).

Based on the aforementioned interpretation of the polygon \(TB – f_{gy}\) in Fig. 5(b), the methodology used for estimating 732
temperatures of TB_{bs}, TB_{ws}, TB_{fgv}, TB_{fsv}, and TB_{fcsv} are estimated by interpreting the bare soil, dry surface, full-cover vegetation, and wet surface edges of the polygon in (b). The estimation of TB_{bs} using low-resolution temperature data is illustrated with aggregated ASTER temperature in (c) and MODIS temperature in (d).

Fig. 5. (a) Scatterplot of PLMR incidence-corrected brightness temperature TB versus ASTER land surface temperature and (b) versus ASTER fractional green vegetation cover. (c) Scatterplot of aggregated TB versus aggregated ASTER temperature and (d) versus MODIS temperature. Extreme brightness temperatures TB_{bs}, TB_{fgv}, TB_{fsv}, and TB_{fcsv} are estimated by interpreting the bare soil, dry surface, full-cover vegetation, and wet surface edges of the polygon in (b). The estimation of TB_{bs} using low-resolution temperature data is illustrated with aggregated ASTER temperature in (c) and MODIS temperature in (d).

A. Application to Aggregated ASTER Data

1) End-Members Derived From High-Resolution Data: The approach is first implemented using the end-members estimated from high-resolution ASTER temperature data. This allows testing the robustness of the model in (15) and (16) independently of the methodology used for extrapolating the nine 782 end-members TB_{bs}, TB_{ws}, TB_{fgv}, TB_{fsv}, TB_{bs}, TB_{ws}, TB_{fgv}, TB_{fsv}, and TB_{fcsv}. 784

Fig. 6 shows the output images of the eight disaggregation algorithms, which are to be compared with the reference image derived from ASTER land surface temperature. One observes that the disaggregated temperature is successively improved by including additional factors in the disaggregation, which suggests that the methodology is able to take into account several independent factors. Although the boxy artifact at 1-km resolution is successively reduced from T^{(0)} to T^{(q)}, it is still apparent for T^{(q)}. This effect may be due to the following: 1) 792 other factors that are not taken into account in the procedure, such as green vegetation water stress, wind speed, surface emissivity, surface albedo, etc.; 2) errors in estimated f_{fgv}, f_{s}, f_{b}, and/or 3) resampling errors at 250-m resolution. 797

Table IV lists the RMSD, correlation coefficient, and slope between the disaggregated and ASTER temperatures for each 799 of the eight disaggregation algorithms. The error is successively decreased from 1.65 °C to 1.06 °C, while the correlation coefficient and slope are successively increased from 0.79 and 0.63 to 0.89 and 0.88, respectively. When comparing D1, D2, D1’, D2’, D2’’, D2’’, and D2’’, no significant differences are observed between all four algorithms in terms of root-mean-square error, correlation coefficient, and slope. Note that, in this paper, f_{sv} was estimated more accurately on a 0.09 pixel-by-pixel basis. Nevertheless, this comparison suggests that D1’ seems to be equivalent to D1 and D2’ equivalent to D2, which justifies the use of the T_{mod} model.
The main advantage of the new approach is to take into account a number of additional factors, including fractional open water and soil evaporative efficiency. When comparing the results obtained for $D_3'$, $D_4'$, and $D_4''$ in Table IV, it is observed that the disaggregated temperature is significantly improved against the classical approaches $D_1$ and $D_2$. Moreover, the statistical results are successively improved by including $f_{ow}$, $\beta$, and $\beta'$. Fig. 7 shows the improvement, especially in the slope between the disaggregated and ASTER temperatures. The good results obtained for $D_4''$ indicate that the performance of disaggregation algorithms is intimately related to the following:

1) the capability of separating the independent factors that impact on surface temperature and
2) the ability to integrate them consistently into the procedure.

2) End-Members Derived From Aggregated ASTER Data:

As disaggregation procedures $D_1'$, $D_2'$, $D_3'$, $D_4'$, and $D_4''$ are subjected to uncertainties in land surface temperature and brightness temperature end-members, the five algorithms are next tested using the end-members estimated from kilometer-ric temperature data, as presented in Section V. Aggregated ASTER (instead of MODIS) data are used to evaluate the
Fig. 8. MODIS temperature (1 km) is disaggregated by each of the eight algorithms and is plotted against high-resolution ASTER temperature.

TABLE V
RMSD, CORRELATION COEFFICIENT (R), AND SLOPE BETWEEN THE DISAGGREGATED AND ASTER TEMPERATURES. THE RESULTS CORRESPOND TO THE END-MEMBERS EXTRAPOLATED USING MODIS TEMPERATURE DATA

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>RMSD 1°C</th>
<th>R</th>
<th>Slope</th>
</tr>
</thead>
<tbody>
<tr>
<td>D0</td>
<td>3.19</td>
<td>0.60</td>
<td>0.33</td>
</tr>
<tr>
<td>D1</td>
<td>3.08</td>
<td>0.67</td>
<td>0.39</td>
</tr>
<tr>
<td>D2</td>
<td>3.11</td>
<td>0.66</td>
<td>0.37</td>
</tr>
<tr>
<td>D1'</td>
<td>3.09</td>
<td>0.67</td>
<td>0.39</td>
</tr>
<tr>
<td>D2'</td>
<td>3.12</td>
<td>0.65</td>
<td>0.39</td>
</tr>
<tr>
<td>D3'</td>
<td>3.06</td>
<td>0.69</td>
<td>0.42</td>
</tr>
<tr>
<td>D4'</td>
<td>2.98</td>
<td>0.73</td>
<td>0.50</td>
</tr>
<tr>
<td>D4''</td>
<td>3.03</td>
<td>0.70</td>
<td>0.52</td>
</tr>
</tbody>
</table>

VII. SENSITIVITY ANALYSIS

To further assess the stability of the new D' algorithms based on radiative transfer, two sensitivity analyses are conducted by the following: 1) adding a Gaussian noise on kilometric temperatures and high-resolution brightness temperatures and 2) estimating the contribution of each factor on the variability of modeled land surface temperature.

A. Uncertainty in End-Members

To test the stability of the method for estimating the nine end-members (Tb_ds, Tb_ws, Tfgv, Tfcv, Tb_ds, Tb_ws, Tfgv, Tfcv_ds) from low-resolution MODIS temperature data, a Gaussian noise with a standard deviation of 1 °C is added to the kilometric (aggregated ASTER) land surface temperature data set, and a Gaussian noise with a standard deviation of 2 K is added to the high-resolution brightness temperature data set. An ensemble of 100 data sets is generated and used as input to the disaggregation algorithms.
TABLE VI
MEAN AND STANDARD DEVIATION OF LAND SURFACE TEMPERATURE AND L-BAND BRIGHTNESS TEMPERATURE END-MEMBERS EXTRAPOLATED USING KILOMETRIC TEMPERATURE DATA. FOR THE CONVENIENCE OF THE READER, THE UNIT IS DEGREE CELSIUS FOR RADIOMETRIC TEMPERATURE AND KELVIN FOR BRIGHTNESS TEMPERATURE.

<table>
<thead>
<tr>
<th>End-member</th>
<th>Mean</th>
<th>St. dev.</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{b,ds}$</td>
<td>40.8</td>
<td>0.8</td>
<td>°C</td>
</tr>
<tr>
<td>$T_{b,ws}$</td>
<td>25.7</td>
<td>1.5</td>
<td>°C</td>
</tr>
<tr>
<td>$T_{fsg}$</td>
<td>21.0</td>
<td>0</td>
<td>°C</td>
</tr>
<tr>
<td>$T_{fsv}$</td>
<td>33.1</td>
<td>1.3</td>
<td>°C</td>
</tr>
<tr>
<td>$T_{b,ds}$</td>
<td>246</td>
<td>3.2</td>
<td>K</td>
</tr>
<tr>
<td>$T_{b,ws}$</td>
<td>193</td>
<td>1.4</td>
<td>K</td>
</tr>
<tr>
<td>$T_{fsg,ws}$</td>
<td>204</td>
<td>2.3</td>
<td>K</td>
</tr>
<tr>
<td>$T_{fsv,ds}$</td>
<td>240</td>
<td>1.5</td>
<td>K</td>
</tr>
<tr>
<td>$T_{fsv,ds}$</td>
<td>281</td>
<td>1.0</td>
<td>K</td>
</tr>
</tbody>
</table>

TABLE VII
RMSD, CORRELATION COEFFICIENT ($R$), AND SLOPE BETWEEN THE DISAGGREGATED AND ASTER TEMPERATURES FOR THE DATA INCLUDING ALL THE 100 ARTIFICIALLY NOISED DATA SETS.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>RMSD °C</th>
<th>R</th>
<th>Slope</th>
</tr>
</thead>
<tbody>
<tr>
<td>D0</td>
<td>1.81</td>
<td>0.75</td>
<td>0.63</td>
</tr>
<tr>
<td>D1</td>
<td>1.58</td>
<td>0.82</td>
<td>0.76</td>
</tr>
<tr>
<td>D2</td>
<td>1.54</td>
<td>0.83</td>
<td>0.76</td>
</tr>
<tr>
<td>D1′</td>
<td>1.57</td>
<td>0.82</td>
<td>0.73</td>
</tr>
<tr>
<td>D2′</td>
<td>1.54</td>
<td>0.83</td>
<td>0.74</td>
</tr>
<tr>
<td>D3′</td>
<td>1.44</td>
<td>0.85</td>
<td>0.78</td>
</tr>
<tr>
<td>D4′</td>
<td>1.39</td>
<td>0.87</td>
<td>0.87</td>
</tr>
<tr>
<td>D4″</td>
<td>1.48</td>
<td>0.86</td>
<td>0.89</td>
</tr>
</tbody>
</table>

