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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 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 respon-

sible 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

RE MOTELY 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 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 kilometer 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 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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80 The accuracy in disaggregated temperature was improved by  
81 taking into account fractional senescent vegetation cover in  
82 addition to fractional green vegetation cover.

83 Fractional green and senescent vegetation covers, however,  
84 are not the only factors explaining the spatial variations of land  
85 surface temperature, especially over irrigated areas where crop  
86 fields may have different moisture status to the surrounds. In  
87 particular, the temperature over a flooded crop field may be  
88 drastically different from the temperature over a mature crop  
89 field. Therefore, the fraction of open water is an important  
90 variable to represent the spatial variations of land surface tem-  
91 perature. Over nonwatered land surfaces, the soil evaporative  
92 efficiency (ratio of actual to potential soil evaporation) is a  
93 signature of the capacity of the soil to evaporate its water  
94 content in the near surface and thus to counter an increase of  
95 its thermodynamic temperature. Consequently, soil evaporative  
96 efficiency is also an essential variable to describe the spatial  
97 variations of land surface temperature. Moreover, knowledge  
98 of soil evaporative efficiency is needed to decouple the effects  
99 of soil and vegetation hydric status on the surface energy  
100 budget and hence to better represent the resultant radiative  
101 surface temperature. As an example, the crop water stress index  
102 (CWSI) [6], [7] can be used to detect plant stress based on the  
103 difference between foliage and air temperature. Nevertheless,  
104 the application of the CWSI to partially vegetated areas is  
105 subjected to large uncertainties because the soil background  
106 may have a different temperature to the plants [7] depending  
107 on soil evaporative efficiency. Another example is provided by  
108 Moran *et al.* [8] who proposed the vegetation index/temperature  
109 (VIT) trapezoid to estimate a most probable range of plant  
110 stress over partially vegetated fields. It is a three-step procedure  
111 in which the following steps are performed: 1) the temperatures  
112 of the four vertices of the VIT trapezoid are estimated using an  
113 energy budget model; 2) the minimum and maximum probable  
114 vegetation temperatures are estimated from the measured com-  
115 posite land surface temperature, together with the maximum  
116 and minimum simulated soil temperatures; and 3) the minimum  
117 and maximum probable CWSIs are computed by normalizing  
118 the minimum and maximum probable vegetation temperatures  
119 from the vegetation temperature extremes simulated by the  
120 energy budget model. The point is that this approach does not  
121 allow estimating a single CWSI value because the retrieval  
122 problem is underdetermined. In particular, Moran *et al.* [8]  
123 noted that “with knowledge of a second point within the  
124 hourglass (perhaps soil temperature), it would be possible to  
125 infer [the canopy-air temperature] difference and pinpoint the  
126 CWSI value.” In the latter case, knowledge of soil temperature  
127 is equivalent to knowledge of soil evaporative efficiency, which  
128 would remove the underdetermination of the VIT trapezoid.

129 The objective of this paper is to develop a new disaggrega-  
130 tion methodology of kilometeric land surface temperature using  
131 hectometric multivariable ancillary data. The approach is based  
132 on a radiative transfer equation that estimates differences in  
133 temperature data at hectometric resolution. Specifically, the use  
134 of a radiative transfer equation allows the following: 1) includ-  
135 ing variables other than those used by previous disaggregation  
136 approaches and 2) deducing the most pertinent variables. In  
137 addition to fractional green and senescent vegetation covers, the

new methodology includes the variability at hectometric reso- 138  
lution of fractional open water and soil evaporative efficiency. 139  
With respect to other disaggregation algorithms in literature 140  
[4], [5], the proposed technique differs in the following four 141  
main aspects: 1) it relies on a physically based radiative transfer 142  
equation rather than empirical linear regressions; 2) it takes 143  
into account the fractional open water derived from shortwave- 144  
infrared band as required; 3) it takes into account the soil hydric 145  
status via microwave-derived soil evaporative efficiency; and 146  
4) it allows the relative weight of each parameter used for 147  
disaggregating temperature to be quantified. 148

The new disaggregation technique is compared to the ex- 149  
isting approaches using data collected during the National 150  
Airborne Field Experiment in 2006 (NAFE’06; [9]). The ex- 151  
perimental site covers a 5 km by 32 km irrigated agricultural 152  
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 159  
MODIS products [5]. Disaggregation algorithms are then ap- 160  
plied to MODIS data. 161

## 162 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. 169

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. 180

### 181 A. PLMR

The Polarimetric L-band Multibeam Radiometer (PLMR) is 182  
an airborne instrument that measures both H and V polariza- 183  
tions using a single receiver with polarization switching at view 184  
angles of  $\pm 7^\circ$ ,  $\pm 21.5^\circ$ , and  $\pm 38.5^\circ$ . The accuracy of the PLMR 185  
is estimated to be better than 2 K and 3 K in the H and V 186  
polarization, respectively [10]. 187

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

192 given incidence angle (approximately  $7^\circ$ ,  $21.5^\circ$ , or  $38.5^\circ$ ). Data  
193 were processed for incidence angle and beam location on the  
194 ground by taking into account aircraft position, attitude, and  
195 ground topography.

196 As the sensitivity to soil moisture is higher for H-polarized  
197 brightness temperature than for V-polarized brightness temper-  
198 ature, only the H-polarized brightness temperature  $TB$  is used  
199 in this paper. Preprocessing of  $TB$  consists of the following:  
200 1) resampling H-polarized PLMR data at 250-m resolution  
201 on a grid that matches in symmetry to the flight lines over  
202 the 5 km by 32 km area and 2) converting the resampled  
203  $TB$  to an equivalent value at  $21.5^\circ$  incidence angle. The in-  
204 cidence angle  $21.5^\circ$  is chosen to minimize conversion errors.  
205 The angular conversion involves the brightness temperature  
206 collected by inner beams at approximately  $7^\circ$  incidence angle  
207 being multiplied by the ratio  $\overline{TB_{MB}}/\overline{TB_{IB}}$ , with  $\overline{TB_{MB}}$  and  
208  $\overline{TB_{IB}}$  being the mean brightness temperatures collected by the  
209 middle and inner beams, respectively. Similarly, the brightness  
210 temperature collected by the outer beams at approximately  
211  $38.5^\circ$  incidence angle is multiplied by the ratio  $\overline{TB_{MB}}/\overline{TB_{OB}}$ ,  
212 with  $\overline{TB_{OB}}$  being the mean brightness temperature collected by  
213 the outer beams. Mean brightness temperatures  $\overline{TB_{IB}}$ ,  $\overline{TB_{MB}}$ ,  
214 and  $\overline{TB_{OB}}$  are computed as the average (for all flight lines)  
215 of the  $TB$  collected by the beams pointing at  $\pm 7^\circ$ ,  $\pm 21.5^\circ$ ,  
216 and  $\pm 38.5^\circ$ , respectively. This technique was already used in  
217 [11] to generate  $TB$  images by assuming that the impact of  
218 soil moisture and biomass on the angular dependence of  $TB$  is  
219 negligible or small. In this paper, a slightly different approach  
220 is adopted to take into account the variations in aircraft attitude  
221 during data collection, which made the incidence angle  $\theta$  os-  
222 cillate around  $7^\circ$ ,  $21.5^\circ$ , and  $38.5^\circ$ . The brightness temperature  
223  $TB(\theta)$  observed at the incidence angle  $\theta$  is multiplied by the  
224 ratio  $\overline{TB_{MB}}/\overline{TB_{interp}(\theta)}$ , with  $\overline{TB_{interp}(\theta)}$  being the mean  
225 brightness temperature linearly interpolated at  $\theta$  incidence an-  
226 gle from the mean data collected by the inner, middle, and outer  
227 beams.

## 228 B. ASTER

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

238 The ASTER overpass of the NAFE'06 site was on  
239 November 16, 2006. Official ASTER products [12] were used  
240 here for surface reflectance (AST\_07) and radiometric temper-  
241 ature (AST\_08) with accuracies of 5% and 1.5 K, respectively  
242 [13]–[19]. They were downloaded from the Earth Observing  
243 System Data Gateway (EDG).

244 ASTER 15-m resolution red (B2) and near-infrared (B3)  
245 bands were extracted over the 5 km by 32 km area and re-  
246 sampled at 250-m resolution to match the spatial resolution  
247 and extent of PLMR observations. The ASTER 30-m resolution

B5 band (1.60–1.70  $\mu\text{m}$ ) was extracted over the 5 km by 248  
32 km study area and resampled at 50-m resolution. Fractional 249  
open water was estimated using B5 band [20] based on a 250  
threshold method. Consequently, B5 data were resampled at 251  
a resolution finer than that (250 m) of PLMR data to classify 252  
open water pixels at 50-m resolution and to obtain fractional 253  
open water at 250-m resolution from the binary classification. 254  
ASTER 90-m resolution radiometric temperature was extracted 255  
over the 5 km by 32 km area and aggregated at 250-m res- 256  
olution to match the spatial resolution and extent of PLMR 257  
observations. Aggregation was achieved by linearly averaging 258  
high-resolution surface temperatures, i.e., without accounting 259  
for the nonlinear relationship between physical temperature and 260  
radiance. This choice was motivated by the results of [21], 261  
which compared the temperature aggregated using different 262  
scaling approaches and obtained very low differences (maxi- 263  
mum difference of  $0.2^\circ\text{C}$ ). 264

## 265 C. MODIS

The MODIS/Terra data were collected concurrently with 266  
ASTER data. MODIS official products consisted of the 928-m 267  
resolution surface skin temperature (MOD11-L2) retrieved by 268  
the “generalized split window” algorithm [22]–[24] and reg- 269  
istered in the sinusoidal projection. The MODIS Reprojection 270  
Tool was used to project MOD11-L2 data in UTM WGS 1984 271  
55S with a sampling interval of 1 km. 272

In this paper, the disaggregation of 1-km MODIS tempera- 273  
ture is evaluated using high-resolution ASTER data. To distin- 274  
guish the errors associated with the disaggregation technique 275  
and the errors associated with the discrepancy between MODIS 276  
and ASTER temperature products, a comparison is made be- 277  
tween ASTER and MODIS data at 1-km resolution over the 278  
5 km by 32 km study area. The ASTER data are aggregated 279  
at the MODIS spatial resolution (1 km) by linearly averaging 280  
high-resolution temperatures. The root-mean-square difference 281  
(RMSD), bias, correlation coefficient, and slope of the linear 282  
regression between MODIS and aggregated ASTER data are 283  
 $2.7^\circ\text{C}$ ,  $-2.3^\circ\text{C}$ , 0.75, and 0.52, respectively. The discrepancy 284  
between MODIS and ASTER data, which is mainly explained 285  
here by a significant bias and a relatively low slope of the linear 286  
regression, is on the same order of magnitude as the mean 287  
difference (about  $3^\circ\text{C}$ ) reported in literature [5], [21], [25]. 288

## 289 III. DISAGGREGATION ALGORITHMS

This paper aims to compare different approaches for dis- 290  
aggregating kilometric MODIS land surface temperature data. 291  
The study uses aggregated ASTER and real MODIS data 292  
and demonstrates the disaggregation at 250-m resolution. The 293  
resolution of 250 m is chosen to match with the lowest reso- 294  
lution at which ancillary data composed of red, near-infrared, 295  
shortwave-infrared, and microwave-L bands are available. In 296  
this case study, the target scale is determined by the resolution 297  
(250 m) of airborne microwave data. 298

As shown in the schematic diagram of Fig. 1, the disaggre- 299  
gation algorithms are noted as  $Dk$ , with  $k$  being the number 300  
of factors taken into account in the disaggregation. The new 301

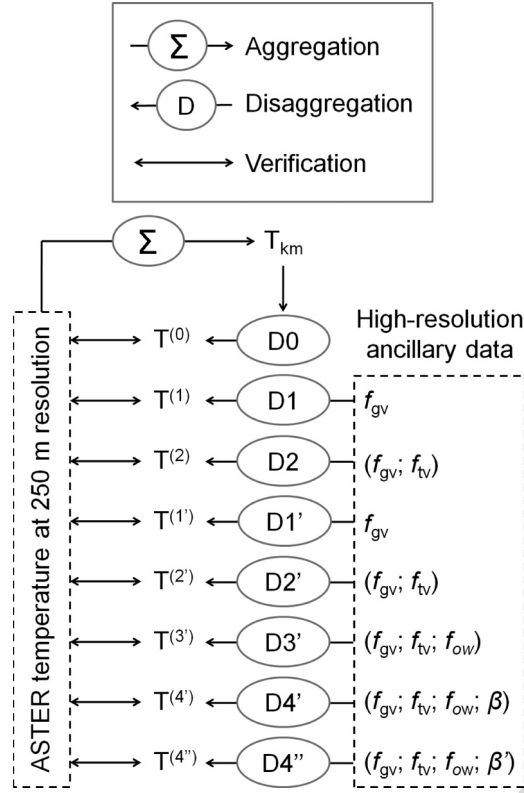


Fig. 1. Schematic diagram presenting the different disaggregation algorithms of kilometric temperature  $T_{km}$  and the verification strategy at high (250 m) resolution.

algorithms are noted as  $Dk'$ . D0 does not use any ancillary data, while D1 is based on a linear regression between land surface temperature and fractional green (photosynthetically active) vegetation cover. Fractional green vegetation cover  $f_{gv}$  is defined as the surface area of green vegetation per unit area of soil. D1 is the same as in [4]. D2 is based on D1 but takes into account both fractional green and total vegetation covers. Fractional vegetation cover  $f_{tv}$  is defined as the total surface area of (green plus senescent) vegetation per unit area of soil. D2 is the same as in [5]. The new algorithms D1', D2', D3', and D4' (and D4'') are all derived from a radiative transfer equation. The four algorithms differ with regard to the number of factors which are explicitly taken into account. D1' includes the variability of  $f_{gv}$  and is thus a substitute for D1 based on radiative transfer. D2' includes the variability of both  $f_{gv}$  and  $f_{tv}$  and is thus a substitute for D2 based on radiative transfer. The other algorithms D3' and D4' integrate additional variables. D3' includes the variability of  $f_{gv}$ ,  $f_{tv}$ , and fractional open water  $f_{ow}$ . D4' includes the variability of  $f_{gv}$ ,  $f_{tv}$ ,  $f_{ow}$ , and soil evaporative efficiency (ratio of actual to potential soil evaporation)  $\beta$ . D4'' is the same as D4' but with a different formulation for soil evaporative efficiency.

D0 sets the disaggregated temperature as

$$T^{(0)} = T_{km} \quad (1)$$

with  $T_{km}$  being the land surface temperature observed at kilometric resolution.

Using D1, the disaggregated temperature is computed as 327

$$T^{(1)} = T_{km} + \mathbf{a}_1 \times (f_{gv} - \langle f_{gv} \rangle_{km}) \quad (2)$$

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  $\mathbf{a}_1$  being the slope of the linear regression between  $T_{km}$  and  $\langle f_{gv} \rangle_{km}$ . Note that the variables defined at kilometric resolution are noted with the subscript km.

Using D2, the disaggregated temperature is computed as 333

$$T^{(2)} = T_{km} + \mathbf{a}_1^{\text{proj}} \times (f_{gv}^{\text{proj}} - \langle f_{gv} \rangle_{km}) \quad (3)$$

with  $f_{gv}^{\text{proj}}$  being the projected  $f_{gv}$  and  $\mathbf{a}_1^{\text{proj}}$  being the slope of the linear regression between  $T_{km}$  and the projected  $f_{gv}$  estimated at kilometric resolution  $f_{gv,km}^{\text{proj}}$ . Note that the variables defined at the image scale are written in bold. The notion of a “projected variable” was introduced in [26]. It is a robust tool that strengthens the correlation between two variables by representing the dependence of these variables on other additional variables. In [5], the projection technique was applied to fractional green vegetation cover to artificially improve the spatial correlation between  $T$  and  $f_{gv}$  by taking into account the dependence of  $T$  on  $f_{tv}$ . The projected fractional green vegetation cover is computed as 345

$$f_{gv}^{\text{proj}} = f_{gv} - \frac{\mathbf{T}_{fcsv} - (\mathbf{T}_{b,ds} + \mathbf{T}_{b,ws})/2}{\mathbf{T}_{fcsv} - \mathbf{T}_{fcgv}} \times (f_{tv} - \langle f_{tv} \rangle_{km}) \quad (4)$$

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,  $\mathbf{T}_{b,ws}$  being the temperature of wet bare soil,  $\mathbf{T}_{b,ds}$  being the temperature of dry bare soil,  $\mathbf{T}_{fcgv}$  being the temperature of full-cover green vegetation, and  $\mathbf{T}_{fcsv}$  being the temperature of full-cover senescent vegetation (notations are summarized in Table I). Following the interpretation of the “triangle method” [27],  $\mathbf{T}_{b,ws}$ ,  $\mathbf{T}_{b,ds}$ ,  $\mathbf{T}_{fcgv}$ , and  $\mathbf{T}_{fcsv}$  correspond to the minimum and maximum soil and vegetation temperatures within the study area, respectively. It is reminded that  $f_{tv} = f_{gv} + f_{sv}$ , with  $f_{gv}$  and  $f_{sv}$  being the fractional green and senescent vegetation covers, respectively.

In (4), the projected fractional green vegetation cover estimated at kilometric resolution is 359

$$f_{gv,km}^{\text{proj}} = \langle f_{gv} \rangle_{km} - \frac{\mathbf{T}_{fcsv} - (\mathbf{T}_{b,ds} + \mathbf{T}_{b,ws})/2}{\mathbf{T}_{fcsv} - \mathbf{T}_{fcgv}} \times (\langle f_{tv} \rangle_{km} - \mathbf{f}_{tv}) \quad (5)$$

with  $\mathbf{f}_{tv}$  being the mean  $f_{tv}$  over the whole study area. 360

The new algorithms D' use a radiative transfer equation to model the spatial variability of disaggregated temperature 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 a substitute for D1 based on radiative transfer. It expresses disaggregated temperature as 366

$$T^{(1')} = T_{km} + \Delta T^{(1')} \quad (6)$$

TABLE I  
 INTERPRETATION OF THE VERTICES IN THE GENERALIZED “TRIANGLE APPROACH”

Vertex	Surface type	Near-surface soil hydric status	Abbreviation
<b>A</b>	Bare soil	Dry	b,ds
<b>B</b>	Bare soil	Wet	b,ws
<b>C</b>	Full-cover green vegetation	Wet or dry	fcgv
<b>C'</b>	Full-cover green vegetation	Wet	fcgv,ws
<b>C''</b>	Full-cover green vegetation	Dry	fcgv,ds
<b>D</b>	Full-cover senescent vegetation	Wet or dry	fcsv
<b>D'</b>	Full-cover senescent vegetation	Dry	fcsv,ds

367 with  $\Delta T^{(1')}$  being the difference between the temperature  
 368 simulated using high-resolution  $f_{gv}$  and that aggregated within  
 369 the 1-km resolution pixel

$$\Delta T^{(1')} = T_{\text{mod}} (f_{gv}, \langle f_{tv} \rangle_{\text{km}}, \langle f_{ow} \rangle_{\text{km}}, \langle \beta \rangle_{\text{km}}) - \langle T_{\text{mod}} (f_{gv}, \langle f_{tv} \rangle_{\text{km}}, \langle f_{ow} \rangle_{\text{km}}, \langle \beta \rangle_{\text{km}}) \rangle_{\text{km}} \quad (7)$$

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

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

$$\Delta T^{(2')} = T_{\text{mod}} (f_{gv}, f_{tv}, \langle f_{ow} \rangle_{\text{km}}, \langle \beta \rangle_{\text{km}}) - \langle T_{\text{mod}} (f_{gv}, f_{tv}, \langle f_{ow} \rangle_{\text{km}}, \langle \beta \rangle_{\text{km}}) \rangle_{\text{km}} \quad (8)$$

379  $D3'$  is derived from the same radiative transfer equation and  
 380 includes the variability of  $f_{gv}$ ,  $f_{tv}$ , and  $f_{ow}$  at high resolution.  
 381 It determines the disaggregated temperature using (6) but with  
 382 the simulated temperature difference  $\Delta T^{(3')}$  written as

$$\Delta T^{(3')} = T_{\text{mod}} (f_{gv}, f_{tv}, f_{ow}, \langle \beta \rangle_{\text{km}}) - \langle T_{\text{mod}} (f_{gv}, f_{tv}, f_{ow}, \langle \beta \rangle_{\text{km}}) \rangle_{\text{km}} \quad (9)$$

383  $D4'$  is derived from the same radiative transfer equation and  
 384 includes the variability of  $f_{gv}$ ,  $f_{tv}$ ,  $f_{ow}$ , and  $\beta$  at high resolu-  
 385 tion. It determines the disaggregated temperature using (6) but  
 386 with the simulated temperature difference  $\Delta T^{(4')}$  written as

$$\Delta T^{(4')} = T_{\text{mod}} (f_{gv}, f_{tv}, f_{ow}, \beta) - \langle T_{\text{mod}} (f_{gv}, f_{tv}, f_{ow}, \beta) \rangle_{\text{km}} \quad (10)$$

387  $D4''$  is an extension of (10) to replace  $\beta$  by another formula-  
 388 tion of soil evaporative efficiency noted as  $\beta'$ .

