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Disaggregation of SMOS Soil Moisture in Southeastern Australia

Olivier Merlin, Christoph Rüdiger, Ahmad Al Bitar, Philippe Richaume, Jeffrey P. Walker, and Yann H. Kerr

Abstract—Disaggregation based on Physical And Theoretical scale Change (DisPATCh) is an algorithm dedicated to the disaggregation of soil moisture observations using high-resolution soil temperature data. DisPATCh converts soil temperature fields into soil moisture fields given a semi-empirical soil evaporative efficiency model and a first-order Taylor series expansion around the field-mean soil moisture. In this study, the disaggregation approach is applied to soil moisture and ocean salinity (SMOS) data over the 500 km by 100 km AACES (Australian Airborne Calibration/validation Experiments for SMOS) area. The 40-km resolution SMOS surface soil moisture pixels are disaggregated at 1-km resolution using the soil skin temperature derived from moderate resolution imaging spectroradiometer (MODIS) data, and subsequently compared with the AACES intensive ground measurements aggregated at 1-km resolution. The objective is to test DisPATCh under various surface and atmospheric conditions. It is found that the accuracy of disaggregation products varies greatly according to season: while the correlation coefficient between disaggregated and *in situ* soil moisture is about 0.7 during the summer AACES, it is approximately zero during the winter AACES, consistent with a weaker coupling between evaporation and surface soil moisture in temperate than in semi-arid climate. Moreover, during the summer AACES, the correlation coefficient between disaggregated and *in situ* soil moisture is increased from 0.70 to 0.85, by separating the 1-km pixels where MODIS temperature is mainly controlled by soil evaporation, from those where MODIS temperature is controlled by both soil evaporation and vegetation transpiration. It is also found that the 5-km resolution atmospheric correction of the official MODIS temperature data has a significant impact on DisPATCh output. An alternative atmospheric correction at 40-km resolution increases the correlation coefficient between disaggregated and *in situ* soil moisture from 0.72 to 0.82 during the summer AACES. Results indicate that

DisPATCh has a strong potential in low-vegetated semi-arid areas where it can be used as a tool to evaluate SMOS data (by reducing the mismatch in spatial extent between SMOS observations and localized *in situ* measurements), and as a further step, to derive a 1-km resolution soil moisture product adapted for large-scale hydrological studies.

Index Terms—AACES, calibration/validation, disaggregation, Disaggregation based on Physical And Theoretical scale Change (DisPATCh), field campaign, moderate resolution imaging spectroradiometer (MODIS), soil moisture and ocean salinity (SMOS).

I. INTRODUCTION

PASSIVE MICROWAVE remote sensing has the capability to provide key elements of the terrestrial hydrological cycle such as surface soil moisture [1], [2] and overland precipitation [3], [4]. Nevertheless, due to the large discrepancy between the observation scale (several tens of km) and the scale of physical interactions with the land surface (one wavelength or several cm), the radiative transfer models applied to passive microwave remote sensing data are only semiphysically based. Consequently, the retrieval process of land surface parameters from microwave brightness temperatures requires ancillary data for calibration and validation purposes [5]. It also requires a strategy to use such ancillary data since ground-based sampling is often made over a small area/point, which contrasts with the large integrated extent of spaceborne passive microwave observations.

The soil moisture and ocean salinity (SMOS), [6] satellite was launched on November 2, 2009. Over land, the SMOS mission aims at providing ~5 cm surface soil moisture data at a spatial resolution better than 50 km and a repeat cycle of less than 3 days. The payload is a 2-D interferometer equipped with 69 individual L-band antennas regularly spaced along Y-shaped arms. This new concept allows observing all pixels in the 1000 km wide field of view at a range of incidence angles. It also allows reconstructing brightness temperatures on a fixed sampling grid [7].

Since the SMOS launch, various field experiments (the HOBE site in Denmark [8], the Mali site in Western Africa [9], the SMOSMANIA site in Southwestern France [10] just to name a few) have been undertaken to validate SMOS reconstructed brightness temperatures and soil moisture retrievals. The AACES (Australian Airborne Calibration/validation Experiment for SMOS, [11]) is one of the most comprehensive campaigns worldwide dedicated to SMOS calibration/validation. A series of two experiments were undertaken in 2010, AACES-1 in January-February (Austral summer) and

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83 AACES-2 in September (Austral winter). The data collected
84 in AACES include 1-km resolution airborne L-band brightness
85 temperature mapped over a 500 km by 100 km area, 20 days
86 of very intensive ground measurements and 20 5 km by 2 km
87 ground sampling areas.

88 Even though the AACES ground measurements are very
89 extensive, it is not feasible to cover the whole extent of a
90 SMOS pixel by ground sampling alone. This is the reason why
91 most validation strategies of spaceborne passive microwave
92 data using *in situ* measurements have been based on the as-
93 sumption that local observations are representative of a much
94 larger spatial extent (i.e., the size of a microwave pixel). In the
95 heterogeneous case where this assumption does not hold, up-
96 scaling approaches [12], [13] have been developed to relate the
97 available ground observations to satellite scale soil moisture.
98 Such approaches are very useful over sites which have been
99 monitored for a long time and where extensive measurements
100 have been made over a range of spatial scales. However, aggre-
101 gation rules are difficult to build over sites which have been set
102 up recently, or where no extensive field campaigns have been
103 undertaken.

104 This study develops a methodology to facilitate the cali-
105 bration and validation of SMOS data using localized ground
106 measurements, such as those collected during AACES. The
107 methodology combines upscaling (aggregation) and downscal-
108 ing (disaggregation) approaches to make remote sensing and
109 *in situ* observations match at an intermediate spatial resolution
110 of 1 km. The key step in the procedure is a disaggregation
111 algorithm of passive microwave soil moisture using kilometric
112 optical data [14]–[16]. Disaggregating SMOS soil moisture can
113 solve the disparity of spatial scales between satellite and *in situ*
114 observations. However, the validation of spaceborne data by
115 means of a disaggregation approach requires the uncertainties
116 and potential error sources in downscaled data to be assessed.
117 Generally speaking, disaggregation is a compromise between
118 downscaling resolution and accuracy. The higher downscaling
119 resolution, the more disaggregated values are spatially repre-
120 sentative of ground observations, but typically have a lower
121 accuracy and vice versa [17]. In this context, a disaggrega-
122 tion algorithm named Disaggregation based on Physical And
123 Theoretical scale Change (DisPATCH) is applied to 40-km
124 resolution SMOS soil moisture over the AACES area using 1-
125 km resolution Moderate resolution Imaging Spectroradiometer
126 (MODIS) data. The objective is to test DisPATCH under various
127 surface and atmospheric conditions. Specifically, the impact
128 of climatic (evaporative demand), meteorologic (presence of
129 clouds), and vegetation (cover and water status) conditions on
130 1-km resolution disaggregated soil moisture is evaluated both
131 qualitatively by visual assessment of disaggregation images and
132 quantitatively by comparing DisPATCH output with AACES
133 intensive ground measurements.

134 The AACES, SMOS, and MODIS data used in this study
135 are first described. Next, the disaggregation methodology is
136 presented followed by a step-by-step description of the Dis-
137 PATCH algorithm. Results of the comparison between disag-
138 gregated SMOS soil moisture and *in situ* measurements are
139 then reported. To test DisPATCH under various surface and
140 atmospheric conditions, the algorithm is run during AACES-1

and AACES-2 in different modes, by including (or not) a 141
correction for vegetation and atmospheric effects. Finally, some 142
perspectives in the use of DisPATCH for validating SMOS data 143
using ground-based sampling are given. 144

II. DATA COLLECTION AND PREPROCESSING 145

The AACES experiments were planned to provide ground 146
and airborne soil moisture data over an area of approximately 147
500 km by 100 km during the two main seasons in the 148
Murrumbidgee river catchment, in southeastern Australia. The 149
first AACES campaign (AACES-1) was undertaken in summer 150
2010 from January 18 to February 21, and the second campaign 151
(AACES-2) was undertaken in the following Austral winter 152
from September 11 to September 24 [11]. Fig. 1 presents the 153
study area including the 20 5 km by 2 km ground sampling 154
focus areas. The background image is the MODIS 250-m res- 155
olution 16-day normalized difference vegetation index (NDVI) 156
product of February 2, 2010. The climate of the Murrumbidgee 157
catchment area ranges from semi-arid in the west to alpine in 158
the east, with a strong rainfall and potential evapotranspiration 159
gradient in the west-east direction. Land use is extensive graz- 160
ing in the west, cropping in the center, and mostly grazing/forest 161
in the east (refer to [11] for a detailed account of AACES). 162

A. HDAS 163

During both AACES-1 and AACES-2, a spatially enabled 164
platform (Hydraprobe Data Acquisition System, HDAS) was 165
used to collect extensive measurements of near-surface soil 166
moisture. HDAS is a handheld system combining a soil dielec- 167
tric sensor (Hydraprobe) and a pocket PC with GPS receiver, 168
allowing for direct storage of location and measurement within 169
the GIS software. HDAS measurements were calibrated using 170
the approach presented in [18] with a root mean square error 171
of point estimate of about $0.03 \text{ m}^3/\text{m}^3$. The sampling coverage 172
was two 5 km by 2 km farms per day during AACES-1 and one 173
5 km by 2 km farm per day during AACES-2. Within each farm, 174
a total of six adjacent 5 km long transects separated by 330 m 175
were walked to cover each area of 10 km^2 , and three separate 176
HDAS measurements were made along transects every 50 m. 177

In this study, HDAS soil moisture data are aggregated at 178
1-km resolution by averaging all measurements made within 179
each pixel of the MODIS resolution grid. Out of concern for 180
spatial representativeness of *in situ* observations, only the 1-km 181
pixels whose ground sampling covers more than two third of 182
its surface area are kept for comparison with disaggregation 183
results. The 1-km average of HDAS measurements is denoted 184
 $\langle \text{SM}_{\text{HDAS}} \rangle$ and the standard deviation of *in situ* measurements 185
(denoted σ_{HDAS}) computed to estimate the subpixel variability 186
at 1-km resolution. 187

B. SMOS 188

The version-4 SMOS level-2 soil moisture product is used. 189
This product (released on March 24, 2011) was produced from 190
the reprocessed level 1C data, and the version-4 level-2 soil 191
moisture algorithm. SMOS has a 6 am (ascending) and 6 pm 192

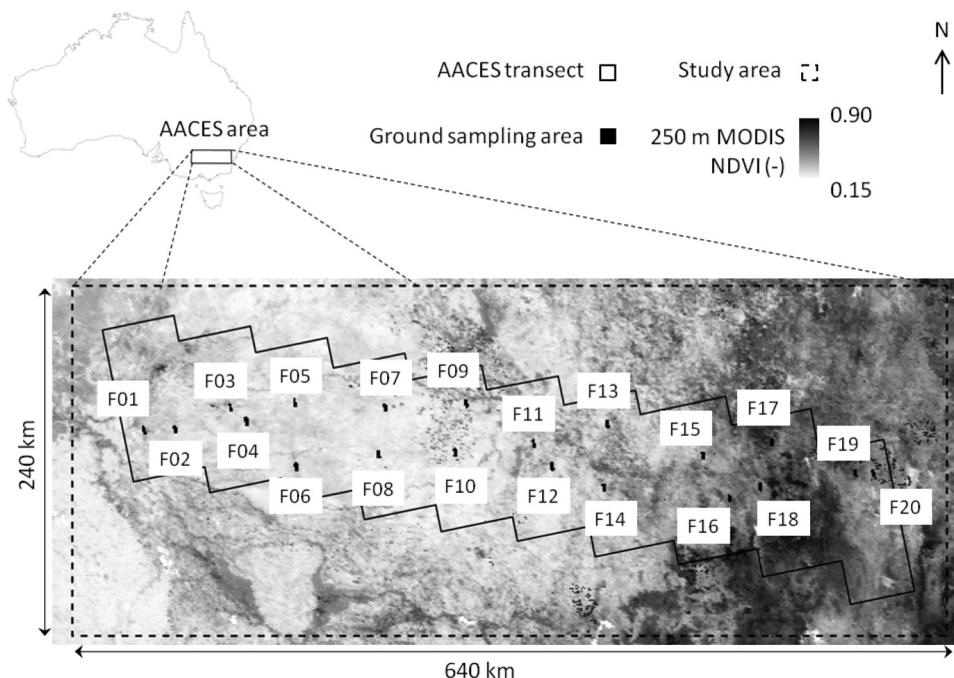


Fig. 1. Overview of the study area. During AACES, ten 100 km by 50 km patches were overflowed by an airborne L-band radiometer. Within each patch, two 5 km by 2 km subareas were sampled to collect spatial soil moisture measurements. In this study, DisPATCH is run over a 640 by 240 km area including the whole AACES area, and disaggregation results are evaluated over the ground sampling areas.

193 (descending) equator crossing time. The sampling grid of the
 194 SMOS level-2 soil moisture product is called DGG or discrete
 195 global grid [19], [20] and has a node separation of about
 196 15 km. The DGG provides a discretization that is higher than
 197 the SMOS natural pixel size, which is 40 km on average,
 198 ranging from 30 km at boresight to 90 km at high incidence
 199 angles. In this study, the disaggregation procedure takes advan-
 200 tage of the oversampling of SMOS data to potentially reduce
 201 (and provide an estimate of) random errors in disaggregated
 202 SMOS data. Instead of using a single snapshot SMOS im-
 203 age, DisPATCH uses four (overlapping) independent snapshots,
 204 which are generated by: 1) sliding a 40-km resolution grid;
 205 2) extracting the DGG nodes approximately centered on each
 206 40 km pixel. The extraction of SMOS DGG nodes is presented
 207 in [21]. The DGG node(s) that fall(s) near the center of the
 208 40-km resolution pixels with a ± 10 -km tolerance are se-
 209 lected. If more than one DGG is selected, the associated soil
 210 moisture values are averaged to produce a single value for each
 211 40-km resolution pixel. The 40-km resolution grid that fits the
 212 study area corresponds to what is termed here Resampling 1.
 213 Similarly, Resampling 2, 3, and 4 are performed by sliding the
 214 40-km resolution grid to coordinates $(+20 \text{ km}, 0)$, $(0, -20 \text{ km})$,
 215 and $(+20 \text{ km}, -20 \text{ km})$, respectively. The four 40-km resolu-
 216 tion SMOS data sets are then used independently as input to
 217 DisPATCH.

218 C. MODIS

219 The MODIS data used in this paper are composed of:

- 220 • Version-5 MODIS/Terra land surface temperature and
 221 emissivity daily level-3 global 1-km grid product
 222 (MOD11A1) and version-5 MODIS/Aqua land surface

temperature and emissivity daily level-3 global 1-km grid
 223 product (MYD11A1). The land surface temperature data
 224 set is the main component of DisPATCH. It is used to
 225 estimate 1-km resolution soil evaporative efficiency at
 226 10 am (Terra data) and 1 pm (Aqua data) [22].

- 227 • Version-5 MODIS/Terra vegetation indices 16-day level-3
 228 global 1-km grid product (MOD13A2). The NDVI data set
 229 is used in DisPATCH to estimate the fractional vegetation
 230 cover at 1-km resolution [23].
- 231 • Version-5 MODIS/Terra+Aqua albedo 16-day level-3
 232 global 1-km grid product (MCD43B3). The surface albedo
 233 data set is used in DisPATCH to estimate the vegetation
 234 temperature at maximum water stress from the space land
 235 surface temperature albedo [24]. The MCD43B3 product
 236 provides 1-km data describing both directional hemispher-
 237 ical reflectance (black-sky albedo) at local solar noon
 238 and bihemispherical reflectance (white-sky albedo). In this
 239 study, surface albedo refers to the MODIS shortwave white
 240 sky albedo.
- 241 • MODIS/Terra level-1B calibrated radiances swath 1-km
 242 grid product (MOD021KM) and MODIS/Aqua level-
 243 1B calibrated radiances swath 1-km grid product
 244 (MYD021KM). The radiance data set is used to derive
 245 a land surface temperature data set that differs from the
 246 official MOD11A1 and MYD11A1 products with respect
 247 to atmospheric correction.

248 Products MOD11A1, MYD11A1, MOD13A2, and
 249 MCD43B3 were downloaded through the NASA Warehouse
 250 Inventory Search Tool (WIST <http://wist.echo.nasa.gov/>) and
 251 products MOD021KM and MYD021KM were downloaded
 252 through the NASA Level 1 and Atmosphere Archive and Dis-
 253 tribution System (LAADS <http://ladsweb.nascom.nasa.gov/>).
 254

TABLE I
SCALE AND OFFSET VALUES USED TO CONVERT TERRA (AND AQUA)
MODIS RADIANCE DATA TO PHYSICAL RADIANCE
VALUES OVER THE AACES AREA

Thermal band	Scale ($\text{W m}^{-2} \text{sr}^{-1}$)	Offset (-)
31	$8.4002 \cdot 10^{-4}$ ($6.5081 \cdot 10^{-4}$)	1577 (2036)
32	$7.2970 \cdot 10^{-4}$ ($5.7100 \cdot 10^{-4}$)	1658 (2119)

255 All products were projected in UTM 55 South with a sampling
256 interval of 1000 m using the MODIS reprojection tool.

257 The level-1B calibrated radiance data (R_{31} and R_{32} for bands
258 31 and 32, respectively) were converted from digital number
259 (DN) to radiance in $\text{W m}^{-2} \text{sr}^{-1}$ using the radiance scales and
260 offsets provided with each MODIS granule as listed in Table I

$$R_{\lambda} = \text{Scale}_{\lambda} \times (\text{DN}_{\lambda} - \text{Offset}_{\lambda}) \quad (1)$$

261 The radiance values were then converted to brightness temper-
262 ature in K using the inverse of the Planck function [25]

$$Tb_{\lambda} = \frac{c_2}{\lambda \ln \left(1 + \frac{c_1}{R_{\lambda} \lambda^5} \right)} \quad (2)$$

263 with $c_1 = 1.19107 \times 10^8 \mu\text{m}^5 \text{W m}^{-2} \text{sr}^{-1}$ and $c_2 =$
264 $1.43883 \times 10^4 \mu\text{m K}$, for center wavelength of the given band
265 ($11.0186 \mu\text{m}$ and $12.0325 \mu\text{m}$ for 31 and 32 band, respectively).

266 D. Overlapping HDAS, SMOS, and MODIS Data and 267 Generating an Input Data Set

268 As indicated in Table II, HDAS soil moisture, SMOS soil
269 moisture, and cloud-free MODIS land surface temperature data
270 have overlapped on five days during AACES-1 (on January
271 28 and 30 and February 15, 18, and 20) and on five days
272 during AACES-2 (on September 11, 13, 21, 22, and 24). On
273 each sampling day, two farms were sampled during AACES-1
274 (except on February 18 when three farms were sampled), and
275 one farm was sampled during AACES-2, so that disaggregation
276 results can be evaluated for ten date-farm units during AACES-
277 1 and five date-farm units during AACES-2.

278 DisPATCh is applied to an input ensemble composed of the
279 different combinations of available SMOS (ascending orbit at
280 6 am and/or descending orbit at 6 pm) and MODIS (onboard
281 Terra platform at 10 am and/or Aqua platform at 1 pm) data. To
282 increase the quantity of input data sets, the MODIS data col-
283 lected on the day before and the day after the SMOS overpass
284 date are also included. For SMOS data on day of year (DoY)
285 51, the clear sky MODIS data collected on DoY 54 are used.
286 Note that one implicitly assumes that no rainfall occurs between
287 MODIS and SMOS overpasses, and that the spatial variability
288 captured by MODIS is relatively similar to the actual variabil-
289 ity of surface soil moisture at the time of SMOS overpass.
290 Moreover, the SMOS data oversampling is used to generate
291 four (overlapping) 40-km resolution SMOS grids on which
292 DisPATCh is run independently, thus increasing the number
293 of downscaled data that could be used in the validation. It is
294 reminded that the spacing (about 15 km) between neighboring
295 SMOS DGG nodes is smaller than the SMOS resolution (about

40 km). By combining the four SMOS grids, the two potential 296
SMOS data sets (two orbits in one day) and the six potential 297
MODIS data sets (three days including two overpasses each), 298
the maximum number of input data sets is 48. The generation 299
of input data sets is shown in Fig. 2 and the number of daily 300
input data sets is indicated for each date-farm unit in Table II. 301

III. DISAGGREGATION ALGORITHM

302

DisPATCh converts 1-km resolution MODIS-derived soil 303
temperature fields into 1-km resolution surface soil moisture 304
fields given a semi-empirical soil evaporative efficiency model 305
[26] and a first-order Taylor series expansion around the 306
40-km resolution SMOS observation. DisPATCh is an im- 307
proved version of the algorithms in [16] and [27], and mainly 308
differs with regard to the representation of the vegetation water 309
status. In previous versions [16], [27], the soil temperature was 310
derived from MODIS land surface temperature by assuming 311
that vegetation was unstressed so that vegetation temperature 312
was uniformly set to the minimum surface temperature ob- 313
served within the SMOS pixel. In this study, the approach in 314
[28] is implemented to take into account vegetation water status 315
in the estimation of soil temperature. 316

A. Disaggregation Methodology

317

The disaggregation procedure decouples the soil evaporation 318
from the 0–5 cm soil layer and the vegetation transpiration 319
from the root-zone soil layer by separating MODIS surface 320
temperature into its soil and vegetation components as in the 321
triangle or trapezoidal method [28], [29]. MODIS-derived soil 322
temperature is then used to estimate soil evaporative efficiency, 323
which is known to be relatively constant during the day on clear 324
sky conditions. MODIS-derived soil evaporative efficiency is 325
finally used as a proxy for surface (0–5 cm) soil moisture 326
variability within the SMOS pixel. The link between surface 327
soil moisture and soil evaporative efficiency at different scales 328
is ensured by a downscaling relationship and a soil evapo- 329
rative efficiency model, as described below in more detail. 330
The originality of DisPATCh relies on a dynamical land cover 331
classification (based on the hourglass approach in [28]) that 332
takes into account the subpixel variability of the sensitivity of 333
soil evaporative efficiency to surface soil moisture. 334

1) *Downscaling Relationship*: The downscaling relation- 335
ship can be written as 336

$$\mathbf{SM}_{1 \text{ km}} = \mathbf{SM}_{\text{SMOS}} + \frac{\partial \mathbf{SM}_{\text{mod}}}{\partial \text{SEE}} \times (\text{SEE}_{\text{MODIS}, 1 \text{ km}} - \langle \text{SEE}_{\text{MODIS}, 1 \text{ km}} \rangle_{40 \text{ km}}) \quad (3)$$

with $\mathbf{SM}_{\text{SMOS}}$ being the SMOS soil moisture (for clarity, 337
the variables defined at SMOS scale are written in bold), 338
 $\text{SEE}_{\text{MODIS}}$ the MODIS-derived soil evaporative efficiency (ra- 339
tio of actual to potential evaporation), $\langle \text{SEE}_{\text{MODIS}} \rangle_{40 \text{ km}}$ its 340
average within a SMOS pixel and $\partial \mathbf{SM}_{\text{mod}} / \partial \text{SEE}$ the partial 341
derivative evaluated at SMOS scale of soil moisture with re- 342
spect to soil evaporative efficiency. Note that the linearity of (3) 343
implies that a possible bias in SMOS data would produce the 344

TABLE II
LIST OF OVERLAPPING HDAS, SMOS, AND MODIS (MOD11A1 AND MYD11A1) DATA DURING AACES-1 AND AACES-2. ONLY THE SMOS DATA COLLECTED ON THE SAME DAY AS GROUND SAMPLING HAVE BEEN CONSIDERED. THE MODIS DATA CONSIDERED AS INPUT TO DISPATCH HAVE BEEN COLLECTED WITHIN PLUS OR MINUS ONE DAY EITHER SIDE THE GROUND SAMPLING (AND SMOS OVERPASS) DATE. ON EACH SAMPLING DATE, THE RESULTANT NUMBER OF INPUT DATA SETS TO DISPATCH IS ALSO INDICATED

Experiment	Sampling date	DoY	Farm	SMOS overpass time	Cloud free MODIS data (DoY)	Number of input data sets to DisPATCH
AACES-1	28 January	28	F05	6 am	Terra (27,29) & Aqua (29)	3
	30 January	30	F07	6 am	Terra (29,30) & Aqua (29)	12
	,	,	F08	6 am	Terra (29,30) & Aqua (29)	9-12
	15 February	46	F15	6 am & 6 pm	Terra (46) & Aqua (47)	8-14
	,	,	F16	6 am & 6 pm	Terra (46) & Aqua (47)	8-10
	18 February	49	F17	6 am & 6 pm	Terra (48,50) & Aqua (48,49,50)	30-38
	,	,	F18	6 am & 6 pm	Terra (48,50) & Aqua (48,49,50)	24-30
	,	,	F20	6 am & 6 pm	Terra (48,50) & Aqua (48,49,50)	34-40
	20 February	51	F19	6 am & 6 pm	Terra (54) & Aqua (54)	6-8
,	,	F20	6 am & 6 pm	Terra (54) & Aqua (54)	16	
AACES-2	11 September	254	F09	6 am & 6 pm	Terra (253,254) & Aqua (254)	6-14
	13 September	256	F07	6 am & 6 pm	Terra (256)	8
	21 September	264	F13	6 am & 6 pm	Terra (263) & Aqua (264)	16
	22 September	265	F15	6 am & 6 pm	Terra (265) & Aqua (264,266)	16
	24 September	267	F09	6 am & 6 pm	Terra (267) & Aqua (266,267,268)	24-32

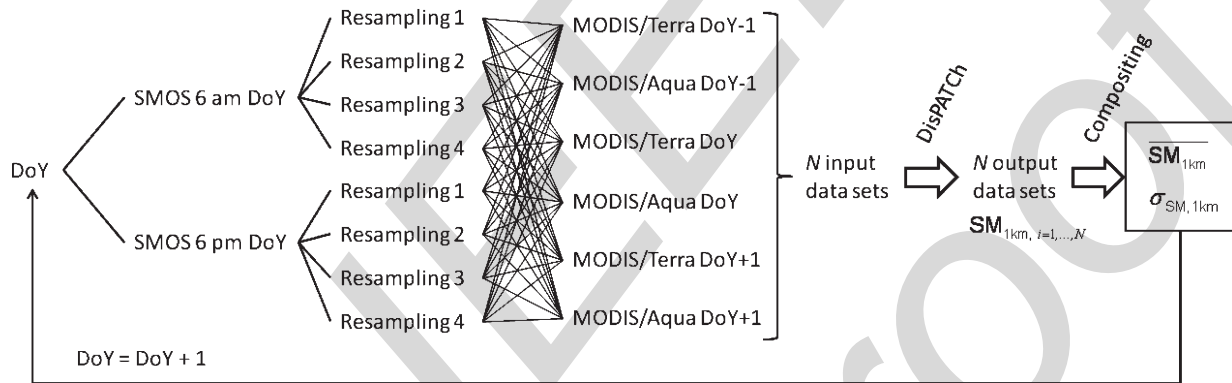


Fig. 2. Schematic diagram presenting the combination of SMOS and MODIS to generate an ensemble of input data to DisPATCH. The output data are composited at 1-km resolution by computing the average ($\overline{SM}_{1\text{ km}}$) and standard deviation ($\sigma_{SM, 1\text{ km}}$) of disaggregated SMOS soil moisture.