Fig. 9. As for Fig. 7 but using all the 100 artificially noised input data sets.

in land surface temperature is derived by computing the first partial derivative of $T_{mod}$ from (15) and (16)

$$\frac{\partial T_{mod}}{\partial f_{sv}} = -(1 - f_{ow})(T_{fsv} - T_{fsgv}).$$

Similarly, the first partial derivative of $T_{mod}$ is computed with respect to $f_{sv}$

$$\frac{\partial T_{mod}}{\partial f_{sv}} = -(1 - f_{ow})(1 - f_{tv})T_{b,ws} - (1 - f_{tv})T_{b,ds} - T_{fcsv} - T_{fsv}.$$  

with respect to $f_{ow}$

$$\frac{\partial T_{mod}}{\partial f_{ow}} = -(f_{gv}T_{fsgv} + (f_{tv} - f_{gv})T_{fcsv} + (1 - f_{tv})(\beta T_{b,ws} + (1 - \beta)T_{b,ds} - T_{fsgv}).$$

and with respect to $\beta$

$$\frac{\partial T_{mod}}{\partial \beta} = -(1 - f_{ow})(1 - f_{tv})(T_{b,ds} - T_{b,ws}).$$

Table VIII lists the standard deviation of each parameter within the study area, the average of partial derivatives, and the relative weight of each parameter on the variability of modeled land surface temperature. The relative weights of $f_{gv}$, $f_{sv}$, $f_{ow}$, and $\beta$ are estimated as the mean partial derivative times the standard deviation. Results indicate that all parameters have a negative impact on $T$. More interestingly, $f_{gv}$ appears to be the most significant variability factor, with a relative weight of 42%, which is consistent with NDVI-based approaches [4].
TABLE VIII

<table>
<thead>
<tr>
<th>Factor</th>
<th>Standard deviation</th>
<th>Mean partial derivative °C</th>
<th>Impact on $T_{mod}$ (percentage of total) °C (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f_{GV}$</td>
<td>0.11</td>
<td>-13</td>
<td>0.97 (42)</td>
</tr>
<tr>
<td>$f_{SW}$</td>
<td>0.19</td>
<td>-2.0</td>
<td>0.26 (11)</td>
</tr>
<tr>
<td>$f_{OW}$</td>
<td>0.06</td>
<td>-11</td>
<td>0.45 (20)</td>
</tr>
<tr>
<td>$\beta'$</td>
<td>0.19</td>
<td>-4.8</td>
<td>0.17 (27)</td>
</tr>
</tbody>
</table>

The second and third most significant variability factors are soil evaporative efficiency and fractional open water, with relative weights of 27% and 20%, respectively. Finally, fractional senescent vegetation cover represents only 11% of the variability in land surface temperature. The low impact of $f_{GV}$ can be associated with the low mean partial derivative. In particular, $\partial T_{mod}/\partial f_{GV}$ is low because the temperature difference between dry bare soil ($T_{b,d}$) and full-cover senescent vegetation ($T_{T_{ferv}}$) is also low in our case study.

The relative weights in Table VIII are now related with the disaggregation results in Table III. Consequently, the poor improvement of D2 against D1 (and D2' against D1') can be attributed to the relatively low weight of $f_{SW}$ in the variability of land surface temperature. Conversely, the significant improvements of D4'' against D3', D3' against D2', and D1 (and D1') against D0 are attributed to the large weights of $\beta'$, $f_{OW}$, and $f_{GV}$, respectively.

In summary, the variability of land surface temperature is reasonably represented by model $T_{mod}$. Moreover, the approach allows the relative weight of each variability factor to be taken into account in the disaggregation procedure.

VIII. SUMMARY AND CONCLUSION

A new disaggregation methodology for land surface temperature has been developed to integrate the main surface parameters involved in the surface energy budget. It is based on a linearized radiative transfer equation, which distinguishes between soil, vegetation, and water temperature, and uses soil evaporative efficiency and fractional senescent vegetation cover to parameterize/estimate soil and vegetation hydric status, respectively. The approach is implemented using four parameters: the fraction of green vegetation cover derived from red and near-infrared bands, the fraction of senescent vegetation cover derived from red and near-infrared bands, the fraction of open water derived from shortwave-infrared band, and the soil evaporative efficiency derived from microwave-L band.

It is tested over a 5 km by 32 km area of irrigated land in Australia, including flooded rice crops, using ASTER and Landsat-5 band airborne data. Low-resolution land surface temperature is simulated by aggregating ASTER land surface temperature at 1-km resolution, and the disaggregated temperature is compared to high-resolution ASTER temperature. The results indicate that the methodology is able to separate efficiently the independent factors that impact surface temperature and to integrate them consistently into the disaggregation procedure. The error in disaggregated temperature is successively reduced from 975 to 1.65 °C to 1.16 °C by including each of the four parameters. The correlation coefficient and slope between the disaggregated and ASTER temperatures are improved from 0.79 to 0.89 and 0.63 to 0.88, respectively. Moreover, the radiative transfer equation allows quantifying the impact at high resolution of each parameter on land surface temperature. In this case study, fractional green vegetation cover is responsible for 42% of the variability in disaggregated land surface temperature, fractional senescent vegetation cover for 11%, fractional open water for 20%, and soil evaporative efficiency for 23%.

Note that the approach presented in this paper did not take into account the water stress of green vegetation because none of the considered parameters (fractional green vegetation cover, fractional senescent vegetation cover, fractional open water, and soil evaporative efficiency) could describe the hydric status of photosynthetically active (green) vegetation. The analysis was conducted solely in a highly irrigated environment in which vegetation water stress was small. However, in most cases, the vegetation water stress might not be negligible for natural areas. In the presence of water-stressed green vegetation, the scatterplot (temperature versus green vegetation cover) would need to be transformed into a trapezoidal shape with four vertices rather than a triangle. In such conditions, the disaggregation problem would be partly undetermined since the partitioning between unstressed and stressed green vegetations would not be represented. Consequently, the approaches shown here are not expected to be representative of other less extreme environments than the present irrigated area. Nevertheless, one should keep in mind that improving the spatial resolution of land surface temperature data via disaggregation is only relevant in the conditions where the spatial variability of temperature is large.

Although the approach was successfully applied to airborne and satellite data collected during NAFE’06, further research is needed to test the disaggregation approach on a routine basis. One may anticipate that fractional green and senescent vegetation covers could be derived accurately using FORMOSAT-2 like data. The FORMOSAT-2 instrument [52] provides shortwave data at high spatial resolution (8 m) and high temporal frequency (potentially one image per day), which allow a fine analysis of the seasonality of canopies during the crop cycle [5], [33], [34]. Fractional open water could be derived from Landsat-5 data (e.g., [20]). Although the repeat cycle of Landsat (16 days) is longer than the temporal resolution needed for land surface temperature, the seasonal variations of water bodies are...
for their participation in collecting this extensive data set. The authors would like to thank the NAFE'06 participants for their participation in collecting this extensive data set.

REFERENCES


AUTHOR QUERIES

AUTHOR PLEASE ANSWER ALL QUERIES

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AQ2 = The sentence that starts with “It is a three-step procedure...” was modified to properly introduce the list. Please check if the thought is preserved, and correct if necessary.

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Multidimensional Disaggregation of Land Surface Temperature Using High-Resolution Red, Near-Infrared, Shortwave-Infrared, and Microwave-L Bands

Olivier Merlin, Frédéric Jacob, Jean-Pierre Wigneron, Jeffrey Walker, and Ghani Chehbouni

Abstract—Land surface temperature data are rarely available at high temporal and spatial resolutions at the same locations. To fill this gap, the low spatial resolution data can be disaggregated at high temporal frequency using empirical relationships between remotely sensed temperature and fractional green (photosynthetically active) and senescent vegetation covers. In this paper, a new disaggregation methodology is developed by physically linking remotely sensed surface temperature to fractional green and senescent vegetation covers using a radiative transfer equation. Moreover, the methodology is implemented with two additional factors related to the energy budget of irrigated areas, being the fraction of open water and soil evaporative efficiency (ratio of actual to potential soil evaporation). The approach is tested over a 5 km by 32 km irrigated agricultural area in Australia using airborne Polorimetric L-band Multibeam Radiometer brightness temperature and spaceborne Advanced Scanning Thermal Emission and Reflection radiometer (ASTER) multispectral data. Fractional green vegetation cover, fractional senescent vegetation cover, fractional open water, and soil evaporative efficiency are derived from red, near-infrared, shortwave-infrared, and microwave-L band data. Low-resolution land surface temperature is simulated by aggregating ASTER land surface temperature to 1-km resolution, and the disaggregated temperature is verified against the high-resolution ASTER temperature data initially used in the aggregation process. The error in disaggregated temperature is successively reduced from 1.65 °C to 1.16 °C by including each of the four parameters. The correlation coefficient and slope between the disaggregated and ASTER temperatures are improved from 0.79 to 0.89 and from 0.63 to 0.88, respectively. Moreover, the radiative transfer equation allows quantification of the impact on disaggregation of the temperature at high resolution for each parameter: fractional green vegetation cover is responsible for 42% of the variability in disaggregated temperature, fractional senescent vegetation cover for 11%, fractional open water for 20%, and soil evaporative efficiency for 27%.