389 The high- to low-resolution simulated temperature difference  
 390 in (7)–(10) is computed using a linearized radiative transfer  
 391 equation [5], [28], [29]. Modeled land surface temperature  
 392  $T_{\text{mod}}$  is written as

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

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

Nonwatered land surface temperature is expressed as 395

$$T_{nw} = f_{gv}\mathbf{T}_{fcgv} + (f_{tv} - f_{gv})\mathbf{T}_{fcsv} + (1 - f_{tv})T_{bs} \quad (12)$$

with  $\mathbf{T}_{fcgv}$  and  $\mathbf{T}_{fcsv}$  being the temperature of full-cover green 396  
 and senescent vegetations, respectively, and  $T_{bs}$  being the bare 397  
 soil temperature. With the soil evaporative efficiency defined 398  
 [30] as 399

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

the bare soil temperature can be expressed as 400

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

By assuming that water temperature is close to well-watered 401  
 green vegetation [27], modeled land surface temperature 402  
 becomes 403

$$T_{\text{mod}} = f_{ow}\mathbf{T}_{fcgv} + (1 - f_{ow})T_{nw} \quad (15)$$

with the nonwatered land surface temperature expressed as 404

$$T_{nw} = f_{gv}\mathbf{T}_{fcgv} + (f_{tv} - f_{gv})\mathbf{T}_{fcsv} + (1 - f_{tv})[\beta\mathbf{T}_{b,ws} + (1 - \beta)\mathbf{T}_{b,ds}] \quad (16)$$

The temperature extremes  $\mathbf{T}_{b,ds}$ ,  $\mathbf{T}_{b,ws}$ ,  $\mathbf{T}_{fcgv}$ , and  $\mathbf{T}_{fcsv}$  are 405  
 extrapolated (according to Section V) from low-resolution land 406  
 surface temperatures using high-resolution ancillary data [5]. 407

#### IV. DERIVATION OF BIOPHYSICAL VARIABLES 408

The four variables used by the disaggregation methodol- 409  
 ogy are the following: fractional green vegetation cover  $f_{gv}$ , 410  
 fractional total (green plus senescent) vegetation cover  $f_{tv}$ , 411  
 fractional open water  $f_{ow}$ , and soil evaporative efficiency  $\beta$ . 412  
 All of these variables are estimated from ASTER red, near- 413  
 infrared, and shortwave-infrared reflectance products and from 414  
 the PLMR H-polarized brightness temperature converted at an 415  
 incidence angle of 21.5°. 416

##### A. Fractional Green Vegetation Cover 417

Fractional green vegetation cover can be estimated from the 418  
 Normalized Difference Vegetation Index (NDVI) as in [31] 419

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

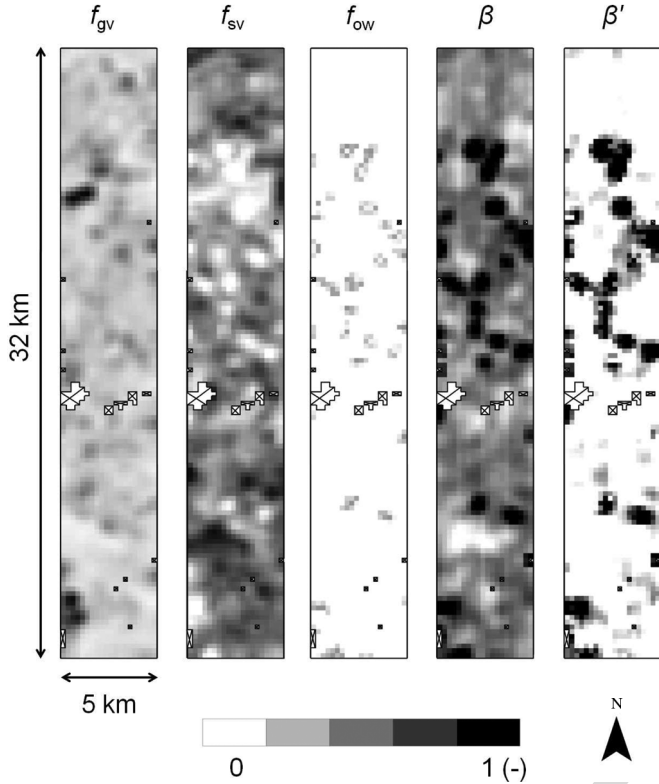


Fig. 2. Images of fractional green vegetation cover  $f_{gv}$ , fractional senescent vegetation cover  $f_{sv} = f_{tv} - f_{gv}$ , fractional open water  $f_{ow}$ , soil evaporative efficiency  $\beta$ , and soil evaporative efficiency  $\beta'$ . Note that 2% of the 5 km by 32 km area is contaminated by clouds and cloud shadow. Contaminated 250-m resolution pixels are represented by crossed-out surfaces.

420 with  $NDVI_{bs}$  and  $NDVI_{fcgv}$  being the NDVI over bare  
421 soil and full-cover green vegetation, respectively. NDVI is  
422 computed as the difference between near-infrared and red bands  
423 divided by their sum. The spatial variation of fractional green  
424 vegetation cover over the study area is shown in Fig. 2.

#### 425 B. Fractional Total (Green Plus Senescent) Vegetation Cover

426 Fractional total vegetation cover is estimated by correlating  
427  $f_{tv}$  with surface albedo for green vegetation and by setting  $f_{tv}$   
428 to the maximum  $f_{gv}$  for senescent vegetation. This methodol-  
429 ogy [5] is based on two assumptions, which are generally met in  
430 agricultural areas: 1) soil albedo is generally lower than green  
431 vegetation albedo, and 2) green vegetation albedo is lower than  
432 senescent vegetation albedo. Although a time series of red and  
433 near-infrared data would be required to estimate soil albedo  
434 and green vegetation albedo on a pixel-by-pixel basis [5], only  
435 one ASTER scene is available for this study period. Therefore,  
436 an alternate approach is adopted. Surface albedo is modeled  
437 as a linear mixing of vegetation and soil components (e.g.,  
438 [32] and [33])

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

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

By inverting (18), fractional vegetation cover is expressed as 443

$$f_{tv} = \frac{\alpha - \alpha_{bs} + f_{gv}(\alpha_{fcsv} - \alpha_{fcgv})}{\alpha_{fcsv} - \alpha_{bs}} \quad (19)$$

with  $\alpha$  being the surface albedo estimated as a weighted sum of 444  
red and near-infrared reflectances using the coefficients given in 445  
[34] and validated in [35]–[38]. As stated previously, our case 446  
study does not allow calibrating  $\alpha_{bs}$ ,  $\alpha_{fcgv}$ , and  $\alpha_{fcsv}$  on a 447  
pixel-by-pixel basis. Consequently, the value of  $f_{tv}$  computed 448  
from (19) may, on some occasions, be lower than  $f_{gv}$  or larger 449  
than 1. To avoid nonphysical values,  $f_{tv}$  is set to  $f_{gv}$  and 1 in 450  
the former and latter case, respectively. 451

The spatial variation of fractional senescent vegetation cover 452  
( $f_{sv} = f_{tv} - f_{gv}$ ) over the study area is shown in Fig. 2. Note 453  
that NAFE'06 was undertaken at the beginning of the summer 454  
agricultural season so that all irrigated crops were green and 455  
healthy. 456

#### C. Fractional Open Water 457

The fraction of open water within each 250-m resolution 458  
pixel is estimated using 50-m resolution resampled ASTER 459  
B5 reflectance product. Various studies have indicated that the 460  
shortwave-infrared band centered at around  $1 \mu\text{m}$  is highly 461  
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 464  
nonwatered surface. The threshold value is estimated as 0.170 465  
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 467  
shown in Fig. 2. Open water represents 5% of the study area 468  
and is attributed to rice cropping. 469

#### D. Soil Evaporative Efficiency 470

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. 476

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 480

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

with  $TB_{b,ws}$  and  $TB_{fcsv,ds}$  being the minimum and max- 481  
imum 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. 488

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

TABLE II  
NDVI AND SURFACE ALBEDO END-MEMBERS

End-member	Value	Unit
$\text{NDVI}_{\text{bs}}$	0.15	-
$\text{NDVI}_{\text{fcgv}}$	0.65	-
$\alpha_{\text{bs}}$	0.17	-
$\alpha_{\text{fcgv}}$	0.22	-
$\alpha_{\text{fcsv}}$	0.31	-

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

$$\beta' = 0 \quad \text{if } TB > TB_{\text{ds}} \quad (21)$$

$$\beta' = 1 - \frac{TB - TB_{\text{ws}}}{TB_{\text{ds}} - TB_{\text{ws}}} \quad \text{if } TB \leq TB_{\text{ds}} \quad (22)$$

500 with  $TB_{\text{ds}}$  and  $TB_{\text{ws}}$  being the “dry soil” and “wet soil”  
501 brightness temperatures, respectively, both being estimated for  
502  $f_{\text{sv}} = 0$ . 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  $TB_{\text{b,ds}}$ ) and the brightness temperature over full-  
506 cover green vegetation with dry soil (noted as  $TB_{\text{fcgv,ds}}$ )

$$TB_{\text{ds}} = f_{\text{gv}} TB_{\text{fcgv,ds}} + (1 - f_{\text{gv}}) TB_{\text{b,ds}}. \quad (23)$$

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  $TB_{\text{b,ws}}$ ) and the brightness temperature over full-  
510 cover green vegetation with wet soil (noted as  $TB_{\text{fcgv,ws}}$ )

$$TB_{\text{ws}} = f_{\text{gv}} TB_{\text{fcgv,ws}} + (1 - f_{\text{gv}}) TB_{\text{b,ws}}. \quad (24)$$

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:  $\text{NDVI}_{\text{bs}}$ ,  $\text{NDVI}_{\text{fcgv}}$ ,  $\alpha_{\text{bs}}$ ,  
516  $\alpha_{\text{fcgv}}$ ,  $\alpha_{\text{fcsv}}$ ,  $T_{\text{b,ws}}$ ,  $T_{\text{b,ds}}$ ,  $T_{\text{fcgv}}$ ,  $T_{\text{fcsv}}$ ,  $TB_{\text{b,ws}}$ ,  $TB_{\text{b,ds}}$ ,  
517  $TB_{\text{fcgv,ws}}$ ,  $TB_{\text{fcgv,ds}}$ , and  $TB_{\text{fcsv,ds}}$ . For the convenience  
518 of the reader, the unit is degree Celsius for radiometric temper-  
519 ature and kelvin for brightness temperature.

### 520 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  $\text{NDVI}_{\text{bs}}$  and  $\text{NDVI}_{\text{fcgv}}$  are reported in Table II.

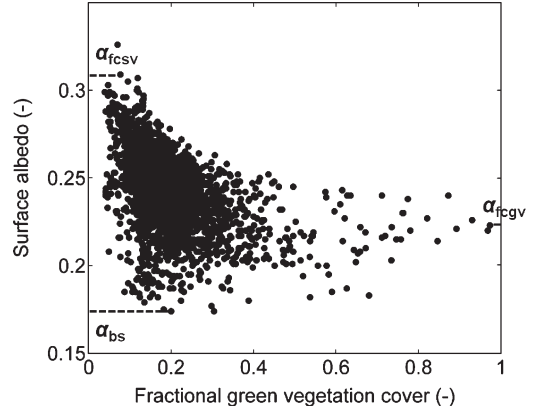


Fig. 3. ASTER surface albedo  $\alpha$  plotted against ASTER fractional green vegetation cover  $f_{\text{gv}}$ . Three particular values of  $\alpha$  are identified: the soil albedo  $\alpha_{\text{bs}}$  estimated as the minimum surface albedo, the green vegetation albedo  $\alpha_{\text{fcgv}}$  estimated as the albedo corresponding to the largest  $f_{\text{gv}}$ , and the senescent vegetation albedo  $\alpha_{\text{fcsv}}$  estimated as the maximum surface albedo.

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]. 535

### B. Albedo

536  
Fig. 3 shows the space defined by surface albedo  $\alpha$  and 537  
fractional green vegetation cover  $f_{\text{gv}}$ . Pixels including open 538  
water are removed from the scatterplot. The soil albedo  $\alpha_{\text{bs}}$  539  
is defined as the minimum ASTER surface albedo observed 540  
within the study area by assuming that the dependence of 541  
 $\alpha_{\text{bs}}$  on soil moisture is small compared to the dependence of 542  
 $\alpha$  on vegetation cover. The green vegetation albedo  $\alpha_{\text{fcgv}}$  is 543  
estimated as the surface albedo corresponding to maximum 544  
fractional green vegetation cover. The senescent vegetation 545  
albedo  $\alpha_{\text{fcsv}}$  is estimated as the maximum surface albedo 546  
observed within the study area. Values for  $\alpha_{\text{bs}}$ ,  $\alpha_{\text{fcgv}}$ , and 547  
 $\alpha_{\text{fcsv}}$  are reported in Table II. 548

### 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. 552

- 1) When estimating temperature end-members from 250-m 553  
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. 559



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

End-member	High-resolution $T$	Aggregated ASTER $T_{km}$	MODIS $T_{km}$	Unit
$T_{b,ds}$	38	40.2	38.9	$^{\circ}\text{C}$
$T_{b,ws}$	25	27.6	26.2	$^{\circ}\text{C}$
$T_{fegv}$	21	21.0	21.0	$^{\circ}\text{C}$
$T_{fcsv}$	34	32.0	28.7	$^{\circ}\text{C}$
$TB_{b,ds}$	240	246	241	K
$TB_{b,ws}$	190	193	193	K
$TB_{fegv,ws}$	205	205	205	K
$TB_{fegv,ds}$	240	240	240	K
$TB_{fcsv,ds}$	280	280	280	K

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  $T_{b,ws}$ ,  $T_{b,ds}$ ,  $T_{fegv}$ , 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 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 system for polygon vertices A, B, C, and D is summarized in Table I, and the corresponding temperature values  $T_{b,ds}$ ,  $T_{b,ws}$ ,  $T_{fegv}$ , and  $T_{fcsv}$  are reported in Table III.

In this paper, high-resolution temperature  $T$  is assumed to be unavailable. Consequently, the extreme temperatures  $T_{b,ds}$ ,  $T_{b,ws}$ ,  $T_{fegv}$ , and  $T_{fcsv}$  are extrapolated from the spaces  $T_{km} - \langle f_{gv} \rangle_{km}$  and  $T_{km} - \langle \alpha \rangle_{km}$  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  $(1, T_{fegv})$  in Fig. 4(c) (Fig. 4(e) for MODIS temperature) and at  $(\alpha_{fegv}, T_{fegv})$  in Fig. 4(d) [Fig. 4(f)]. In this paper,  $T_{fegv}$  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  $(\alpha_{fegv}, T_a)$  in Fig. 4(d) [Fig. 4(f)].

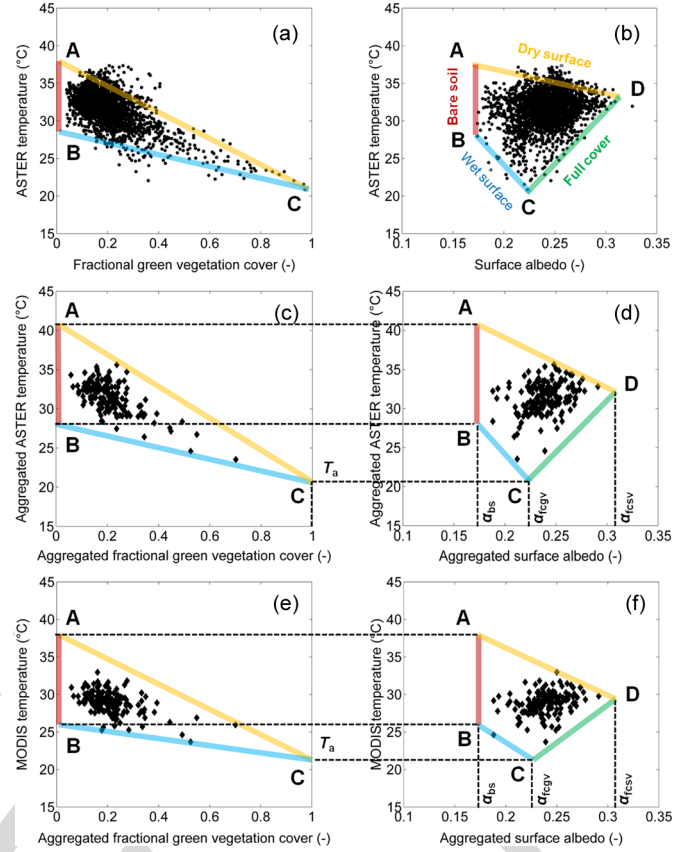


Fig. 4. (a) Scatterplot of ASTER temperature versus fractional green vegetation cover and (b) versus surface albedo, (c) scatterplot of aggregated ASTER temperature versus aggregated fractional green vegetation cover and (d) versus aggregated surface albedo, and (e) scatterplot of MODIS temperature versus aggregated fractional green vegetation cover and (f) versus aggregated surface albedo. The vertices A, B, C, and D obtained using high-resolution data in (a) and (b) are extrapolated using low-resolution data in (c), (d), (e), and (f) from ancillary data composed of air temperature  $T_a$ , soil albedo  $\alpha_{bs}$ , green vegetation albedo  $\alpha_{fegv}$ , and senescent vegetation albedo  $\alpha_{fcsv}$ .