345 same bias in disaggregated data [30]. Consequently, although
346 the possible presence of a bias in SMOS data limits the accuracy
347 in the disaggregated soil moisture, it is not a limiting factor to
348 the applicability of DisPATCH. MODIS derived soil evaporative
349 efficiency is expressed as a linear function of soil temperature

$$SEE_{\text{MODIS}, 1\text{ km}} = \frac{T_{s, \max} - T_{s, 1\text{ km}}}{T_{s, \max} - T_{s, \min}} \quad (4)$$

350 with T_s being the MODIS-derived soil skin temperature,
351 $T_{s, \max}$ the soil skin temperature at $SEE = 0$ and $T_{s, \min}$
352 the soil skin temperature at $SEE = 1$. The linearity of the
353 relationship between soil evaporative efficiency and surface
354 soil temperature was verified using the physically based dual
355 source energy budget model in [31] using a synthetic data set
356 composed of a range of surface soil moisture values and differ-
357 ent atmospheric conditions (results not shown). End-members
358 $T_{s, \min}$ and $T_{s, \max}$ are estimated from the polygons obtained

by plotting MODIS surface temperature against MODIS NDVI 359
and MODIS albedo as in [24]. Derivation of soil temperature is 360
based on a linear decomposition of the surface temperature into 361
its soil and vegetation components as a good approximation of 362
the relationship with fourth power for temperatures [32], [33] 363
and consistent with the triangle method. MODIS-derived soil 364
skin temperature is expressed as 365

$$T_{s, 1\text{ km}} = \frac{T_{\text{MODIS}} - f_{v, 1\text{ km}} T_{v, 1\text{ km}}}{1 - f_{v, 1\text{ km}}} \quad (5)$$

with T_{MODIS} being the 1-km resolution MODIS land sur- 366
face temperature, f_v the MODIS-derived fractional vegetation 367
cover, and T_v the vegetation temperature. In this study, vegeta- 368
tion temperature is estimated using the approach proposed by 369
[28]. In (5), fractional vegetation cover is written as 370

$$f_{v, 1\text{ km}} = \frac{\text{NDVI}_{\text{MODIS}} - \text{NDVI}_s}{\text{NDVI}_v - \text{NDVI}_s} \quad (6)$$

371 with $NDVI_{MODIS}$ being the 1-km resolution MODIS NDVI,
 372 $NDVI_s$ the NDVI corresponding to bare soil, and $NDVI_v$ the
 373 NDVI corresponding to full-cover vegetation. Minimum and
 374 maximum NDVI values are set to 0.15 and 0.90, respectively.

375 In [16], the accuracy and robustness of the disaggregation
 376 methodology were tested using three different formulations of
 377 soil evaporative efficiency [26], [34], [35]. Results based on the
 378 NAFE'06 data set [36], which was collected over a 60 km by
 379 40 km area in the AACES area, indicated that the model in
 380 [26] was better adapted for conditions where soil properties are
 381 unknown at high resolution. Consequently, the partial derivative
 382 in (3) is computed using the soil evaporative efficiency model
 383 in [26]

$$SEE_{mod} = \frac{1}{2} - \frac{1}{2} \cos(\pi \cdot SM/SM_p) \quad (7)$$

384 with SM_p being a soil parameter (in soil moisture unit). In
 385 [26], SM_p was set to the soil moisture at field capacity. In
 386 DisPATCH, SM_p is retrieved at 40-km resolution from SMOS
 387 and aggregated MODIS data [16]. By inverting (7), one obtains

$$SM_{mod} = \frac{SM_p}{\pi} \cos^{-1}(1 - 2 SEE) \quad (8)$$

388 2) *Vegetation Temperature*: Vegetation temperature in (5) is
 389 estimated at 1-km resolution with the ‘‘hourglass’’ approach in
 390 [28]. By plotting the diagonals in the quadrilateral in Fig. 3,
 391 four areas are distinguished in the space defined by surface
 392 temperature and fractional vegetation cover. In zone A, land
 393 surface temperature is mainly controlled by soil evaporation
 394 leading to optimal sensitivity to surface soil moisture. In zone
 395 D, land surface temperature is mainly controlled by vegetation
 396 transpiration with no sensitivity to surface soil moisture. In
 397 zones B and C, land surface temperature is controlled by both
 398 soil evaporation and vegetation transpiration with intermediate
 399 (average) sensitivity to surface soil moisture. Based on this un-
 400 derstanding, vegetation temperature is estimated in a different
 401 manner in each zone.

402 For a given data point located in Zone A, vegetation temper-
 403 ature is

$$T_{v,1 km} = (T_{v,min} + T_{v,max})/2 \quad (9)$$

404 with $T_{v,min}$ and $T_{v,max}$ being the vegetation temperature
 405 at minimum and maximum water stress, respectively. End-
 406 members $T_{v,min}$ and $T_{v,max}$ are estimated from the poly-
 407 gons obtained by plotting MODIS surface temperature against
 408 MODIS NDVI and MODIS albedo as in [24].

409 For a given data point located in Zone B, vegetation temper-
 410 ature is

$$T_{v,1 km} = (T_{v,min,1 km} + T_{v,max})/2 \quad (10)$$

411 with $T_{v,min,1 km}$ being the vegetation temperature associated
 412 with $SEE = 0$ ($T_s = T_{s,max}$).

413 For a given data point located in Zone C, vegetation temper-
 414 ature is

$$T_{v,1 km} = (T_{v,min} + T_{v,max,1 km})/2 \quad (11)$$

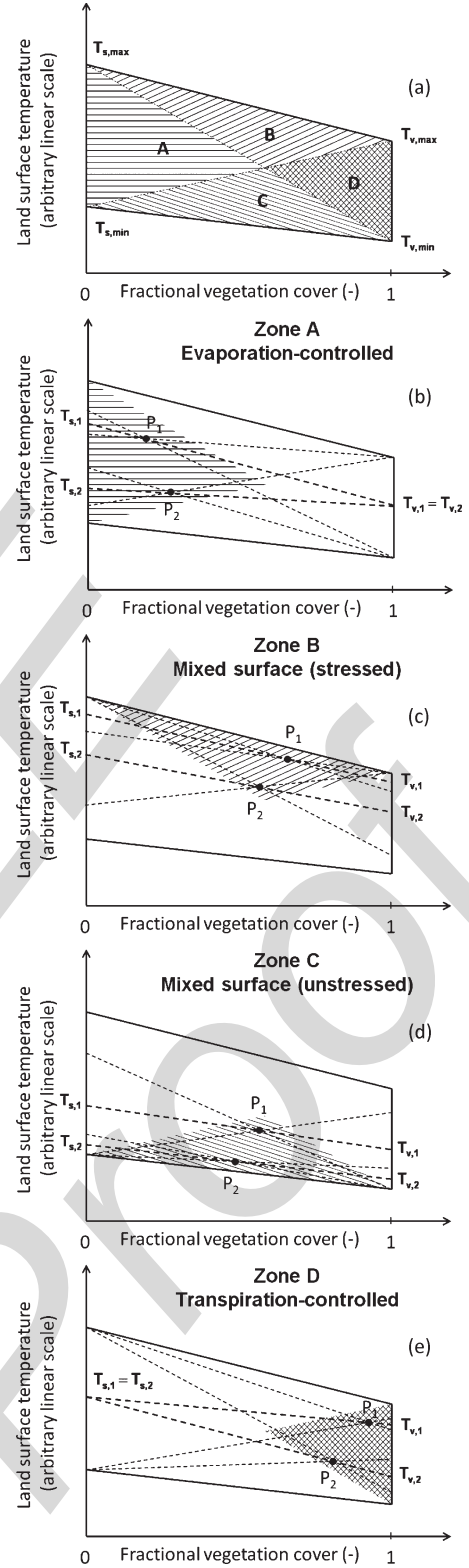


Fig. 3. Polygon defined in the land surface temperature-fractional vegetation cover space contains four distinct zones A, B, C, and D. In Zone A (soil-dominated area), the estimated vegetation temperature is constant leading to optimal sensitivity of estimated soil temperature to surface soil moisture. In Zone D, the estimated soil temperature is constant with no sensitivity to surface soil moisture. In Zone B and C (mixed surface), surface temperature is both controlled by soil evaporation and vegetation transpiration with intermediate (average) sensitivity of estimated soil temperature to surface soil moisture. DisPATCH can be run in the Zone A+B+C mode or in the Zone A only mode.

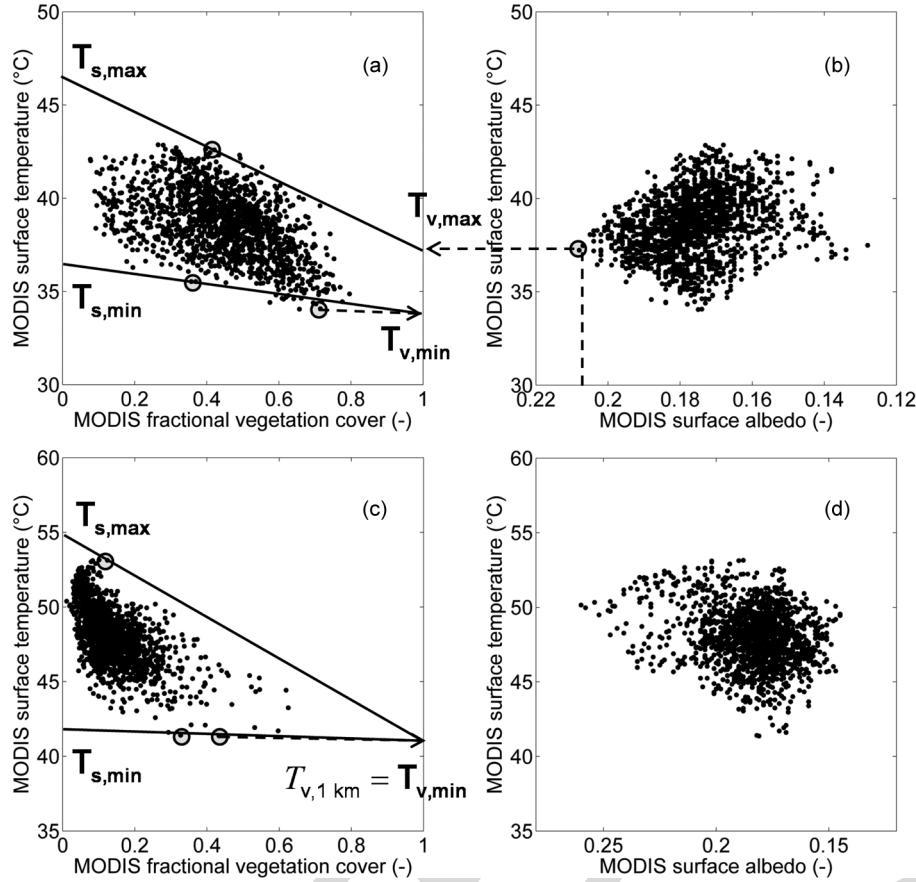


Fig. 4. Temperature end-members $T_{s,\min}$, $T_{s,\max}$, $T_{v,\min}$, and $T_{v,\max}$ are estimated from the surface temperature-fractional vegetation cover space and the surface temperature-surface albedo space within two given SMOS pixels. In (b), the pixel corresponding to the largest MODIS albedo has a fractional vegetation cover larger than 0.5, so that $T_{v,\max}$ is set to its surface temperature. In (d), the pixel corresponding to the largest MODIS albedo has a fractional vegetation cover lower than 0.5, so that $T_{v,\max}$ is set to $T_{v,\min}$.

415 with $T_{v,\max,1\text{ km}}$ being the vegetation temperature associated
 416 with $SEE = 1$ ($T_s = T_{s,\min}$).

417 For a given data point located in Zone D, vegetation temper-
 418 ature is

$$T_{v,1\text{ km}} = (T_{v,\min,1\text{ km}} + T_{s,\max,1\text{ km}})/2 \quad (12)$$

419 3) *End-Members*: End-members $T_{s,\min}$, $T_{s,\max}$, $T_{v,\min}$
 420 and $T_{v,\max}$ are estimated by combining the spatial information
 421 provided by the surface temperature-fractional vegetation cover
 422 space and the surface temperature-albedo space plotted using
 423 MODIS data collected in a 40-km resolution SMOS pixel. An
 424 illustration is provided in Fig. 4 for two given SMOS pixels.

- 425 • $T_{v,\min}$: the vegetation temperature at minimum vegeta-
 426 tion water stress is set to the minimum MODIS surface
 427 temperature in the SMOS pixel [see Fig. 4(a) and (c)].
- 428 • $T_{v,\max}$: the vegetation temperature at maximum vegeta-
 429 tion water stress is set to the MODIS surface tempera-
 430 ture of the pixel with the maximum value of MODIS albedo
 431 in the SMOS pixel [see Fig. 4(b)]. If the fractional vegeta-
 432 tion cover of that pixel is lower than 0.5 [see Fig. 4(d)], the veg-
 433 etation temperature at maximum vegetation water stress
 434 is alternatively set to $T_{v,\min}$, meaning that vegetation is
 435 unstressed within the SMOS pixel. The condition based
 436 on fractional vegetation cover is lower than 0.5 aims to
 437 increase the robustness of the determination approach of

$T_{v,\max}$, particularly in the SMOS pixels where all surface 438
 conditions are not met. 439

- $T_{s,\min}$: the soil temperature at $SEE = 1$ is extrapolated 440
 along the wet soil edge at $f_v = 0$. The wet soil edge 441
 is defined as the line passing through $(1, T_{v,\min})$ and 442
 through the data point such that all the data points with 443
 $f_v < 0.5$ are located above the wet soil edge [see Fig. 4(a) 444
 and (c)]. 445
- $T_{s,\max}$: the soil temperature at $SEE = 0$ is extrapolated 446
 along the dry soil edge at $f_v = 0$. The dry soil edge 447
 is defined as the line passing through $(1, T_{v,\max})$ and 448
 through the data point such that all the data points with 449
 $f_v < 0.5$ are located below the dry soil edge [see Fig. 4(a) 450
 and (c)]. 451

B. Atmospheric Correction 452

In MOD11A1 and MYD11A1 products, the land surface 453
 temperature is derived from MODIS thermal radiances using 454
 the split window algorithm [37] 455

$$T_{\text{MODIS}} = C + \left(A_1 + A_2 \frac{1 - \epsilon}{\epsilon} + A_3 \frac{\Delta \epsilon}{\epsilon^2} \right) \frac{Tb_{31} + Tb_{32}}{2} + \left(B_1 + B_2 \frac{1 - \epsilon}{\epsilon} + B_3 \frac{\Delta \epsilon}{\epsilon^2} \right) \frac{Tb_{31} - Tb_{32}}{2} \quad (13)$$

456 with Tb_{31} and Tb_{32} being the brightness temperatures mea-
 457 sured in the MODIS bands 31 and 32, respectively, ϵ_{31} and ϵ_{32}
 458 the surface emissivities estimated in the respective bands, and
 459 $A_1, A_2, A_3, B_1, B_2, B_3,$ and C regression coefficients. These
 460 coefficients are available during algorithm execution via a look
 461 up table stratified by subranges of near surface air temperature
 462 and total column water vapor. These input field are obtained at
 463 a 5-km resolution from the MODIS07_L2 product.

464 Given that regression coefficients in (13) are provided at
 465 5-km resolution, the atmospheric corrections on the MODIS
 466 land surface temperature product are actually made at 5-km
 467 resolution. To test whether atmospheric corrections on MODIS
 468 temperature have an impact on disaggregation results, a differ-
 469 ent procedure is proposed to obtain another temperature data
 470 set whose atmospheric corrections are operated at the scale
 471 of a SMOS pixel, i.e., at 40-km resolution (instead of 5-km
 472 resolution for the official MODIS temperature product). The
 473 approach is to normalize the mean MODIS radiance-derived
 474 brightness temperature at the SMOS resolution. Normalization
 475 is done by adjusting the minimum and maximum mean MODIS
 476 brightness temperature to the minimum and maximum value
 477 of the official MODIS land surface temperature product within
 478 the SMOS pixel, respectively. The new temperature noted
 479 $T_{MODIS}^{unif. corr.}$ (uniform atmospheric corrections) is written

$$T_{MODIS}^{unif. corr.} = T_{MODIS, min} + (T_{MODIS, max} - T_{MODIS, min}) \times \frac{Tb_{31} + Tb_{32} - \text{Min}(Tb_{31} + Tb_{32})}{\text{Max}(Tb_{31} + Tb_{32}) - \text{Min}(Tb_{31} + Tb_{32})} \quad (14)$$

480 with $T_{MODIS, min}$ and $T_{MODIS, max}$ being the minimum and
 481 maximum MODIS land surface temperature within the SMOS
 482 pixel, and $\text{Min}()$ and $\text{Max}()$ the function that returns the mini-
 483 mum and maximum value within the SMOS pixel, respectively.
 484 Note that the underlying assumptions of (14) are:

- 485 • near surface air temperature and column water vapor vary
 486 at scales larger than 40 km (size of a SMOS pixel).
- 487 • surface emissivity is close to 1.

488 C. Algorithm

489 The steps used in applying DisPATCH include: 1) select-
 490 ing the SMOS pixels with at least 90% (clear sky) MODIS-
 491 retrieved land surface temperature coverage; 2) computing
 492 soil evaporative efficiency over nominal MODIS pixels with
 493 (4); 3) estimating soil evaporative efficiency over non-nominal
 494 MODIS pixels; 4) retrieving parameter SM_p ; 5) applying the
 495 downscaling relationship of (3); 6) correcting disaggregated
 496 soil moisture by the SMOS pixel weighting function; and 7)
 497 compositing on a daily basis the disaggregation output en-
 498 semble [21]. The input and output data and their link within
 499 DisPATCH are summarized in Fig. 5.

500 1) *Selecting Clear Sky SMOS Pixels:* A threshold of 90%
 501 cloud-free MODIS coverage is used to select the SMOS pix-
 502 els to be disaggregated. In the official MODIS land surface
 503 temperature product (MOD11A1 for Terra and MYD11A1 for
 504 Aqua), the data affected by the presence of clouds are already
 505 masked. Hence, selection of the 90% clear sky SMOS pixels is

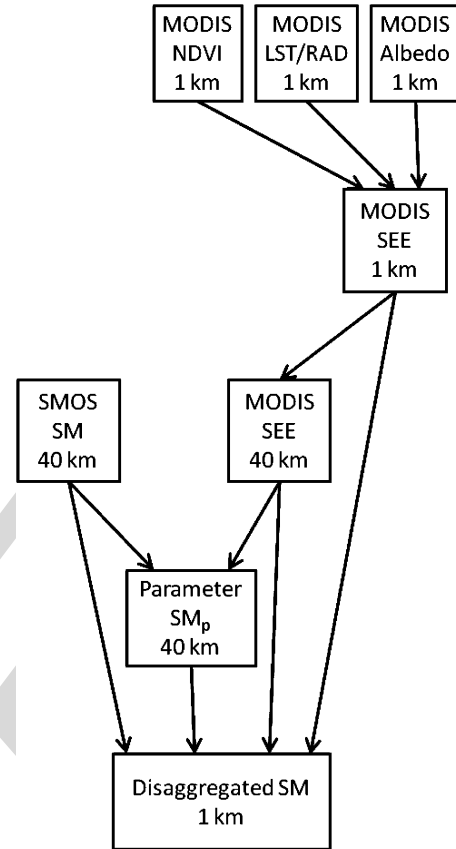


Fig. 5. Schematic diagram presenting the input and output data of DisPATCH.

506 directly based on the MODIS land surface temperature product
 507 masking.

508 2) *Non-Nominal Pixels:* Nominal MODIS pixels are de-
 509 fined as the 1-km resolution pixels that do not include open
 510 water and where land surface temperature is actually retrieved.
 511 Open water pixels are flagged in the algorithm when MODIS
 512 NDVI retrievals yield negative values. The soil evaporative
 513 efficiency of open water pixels is set to 1. The emerged pixels
 514 where land surface temperature is not retrieved (due to the
 515 presence of some clouds within the SMOS pixel) are processed
 516 as pixels with mean surface conditions. In practice, the soil
 517 evaporative efficiency of cloudy pixels (which represent less
 518 than 10% of the surface area within the SMOS pixel) is set to
 519 the mean soil evaporative efficiency calculated over the clear
 520 sky MODIS pixels. Allocating a soil evaporative efficiency
 521 value to non-nominal pixels allows DisPATCH to be run over a
 522 wider range of SMOS pixels, including those partially covered
 523 by clouds. However, non-nominal 1-km resolution pixels are
 524 flagged and discarded from the disaggregation output ensemble.