Index Terms—Advanced Scanning Thermal Emission and Reflection radiometer (ASTER), brightness temperature, disaggregation, evaporative efficiency, land surface temperature, Moderate Resolution Imaging Spectroradiometer (MODIS), multispectral, open water, soil moisture, vegetation fraction.

I. INTRODUCTION

REOTELY sensed land surface temperature is a signature of the thermodynamic equilibrium state of the surface skin. Consequently, it provides the potential to monitor dynamic information on instantaneous energy and water fluxes at the land-surface–atmosphere interface. Nevertheless, the operational use of thermal remote sensing for hydrological and water resource management studies has been limited to regional scale applications (e.g., [1] and [2]) mainly because the spatial resolution (larger than 1 km) of current high temporal resolution thermal sensors is too coarse to represent the heterogeneity of man-made landscapes. For example, the Moderate Resolution Imaging Spectroradiometer (MODIS) has a revisit frequency of 1 or 2 times per day but a spatial resolution of only 1 km, while the Advanced Scanning Thermal Emission and Reflection radiometer (ASTER) has a spatial resolution of 90 m but a 61 revisit time of only 16 days.

The use of remotely sensed land surface temperature over agricultural areas requires data at both high spatial and temporal resolutions [3]. While there is a lack of high spatial resolution thermal data from satellite with high frequency, there is the potential for land surface temperature derived from kilomet-Resolution Imaging Spectroradiometer (MODIS) and the collaboration of a large number of scientists from throughout Australia, U.S., and Europe. Initial setup and maintenance of the study catchments were made possible through infrastructure (LE0453434 and LE0560930) and research (DP0557543) funding from the Australian Research Council and by the CRC for Catchment Hydrology.

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Color versions of one or more of the figures in this paper are available online at [link].

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Digital Object Identifier 10.1109/TGRS.2011.2169802.
The accuracy in disaggregated temperature was improved by taking into account fractional senescent vegetation cover in addition to fractional green vegetation cover.

Fractional green and senescent vegetation covers, however, are not the only factors explaining the spatial variations of land surface temperature, especially over irrigated areas where crop fields may have different moisture status to the surroundings. In particular, the temperature over a flooded crop field may be drastically different from the temperature over a mature crop field. Therefore, the fraction of open water is an important variable to represent the spatial variations of land surface temperature. Over nonwatered land surfaces, the soil evaporative efficiency (ratio of actual to potential soil evaporation) is a signature of the capacity of the soil to evaporate its water content in the near surface and thus to counter an increase of its thermodynamic temperature. Consequently, soil evaporative efficiency is also an essential variable to describe the spatial variations of land surface temperature. Moreover, knowledge of soil evaporative efficiency is needed to decouple the effects of soil and vegetation hydraulic status on the surface energy budget and hence to better represent the resultant radiative surface temperature. As an example, the crop water stress index (CWSI) [6], [7] can be used to detect plant stress based on the difference between foliage and air temperature. Nevertheless, the application of the CWSI to partially vegetated areas is subjected to large uncertainties because the soil background may have a different temperature to the plants [7] depending on soil evaporative efficiency. Another example is provided by Moran et al. [8] who proposed the vegetation index/temperature (VIT) trapezoid to estimate a most probable range of plant stress over partially vegetated fields. It is a three-step procedure in which the following steps are performed: 1) the temperatures of the four vertices of the VIT trapezoid are estimated using an energy budget model; 2) the minimum and maximum probable vegetation temperatures are estimated from the measured postive land surface temperature, together with the maximum and minimum simulated soil temperatures; and 3) the minimum and maximum probable CWSIs are computed by normalizing the minimum and maximum probable vegetation temperatures from the vegetation temperature extremes simulated by the energy budget model. The point is that this approach does not allow estimating a single CWSI value because the retrieval problem is underdetermined. In particular, Moran et al. [8] noted that “with knowledge of a second point within the hourglass (perhaps soil temperature), it would be possible to infer [the canopy-air temperature] difference and pinpoint the CWSI value.” In the latter case, knowledge of soil temperature is equivalent to knowledge of soil evaporative efficiency, which would remove the underdetermination of the VIT trapezoid.

The objective of this paper is to develop a new disaggregation methodology of kilometric land surface temperature using hectometric multivariable ancillary data. The approach is based on a radiative transfer equation that estimates differences in temperature data at hectometric resolution. Specifically, the use of a radiative transfer equation allows the following: 1) including variables other than those used by previous disaggregation approaches and 2) deducing the most pertinent variables. In addition to fractional green and senescent vegetation covers, the new methodology includes the variability at hectometric resolution of fractional open water and soil evaporative efficiency. With respect to other disaggregation algorithms in literature [4], [5], the proposed technique differs in the following four main aspects: 1) it relies on a physically based radiative transfer equation rather than empirical linear regressions; 2) it takes into account the fractional open water derived from shortwave-irradiated band as required; 3) it takes into account the soil hydric status via microwave-derived soil evaporative efficiency; and 4) it allows the relative weight of each parameter used for the disaggregating temperature to be quantified.

The new disaggregation technique is compared to the existing approaches using data collected during the National Airborne Field Experiment in 2006 (NAFE’06; [9]). The experimental site covers a 5 km by 32 km irrigated agricultural area, which included approximately 5% of flooded rice crops 153 during NAFE’06. Disaggregation algorithms are first tested by 154 aggregating ASTER temperature at 1-km resolution and by 155 comparing the disaggregated temperature to the high-resolution 156 ASTER temperature initially used in the aggregation process. 157 The application to aggregated ASTER data allows evaluating 158 approaches independently of differences between ASTER and MODIS products [5]. Disaggregation algorithms are then applied to MODIS data.

II. EXPERIMENTAL DATA

The study area is a 5 km by 32 km area included in the 163 Coleambally Irrigation Area (CIA) located in the flat west-164 ern plains of the Murrumbidgee catchment in southeastern 165 Australia (35° S, 146° E). The principal summer crops grown 166 in the CIA are rice, maize, and soybeans, while winter crops 167 include wheat, barley, oats, and canola. In November, rice crops 168 are flooded under 30 cm height of irrigation water.

The NAFE’06 was conducted from October 31 to 170 November 20, 2006, over a 40 km by 60 km area, with more 171 detailed flights over the 5 km by 32 km focus area studied 172 in this paper. While a full description of the NAFE’06 data 173 set is given in [9], a brief overview of the most pertinent 174 details is provided here. The data used in this paper are 175 comprised of airborne L-band brightness temperature; ASTER 176 red, near-infrared, and shortwave-infrared reflectances; ASTER 177 land surface temperature data (resampled at 250-m resolution); 178 MODIS land surface temperature data; and air temperature data 179 collected by a meteorological station in the NAFE’06 area.

A. PLMR

The Polarimetric L-band Multibeam Radiometer (PLMR) is an airborne instrument that measures both H and V polarizations using a single receiver with polarization switching at view angles of ±7°, ±21.5°, and ±38.5°. The accuracy of the PLMR is estimated to be better than 2 K and 3 K in the H and V polarizations, respectively [10]. During NAFE’06, the PLMR flew on November 14 to collect 188 L-band brightness temperature at 250-m resolution over the 189 5 km by 32 km area in the CIA. PLMR was mounted in the 190 across-track configuration so that each pixel was observed at a 191
given incidence angle (approximately 7°, 21.5°, or 38.5°). Data were processed for incidence angle and beam location on the ground by taking into account aircraft position, attitude, and ground topography.

As the sensitivity to soil moisture is higher for H-polarized brightness temperature than for V-polarized brightness temperature, only the H-polarized brightness temperature TB is used in this paper. Preprocessing of TB consists of the following: 1) resampling H-polarized PLMR data at 250-m resolution on a grid that matches in symmetry to the flight lines over the 5 km by 32 km area and 2) converting the resampled TB to an equivalent value at 21.5° incidence angle. The incidence angle 21.5° is chosen to minimize conversion errors. The angular conversion involves the brightness temperature collected by inner beams at approximately 7° incidence angle being multiplied by the ratio \( \frac{TB_{MB}}{TB_{OB}} \), with \( TB_{MB} \) and \( TB_{OB} \) being the mean brightness temperatures collected by the middle and inner beams, respectively. Similarly, the brightness temperature collected by the outer beams at approximately 38.5° incidence angle is multiplied by the ratio \( \frac{TB_{OB}}{TB_{DB}} \), with \( TB_{OB} \) and \( TB_{DB} \) being the mean brightness temperatures collected by the outer and back beams. Mean brightness temperatures \( TB_{IB}, TB_{MB}, \) and \( TB_{OB} \) are computed as the average (for all flight lines) of the TB collected by the beams pointing at \( \pm 7°, \pm 21.5°, \) and \( \pm 38.5° \), respectively. This technique was already used in [11] to generate TB images by assuming that the impact of soil moisture and biomass on the angular dependance of TB is negligible or small. In this paper, a slightly different approach is adopted to take into account the variations in aircraft attitude during data collection, which made the incidence angle \( \theta \) oscillate around 7° during data collection, thus modifying the incidence angle. The in- and out-beam brightness temperature \( TB_{MB} \) and \( TB_{OB} \) were then multiplied by a factor \( \frac{TB_{MB}}{TB_{OB}} \), respectively, to generate TB images.

\[ \left( \frac{TB_{MB}}{TB_{OB}} \right) \]

B. ASTER

The ASTER instrument was launched in 1999 aboard Terra, a sun synchronous platform with 11:00 UTC descending Equator crossing and a 16-day revisit cycle. An ASTER scene covers an area of approximately 60 km by 60 km and consists of 14 nadir-looking bands and one oblique-looking band to create stereobased digital elevation models. The three nadir-looking bands in the visible and near infrared have a 15-m resolution. The six bands in the shortwave-infrared have a 30-m resolution. Finally, there are five thermal infrared bands with a 90-m resolution.