- 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  $\langle f_{gv} \rangle_{km} = 0$ . 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  $T_{km} - \langle f_{gv} \rangle_{km}$ . The off-set of (BC) is determined from C.
- 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)] at the intersection between (AC) and the vertical line  $\langle f_{gv} \rangle_{km} = 0$ . 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  $T_{km} - \langle f_{gv} \rangle_{km}$ . The off-set of (AC) is determined from C.
- 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 between (AD) and the vertical line  $\langle \alpha \rangle_{km} = \alpha_{fcsv}$ . The line (AD) is considered as being parallel to (BC)[5]. Consequently, the slope of (AD) is determined from 619

620 the slope of (BC). The off-set of (AD) is determined  
 621 from A. Note that the lines (AD) and (BC) might  
 622 not be strictly parallel. This may be due to a lack of  
 623 representativeness of the surface conditions captured at  
 624 250-m resolution within the study area. In that case, one  
 625 or several data points may be located above (AD). To  
 626 circumvent this artifact, the slope of (AD) in Fig. 4(d)  
 627 [Fig. 4(f)] is increased so that all data points will be  
 628 located below the “dry surface” edge.

629 Table III lists the four temperature end-members: 1) esti-  
 630 mated from Fig. 4(a) and (b) using high-resolution ASTER  
 631 data; 2) extrapolated from Fig. 4(c) and (d) using aggregated  
 632 ASTER temperature data; and 3) extrapolated from Fig. 4(e)  
 633 and (f) using MODIS temperature data. The values extrapo-  
 634 lated from aggregated ASTER and MODIS temperatures are  
 635 rather close to those estimated from high-resolution ASTER  
 636 temperature data, with the maximum difference in extrapolated  
 637 temperatures being 2.6 °C, except for  $T_{f_{csv}}$  using MODIS  
 638 data. In the latter case, the significant underestimation (5.3 °C)  
 639 of  $T_{f_{csv}}$  can be explained by the following: 1) the negative  
 640 mean difference (−2.3 °C) between MODIS and ASTER data  
 641 and/or 2) the smaller range of (spatial dynamics) of 1-km  
 642 resolution MODIS data in relation to 1-km aggregated ASTER  
 643 data [please compare Fig. 4(c) with Fig. 4(e), and Fig. 4(d) with  
 644 Fig. 4(f)].

#### 645 D. Brightness Temperature

646 To estimate soil evaporative efficiency  $\beta$  in (20) and  $\beta'$   
 647 in (22), five brightness temperature values corresponding to  
 648 extreme surface conditions are required:  $T_{B_{b,ds}}$ ,  $T_{B_{b,ws}}$ ,  
 649  $T_{B_{f_{gv,ws}}}$ ,  $T_{B_{f_{gv,ds}}}$ , and  $T_{B_{f_{csv,ds}}}$ . In this paper, those  
 650 five values are estimated from a generalized version [5], [9] of  
 651 the classical “triangle method” [27].

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

- 660 1) Vertex at minimum brightness temperature: L-band ra-  
 661 diative transfer models predict an increase of brightness  
 662 temperature with biomass and a decrease of brightness  
 663 temperature with surface soil moisture (e.g., [48] and  
 664 [49]). Therefore, the point at minimum brightness tem-  
 665 perature corresponds to wet bare soil. This vertex is noted  
 666 as B in Fig. 5(a), which is consistent with Fig. 4.
- 667 2) Vertex at maximum land surface temperature: the triangle  
 668 method predicts a decrease of land surface temperature  
 669 with both vegetation cover and surface soil moisture.  
 670 Therefore, the point at maximum land surface tempera-  
 671 ture corresponds to dry bare soil. This vertex is noted as  
 672 A in Fig. 5(a), which is consistent with Fig. 4.
- 673 3) Vertex at maximum brightness temperature: being con-  
 674 sistent with an increase of vegetation emission with  
 675 biomass and a decrease of soil emission with surface soil

moisture, the point at maximum brightness temperature 676  
 corresponds to full-cover vegetation with dry soil. It 677  
 could correspond to full-cover green vegetation. How- 678  
 ever, the associated land surface temperature in Fig. 5(a) 679  
 is much larger than that over full-cover green vegetation 680  
 (21 °C) and rather close to the temperature over full- 681  
 cover senescent vegetation (34 °C). Therefore, the point 682  
 at maximum brightness temperature corresponds to full- 683  
 cover senescent vegetation with dry soil. This vertex 684  
 is noted as D' in Fig. 5(a), which is consistent with 685  
 Fig. 4. A prime mark indicates that D' corresponds to a 686  
 dry soil, whereas D does not specify soil hydric status. 687  
 Note that D' does not necessarily correspond to dry 688  
 senescent vegetation since wet senescent vegetation can 689  
 lead to large values of brightness temperature [50]. In 690  
 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]. 696

- 4) Vertices at minimum land surface temperature: two more 697  
 vertices are apparent in the counterclockwise direction. 698  
 Being consistent with a decrease of land surface tem- 699  
 perature with green vegetation, both points correspond 700  
 to full-cover green vegetation. As vegetation is partially 701  
 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  $T_B$  [noted as C'' in Fig. 5(a)] 704  
 corresponds to full-cover green vegetation with dry soil, 705  
 and the point with a lower  $T_B$  [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 708  
 in this paper, brightness temperature end-members are not 709  
 estimated from the polygon  $T_B - T$  in Fig. 5(a) but from 710  
 the polygon  $T_B - f_{gv}$  shown in Fig. 5(b). The following is 711  
 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. 714

- 1) Vertex B corresponds to wet bare soil. It is located at 715  
 the minimum value of brightness temperature such that 716  
 $f_{gv} = 0$ . 717
- 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 720  
 and senescent vegetation. 721
- 3) Vertex D' corresponds to full-cover senescent vegetation 722  
 with dry soil. It is located at the maximum value of 723  
 brightness temperature. 724
- 4) Vertex C'' corresponds to full-cover green vegetation 725  
 with dry soil. It is located at the maximum value of 726  
 brightness temperature such that  $f_{gv} = 1$ . 727
- 5) Vertex C' corresponds to full-cover green vegetation with 728  
 wet soil. It is located at the minimum value of brightness 729  
 temperature such that  $f_{gv} = 1$ . 730

Based on the aforementioned interpretation of the polygon 731  
 $T_B - f_{gv}$  in Fig. 5(b), the methodology used for estimating 732

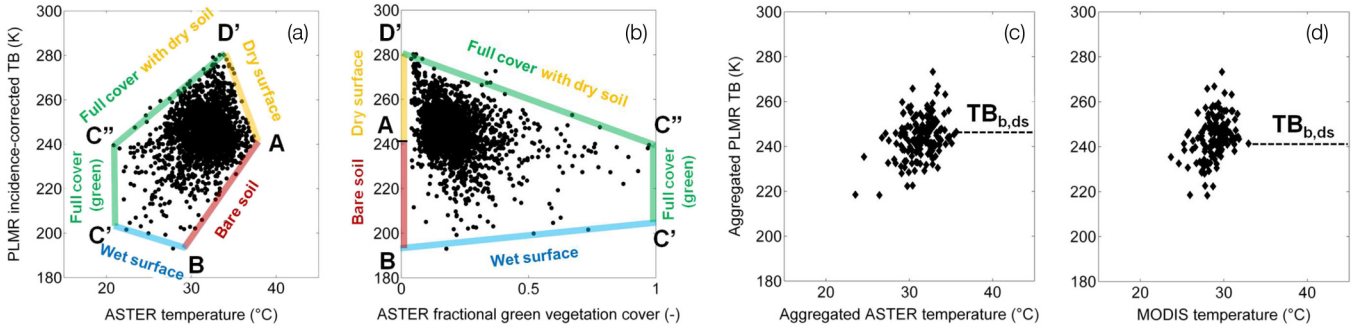


Fig. 5. (a) Scatterplot of PLMR incidence-corrected brightness temperature  $TB$  versus ASTER land surface temperature and (b) versus ASTER fractional green vegetation cover, and (c) scatterplot of aggregated  $TB$  versus aggregated ASTER temperature and (d) versus MODIS temperature. Extreme brightness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

733  $TB_{b,ds}$ ,  $TB_{b,ws}$ ,  $TB_{fcgv,ws}$ ,  $TB_{fcgv,ds}$ , and  $TB_{fcsv,ds}$  is  
734 detailed in the following.

- 735 1) The brightness temperature over full-cover dry surface  
736 ( $TB_{fcsv,ds}$ ) and over wet bare soil ( $TB_{b,ws}$ ) are set  
737 to the maximum and minimum brightness temperatures  
738 observed within the study area, respectively.
- 739 2) The brightness temperatures over full-cover green veg-  
740 etation with wet soil ( $TB_{fcgv,ws}$ ) and over full-cover  
741 green vegetation with dry soil ( $TB_{fcgv,ds}$ ) are estimated  
742 as the brightness temperature extrapolated at  $f_{gv} = 1$  in  
743 Fig. 5(b) along the “wet soil” and the “full-cover dry  
744 soil” edge, respectively. The slope of the lines ( $BC'$ )  
745 and ( $D'C''$ ) are determined so that all of the points with  
746  $f_{gv} > 0.5$  be above and below the “wet soil” and “full-  
747 cover dry soil” edges, respectively.
- 748 3) Vertex A cannot be identified in the space  $TB - f_{gv}$ .  
749 Consequently,  $TB_{b,ds}$  is set to the brightness tempera-  
750 ture corresponding to the maximum  $T_{km}$  (see Fig. 5(c) for  
751 aggregated ASTER temperature and Fig. 5(d) for MODIS  
752 temperature data).

753 Table III lists the five brightness temperature end-members:  
754 1) estimated from Fig. 5(a) using high-resolution ASTER data;  
755 2) estimated from Fig. 5(b) and (c) using high-resolution  
756 fractional green vegetation cover and aggregated ASTER tem-  
757 perature data; and 3) estimated from Fig. 5(b) and (d) using  
758 high-resolution fractional green vegetation cover and MODIS  
759 temperature data. Values estimated from low-resolution tem-  
760 perature are remarkably close to those estimated from high-  
761 resolution ASTER temperature data (Table III), except for  
762  $TB_{b,ds}$  with a difference of 6 K. This difference is apparently  
763 due to the lack of representativeness of kilometric aggregated  
764 brightness temperature and the method for estimating  $TB_{b,ds}$   
765 at kilometric scale. Note, however, that a 6-K difference is still  
766 relatively low compared to the range (190 K–280 K) covered  
767 by brightness temperature values.

768

## VI. APPLICATION

769 The disaggregation algorithms presented here are applied  
770 to the NAFE'06 data set. ASTER land surface temperature is  
771 aggregated at 1-km resolution, and kilometric temperature is  
772 used as input to D0, D1, D1', D2, D2', D3', D4', and D4''. As

shown in Fig. 1, the verification strategy consists in comparing  
773 disaggregation results at 250-m resolution with ASTER land  
774 surface temperature. An application to MODIS data is also  
775 presented. 776

### A. Application to Aggregated ASTER Data 777

1) *End-Members Derived From High-Resolution Data:* The  
778 approach is first implemented using the end-members estimated  
779 from high-resolution ASTER temperature data. This allows  
780 testing the robustness of the model in (15) and (16) inde-  
781 pendently of the methodology used for extrapolating the nine  
782 end-members  $T_{b,ds}$ ,  $T_{b,ws}$ ,  $T_{fcgv}$ ,  $T_{fcsv}$ ,  $TB_{b,ds}$ ,  $TB_{b,ws}$ ,  
783  $TB_{fcgv,ws}$ ,  $TB_{fcgv,ds}$ , and  $TB_{fcsv,ds}$ . 784

Fig. 6 shows the output images of the eight disaggregation  
785 algorithms, which are to be compared with the reference image  
786 derived from ASTER land surface temperature. One observes  
787 that the disaggregated temperature is successively improved  
788 by including additional factors in the disaggregation, which  
789 indicates that the methodology is able to take into account  
790 several independent factors. Although the boxy artifact at 1-km  
791 resolution is successively reduced from  $T^{(0)}$  to  $T^{(4'')}$ , it is still  
792 apparent for  $T^{(4'')}$ . This effect may be due to the following: 1)  
793 other factors that are not taken into account in the procedure,  
794 such as green vegetation water stress, wind speed, surface  
795 emissivity, surface albedo, etc.; 2) errors in estimated  $f_{gv}$ ,  $f_{sv}$ ,  
796  $f_{ow}$ , and  $\beta$ ; and/or 3) resampling errors at 250-m resolution. 797

Table IV lists the RMSD, correlation coefficient, and slope  
798 between the disaggregated and ASTER temperatures for each  
799 of the eight disaggregation algorithms. The error is successively  
800 decreased from 1.65 °C to 1.16 °C, while the correlation coef-  
801 ficient and slope are successively increased from 0.79 and 0.63  
802 to 0.89 and 0.88, respectively. When comparing D1, D2, D1',  
803 and D2', no significant differences are observed between all  
804 four algorithms in terms of root-mean-square error, correlation  
805 coefficient, and slope. Note that, in this paper,  $f_{tv}$  was estimated  
806 in a different way than in [5] because only one visible and  
807 near-infrared image was available and a FORMOSAT-like time  
808 series would be required to derive  $f_{tv}$  more accurately on a  
809 pixel-by-pixel basis. Nevertheless, this comparison suggests  
810 that D1' seems to be equivalent to D1 and D2' equivalent to  
811 D2, which justifies the use of the  $T_{mod}$  model. 812

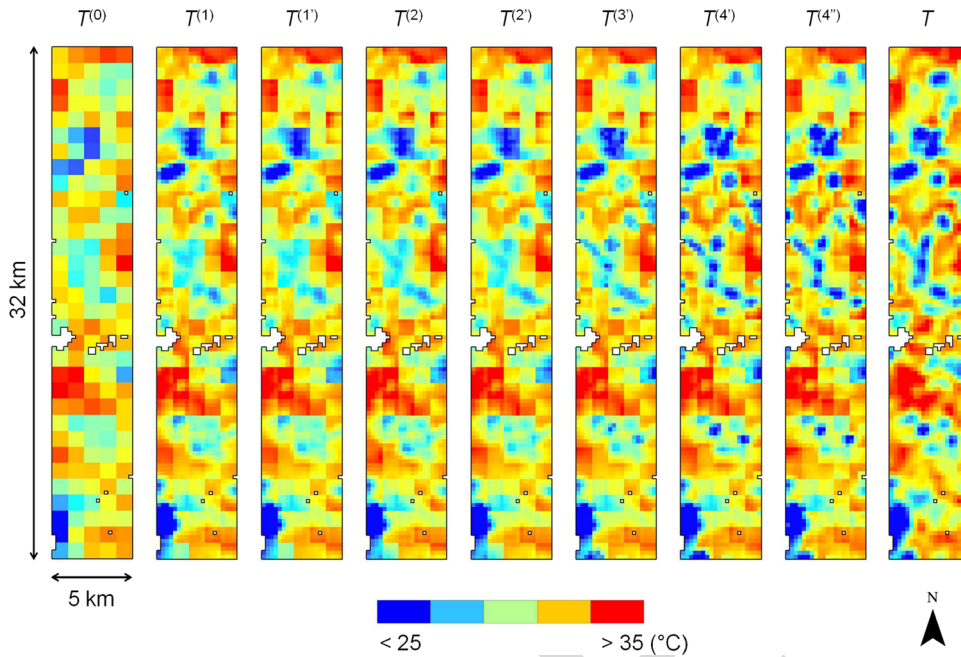


Fig. 6. Maps of the temperature disaggregated by the eight algorithms as compared with the map (right) of high-resolution ASTER temperature.

TABLE IV  
RMSD, CORRELATION COEFFICIENT ( $R$ ), AND SLOPE BETWEEN THE DISAGGREGATED AND ASTER TEMPERATURES. THE RESULTS CORRESPOND TO THE END-MEMBERS ESTIMATED USING HIGH-RESOLUTION ASTER TEMPERATURE DATA (TO THE END-MEMBERS EXTRAPOLATED USING AGGREGATED ASTER TEMPERATURE DATA)

Algorithm	RMSD °C	R	Slope
D0	1.65	0.79	0.63
D1	1.39	0.86	0.76
D2	1.35 (1.35)	0.87 (0.87)	0.76 (0.76)
D1'	1.38 (1.39)	0.86 (0.86)	0.74 (0.72)
D2'	1.30 (1.40)	0.88 (0.86)	0.75 (0.73)
D3'	1.22 (1.27)	0.89 (0.88)	0.78 (0.76)
D4'	1.15 (1.15)	0.91 (0.91)	0.86 (0.84)
D4''	1.16 (1.24)	0.89 (0.80)	0.88 (0.86)

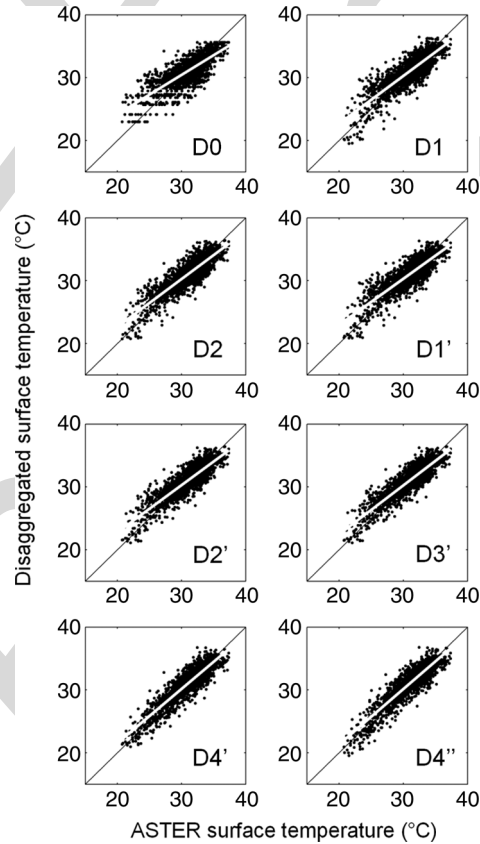


Fig. 7. Aggregated ASTER temperature (1 km) is disaggregated by each of the eight algorithms and is plotted against high-resolution ASTER temperature.

813 The main advantage of the new approach is to take into  
 814 account a number of additional factors, including fractional  
 815 open water and soil evaporative efficiency. When comparing the  
 816 results obtained for D3', D4', and D4'' in Table IV, it is observed  
 817 that the disaggregated temperature is significantly improved  
 818 against the classical approaches D1 and D2. Moreover, the  
 819 statistical results are successively improved by including  $f_{ow}$ ,  
 820  $\beta$ , and  $\beta'$ . Fig. 7 shows the improvement, especially in the  
 821 slope between the disaggregated and ASTER temperatures. The  
 822 good results obtained for D4'' indicate that the performance of  
 823 disaggregation algorithms is intimately related to the following:  
 824 1) the capability of separating the independent factors that  
 825 impact on surface temperature and 2) the ability to integrate  
 826 them consistently into the procedure.