525 3) *Forested Areas:* In this study, DisPATCH is applied to all
 526 the SMOS pixels where the soil moisture retrieval is successful,
 527 even those including forest class, as long as the 1 km MODIS
 528 pixels are in Zone A, B or C (see Fig. 3). This choice is
 529 relevant here because the ACES extensive data were almost
 530 exclusively collected in agricultural areas (cropping/grazing),
 531 so forests for this study are not an issue. In the case of a
 532 mixed SMOS pixel including a significant fraction of forest,
 533 DisPATCH should be applied to the surface area of the dominant

534 class, thus excluding the surface area of the minority land cover
535 classes.

536 4) *Calibration*: The soil moisture parameter SM_p used to
537 compute $\partial SM_{mod}/\partial SEE$ in (3) is estimated by inverting the
538 SEE model in (7) at SMOS resolution

$$SM_p = \frac{\pi \cdot SM_{SMOS}}{\cos^{-1}(1 - 2\langle SEE_{MODIS, 1 \text{ km}} \rangle_{40 \text{ km}})} \quad (15)$$

539 A value of SM_p is obtained for each SMOS pixel and each
540 input data set. Note that the main assumption limiting validity
541 of the calibration approach is the soil evaporative efficiency
542 model [26] itself. The soil evaporative efficiency model in [26]
543 was chosen for its simplicity (one parameter) and its ability
544 to represent the general behavior of soil evaporative efficiency
545 over the full range of soil moisture: particularly the null deriva-
546 tive at zero and at maximum soil moisture, and an inflexion
547 point in between [38]. However, it has some inconsistencies.
548 In particular, [38] have indicated that 1) potential evaporation
549 is physically reached at soil saturation and not at field capac-
550 ity; therefore the model in [26] should be (strictly speaking)
551 parameterized by the soil moisture at saturation and not by the
552 soil moisture at field capacity, and 2) soil evaporative efficiency
553 varies with potential evaporation, meaning that the soil moisture
554 parameter (set to the soil moisture at field capacity in [26])
555 should theoretically vary in time with atmospheric evaporative
556 demand. Consequently, the SM_p retrieved from SMOS and
557 MODIS data using the model in [26] is definitely not the soil
558 moisture at field capacity as in [26], although it could be in part
559 related to it. In this study, SM_p is therefore considered to be a
560 fitting parameter self-estimated by DisPATCH.

561 5) *Weighting Function*: A SMOS pixel WEighting Function
562 (WEF) is used to take into account the impact of soil mois-
563 ture distribution on the SMOS scale soil moisture as seen by
564 SMOS radiometer. A centrosymmetric analytical approxima-
565 tion MEAN_WEF is provided in [19], [20]

$$MEAN_WEF(\rho) = C_{MWEF2} + WEF_A \left(\frac{\rho}{C_{MWEF1}} \cdot \frac{\pi}{C_{WEF1}} \right) \quad (16)$$

566 with ρ being the distance from the SMOS pixel center, and
567 $C_{MWEF1} = 40 \text{ km}$, $C_{MWEF2} = 0.027$, $C_{WEF1} = 73.30$ and

$$WEF_A(\rho') = \frac{[\text{sinc}(C_{WEF1} \cdot \rho')]^{C_{WEF2}}}{1 + C_{WEF3} \cdot \rho'^{C_{WEF4}}} \quad (17)$$

568 with ρ' being the distance in the director cosines coordinates,
569 $\text{sinc}(x) = \sin(x)/x$, and $C_{WEF2} = 1.4936$, $C_{WEF3} = 524.5$
570 and $C_{WEF4} = 2.103$.

571 A correction is applied to disaggregated soil moisture in (3)

$$SM_{1 \text{ km}}^{wef \text{ corr.}} = SM_{1 \text{ km}} + \frac{\sum MEAN_WEF(\rho) \cdot SM_{1 \text{ km}}(\rho)}{\sum MEAN_WEF(\rho)} - SM_{SMOS} \quad (18)$$

572 with $SM_{1 \text{ km}}^{wef \text{ corr.}}$ being the WEF-corrected disaggregated
573 soil moisture. Mathematically speaking, one should replace
574 SM_{SMOS} with $\sum MEAN_WEF \cdot SM_{1 \text{ km}} / \sum MEAN_WEF$
575 in (3) and (15) and run an iteration loop until convergence

of $SM_{1 \text{ km}}^{wef \text{ corr.}}$ values. However, the impact of the WEF on
disaggregated soil moisture is expected to be low so that the
simple correction in (18) is considered to be sufficient for the
purpose of the study.

6) *Disaggregation Output*: The downscaling relationship in
(3) is applied to each input data set, and the disaggregated soil
moisture data ensemble is averaged on each 1-km resolution
pixel within the study area. Averaging is a way to reduce
random uncertainties in the disaggregation output. In [17], [27],
disaggregated soil moisture was averaged in space (aggregated)
at the expense of downscaling resolution. Herein, temporal
averaging [30] is preferred to keep an optimal downscaling
resolution. Note that a condition to average disaggregated soil
moisture in time is the availability of thermal infrared data
at high temporal frequency. Another significant advantage of
applying DisPATCH to an input ensemble is to provide an
estimate of the uncertainty in 1-km resolution disaggregated
soil moisture, e.g., by computing the standard deviation within
the output ensemble.

IV. APPLICATION

To test DisPATCH under various surface and atmospheric
conditions, the algorithm is run during AACES-1 and AACES-
2 in different modes, by including (or not) a correction for
vegetation and atmospheric effects. In each case, disaggregated
SMOS soil moisture and HDAS measurements are compared
at 1-km resolution for all date-farm units with overlapping
HDAS/SMOS/MODIS data.

A. Null Hypothesis

In this study, the null hypothesis is defined as the application
of DisPATCH with parameter SM_p set to zero in (8). Hence,
the downscaling relationship in (3) becomes

$$SM_{1 \text{ km}} = SM_{SMOS} \quad (19)$$

meaning that no 1-km information is used. Defining a null
hypothesis is useful to test whether DisPATCH is able to re-
produce the subpixel variability within the $\sim 10 \text{ km}^2$ sam-
pling farms with better skill than simply assuming a uniform
moisture condition. Statistical results in terms of root mean
square difference, mean difference, correlation coefficient, and
slope of the linear regression between the SMOS soil moisture
disaggregated with (19) and *in situ* measurements are listed in
Table III. One observes that the root mean square difference
is generally explained by a (negative) bias in SMOS data and
that none of the correlations evaluated at 1-km resolution for
each farm separately is statistically significant (all calculated p-
values are larger than 0.10). Thus, the rationale for developing
DisPATCH is to improve the correlation at fine scale between
SMOS and ground soil moisture and to reduce the bias in
disaggregated SMOS data in the specific case where the bias
in SMOS data at the farm scale is due to the heterogeneity of
soil moisture within the SMOS pixel.

TABLE III
DISPATCH IS RUN WITH NO 1-km INFORMATION (SM_p SET TO ZERO) AND STATISTICAL RESULTS ARE LISTED IN TERMS OF ROOT MEAN SQUARE DIFFERENCE (RMSD), MEAN DIFFERENCE (BIAS), CORRELATION COEFFICIENT (R), AND SLOPE OF THE LINEAR REGRESSION BETWEEN 1-km RESOLUTION DISAGGREGATED SMOS SOIL MOISTURE AND 1-km AGGREGATED *In Situ* MEASUREMENTS. THE MEAN AND STANDARD DEVIATION OF GROUND MEASUREMENTS ($\langle SM_{HDAS} \rangle$ AND σ_{HDAS}), THE NUMBER OF CONSIDERED 1-km PIXELS, AND STATISTICAL SIGNIFICANCE (P-VALUE) ARE ALSO LISTED FOR EACH DATE-FARM UNIT

DoY/Farm	$\langle SM_{HDAS} \rangle$ (m^3/m^3)	σ_{HDAS} (m^3/m^3)	Number of 1 km pixels	RMSD (m^3/m^3)	Bias (m^3/m^3)	R^\dagger (-)	Slope ‡ (-)	p-value (-)
28/F05	0.04	0.02	7	0.04	-0.04	-	-	1.0
30/F07	0.02	0.03	8	0.02	-0.02	-	-	1.0
30/F08	0.03	0.02	7	0.02	-0.02	-	-	0.69
46/F15	0.29	0.05	8	0.04	0.03	-	-	0.91
46/F16	0.34	0.06	8	0.09	-0.08	-	-	1.0
49/F17	0.21	0.06	8	0.04	-0.04	-	-	0.66
49/F18	0.25	0.07	6	0.08	-0.08	-	-	0.42
49/F20	0.20	0.09	4	0.02	-0.007	-	-	0.87
51/F19	0.24	0.08	6	0.13	-0.13	-	-	0.77
51/F20	0.20	0.10	6	0.09	-0.08	-	-	0.79
AACES-1 mean ‡	-	-	-	-	-	-	-	>0.10
254/F09	0.33	0.07	9	0.13	-0.13	-	-	0.13
256/F07	0.36	0.10	8	0.19	-0.18	-	-	0.15
264/F13	0.30	0.07	8	0.18	-0.17	-	-	1.0
265/F15	0.25	0.06	7	0.05	-0.05	-	-	1.0
267/F09	0.21	0.07	9	0.14	-0.14	-	-	0.43
AACES-2 mean ‡	-	-	-	-	-	-	-	>0.10

† R and slope values are reported if p-value < 0.10.

‡ the mean values computed for AACES-1 and AACES-2 include only statistically significant (p-value < 0.10) results.

625 B. Visual Assessment of Disaggregation Images

626 As an example, DisPATCH is applied on DoY 49 over a 120
627 km by 80 km subarea including the farms F16, F17, F18, F19,
628 and F20. The images of 1-km resolution disaggregated SMOS
629 soil moisture are presented in Fig. 6. DisPATCH is run with
630 SM_p set to zero (null hypothesis) and in four distinct modes
631 corresponding to the combinations of the “LST” (the official
632 MODIS land surface temperature product is used) and “RAD”
633 [the land surface temperature is derived from MODIS radiances
634 using (14)] modes and the “Zone A+B+C” (the vegetation-
635 transpiration dominated 1-km pixels are discarded) and “Zone
636 A only” (only the soil evaporation-dominated 1-km pixels are
637 selected) modes.

638 In Fig. 6, the SMOS DGG nodes where level-2 soil moisture
639 is successfully retrieved are overlaid on the image correspond-
640 ing to the null hypothesis (resampled SMOS data with no 1-km
641 information) for 6 am and 6 pm overpass times separately. The
642 gaps in SMOS data in the lower middle part of the images
643 are due to topography flagging over the Australian Alps. In
644 the version-4 SMOS level-2 processor, soil moisture is not
645 retrieved at the DGG nodes where the topography effects on
646 simulated brightness temperatures exceed a certain threshold,
647 so as to prevent large errors in soil moisture values. The appar-
648 ent resolution of the null hypothesis image is 20 km because
649 it is generated from the composition of four 40-km resolution
650 resampled SMOS snapshot images, whose resampling grids are

651 separated by 20 km (the SMOS level-2 data resampling strategy
652 was described in Section II-B.).

Note that the disaggregation products in the Zone A+B+C
653 mode cover an area larger than the area sampled by SMOS
654 data, because the SMOS resolution (about 40 km) is larger
655 than the SMOS product sampling length (about 15 km), but
656 does not provide disaggregated values at a distance larger than
657 20 km from the successful retrieval nodes. Concerning the Zone
658 A only mode, disaggregation products do not cover an area
659 larger than the SMOS sampling area because the Australian
660 Alps are surrounded by forests where the fraction of bare soil is
661 less than elsewhere in the area, and which correspond to Zone
662 B or C in the hourglass in Fig. 3.

663 When looking at the images obtained in the Zone A+B+C
664 mode in Fig. 6, one observes that the spatial structures of
665 1-km disaggregated SMOS soil moisture encompass, but does
666 not seem to be correlated with, the SMOS data sampling
667 length. However, a “boxy artifact” is still apparent at 20-km
668 resolution, which is the separation length of the SMOS data
669 resampling grids as explained in Section II-B. The notion of
670 “boxy artifact” was introduced by [39] to analyze the quality of
671 a disaggregation approach. The less apparent the low-resolution
672 boxes, the better the disaggregation skill of the algorithm to
673 spatially connect high-resolution disaggregated values between
674 neighboring low-resolution pixels, and thus to derive a realistic
675 high-resolution soil moisture field. When comparing the images
676 obtained in the Zone A+B+C mode with those obtained in the
677

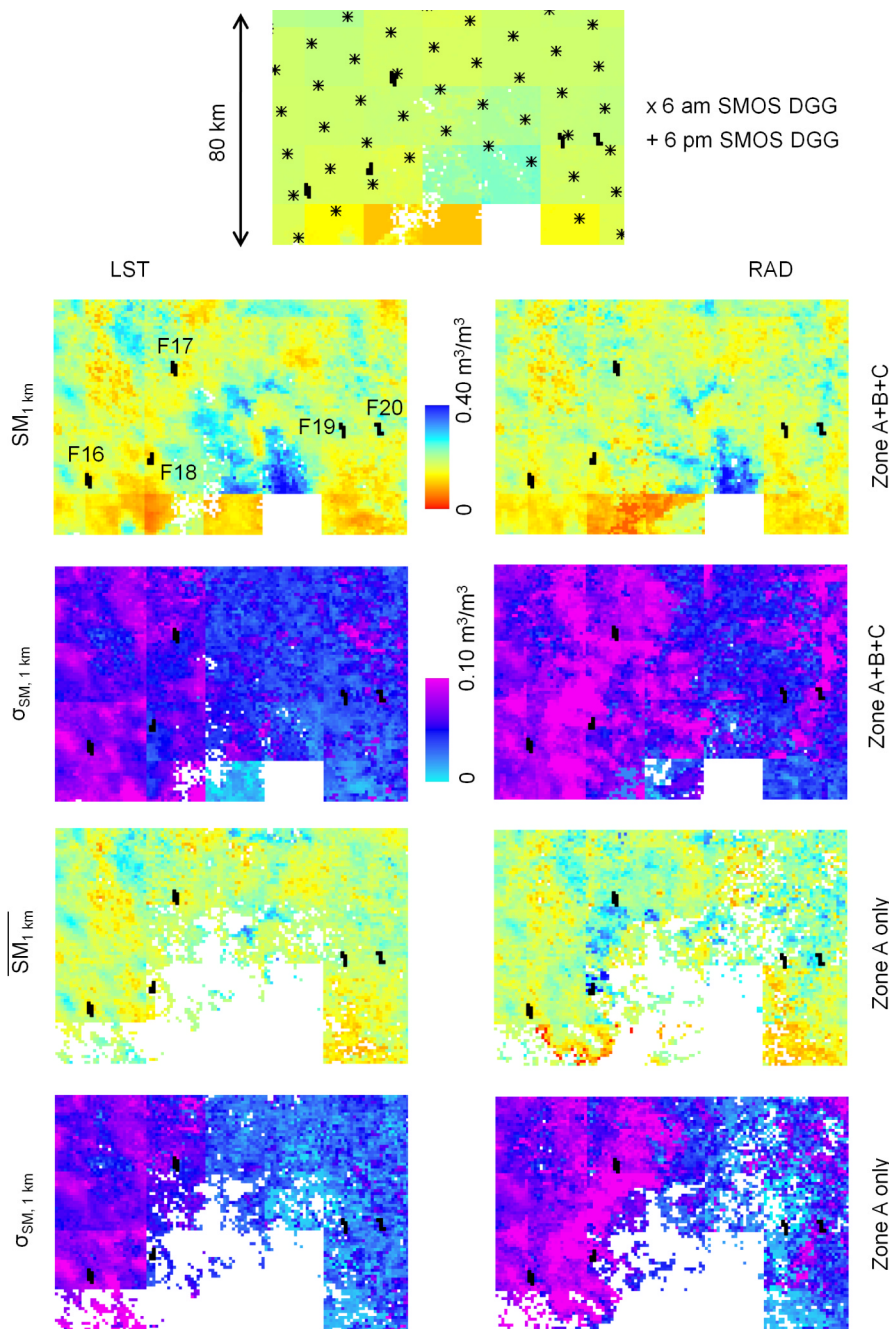


Fig. 6. Images of disaggregation results over a 120 km by 80 km subarea on DoY 49. The disaggregated soil moisture ($\overline{SM}_{1 \text{ km}}$) and its estimated uncertainty ($\sigma_{SM,1 \text{ km}}$) are compared in the LST and RAD modes and in the Zone A+B+C and Zone A only modes. Sampling farms are overlaid on all images. SMOS DGG nodes are overlaid on the image corresponding to the null hypothesis (no 1-km resolution information) presented at top.

678 Zone A only mode, one observes that the 20-km resolution boxy
 679 artifact is less apparent in the Zone A only mode, consistent
 680 with the better sensitivity of MODIS-derived SEE with soil-
 681 dominated pixels (Zone A) than with mixed-surface (Zone B
 682 and C) pixels. In Fig. 6, the images obtained in the LST and
 683 RAD mode highlight different spatial structures. In general,
 684 there are less data gaps in the RAD than in the LST mode.
 685 However, ground validation data are required to assess their
 686 relative quality/accuracy.

687 As an assessment of the uncertainty in composited soil mois-
 688 ture disaggregation, the standard deviation within the disaggre-
 689 gation output ensemble is also reported for each disaggregation

product in Fig. 6. The same observations can be made as with 690
 the soil moisture images: spatial structures are more visible, and 691
 the boxy artifact is less apparent in the RAD than in the LST 692
 mode. In general, the estimated uncertainty in disaggregated 693
 products is larger in the RAD than in the LST mode, regardless 694
 of the Zone (A+B+C or A only) mode. 695

C. SMOS Weighting Function

696

To evaluate the impact of the SMOS instrument weighting 697
 function on disaggregation results, DisPATCH is run with (and 698
 without) the WEF correction in (18). The expected effect of the 699

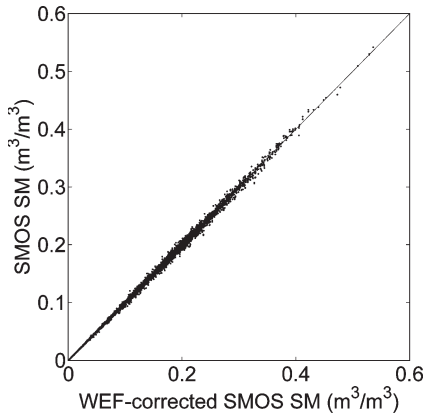


Fig. 7. Uncorrected versus WEF-corrected SMOS soil moisture for the entire data set.

700 WEF is a bias at 40 km resolution on disaggregated soil mois-
 701 ture. Fig. 7 plots the uncorrected against WEF-corrected SMOS
 702 soil moisture for the entire data set including both AACES-1
 703 and AACES-2 experiments. The WEF correction has very
 704 little impact on disaggregated soil moisture with a maximum
 705 difference between uncorrected and WEF-corrected SMOS soil
 706 moisture of $0.02 \text{ m}^3/\text{m}^3$, a mean difference of approximately
 707 zero, and a standard deviation of $0.003 \text{ m}^3/\text{m}^3$. Although the
 708 difference is small with this data set, WEF-corrected products
 709 are expected to be more realistic. Therefore, the correction in
 710 (18) is used in all the DisPATCH runs that follow.

711 D. Quantitative Comparison With In Situ Measurements

712 Fig. 8 presents the scatterplots of 1-km resolution disaggre-
 713 gated SMOS soil moisture versus 1-km resolution aggregated
 714 *in situ* measurements for the ten date-farm units during
 715 AACES-1. On each graph are plotted the soil moisture dis-
 716 aggregated in the Zone A+B+C mode (empty squares) and
 717 the soil moisture disaggregated in the Zone A only mode
 718 (black squares). At the beginning of AACES-1, conditions are
 719 very dry so that SMOS retrievals are close to zero and the
 720 variability of *in situ* measurements is low (about $0.02 \text{ m}^3/\text{m}^3$).
 721 In such conditions, no useful information is expected from the
 722 application of DisPATCH, and the statistical results in terms of
 723 spatial correlation are not meaningful for DoY 28/F05, DoY
 724 30/F07 and DoY 30/F08. While wetter conditions occur after
 725 DoY 30, cloud cover prevents DisPATCH to be run (MODIS
 726 data are unavailable) until DoY 46. On DoY 46, the average
 727 and standard deviation of *in situ* soil moisture measurements is
 728 $0.32 \text{ m}^3/\text{m}^3$ and $0.06 \text{ m}^3/\text{m}^3$, respectively. The spatial variabil-
 729 ity of 1-km soil moisture is nicely captured by DisPATCH no-
 730 tably in the RAD mode. On DoY 49, the disaggregated SMOS
 731 soil moisture is still correlated with the *in situ* measurements
 732 made in three farms (F17, F18, and F20). On the last ground
 733 sampling day, disaggregation results are significantly correlated
 734 with *in situ* measurements in F19, but not in F20. The poor
 735 results obtained with DoY 51/F20 is probably due to the time
 736 gap (3 days) between ground sampling date (DoY 51) and
 737 MODIS overpass day (DoY 54).