The ASTER overpass of the NAFE’06 site was on November 16, 2006. Official ASTER products [12] were used here for surface reflectance (AST_07) and radiometric temperature (AST_08) with accuracies of 5% and 1.5 K, respectively [13]–[19]. They were downloaded from the Earth Observing System Data Gateway (EDG).

ASTER 15-m resolution red (B2) and near-infrared (B3) bands were extracted over the 5 km by 32 km area and resampled at 250-m resolution to match the spatial resolution and extent of PLMR observations. The ASTER 30-m resolution B5 band (1.60–1.70 \( \mu m \)) was extracted over the 5 km by 32 km study area and resampled at 50-m resolution. Fractional open water was estimated using B5 band [20] based on a 250-km threshold method. Consequently, B5 data were resampled at a resolution finer than that (250 m) of PLMR data to classify open water pixels at 50-m resolution and to obtain fractional open water at 250-m resolution from the binary classification.

ASTER 90-m resolution radiometric temperature was extracted over the 5 km by 32 km area and aggregated at 250-m resolution to match the spatial resolution and extent of PLMR observations. Aggregation was achieved by linearly averaging high-resolution surface temperatures, i.e., without accounting for the nonlinear relationship between physical temperature and radiance. This choice was motivated by the results of [21, 261 which compared the temperature aggregated using different scaling approaches and obtained very low differences (maximum difference of 0.2 °C).

C. MODIS

The MODIS/Terra data were collected concurrently with ASTER data: MODIS official products consisted of the 928-m resolution surface skin temperature (MOD11-L2) retrieved by the “generalized split window” algorithm [22]–[24] and registered in the sinusoidal projection. The MODIS Reprojection Tool was used to project MOD11-L2 data in UTM WGS 1984 55S with a sampling interval of 1 km.

In this paper, the disaggregation of 1-km MODIS temperature is evaluated using high-resolution ASTER data. To distinguish the errors associated with the disaggregation technique and the errors associated with the discrepancy between MODIS and ASTER temperature products, a comparison is made between ASTER and MODIS data at 1-km resolution over the 5 km by 32 km study area. The ASTER data are aggregated at the MODIS spatial resolution (1 km) by linearly averaging high-resolution temperatures. The root-mean-square difference (RMSD), bias, correlation coefficient, and slope of the linear regression between MODIS and aggregated ASTER data are 2.7 °C, −2.3 °C, 0.75, and 0.52, respectively. The discrepancy here by a significant bias and a relatively low slope of the linear regression, is on the same order of magnitude as the mean difference (about 3 °C) reported in literature [5], [21], [25].

III. DISAGGREGATION ALGORITHMS

This paper aims to compare different approaches for disaggregating kilometric MODIS land surface temperature data. The study uses aggregated ASTER and real MODIS data and demonstrates the disaggregation at 250-m resolution. The resolution of 250 m is chosen to match with the lowest resolution at which ancillary data composed of red, near-infrared, shortwave-infrared, and microwave-L bands are available. In this case study, the target scale is determined by the resolution (250 m) of airborne microwave data.

As shown in the schematic diagram of Fig. 1, the disaggregation algorithms are noted as \( D_k \), with \( k \) being the number of factors taken into account in the disaggregation. The new
302 algorithms are noted as Dk’. D0 does not use any ancillary 303 data, while D1 is based on a linear regression between land 304 surface temperature and fractional green (photosynthetically 305 active) vegetation cover. Fractional green vegetation cover \( f_{gv} \) 306 is defined as the surface area of green vegetation per unit area 307 of soil. D1 is the same as in [4]. D2 is based on D1 but 308 takes into account both fractional green and total vegetation 309 covers. Fractional vegetation cover \( f_{tv} \), is defined as the total 310 surface area of (green plus senescent) vegetation per unit area 311 of soil. D2 is the same as in [5]. The new algorithms D1’, 312 D2’, D3’, and D4’ (and D4’′) are all derived from a radiative 313 transfer equation. The four algorithms differ with regard to the 314 number of factors which are explicitly taken into account. D1’ 315 includes the variability of \( f_{gv} \) and is thus a substitute for D1 316 based on radiative transfer. D2’ includes the variability of both 317 \( f_{gv} \) and \( f_{tv} \) and is thus a substitute for D2 based on radiative 318 transfer. The other algorithms D3’ and D4’ integrate additional 319 variables. D3’ includes the variability of \( f_{gw}, f_{sv} \), and fractional 320 open water \( f_{ow} \). D4’ includes the variability of \( f_{gw}, f_{tv}, f_{ow} \), 321 and soil evaporative efficiency (ratio of actual to potential soil 322 evaporation) \( \beta \). D4’′ is the same as D4’ but with a different 323 formulation for soil evaporative efficiency.

D0 sets the disaggregated temperature as 324

\[
T^{(0)} = T_{km}
\]

325 with \( T_{km} \) being the land surface temperature observed at kilo-
326 metric resolution.

Using D1, the disaggregated temperature is computed as 327

\[
T^{(1)} = T_{km} + a_1 \times (f_{gv} - (f_{gv})_{km})
\]

328 with \( f_{gv} \) being the fractional green vegetation cover derived at 329 high resolution, \( (f_{gv})_{km} \) being the \( f_{gv} \) aggregated at kilometric 330 resolution, and \( a_1 \) being the slope of the linear regression 331 between \( T_{km} \) and \( (f_{gv})_{km} \). Note that the variables defined at 332 kilometric resolution are noted with the subscript km.

Using D2, the disaggregated temperature is computed as 333

\[
T^{(2)} = T_{km} + a_{1}^{proj} \times (f_{gv}^{proj} - (f_{gv})_{km})
\]

334 with \( f_{gv}^{proj} \) being the projected \( f_{gv} \) and \( a_{1}^{proj} \) being the slope 335 of the linear regression between \( T_{km} \) and the projected \( f_{gv} \) es-
336 timated at kilometric resolution \( f_{gv,km}^{proj} \). Note that the variables 337 defined at the image scale are written in bold. The notion of 338 a “projected variable” was introduced in [26]. It is a robust 339 tool that strengthens the correlation between two variables by 340 representing the dependence of these variables on other addi-
341 tional variables. In [5], the projection technique was applied 342 to fractional green vegetation cover to artificially improve the 343 spatial correlation between \( T \) and \( f_{gv} \) by taking into account 344 the dependence of \( T \) on \( f_{tv} \). The projected fractional green 344 vegetation cover is computed as 345

\[
f_{gv}^{proj} = f_{gv} - \frac{T_{fcsv} - (T_{b,bs} + T_{b,ws})/2}{T_{fcsv} - T_{fgsv}} \times (f_{tv} - (f_{tv})_{km})
\]

346 with \( f_{tv} \) being the fractional total vegetation cover derived at 347 high resolution, \( (f_{tv})_{km} \) being the \( f_{tv} \) aggregated at kilometric 348 resolution, \( T_{b,ws} \) being the temperature of wet bare soil, \( 349 T_{fcsv} \) the temperature of full-cover green vegetation, and \( T_{fgsv} \) 350 the temperature of full-cover senescent vegetation (notations 351 are summarized in Table I). Following the interpretation of 352 the “triangle method” [27], \( T_{b,bs}, T_{b,ds}, T_{fgsv} \), and \( T_{fcsv} \) 353 correspond to the minimum and maximum soil and vegetation 354 temperatures within the study area, respectively. It is reminded 355 that \( f_{tv} = f_{gv} + f_{sv} \), with \( f_{gv} \) and \( f_{sv} \) being the fractional 356 green and senescent vegetation covers, respectively.

In (4), the projected fractional green vegetation cover esti-
357 mated at kilometric resolution is 358

\[
f_{gv,km}^{proj} = (f_{gv})_{km} - \frac{T_{fcsv} - (T_{b,bs} + T_{b,ws})/2}{T_{fcsv} - T_{fgsv}} \times (f_{tv} - (f_{tv})_{km})
\]

359 with \( f_{tv} \) being the mean \( f_{tv} \) over the whole study area.