827 2) *End-Members Derived From Aggregated ASTER Data:*  
 828 As disaggregation procedures D1', D2', D3', D4', and D4''

are subjected to uncertainties in land surface temperature and 829  
 brightness temperature end-members, the five algorithms are 830  
 next tested using the end-members estimated from kilomet- 831  
 ric temperature data, as presented in Section V. Aggregated 832  
 ASTER (instead of MODIS) data are used to evaluate the 833

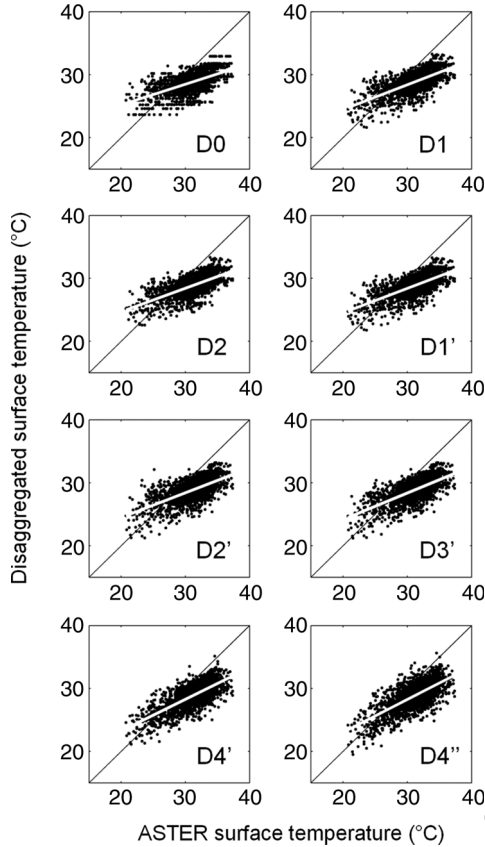


Fig. 8. MODIS temperature (1 km) is disaggregated by each of the eight algorithms and is plotted against high-resolution ASTER temperature.

834 impact of end-members regardless of the discrepancy between  
835 MODIS and ASTER temperatures.

836 Table IV lists the RMSD, correlation coefficient, and slope  
837 between the disaggregated and ASTER temperatures for each  
838 of the five algorithms. Results are compared with those ob-  
839 tained using the end-members estimated from high-resolution  
840 ASTER temperature. In general, the error is slightly larger,  
841 and the correlation coefficient and slope are slightly lower us-  
842 ing extrapolated end-members. Nevertheless, the disaggregated  
843 temperature is still much improved by applying  $D4''$  instead of  
844  $D1'$ , with the correlation coefficient and slope increasing from  
845 0.74 to 0.88 and from 0.72 to 0.86, respectively. Consequently,  
846 the extrapolation of end-members from kilometric data is not  
847 found to be a limiting factor in the methodology.

#### 848 B. Application to MODIS Data

849 Disaggregation algorithms  $D0$ ,  $D1$ ,  $D1'$ ,  $D2$ ,  $D2'$ ,  $D3'$ ,  $D4'$ ,  
850 and  $D4''$  are then applied to MODIS data. In this case, end-  
851 members are derived from MODIS data. Fig. 8 shows the scat-  
852 terplot of disaggregated MODIS versus ASTER temperature for  
853 each algorithm separately. One observes that the new methodol-  
854 ogy improves the correlation and slope of the linear regression  
855 between the disaggregated and ASTER temperatures. However,  
856 a systematic negative bias is apparent in the disaggregated  
857 temperature. Table V lists the RMSD, correlation coefficient,  
858 and slope between the disaggregated and ASTER temperatures  
859 for each of the eight algorithms. The error slightly decreases

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

Algorithm	RMSD °C	R -	Slope -
D0	3.19	0.60	0.33
D1	3.08	0.67	0.39
D2	3.11	0.66	0.37
$D1'$	3.09	0.67	0.39
$D2'$	3.12	0.65	0.39
$D3'$	3.06	0.69	0.42
$D4'$	2.98	0.73	0.50
$D4''$	3.03	0.70	0.52

from 3.2 °C to 3.0 °C, while the correlation coefficient and 860  
slope increase from 0.6 and 0.3 to 0.7 and 0.5, respectively. 861  
The results obtained for  $D3'$  and  $D4'$  in Table V indicate that 862  
the disaggregated temperature is improved against the classical 863  
approaches  $D1$  and  $D2$ . As for the application to aggregated 864  
ASTER data, the statistical results are successively improved 865  
by including  $f_{ow}$ ,  $\beta$ , and  $\beta'$ . However, the improvement with 866  
MODIS data is not as visible as with aggregated ASTER 867  
data because the difference between MODIS and ASTER data 868  
(please refer to Section II-C) has the same order of magnitude 869  
as the subpixel variability at 250-m resolution (see RMSD for 870  
 $D0$  in Table V). In particular, the mean bias and the relatively 871  
low slope of the linear regression between the disaggregated 872  
and ASTER data are associated with the discrepancy at 1-km 873  
resolution between the MODIS and ASTER temperature data. 874

## VII. SENSITIVITY ANALYSIS

875

To further assess the stability of the new  $D'$  algorithms based 876  
on radiative transfer, two sensitivity analyses are conducted 877  
by the following: 1) adding a Gaussian noise on kilometric 878  
temperatures and high-resolution brightness temperatures and 879  
2) estimating the contribution of each factor on the variability 880  
of modeled land surface temperature. 881

### A. Uncertainty in End-Members

882

To test the stability of the method for estimating the nine 883  
end-members ( $T_{b,ds}$ ,  $T_{b,ws}$ ,  $T_{fcgv}$ ,  $T_{fcsv}$ ,  $T_{b,ds}$ ,  $T_{b,ws}$ , 884  
 $T_{b,ds}$ ,  $T_{b,ws}$ ,  $T_{b,ds}$ ,  $T_{b,ws}$ ,  $T_{b,ds}$ ,  $T_{b,ws}$ ,  $T_{b,ds}$ ,  $T_{b,ws}$ , 885  
 $T_{b,ds}$ ,  $T_{b,ws}$ ,  $T_{b,ds}$ ,  $T_{b,ws}$ ,  $T_{b,ds}$ ,  $T_{b,ws}$ ) from low-resolution 886  
temperature data, a Gaussian noise with a standard deviation 887  
of 1 °C is added to the kilometric (aggregated ASTER) land 888  
surface temperature data set, and a Gaussian noise with a stan- 889  
dard deviation of 2 K is added to the high-resolution brightness 890  
temperature data set. An ensemble of 100 data sets is generated 891  
and used as input to the disaggregation algorithms.

Table VI reports the average and standard deviation of ex- 892  
trapolated end-members computed within the ensemble of 100 893  
artificially perturbed data sets. Results indicate that the method 894  
for extrapolating end-members is stable for all end-members. 895

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

End-member	Mean	St. dev.	Unit
$T_{b,ds}$	40.8	0.8	$^{\circ}\text{C}$
$T_{b,ws}$	25.7	1.5	$^{\circ}\text{C}$
$T_{fcgv}$	21.0	0	$^{\circ}\text{C}$
$T_{fsv}$	33.1	1.3	$^{\circ}\text{C}$
$TB_{b,ds}$	246	3.2	K
$TB_{b,ws}$	193	1.4	K
$TB_{fcgv,ws}$	204	2.3	K
$TB_{fcgv,ds}$	240	1.5	K
$TB_{fsv,ds}$	281	1.0	K

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

Algorithm	RMSD $^{\circ}\text{C}$	R -	Slope -
D0	1.81	0.75	0.63
D1	1.58	0.82	0.76
D2	1.54	0.83	0.76
D1'	1.57	0.82	0.73
D2'	1.54	0.83	0.74
D3'	1.44	0.85	0.78
D4'	1.39	0.87	0.87
D4''	1.48	0.86	0.89

896 Table VII lists the RMSD, correlation coefficient, and slope  
897 between the disaggregated and ASTER temperatures for all 100  
898 data sets. Although the results are generally degraded by using  
899 noisy input data sets, D4'' is still superior to all other algorithms  
900 (see Fig. 9). Therefore, the integration of fractional open water  
901 and soil evaporative efficiency into the disaggregation is able to  
902 improve the representation of land surface temperature variabil-  
903 ity despite the uncertainties in  $f_{ow}$  and  $\beta'$ , and the uncertainties  
904 in extrapolated end-members.

### 905 B. Weighting Variability Factors

906 Results with the NAFE'06 data set have indicated that the  
907 new D' algorithms based on radiative transfer significantly  
908 improve (in relation to D1 and D2 methods) the representation  
909 of disaggregated temperature by directly integrating the various  
910 input parameters of the radiative transfer equation. Another ad-  
911 vantage of the proposed methodology is to quantify the weight  
912 of these input parameters. Here, the relative weights of  $f_{gv}$ ,  
913  $f_{sv}$ ,  $f_{ow}$ , and  $\beta'$  are compared, and the relative improvement in  
914 disaggregated temperature when including these factors in the  
915 disaggregation is assessed. The weight of  $f_{gv}$  on the variability

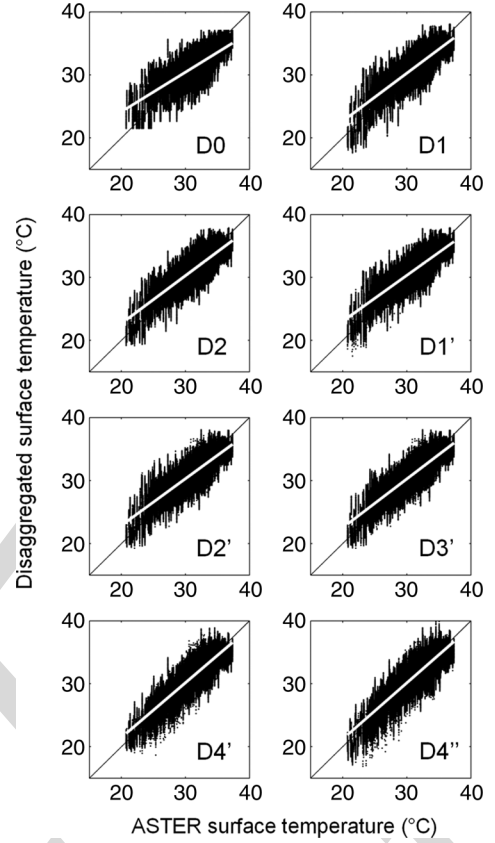


Fig. 9. As for Fig. 7 but using all the 100 artificially noised input data sets.

in land surface temperature is derived by computing the first 916  
partial derivative of  $T_{mod}$  from (15) and (16) 917

$$\frac{\partial T_{mod}}{\partial f_{gv}} = -(1 - f_{ow})(T_{fcsv} - T_{fcgv}). \quad (25)$$

Similarly, the first partial derivative of  $T_{mod}$  is computed with 918  
respect to  $f_{sv}$  919

$$\frac{\partial T_{mod}}{\partial f_{sv}} = -(1 - f_{ow})[\beta' T_{b,ws} + (1 - \beta') T_{b,ds} - T_{fcsv}] \quad (26)$$

with respect to  $f_{ow}$  920

$$\frac{\partial T_{mod}}{\partial f_{ow}} = -[f_{gv} T_{fcgv} + (f_{tv} - f_{gv}) T_{fcsv} + (1 - f_{tv})(\beta' T_{b,ws} + (1 - \beta') T_{b,ds}) - T_{fcgv}] \quad (27)$$

and with respect to  $\beta'$  921

$$\frac{\partial T_{mod}}{\partial \beta'} = -(1 - f_{ow})(1 - f_{tv})(T_{b,ds} - T_{b,ws}). \quad (28)$$

Table VIII lists the standard deviation of each parameter 922  
within the study area, the average of partial derivatives, and the 923  
relative weight of each parameter on the variability of modeled 924  
land surface temperature. The relative weights of  $f_{gv}$ ,  $f_{sv}$ ,  $f_{ow}$ , 925  
and  $\beta'$  are estimated as the mean partial derivative times the 926  
standard deviation. Results indicate that all parameters have a 927  
negative impact on  $T$ . More interestingly,  $f_{gv}$  appears to be 928  
the most significant variability factor, with a relative weight 929  
of 42%, which is consistent with NDVI-based approaches [4]. 930

TABLE VIII  
STANDARD DEVIATION, MEAN PARTIAL DERIVATIVE, AND IMPACT ON HIGH-RESOLUTION MODELED TEMPERATURE OF EACH OF THE FOUR PARAMETERS: FRACTIONAL GREEN VEGETATION COVER, FRACTIONAL SENESCENT VEGETATION COVER, FRACTIONAL OPEN WATER, AND SOIL EVAPORATIVE EFFICIENCY

Factor	Standard deviation	Mean partial derivative	Impact on $T_{\text{mod}}$ (percentage of total)
-	-	$^{\circ}\text{C}$	$^{\circ}\text{C}$ (%)
$f_{\text{gv}}$	0.11	-13	0.97 (42)
$f_{\text{sv}}$	0.19	-2.0	0.26 (11)
$f_{\text{ow}}$	0.06	-11	0.45 (20)
$\beta'$	0.19	-4.8	0.17 (27)

931 The second and third most significant variability factors are soil  
932 evaporative efficiency and fractional open water, with relative  
933 weights of 27% and 20%, respectively. Finally, fractional senes-  
934 cent vegetation cover represents only 11% of the variability  
935 in land surface temperature. The low impact of  $f_{\text{sv}}$  can be  
936 associated with the low mean partial derivative. In particular,  
937  $\partial T_{\text{mod}} / \partial f_{\text{sv}}$  is low because the temperature difference be-  
938 tween dry bare soil ( $T_{\text{b,ds}}$ ) and full-cover senescent vegetation  
939 ( $T_{\text{fcsv}}$ ) is also low in our case study.

940 The relative weights in Table VIII are now related with  
941 the disaggregation results in Table III. Consequently, the poor  
942 improvement of D2 against D1 (and D2' against D1') can be  
943 attributed to the relatively low weight of  $f_{\text{sv}}$  in the variability of  
944 land surface temperature. Conversely, the significant improve-  
945 ments of D4' against D3', D3' against D2', and D1 (and D1')  
946 against D0 are attributed to the large weights of  $\beta'$ ,  $f_{\text{ow}}$ , and  
947  $f_{\text{gv}}$ , respectively.

948 In summary, the variability of land surface temperature is rea-  
949 sonably represented by model  $T_{\text{mod}}$ . Moreover, the approach  
950 allows the relative weight of each variability factor to be taken  
951 into account in the disaggregation procedure.

## 52 VIII. SUMMARY AND CONCLUSION

953 A new disaggregation methodology for land surface tem-  
954 perature has been developed to integrate the main surface  
955 parameters involved in the surface energy budget. It is based  
956 on a linearized radiative transfer equation, which distinguishes  
957 between soil, vegetation, and water temperature, and uses soil  
958 evaporative efficiency and fractional senescent vegetation cover  
959 to parameterize/estimate soil and vegetation hydric status, re-  
960 spectively. The approach is implemented using four parame-  
961 ters: the fraction of green vegetation cover derived from red  
962 and near-infrared bands, the fraction of senescent vegetation  
963 cover derived from red and near-infrared bands, the fraction  
964 of open water derived from shortwave-infrared band, and the  
965 soil evaporative efficiency derived from microwave-L band.  
966 It is tested over a 5 km by 32 km area of irrigated land in  
967 Australia, including flooded rice crops, using ASTER and L-  
968 band airborne data. Low-resolution land surface temperature  
969 is simulated by aggregating ASTER land surface tempera-  
970 ture at 1-km resolution, and the disaggregated temperature is  
971 compared to high-resolution ASTER temperature. The results  
972 indicate that the methodology is able to separate efficiently the  
973 independent factors that impact surface temperature and to inte-  
974 grate them consistently into the disaggregation procedure. The

error in disaggregated temperature is successively reduced from 975  
1.65  $^{\circ}\text{C}$  to 1.16  $^{\circ}\text{C}$  by including each of the four parameters. 976  
The correlation coefficient and slope between the disaggregated 977  
and ASTER temperatures are improved from 0.79 to 0.89 and 978  
from 0.63 to 0.88, respectively. Moreover, the radiative transfer 979  
equation allows quantifying the impact at high resolution of 980  
each parameter on land surface temperature. In this case study, 981  
fractional green vegetation cover is responsible for 42% of the 982  
variability in disaggregated land surface temperature, fractional 983  
senescent vegetation cover for 11%, fractional open water for 984  
20%, and soil evaporative efficiency for 27%. 985

Note that the approach presented in this paper did not take 986  
into account the water stress of green vegetation because none 987  
of the considered parameters (fractional green vegetation cover, 988  
fractional senescent vegetation cover, fractional open water, and 989  
soil evaporative efficiency) could describe the hydric status of 990  
photosynthetically active (green) vegetation. The analysis was 991  
conducted solely in a highly irrigated environment in which 992  
vegetation water stress was small. However, in most cases, 993  
the vegetation water stress might not be negligible for natural 994  
areas. In the presence of water-stressed green vegetation, the 995  
scatterplot (temperature versus green vegetation cover) would 996  
be transformed into a trapezoidal shape with four vertices 997  
rather than a triangle. In such conditions, the disaggregation 998  
problem would be partly undetermined since the partitioning 999  
between unstressed and stressed green vegetations would not 1000  
be represented. Consequently, the approaches shown here are 1001  
not expected to be representative of other less extreme environ- 1002  
ments than the present irrigated area. Nevertheless, one should 1003  
keep in mind that improving the spatial resolution of land 1004  
surface temperature data via disaggregation is only relevant in 1005  
the conditions where the spatial variability of temperature is 1006  
large. 1007

Although the approach was successfully applied to airborne 1008  
and satellite data collected during NAFE'06, further research is 1009  
needed to test the disaggregation approach on a routine basis. 1010  
One may anticipate that fractional green and senescent vege- 1011  
tation covers could be derived accurately using FORMOSAT- 1012  
like data. The FORMOSAT-2 instrument [52] provides short- 1013  
wave data at high spatial resolution (8 m) and high temporal 1014  
frequency (potentially one image per day), which allow a fine 1015  
analysis of the seasonality of canopies during the crop cycle 1016  
[5], [53], [54]. Fractional open water could be derived from 1017  
Landsat-5 data (e.g., [20]). Although the repeat cycle of Landsat 1018  
(16 days) is longer than the temporal resolution needed for land 1019  
surface temperature, the seasonal variations of water bodies 1020

1021 such as irrigation canals and flooded fields are expected to  
 1022 be low. Soil evaporative efficiency could be derived at high  
 1023 resolution from active microwave sensors, such as the Phased  
 1024 Array L-band SAR (PALSAR) [55]. Soil evaporative efficiency  
 1025 formulas express evaporation as a function of normalized sur-  
 1026 face soil moisture. Therefore, soil evaporative efficiency is  
 1027 equivalent to a soil moisture index, which could be replaced  
 1028 in (20) by the radar-derived soil wetness index computed as  
 1029 the observed to minimal backscattering coefficient difference  
 1030 divided by the maximal to minimal backscattering coefficient  
 1031 difference [56], [57]. Note, however, that the temporal coverage  
 1032 of the PALSAR fine beam dual polarization mode is relatively  
 1033 low, with a revisit cycle of 46 days. Consequently, accurate  
 1034 disaggregation of land surface temperature would still rely on  
 1035 the availability of high-resolution radar data.

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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 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 respon-

sible 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

RE MOTELY 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 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 kilometer 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 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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80 The accuracy in disaggregated temperature was improved by  
81 taking into account fractional senescent vegetation cover in  
82 addition to fractional green vegetation cover.