738 Statistical results in terms of root mean square difference,
 739 mean difference, correlation coefficient, and slope of the linear

regression between the SMOS soil moisture disaggregated in 740
 the Zone A+B+C mode and aggregated *in situ* measurements 741
 are listed in Table IV. Statistical significance (p-value) is also 742
 reported for each date-farm unit to select statistically significant 743
 (p-value < 0.10) results. Although the disaggregation of SMOS 744
 data on extensively dry DoY 30 does not provide any additional 745
 information (soil is uniformly dry), the observed correlation 746
 between disaggregated (LST mode) and *in situ* soil moisture 747
 is statistically significant, and the correlation coefficient value 748
 is negative (-0.70 and -0.95 at F07 and F08, respectively). 749
 One plausible explanation is the opposite effect of soil temper- 750
 ature on HDAS soil moisture measurements and on MODIS- 751
 derived soil evaporative efficiency: a slight undercorrection of 752
 the temperature-corrected hydraprobe measurements at high 753
 temperature [18] results in a slight increase of soil moisture 754
 estimate with soil temperature, while an increase of soil temper- 755
 ature makes soil evaporative efficiency decrease. Nevertheless, 756
 the possible impact of soil temperature on HDAS measurements 757
 is very low with a slope of the linear regression between 758
 disaggregated SMOS and *in situ* soil moisture calculated as 759
 -0.08 and -0.03 for F07 and F08, respectively. When selecting 760
 statistically significant results (p-value < 0.10) and discarding 761
 data for DoY 30, the mean correlation coefficient and slope in 762
 RAD mode are 0.75 and 0.58 , respectively. 763

Fig. 9 presents the scatterplots of 1-km resolution disaggre- 764
 gated SMOS soil moisture versus 1-km resolution aggregated *in* 765
situ measurements for the five date-farm units during AACES- 766
 2. On each graph are plotted the soil moisture disaggregated in 767
 the Zone A+B+C mode (empty squares) and the soil moisture 768
 disaggregated in the Zone A only mode (black squares). The 769
 surface conditions of AACES-2 were relatively wet with a mean 770
 soil moisture value estimated as $0.29 \text{ m}^3/\text{m}^3$. The disaggre- 771
 gated SMOS soil moisture does not correlate well with *in situ* 772
 measurements with a p-value larger than 0.10 for all sampling 773
 days, except for DoY 256/F07 in LST mode (see Table IV). The 774
 negative correlation coefficient (-0.73) obtained on DoY 256 is 775
 discussed when comparing the Zone A+B+C and Zone A only 776
 modes in Section IV-F. In general, statistical results in Table IV 777
 indicate that DisPATCH does not succeed in representing the 778
 variability of soil moisture at 1-km resolution during AACES- 779
 2. In fact, DisPATCH is based on the tight coupling that occurs 780
 between soil moisture and evaporation under high evaporative 781
 demand conditions [40]. This coupling seems to be weak in 782
 September over the study area so that the disaggregation results 783
 at 1-km resolution are not reliable. 784

For DoY 264/F13, however, an interesting feature is ob- 785
 served on the graph corresponding to the RAD and Zone A 786
 only modes. When removing the (three) black squares with 787
 the largest errorbars, the correlation coefficient and the slope 788
 of the linear regression between disaggregated and *in situ* 789
 observations becomes 0.9 and 0.7 , respectively. This suggests 790
 that: 1) the standard deviation within the disaggregation output 791
 ensemble can be a good estimate of the uncertainty in the 792
 composited disaggregation product; and 2) the applicability of 793
 DisPATCH is greatly dependent on the quality of MODIS land 794
 surface temperature. Note that in this study, a choice was made 795
 to maximize the number of data points used in the comparison 796
 with *in situ* measurements. Consequently, all the cloud-free 797

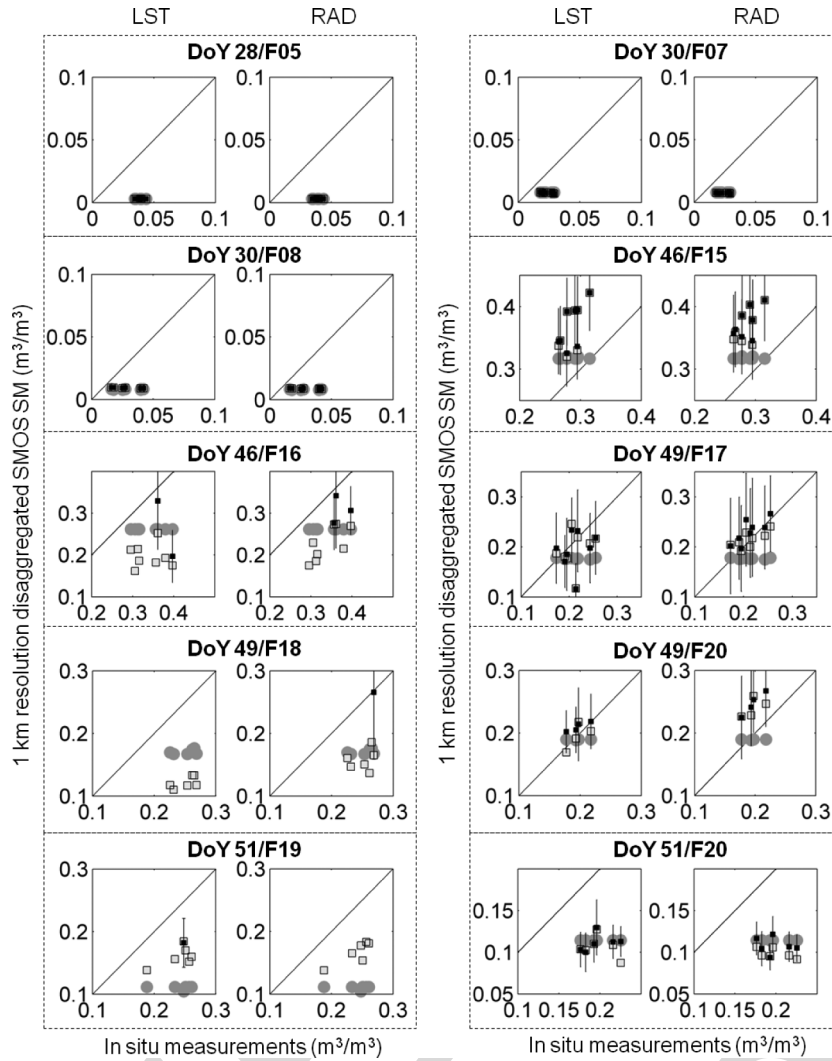


Fig. 8. Scatterplots of 1-km resolution disaggregated SMOS soil moisture versus 1-km resolution aggregated *in situ* measurements for each of the ten date-farm data sets during AACES-1. The filled circles correspond to disaggregation with no 1-km information, empty squares to Zone A+B+C mode and black squares to Zone A only mode. For the Zone A only mode, the uncertainty in disaggregated soil moisture is represented by vertical errorbars.

798 MODIS land surface temperature data were used regardless
 799 of the MODIS land surface temperature quality index. Further
 800 research should be conducted to assess whether selecting the
 801 MODIS pixel with the best MODIS land surface temperature
 802 quality index would improve the disaggregation results. This
 803 would be possible using the AACES airborne data, which cover
 804 a much larger area than *in situ* measurements.

805 *E. Atmospheric Corrections*

806 The impact of atmospheric corrections on DisPATCH output
 807 is analyzed by comparing the disaggregation results obtained
 808 in the LST and RAD mode. Quantitative comparison between
 809 LST and RAD modes is provided in Table IV in terms of root
 810 mean square difference, mean difference, correlation coeffi-
 811 cient, and slope of the linear regression between disaggregated
 812 SMOS soil moisture and aggregated *in situ* measurements.
 813 Correlation coefficient and slope values are reported only if
 814 the p-value (statistical significance) is lower than 0.10. It is
 815 apparent that statistical results are better in the RAD than in

the LST mode. When including all dates, the mean bias is 816
 decreased from $-0.05 \text{ m}^3/\text{m}^3$ in LST mode to $-0.03 \text{ m}^3/\text{m}^3$ 817
 in RAD mode during AACES-1. When selecting statistically 818
 significant results (p-value < 0.10) and discarding data for 819
 DoY 30, the mean correlation coefficient and slope is 0.75 and 820
 0.58 in RAD mode, and 0.65 and 1.5 in LST mode, respectively. 821
 Note that the improvement is very significant for DoY 46/F16 822
 with a correlation coefficient and slope increasing from about 823
 zero to 0.7 and 0.8, respectively. 824

The fact that the results obtained in RAD mode are superior 825
 to those obtained in LST mode indicates that the atmospheric 826
 corrections of the official MODIS land surface temperature 827
 add significant uncertainties in the disaggregation products. 828
 One rationale may be that the information used in atmospheric 829
 corrections (notably air temperature and water vapor profile 830
 data) are subjected to large uncertainties at 5-km resolution. 831
 As DisPATCH is based on the spatial variations of MODIS 832
 temperature relative to the 40 km scale mean, the atmospheric 833
 corrections on the land surface temperature data are not nec- 834
 essary at 5 km (as it is done in the MODIS temperature 835

TABLE IV
DISPATCH IS RUN IN THE ZONE A+B+C MODE AND STATISTICAL RESULTS ARE LISTED IN TERMS OF ROOT MEAN SQUARE DIFFERENCE (RMSD), MEAN DIFFERENCE (BIAS), CORRELATION COEFFICIENT (R), AND SLOPE OF THE LINEAR REGRESSION BETWEEN 1-KM RESOLUTION DISAGGREGATED SMOS SOIL MOISTURE AND 1-KM AGGREGATED *In Situ* MEASUREMENTS. THE RESULTS OBTAINED USING THE RADIANCE-DERIVED LAND SURFACE TEMPERATURE DATA (RAD MODE) AND USING THE OFFICIAL MODIS LAND SURFACE TEMPERATURE DATA (LST MODE IN PARENTHESIS) ARE COMPARED. THE MEAN AND STANDARD DEVIATION OF GROUND MEASUREMENTS ($\langle SM_{HDAS} \rangle$ AND σ_{HDAS}), THE NUMBER OF CONSIDERED 1-KM PIXELS AND STATISTICAL SIGNIFICANCE (P-VALUE) ARE ALSO LISTED FOR EACH DATE-FARM UNIT

DoY/Farm	$\langle SM_{HDAS} \rangle$ (m^3/m^3)	σ_{HDAS} (m^3/m^3)	Number of 1 km pixels	RMSD (m^3/m^3)	Bias (m^3/m^3)	R^\dagger (-)	Slope ‡ (-)	p-value (-)
28/F05	0.04	0.02	7 (7)	0.04 (0.04)	-0.04 (-0.04)	- (-)	- (-)	0.72 (0.80)
30/F07	0.02	0.03	8 (8)	0.02 (0.02)	-0.02 (-0.02)	- (-0.70)	- (-0.08)	0.20 (0.05)
30/F08	0.03	0.02	7 (7)	0.02 (0.02)	-0.02 (-0.02)	- (-0.95)	- (-0.03)	0.11 (0.001)
46/F15	0.29	0.05	8 (8)	0.09 (0.09)	0.09 (0.08)	- (0.65)	- (1.5)	0.12 (0.08)
46/F16	0.34	0.06	8 (8)	0.12 (0.15)	-0.11 (-0.14)	0.72 (-)	0.76 (-)	0.04 (0.95)
49/F17	0.21	0.06	8 (8)	0.02 (0.04)	0.00 (-0.02)	0.70 (-)	0.42 (-)	0.05 (0.54)
49/F18	0.25	0.07	6 (6)	0.10 (0.13)	-0.09 (-0.13)	- (-)	- (-)	0.60 (0.20)
49/F20	0.20	0.09	4 (4)	0.05 (0.01)	0.04 (0.00)	- (-)	- (-)	0.41 (0.32)
51/F19	0.24	0.08	6 (6)	0.07 (0.08)	-0.07 (-0.08)	0.84 (-)	0.56 (-)	0.04 (0.19)
51/F20	0.20	0.10	6 (6)	0.10 (0.09)	-0.10 (-0.09)	- (-)	- (-)	0.17 (0.51)
AACES-1 mean ‡	0.26 (0.29)	0.07 (0.05)	7 (8)	0.07 (0.09)	-0.06 (-0.08)	0.75 (0.65)	0.58 (1.5)	0.04 (0.08)
254/F09	0.33	0.07	9 (9)	0.18 (0.14)	-0.16 (-0.11)	- (-)	- (-)	0.17 (0.74)
256/F07	0.36	0.10	8 (9)	0.12 (0.19)	-0.10 (-0.18)	- (-0.73)	- (-0.47)	0.12 (0.04)
264/F13	0.30	0.07	8 (8)	0.16 (0.19)	-0.14 (-0.16)	- (-)	- (-)	0.59 (0.47)
265/F15	0.25	0.06	7 (7)	0.16 (0.18)	0.01 (0.03)	- (-)	- (-)	0.32 (0.34)
267/F09	0.21	0.07	9 (9)	0.16 (0.15)	-0.15 (-0.15)	- (-)	- (-)	0.90 (0.86)
AACES-2 mean ‡	0.36	0.10	- (9)	- (0.19)	- (-0.18)	- (-0.73)	- (-0.47)	>0.10 (0.04)

† R and slope values are reported if p-value < 0.10.

‡ the mean values computed for AACES-1 and AACES-2 include only statistically significant (p-value < 0.10) results and discard extensive dry days DoY 28-30.

836 algorithm). An atmospheric correction at 40-km resolution is
837 sufficient and provides even better disaggregation results that
838 applying an atmospheric correction at 5-km resolution.

839 F. Vegetation Cover

840 The impact of vegetation cover on DisPATCH output during
841 AACES-1 is analyzed by comparing the disaggregation results
842 obtained in the Zone A+B+C and Zone A only mode. Quan-
843 titative comparison between Zone A+B+C and Zone A only
844 modes is provided in Tables IV and V in terms of root mean
845 square difference, mean difference, correlation coefficient, and
846 slope of the linear regression between disaggregated SMOS soil
847 moisture and aggregated *in situ* measurements. It is apparent
848 that statistical results are generally better in the Zone A only
849 than in the Zone A+B+C mode for both LST and RAD modes.
850 In the RAD mode for instance, the mean correlation coefficient
851 is increased from 0.75 in the Zone A+B+C mode (Table IV) to
852 0.89 in the Zone A only mode (Table V). Also the mean slope
853 is closer to 1 as it switches from 0.58 in the Zone A+B+C mode
854 (Table IV) to 0.91 in the Zone A only mode (Table V). Con-
855 sequently, results are consistent with the hourglass approach in
856 Fig. 3 that predicts a lower sensitivity of MODIS-derived soil
857 temperature to soil moisture in Zone B and C, Zone A having

the highest potential for estimating soil moisture variability 858
from MODIS temperature. 859

On DoY 256, the negative correlation appearing in Zone 860
A+B+C mode (Table IV) is not significant in Zone A only mode 861
(Table V), suggesting that the contradictory result obtained on 862
DoY 256 is probably an artifact due to the small sample size. 863

Note that one drawback of the Zone A only mode is the larger 864
amount of data gaps in the soil moisture images. Therefore, 865
the use of both modes is a compromise between application 866
coverage and accuracy in the disaggregation output. 867

G. Distinguishing Between SMOS and DisPATCH Errors 868

By solving the extent mismatch between 40-km resolution 869
remote sensing observation and localized *in situ* measurements, 870
DisPATCH could be used as a tool to help improve the validation 871
strategies of SMOS data in low-vegetated semi-arid regions. It 872
also would reduce the coverage requirements identified by [41] 873
for airborne validation campaigns. However, such a validation 874
approach requires separating the different error sources that 875
may be attributed to SMOS soil moisture and to DisPATCH. 876
One solution is to estimate the errors attributed to DisPATCH 877
and then deduce the errors attributed to SMOS soil moisture. To 878
estimate the errors that are associated with the disaggregation 879

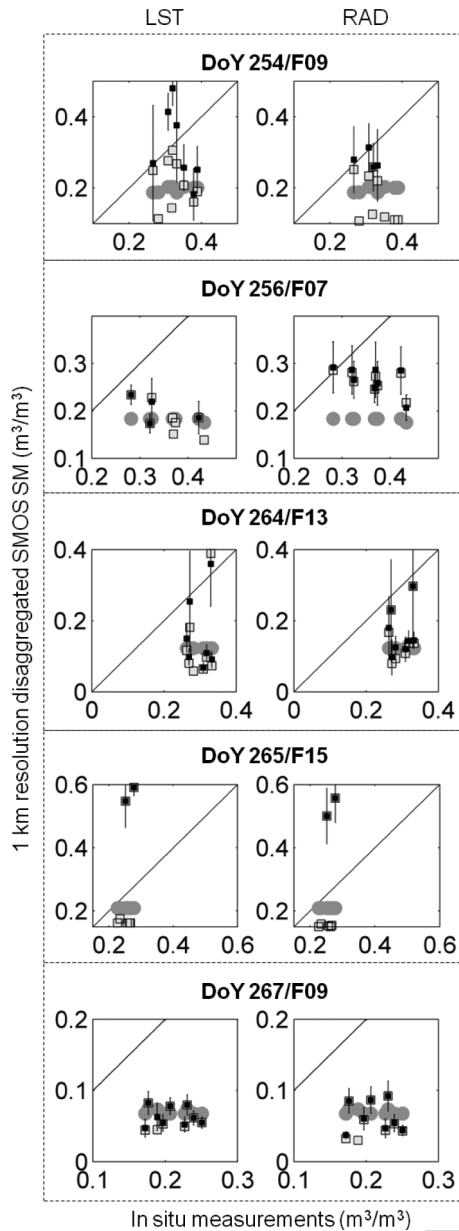


Fig. 9. Scatterplots of 1-km resolution disaggregated SMOS soil moisture versus 1-km resolution aggregated *in situ* measurements for each of the five date-farm data sets during AACES-2. The filled circles correspond to disaggregation with no 1-km information, empty squares to Zone A+B+C mode and black squares to Zone A only mode. For the Zone A only mode, the uncertainty in disaggregated soil moisture is represented by vertical errorbars.

880 methodology, it is suggested to analyze the spatial correla-
 881 tion between 1-km disaggregated SMOS soil moisture and
 882 *in situ* measurements. If the correlation is significant, then the
 883 disaggregation product is likely to be sufficiently accurate for
 884 validating SMOS data.

885 Note that the errors in DisPATCH are in part coupled with
 886 the errors in SMOS soil moisture, particularly because SMOS
 887 is an input to DisPATCH. However, any uncertainties in SMOS
 888 soil moisture should not impact the disaggregation results at a
 889 distance shorter than the SMOS data sampling length (15 km).
 890 This is the reason why such a validation strategy should be
 891 conducted with ground measurements made within a distance
 892 radius of 15 km.

In this study case, five date-farm units including DoY 893
 46/F15, DoY 46/F16, DoY 49/F17, DoY 49/F18, and DoY 894
 49/F20 indicate a significant correlation between disaggregated 895
 SMOS soil moisture and *in situ* measurements. For these units, 896
 the root mean square error in disaggregated SMOS soil mois- 897
 ture is mainly explained by a bias in disaggregated soil moisture 898
 (see Table IV). However, no conclusion can be drawn from 899
 these data because: 1) the bias is sometimes positive (DoY 900
 46/F15, DoY 49/F20), and sometimes negative (DoY 46/F16, 901
 DoY 49/F17, DoY 49/F18); and 2) the comparison is made only 902
 once for each farm, which does not allow analyzing the tempo- 903
 ral behavior. Such a validation approach could be undertaken 904
 in the near future using the OzNet (<http://www.oznet.org.au/>, 905
 [42]) soil moisture monitoring network, providing continuous 906
 measurements at 68 sites within the Murrumbidgee catchment 907
 area. 908

H. Subpixel Variability and Assimilation Perspectives 909

DisPATCH is successively run in LST or RAD mode and in 910
 Zone A+B+C or Zone A only mode during AACES-1. Fig. 10 911
 plots for each case the estimated uncertainty in disaggregated 912
 soil moisture (computed as the standard deviation of the disag- 913
 gregation output ensemble) against the subpixel variability of 914
 1-km resolution *in situ* measurements (computed as the stan- 915
 dard deviation of the *in situ* measurements made within 916
 1-km pixels). The data corresponding to DoY 51 are plotted 917
 separately because of the time gap between HDAS/SMOS 918
 (DoY 51) and MODIS (DoY 54) collection time. It is interest- 919
 ing to observe that the estimated uncertainty in disaggregated 920
 soil moisture is closely related to the observed subpixel vari- 921
 ability of *in situ* measurements. Hence, $\sigma_{SM,1\text{ km}}$ could be used 922
 as a proxy for representing the soil moisture variability at scales 923
 finer than 1-km resolution. Concerning the data on DoY 51, the 924
 linear regression is clearly off the 1:1 line. This is consistent 925
 with a decrease of the spatial variability in soil moisture during 926
 a dry down period [43]. In particular, the spatial variability 927
 in soil moisture is expected to be lower on DoY 54 than on 928
 DoY 51. 929

The correlation between the estimated uncertainty in disag- 930
 gregated soil moisture and the subpixel soil moisture variability 931
 makes an additional link between DisPATCH output and assim- 932
 ilation schemes into hydrological models. A number of optimal 933
 assimilation methodologies have been developed to combine 934
 model predictions with remote sensing observations. However, 935
 any so-called optimal assimilation technique stops being opti- 936
 mal if the uncertainty in remotely sensed data is unknown or 937
 estimated with a large uncertainty. In the perspective of assim- 938
 ilating disaggregated SMOS data into land surface models, one 939
 should keep in mind that the error information on observable 940
 variables is as crucial as the observations themselves, e.g., [44]. 941

V. SUMMARY AND CONCLUSION 942

DisPATCH is an algorithm dedicated to the disaggregation of 943
 soil moisture observations using high-resolution soil tempera- 944
 ture data. It converts soil temperature fields into soil moisture 945
 fields given a semi-empirical soil evaporative efficiency model 946

TABLE V

DISPATCH IS RUN IN THE ZONE A ONLY MODE, AND STATISTICAL RESULTS ARE LISTED IN TERMS OF ROOT MEAN SQUARE DIFFERENCE (RMSD), MEAN DIFFERENCE (BIAS), CORRELATION COEFFICIENT (R), AND SLOPE OF THE LINEAR REGRESSION BETWEEN 1-KM RESOLUTION DISAGGREGATED SMOS SOIL MOISTURE AND 1-KM AGGREGATED *In Situ* MEASUREMENTS. THE RESULTS OBTAINED USING THE RADIANCE-DERIVED LAND SURFACE TEMPERATURE DATA (RAD MODE) AND USING THE OFFICIAL MODIS LAND SURFACE TEMPERATURE DATA (LST MODE IN PARENTHESIS) ARE COMPARED. THE MEAN AND STANDARD DEVIATION OF GROUND MEASUREMENTS ($\langle SM_{HDAS} \rangle$ AND σ_{HDAS}), THE NUMBER OF CONSIDERED 1-KM PIXELS AND STATISTICAL SIGNIFICANCE (P-VALUE) ARE ALSO LISTED FOR EACH DATE-FARM UNIT

DoY/Farm	$\langle SM_{HDAS} \rangle$ (m^3/m^3)	σ_{HDAS} (m^3/m^3)	Number of 1 km pixels	RMSD* (m^3/m^3)	Bias* (m^3/m^3)	R [†] (-)	Slope [†] (-)	p-value (-)
28/F05	0.04	0.02	7 (7)	0.04 (0.04)	-0.04 (-0.04)	- (-)	- (-)	0.72 (0.80)
30/F07	0.02	0.03	8 (8)	0.02 (0.02)	-0.02 (-0.02)	- (-0.70)	- (-0.08)	0.20 (0.05)
30/F08	0.03	0.02	7 (7)	0.02 (0.02)	-0.02 (-0.02)	- (-0.95)	- (-0.03)	0.11 (0.001)
46/F15	0.29	0.05	8 (8)	0.09 (0.09)	0.09 (0.08)	- (0.66)	- (1.4)	0.13 (0.07)
46/F16	0.34	0.06	3 (2)	0.07 (0.14)	-0.06 (-0.12)	- (-)	- (-)	0.96 (-)
49/F17	0.21	0.06	8 (8)	0.02 (0.04)	0.02 (-0.02)	0.79 (-)	0.71 (-)	0.02 (0.64)
49/F18	0.25	0.07	1 (0)	- (-)	- (-)	- (-)	- (-)	0.20 (0.20)
49/F20	0.20	0.09	4 (4)	0.05 (0.02)	0.05 (0.01)	0.98 (0.92)	1.1 (0.42)	0.02 (0.08)
51/F19	0.24	0.08	0 (1)	- (-)	- (-)	- (-)	- (-)	0.19 (0.19)
51/F20	0.20	0.10	6 (6)	0.09 (0.09)	-0.09 (-0.09)	- (-)	- (-)	0.70 (0.45)
AACES-1 mean [‡]	0.21 (0.25)	0.08 (0.07)	6 (6)	0.04 (0.06)	0.04 (0.05)	0.89 (0.79)	0.91 (0.91)	0.02 (0.08)
254/F09	0.33	0.07	4 (7)	0.05 (0.12)	-0.03 (-0.02)	- (-)	- (-)	0.70 (0.30)
256/F07	0.36	0.10	8 (4)	0.12 (0.15)	-0.10 (-0.13)	- (-)	- (-)	0.13 (0.43)
264/F13	0.30	0.07	8 (7)	0.14 (0.17)	-0.13 (-0.14)	- (-)	- (-)	0.64 (0.86)
265/F15	0.25	0.06	2 (2)	0.26 (0.30)	0.26 (0.30)	- (-)	- (-)	- (-)
267/F09	0.21	0.07	8 (9)	0.15 (0.15)	-0.15 (-0.15)	- (-)	- (-)	0.77 (0.85)
AACES-2 mean [‡]	-	-	- (-)	- (-)	- (-)	- (-)	- (-)	>0.10 (>0.10)

* RMSD and bias values are computed if the number of 1 km pixels > 1.

[†] R and slope values are reported if p-value < 0.10.

[‡] the mean values computed for AACES-1 and AACES-2 include only statistically significant (p-value < 0.10) results and discard extensive dry days DoY 28-30.