The new algorithms D’ use a radiative transfer equation 361 to model the spatial variability of disaggregated temperature 362 within each 1-km resolution pixel, using ancillary data avail-
363 able at high resolution such as \( f_{gv}, f_{tv}, f_{ow} \), and \( \beta \). D1’ is 364 a substitute for D1 based on radiative transfer. It expresses 365 disaggregated temperature as 366

\[
T^{(1')} = T_{km} + \Delta T^{(1')}
\]
Interpretation of the Vertices in the Generalized “Triangle Approach”

<table>
<thead>
<tr>
<th>Vertex</th>
<th>Surface type</th>
<th>Near-surface soil hydric status</th>
<th>Abbreviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Bare soil</td>
<td>Dry</td>
<td>b,ds</td>
</tr>
<tr>
<td>B</td>
<td>Bare soil</td>
<td>Wet</td>
<td>b,ws</td>
</tr>
<tr>
<td>C</td>
<td>Full-cover green vegetation</td>
<td>Wet or dry</td>
<td>fegv</td>
</tr>
<tr>
<td>C’</td>
<td>Full-cover green vegetation</td>
<td>Wet</td>
<td>fegv,ws</td>
</tr>
<tr>
<td>C''</td>
<td>Full-cover green vegetation</td>
<td>Dry</td>
<td>fegv,ds</td>
</tr>
<tr>
<td>D</td>
<td>Full-cover senescent vegetation</td>
<td>Wet or dry</td>
<td>fesv</td>
</tr>
<tr>
<td>D’</td>
<td>Full-cover senescent vegetation</td>
<td>Dry</td>
<td>fesv,ds</td>
</tr>
</tbody>
</table>

Nonwatered land surface temperature is expressed as

$$T_{nw} = f_{gv} T_{fgv} + (f_{tv} - f_{gv}) T_{fesv} + (1 - f_{tv}) T_{bs} \tag{12}$$

with $T_{fgv}$ and $T_{fesv}$ being the temperature of full-cover green vegetation and senescent vegetation, respectively, and $T_{bs}$ being the bare soil temperature. With the soil evaporative efficiency defined as

$$\beta = \frac{T_{b,ds} - T_{bs}}{T_{b,ds} - T_{b,ws}} \tag{13}$$

the bare soil temperature can be expressed as

$$T_{bs} = \beta T_{b,ws} + (1 - \beta) T_{b,ds} \tag{14}$$

By assuming that water temperature is close to well-watered green vegetation [27], modeled land surface temperature becomes

$$T_{mod} = f_{ow} T_{fgv} + (1 - f_{ow}) T_{nw} \tag{15}$$

with the nonwatered land surface temperature expressed as

$$T_{nw} = f_{gv} T_{fgv} + (f_{tv} - f_{gv}) T_{fesv} + (1 - f_{tv}) T_{bs} \tag{16}$$

The temperature extremes $T_{b,ds}$, $T_{b,ws}$, $T_{fgv}$, and $T_{fesv}$ are extrapolated (according to Section V) from low-resolution land surface temperatures using high-resolution ancillary data [5].

IV. Derivation of Biophysical Variables

The four variables used by the disaggregation methodology are the following: fractional green vegetation cover $f_{gv}$, fractional total (green plus senescent) vegetation cover $f_{tv}$, fractional open water $f_{ow}$, and soil evaporative efficiency $\beta$. All of these variables are estimated from ASTER red, near-infrared, and shortwave-infrared reflectance products and from the PLMR H-polarized brightness temperature converted at an incidence angle of 21.5°.

A. Fractional Green Vegetation Cover

Fractional green vegetation cover can be estimated from the Normalized Difference Vegetation Index (NDVI) as in [31]

$$f_{gv} = \frac{\text{NDVI} - \text{NDVI}_{bs}}{\text{NDVI}_{fgv} - \text{NDVI}_{bs}} \tag{17}$$
Fractional Total (Green Plus Senescent) Vegetation Cover

Fractional total vegetation cover is estimated by correlating $f_{tv}$ with surface albedo for green vegetation and by setting $f_{tv}$ to the maximum $f_{gv}$ for senescent vegetation. This methodology [5] is based on two assumptions, which are generally met in agricultural areas: 1) soil albedo is generally lower than green vegetation albedo and 2) green vegetation albedo is lower than agricultural areas. Note that 2% of the 5 km by 32 km area is contaminated by clouds and cloud shadow. Contaminated 250-m resolution pixels are represented by crossed-out surfaces.

\begin{equation}
\alpha = (1 - f_{tv})\alpha_{bs} + f_{gv}\alpha_{fgv} + (f_{tv} - f_{gv})\alpha_{fcsv} \tag{18}
\end{equation}

with $\alpha_{bs}$, $\alpha_{fgv}$, and $\alpha_{fcsv}$ being the albedo for bare soil, full-440 cover green vegetation, and full-cover senescent vegetation, respectively, and with the end-members $\alpha_{bs}$, $\alpha_{fgv}$, and $\alpha_{fcsv}$ estimated in Section V.

By inverting (18), fractional vegetation cover is expressed as

\begin{equation}
f_{tv} = \frac{\alpha - \alpha_{bs} + f_{gv}(\alpha_{fcsv} - \alpha_{fgv})}{\alpha_{fcsv} - \alpha_{bs}} \tag{19}
\end{equation}

with $\alpha$ being the surface albedo estimated as a weighted sum of red and near-infrared reflectances using the coefficients given in [44] and validated in [35]–[38]. As stated previously, our case does not allow calibrating $\alpha_{bs}$, $\alpha_{fgv}$, and $\alpha_{fcsv}$ on a 447-pixel-by-pixel basis. Consequently, the value of $f_{tv}$ computed from (19) may, on some occasions, be lower than $f_{gv}$ or larger than 1. To avoid nonphysical values, $f_{tv}$ is set to 0 and 1 in 450 the former and latter case, respectively.

The spatial variation of fractional senescent vegetation cover ($sv$) over the study area is shown in Fig. 2. Open water represents 5% of the study area and is attributed to rice cropping.

D. Soil Evaporative Efficiency

Soil evaporative efficiency $\beta$ is defined as the ratio of actual 471 to potential soil evaporation. In this paper, $\beta$ is estimated from 472 PLMR brightness temperatures. Two different formulations 473 are used to evaluate the coupling effects of near-surface soil 474 moisture, $f_{gv}$, and $f_{sv}$ on microwave-derived soil evaporative 475 efficiency.

By assuming that brightness temperature is mainly sensitive 477 to surface soil moisture [41] and that soil evaporative efficiency 478 is mainly driven by surface soil moisture [42], [43], soil evapo- 479 rative efficiency can be estimated as

\begin{equation}
\beta = 1 - \frac{TB - TB_{b,ws}}{TB_{fcsv,ds} - TB_{b,ws}} \tag{20}
\end{equation}

with $TB_{b,ws}$ and $TB_{fcsv,ds}$ being the minimum and max- 481imum brightness temperatures observed over the study area, 482 respectively. As brightness temperature generally decreases 483 with surface soil moisture and increases with vegetation cover 484 [44], $TB_{b,ws}$ and $TB_{fcsv,ds}$ are interpreted as the brightness 485 temperatures over wet bare soil and full-cover senescent vege-486
tation with dry soil, respectively. The spatial variation of $\beta$ over 487 the study area is shown in Fig. 2.

Since brightness temperature also depends on biomass (e.g., 489 [45]), a second formulation of soil evaporative efficiency $\beta'$ is 490

![Fig. 2. Images of fractional green vegetation cover $f_{gv}$, fractional senescent vegetation cover $f_{sv}$, fractional open water $f_{ow}$, soil evaporative efficiency $\beta$, and soil evaporative efficiency $\beta'$.](image-url)
derived in order to decouple the effects of soil moisture, $f_{sv}$, and $f_{sv}$ on $TB$. As in [46], the assumption is that, for a given vegetated pixel, if vegetation is partially stressed (i.e., $f_{sv} > 0$ or $f_{sv} = f_{gv}$), then near-surface soil moisture availability is zero (i.e., $\beta' = 0$). Alternatively, if that pixel does not contain senescent vegetation (i.e., $f_{sv} = 0$ or $f_{sv} = f_{gv}$), then $\beta'$ is computed as the ratio of the measured “dry soil” brightness temperature difference to the “dry soil”–“wet soil” brightness temperature difference. Formally, one writes

$$\beta' = \begin{cases} 0 & \text{if } TB > TB_{ds} \\ 1 - \frac{TB - TB_{ws}}{TB_{ds} - TB_{ws}} & \text{if } TB \leq TB_{ds} \end{cases}$$

with $TB_{ds}$ and $TB_{ws}$ being the “dry soil” and “wet soil” brightness temperatures, respectively, both being estimated for a weighted sum of the brightness temperature over dry bare soil and the brightness temperature over full-cover green vegetation with dry soil (noted as $TB_{b,ds}$) and the brightness temperature over full-cover green vegetation with wet soil (noted as $TB_{fgv,ds}$)

$$TB_{ds} = f_{gv}TB_{fgv,ds} + (1 - f_{gv})TB_{b,ds}.$$  

Similarly, the “wet soil” brightness temperature is computed as a weighted sum of the brightness temperature over wet bare soil and the brightness temperature over full-cover green vegetation with wet soil (noted as $TB_{fgv,ws}$)

$$TB_{ws} = f_{gv}TB_{fgv,ws} + (1 - f_{gv})TB_{b,ws}.$$  

The spatial variation of $\beta'$ over the study area is shown in Fig. 2.

### V. Estimating End-Members

A key step in the disaggregation procedure is estimating the 14 end-members from ASTER and PLMR data. They are composed of the following: $NDVI_{bs}$, $NDVI_{fgv}$, $\alpha_{bs}$, $\alpha_{fgv}$, $\alpha_{fcsv}$, $T_{b,ws}$, $T_{b,ds}$, $T_{fgv}$, $T_{fcsv}$, $TB_{b,ws}$, $TB_{b,ds}$, $TB_{fgv,ws}$, $TB_{fgv,ds}$, and $TB_{fcsv,ds}$. For the convenience of the reader, the unit is degree Celsius for radiometric temperatures and kelvin for brightness temperature.

#### A. NDVI

$NDVI_{bs}$ and $NDVI_{fgv}$ end-members are estimated as the minimum and maximum NDVI observed over the 5 km by 32 km area for bare soil and full-cover green vegetation, respectively. Values for $NDVI_{bs}$ and $NDVI_{fgv}$ are reported in Table II.