83 Fractional green and senescent vegetation covers, however,  
84 are not the only factors explaining the spatial variations of land  
85 surface temperature, especially over irrigated areas where crop  
86 fields may have different moisture status to the surrounds. In  
87 particular, the temperature over a flooded crop field may be  
88 drastically different from the temperature over a mature crop  
89 field. Therefore, the fraction of open water is an important  
90 variable to represent the spatial variations of land surface tem-  
91 perature. Over nonwatered land surfaces, the soil evaporative  
92 efficiency (ratio of actual to potential soil evaporation) is a  
93 signature of the capacity of the soil to evaporate its water  
94 content in the near surface and thus to counter an increase of  
95 its thermodynamic temperature. Consequently, soil evaporative  
96 efficiency is also an essential variable to describe the spatial  
97 variations of land surface temperature. Moreover, knowledge  
98 of soil evaporative efficiency is needed to decouple the effects  
99 of soil and vegetation hydric status on the surface energy  
100 budget and hence to better represent the resultant radiative  
101 surface temperature. As an example, the crop water stress index  
102 (CWSI) [6], [7] can be used to detect plant stress based on the  
103 difference between foliage and air temperature. Nevertheless,  
104 the application of the CWSI to partially vegetated areas is  
105 subjected to large uncertainties because the soil background  
106 may have a different temperature to the plants [7] depending  
107 on soil evaporative efficiency. Another example is provided by  
108 Moran *et al.* [8] who proposed the vegetation index/temperature  
109 (VIT) trapezoid to estimate a most probable range of plant  
110 stress over partially vegetated fields. It is a three-step procedure  
111 in which the following steps are performed: 1) the temperatures  
112 of the four vertices of the VIT trapezoid are estimated using an  
113 energy budget model; 2) the minimum and maximum probable  
114 vegetation temperatures are estimated from the measured com-  
115 posite land surface temperature, together with the maximum  
116 and minimum simulated soil temperatures; and 3) the minimum  
117 and maximum probable CWSIs are computed by normalizing  
118 the minimum and maximum probable vegetation temperatures  
119 from the vegetation temperature extremes simulated by the  
120 energy budget model. The point is that this approach does not  
121 allow estimating a single CWSI value because the retrieval  
122 problem is underdetermined. In particular, Moran *et al.* [8]  
123 noted that “with knowledge of a second point within the  
124 hourglass (perhaps soil temperature), it would be possible to  
125 infer [the canopy-air temperature] difference and pinpoint the  
126 CWSI value.” In the latter case, knowledge of soil temperature  
127 is equivalent to knowledge of soil evaporative efficiency, which  
128 would remove the underdetermination of the VIT trapezoid.

129 The objective of this paper is to develop a new disaggrega-  
130 tion methodology of kilometeric land surface temperature using  
131 hectometric multivariable ancillary data. The approach is based  
132 on a radiative transfer equation that estimates differences in  
133 temperature data at hectometric resolution. Specifically, the use  
134 of a radiative transfer equation allows the following: 1) includ-  
135 ing variables other than those used by previous disaggregation  
136 approaches and 2) deducing the most pertinent variables. In  
137 addition to fractional green and senescent vegetation covers, the

new methodology includes the variability at hectometric reso- 138  
lution of fractional open water and soil evaporative efficiency. 139  
With respect to other disaggregation algorithms in literature 140  
[4], [5], the proposed technique differs in the following four 141  
main aspects: 1) it relies on a physically based radiative transfer 142  
equation rather than empirical linear regressions; 2) it takes 143  
into account the fractional open water derived from shortwave- 144  
infrared band as required; 3) it takes into account the soil hydric 145  
status via microwave-derived soil evaporative efficiency; and 146  
4) it allows the relative weight of each parameter used for 147  
disaggregating temperature to be quantified. 148

The new disaggregation technique is compared to the ex- 149  
isting approaches using data collected during the National 150  
Airborne Field Experiment in 2006 (NAFE’06; [9]). The ex- 151  
perimental site covers a 5 km by 32 km irrigated agricultural 152  
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 159  
MODIS products [5]. Disaggregation algorithms are then ap- 160  
plied to MODIS data. 161

## 162 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. 169

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. 180

### 181 A. PLMR

The Polarimetric L-band Multibeam Radiometer (PLMR) is 182  
an airborne instrument that measures both H and V polariza- 183  
tions using a single receiver with polarization switching at view 184  
angles of  $\pm 7^\circ$ ,  $\pm 21.5^\circ$ , and  $\pm 38.5^\circ$ . The accuracy of the PLMR 185  
is estimated to be better than 2 K and 3 K in the H and V 186  
polarization, respectively [10]. 187

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

192 given incidence angle (approximately  $7^\circ$ ,  $21.5^\circ$ , or  $38.5^\circ$ ). Data  
 193 were processed for incidence angle and beam location on the  
 194 ground by taking into account aircraft position, attitude, and  
 195 ground topography.

196 As the sensitivity to soil moisture is higher for H-polarized  
 197 brightness temperature than for V-polarized brightness temper-  
 198 ature, only the H-polarized brightness temperature  $TB$  is used  
 199 in this paper. Preprocessing of  $TB$  consists of the following:  
 200 1) resampling H-polarized PLMR data at 250-m resolution  
 201 on a grid that matches in symmetry to the flight lines over  
 202 the 5 km by 32 km area and 2) converting the resampled  
 203  $TB$  to an equivalent value at  $21.5^\circ$  incidence angle. The in-  
 204 cidence angle  $21.5^\circ$  is chosen to minimize conversion errors.  
 205 The angular conversion involves the brightness temperature  
 206 collected by inner beams at approximately  $7^\circ$  incidence angle  
 207 being multiplied by the ratio  $\overline{TB_{MB}}/\overline{TB_{IB}}$ , with  $\overline{TB_{MB}}$  and  
 208  $\overline{TB_{IB}}$  being the mean brightness temperatures collected by the  
 209 middle and inner beams, respectively. Similarly, the brightness  
 210 temperature collected by the outer beams at approximately  
 211  $38.5^\circ$  incidence angle is multiplied by the ratio  $\overline{TB_{MB}}/\overline{TB_{OB}}$ ,  
 212 with  $\overline{TB_{OB}}$  being the mean brightness temperature collected by  
 213 the outer beams. Mean brightness temperatures  $\overline{TB_{IB}}$ ,  $\overline{TB_{MB}}$ ,  
 214 and  $\overline{TB_{OB}}$  are computed as the average (for all flight lines)  
 215 of the  $TB$  collected by the beams pointing at  $\pm 7^\circ$ ,  $\pm 21.5^\circ$ ,  
 216 and  $\pm 38.5^\circ$ , respectively. This technique was already used in  
 217 [11] to generate  $TB$  images by assuming that the impact of  
 218 soil moisture and biomass on the angular dependence of  $TB$  is  
 219 negligible or small. In this paper, a slightly different approach  
 220 is adopted to take into account the variations in aircraft attitude  
 221 during data collection, which made the incidence angle  $\theta$  os-  
 222 cillate around  $7^\circ$ ,  $21.5^\circ$ , and  $38.5^\circ$ . The brightness temperature  
 223  $TB(\theta)$  observed at the incidence angle  $\theta$  is multiplied by the  
 224 ratio  $\overline{TB_{MB}}/\overline{TB_{interp}(\theta)}$ , with  $\overline{TB_{interp}(\theta)}$  being the mean  
 225 brightness temperature linearly interpolated at  $\theta$  incidence an-  
 226 gle from the mean data collected by the inner, middle, and outer  
 227 beams.

## 228 B. ASTER

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

238 The ASTER overpass of the NAFE'06 site was on  
 239 November 16, 2006. Official ASTER products [12] were used  
 240 here for surface reflectance (AST\_07) and radiometric temper-  
 241 ature (AST\_08) with accuracies of 5% and 1.5 K, respectively  
 242 [13]–[19]. They were downloaded from the Earth Observing  
 243 System Data Gateway (EDG).

244 ASTER 15-m resolution red (B2) and near-infrared (B3)  
 245 bands were extracted over the 5 km by 32 km area and re-  
 246 sampled at 250-m resolution to match the spatial resolution  
 247 and extent of PLMR observations. The ASTER 30-m resolution

B5 band (1.60–1.70  $\mu\text{m}$ ) was extracted over the 5 km by 248  
 32 km study area and resampled at 50-m resolution. Fractional 249  
 open water was estimated using B5 band [20] based on a 250  
 threshold method. Consequently, B5 data were resampled at 251  
 a resolution finer than that (250 m) of PLMR data to classify 252  
 open water pixels at 50-m resolution and to obtain fractional 253  
 open water at 250-m resolution from the binary classification. 254  
 ASTER 90-m resolution radiometric temperature was extracted 255  
 over the 5 km by 32 km area and aggregated at 250-m res- 256  
 olution to match the spatial resolution and extent of PLMR 257  
 observations. Aggregation was achieved by linearly averaging 258  
 high-resolution surface temperatures, i.e., without accounting 259  
 for the nonlinear relationship between physical temperature and 260  
 radiance. This choice was motivated by the results of [21], 261  
 which compared the temperature aggregated using different 262  
 scaling approaches and obtained very low differences (maxi- 263  
 mum difference of 0.2  $^\circ\text{C}$ ). 264

## 265 C. MODIS

The MODIS/Terra data were collected concurrently with 266  
 ASTER data. MODIS official products consisted of the 928-m 267  
 resolution surface skin temperature (MOD11-L2) retrieved by 268  
 the “generalized split window” algorithm [22]–[24] and reg- 269  
 istered in the sinusoidal projection. The MODIS Reprojection 270  
 Tool was used to project MOD11-L2 data in UTM WGS 1984 271  
 55S with a sampling interval of 1 km. 272

In this paper, the disaggregation of 1-km MODIS tempera- 273  
 ture is evaluated using high-resolution ASTER data. To distin- 274  
 guish the errors associated with the disaggregation technique 275  
 and the errors associated with the discrepancy between MODIS 276  
 and ASTER temperature products, a comparison is made be- 277  
 tween ASTER and MODIS data at 1-km resolution over the 278  
 5 km by 32 km study area. The ASTER data are aggregated 279  
 at the MODIS spatial resolution (1 km) by linearly averaging 280  
 high-resolution temperatures. The root-mean-square difference 281  
 (RMSD), bias, correlation coefficient, and slope of the linear 282  
 regression between MODIS and aggregated ASTER data are 283  
 2.7  $^\circ\text{C}$ ,  $-2.3^\circ\text{C}$ , 0.75, and 0.52, respectively. The discrepancy 284  
 between MODIS and ASTER data, which is mainly explained 285  
 here by a significant bias and a relatively low slope of the linear 286  
 regression, is on the same order of magnitude as the mean 287  
 difference (about 3  $^\circ\text{C}$ ) reported in literature [5], [21], [25]. 288

## 289 III. DISAGGREGATION ALGORITHMS

This paper aims to compare different approaches for dis- 290  
 aggregating kilometric MODIS land surface temperature data. 291  
 The study uses aggregated ASTER and real MODIS data 292  
 and demonstrates the disaggregation at 250-m resolution. The 293  
 resolution of 250 m is chosen to match with the lowest reso- 294  
 lution at which ancillary data composed of red, near-infrared, 295  
 shortwave-infrared, and microwave-L bands are available. In 296  
 this case study, the target scale is determined by the resolution 297  
 (250 m) of airborne microwave data. 298

As shown in the schematic diagram of Fig. 1, the disaggre- 299  
 gation algorithms are noted as  $Dk$ , with  $k$  being the number 300  
 of factors taken into account in the disaggregation. The new 301

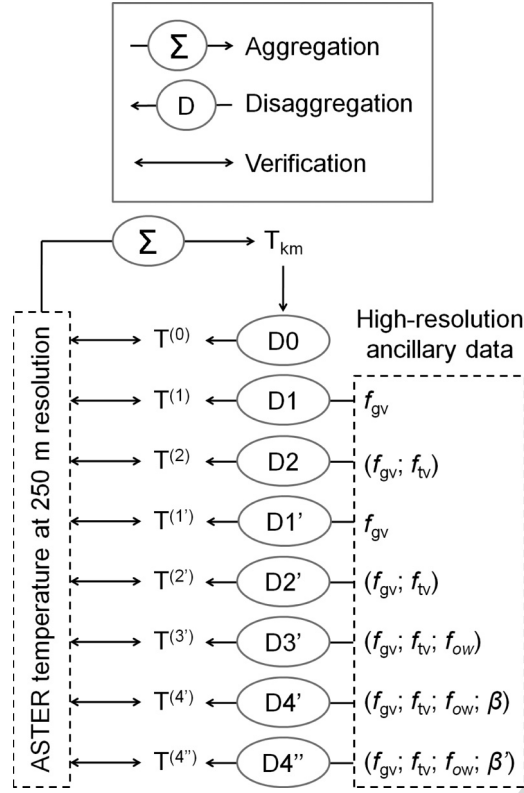


Fig. 1. Schematic diagram presenting the different disaggregation algorithms of kilometric temperature  $T_{km}$  and the verification strategy at high (250 m) resolution.

algorithms are noted as  $Dk'$ . D0 does not use any ancillary data, while D1 is based on a linear regression between land surface temperature and fractional green (photosynthetically active) vegetation cover. Fractional green vegetation cover  $f_{gv}$  is defined as the surface area of green vegetation per unit area of soil. D1 is the same as in [4]. D2 is based on D1 but takes into account both fractional green and total vegetation covers. Fractional vegetation cover  $f_{tv}$  is defined as the total surface area of (green plus senescent) vegetation per unit area of soil. D2 is the same as in [5]. The new algorithms D1', D2', D3', and D4' (and D4'') are all derived from a radiative transfer equation. The four algorithms differ with regard to the number of factors which are explicitly taken into account. D1' includes the variability of  $f_{gv}$  and is thus a substitute for D1 based on radiative transfer. D2' includes the variability of both  $f_{gv}$  and  $f_{tv}$  and is thus a substitute for D2 based on radiative transfer. The other algorithms D3' and D4' integrate additional variables. D3' includes the variability of  $f_{gv}$ ,  $f_{tv}$ , and fractional open water  $f_{ow}$ . D4' includes the variability of  $f_{gv}$ ,  $f_{tv}$ ,  $f_{ow}$ , and soil evaporative efficiency (ratio of actual to potential soil evaporation)  $\beta$ . D4'' is the same as D4' but with a different formulation for soil evaporative efficiency.

D0 sets the disaggregated temperature as

$$T^{(0)} = T_{km} \quad (1)$$

with  $T_{km}$  being the land surface temperature observed at kilometric resolution.

Using D1, the disaggregated temperature is computed as 327

$$T^{(1)} = T_{km} + \mathbf{a}_1 \times (f_{gv} - \langle f_{gv} \rangle_{km}) \quad (2)$$

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  $\mathbf{a}_1$  being the slope of the linear regression between  $T_{km}$  and  $\langle f_{gv} \rangle_{km}$ . Note that the variables defined at kilometric resolution are noted with the subscript km.

Using D2, the disaggregated temperature is computed as 333

$$T^{(2)} = T_{km} + \mathbf{a}_1^{\text{proj}} \times (f_{gv}^{\text{proj}} - \langle f_{gv} \rangle_{km}) \quad (3)$$

with  $f_{gv}^{\text{proj}}$  being the projected  $f_{gv}$  and  $\mathbf{a}_1^{\text{proj}}$  being the slope of the linear regression between  $T_{km}$  and the projected  $f_{gv}$  estimated at kilometric resolution  $f_{gv,km}^{\text{proj}}$ . Note that the variables defined at the image scale are written in bold. The notion of a “projected variable” was introduced in [26]. It is a robust tool that strengthens the correlation between two variables by representing the dependence of these variables on other additional variables. In [5], the projection technique was applied to fractional green vegetation cover to artificially improve the spatial correlation between  $T$  and  $f_{gv}$  by taking into account the dependence of  $T$  on  $f_{tv}$ . The projected fractional green vegetation cover is computed as 345

$$f_{gv}^{\text{proj}} = f_{gv} - \frac{\mathbf{T}_{fcsv} - (\mathbf{T}_{b,ds} + \mathbf{T}_{b,ws})/2}{\mathbf{T}_{fcsv} - \mathbf{T}_{fcgv}} \times (f_{tv} - \langle f_{tv} \rangle_{km}) \quad (4)$$

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,  $\mathbf{T}_{b,ws}$  being the temperature of wet bare soil,  $\mathbf{T}_{b,ds}$  being the temperature of dry bare soil,  $\mathbf{T}_{fcgv}$  being the temperature of full-cover green vegetation, and  $\mathbf{T}_{fcsv}$  being the temperature of full-cover senescent vegetation (notations are summarized in Table I). Following the interpretation of the “triangle method” [27],  $\mathbf{T}_{b,ws}$ ,  $\mathbf{T}_{b,ds}$ ,  $\mathbf{T}_{fcgv}$ , and  $\mathbf{T}_{fcsv}$  correspond to the minimum and maximum soil and vegetation temperatures within the study area, respectively. It is reminded that  $f_{tv} = f_{gv} + f_{sv}$ , with  $f_{gv}$  and  $f_{sv}$  being the fractional green and senescent vegetation covers, respectively.

In (4), the projected fractional green vegetation cover estimated at kilometric resolution is 359

$$f_{gv,km}^{\text{proj}} = \langle f_{gv} \rangle_{km} - \frac{\mathbf{T}_{fcsv} - (\mathbf{T}_{b,ds} + \mathbf{T}_{b,ws})/2}{\mathbf{T}_{fcsv} - \mathbf{T}_{fcgv}} \times (\langle f_{tv} \rangle_{km} - \mathbf{f}_{tv}) \quad (5)$$

with  $\mathbf{f}_{tv}$  being the mean  $f_{tv}$  over the whole study area. 360

The new algorithms  $D'$  use a radiative transfer equation to model the spatial variability of disaggregated temperature 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 a substitute for D1 based on radiative transfer. It expresses disaggregated temperature as 366

$$T^{(1')} = T_{km} + \Delta T^{(1')} \quad (6)$$

TABLE I  
 INTERPRETATION OF THE VERTICES IN THE GENERALIZED “TRIANGLE APPROACH”

Vertex	Surface type	Near-surface soil hydric status	Abbreviation
<b>A</b>	Bare soil	Dry	b,ds
<b>B</b>	Bare soil	Wet	b,ws
<b>C</b>	Full-cover green vegetation	Wet or dry	fcgv
<b>C'</b>	Full-cover green vegetation	Wet	fcgv,ws
<b>C''</b>	Full-cover green vegetation	Dry	fcgv,ds
<b>D</b>	Full-cover senescent vegetation	Wet or dry	fcsv
<b>D'</b>	Full-cover senescent vegetation	Dry	fcsv,ds

367 with  $\Delta T^{(1')}$  being the difference between the temperature  
 368 simulated using high-resolution  $f_{gv}$  and that aggregated within  
 369 the 1-km resolution pixel

$$\Delta T^{(1')} = T_{\text{mod}} (f_{gv}, \langle f_{tv} \rangle_{\text{km}}, \langle f_{ow} \rangle_{\text{km}}, \langle \beta \rangle_{\text{km}}) - \langle T_{\text{mod}} (f_{gv}, \langle f_{tv} \rangle_{\text{km}}, \langle f_{ow} \rangle_{\text{km}}, \langle \beta \rangle_{\text{km}}) \rangle_{\text{km}} \quad (7)$$

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

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

$$\Delta T^{(2')} = T_{\text{mod}} (f_{gv}, f_{tv}, \langle f_{ow} \rangle_{\text{km}}, \langle \beta \rangle_{\text{km}}) - \langle T_{\text{mod}} (f_{gv}, f_{tv}, \langle f_{ow} \rangle_{\text{km}}, \langle \beta \rangle_{\text{km}}) \rangle_{\text{km}} \quad (8)$$

379  $D3'$  is derived from the same radiative transfer equation and  
 380 includes the variability of  $f_{gv}$ ,  $f_{tv}$ , and  $f_{ow}$  at high resolution.  
 381 It determines the disaggregated temperature using (6) but with  
 382 the simulated temperature difference  $\Delta T^{(3')}$  written as

$$\Delta T^{(3')} = T_{\text{mod}} (f_{gv}, f_{tv}, f_{ow}, \langle \beta \rangle_{\text{km}}) - \langle T_{\text{mod}} (f_{gv}, f_{tv}, f_{ow}, \langle \beta \rangle_{\text{km}}) \rangle_{\text{km}} \quad (9)$$

383  $D4'$  is derived from the same radiative transfer equation and  
 384 includes the variability of  $f_{gv}$ ,  $f_{tv}$ ,  $f_{ow}$ , and  $\beta$  at high resolu-  
 385 tion. It determines the disaggregated temperature using (6) but  
 386 with the simulated temperature difference  $\Delta T^{(4')}$  written as

$$\Delta T^{(4')} = T_{\text{mod}} (f_{gv}, f_{tv}, f_{ow}, \beta) - \langle T_{\text{mod}} (f_{gv}, f_{tv}, f_{ow}, \beta) \rangle_{\text{km}} \quad (10)$$

387  $D4''$  is an extension of (10) to replace  $\beta$  by another formula-  
 388 tion of soil evaporative efficiency noted as  $\beta'$ .