947 and a first-order Taylor series expansion around the field-mean
948 soil moisture. In this study, the disaggregation approach is ap-
949 plied to 40-km resolution version-4 SMOS level-2 soil moisture
950 using 1-km resolution MODIS data. The objective is to test
951 DisPATCH under different surface and atmospheric conditions
952 using the very intensive ground measurements collected in
953 southeastern Australia during the 2010 summer and winter
954 AACES campaigns. Those measurements are aggregated at
955 the downscaling resolution (1 km) and subsequently compared
956 to the disaggregated SMOS soil moisture. Over the study
957 area, climatic (evaporative demand), meteorologic (presence
958 of clouds), and vegetation (cover and water status) conditions
959 are strong constraints on disaggregation results. The quality
960 of disaggregation products varies greatly according to season:
961 while the correlation coefficient between disaggregated and
962 *in situ* soil moisture is 0.7 during the summer AACES, it
963 is about zero during the winter AACES, consistent with a
964 weaker coupling between evaporation and surface moisture
965 in temperate than in semi-arid climate. Moreover, vegetation
966 cover prevents the soil temperature to be retrieved from thermal
967 infrared data and the vegetation water stress may increase the
968 remotely sensed land surface temperature independent of near-
969 surface soil moisture. By separating the 1-km pixels where
970 MODIS temperature is mainly controlled by soil evaporation,

from those where MODIS temperature is controlled by both 971
soil evaporation and vegetation transpiration, the correlation 972
coefficient between disaggregated and *in situ* soil moisture is 973
increased from 0.70 to 0.85 during the summer AACES cam- 974
paign. Also, cloud cover totally obscures the surface during rain 975
events, and on clear sky days, the water vapor in the atmosphere 976
significantly affects the quality of land surface temperature 977
data. It is found that the 5-km resolution atmospheric correction 978
of the official MODIS temperature data has significant impact 979
on DisPATCH output. An alternative atmospheric correction at 980
40-km resolution increases the correlation coefficient between 981
disaggregated and *in situ* soil moisture from 0.72 to 0.82 during 982
the summer AACES. 983

The above limitations must be kept in mind when using 984
DisPATCH as a tool for validating SMOS soil moisture. Over 985
semi-arid areas, disaggregation can solve the extent mismatch 986
between the 40-km resolution SMOS data and localized *in situ* 987
measurements. However, the validation of SMOS using Dis- 988
PATCH requires separation of the errors associated with SMOS 989
data and the errors associated with DisPATCH. As SMOS data 990
are an input to DisPATCH, the errors in DisPATCH are also 991
linked to the uncertainty in SMOS soil moisture. Nevertheless, 992
one way to identify the error sources specifically attributed 993
to DisPATCH is to analyze the spatial correlation between 994

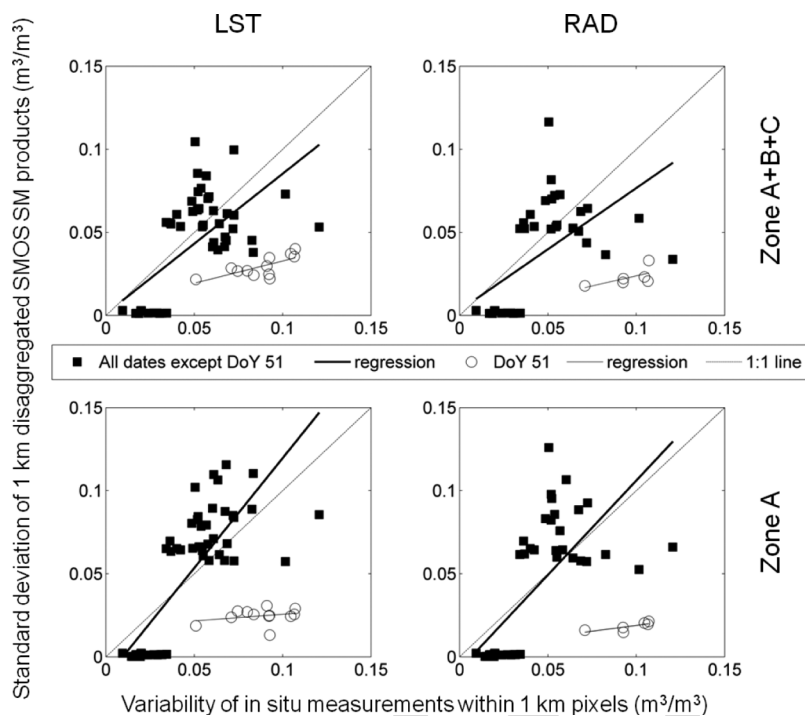


Fig. 10. Estimated uncertainty in disaggregated soil moisture ($\sigma_{SM, 1 km}$) versus subpixel variability of 1 km resolution *in situ* measurements for DisPATCH run in LST or RAD mode and Zone A+B+C or Zone A only mode.

995 disaggregated SMOS data and the *in situ* measurements made
 996 at a distance larger than the downscaling resolution (1 km with
 997 MODIS data) and smaller than the SMOS data sampling length
 998 (15 km).

999 Based on the results obtained using the AACES *in situ*
 1000 measurements, several improvements of DisPATCH can be
 1001 suggested:

- 1002 • Use of the MODIS land surface temperature quality index
 1003 to select the SMOS pixels with the highest MODIS data
 1004 quality.
- 1005 • Correcting the MODIS land surface temperature for topog-
 1006 raphy and illumination effects [45]. Within a 40-km
 1007 SMOS resolution pixel, the elevation range may be very
 1008 significant and thus induce a variability in land sur-
 1009 face temperature that is not attributed to surface soil
 1010 moisture.
- 1011 • Use of ancillary air temperature data to constrain the
 1012 estimation of end-members. The unstressed vegetation
 1013 temperature $T_{v,min}$ could be set to the air temperature
 1014 instead of the minimum MODIS land surface temperature.
 1015 This would make the estimation of $T_{v,min}$ less dependent
 1016 on the representativeness of the surface conditions met
 1017 within the SMOS pixel [24].
- 1018 • Accounting for the dependency of soil evaporative effi-
 1019 ciency to potential evaporation, by replacing the model in
 1020 [26] with the model in [38].
- 1021 • Estimating an optimal downscaling resolution for each
 1022 season: as the sensitivity of soil evaporative efficiency to
 1023 soil moisture is lower in the winter months than in the sum-
 1024 mer months, aggregating DisPATCH output may improve
 1025 the quality of disaggregation products at the expense of
 1026 spatial resolution [17].

A robust disaggregation methodology of SMOS soil moisture
 at 1-km resolution, which would provide both disaggregated
 soil moisture and its uncertainty at 1-km resolution is a crucial
 step toward the application of SMOS data to hydrological
 studies.

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Disaggregation of SMOS Soil Moisture in Southeastern Australia

Olivier Merlin, Christoph Rüdiger, Ahmad Al Bitar, Philippe Richaume, Jeffrey P. Walker, and Yann H. Kerr

Abstract—Disaggregation based on Physical And Theoretical scale Change (DisPATCh) is an algorithm dedicated to the disaggregation of soil moisture observations using high-resolution soil temperature data. DisPATCh converts soil temperature fields into soil moisture fields given a semi-empirical soil evaporative efficiency model and a first-order Taylor series expansion around the field-mean soil moisture. In this study, the disaggregation approach is applied to soil moisture and ocean salinity (SMOS) data over the 500 km by 100 km AACES (Australian Airborne Calibration/validation Experiments for SMOS) area. The 40-km resolution SMOS surface soil moisture pixels are disaggregated at 1-km resolution using the soil skin temperature derived from moderate resolution imaging spectroradiometer (MODIS) data, and subsequently compared with the AACES intensive ground measurements aggregated at 1-km resolution. The objective is to test DisPATCh under various surface and atmospheric conditions. It is found that the accuracy of disaggregation products varies greatly according to season: while the correlation coefficient between disaggregated and *in situ* soil moisture is about 0.7 during the summer AACES, it is approximately zero during the winter AACES, consistent with a weaker coupling between evaporation and surface soil moisture in temperate than in semi-arid climate. Moreover, during the summer AACES, the correlation coefficient between disaggregated and *in situ* soil moisture is increased from 0.70 to 0.85, by separating the 1-km pixels where MODIS temperature is mainly controlled by soil evaporation, from those where MODIS temperature is controlled by both soil evaporation and vegetation transpiration. It is also found that the 5-km resolution atmospheric correction of the official MODIS temperature data has a significant impact on DisPATCh output. An alternative atmospheric correction at 40-km resolution increases the correlation coefficient between disaggregated and *in situ* soil moisture from 0.72 to 0.82 during the summer AACES. Results indicate that

DisPATCh has a strong potential in low-vegetated semi-arid areas where it can be used as a tool to evaluate SMOS data (by reducing the mismatch in spatial extent between SMOS observations and localized *in situ* measurements), and as a further step, to derive a 1-km resolution soil moisture product adapted for large-scale hydrological studies.

Index Terms—AACES, calibration/validation, disaggregation, Disaggregation based on Physical And Theoretical scale Change (DisPATCh), field campaign, moderate resolution imaging spectroradiometer (MODIS), soil moisture and ocean salinity (SMOS).

I. INTRODUCTION

PASSIVE MICROWAVE remote sensing has the capability to provide key elements of the terrestrial hydrological cycle such as surface soil moisture [1], [2] and overland precipitation [3], [4]. Nevertheless, due to the large discrepancy between the observation scale (several tens of km) and the scale of physical interactions with the land surface (one wavelength or several cm), the radiative transfer models applied to passive microwave remote sensing data are only semiphysically based. Consequently, the retrieval process of land surface parameters from microwave brightness temperatures requires ancillary data for calibration and validation purposes [5]. It also requires a strategy to use such ancillary data since ground-based sampling is often made over a small area/point, which contrasts with the large integrated extent of spaceborne passive microwave observations.

The soil moisture and ocean salinity (SMOS), [6] satellite was launched on November 2, 2009. Over land, the SMOS mission aims at providing ~5 cm surface soil moisture data at a spatial resolution better than 50 km and a repeat cycle of less than 3 days. The payload is a 2-D interferometer equipped with 69 individual L-band antennas regularly spaced along Y-shaped arms. This new concept allows observing all pixels in the 1000 km wide field of view at a range of incidence angles. It also allows reconstructing brightness temperatures on a fixed sampling grid [7].

Since the SMOS launch, various field experiments (the HOBE site in Denmark [8], the Mali site in Western Africa [9], the SMOSMANIA site in Southwestern France [10] just to name a few) have been undertaken to validate SMOS reconstructed brightness temperatures and soil moisture retrievals. The AACES (Australian Airborne Calibration/validation Experiment for SMOS, [11]) is one of the most comprehensive campaigns worldwide dedicated to SMOS calibration/validation. A series of two experiments were undertaken in 2010, AACES-1 in January-February (Austral summer) and

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83 AACES-2 in September (Austral winter). The data collected
84 in AACES include 1-km resolution airborne L-band brightness
85 temperature mapped over a 500 km by 100 km area, 20 days
86 of very intensive ground measurements and 20 5 km by 2 km
87 ground sampling areas.

88 Even though the AACES ground measurements are very
89 extensive, it is not feasible to cover the whole extent of a
90 SMOS pixel by ground sampling alone. This is the reason why
91 most validation strategies of spaceborne passive microwave
92 data using *in situ* measurements have been based on the as-
93 sumption that local observations are representative of a much
94 larger spatial extent (i.e., the size of a microwave pixel). In the
95 heterogeneous case where this assumption does not hold, up-
96 scaling approaches [12], [13] have been developed to relate the
97 available ground observations to satellite scale soil moisture.
98 Such approaches are very useful over sites which have been
99 monitored for a long time and where extensive measurements
100 have been made over a range of spatial scales. However, aggre-
101 gation rules are difficult to build over sites which have been set
102 up recently, or where no extensive field campaigns have been
103 undertaken.

104 This study develops a methodology to facilitate the cali-
105 bration and validation of SMOS data using localized ground
106 measurements, such as those collected during AACES. The
107 methodology combines upscaling (aggregation) and downscal-
108 ing (disaggregation) approaches to make remote sensing and
109 *in situ* observations match at an intermediate spatial resolution
110 of 1 km. The key step in the procedure is a disaggregation
111 algorithm of passive microwave soil moisture using kilometric
112 optical data [14]–[16]. Disaggregating SMOS soil moisture can
113 solve the disparity of spatial scales between satellite and *in situ*
114 observations. However, the validation of spaceborne data by
115 means of a disaggregation approach requires the uncertainties
116 and potential error sources in downscaled data to be assessed.
117 Generally speaking, disaggregation is a compromise between
118 downscaling resolution and accuracy. The higher downscaling
119 resolution, the more disaggregated values are spatially repre-
120 sentative of ground observations, but typically have a lower
121 accuracy and vice versa [17]. In this context, a disaggrega-
122 tion algorithm named Disaggregation based on Physical And
123 Theoretical scale Change (DisPATCH) is applied to 40-km
124 resolution SMOS soil moisture over the AACES area using 1-
125 km resolution Moderate resolution Imaging Spectroradiometer
126 (MODIS) data. The objective is to test DisPATCH under various
127 surface and atmospheric conditions. Specifically, the impact
128 of climatic (evaporative demand), meteorologic (presence of
129 clouds), and vegetation (cover and water status) conditions on
130 1-km resolution disaggregated soil moisture is evaluated both
131 qualitatively by visual assessment of disaggregation images and
132 quantitatively by comparing DisPATCH output with AACES
133 intensive ground measurements.

134 The AACES, SMOS, and MODIS data used in this study
135 are first described. Next, the disaggregation methodology is
136 presented followed by a step-by-step description of the Dis-
137 PATCH algorithm. Results of the comparison between disag-
138 gregated SMOS soil moisture and *in situ* measurements are
139 then reported. To test DisPATCH under various surface and
140 atmospheric conditions, the algorithm is run during AACES-1

and AACES-2 in different modes, by including (or not) a 141
correction for vegetation and atmospheric effects. Finally, some 142
perspectives in the use of DisPATCH for validating SMOS data 143
using ground-based sampling are given. 144

II. DATA COLLECTION AND PREPROCESSING 145

The AACES experiments were planned to provide ground 146
and airborne soil moisture data over an area of approximately 147
500 km by 100 km during the two main seasons in the 148
Murrumbidgee river catchment, in southeastern Australia. The 149
first AACES campaign (AACES-1) was undertaken in summer 150
2010 from January 18 to February 21, and the second campaign 151
(AACES-2) was undertaken in the following Austral winter 152
from September 11 to September 24 [11]. Fig. 1 presents the 153
study area including the 20 5 km by 2 km ground sampling 154
focus areas. The background image is the MODIS 250-m res- 155
olution 16-day normalized difference vegetation index (NDVI) 156
product of February 2, 2010. The climate of the Murrumbidgee 157
catchment area ranges from semi-arid in the west to alpine in 158
the east, with a strong rainfall and potential evapotranspiration 159
gradient in the west-east direction. Land use is extensive graz- 160
ing in the west, cropping in the center, and mostly grazing/forest 161
in the east (refer to [11] for a detailed account of AACES). 162

A. HDAS 163

During both AACES-1 and AACES-2, a spatially enabled 164
platform (Hydrprobe Data Acquisition System, HDAS) was 165
used to collect extensive measurements of near-surface soil 166
moisture. HDAS is a handheld system combining a soil dielec- 167
tric sensor (Hydrprobe) and a pocket PC with GPS receiver, 168
allowing for direct storage of location and measurement within 169
the GIS software. HDAS measurements were calibrated using 170
the approach presented in [18] with a root mean square error 171
of point estimate of about $0.03 \text{ m}^3/\text{m}^3$. The sampling coverage 172
was two 5 km by 2 km farms per day during AACES-1 and one 173
5 km by 2 km farm per day during AACES-2. Within each farm, 174
a total of six adjacent 5 km long transects separated by 330 m 175
were walked to cover each area of 10 km^2 , and three separate 176
HDAS measurements were made along transects every 50 m. 177

In this study, HDAS soil moisture data are aggregated at 178
1-km resolution by averaging all measurements made within 179
each pixel of the MODIS resolution grid. Out of concern for 180
spatial representativeness of *in situ* observations, only the 1-km 181
pixels whose ground sampling covers more than two third of 182
its surface area are kept for comparison with disaggregation 183
results. The 1-km average of HDAS measurements is denoted 184
 $\langle \text{SM}_{\text{HDAS}} \rangle$ and the standard deviation of *in situ* measurements 185
(denoted σ_{HDAS}) computed to estimate the subpixel variability 186
at 1-km resolution. 187

B. SMOS 188

The version-4 SMOS level-2 soil moisture product is used. 189
This product (released on March 24, 2011) was produced from 190
the reprocessed level 1C data, and the version-4 level-2 soil 191
moisture algorithm. SMOS has a 6 am (ascending) and 6 pm 192

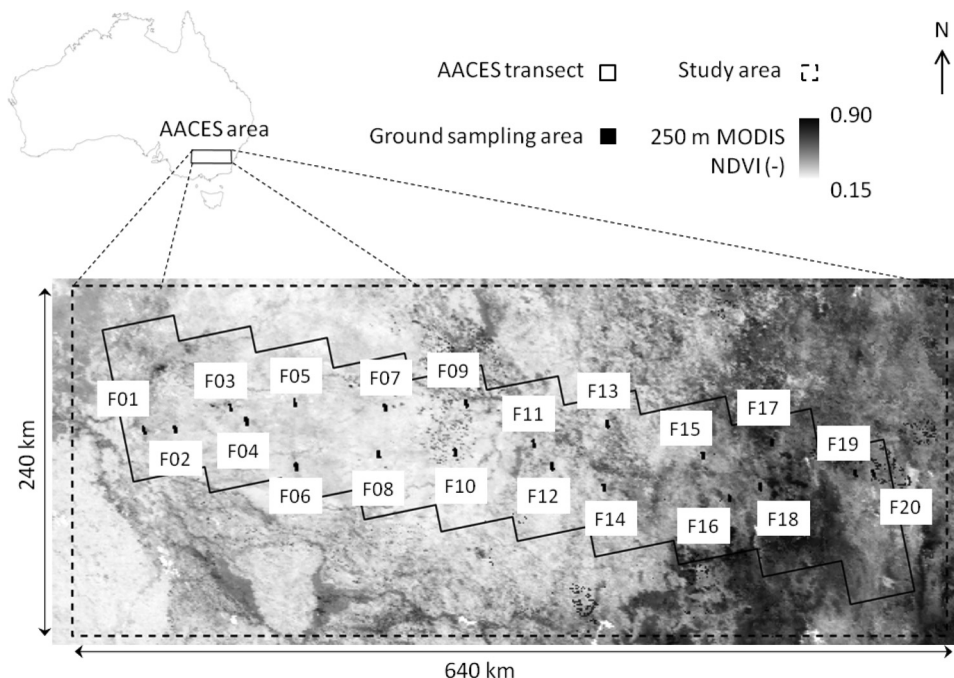


Fig. 1. Overview of the study area. During AACES, ten 100 km by 50 km patches were overflowed by an airborne L-band radiometer. Within each patch, two 5 km by 2 km subareas were sampled to collect spatial soil moisture measurements. In this study, DisPATCH is run over a 640 by 240 km area including the whole AACES area, and disaggregation results are evaluated over the ground sampling areas.

193 (descending) equator crossing time. The sampling grid of the
 194 SMOS level-2 soil moisture product is called DGG or discrete
 195 global grid [19], [20] and has a node separation of about
 196 15 km. The DGG provides a discretization that is higher than
 197 the SMOS natural pixel size, which is 40 km on average,
 198 ranging from 30 km at boresight to 90 km at high incidence
 199 angles. In this study, the disaggregation procedure takes advan-
 200 tage of the oversampling of SMOS data to potentially reduce
 201 (and provide an estimate of) random errors in disaggregated
 202 SMOS data. Instead of using a single snapshot SMOS im-
 203 age, DisPATCH uses four (overlapping) independent snapshots,
 204 which are generated by: 1) sliding a 40-km resolution grid;
 205 2) extracting the DGG nodes approximately centered on each
 206 40 km pixel. The extraction of SMOS DGG nodes is presented
 207 in [21]. The DGG node(s) that fall(s) near the center of the
 208 40-km resolution pixels with a ± 10 -km tolerance are se-
 209 lected. If more than one DGG is selected, the associated soil
 210 moisture values are averaged to produce a single value for each
 211 40-km resolution pixel. The 40-km resolution grid that fits the
 212 study area corresponds to what is termed here Resampling 1.
 213 Similarly, Resampling 2, 3, and 4 are performed by sliding the
 214 40-km resolution grid to coordinates $(+20 \text{ km}, 0)$, $(0, -20 \text{ km})$,
 215 and $(+20 \text{ km}, -20 \text{ km})$, respectively. The four 40-km resolu-
 216 tion SMOS data sets are then used independently as input to
 217 DisPATCH.

218 C. MODIS

219 The MODIS data used in this paper are composed of:

- 220 • Version-5 MODIS/Terra land surface temperature and
 221 emissivity daily level-3 global 1-km grid product
 222 (MOD11A1) and version-5 MODIS/Aqua land surface

temperature and emissivity daily level-3 global 1-km grid
 223 product (MYD11A1). The land surface temperature data
 224 set is the main component of DisPATCH. It is used to
 225 estimate 1-km resolution soil evaporative efficiency at
 226 10 am (Terra data) and 1 pm (Aqua data) [22].

- 227 • Version-5 MODIS/Terra vegetation indices 16-day level-3
 228 global 1-km grid product (MOD13A2). The NDVI data set
 229 is used in DisPATCH to estimate the fractional vegetation
 230 cover at 1-km resolution [23].
- 231 • Version-5 MODIS/Terra+Aqua albedo 16-day level-3
 232 global 1-km grid product (MCD43B3). The surface albedo
 233 data set is used in DisPATCH to estimate the vegetation
 234 temperature at maximum water stress from the space land
 235 surface temperature albedo [24]. The MCD43B3 product
 236 provides 1-km data describing both directional hemispher-
 237 ical reflectance (black-sky albedo) at local solar noon
 238 and bihemispherical reflectance (white-sky albedo). In this
 239 study, surface albedo refers to the MODIS shortwave white
 240 sky albedo.
- 241 • MODIS/Terra level-1B calibrated radiances swath 1-km
 242 grid product (MOD021KM) and MODIS/Aqua level-
 243 1B calibrated radiances swath 1-km grid product
 244 (MYD021KM). The radiance data set is used to derive
 245 a land surface temperature data set that differs from the
 246 official MOD11A1 and MYD11A1 products with respect
 247 to atmospheric correction.

248 Products MOD11A1, MYD11A1, MOD13A2, and
 249 MCD43B3 were downloaded through the NASA Warehouse
 250 Inventory Search Tool (WIST <http://wist.echo.nasa.gov/>) and
 251 products MOD021KM and MYD021KM were downloaded
 252 through the NASA Level 1 and Atmosphere Archive and Dis-
 253 tribution System (LAADS <http://ladsweb.nascom.nasa.gov/>).
 254

TABLE I
SCALE AND OFFSET VALUES USED TO CONVERT TERRA (AND AQUA)
MODIS RADIANCE DATA TO PHYSICAL RADIANCE
VALUES OVER THE AACES AREA

Thermal band	Scale ($\text{W m}^{-2} \text{sr}^{-1}$)	Offset (-)
31	$8.4002 \cdot 10^{-4}$ ($6.5081 \cdot 10^{-4}$)	1577 (2036)
32	$7.2970 \cdot 10^{-4}$ ($5.7100 \cdot 10^{-4}$)	1658 (2119)

255 All products were projected in UTM 55 South with a sampling
256 interval of 1000 m using the MODIS reprojection tool.