#### B. Albedo

Fig. 3 shows the space defined by surface albedo $\alpha$ and fractional green vegetation cover $f_{gv}$. Pixels including open water are removed from the scatterplot. The soil albedo $\alpha_{bs}$ is defined as the minimum ASTER surface albedo observed within the study area by assuming that the dependence of $\alpha_{bs}$ on soil moisture is small compared to the dependence of $\alpha$ on vegetation cover. The green vegetation albedo $\alpha_{fgv}$ is estimated as the surface albedo corresponding to maximum fractional green vegetation cover. The senescent vegetation albedo $\alpha_{fcsv}$ is estimated as the maximum surface albedo observed within the study area. Values for $\alpha_{bs}$, $\alpha_{fgv}$, and $\alpha_{fcsv}$ are reported in Table II.

#### C. Land Surface Temperature

As the range of surface conditions varies with spatial resolution, two different procedures are developed to estimate temperature end-members.

1) When estimating temperature end-members from 250-m resolution data, one pixel is identified as fully covered green vegetation, one pixel as fully covered senescent vegetation, one pixel as bare dry soil, and one pixel as bare wet soil. In this case, it is assumed that all extreme conditions are included at high resolution within the study domain.

### Table II

**NDVI and Surface Albedo End-Members**

<table>
<thead>
<tr>
<th>End-member</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$NDVI_{bs}$</td>
<td>0.15</td>
<td>-</td>
</tr>
<tr>
<td>$NDVI_{fgv}$</td>
<td>0.65</td>
<td>-</td>
</tr>
<tr>
<td>$\alpha_{bs}$</td>
<td>0.17</td>
<td>-</td>
</tr>
<tr>
<td>$\alpha_{fgv}$</td>
<td>0.22</td>
<td>-</td>
</tr>
<tr>
<td>$\alpha_{fcsv}$</td>
<td>0.31</td>
<td>-</td>
</tr>
</tbody>
</table>

**Fig. 3.** ASTER surface albedo $\alpha$ plotted against ASTER fractional green vegetation cover $f_{gv}$. Three particular values of $\alpha$ are identified: the soil albedo $\alpha_{bs}$ estimated as the minimum surface albedo, the green vegetation albedo $\alpha_{fgv}$ estimated as the albedo corresponding to the largest $f_{gv}$, and the senescent vegetation albedo $\alpha_{fcsv}$ estimated as the maximum surface albedo.
2) When estimating temperature end-members from 1-km resolution data (as in the operational scenario), none of the pixels are identified as representative of any extreme condition. Temperature end-members are extrapolated from 1-km temperature data using ancillary data composed of air temperature, soil albedo, green vegetation albedo, and senescent vegetation albedo as described in the following.

End-members $T_{b,ws}$, $T_{b,das}$, $T_{fcgv}$, and $T_{fcsv}$ are determined by analyzing the consistency of the diagrams in Fig. 4. Fig. 4(a) shows the space defined by ASTER land surface temperature and ASTER fractional green vegetation cover. The three edges of the triangle $T - f_{gv}$ are interpreted [27] as “bare soil” between A and B, “wet surface” between B and C, and “dry soil” between C and A. Fig. 4(b) shows the space defined by ASTER land surface temperature and ASTER surface albedo. An interpolation of the polygon $T - \alpha$ is provided in [5], which is consistent with the triangle method. The four edges are interpreted as “bare soil” between A and B, “wet surface” between B and C, “full cover” between C and D, and “dry surface” between D and A. The notation system for polygon vertices A, B, C, and D is summarized in Table I, and the corresponding temperature values $T_{b,das}$, $T_{b,ws}$, $T_{fcgv}$, and $T_{fcsv}$ are reported in Table III.

In this paper, high-resolution temperature $T$ is assumed to be unavailable. Consequently, the extreme temperatures $T_{b,ws}$, $T_{b,das}$, $T_{fcgv}$, and $T_{fcsv}$ are extrapolated from the spaces $T_{km} - f_{gv} = 0$ and $T_{km} - \alpha = 0$ defined at kilometric resolution (see Fig. 4(c) and (d) for aggregated ASTER temperature and Fig. 4(e) and (f) for MODIS temperature). An approach similar to [5] is used as follows.

1) Vertex C corresponds to full-cover green vegetation and is located at $(1, T_{fcgv})$ in Fig. 4(c) (Fig. 4(e) for MODIS temperature) and at $(\alpha_{fcgv}, T_{fcgv})$ in Fig. 4(d) [Fig. 4(f)]. In this paper, $T_{fcgv}$ is set to the air temperature $T_a$ measured at the time of ASTER overpass. Vertex C is thus placed at $(1, T_a)$ in Fig. 4(c) [Fig. 4(e)] and at $(\alpha_{fcgv}, T_a)$ in Fig. 4(d) [Fig. 4(f)].

2) Vertex B corresponds to wet bare soil and is located at $(0, T_{b,ws})$ in Fig. 4(c) [Fig. 4(e) and at $(\alpha_{bs}, T_{b,ws})$ in Fig. 4(d) [Fig. 4(f)]. It is placed in Fig. 4(c) [Fig. 4(e)] at the intersection between (BC) and the vertical line $f_{gv} = 0$. The slope of (BC) is computed as the slope of the linear regression of the data points corresponding to the “wet surface” edge of the triangle $T_{km} - f_{gv}$. The off-set of (BC) is determined from C.

3) Vertex A corresponds to dry bare soil and is located at $(0, T_{b,das})$ in Fig. 4(c) [Fig. 4(e)] and at $(\alpha_{bs}, T_{b,das})$ in Fig. 4(d) [Fig. 4(f)]. It is placed in Fig. 4(c) [Fig. 4(e)] at the intersection between (AC) and the vertical line $f_{gv} = 0$. The slope of (AC) is computed as the slope of the linear regression of the data points corresponding to the “dry soil” edge of the triangle $T_{km} - f_{gv}$. The off-set of (AC) is determined from C.

4) Vertex D corresponds to full-cover senescent vegetation and is located at $(\alpha_{fcsv}, T_{fcsv})$ in Fig. 4(d) [Fig. 4(f)]. It is placed in Fig. 4(d) [Fig. 4(f)] at the intersection 616 between (AD) and the vertical line $\alpha = \alpha_{fcsv}$. The 617 line (AD) is considered as being parallel to (BC)[5]. 618 Consequently, the slope of (AD) is determined from 619

### Table III

<table>
<thead>
<tr>
<th>End-member</th>
<th>High-resolution</th>
<th>Aggregated ASTER</th>
<th>MODIS</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{b,ws}$</td>
<td>38</td>
<td>40.2</td>
<td>38.9 °C</td>
</tr>
<tr>
<td>$T_{b,das}$</td>
<td>25</td>
<td>27.6</td>
<td>26.2 °C</td>
</tr>
<tr>
<td>$T_{fcgv}$</td>
<td>21</td>
<td>21.0</td>
<td>21.0 °C</td>
</tr>
<tr>
<td>$T_{fcsv}$</td>
<td>34</td>
<td>32.0</td>
<td>28.7 °C</td>
</tr>
<tr>
<td>$T_{b,ws}$</td>
<td>240</td>
<td>246</td>
<td>241 K</td>
</tr>
<tr>
<td>$T_{b,das}$</td>
<td>190</td>
<td>193</td>
<td>193 K</td>
</tr>
<tr>
<td>$T_{fcgv}$</td>
<td>205</td>
<td>205</td>
<td>205 K</td>
</tr>
<tr>
<td>$T_{fcsv}$</td>
<td>240</td>
<td>240</td>
<td>240 K</td>
</tr>
<tr>
<td>$T_{fcsv}$</td>
<td>280</td>
<td>280</td>
<td>280 K</td>
</tr>
</tbody>
</table>
the slope of \((BC)\). The off-set of \((AD)\) is determined from \(A\). Note that the lines \((AD)\) and \((BC)\) might not be strictly parallel. This may be due to a lack of representativeness of the surface conditions captured at 250-m resolution within the study area. In that case, one or several data points may be located above \((AD)\). To circumvent this artifact, the slope of \((AD)\) in Fig. 4(d) \([\text{Fig. 4(f)}]\) is increased so that all data points will be located below the “dry surface” edge.

Table III lists the four temperature end-members: 1) estimated from Fig. 4(a) and (b) using high-resolution ASTER data; 2) extrapolated from Fig. 4(c) and (d) using aggregated ASTER temperature data; and 3) extrapolated from Fig. 4(e) and (f) using MODIS temperature data. The values extrapolated from aggregated ASTER and MODIS temperatures are not reported in the table. The methodology used for estimating \(T_{\text{fev}}\) using MODIS data. In the latter case, the significant underestimation \((5.3\,^\circ \text{C})\) of \(T_{\text{fev}}\) can be explained by the following: 1) the negative mean difference \((-2.3\,^\circ \text{C})\) between MODIS and ASTER data and/or 2) the smaller range of (spatial dynamics) of 1-km resolution MODIS data in relation to 1-km aggregated ASTER data \([\text{please compare Fig. 4(c) with Fig. 4(e), and Fig. 4(d) with Fig. 4(f)}]\).

D. Brightness Temperature

To estimate soil evaporative efficiency \(\beta\) in (20) and \(\beta'\) in (22), five brightness temperature values corresponding to extreme surface conditions are required: \(TB_{b, ws}, TB_{f_{\text{fgv}}, ws}, TB_{f_{\text{fgv}}, ds}, \text{ and } TB_{f_{\text{fev}}, ds}\). In this paper, those five values are estimated from a generalized version \([5, 9]\) of the classical “triangle method” \([27]\).