389 The high- to low-resolution simulated temperature difference  
 390 in (7)–(10) is computed using a linearized radiative transfer  
 391 equation [5], [28], [29]. Modeled land surface temperature  
 392  $T_{\text{mod}}$  is written as

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

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

Nonwatered land surface temperature is expressed as 395

$$T_{nw} = f_{gv}\mathbf{T}_{fcgv} + (f_{tv} - f_{gv})\mathbf{T}_{fcsv} + (1 - f_{tv})T_{bs} \quad (12)$$

with  $\mathbf{T}_{fcgv}$  and  $\mathbf{T}_{fcsv}$  being the temperature of full-cover green 396  
 and senescent vegetations, respectively, and  $T_{bs}$  being the bare 397  
 soil temperature. With the soil evaporative efficiency defined 398  
 [30] as 399

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

the bare soil temperature can be expressed as 400

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

By assuming that water temperature is close to well-watered 401  
 green vegetation [27], modeled land surface temperature 402  
 becomes 403

$$T_{\text{mod}} = f_{ow}\mathbf{T}_{fcgv} + (1 - f_{ow})T_{nw} \quad (15)$$

with the nonwatered land surface temperature expressed as 404

$$T_{nw} = f_{gv}\mathbf{T}_{fcgv} + (f_{tv} - f_{gv})\mathbf{T}_{fcsv} + (1 - f_{tv})[\beta\mathbf{T}_{b,ws} + (1 - \beta)\mathbf{T}_{b,ds}] \quad (16)$$

The temperature extremes  $\mathbf{T}_{b,ds}$ ,  $\mathbf{T}_{b,ws}$ ,  $\mathbf{T}_{fcgv}$ , and  $\mathbf{T}_{fcsv}$  are 405  
 extrapolated (according to Section V) from low-resolution land 406  
 surface temperatures using high-resolution ancillary data [5]. 407

#### IV. DERIVATION OF BIOPHYSICAL VARIABLES 408

The four variables used by the disaggregation methodol- 409  
 ogy are the following: fractional green vegetation cover  $f_{gv}$ , 410  
 fractional total (green plus senescent) vegetation cover  $f_{tv}$ , 411  
 fractional open water  $f_{ow}$ , and soil evaporative efficiency  $\beta$ . 412  
 All of these variables are estimated from ASTER red, near- 413  
 infrared, and shortwave-infrared reflectance products and from 414  
 the PLMR H-polarized brightness temperature converted at an 415  
 incidence angle of 21.5°. 416

##### A. Fractional Green Vegetation Cover 417

Fractional green vegetation cover can be estimated from the 418  
 Normalized Difference Vegetation Index (NDVI) as in [31] 419

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

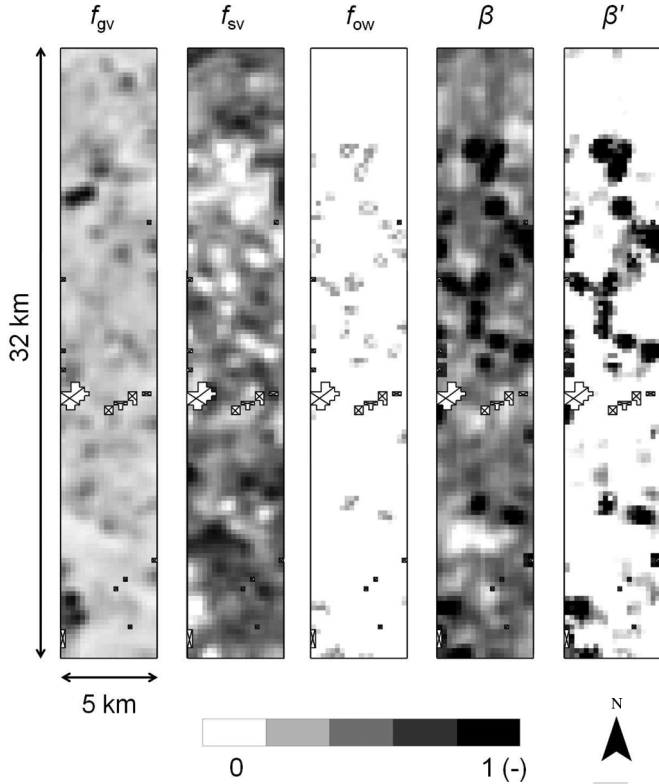


Fig. 2. Images of fractional green vegetation cover  $f_{gv}$ , fractional senescent vegetation cover  $f_{sv} = f_{tv} - f_{gv}$ , fractional open water  $f_{ow}$ , soil evaporative efficiency  $\beta$ , and soil evaporative efficiency  $\beta'$ . Note that 2% of the 5 km by 32 km area is contaminated by clouds and cloud shadow. Contaminated 250-m resolution pixels are represented by crossed-out surfaces.

420 with  $NDVI_{bs}$  and  $NDVI_{fcgv}$  being the NDVI over bare  
421 soil and full-cover green vegetation, respectively. NDVI is  
422 computed as the difference between near-infrared and red bands  
423 divided by their sum. The spatial variation of fractional green  
424 vegetation cover over the study area is shown in Fig. 2.

#### 425 B. Fractional Total (Green Plus Senescent) Vegetation Cover

426 Fractional total vegetation cover is estimated by correlating  
427  $f_{tv}$  with surface albedo for green vegetation and by setting  $f_{tv}$   
428 to the maximum  $f_{gv}$  for senescent vegetation. This methodol-  
429 ogy [5] is based on two assumptions, which are generally met in  
430 agricultural areas: 1) soil albedo is generally lower than green  
431 vegetation albedo, and 2) green vegetation albedo is lower than  
432 senescent vegetation albedo. Although a time series of red and  
433 near-infrared data would be required to estimate soil albedo  
434 and green vegetation albedo on a pixel-by-pixel basis [5], only  
435 one ASTER scene is available for this study period. Therefore,  
436 an alternate approach is adopted. Surface albedo is modeled  
437 as a linear mixing of vegetation and soil components (e.g.,  
438 [32] and [33])

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

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

By inverting (18), fractional vegetation cover is expressed as 443

$$f_{tv} = \frac{\alpha - \alpha_{bs} + f_{gv}(\alpha_{fcsv} - \alpha_{fcgv})}{\alpha_{fcsv} - \alpha_{bs}} \quad (19)$$

with  $\alpha$  being the surface albedo estimated as a weighted sum of 444  
red and near-infrared reflectances using the coefficients given in 445  
[34] and validated in [35]–[38]. As stated previously, our case 446  
study does not allow calibrating  $\alpha_{bs}$ ,  $\alpha_{fcgv}$ , and  $\alpha_{fcsv}$  on a 447  
pixel-by-pixel basis. Consequently, the value of  $f_{tv}$  computed 448  
from (19) may, on some occasions, be lower than  $f_{gv}$  or larger 449  
than 1. To avoid nonphysical values,  $f_{tv}$  is set to  $f_{gv}$  and 1 in 450  
the former and latter case, respectively. 451

The spatial variation of fractional senescent vegetation cover 452  
( $f_{sv} = f_{tv} - f_{gv}$ ) over the study area is shown in Fig. 2. Note 453  
that NAFE'06 was undertaken at the beginning of the summer 454  
agricultural season so that all irrigated crops were green and 455  
healthy. 456

#### C. Fractional Open Water 457

The fraction of open water within each 250-m resolution 458  
pixel is estimated using 50-m resolution resampled ASTER 459  
B5 reflectance product. Various studies have indicated that the 460  
shortwave-infrared band centered at around  $1 \mu\text{m}$  is highly 461  
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 464  
nonwatered surface. The threshold value is estimated as 0.170 465  
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 467  
shown in Fig. 2. Open water represents 5% of the study area 468  
and is attributed to rice cropping. 469

#### D. Soil Evaporative Efficiency 470

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. 476

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 480

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

with  $TB_{b,ws}$  and  $TB_{fcsv,ds}$  being the minimum and max- 481  
imum 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. 488

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



TABLE II  
NDVI AND SURFACE ALBEDO END-MEMBERS

End-member	Value	Unit
$\text{NDVI}_{\text{bs}}$	0.15	-
$\text{NDVI}_{\text{fcgv}}$	0.65	-
$\alpha_{\text{bs}}$	0.17	-
$\alpha_{\text{fcgv}}$	0.22	-
$\alpha_{\text{fcsv}}$	0.31	-

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

$$\beta' = 0 \quad \text{if } TB > TB_{\text{ds}} \quad (21)$$

$$\beta' = 1 - \frac{TB - TB_{\text{ws}}}{TB_{\text{ds}} - TB_{\text{ws}}} \quad \text{if } TB \leq TB_{\text{ds}} \quad (22)$$

500 with  $TB_{\text{ds}}$  and  $TB_{\text{ws}}$  being the “dry soil” and “wet soil”  
501 brightness temperatures, respectively, both being estimated for  
502  $f_{\text{sv}} = 0$ . 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  $TB_{\text{b,ds}}$ ) and the brightness temperature over full-  
506 cover green vegetation with dry soil (noted as  $TB_{\text{fcgv,ds}}$ )

$$TB_{\text{ds}} = f_{\text{gv}} TB_{\text{fcgv,ds}} + (1 - f_{\text{gv}}) TB_{\text{b,ds}}. \quad (23)$$

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  $TB_{\text{b,ws}}$ ) and the brightness temperature over full-  
510 cover green vegetation with wet soil (noted as  $TB_{\text{fcgv,ws}}$ )

$$TB_{\text{ws}} = f_{\text{gv}} TB_{\text{fcgv,ws}} + (1 - f_{\text{gv}}) TB_{\text{b,ws}}. \quad (24)$$

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:  $\text{NDVI}_{\text{bs}}$ ,  $\text{NDVI}_{\text{fcgv}}$ ,  $\alpha_{\text{bs}}$ ,  
516  $\alpha_{\text{fcgv}}$ ,  $\alpha_{\text{fcsv}}$ ,  $T_{\text{b,ws}}$ ,  $T_{\text{b,ds}}$ ,  $T_{\text{fcgv}}$ ,  $T_{\text{fcsv}}$ ,  $TB_{\text{b,ws}}$ ,  $TB_{\text{b,ds}}$ ,  
517  $TB_{\text{fcgv,ws}}$ ,  $TB_{\text{fcgv,ds}}$ , and  $TB_{\text{fcsv,ds}}$ . For the convenience  
518 of the reader, the unit is degree Celsius for radiometric temper-  
519 ature and kelvin for brightness temperature.

### 520 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  $\text{NDVI}_{\text{bs}}$  and  $\text{NDVI}_{\text{fcgv}}$  are reported in Table II.

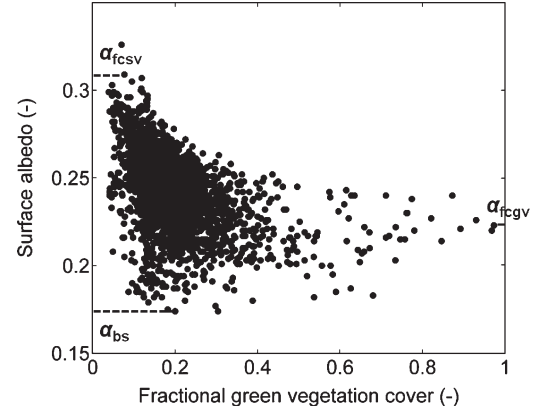


Fig. 3. ASTER surface albedo  $\alpha$  plotted against ASTER fractional green vegetation cover  $f_{\text{gv}}$ . Three particular values of  $\alpha$  are identified: the soil albedo  $\alpha_{\text{bs}}$  estimated as the minimum surface albedo, the green vegetation albedo  $\alpha_{\text{fcgv}}$  estimated as the albedo corresponding to the largest  $f_{\text{gv}}$ , and the senescent vegetation albedo  $\alpha_{\text{fcsv}}$  estimated as the maximum surface albedo.

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]. 535

### B. Albedo

536  
537 Fig. 3 shows the space defined by surface albedo  $\alpha$  and  
fractional green vegetation cover  $f_{\text{gv}}$ . Pixels including open 538  
water are removed from the scatterplot. The soil albedo  $\alpha_{\text{bs}}$  539  
is defined as the minimum ASTER surface albedo observed 540  
within the study area by assuming that the dependence of 541  
 $\alpha_{\text{bs}}$  on soil moisture is small compared to the dependence of 542  
 $\alpha$  on vegetation cover. The green vegetation albedo  $\alpha_{\text{fcgv}}$  is 543  
estimated as the surface albedo corresponding to maximum 544  
fractional green vegetation cover. The senescent vegetation 545  
albedo  $\alpha_{\text{fcsv}}$  is estimated as the maximum surface albedo 546  
observed within the study area. Values for  $\alpha_{\text{bs}}$ ,  $\alpha_{\text{fcgv}}$ , and 547  
 $\alpha_{\text{fcsv}}$  are reported in Table II. 548

### C. Land Surface Temperature

549  
550 As the range of surface conditions varies with spatial res-  
olution, two different procedures are developed to estimate 551  
temperature end-members. 552

- 1) When estimating temperature end-members from 250-m 553  
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. 559

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

End-member	High-resolution $T$	Aggregated ASTER $T_{km}$	MODIS $T_{km}$	Unit
$T_{b,ds}$	38	40.2	38.9	$^{\circ}\text{C}$
$T_{b,ws}$	25	27.6	26.2	$^{\circ}\text{C}$
$T_{fegv}$	21	21.0	21.0	$^{\circ}\text{C}$
$T_{fcsv}$	34	32.0	28.7	$^{\circ}\text{C}$
$TB_{b,ds}$	240	246	241	K
$TB_{b,ws}$	190	193	193	K
$TB_{fegv,ws}$	205	205	205	K
$TB_{fegv,ds}$	240	240	240	K
$TB_{fcsv,ds}$	280	280	280	K

560 2) When estimating temperature end-members from 1-km  
561 resolution data (as in the operational scenario), none of  
562 the pixels are identified as representative of any extreme  
563 condition. Temperature end-members are extrapolated  
564 from 1-km temperature data using ancillary data com-  
565 posed of air temperature, soil albedo, green vegetation  
566 albedo, and senescent vegetation albedo as described in  
567 the following.

568 End-members  $T_{b,ws}$ ,  $T_{b,ds}$ ,  $T_{fegv}$ , and  $T_{fcsv}$  are deter-  
569 mined by analyzing the consistency of the diagrams in Fig. 4.  
570 Fig. 4(a) shows the space defined by ASTER land surface  
571 temperature and ASTER fractional green vegetation cover. The  
572 three edges of the triangle  $T - f_{gv}$  are interpreted [27] as “bare  
573 soil” between A and B, “wet surface” between B and C, and  
574 “dry soil” between C and A. Fig. 4(b) shows the space de-  
575 fined by ASTER land surface temperature and ASTER surface  
576 albedo. An interpretation of the polygon  $T - \alpha$  is provided  
577 in [5], which is consistent with the triangle method. The four  
578 edges are interpreted as “bare soil” between A and B, “wet  
579 surface” between B and C, “full cover” between C and D,  
580 and “dry surface” between D and A. The notation system for  
581 polygon vertices A, B, C, and D is summarized in Table I, and  
582 the corresponding temperature values  $T_{b,ds}$ ,  $T_{b,ws}$ ,  $T_{fegv}$ ,  
583 and  $T_{fcsv}$  are reported in Table III.

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

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

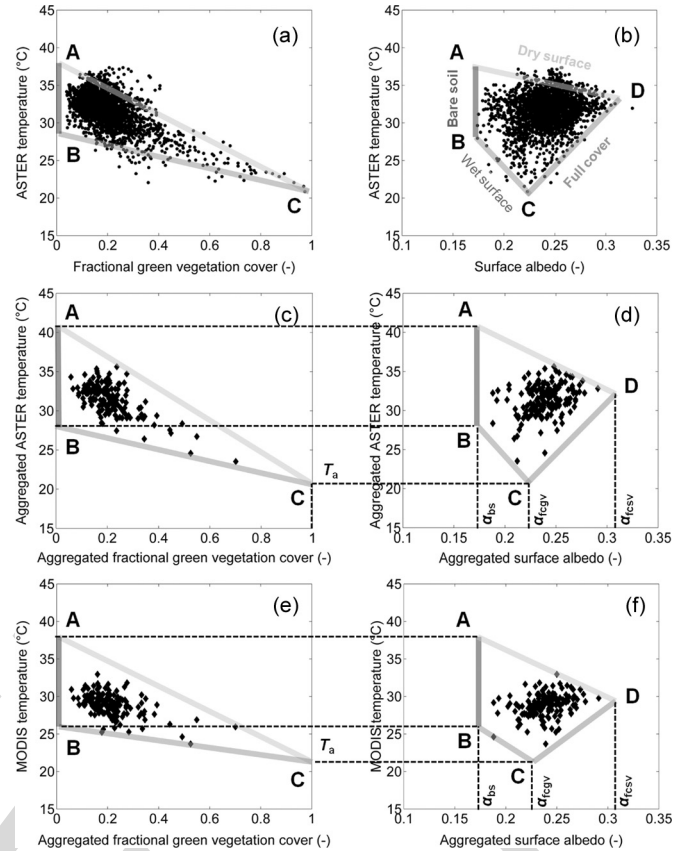


Fig. 4. (a) Scatterplot of ASTER temperature versus fractional green vegetation cover and (b) versus surface albedo, (c) scatterplot of aggregated ASTER temperature versus aggregated fractional green vegetation cover and (d) versus aggregated surface albedo, and (e) scatterplot of MODIS temperature versus aggregated fractional green vegetation cover and (f) versus aggregated surface albedo. The vertices A, B, C, and D obtained using high-resolution data in (a) and (b) are extrapolated using low-resolution data in (c), (d), (e), and (f) from ancillary data composed of air temperature  $T_a$ , soil albedo  $\alpha_{bs}$ , green vegetation albedo  $\alpha_{fegv}$ , and senescent vegetation albedo  $\alpha_{fcsv}$ .