257 The level-1B calibrated radiance data (R_{31} and R_{32} for bands
258 31 and 32, respectively) were converted from digital number
259 (DN) to radiance in $\text{W m}^{-2} \text{sr}^{-1}$ using the radiance scales and
260 offsets provided with each MODIS granule as listed in Table I

$$R_{\lambda} = \text{Scale}_{\lambda} \times (\text{DN}_{\lambda} - \text{Offset}_{\lambda}) \quad (1)$$

261 The radiance values were then converted to brightness temper-
262 ature in K using the inverse of the Planck function [25]

$$Tb_{\lambda} = \frac{c_2}{\lambda \ln \left(1 + \frac{c_1}{R_{\lambda} \lambda^5} \right)} \quad (2)$$

263 with $c_1 = 1.19107 \times 10^8 \mu\text{m}^5 \text{W m}^{-2} \text{sr}^{-1}$ and $c_2 =$
264 $1.43883 \times 10^4 \mu\text{m K}$, for center wavelength of the given band
265 ($11.0186 \mu\text{m}$ and $12.0325 \mu\text{m}$ for 31 and 32 band, respectively).

266 D. Overlapping HDAS, SMOS, and MODIS Data and 267 Generating an Input Data Set

268 As indicated in Table II, HDAS soil moisture, SMOS soil
269 moisture, and cloud-free MODIS land surface temperature data
270 have overlapped on five days during AACES-1 (on January
271 28 and 30 and February 15, 18, and 20) and on five days
272 during AACES-2 (on September 11, 13, 21, 22, and 24). On
273 each sampling day, two farms were sampled during AACES-1
274 (except on February 18 when three farms were sampled), and
275 one farm was sampled during AACES-2, so that disaggregation
276 results can be evaluated for ten date-farm units during AACES-
277 1 and five date-farm units during AACES-2.

278 DisPATCh is applied to an input ensemble composed of the
279 different combinations of available SMOS (ascending orbit at
280 6 am and/or descending orbit at 6 pm) and MODIS (onboard
281 Terra platform at 10 am and/or Aqua platform at 1 pm) data. To
282 increase the quantity of input data sets, the MODIS data col-
283 lected on the day before and the day after the SMOS overpass
284 date are also included. For SMOS data on day of year (DoY)
285 51, the clear sky MODIS data collected on DoY 54 are used.
286 Note that one implicitly assumes that no rainfall occurs between
287 MODIS and SMOS overpasses, and that the spatial variability
288 captured by MODIS is relatively similar to the actual variabil-
289 ity of surface soil moisture at the time of SMOS overpass.
290 Moreover, the SMOS data oversampling is used to generate
291 four (overlapping) 40-km resolution SMOS grids on which
292 DisPATCh is run independently, thus increasing the number
293 of downscaled data that could be used in the validation. It is
294 reminded that the spacing (about 15 km) between neighboring
295 SMOS DGG nodes is smaller than the SMOS resolution (about

40 km). By combining the four SMOS grids, the two potential 296
SMOS data sets (two orbits in one day) and the six potential 297
MODIS data sets (three days including two overpasses each), 298
the maximum number of input data sets is 48. The generation 299
of input data sets is shown in Fig. 2 and the number of daily 300
input data sets is indicated for each date-farm unit in Table II. 301

III. DISAGGREGATION ALGORITHM

302

DisPATCh converts 1-km resolution MODIS-derived soil 303
temperature fields into 1-km resolution surface soil moisture 304
fields given a semi-empirical soil evaporative efficiency model 305
[26] and a first-order Taylor series expansion around the 306
40-km resolution SMOS observation. DisPATCh is an im- 307
proved version of the algorithms in [16] and [27], and mainly 308
differs with regard to the representation of the vegetation water 309
status. In previous versions [16], [27], the soil temperature was 310
derived from MODIS land surface temperature by assuming 311
that vegetation was unstressed so that vegetation temperature 312
was uniformly set to the minimum surface temperature ob- 313
served within the SMOS pixel. In this study, the approach in 314
[28] is implemented to take into account vegetation water status 315
in the estimation of soil temperature. 316

A. Disaggregation Methodology

317

The disaggregation procedure decouples the soil evaporation 318
from the 0–5 cm soil layer and the vegetation transpiration 319
from the root-zone soil layer by separating MODIS surface 320
temperature into its soil and vegetation components as in the 321
triangle or trapezoidal method [28], [29]. MODIS-derived soil 322
temperature is then used to estimate soil evaporative efficiency, 323
which is known to be relatively constant during the day on clear 324
sky conditions. MODIS-derived soil evaporative efficiency is 325
finally used as a proxy for surface (0–5 cm) soil moisture 326
variability within the SMOS pixel. The link between surface 327
soil moisture and soil evaporative efficiency at different scales 328
is ensured by a downscaling relationship and a soil evapo- 329
rative efficiency model, as described below in more detail. 330
The originality of DisPATCh relies on a dynamical land cover 331
classification (based on the hourglass approach in [28]) that 332
takes into account the subpixel variability of the sensitivity of 333
soil evaporative efficiency to surface soil moisture. 334

1) *Downscaling Relationship*: The downscaling relation- 335
ship can be written as 336

$$\mathbf{SM}_{1 \text{ km}} = \mathbf{SM}_{\text{SMOS}} + \frac{\partial \mathbf{SM}_{\text{mod}}}{\partial \text{SEE}} \times (\text{SEE}_{\text{MODIS}, 1 \text{ km}} - \langle \text{SEE}_{\text{MODIS}, 1 \text{ km}} \rangle_{40 \text{ km}}) \quad (3)$$

with $\mathbf{SM}_{\text{SMOS}}$ being the SMOS soil moisture (for clarity, 337
the variables defined at SMOS scale are written in bold), 338
 $\text{SEE}_{\text{MODIS}}$ the MODIS-derived soil evaporative efficiency (ra- 339
tio of actual to potential evaporation), $\langle \text{SEE}_{\text{MODIS}} \rangle_{40 \text{ km}}$ its 340
average within a SMOS pixel and $\partial \mathbf{SM}_{\text{mod}} / \partial \text{SEE}$ the partial 341
derivative evaluated at SMOS scale of soil moisture with re- 342
spect to soil evaporative efficiency. Note that the linearity of (3) 343
implies that a possible bias in SMOS data would produce the 344

TABLE II
LIST OF OVERLAPPING HDAS, SMOS, AND MODIS (MOD11A1 AND MYD11A1) DATA DURING AACES-1 AND AACES-2. ONLY THE SMOS DATA COLLECTED ON THE SAME DAY AS GROUND SAMPLING HAVE BEEN CONSIDERED. THE MODIS DATA CONSIDERED AS INPUT TO DISPATCH HAVE BEEN COLLECTED WITHIN PLUS OR MINUS ONE DAY EITHER SIDE THE GROUND SAMPLING (AND SMOS OVERPASS) DATE. ON EACH SAMPLING DATE, THE RESULTANT NUMBER OF INPUT DATA SETS TO DISPATCH IS ALSO INDICATED

Experiment	Sampling date	DoY	Farm	SMOS overpass time	Cloud free MODIS data (DoY)	Number of input data sets to DisPATCH
AACES-1	28 January	28	F05	6 am	Terra (27,29) & Aqua (29)	3
	30 January	30	F07	6 am	Terra (29,30) & Aqua (29)	12
	,	,	F08	6 am	Terra (29,30) & Aqua (29)	9-12
	15 February	46	F15	6 am & 6 pm	Terra (46) & Aqua (47)	8-14
	,	,	F16	6 am & 6 pm	Terra (46) & Aqua (47)	8-10
	18 February	49	F17	6 am & 6 pm	Terra (48,50) & Aqua (48,49,50)	30-38
	,	,	F18	6 am & 6 pm	Terra (48,50) & Aqua (48,49,50)	24-30
	,	,	F20	6 am & 6 pm	Terra (48,50) & Aqua (48,49,50)	34-40
	20 February	51	F19	6 am & 6 pm	Terra (54) & Aqua (54)	6-8
,	,	F20	6 am & 6 pm	Terra (54) & Aqua (54)	16	
AACES-2	11 September	254	F09	6 am & 6 pm	Terra (253,254) & Aqua (254)	6-14
	13 September	256	F07	6 am & 6 pm	Terra (256)	8
	21 September	264	F13	6 am & 6 pm	Terra (263) & Aqua (264)	16
	22 September	265	F15	6 am & 6 pm	Terra (265) & Aqua (264,266)	16
	24 September	267	F09	6 am & 6 pm	Terra (267) & Aqua (266,267,268)	24-32

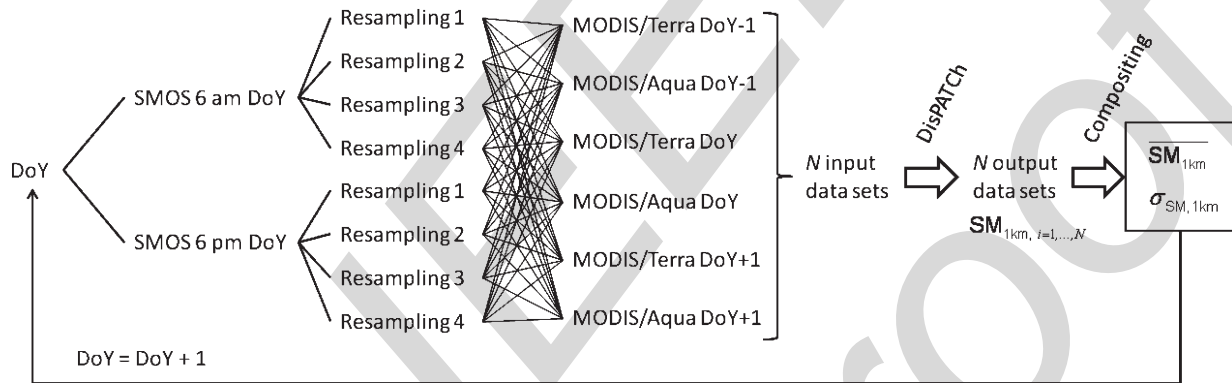


Fig. 2. Schematic diagram presenting the combination of SMOS and MODIS to generate an ensemble of input data to DisPATCH. The output data are composited at 1-km resolution by computing the average ($\overline{SM}_{1\text{ km}}$) and standard deviation ($\sigma_{SM, 1\text{ km}}$) of disaggregated SMOS soil moisture.

345 same bias in disaggregated data [30]. Consequently, although
346 the possible presence of a bias in SMOS data limits the accuracy
347 in the disaggregated soil moisture, it is not a limiting factor to
348 the applicability of DisPATCH. MODIS derived soil evaporative
349 efficiency is expressed as a linear function of soil temperature

$$SEE_{\text{MODIS}, 1\text{ km}} = \frac{T_{s, \text{max}} - T_{s, 1\text{ km}}}{T_{s, \text{max}} - T_{s, \text{min}}} \quad (4)$$

350 with T_s being the MODIS-derived soil skin temperature,
351 $T_{s, \text{max}}$ the soil skin temperature at $SEE = 0$ and $T_{s, \text{min}}$
352 the soil skin temperature at $SEE = 1$. The linearity of the
353 relationship between soil evaporative efficiency and surface
354 soil temperature was verified using the physically based dual
355 source energy budget model in [31] using a synthetic data set
356 composed of a range of surface soil moisture values and differ-
357 ent atmospheric conditions (results not shown). End-members
358 $T_{s, \text{min}}$ and $T_{s, \text{max}}$ are estimated from the polygons obtained

by plotting MODIS surface temperature against MODIS NDVI 359
and MODIS albedo as in [24]. Derivation of soil temperature is 360
based on a linear decomposition of the surface temperature into 361
its soil and vegetation components as a good approximation of 362
the relationship with fourth power for temperatures [32], [33] 363
and consistent with the triangle method. MODIS-derived soil 364
skin temperature is expressed as 365

$$T_{s, 1\text{ km}} = \frac{T_{\text{MODIS}} - f_{v, 1\text{ km}} T_{v, 1\text{ km}}}{1 - f_{v, 1\text{ km}}} \quad (5)$$

with T_{MODIS} being the 1-km resolution MODIS land sur- 366
face temperature, f_v the MODIS-derived fractional vegetation 367
cover, and T_v the vegetation temperature. In this study, vegeta- 368
tion temperature is estimated using the approach proposed by 369
[28]. In (5), fractional vegetation cover is written as 370

$$f_{v, 1\text{ km}} = \frac{\text{NDVI}_{\text{MODIS}} - \text{NDVI}_s}{\text{NDVI}_v - \text{NDVI}_s} \quad (6)$$

371 with $NDVI_{MODIS}$ being the 1-km resolution MODIS NDVI,
 372 $NDVI_s$ the NDVI corresponding to bare soil, and $NDVI_v$ the
 373 NDVI corresponding to full-cover vegetation. Minimum and
 374 maximum NDVI values are set to 0.15 and 0.90, respectively.

375 In [16], the accuracy and robustness of the disaggregation
 376 methodology were tested using three different formulations of
 377 soil evaporative efficiency [26], [34], [35]. Results based on the
 378 NAFE'06 data set [36], which was collected over a 60 km by
 379 40 km area in the AACES area, indicated that the model in
 380 [26] was better adapted for conditions where soil properties are
 381 unknown at high resolution. Consequently, the partial derivative
 382 in (3) is computed using the soil evaporative efficiency model
 383 in [26]

$$SEE_{mod} = \frac{1}{2} - \frac{1}{2} \cos(\pi \cdot SM/SM_p) \quad (7)$$

384 with SM_p being a soil parameter (in soil moisture unit). In
 385 [26], SM_p was set to the soil moisture at field capacity. In
 386 DisPATCH, SM_p is retrieved at 40-km resolution from SMOS
 387 and aggregated MODIS data [16]. By inverting (7), one obtains

$$SM_{mod} = \frac{SM_p}{\pi} \cos^{-1}(1 - 2 SEE) \quad (8)$$

388 2) *Vegetation Temperature*: Vegetation temperature in (5) is
 389 estimated at 1-km resolution with the ‘‘hourglass’’ approach in
 390 [28]. By plotting the diagonals in the quadrilateral in Fig. 3,
 391 four areas are distinguished in the space defined by surface
 392 temperature and fractional vegetation cover. In zone A, land
 393 surface temperature is mainly controlled by soil evaporation
 394 leading to optimal sensitivity to surface soil moisture. In zone
 395 D, land surface temperature is mainly controlled by vegetation
 396 transpiration with no sensitivity to surface soil moisture. In
 397 zones B and C, land surface temperature is controlled by both
 398 soil evaporation and vegetation transpiration with intermediate
 399 (average) sensitivity to surface soil moisture. Based on this un-
 400 derstanding, vegetation temperature is estimated in a different
 401 manner in each zone.

402 For a given data point located in Zone A, vegetation temper-
 403 ature is

$$T_{v,1 km} = (T_{v,min} + T_{v,max})/2 \quad (9)$$

404 with $T_{v,min}$ and $T_{v,max}$ being the vegetation temperature
 405 at minimum and maximum water stress, respectively. End-
 406 members $T_{v,min}$ and $T_{v,max}$ are estimated from the poly-
 407 gons obtained by plotting MODIS surface temperature against
 408 MODIS NDVI and MODIS albedo as in [24].

409 For a given data point located in Zone B, vegetation temper-
 410 ature is

$$T_{v,1 km} = (T_{v,min,1 km} + T_{v,max})/2 \quad (10)$$

411 with $T_{v,min,1 km}$ being the vegetation temperature associated
 412 with $SEE = 0$ ($T_s = T_{s,max}$).

413 For a given data point located in Zone C, vegetation temper-
 414 ature is

$$T_{v,1 km} = (T_{v,min} + T_{v,max,1 km})/2 \quad (11)$$

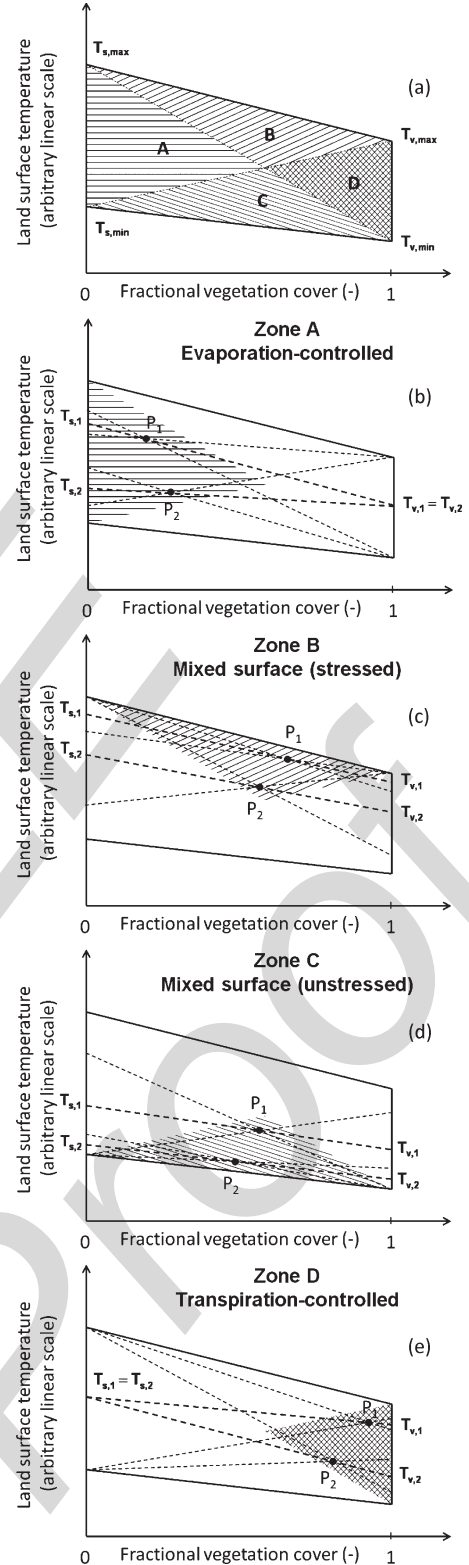


Fig. 3. Polygon defined in the land surface temperature-fractional vegetation cover space contains four distinct zones A, B, C, and D. In Zone A (soil-dominated area), the estimated vegetation temperature is constant leading to optimal sensitivity of estimated soil temperature to surface soil moisture. In Zone D, the estimated soil temperature is constant with no sensitivity to surface soil moisture. In Zone B and C (mixed surface), surface temperature is both controlled by soil evaporation and vegetation transpiration with intermediate (average) sensitivity of estimated soil temperature to surface soil moisture. DisPATCH can be run in the Zone A+B+C mode or in the Zone A only mode.

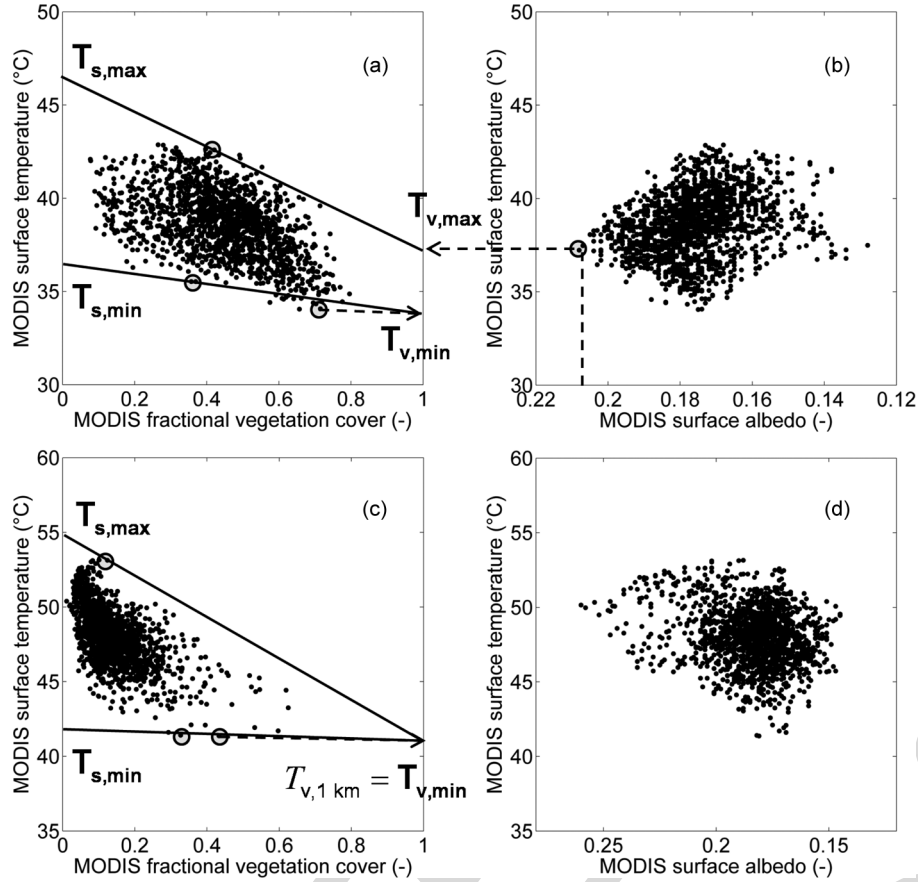


Fig. 4. Temperature end-members $T_{s,\min}$, $T_{s,\max}$, $T_{v,\min}$, and $T_{v,\max}$ are estimated from the surface temperature-fractional vegetation cover space and the surface temperature-surface albedo space within two given SMOS pixels. In (b), the pixel corresponding to the largest MODIS albedo has a fractional vegetation cover larger than 0.5, so that $T_{v,\max}$ is set to its surface temperature. In (d), the pixel corresponding to the largest MODIS albedo has a fractional vegetation cover lower than 0.5, so that $T_{v,\max}$ is set to $T_{v,\min}$.

415 with $T_{v,\max,1\text{ km}}$ being the vegetation temperature associated
 416 with $SEE = 1$ ($T_s = T_{s,\min}$).

417 For a given data point located in Zone D, vegetation temper-
 418 ature is

$$T_{v,1\text{ km}} = (T_{v,\min,1\text{ km}} + T_{s,\max,1\text{ km}})/2 \quad (12)$$

419 3) *End-Members*: End-members $T_{s,\min}$, $T_{s,\max}$, $T_{v,\min}$
 420 and $T_{v,\max}$ are estimated by combining the spatial information
 421 provided by the surface temperature-fractional vegetation cover
 422 space and the surface temperature-albedo space plotted using
 423 MODIS data collected in a 40-km resolution SMOS pixel. An
 424 illustration is provided in Fig. 4 for two given SMOS pixels.

- 425 • $T_{v,\min}$: the vegetation temperature at minimum vegeta-
 426 tion water stress is set to the minimum MODIS surface
 427 temperature in the SMOS pixel [see Fig. 4(a) and (c)].
- 428 • $T_{v,\max}$: the vegetation temperature at maximum vegeta-
 429 tion water stress is set to the MODIS surface tempera-
 430 ture of the pixel with the maximum value of MODIS albedo
 431 in the SMOS pixel [see Fig. 4(b)]. If the fractional vegeta-
 432 tion cover of that pixel is lower than 0.5 [see Fig. 4(d)], the veg-
 433 etation temperature at maximum vegetation water stress
 434 is alternatively set to $T_{v,\min}$, meaning that vegetation is
 435 unstressed within the SMOS pixel. The condition based
 436 on fractional vegetation cover is lower than 0.5 aims to
 437 increase the robustness of the determination approach of

$T_{v,\max}$, particularly in the SMOS pixels where all surface 438
 conditions are not met. 439

- $T_{s,\min}$: the soil temperature at $SEE = 1$ is extrapolated 440
 along the wet soil edge at $f_v = 0$. The wet soil edge 441
 is defined as the line passing through $(1, T_{v,\min})$ and 442
 through the data point such that all the data points with 443
 $f_v < 0.5$ are located above the wet soil edge [see Fig. 4(a) 444
 and (c)]. 445
- $T_{s,\max}$: the soil temperature at $SEE = 0$ is extrapolated 446
 along the dry soil edge at $f_v = 0$. The dry soil edge 447
 is defined as the line passing through $(1, T_{v,\max})$ and 448
 through the data point such that all the data points with 449
 $f_v < 0.5$ are located below the dry soil edge [see Fig. 4(a) 450
 and (c)]. 451

B. Atmospheric Correction 452

In MOD11A1 and MYD11A1 products, the land surface 453
 temperature is derived from MODIS thermal radiances using 454
 the split window algorithm [37] 455

$$T_{\text{MODIS}} = C + \left(A_1 + A_2 \frac{1 - \epsilon}{\epsilon} + A_3 \frac{\Delta \epsilon}{\epsilon^2} \right) \frac{Tb_{31} + Tb_{32}}{2} + \left(B_1 + B_2 \frac{1 - \epsilon}{\epsilon} + B_3 \frac{\Delta \epsilon}{\epsilon^2} \right) \frac{Tb_{31} - Tb_{32}}{2} \quad (13)$$

456 with Tb_{31} and Tb_{32} being the brightness temperatures mea-
 457 sured in the MODIS bands 31 and 32, respectively, ϵ_{31} and ϵ_{32}
 458 the surface emissivities estimated in the respective bands, and
 459 $A_1, A_2, A_3, B_1, B_2, B_3,$ and C regression coefficients. These
 460 coefficients are available during algorithm execution via a look
 461 up table stratified by subranges of near surface air temperature
 462 and total column water vapor. These input field are obtained at
 463 a 5-km resolution from the MODIS07_L2 product.