Fig. 5(a) shows the space defined by PLMR brightness temperature and ASTER land surface temperature. In the following, an original interpretation of the five vertices \(D\) visible in Fig. 5(a) is provided, which is consistent with both the classical “triangle method” and the state-of-the-art L-band radiative transfer models. Vertices are presented successively in the counterclockwise direction, and the correspondence with vegetation and soil conditions is summarized in Table I.

1) Vertex at minimum brightness temperature: L-band radiative transfer models predict an increase of brightness temperature with biomass and a decrease of brightness temperature with surface soil moisture. Therefore, the point at minimum brightness temperature corresponds to a different soil hydric status. The point \(B\) in Fig. 5(a), which is consistent with Fig. 4.

2) Vertex \(A\) corresponds to bare dry soil. It is apparent in the counterclockwise direction in Fig. 5(a) but from 710 the polygon \(TB - f_{\text{gv}}\) shown in Fig. 5(b). The following is an interpretation of the polygon in Fig. 5(b), based on the relationship between the vertices in Fig. 5(a) and the consistency with the polygon in Fig. 5(a).

- Vertex D' corresponds to full-cover senescent vegetation with dry soil. It is located at the maximum value of brightness temperature such that \(f_{\text{gv}} = 1\).
- Vertex C' corresponds to full-cover green vegetation with wet soil. It is located at the minimum value of brightness temperature such that \(f_{\text{gv}} = 1\).

Based on the aforementioned interpretation of the polygon \(TB - f_{\text{gv}}\) in Fig. 5(b), the methodology used for estimating
temperatures $TB$ used as input to $D_0$, $D_1$, $D_2$, which justifies the use of the $T_{\text{mod}}$ model.

VI. APPLICATION

The disaggregation algorithms presented here are applied to the NAFE’06 data set. ASTER land surface temperature is aggregated at 1-km resolution, and kilometric temperature is used as input to $D_0$, $D_1$, $D_1'$, $D_2$, $D_2'$, $D_3'$, $D_4'$, and $D_4''$. As shown in Fig. 1, the verification strategy consists in comparing disaggregation results at 250-m resolution with ASTER land surface temperature. An application to MODIS data is also presented.

A. Application to Aggregated ASTER Data

1) End-Members Derived From High-Resolution Data: The approach is first implemented using the end-members estimated from high-resolution ASTER temperature data. This allows testing the robustness of the model in (15) and (16) independently of the methodology used for extrapolating the nine end-members $T_{b,ds}, T_{b,ws}, T_{f_{\text{fgv}}, ws}, T_{f_{\text{fgv}}, ds}, T_{f_{\text{csv}}, ws}, T_{f_{\text{csv}}, ds}, T_{f_{\text{fgv}}, ws}, T_{f_{\text{fgv}}, ds}, \text{ and } T_{\text{f_{csv}}}$.

Fig. 6 shows the output images of the eight disaggregation algorithms, which are to be compared with the reference image $T_{\text{obs}}$ derived from ASTER land surface temperature. One observes that the disaggregated temperature is successively improved by including additional factors in the disaggregation, which indicates that the methodology is able to take into account several independent factors. Although the boxy artifact at 1-km resolution is successively reduced from $T^{(0)}$ to $T^{(4')}$, it is still apparent for $T^{(4)}$. This effect may be due to the following: 1) other factors that are not taken into account in the procedure, such as vegetation water stress, wind speed, surface emissivity, surface albedo, etc.; 2) errors in estimated $f_{\text{fgv}}$, $f_{\text{csv}}$, $f_{\text{ow}}$, and/or 3) resampling errors at 250-m resolution.

Table IV lists the RMSE, correlation coefficient, and slope between the disaggregated and ASTER temperatures for each $T_{\text{mod}}$ of the eight disaggregation algorithms. The error is successively decreased from 1.65°C to 1.16°C, while the correlation coefficient is 0.8 and 0.88, respectively. When comparing $D_1$, $D_2$, $D_1'$, $D_2'$, $D_3'$, and $D_4'$, no significant differences are observed between all four algorithms in terms of root-mean-square error, correlation coefficient, and slope. Note that, in this paper, $f_{\text{csv}}$ was estimated in a different way than in [5] because only one visible and near-infrared image was available and a FORMOSAT-like time series would be required to derive $f_{\text{csv}}$ more accurately on a pixel-by-pixel basis. Nevertheless, this comparison suggests that $D_1'$ seems to be equivalent to $D_1$ and $D_2'$ equivalent to $D_2$, which justifies the use of the $T_{\text{mod}}$ model.
The main advantage of the new approach is to take into account a number of additional factors, including fractional open water and soil evaporative efficiency. When comparing the results obtained for D3', D4', and D4'' in Table IV, it is observed that the disaggregated temperature is significantly improved against the classical approaches D1 and D2. Moreover, the statistical results are successively improved by including \( f_{ow} \), \( \beta \), and \( \beta' \). Fig. 7 shows the improvement, especially in the slope between the disaggregated and ASTER temperatures. The good results obtained for D4'' indicate that the performance of disaggregation algorithms is intimately related to the following:

1) the capability of separating the independent factors that impact on surface temperature and
2) the ability to integrate them consistently into the procedure.

2) End-Members Derived From Aggregated ASTER Data:

As disaggregation procedures D1', D2', D3', D4', and D4'' are subjected to uncertainties in land surface temperature and brightness temperature end-members, the five algorithms are next tested using the end-members estimated from kilomet- ric temperature data, as presented in Section V. Aggregated ASTER (instead of MODIS) data are used to evaluate the
impact of end-members regardless of the discrepancy between MODIS and ASTER temperatures.

Table IV lists the RMSD, correlation coefficient, and slope between the disaggregated and ASTER temperatures for each of the five algorithms. Results are compared with those obtained using the end-members estimated from high-resolution ASTER temperature. In general, the error is slightly larger, and the correlation coefficient and slope are slightly lower using extrapolated end-members. Nevertheless, the disaggregated temperature is still much improved by applying $D''$ instead of $D'$, with the correlation coefficient and slope increasing from 0.74 to 0.88 and from 0.72 to 0.86, respectively. Consequently, the extrapolation of end-members from kilometric data is not found to be a limiting factor in the methodology.

**B. Application to MODIS Data**

Disaggregation algorithms $D_0$, $D_1$, $D'_1$, $D_2$, $D'_2$, $D'_3$, $D'_4$, and $D''$ are then applied to MODIS data. In this case, end-members are derived from MODIS data. Fig. 8 shows the scatterplot of disaggregated MODIS versus ASTER temperature for each algorithm separately. One observes that the new methodology improves the correlation and slope of the linear regression between the disaggregated and ASTER temperatures. However, a systematic negative bias is apparent in the disaggregated temperature. Table V lists the RMSD, correlation coefficient, and slope for each of the eight algorithms. The error slightly decreases from 3.2 °C to 3.0 °C, while the correlation coefficient and slope increase from 0.6 and 0.3 to 0.7 and 0.5, respectively. The results obtained for $D'_3$ and $D''$ in Table V indicate that the disaggregated temperature is improved against the classical approaches $D_1$ and $D_2$. As for the application to aggregated ASTER data, the statistical results are successively improved by including $f_{row}$, $\beta$, and $\beta'$. However, the improvement with MODIS data is not as visible as with aggregated ASTER data because the difference between MODIS and ASTER data has the same order of magnitude as the subpixel variability at 250-m resolution (see RMSD for $D_0$ in Table V). In particular, the mean bias and the relatively low slope of the linear regression between the disaggregated and ASTER data are associated with the discrepancy at 1-km resolution between the MODIS and ASTER temperature data.

**TABLE V**

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>RMSD °C</th>
<th>$R$</th>
<th>Slope</th>
</tr>
</thead>
<tbody>
<tr>
<td>$D_0$</td>
<td>3.19</td>
<td>0.60</td>
<td>0.33</td>
</tr>
<tr>
<td>$D_1$</td>
<td>3.08</td>
<td>0.67</td>
<td>0.39</td>
</tr>
<tr>
<td>$D_2$</td>
<td>3.11</td>
<td>0.66</td>
<td>0.37</td>
</tr>
<tr>
<td>$D'_1$</td>
<td>3.09</td>
<td>0.67</td>
<td>0.39</td>
</tr>
<tr>
<td>$D'_2$</td>
<td>3.12</td>
<td>0.65</td>
<td>0.39</td>
</tr>
<tr>
<td>$D'_3$</td>
<td>3.06</td>
<td>0.69</td>
<td>0.42</td>
</tr>
<tr>
<td>$D'_4$</td>
<td>2.98</td>
<td>0.73</td>
<td>0.50</td>
</tr>
<tr>
<td>$D''$</td>
<td>3.03</td>
<td>0.70</td>
<td>0.52</td>
</tr>
</tbody>
</table>

**VII. Sensitivity Analysis**

To further assess the stability of the new $D'$ algorithms based on radiative transfer, two sensitivity analyses are conducted by the following: 1) adding a Gaussian noise on kilometric temperatures and high-resolution brightness temperatures and 2) estimating the contribution of each factor on the variability of modeled land surface temperature.