- 2) Vertex B corresponds to wet bare soil and is located at 598  $(0, T_{b,ws})$  in Fig. 4(c) [Fig. 4(e)] and at  $(\alpha_{bs}, T_{b,ws})$  in 599 Fig. 4(d) [Fig. 4(f)]. It is placed in Fig. 4(c) [Fig. 4(e)] 600 at the intersection between (BC) and the vertical line 601  $\langle f_{gv} \rangle_{km} = 0$ . The slope of (BC) is computed as the slope 602 of the linear regression of the data points corresponding 603 to the “wet surface” edge of the triangle  $T_{km} - \langle f_{gv} \rangle_{km}$ . 604 The off-set of (BC) is determined from C. 605
- 3) Vertex A corresponds to dry bare soil and is located at 606  $(0, T_{b,ds})$  in Fig. 4(c) [Fig. 4(e)] and at  $(\alpha_{bs}, T_{b,ds})$  in 607 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 609  $\langle f_{gv} \rangle_{km} = 0$ . 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  $T_{km} - \langle f_{gv} \rangle_{km}$ . The 612 off-set of (AC) is determined from C. 613
- 4) Vertex D corresponds to full-cover senescent vegetation 614 and is located at  $(\alpha_{fcsv}, T_{fcsv})$  in Fig. 4(d) [Fig. 4(f)]. 615 It is placed in Fig. 4(d) [Fig. 4(f)] at the intersection 616 between (AD) and the vertical line  $\langle \alpha \rangle_{km} = \alpha_{fcsv}$ . The 617 line (AD) is considered as being parallel to (BC)[5]. 618 Consequently, the slope of (AD) is determined from 619

620 the slope of (BC). The off-set of (AD) is determined  
 621 from A. Note that the lines (AD) and (BC) might  
 622 not be strictly parallel. This may be due to a lack of  
 623 representativeness of the surface conditions captured at  
 624 250-m resolution within the study area. In that case, one  
 625 or several data points may be located above (AD). To  
 626 circumvent this artifact, the slope of (AD) in Fig. 4(d)  
 627 [Fig. 4(f)] is increased so that all data points will be  
 628 located below the “dry surface” edge.

629 Table III lists the four temperature end-members: 1) esti-  
 630 mated from Fig. 4(a) and (b) using high-resolution ASTER  
 631 data; 2) extrapolated from Fig. 4(c) and (d) using aggregated  
 632 ASTER temperature data; and 3) extrapolated from Fig. 4(e)  
 633 and (f) using MODIS temperature data. The values extrapo-  
 634 lated from aggregated ASTER and MODIS temperatures are  
 635 rather close to those estimated from high-resolution ASTER  
 636 temperature data, with the maximum difference in extrapolated  
 637 temperatures being 2.6 °C, except for  $T_{f_{csv}}$  using MODIS  
 638 data. In the latter case, the significant underestimation (5.3 °C)  
 639 of  $T_{f_{csv}}$  can be explained by the following: 1) the negative  
 640 mean difference (−2.3 °C) between MODIS and ASTER data  
 641 and/or 2) the smaller range of (spatial dynamics) of 1-km  
 642 resolution MODIS data in relation to 1-km aggregated ASTER  
 643 data [please compare Fig. 4(c) with Fig. 4(e), and Fig. 4(d) with  
 644 Fig. 4(f)].

#### 645 D. Brightness Temperature

646 To estimate soil evaporative efficiency  $\beta$  in (20) and  $\beta'$   
 647 in (22), five brightness temperature values corresponding to  
 648 extreme surface conditions are required:  $T_{B,ds}$ ,  $T_{B,ws}$ ,  
 649  $T_{B_{f_{gv},ws}}$ ,  $T_{B_{f_{gv},ds}}$ , and  $T_{B_{f_{csv},ds}}$ . In this paper, those  
 650 five values are estimated from a generalized version [5], [9] of  
 651 the classical “triangle method” [27].

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

- 660 1) Vertex at minimum brightness temperature: L-band ra-  
 661 diative transfer models predict an increase of brightness  
 662 temperature with biomass and a decrease of brightness  
 663 temperature with surface soil moisture (e.g., [48] and  
 664 [49]). Therefore, the point at minimum brightness tem-  
 665 perature corresponds to wet bare soil. This vertex is noted  
 666 as B in Fig. 5(a), which is consistent with Fig. 4.
- 667 2) Vertex at maximum land surface temperature: the triangle  
 668 method predicts a decrease of land surface temperature  
 669 with both vegetation cover and surface soil moisture.  
 670 Therefore, the point at maximum land surface tempera-  
 671 ture corresponds to dry bare soil. This vertex is noted as  
 672 A in Fig. 5(a), which is consistent with Fig. 4.
- 673 3) Vertex at maximum brightness temperature: being con-  
 674 sistent with an increase of vegetation emission with  
 675 biomass and a decrease of soil emission with surface soil

moisture, the point at maximum brightness temperature 676  
 corresponds to full-cover vegetation with dry soil. It 677  
 could correspond to full-cover green vegetation. How- 678  
 ever, the associated land surface temperature in Fig. 5(a) 679  
 is much larger than that over full-cover green vegetation 680  
 (21 °C) and rather close to the temperature over full- 681  
 cover senescent vegetation (34 °C). Therefore, the point 682  
 at maximum brightness temperature corresponds to full- 683  
 cover senescent vegetation with dry soil. This vertex 684  
 is noted as  $D'$  in Fig. 5(a), which is consistent with 685  
 Fig. 4. A prime mark indicates that  $D'$  corresponds to a 686  
 dry soil, whereas  $D$  does not specify soil hydric status. 687  
 Note that  $D'$  does not necessarily correspond to dry 688  
 senescent vegetation since wet senescent vegetation can 689  
 lead to large values of brightness temperature [50]. In 690  
 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]. 696

- 4) Vertices at minimum land surface temperature: two more 697  
 vertices are apparent in the counterclockwise direction. 698  
 Being consistent with a decrease of land surface tem- 699  
 perature with green vegetation, both points correspond 700  
 to full-cover green vegetation. As vegetation is partially 701  
 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  $T_B$  [noted as  $C''$  in Fig. 5(a)] 704  
 corresponds to full-cover green vegetation with dry soil, 705  
 and the point with a lower  $T_B$  [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 708  
 in this paper, brightness temperature end-members are not 709  
 estimated from the polygon  $T_B - T$  in Fig. 5(a) but from 710  
 the polygon  $T_B - f_{gv}$  shown in Fig. 5(b). The following is 711  
 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. 714

- 1) Vertex B corresponds to wet bare soil. It is located at 715  
 the minimum value of brightness temperature such that 716  
 $f_{gv} = 0$ . 717
- 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 720  
 and senescent vegetation. 721
- 3) Vertex  $D'$  corresponds to full-cover senescent vegetation 722  
 with dry soil. It is located at the maximum value of 723  
 brightness temperature. 724
- 4) Vertex  $C''$  corresponds to full-cover green vegetation 725  
 with dry soil. It is located at the maximum value of 726  
 brightness temperature such that  $f_{gv} = 1$ . 727
- 5) Vertex  $C'$  corresponds to full-cover green vegetation with 728  
 wet soil. It is located at the minimum value of brightness 729  
 temperature such that  $f_{gv} = 1$ . 730

Based on the aforementioned interpretation of the polygon 731  
 $T_B - f_{gv}$  in Fig. 5(b), the methodology used for estimating 732

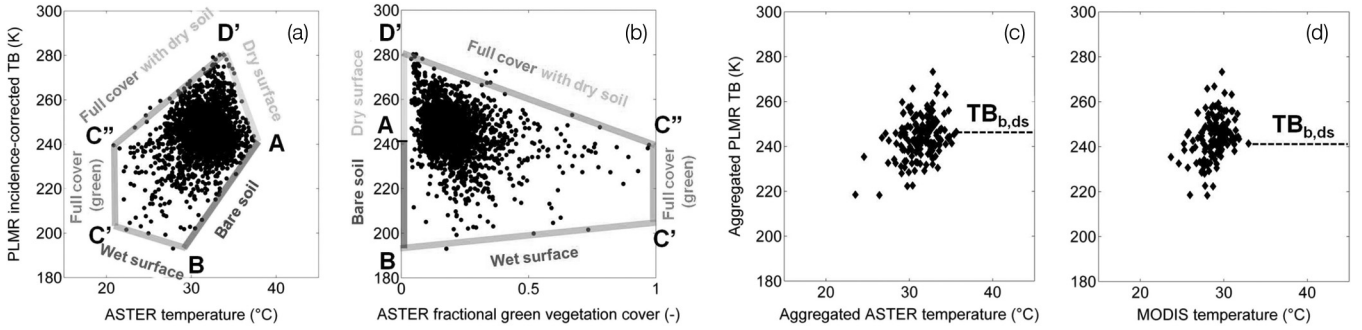


Fig. 5. (a) Scatterplot of PLMR incidence-corrected brightness temperature  $TB$  versus ASTER land surface temperature and (b) versus ASTER fractional green vegetation cover, and (c) scatterplot of aggregated  $TB$  versus aggregated ASTER temperature and (d) versus MODIS temperature. Extreme brightness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

733  $T_{b,ds}$ ,  $T_{b,ws}$ ,  $T_{fcgv,ws}$ ,  $T_{fcgv,ds}$ , and  $T_{fcsv,ds}$  is  
734 detailed in the following.

- 735 1) The brightness temperature over full-cover dry surface  
736 ( $T_{fcsv,ds}$ ) and over wet bare soil ( $T_{b,ws}$ ) are set  
737 to the maximum and minimum brightness temperatures  
738 observed within the study area, respectively.
- 739 2) The brightness temperatures over full-cover green veg-  
740 etation with wet soil ( $T_{fcgv,ws}$ ) and over full-cover  
741 green vegetation with dry soil ( $T_{fcgv,ds}$ ) are estimated  
742 as the brightness temperature extrapolated at  $f_{gv} = 1$  in  
743 Fig. 5(b) along the “wet soil” and the “full-cover dry  
744 soil” edge, respectively. The slope of the lines ( $BC'$ )  
745 and ( $D'C''$ ) are determined so that all of the points with  
746  $f_{gv} > 0.5$  be above and below the “wet soil” and “full-  
747 cover dry soil” edges, respectively.
- 748 3) Vertex A cannot be identified in the space  $TB - f_{gv}$ .  
749 Consequently,  $T_{b,ds}$  is set to the brightness tempera-  
750 ture corresponding to the maximum  $T_{km}$  (see Fig. 5(c) for  
751 aggregated ASTER temperature and Fig. 5(d) for MODIS  
752 temperature data).

753 Table III lists the five brightness temperature end-members:  
754 1) estimated from Fig. 5(a) using high-resolution ASTER data;  
755 2) estimated from Fig. 5(b) and (c) using high-resolution  
756 fractional green vegetation cover and aggregated ASTER tem-  
757 perature data; and 3) estimated from Fig. 5(b) and (d) using  
758 high-resolution fractional green vegetation cover and MODIS  
759 temperature data. Values estimated from low-resolution tem-  
760 perature are remarkably close to those estimated from high-  
761 resolution ASTER temperature data (Table III), except for  
762  $T_{b,ds}$  with a difference of 6 K. This difference is apparently  
763 due to the lack of representativeness of kilometric aggregated  
764 brightness temperature and the method for estimating  $T_{b,ds}$   
765 at kilometric scale. Note, however, that a 6-K difference is still  
766 relatively low compared to the range (190 K–280 K) covered  
767 by brightness temperature values.

768

## VI. APPLICATION

769 The disaggregation algorithms presented here are applied  
770 to the NAFE'06 data set. ASTER land surface temperature is  
771 aggregated at 1-km resolution, and kilometric temperature is  
772 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  
773 disaggregation results at 250-m resolution with ASTER land  
774 surface temperature. An application to MODIS data is also  
775 presented. 776

### A. Application to Aggregated ASTER Data 777

1) *End-Members Derived From High-Resolution Data:* The  
778 approach is first implemented using the end-members estimated  
779 from high-resolution ASTER temperature data. This allows  
780 testing the robustness of the model in (15) and (16) inde-  
781 pendently of the methodology used for extrapolating the nine  
782 end-members  $T_{b,ds}$ ,  $T_{b,ws}$ ,  $T_{fcgv}$ ,  $T_{fcsv}$ ,  $T_{b,ds}$ ,  $T_{b,ws}$ ,  
783  $T_{fcgv,ws}$ ,  $T_{fcgv,ds}$ , and  $T_{fcsv,ds}$ . 784

Fig. 6 shows the output images of the eight disaggregation  
785 algorithms, which are to be compared with the reference image  
786 derived from ASTER land surface temperature. One observes  
787 that the disaggregated temperature is successively improved  
788 by including additional factors in the disaggregation, which  
789 indicates that the methodology is able to take into account  
790 several independent factors. Although the boxy artifact at 1-km  
791 resolution is successively reduced from  $T^{(0)}$  to  $T^{(4'')}$ , it is still  
792 apparent for  $T^{(4'')}$ . This effect may be due to the following: 1)  
793 other factors that are not taken into account in the procedure,  
794 such as green vegetation water stress, wind speed, surface  
795 emissivity, surface albedo, etc.; 2) errors in estimated  $f_{gv}$ ,  $f_{sv}$ ,  
796  $f_{ow}$ , and  $\beta$ ; and/or 3) resampling errors at 250-m resolution. 797

Table IV lists the RMSD, correlation coefficient, and slope  
798 between the disaggregated and ASTER temperatures for each  
799 of the eight disaggregation algorithms. The error is successively  
800 decreased from 1.65 °C to 1.16 °C, while the correlation coef-  
801 ficient and slope are successively increased from 0.79 and 0.63  
802 to 0.89 and 0.88, respectively. When comparing  $D_1$ ,  $D_2$ ,  $D_1'$ ,  
803 and  $D_2'$ , no significant differences are observed between all  
804 four algorithms in terms of root-mean-square error, correlation  
805 coefficient, and slope. Note that, in this paper,  $f_{tv}$  was estimated  
806 in a different way than in [5] because only one visible and  
807 near-infrared image was available and a FORMOSAT-like time  
808 series would be required to derive  $f_{tv}$  more accurately on a  
809 pixel-by-pixel basis. Nevertheless, this comparison suggests  
810 that  $D_1'$  seems to be equivalent to  $D_1$  and  $D_2'$  equivalent to  
811  $D_2$ , which justifies the use of the  $T_{mod}$  model. 812

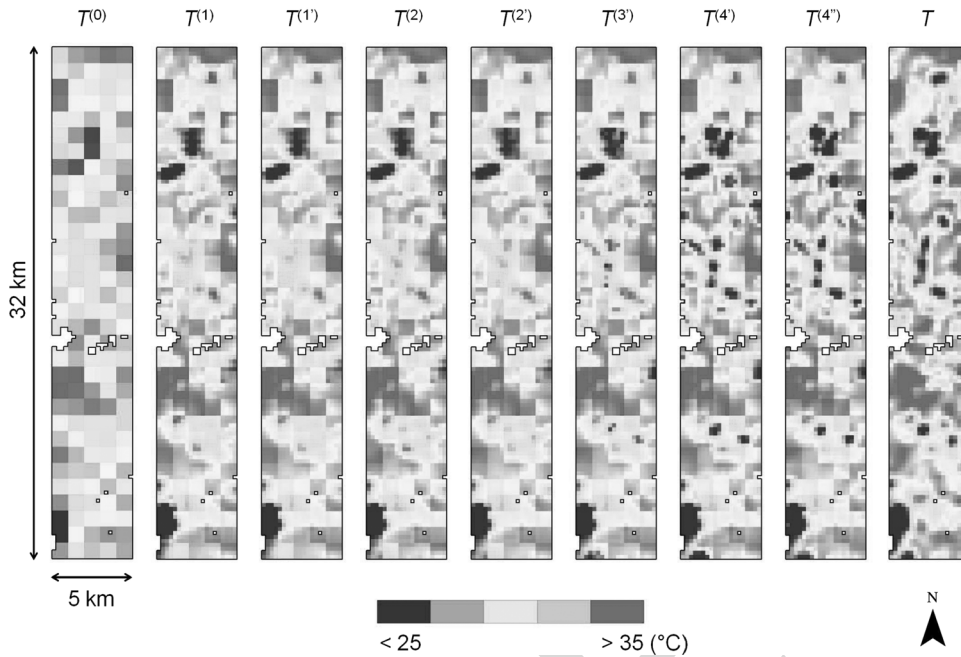


Fig. 6. Maps of the temperature disaggregated by the eight algorithms as compared with the map (right) of high-resolution ASTER temperature.

TABLE IV  
RMSD, CORRELATION COEFFICIENT ( $R$ ), AND SLOPE BETWEEN THE DISAGGREGATED AND ASTER TEMPERATURES. THE RESULTS CORRESPOND TO THE END-MEMBERS ESTIMATED USING HIGH-RESOLUTION ASTER TEMPERATURE DATA (TO THE END-MEMBERS EXTRAPOLATED USING AGGREGATED ASTER TEMPERATURE DATA)

Algorithm	RMSD °C	R	Slope
D0	1.65	0.79	0.63
D1	1.39	0.86	0.76
D2	1.35 (1.35)	0.87 (0.87)	0.76 (0.76)
D1'	1.38 (1.39)	0.86 (0.86)	0.74 (0.72)
D2'	1.30 (1.40)	0.88 (0.86)	0.75 (0.73)
D3'	1.22 (1.27)	0.89 (0.88)	0.78 (0.76)
D4'	1.15 (1.15)	0.91 (0.91)	0.86 (0.84)
D4''	1.16 (1.24)	0.89 (0.80)	0.88 (0.86)

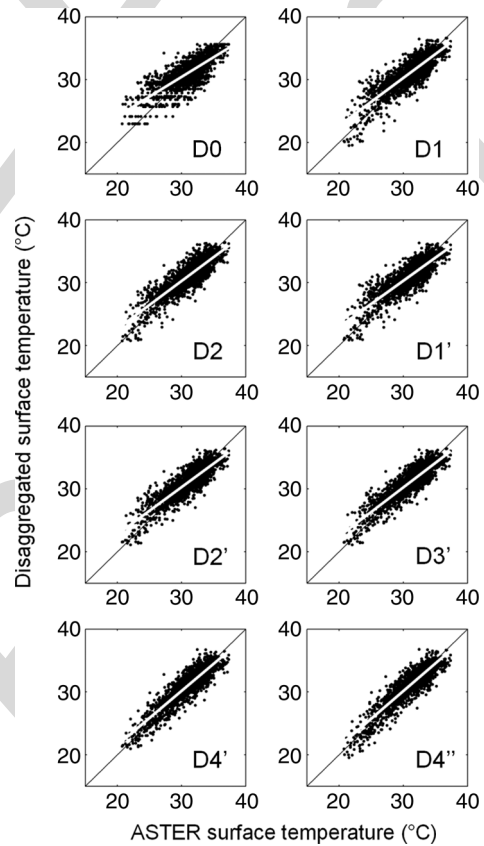


Fig. 7. Aggregated ASTER temperature (1 km) is disaggregated by each of the eight algorithms and is plotted against high-resolution ASTER temperature.

813 The main advantage of the new approach is to take into  
 814 account a number of additional factors, including fractional  
 815 open water and soil evaporative efficiency. When comparing the  
 816 results obtained for D3', D4', and D4'' in Table IV, it is observed  
 817 that the disaggregated temperature is significantly improved  
 818 against the classical approaches D1 and D2. Moreover, the  
 819 statistical results are successively improved by including  $f_{ow}$ ,  
 820  $\beta$ , and  $\beta'$ . Fig. 7 shows the improvement, especially in the  
 821 slope between the disaggregated and ASTER temperatures. The  
 822 good results obtained for D4'' indicate that the performance of  
 823 disaggregation algorithms is intimately related to the following:  
 824 1) the capability of separating the independent factors that  
 825 impact on surface temperature and 2) the ability to integrate  
 826 them consistently into the procedure.