464 Given that regression coefficients in (13) are provided at
 465 5-km resolution, the atmospheric corrections on the MODIS
 466 land surface temperature product are actually made at 5-km
 467 resolution. To test whether atmospheric corrections on MODIS
 468 temperature have an impact on disaggregation results, a differ-
 469 ent procedure is proposed to obtain another temperature data
 470 set whose atmospheric corrections are operated at the scale
 471 of a SMOS pixel, i.e., at 40-km resolution (instead of 5-km
 472 resolution for the official MODIS temperature product). The
 473 approach is to normalize the mean MODIS radiance-derived
 474 brightness temperature at the SMOS resolution. Normalization
 475 is done by adjusting the minimum and maximum mean MODIS
 476 brightness temperature to the minimum and maximum value
 477 of the official MODIS land surface temperature product within
 478 the SMOS pixel, respectively. The new temperature noted
 479 $T_{MODIS}^{unif. corr.}$ (uniform atmospheric corrections) is written

$$T_{MODIS}^{unif. corr.} = T_{MODIS, min} + (T_{MODIS, max} - T_{MODIS, min}) \times \frac{Tb_{31} + Tb_{32} - \text{Min}(Tb_{31} + Tb_{32})}{\text{Max}(Tb_{31} + Tb_{32}) - \text{Min}(Tb_{31} + Tb_{32})} \quad (14)$$

480 with $T_{MODIS, min}$ and $T_{MODIS, max}$ being the minimum and
 481 maximum MODIS land surface temperature within the SMOS
 482 pixel, and $\text{Min}()$ and $\text{Max}()$ the function that returns the mini-
 483 mum and maximum value within the SMOS pixel, respectively.
 484 Note that the underlying assumptions of (14) are:

- 485 • near surface air temperature and column water vapor vary
 486 at scales larger than 40 km (size of a SMOS pixel).
- 487 • surface emissivity is close to 1.

488 C. Algorithm

489 The steps used in applying DisPATCH include: 1) select-
 490 ing the SMOS pixels with at least 90% (clear sky) MODIS-
 491 retrieved land surface temperature coverage; 2) computing
 492 soil evaporative efficiency over nominal MODIS pixels with
 493 (4); 3) estimating soil evaporative efficiency over non-nominal
 494 MODIS pixels; 4) retrieving parameter SM_p ; 5) applying the
 495 downscaling relationship of (3); 6) correcting disaggregated
 496 soil moisture by the SMOS pixel weighting function; and 7)
 497 compositing on a daily basis the disaggregation output en-
 498 semble [21]. The input and output data and their link within
 499 DisPATCH are summarized in Fig. 5.

500 1) *Selecting Clear Sky SMOS Pixels:* A threshold of 90%
 501 cloud-free MODIS coverage is used to select the SMOS pix-
 502 els to be disaggregated. In the official MODIS land surface
 503 temperature product (MOD11A1 for Terra and MYD11A1 for
 504 Aqua), the data affected by the presence of clouds are already
 505 masked. Hence, selection of the 90% clear sky SMOS pixels is

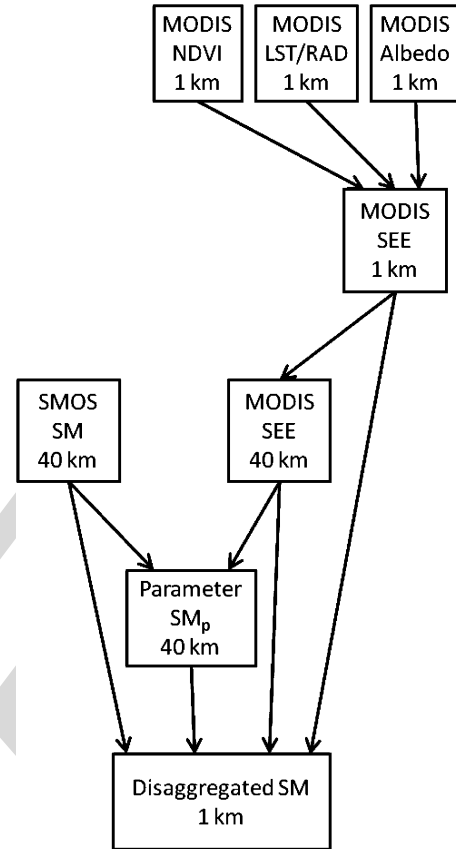


Fig. 5. Schematic diagram presenting the input and output data of DisPATCH.

506 directly based on the MODIS land surface temperature product
 507 masking.

508 2) *Non-Nominal Pixels:* Nominal MODIS pixels are de-
 509 fined as the 1-km resolution pixels that do not include open
 510 water and where land surface temperature is actually retrieved.
 511 Open water pixels are flagged in the algorithm when MODIS
 512 NDVI retrievals yield negative values. The soil evaporative
 513 efficiency of open water pixels is set to 1. The emerged pixels
 514 where land surface temperature is not retrieved (due to the
 515 presence of some clouds within the SMOS pixel) are processed
 516 as pixels with mean surface conditions. In practice, the soil
 517 evaporative efficiency of cloudy pixels (which represent less
 518 than 10% of the surface area within the SMOS pixel) is set to
 519 the mean soil evaporative efficiency calculated over the clear
 520 sky MODIS pixels. Allocating a soil evaporative efficiency
 521 value to non-nominal pixels allows DisPATCH to be run over a
 522 wider range of SMOS pixels, including those partially covered
 523 by clouds. However, non-nominal 1-km resolution pixels are
 524 flagged and discarded from the disaggregation output ensemble.

525 3) *Forested Areas:* In this study, DisPATCH is applied to all
 526 the SMOS pixels where the soil moisture retrieval is successful,
 527 even those including forest class, as long as the 1 km MODIS
 528 pixels are in Zone A, B or C (see Fig. 3). This choice is
 529 relevant here because the ACES extensive data were almost
 530 exclusively collected in agricultural areas (cropping/grazing),
 531 so forests for this study are not an issue. In the case of a
 532 mixed SMOS pixel including a significant fraction of forest,
 533 DisPATCH should be applied to the surface area of the dominant

534 class, thus excluding the surface area of the minority land cover
535 classes.

536 4) *Calibration*: The soil moisture parameter SM_p used to
537 compute $\partial SM_{mod}/\partial SEE$ in (3) is estimated by inverting the
538 SEE model in (7) at SMOS resolution

$$SM_p = \frac{\pi \cdot SM_{SMOS}}{\cos^{-1}(1 - 2\langle SEE_{MODIS, 1 \text{ km}} \rangle_{40 \text{ km}})} \quad (15)$$

539 A value of SM_p is obtained for each SMOS pixel and each
540 input data set. Note that the main assumption limiting validity
541 of the calibration approach is the soil evaporative efficiency
542 model [26] itself. The soil evaporative efficiency model in [26]
543 was chosen for its simplicity (one parameter) and its ability
544 to represent the general behavior of soil evaporative efficiency
545 over the full range of soil moisture: particularly the null deriva-
546 tive at zero and at maximum soil moisture, and an inflexion
547 point in between [38]. However, it has some inconsistencies.
548 In particular, [38] have indicated that 1) potential evaporation
549 is physically reached at soil saturation and not at field capac-
550 ity; therefore the model in [26] should be (strictly speaking)
551 parameterized by the soil moisture at saturation and not by the
552 soil moisture at field capacity, and 2) soil evaporative efficiency
553 varies with potential evaporation, meaning that the soil moisture
554 parameter (set to the soil moisture at field capacity in [26])
555 should theoretically vary in time with atmospheric evaporative
556 demand. Consequently, the SM_p retrieved from SMOS and
557 MODIS data using the model in [26] is definitely not the soil
558 moisture at field capacity as in [26], although it could be in part
559 related to it. In this study, SM_p is therefore considered to be a
560 fitting parameter self-estimated by DisPATCH.

561 5) *Weighting Function*: A SMOS pixel WEighting Function
562 (WEF) is used to take into account the impact of soil mois-
563 ture distribution on the SMOS scale soil moisture as seen by
564 SMOS radiometer. A centrosymmetric analytical approxima-
565 tion MEAN_WEF is provided in [19], [20]

$$MEAN_WEF(\rho) = C_{MWEF2} + WEF_A \left(\frac{\rho}{C_{MWEF1}} \cdot \frac{\pi}{C_{WEF1}} \right) \quad (16)$$

566 with ρ being the distance from the SMOS pixel center, and
567 $C_{MWEF1} = 40 \text{ km}$, $C_{MWEF2} = 0.027$, $C_{WEF1} = 73.30$ and

$$WEF_A(\rho') = \frac{[\text{sinc}(C_{WEF1} \cdot \rho')]^{C_{WEF2}}}{1 + C_{WEF3} \cdot \rho'^{C_{WEF4}}} \quad (17)$$

568 with ρ' being the distance in the director cosines coordinates,
569 $\text{sinc}(x) = \sin(x)/x$, and $C_{WEF2} = 1.4936$, $C_{WEF3} = 524.5$
570 and $C_{WEF4} = 2.103$.

571 A correction is applied to disaggregated soil moisture in (3)

$$SM_{1 \text{ km}}^{wef \text{ corr.}} = SM_{1 \text{ km}} + \frac{\sum MEAN_WEF(\rho) \cdot SM_{1 \text{ km}}(\rho)}{\sum MEAN_WEF(\rho)} - SM_{SMOS} \quad (18)$$

572 with $SM_{1 \text{ km}}^{wef \text{ corr.}}$ being the WEF-corrected disaggregated
573 soil moisture. Mathematically speaking, one should replace
574 SM_{SMOS} with $\sum MEAN_WEF \cdot SM_{1 \text{ km}} / \sum MEAN_WEF$
575 in (3) and (15) and run an iteration loop until convergence

of $SM_{1 \text{ km}}^{wef \text{ corr.}}$ values. However, the impact of the WEF on
disaggregated soil moisture is expected to be low so that the
simple correction in (18) is considered to be sufficient for the
purpose of the study.

6) *Disaggregation Output*: The downscaling relationship in
(3) is applied to each input data set, and the disaggregated soil
moisture data ensemble is averaged on each 1-km resolution
pixel within the study area. Averaging is a way to reduce
random uncertainties in the disaggregation output. In [17], [27],
disaggregated soil moisture was averaged in space (aggregated)
at the expense of downscaling resolution. Herein, temporal
averaging [30] is preferred to keep an optimal downscaling
resolution. Note that a condition to average disaggregated soil
moisture in time is the availability of thermal infrared data
at high temporal frequency. Another significant advantage of
applying DisPATCH to an input ensemble is to provide an
estimate of the uncertainty in 1-km resolution disaggregated
soil moisture, e.g., by computing the standard deviation within
the output ensemble.

IV. APPLICATION

To test DisPATCH under various surface and atmospheric
conditions, the algorithm is run during AACES-1 and AACES-
2 in different modes, by including (or not) a correction for
vegetation and atmospheric effects. In each case, disaggregated
SMOS soil moisture and HDAS measurements are compared
at 1-km resolution for all date-farm units with overlapping
HDAS/SMOS/MODIS data.

A. Null Hypothesis

In this study, the null hypothesis is defined as the application
of DisPATCH with parameter SM_p set to zero in (8). Hence,
the downscaling relationship in (3) becomes

$$SM_{1 \text{ km}} = SM_{SMOS} \quad (19)$$

meaning that no 1-km information is used. Defining a null
hypothesis is useful to test whether DisPATCH is able to re-
produce the subpixel variability within the $\sim 10 \text{ km}^2$ sam-
pling farms with better skill than simply assuming a uniform
moisture condition. Statistical results in terms of root mean
square difference, mean difference, correlation coefficient, and
slope of the linear regression between the SMOS soil moisture
disaggregated with (19) and *in situ* measurements are listed in
Table III. One observes that the root mean square difference
is generally explained by a (negative) bias in SMOS data and
that none of the correlations evaluated at 1-km resolution for
each farm separately is statistically significant (all calculated p-
values are larger than 0.10). Thus, the rationale for developing
DisPATCH is to improve the correlation at fine scale between
SMOS and ground soil moisture and to reduce the bias in
disaggregated SMOS data in the specific case where the bias
in SMOS data at the farm scale is due to the heterogeneity of
soil moisture within the SMOS pixel.

TABLE III
DISPATCH IS RUN WITH NO 1-km INFORMATION (SM_p SET TO ZERO) AND STATISTICAL RESULTS ARE LISTED IN TERMS OF ROOT MEAN SQUARE DIFFERENCE (RMSD), MEAN DIFFERENCE (BIAS), CORRELATION COEFFICIENT (R), AND SLOPE OF THE LINEAR REGRESSION BETWEEN 1-km RESOLUTION DISAGGREGATED SMOS SOIL MOISTURE AND 1-km AGGREGATED *In Situ* MEASUREMENTS. THE MEAN AND STANDARD DEVIATION OF GROUND MEASUREMENTS ($\langle SM_{HDAS} \rangle$ AND σ_{HDAS}), THE NUMBER OF CONSIDERED 1-km PIXELS, AND STATISTICAL SIGNIFICANCE (P-VALUE) ARE ALSO LISTED FOR EACH DATE-FARM UNIT

DoY/Farm	$\langle SM_{HDAS} \rangle$ (m^3/m^3)	σ_{HDAS} (m^3/m^3)	Number of 1 km pixels	RMSD (m^3/m^3)	Bias (m^3/m^3)	R^\dagger (-)	Slope ‡ (-)	p-value (-)
28/F05	0.04	0.02	7	0.04	-0.04	-	-	1.0
30/F07	0.02	0.03	8	0.02	-0.02	-	-	1.0
30/F08	0.03	0.02	7	0.02	-0.02	-	-	0.69
46/F15	0.29	0.05	8	0.04	0.03	-	-	0.91
46/F16	0.34	0.06	8	0.09	-0.08	-	-	1.0
49/F17	0.21	0.06	8	0.04	-0.04	-	-	0.66
49/F18	0.25	0.07	6	0.08	-0.08	-	-	0.42
49/F20	0.20	0.09	4	0.02	-0.007	-	-	0.87
51/F19	0.24	0.08	6	0.13	-0.13	-	-	0.77
51/F20	0.20	0.10	6	0.09	-0.08	-	-	0.79
AACES-1 mean ‡	-	-	-	-	-	-	-	>0.10
254/F09	0.33	0.07	9	0.13	-0.13	-	-	0.13
256/F07	0.36	0.10	8	0.19	-0.18	-	-	0.15
264/F13	0.30	0.07	8	0.18	-0.17	-	-	1.0
265/F15	0.25	0.06	7	0.05	-0.05	-	-	1.0
267/F09	0.21	0.07	9	0.14	-0.14	-	-	0.43
AACES-2 mean ‡	-	-	-	-	-	-	-	>0.10

† R and slope values are reported if p-value < 0.10.

‡ the mean values computed for AACES-1 and AACES-2 include only statistically significant (p-value < 0.10) results.

625 B. Visual Assessment of Disaggregation Images

626 As an example, DisPATCH is applied on DoY 49 over a 120
627 km by 80 km subarea including the farms F16, F17, F18, F19,
628 and F20. The images of 1-km resolution disaggregated SMOS
629 soil moisture are presented in Fig. 6. DisPATCH is run with
630 SM_p set to zero (null hypothesis) and in four distinct modes
631 corresponding to the combinations of the “LST” (the official
632 MODIS land surface temperature product is used) and “RAD”
633 [the land surface temperature is derived from MODIS radiances
634 using (14)] modes and the “Zone A+B+C” (the vegetation-
635 transpiration dominated 1-km pixels are discarded) and “Zone
636 A only” (only the soil evaporation-dominated 1-km pixels are
637 selected) modes.

638 In Fig. 6, the SMOS DGG nodes where level-2 soil moisture
639 is successfully retrieved are overlaid on the image correspond-
640 ing to the null hypothesis (resampled SMOS data with no 1-km
641 information) for 6 am and 6 pm overpass times separately. The
642 gaps in SMOS data in the lower middle part of the images
643 are due to topography flagging over the Australian Alps. In
644 the version-4 SMOS level-2 processor, soil moisture is not
645 retrieved at the DGG nodes where the topography effects on
646 simulated brightness temperatures exceed a certain threshold,
647 so as to prevent large errors in soil moisture values. The appar-
648 ent resolution of the null hypothesis image is 20 km because
649 it is generated from the composition of four 40-km resolution
650 resampled SMOS snapshot images, whose resampling grids are

651 separated by 20 km (the SMOS level-2 data resampling strategy
652 was described in Section II-B.).

Note that the disaggregation products in the Zone A+B+C
653 mode cover an area larger than the area sampled by SMOS
654 data, because the SMOS resolution (about 40 km) is larger
655 than the SMOS product sampling length (about 15 km), but
656 does not provide disaggregated values at a distance larger than
657 20 km from the successful retrieval nodes. Concerning the Zone
658 A only mode, disaggregation products do not cover an area
659 larger than the SMOS sampling area because the Australian
660 Alps are surrounded by forests where the fraction of bare soil is
661 less than elsewhere in the area, and which correspond to Zone
662 B or C in the hourglass in Fig. 3.

663 When looking at the images obtained in the Zone A+B+C
664 mode in Fig. 6, one observes that the spatial structures of
665 1-km disaggregated SMOS soil moisture encompass, but does
666 not seem to be correlated with, the SMOS data sampling
667 length. However, a “boxy artifact” is still apparent at 20-km
668 resolution, which is the separation length of the SMOS data
669 resampling grids as explained in Section II-B. The notion of
670 “boxy artifact” was introduced by [39] to analyze the quality of
671 a disaggregation approach. The less apparent the low-resolution
672 boxes, the better the disaggregation skill of the algorithm to
673 spatially connect high-resolution disaggregated values between
674 neighboring low-resolution pixels, and thus to derive a realistic
675 high-resolution soil moisture field. When comparing the images
676 obtained in the Zone A+B+C mode with those obtained in the
677

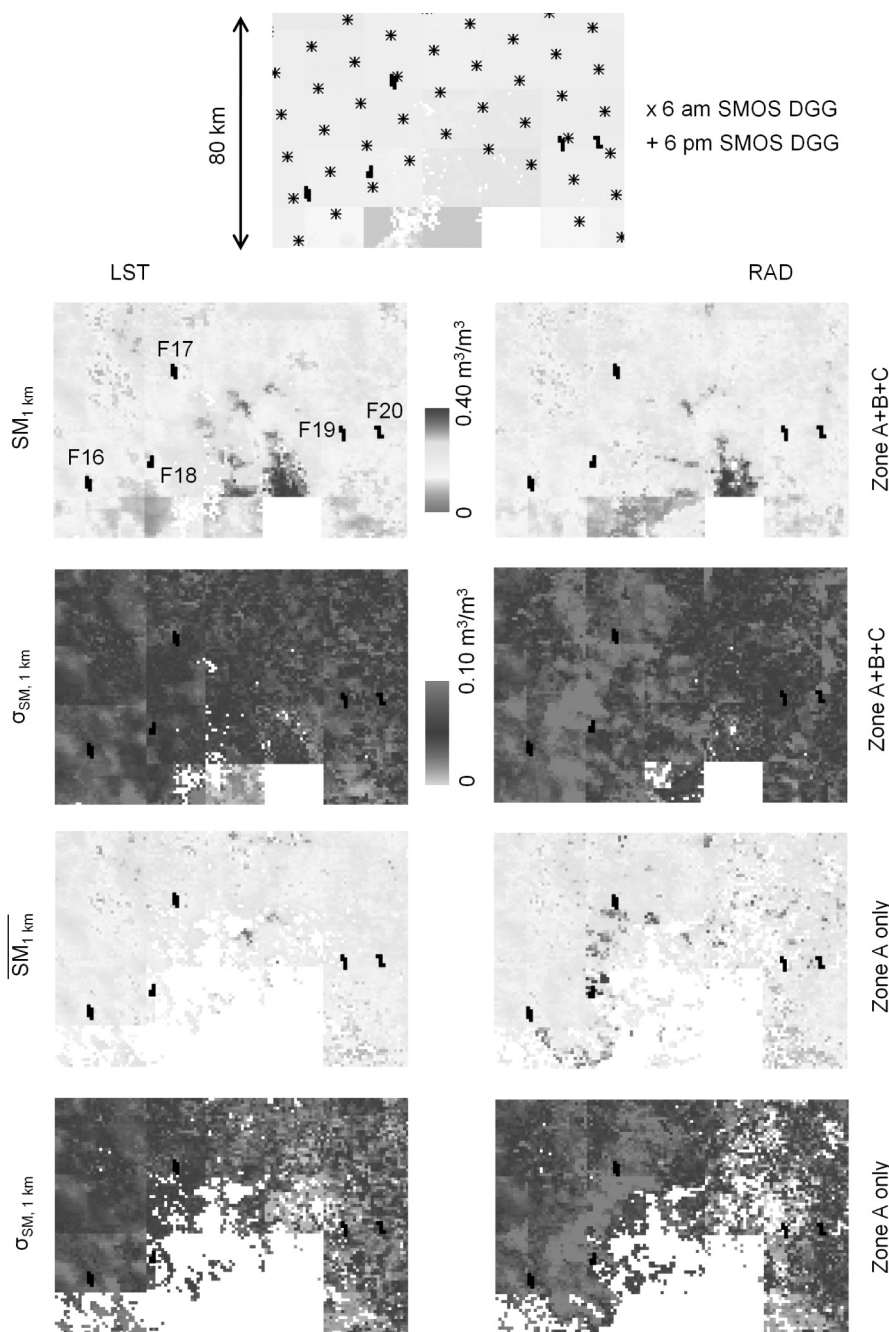


Fig. 6. Images of disaggregation results over a 120 km by 80 km subarea on DoY 49. The disaggregated soil moisture ($\overline{SM}_{1 \text{ km}}$) and its estimated uncertainty ($\sigma_{SM, 1 \text{ km}}$) are compared in the LST and RAD modes and in the Zone A+B+C and Zone A only modes. Sampling farms are overlaid on all images. SMOS DGG nodes are overlaid on the image corresponding to the null hypothesis (no 1-km resolution information) presented at top.

678 Zone A only mode, one observes that the 20-km resolution boxy
 679 artifact is less apparent in the Zone A only mode, consistent
 680 with the better sensitivity of MODIS-derived SEE with soil-
 681 dominated pixels (Zone A) than with mixed-surface (Zone B
 682 and C) pixels. In Fig. 6, the images obtained in the LST and
 683 RAD mode highlight different spatial structures. In general,
 684 there are less data gaps in the RAD than in the LST mode.
 685 However, ground validation data are required to assess their
 686 relative quality/accuracy.