**A. Uncertainty in End-Members**

To test the stability of the method for estimating the nine end-members ($T_{b_{ds}}$, $T_{b_{ds}}$, $T_{fc_{ds}}$, $T_{fc_{ds}}$, $T_{b_{ds}}$, $T_{b_{ds}}$, $T_{fc_{ds}}$, $T_{fc_{ds}}$, $T_{b_{ds}}$, $T_{b_{ds}}$) from low-resolution temperature data, a Gaussian noise with a standard deviation of 1 °C is added to the kilometric (aggregated ASTER) land surface temperature data set, and a Gaussian noise with a standard deviation of 2 K is added to the high-resolution brightness temperature data set. An ensemble of 100 data sets is generated and used as input to the disaggregation algorithms.
TABLE VI
MEAN AND STANDARD DEVIATION OF LAND SURFACE TEMPERATURE AND L-BAND BRIGHTNESS TEMPERATURE END-MEMBERS EXTRAPOLATED USING KILOMETRIC TEMPERATURE DATA. FOR THE CONVENIENCE OF THE READER, THE UNIT IS DEGREE CELSIUS FOR RADIOMETRIC TEMPERATURE AND KELVIN FOR BRIGHTNESS TEMPERATURE.

<table>
<thead>
<tr>
<th>End-member</th>
<th>Mean</th>
<th>St. dev.</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{b,ds}$</td>
<td>40.8</td>
<td>0.8</td>
<td>°C</td>
</tr>
<tr>
<td>$T_{b,ws}$</td>
<td>25.7</td>
<td>1.5</td>
<td>°C</td>
</tr>
<tr>
<td>$T_{fgv}$</td>
<td>21.0</td>
<td>0</td>
<td>°C</td>
</tr>
<tr>
<td>$T_{fcv}$</td>
<td>33.1</td>
<td>1.3</td>
<td>°C</td>
</tr>
<tr>
<td>$TB_{b,ds}$</td>
<td>246</td>
<td>3.2</td>
<td>K</td>
</tr>
<tr>
<td>$TB_{b,ws}$</td>
<td>193</td>
<td>1.4</td>
<td>K</td>
</tr>
<tr>
<td>$TB_{fgv,ws}$</td>
<td>204</td>
<td>2.3</td>
<td>K</td>
</tr>
<tr>
<td>$TB_{fgv,ds}$</td>
<td>240</td>
<td>1.5</td>
<td>K</td>
</tr>
<tr>
<td>$TB_{fcv,ds}$</td>
<td>281</td>
<td>1.0</td>
<td>K</td>
</tr>
</tbody>
</table>

TABLE VII
RMSD, CORRELATION COEFFICIENT ($R$), AND SLOPE BETWEEN THE DISAGGREGATED AND ASTER TEMPERATURES FOR THE DATA INCLUDING ALL THE 100 ARTIFICIALLY NOISED DATA SETS.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>RMSD °C</th>
<th>$R$</th>
<th>Slope</th>
</tr>
</thead>
<tbody>
<tr>
<td>D0</td>
<td>1.81</td>
<td>0.75</td>
<td>0.63</td>
</tr>
<tr>
<td>D1</td>
<td>1.58</td>
<td>0.82</td>
<td>0.76</td>
</tr>
<tr>
<td>D2</td>
<td>1.54</td>
<td>0.83</td>
<td>0.76</td>
</tr>
<tr>
<td>D1'</td>
<td>1.57</td>
<td>0.82</td>
<td>0.73</td>
</tr>
<tr>
<td>D2'</td>
<td>1.54</td>
<td>0.83</td>
<td>0.74</td>
</tr>
<tr>
<td>D3'</td>
<td>1.44</td>
<td>0.85</td>
<td>0.78</td>
</tr>
<tr>
<td>D4'</td>
<td>1.39</td>
<td>0.87</td>
<td>0.87</td>
</tr>
<tr>
<td>D4''</td>
<td>1.48</td>
<td>0.86</td>
<td>0.89</td>
</tr>
</tbody>
</table>

Fig. 9. As for Fig. 7 but using all the 100 artificially noised input data sets.

in land surface temperature is derived by computing the first partial derivative of $T_{mod}$ from (15) and (16)

$$\frac{\partial T_{mod}}{\partial f_{gv}} = -(1-f_{ow})(T_{fcv} - T_{fgv}).$$

Similarly, the first partial derivative of $T_{mod}$ is computed with respect to $f_{sv}$

$$\frac{\partial T_{mod}}{\partial f_{sv}} = -(1-f_{ow})[\beta f_{b,ws} + (1-\beta)f_{b,ds} - T_{fcv}].$$

and with respect to $\beta'$

$$\frac{\partial T_{mod}}{\partial \beta'} = -(1-f_{ow})(1-f_{tv})(T_{b,ds} - T_{b,ws}).$$

Table VIII lists the standard deviation of each parameter within the study area, the average of partial derivatives, and the relative weight of each parameter on the variability of modeled land surface temperature. The relative weights of $f_{gv}$, $f_{sv}$, $f_{ow}$, and $\beta'$ are estimated as the mean partial derivative times the standard deviation. Results indicate that all parameters have a negative impact on $T$. More interestingly, $f_{gv}$ appears to be the most significant variability factor, with a relative weight of 42%, which is consistent with NDVI-based approaches [4].
The second and third most significant variability factors are soil evaporative efficiency and fractional open water, with relative weights of 27% and 20%, respectively. Finally, fractional senescent vegetation cover represents only 11% of the variability in land surface temperature. The low impact of \( f_{sv} \) can be associated with the low mean partial derivative. In particular, \( \partial T_{mod} / \partial f_{sv} \) is low because the temperature difference between dry bare soil (\( T_{b,ds} \)) and full-cover senescent vegetation (\( T_{f,scv} \)) is also low in our case study.

The relative weights in Table VIII are now related with the disaggregation results in Table III. Consequently, the poor improvement of D2 against D1 (and D2 against D1') can be attributed to the relatively low weight of \( f_{sv} \) in the variability of land surface temperature. Conversely, the significant improvements of D4 against D3', D3' against D2', and D1 (and D1') against D0 are attributed to the large weights of \( \beta' \), \( f_{ow} \), and \( f_{sv} \), respectively.

In summary, the variability of land surface temperature is reasonably represented by model \( T_{mod} \). Moreover, the approach allows the relative weight of each variability factor to be taken into account in the disaggregation procedure.

### VIII. SUMMARY AND CONCLUSION

A new disaggregation methodology for land surface temperature has been developed to integrate the main surface parameters involved in the surface energy budget. It is based on a linearized radiative transfer equation, which distinguishes between soil, vegetation, and water temperature, and uses soil evaporative efficiency and fractional senescent vegetation cover to parameterize/estimate soil and vegetation hydric status, respectively. The approach is implemented using four parameters: the fraction of green vegetation cover derived from red and near-infrared bands, the fraction of senescent vegetation cover derived from red and near-infrared bands, the fraction of open water derived from shortwave-infrared band, and the soil evaporative efficiency derived from microwave-L band.

It is tested over a 5 km by 32 km area of irrigated land in Australia, including flooded rice crops, using ASTER and L-band airborne data. Low-resolution land surface temperature is simulated by aggregating ASTER land surface temperature at 1-km resolution, and the disaggregated temperature is compared to high-resolution ASTER temperature. The results indicate that the methodology is able to separate efficiently the independent factors that impact surface temperature and to integrate them consistently into the disaggregation procedure. The error in disaggregated temperature is successively reduced from 975 to 1.65 °C to 1.16 °C by including each of the four parameters. The correlation coefficient and slope between the disaggregated and ASTER temperatures are improved from 0.79 to 0.89 and 0.63 to 0.88, respectively. Moreover, the radiative transfer equation allows quantifying the impact at high resolution of each parameter on land surface temperature. In this case study, fractional green vegetation cover is responsible for 42% of the variability in disaggregated land surface temperature, fractional senescent vegetation cover for 11%, fractional open water for 20%, and soil evaporative efficiency for 23%.

Note that the approach presented in this paper did not take into account the water stress of green vegetation because none of the considered parameters (fractional green vegetation cover, fractional senescent vegetation cover, fractional open water, and soil evaporative efficiency) could describe the hydric status of photosynthetically active (green) vegetation. The analysis was conducted solely in a highly irrigated environment in which water stress was small. However, in most cases, the vegetation water stress might not be negligible for natural areas. In the presence of water-stressed green vegetation, the scatterplot (temperature versus green vegetation cover) would be transformed into a trapezoidal shape with four vertices rather than a triangle. In such conditions, the disaggregation problem would be partly undetermined since the partitioning between unstressed and stressed green vegetations would not be represented. Consequently, the approaches shown here are not expected to be representative of other less extreme environments than the present irrigated area. Nevertheless, one should keep in mind that improving the spatial resolution of land surface temperature data via disaggregation is only relevant in the conditions where the spatial variability of temperature is large.

Although the approach was successfully applied to airborne and satellite data collected during NAFE’06, further research is needed to test the disaggregation approach on a routine basis. One may anticipate that fractional green and senescent vegetation cover, seasonal variability covers could be derived accurately using FORMOSAT-12-like data. The FORMOSAT-2 instrument [52] provides short-wave data at high spatial resolution (8 m) and high temporal frequency (potentially one image per day), which allow a fine analysis of the seasonality of canopies during the crop cycle [5], [53], [54]. Fractional open water could be derived from Landsat-5 data (e.g., [20]). Although the repeat cycle of Landsat (16 days) is longer than the temporal resolution needed for land surface temperature, the seasonal variations of water bodies
The authors would like to thank the NAFE'06 participants for their participation in collecting this extensive data set.

ACKNOWLEDGMENT

The availability of high-resolution radar data.

REFERENCES


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