827 2) *End-Members Derived From Aggregated ASTER Data:*  
 828 As disaggregation procedures D1', D2', D3', D4', and D4''

are subjected to uncertainties in land surface temperature and 829  
 brightness temperature end-members, the five algorithms are 830  
 next tested using the end-members estimated from kilomet- 831  
 ric temperature data, as presented in Section V. Aggregated 832  
 ASTER (instead of MODIS) data are used to evaluate the 833

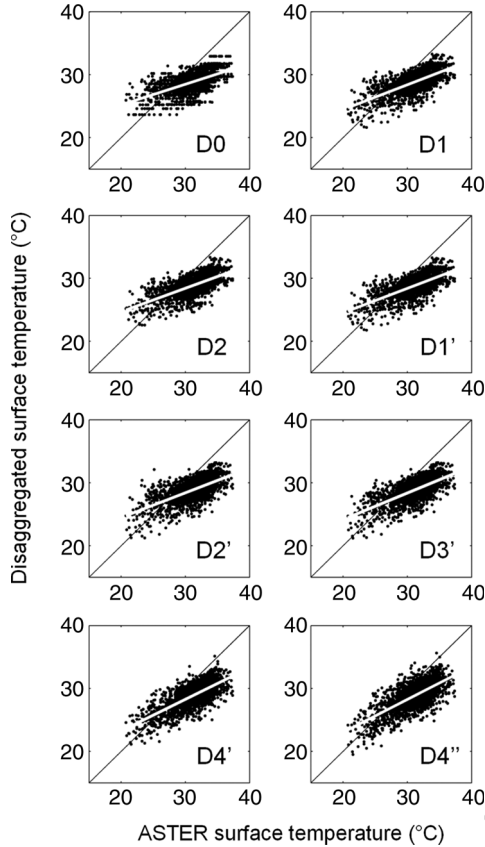


Fig. 8. MODIS temperature (1 km) is disaggregated by each of the eight algorithms and is plotted against high-resolution ASTER temperature.

834 impact of end-members regardless of the discrepancy between  
835 MODIS and ASTER temperatures.

836 Table IV lists the RMSD, correlation coefficient, and slope  
837 between the disaggregated and ASTER temperatures for each  
838 of the five algorithms. Results are compared with those ob-  
839 tained using the end-members estimated from high-resolution  
840 ASTER temperature. In general, the error is slightly larger,  
841 and the correlation coefficient and slope are slightly lower us-  
842 ing extrapolated end-members. Nevertheless, the disaggregated  
843 temperature is still much improved by applying  $D4''$  instead of  
844  $D1'$ , with the correlation coefficient and slope increasing from  
845 0.74 to 0.88 and from 0.72 to 0.86, respectively. Consequently,  
846 the extrapolation of end-members from kilometric data is not  
847 found to be a limiting factor in the methodology.

#### 848 B. Application to MODIS Data

849 Disaggregation algorithms  $D0$ ,  $D1$ ,  $D1'$ ,  $D2$ ,  $D2'$ ,  $D3'$ ,  $D4'$ ,  
850 and  $D4''$  are then applied to MODIS data. In this case, end-  
851 members are derived from MODIS data. Fig. 8 shows the scat-  
852 terplot of disaggregated MODIS versus ASTER temperature for  
853 each algorithm separately. One observes that the new methodol-  
854 ogy improves the correlation and slope of the linear regression  
855 between the disaggregated and ASTER temperatures. However,  
856 a systematic negative bias is apparent in the disaggregated  
857 temperature. Table V lists the RMSD, correlation coefficient,  
858 and slope between the disaggregated and ASTER temperatures  
859 for each of the eight algorithms. The error slightly decreases

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

Algorithm	RMSD °C	R -	Slope -
D0	3.19	0.60	0.33
D1	3.08	0.67	0.39
D2	3.11	0.66	0.37
$D1'$	3.09	0.67	0.39
$D2'$	3.12	0.65	0.39
$D3'$	3.06	0.69	0.42
$D4'$	2.98	0.73	0.50
$D4''$	3.03	0.70	0.52

from 3.2 °C to 3.0 °C, while the correlation coefficient and 860  
slope increase from 0.6 and 0.3 to 0.7 and 0.5, respectively. 861  
The results obtained for  $D3'$  and  $D4'$  in Table V indicate that 862  
the disaggregated temperature is improved against the classical 863  
approaches  $D1$  and  $D2$ . As for the application to aggregated 864  
ASTER data, the statistical results are successively improved 865  
by including  $f_{ow}$ ,  $\beta$ , and  $\beta'$ . However, the improvement with 866  
MODIS data is not as visible as with aggregated ASTER 867  
data because the difference between MODIS and ASTER data 868  
(please refer to Section II-C) has the same order of magnitude 869  
as the subpixel variability at 250-m resolution (see RMSD for 870  
 $D0$  in Table V). In particular, the mean bias and the relatively 871  
low slope of the linear regression between the disaggregated 872  
and ASTER data are associated with the discrepancy at 1-km 873  
resolution between the MODIS and ASTER temperature data. 874

## VII. SENSITIVITY ANALYSIS

875

To further assess the stability of the new  $D'$  algorithms based 876  
on radiative transfer, two sensitivity analyses are conducted 877  
by the following: 1) adding a Gaussian noise on kilometric 878  
temperatures and high-resolution brightness temperatures and 879  
2) estimating the contribution of each factor on the variability 880  
of modeled land surface temperature. 881

### A. Uncertainty in End-Members

882

To test the stability of the method for estimating the nine 883  
end-members ( $T_{b,ds}$ ,  $T_{b,ws}$ ,  $T_{fcgv}$ ,  $T_{fcsv}$ ,  $T_{b,ds}$ ,  $T_{b,ws}$ , 884  
 $T_{b,ds}$ ,  $T_{b,ws}$ ,  $T_{b,ds}$ ,  $T_{b,ws}$ ,  $T_{b,ds}$ ,  $T_{b,ws}$ ,  $T_{b,ds}$ ,  $T_{b,ws}$ , 885  
 $T_{b,ds}$ ,  $T_{b,ws}$ ,  $T_{b,ds}$ ,  $T_{b,ws}$ ,  $T_{b,ds}$ ,  $T_{b,ws}$ ) from low-resolution 886  
temperature data, a Gaussian noise with a standard deviation 887  
of 1 °C is added to the kilometric (aggregated ASTER) land 888  
surface temperature data set, and a Gaussian noise with a stan- 889  
dard deviation of 2 K is added to the high-resolution brightness 890  
temperature data set. An ensemble of 100 data sets is generated 891  
and used as input to the disaggregation algorithms.

Table VI reports the average and standard deviation of ex- 892  
trapolated end-members computed within the ensemble of 100 893  
artificially perturbed data sets. Results indicate that the method 894  
for extrapolating end-members is stable for all end-members. 895

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

End-member	Mean	St. dev.	Unit
$T_{b,ds}$	40.8	0.8	$^{\circ}\text{C}$
$T_{b,ws}$	25.7	1.5	$^{\circ}\text{C}$
$T_{fcgv}$	21.0	0	$^{\circ}\text{C}$
$T_{fsv}$	33.1	1.3	$^{\circ}\text{C}$
$TB_{b,ds}$	246	3.2	K
$TB_{b,ws}$	193	1.4	K
$TB_{fcgv,ws}$	204	2.3	K
$TB_{fcgv,ds}$	240	1.5	K
$TB_{fsv,ds}$	281	1.0	K

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

Algorithm	RMSD $^{\circ}\text{C}$	R -	Slope -
D0	1.81	0.75	0.63
D1	1.58	0.82	0.76
D2	1.54	0.83	0.76
D1'	1.57	0.82	0.73
D2'	1.54	0.83	0.74
D3'	1.44	0.85	0.78
D4'	1.39	0.87	0.87
D4''	1.48	0.86	0.89

896 Table VII lists the RMSD, correlation coefficient, and slope  
897 between the disaggregated and ASTER temperatures for all 100  
898 data sets. Although the results are generally degraded by using  
899 noisy input data sets, D4'' is still superior to all other algorithms  
900 (see Fig. 9). Therefore, the integration of fractional open water  
901 and soil evaporative efficiency into the disaggregation is able to  
902 improve the representation of land surface temperature variabil-  
903 ity despite the uncertainties in  $f_{ow}$  and  $\beta'$ , and the uncertainties  
904 in extrapolated end-members.

### 905 B. Weighting Variability Factors

906 Results with the NAFE'06 data set have indicated that the  
907 new D' algorithms based on radiative transfer significantly  
908 improve (in relation to D1 and D2 methods) the representation  
909 of disaggregated temperature by directly integrating the various  
910 input parameters of the radiative transfer equation. Another ad-  
911 vantage of the proposed methodology is to quantify the weight  
912 of these input parameters. Here, the relative weights of  $f_{gv}$ ,  
913  $f_{sv}$ ,  $f_{ow}$ , and  $\beta'$  are compared, and the relative improvement in  
914 disaggregated temperature when including these factors in the  
915 disaggregation is assessed. The weight of  $f_{gv}$  on the variability

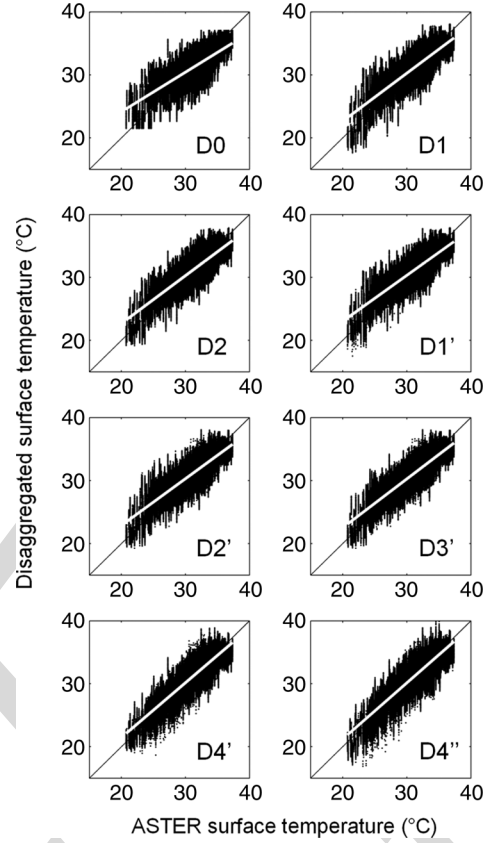


Fig. 9. As for Fig. 7 but using all the 100 artificially noised input data sets.

in land surface temperature is derived by computing the first 916  
partial derivative of  $T_{mod}$  from (15) and (16) 917

$$\frac{\partial T_{mod}}{\partial f_{gv}} = -(1 - f_{ow})(T_{fcsv} - T_{fcgv}). \quad (25)$$

Similarly, the first partial derivative of  $T_{mod}$  is computed with 918  
respect to  $f_{sv}$  919

$$\frac{\partial T_{mod}}{\partial f_{sv}} = -(1 - f_{ow})[\beta' T_{b,ws} + (1 - \beta') T_{b,ds} - T_{fcsv}] \quad (26)$$

with respect to  $f_{ow}$  920

$$\frac{\partial T_{mod}}{\partial f_{ow}} = -[f_{gv} T_{fcgv} + (f_{tv} - f_{gv}) T_{fcsv} + (1 - f_{tv})(\beta' T_{b,ws} + (1 - \beta') T_{b,ds}) - T_{fcgv}] \quad (27)$$

and with respect to  $\beta'$  921

$$\frac{\partial T_{mod}}{\partial \beta'} = -(1 - f_{ow})(1 - f_{tv})(T_{b,ds} - T_{b,ws}). \quad (28)$$

Table VIII lists the standard deviation of each parameter 922  
within the study area, the average of partial derivatives, and the 923  
relative weight of each parameter on the variability of modeled 924  
land surface temperature. The relative weights of  $f_{gv}$ ,  $f_{sv}$ ,  $f_{ow}$ , 925  
and  $\beta'$  are estimated as the mean partial derivative times the 926  
standard deviation. Results indicate that all parameters have a 927  
negative impact on  $T$ . More interestingly,  $f_{gv}$  appears to be 928  
the most significant variability factor, with a relative weight 929  
of 42%, which is consistent with NDVI-based approaches [4]. 930

TABLE VIII  
STANDARD DEVIATION, MEAN PARTIAL DERIVATIVE, AND IMPACT ON HIGH-RESOLUTION MODELED TEMPERATURE OF EACH OF THE FOUR PARAMETERS: FRACTIONAL GREEN VEGETATION COVER, FRACTIONAL SENESCENT VEGETATION COVER, FRACTIONAL OPEN WATER, AND SOIL EVAPORATIVE EFFICIENCY

Factor	Standard deviation	Mean partial derivative	Impact on $T_{\text{mod}}$ (percentage of total)
-	-	$^{\circ}\text{C}$	$^{\circ}\text{C}$ (%)
$f_{\text{gv}}$	0.11	-13	0.97 (42)
$f_{\text{sv}}$	0.19	-2.0	0.26 (11)
$f_{\text{ow}}$	0.06	-11	0.45 (20)
$\beta'$	0.19	-4.8	0.17 (27)

931 The second and third most significant variability factors are soil  
932 evaporative efficiency and fractional open water, with relative  
933 weights of 27% and 20%, respectively. Finally, fractional senes-  
934 cent vegetation cover represents only 11% of the variability  
935 in land surface temperature. The low impact of  $f_{\text{sv}}$  can be  
936 associated with the low mean partial derivative. In particular,  
937  $\partial T_{\text{mod}} / \partial f_{\text{sv}}$  is low because the temperature difference be-  
938 tween dry bare soil ( $T_{\text{b,ds}}$ ) and full-cover senescent vegetation  
939 ( $T_{\text{fcsv}}$ ) is also low in our case study.

940 The relative weights in Table VIII are now related with  
941 the disaggregation results in Table III. Consequently, the poor  
942 improvement of D2 against D1 (and D2' against D1') can be  
943 attributed to the relatively low weight of  $f_{\text{sv}}$  in the variability of  
944 land surface temperature. Conversely, the significant improve-  
945 ments of D4' against D3', D3' against D2', and D1 (and D1')  
946 against D0 are attributed to the large weights of  $\beta'$ ,  $f_{\text{ow}}$ , and  
947  $f_{\text{gv}}$ , respectively.

948 In summary, the variability of land surface temperature is rea-  
949 sonably represented by model  $T_{\text{mod}}$ . Moreover, the approach  
950 allows the relative weight of each variability factor to be taken  
951 into account in the disaggregation procedure.

## 52 VIII. SUMMARY AND CONCLUSION

953 A new disaggregation methodology for land surface tem-  
954 perature has been developed to integrate the main surface  
955 parameters involved in the surface energy budget. It is based  
956 on a linearized radiative transfer equation, which distinguishes  
957 between soil, vegetation, and water temperature, and uses soil  
958 evaporative efficiency and fractional senescent vegetation cover  
959 to parameterize/estimate soil and vegetation hydric status, re-  
960 spectively. The approach is implemented using four parame-  
961 ters: the fraction of green vegetation cover derived from red  
962 and near-infrared bands, the fraction of senescent vegetation  
963 cover derived from red and near-infrared bands, the fraction  
964 of open water derived from shortwave-infrared band, and the  
965 soil evaporative efficiency derived from microwave-L band.  
966 It is tested over a 5 km by 32 km area of irrigated land in  
967 Australia, including flooded rice crops, using ASTER and L-  
968 band airborne data. Low-resolution land surface temperature  
969 is simulated by aggregating ASTER land surface tempera-  
970 ture at 1-km resolution, and the disaggregated temperature is  
971 compared to high-resolution ASTER temperature. The results  
972 indicate that the methodology is able to separate efficiently the  
973 independent factors that impact surface temperature and to inte-  
974 grate them consistently into the disaggregation procedure. The

error in disaggregated temperature is successively reduced from 975  
1.65  $^{\circ}\text{C}$  to 1.16  $^{\circ}\text{C}$  by including each of the four parameters. 976  
The correlation coefficient and slope between the disaggregated 977  
and ASTER temperatures are improved from 0.79 to 0.89 and 978  
from 0.63 to 0.88, respectively. Moreover, the radiative transfer 979  
equation allows quantifying the impact at high resolution of 980  
each parameter on land surface temperature. In this case study, 981  
fractional green vegetation cover is responsible for 42% of the 982  
variability in disaggregated land surface temperature, fractional 983  
senescent vegetation cover for 11%, fractional open water for 984  
20%, and soil evaporative efficiency for 27%. 985

Note that the approach presented in this paper did not take 986  
into account the water stress of green vegetation because none 987  
of the considered parameters (fractional green vegetation cover, 988  
fractional senescent vegetation cover, fractional open water, and 989  
soil evaporative efficiency) could describe the hydric status of 990  
photosynthetically active (green) vegetation. The analysis was 991  
conducted solely in a highly irrigated environment in which 992  
vegetation water stress was small. However, in most cases, 993  
the vegetation water stress might not be negligible for natural 994  
areas. In the presence of water-stressed green vegetation, the 995  
scatterplot (temperature versus green vegetation cover) would 996  
be transformed into a trapezoidal shape with four vertices 997  
rather than a triangle. In such conditions, the disaggregation 998  
problem would be partly undetermined since the partitioning 999  
between unstressed and stressed green vegetations would not 1000  
be represented. Consequently, the approaches shown here are 1001  
not expected to be representative of other less extreme environ- 1002  
ments than the present irrigated area. Nevertheless, one should 1003  
keep in mind that improving the spatial resolution of land 1004  
surface temperature data via disaggregation is only relevant in 1005  
the conditions where the spatial variability of temperature is 1006  
large. 1007

Although the approach was successfully applied to airborne 1008  
and satellite data collected during NAFE'06, further research is 1009  
needed to test the disaggregation approach on a routine basis. 1010  
One may anticipate that fractional green and senescent vege- 1011  
tation covers could be derived accurately using FORMOSAT- 1012  
like data. The FORMOSAT-2 instrument [52] provides short- 1013  
wave data at high spatial resolution (8 m) and high temporal 1014  
frequency (potentially one image per day), which allow a fine 1015  
analysis of the seasonality of canopies during the crop cycle 1016  
[5], [53], [54]. Fractional open water could be derived from 1017  
Landsat-5 data (e.g., [20]). Although the repeat cycle of Landsat 1018  
(16 days) is longer than the temporal resolution needed for land 1019  
surface temperature, the seasonal variations of water bodies 1020



1021 such as irrigation canals and flooded fields are expected to  
 1022 be low. Soil evaporative efficiency could be derived at high  
 1023 resolution from active microwave sensors, such as the Phased  
 1024 Array L-band SAR (PALSAR) [55]. Soil evaporative efficiency  
 1025 formulas express evaporation as a function of normalized sur-  
 1026 face soil moisture. Therefore, soil evaporative efficiency is  
 1027 equivalent to a soil moisture index, which could be replaced  
 1028 in (20) by the radar-derived soil wetness index computed as  
 1029 the observed to minimal backscattering coefficient difference  
 1030 divided by the maximal to minimal backscattering coefficient  
 1031 difference [56], [57]. Note, however, that the temporal coverage  
 1032 of the PALSAR fine beam dual polarization mode is relatively  
 1033 low, with a revisit cycle of 46 days. Consequently, accurate  
 1034 disaggregation of land surface temperature would still rely on  
 1035 the availability of high-resolution radar data.

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 1038 for their participation in collecting this extensive data set.

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- Olivier Merlin**, photograph and biography not available at the time of 1265 AQ4 1266 publication.
- Frédéric Jacob**, photograph and biography not available at the time of 1267 1268 publication.
- Jean-Pierre Wigneron**, photograph and biography not available at the time of 1269 1270 publication.
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