687 As an assessment of the uncertainty in composited soil mois-
 688 ture disaggregation, the standard deviation within the disaggre-
 689 gation output ensemble is also reported for each disaggregation

product in Fig. 6. The same observations can be made as with 690
 the soil moisture images: spatial structures are more visible, and 691
 the boxy artifact is less apparent in the RAD than in the LST 692
 mode. In general, the estimated uncertainty in disaggregated 693
 products is larger in the RAD than in the LST mode, regardless 694
 of the Zone (A+B+C or A only) mode. 695

C. SMOS Weighting Function

696

To evaluate the impact of the SMOS instrument weighting 697
 function on disaggregation results, DisPATCH is run with (and 698
 without) the WEF correction in (18). The expected effect of the 699

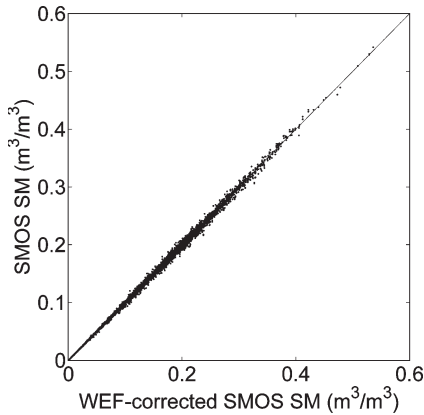


Fig. 7. Uncorrected versus WEF-corrected SMOS soil moisture for the entire data set.

700 WEF is a bias at 40 km resolution on disaggregated soil mois-
 701 ture. Fig. 7 plots the uncorrected against WEF-corrected SMOS
 702 soil moisture for the entire data set including both AACES-1
 703 and AACES-2 experiments. The WEF correction has very
 704 little impact on disaggregated soil moisture with a maximum
 705 difference between uncorrected and WEF-corrected SMOS soil
 706 moisture of $0.02 \text{ m}^3/\text{m}^3$, a mean difference of approximately
 707 zero, and a standard deviation of $0.003 \text{ m}^3/\text{m}^3$. Although the
 708 difference is small with this data set, WEF-corrected products
 709 are expected to be more realistic. Therefore, the correction in
 710 (18) is used in all the DisPATCH runs that follow.

711 D. Quantitative Comparison With In Situ Measurements

712 Fig. 8 presents the scatterplots of 1-km resolution disaggre-
 713 gated SMOS soil moisture versus 1-km resolution aggregated
 714 *in situ* measurements for the ten date-farm units during
 715 AACES-1. On each graph are plotted the soil moisture dis-
 716 aggregated in the Zone A+B+C mode (empty squares) and
 717 the soil moisture disaggregated in the Zone A only mode
 718 (black squares). At the beginning of AACES-1, conditions are
 719 very dry so that SMOS retrievals are close to zero and the
 720 variability of *in situ* measurements is low (about $0.02 \text{ m}^3/\text{m}^3$).
 721 In such conditions, no useful information is expected from the
 722 application of DisPATCH, and the statistical results in terms of
 723 spatial correlation are not meaningful for DoY 28/F05, DoY
 724 30/F07 and DoY 30/F08. While wetter conditions occur after
 725 DoY 30, cloud cover prevents DisPATCH to be run (MODIS
 726 data are unavailable) until DoY 46. On DoY 46, the average
 727 and standard deviation of *in situ* soil moisture measurements is
 728 $0.32 \text{ m}^3/\text{m}^3$ and $0.06 \text{ m}^3/\text{m}^3$, respectively. The spatial variabil-
 729 ity of 1-km soil moisture is nicely captured by DisPATCH no-
 730 tably in the RAD mode. On DoY 49, the disaggregated SMOS
 731 soil moisture is still correlated with the *in situ* measurements
 732 made in three farms (F17, F18, and F20). On the last ground
 733 sampling day, disaggregation results are significantly correlated
 734 with *in situ* measurements in F19, but not in F20. The poor
 735 results obtained with DoY 51/F20 is probably due to the time
 736 gap (3 days) between ground sampling date (DoY 51) and
 737 MODIS overpass day (DoY 54).

738 Statistical results in terms of root mean square difference,
 739 mean difference, correlation coefficient, and slope of the linear

regression between the SMOS soil moisture disaggregated in 740
 the Zone A+B+C mode and aggregated *in situ* measurements 741
 are listed in Table IV. Statistical significance (p-value) is also 742
 reported for each date-farm unit to select statistically significant 743
 (p-value < 0.10) results. Although the disaggregation of SMOS 744
 data on extensively dry DoY 30 does not provide any additional 745
 information (soil is uniformly dry), the observed correlation 746
 between disaggregated (LST mode) and *in situ* soil moisture 747
 is statistically significant, and the correlation coefficient value 748
 is negative (-0.70 and -0.95 at F07 and F08, respectively). 749
 One plausible explanation is the opposite effect of soil temper- 750
 ature on HDAS soil moisture measurements and on MODIS- 751
 derived soil evaporative efficiency: a slight undercorrection of 752
 the temperature-corrected hydraprobe measurements at high 753
 temperature [18] results in a slight increase of soil moisture 754
 estimate with soil temperature, while an increase of soil temper- 755
 ature makes soil evaporative efficiency decrease. Nevertheless, 756
 the possible impact of soil temperature on HDAS measurements 757
 is very low with a slope of the linear regression between 758
 disaggregated SMOS and *in situ* soil moisture calculated as 759
 -0.08 and -0.03 for F07 and F08, respectively. When selecting 760
 statistically significant results (p-value < 0.10) and discarding 761
 data for DoY 30, the mean correlation coefficient and slope in 762
 RAD mode are 0.75 and 0.58, respectively. 763

Fig. 9 presents the scatterplots of 1-km resolution disaggre- 764
 gated SMOS soil moisture versus 1-km resolution aggregated *in* 765
situ measurements for the five date-farm units during AACES- 766
 2. On each graph are plotted the soil moisture disaggregated in 767
 the Zone A+B+C mode (empty squares) and the soil moisture 768
 disaggregated in the Zone A only mode (black squares). The 769
 surface conditions of AACES-2 were relatively wet with a mean 770
 soil moisture value estimated as $0.29 \text{ m}^3/\text{m}^3$. The disaggre- 771
 gated SMOS soil moisture does not correlate well with *in situ* 772
 measurements with a p-value larger than 0.10 for all sampling 773
 days, except for DoY 256/F07 in LST mode (see Table IV). The 774
 negative correlation coefficient (-0.73) obtained on DoY 256 is 775
 discussed when comparing the Zone A+B+C and Zone A only 776
 modes in Section IV-F. In general, statistical results in Table IV 777
 indicate that DisPATCH does not succeed in representing the 778
 variability of soil moisture at 1-km resolution during AACES- 779
 2. In fact, DisPATCH is based on the tight coupling that occurs 780
 between soil moisture and evaporation under high evaporative 781
 demand conditions [40]. This coupling seems to be weak in 782
 September over the study area so that the disaggregation results 783
 at 1-km resolution are not reliable. 784

For DoY 264/F13, however, an interesting feature is ob- 785
 served on the graph corresponding to the RAD and Zone A 786
 only modes. When removing the (three) black squares with 787
 the largest errorbars, the correlation coefficient and the slope 788
 of the linear regression between disaggregated and *in situ* 789
 observations becomes 0.9 and 0.7, respectively. This suggests 790
 that: 1) the standard deviation within the disaggregation output 791
 ensemble can be a good estimate of the uncertainty in the 792
 composited disaggregation product; and 2) the applicability of 793
 DisPATCH is greatly dependent on the quality of MODIS land 794
 surface temperature. Note that in this study, a choice was made 795
 to maximize the number of data points used in the comparison 796
 with *in situ* measurements. Consequently, all the cloud-free 797

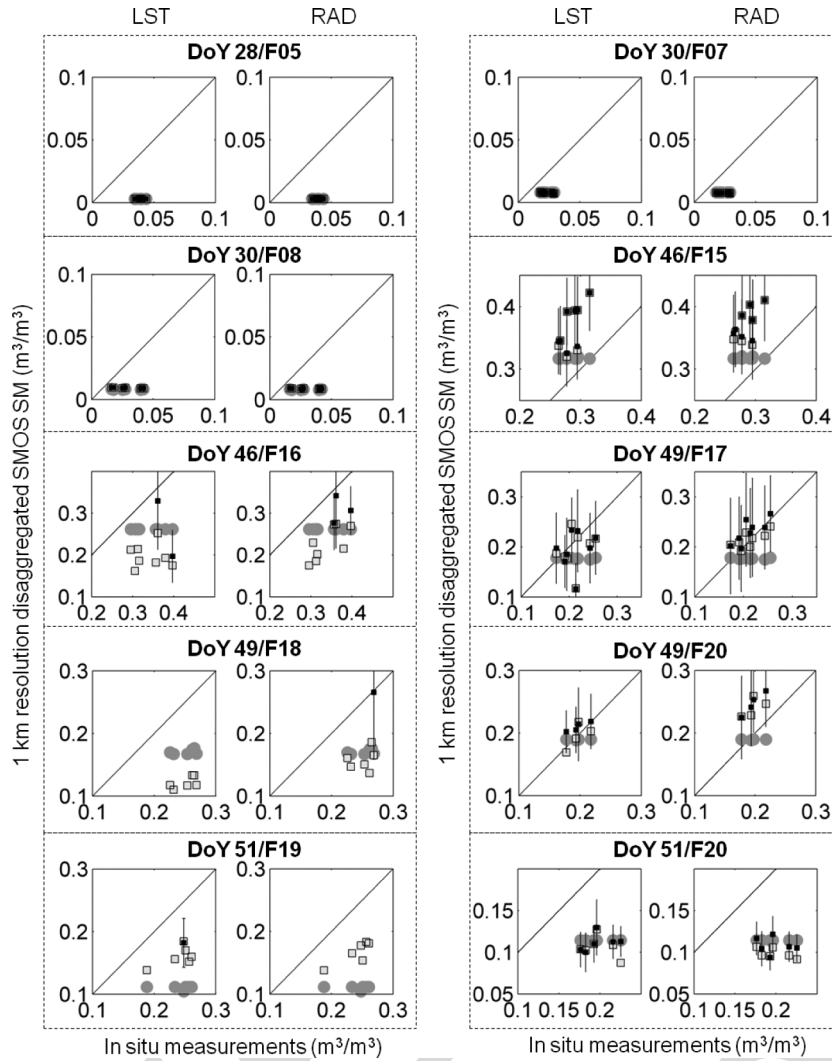


Fig. 8. Scatterplots of 1-km resolution disaggregated SMOS soil moisture versus 1-km resolution aggregated *in situ* measurements for each of the ten date-farm data sets during AACES-1. The filled circles correspond to disaggregation with no 1-km information, empty squares to Zone A+B+C mode and black squares to Zone A only mode. For the Zone A only mode, the uncertainty in disaggregated soil moisture is represented by vertical errorbars.

798 MODIS land surface temperature data were used regardless
 799 of the MODIS land surface temperature quality index. Further
 800 research should be conducted to assess whether selecting the
 801 MODIS pixel with the best MODIS land surface temperature
 802 quality index would improve the disaggregation results. This
 803 would be possible using the AACES airborne data, which cover
 804 a much larger area than *in situ* measurements.

805 *E. Atmospheric Corrections*

806 The impact of atmospheric corrections on DisPATCH output
 807 is analyzed by comparing the disaggregation results obtained
 808 in the LST and RAD mode. Quantitative comparison between
 809 LST and RAD modes is provided in Table IV in terms of root
 810 mean square difference, mean difference, correlation coeffi-
 811 cient, and slope of the linear regression between disaggregated
 812 SMOS soil moisture and aggregated *in situ* measurements.
 813 Correlation coefficient and slope values are reported only if
 814 the p-value (statistical significance) is lower than 0.10. It is
 815 apparent that statistical results are better in the RAD than in

the LST mode. When including all dates, the mean bias is 816
 decreased from $-0.05 \text{ m}^3/\text{m}^3$ in LST mode to $-0.03 \text{ m}^3/\text{m}^3$ 817
 in RAD mode during AACES-1. When selecting statistically 818
 significant results (p-value < 0.10) and discarding data for 819
 DoY 30, the mean correlation coefficient and slope is 0.75 and 820
 0.58 in RAD mode, and 0.65 and 1.5 in LST mode, respectively. 821
 Note that the improvement is very significant for DoY 46/F16 822
 with a correlation coefficient and slope increasing from about 823
 zero to 0.7 and 0.8, respectively. 824

The fact that the results obtained in RAD mode are superior 825
 to those obtained in LST mode indicates that the atmospheric 826
 corrections of the official MODIS land surface temperature 827
 add significant uncertainties in the disaggregation products. 828
 One rationale may be that the information used in atmospheric 829
 corrections (notably air temperature and water vapor profile 830
 data) are subjected to large uncertainties at 5-km resolution. 831
 As DisPATCH is based on the spatial variations of MODIS 832
 temperature relative to the 40 km scale mean, the atmospheric 833
 corrections on the land surface temperature data are not nec- 834
 essary at 5 km (as it is done in the MODIS temperature 835

TABLE IV
DISPATCH IS RUN IN THE ZONE A+B+C MODE AND STATISTICAL RESULTS ARE LISTED IN TERMS OF ROOT MEAN SQUARE DIFFERENCE (RMSD), MEAN DIFFERENCE (BIAS), CORRELATION COEFFICIENT (R), AND SLOPE OF THE LINEAR REGRESSION BETWEEN 1-KM RESOLUTION DISAGGREGATED SMOS SOIL MOISTURE AND 1-KM AGGREGATED *In Situ* MEASUREMENTS. THE RESULTS OBTAINED USING THE RADIANCE-DERIVED LAND SURFACE TEMPERATURE DATA (RAD MODE) AND USING THE OFFICIAL MODIS LAND SURFACE TEMPERATURE DATA (LST MODE IN PARENTHESIS) ARE COMPARED. THE MEAN AND STANDARD DEVIATION OF GROUND MEASUREMENTS ($\langle SM_{HDAS} \rangle$ AND σ_{HDAS}), THE NUMBER OF CONSIDERED 1-KM PIXELS AND STATISTICAL SIGNIFICANCE (P-VALUE) ARE ALSO LISTED FOR EACH DATE-FARM UNIT

DoY/Farm	$\langle SM_{HDAS} \rangle$ (m^3/m^3)	σ_{HDAS} (m^3/m^3)	Number of 1 km pixels	RMSD (m^3/m^3)	Bias (m^3/m^3)	R^\dagger (-)	Slope ‡ (-)	p-value (-)
28/F05	0.04	0.02	7 (7)	0.04 (0.04)	-0.04 (-0.04)	- (-)	- (-)	0.72 (0.80)
30/F07	0.02	0.03	8 (8)	0.02 (0.02)	-0.02 (-0.02)	- (-0.70)	- (-0.08)	0.20 (0.05)
30/F08	0.03	0.02	7 (7)	0.02 (0.02)	-0.02 (-0.02)	- (-0.95)	- (-0.03)	0.11 (0.001)
46/F15	0.29	0.05	8 (8)	0.09 (0.09)	0.09 (0.08)	- (0.65)	- (1.5)	0.12 (0.08)
46/F16	0.34	0.06	8 (8)	0.12 (0.15)	-0.11 (-0.14)	0.72 (-)	0.76 (-)	0.04 (0.95)
49/F17	0.21	0.06	8 (8)	0.02 (0.04)	0.00 (-0.02)	0.70 (-)	0.42 (-)	0.05 (0.54)
49/F18	0.25	0.07	6 (6)	0.10 (0.13)	-0.09 (-0.13)	- (-)	- (-)	0.60 (0.20)
49/F20	0.20	0.09	4 (4)	0.05 (0.01)	0.04 (0.00)	- (-)	- (-)	0.41 (0.32)
51/F19	0.24	0.08	6 (6)	0.07 (0.08)	-0.07 (-0.08)	0.84 (-)	0.56 (-)	0.04 (0.19)
51/F20	0.20	0.10	6 (6)	0.10 (0.09)	-0.10 (-0.09)	- (-)	- (-)	0.17 (0.51)
AACES-1 mean ‡	0.26 (0.29)	0.07 (0.05)	7 (8)	0.07 (0.09)	-0.06 (-0.08)	0.75 (0.65)	0.58 (1.5)	0.04 (0.08)
254/F09	0.33	0.07	9 (9)	0.18 (0.14)	-0.16 (-0.11)	- (-)	- (-)	0.17 (0.74)
256/F07	0.36	0.10	8 (9)	0.12 (0.19)	-0.10 (-0.18)	- (-0.73)	- (-0.47)	0.12 (0.04)
264/F13	0.30	0.07	8 (8)	0.16 (0.19)	-0.14 (-0.16)	- (-)	- (-)	0.59 (0.47)
265/F15	0.25	0.06	7 (7)	0.16 (0.18)	0.01 (0.03)	- (-)	- (-)	0.32 (0.34)
267/F09	0.21	0.07	9 (9)	0.16 (0.15)	-0.15 (-0.15)	- (-)	- (-)	0.90 (0.86)
AACES-2 mean ‡	0.36	0.10	- (9)	- (0.19)	- (-0.18)	- (-0.73)	- (-0.47)	>0.10 (0.04)

† R and slope values are reported if p-value < 0.10.

‡ the mean values computed for AACES-1 and AACES-2 include only statistically significant (p-value < 0.10) results and discard extensive dry days DoY 28-30.

836 algorithm). An atmospheric correction at 40-km resolution is
837 sufficient and provides even better disaggregation results that
838 applying an atmospheric correction at 5-km resolution.

839 F. Vegetation Cover

840 The impact of vegetation cover on DisPATCH output during
841 AACES-1 is analyzed by comparing the disaggregation results
842 obtained in the Zone A+B+C and Zone A only mode. Quan-
843 titative comparison between Zone A+B+C and Zone A only
844 modes is provided in Tables IV and V in terms of root mean
845 square difference, mean difference, correlation coefficient, and
846 slope of the linear regression between disaggregated SMOS soil
847 moisture and aggregated *in situ* measurements. It is apparent
848 that statistical results are generally better in the Zone A only
849 than in the Zone A+B+C mode for both LST and RAD modes.
850 In the RAD mode for instance, the mean correlation coefficient
851 is increased from 0.75 in the Zone A+B+C mode (Table IV) to
852 0.89 in the Zone A only mode (Table V). Also the mean slope
853 is closer to 1 as it switches from 0.58 in the Zone A+B+C mode
854 (Table IV) to 0.91 in the Zone A only mode (Table V). Con-
855 sequently, results are consistent with the hourglass approach in
856 Fig. 3 that predicts a lower sensitivity of MODIS-derived soil
857 temperature to soil moisture in Zone B and C, Zone A having

the highest potential for estimating soil moisture variability 858
from MODIS temperature. 859

On DoY 256, the negative correlation appearing in Zone 860
A+B+C mode (Table IV) is not significant in Zone A only mode 861
(Table V), suggesting that the contradictory result obtained on 862
DoY 256 is probably an artifact due to the small sample size. 863

Note that one drawback of the Zone A only mode is the larger 864
amount of data gaps in the soil moisture images. Therefore, 865
the use of both modes is a compromise between application 866
coverage and accuracy in the disaggregation output. 867

G. Distinguishing Between SMOS and DisPATCH Errors 868

By solving the extent mismatch between 40-km resolution 869
remote sensing observation and localized *in situ* measurements, 870
DisPATCH could be used as a tool to help improve the validation 871
strategies of SMOS data in low-vegetated semi-arid regions. It 872
also would reduce the coverage requirements identified by [41] 873
for airborne validation campaigns. However, such a validation 874
approach requires separating the different error sources that 875
may be attributed to SMOS soil moisture and to DisPATCH. 876
One solution is to estimate the errors attributed to DisPATCH 877
and then deduce the errors attributed to SMOS soil moisture. To 878
estimate the errors that are associated with the disaggregation 879

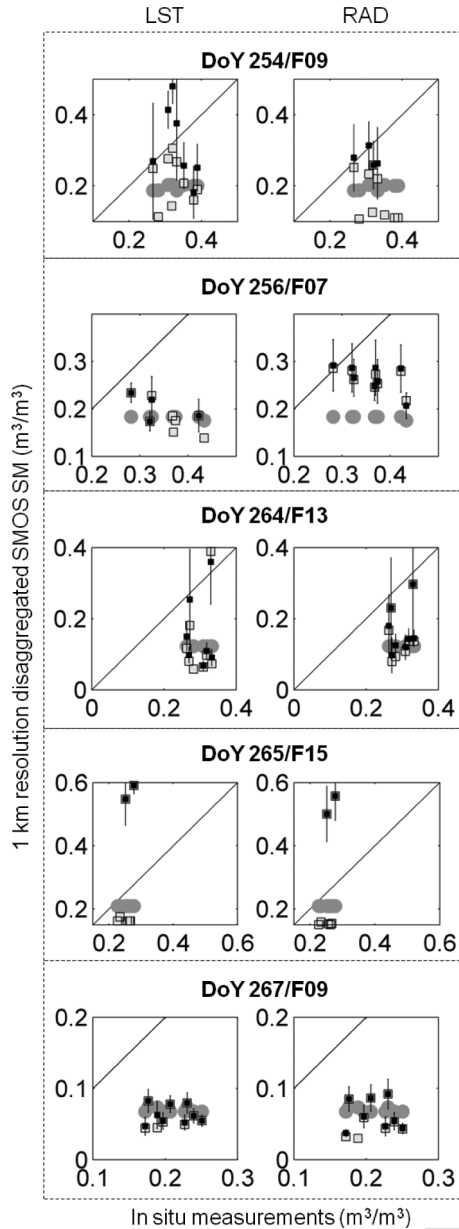


Fig. 9. Scatterplots of 1-km resolution disaggregated SMOS soil moisture versus 1-km resolution aggregated *in situ* measurements for each of the five date-farm data sets during AACES-2. The filled circles correspond to disaggregation with no 1-km information, empty squares to Zone A+B+C mode and black squares to Zone A only mode. For the Zone A only mode, the uncertainty in disaggregated soil moisture is represented by vertical errorbars.

880 methodology, it is suggested to analyze the spatial correla-
 881 tion between 1-km disaggregated SMOS soil moisture and
 882 *in situ* measurements. If the correlation is significant, then the
 883 disaggregation product is likely to be sufficiently accurate for
 884 validating SMOS data.

885 Note that the errors in DisPATCH are in part coupled with
 886 the errors in SMOS soil moisture, particularly because SMOS
 887 is an input to DisPATCH. However, any uncertainties in SMOS
 888 soil moisture should not impact the disaggregation results at a
 889 distance shorter than the SMOS data sampling length (15 km).
 890 This is the reason why such a validation strategy should be
 891 conducted with ground measurements made within a distance
 892 radius of 15 km.

In this study case, five date-farm units including DoY 893
 46/F15, DoY 46/F16, DoY 49/F17, DoY 49/F18, and DoY 894
 49/F20 indicate a significant correlation between disaggregated 895
 SMOS soil moisture and *in situ* measurements. For these units, 896
 the root mean square error in disaggregated SMOS soil mois- 897
 ture is mainly explained by a bias in disaggregated soil moisture 898
 (see Table IV). However, no conclusion can be drawn from 899
 these data because: 1) the bias is sometimes positive (DoY 900
 46/F15, DoY 49/F20), and sometimes negative (DoY 46/F16, 901
 DoY 49/F17, DoY 49/F18); and 2) the comparison is made only 902
 once for each farm, which does not allow analyzing the tempo- 903
 ral behavior. Such a validation approach could be undertaken 904
 in the near future using the OzNet (<http://www.oznet.org.au/>, 905
 [42]) soil moisture monitoring network, providing continuous 906
 measurements at 68 sites within the Murrumbidgee catchment 907
 area. 908

H. Subpixel Variability and Assimilation Perspectives 909

DisPATCH is successively run in LST or RAD mode and in 910
 Zone A+B+C or Zone A only mode during AACES-1. Fig. 10 911
 plots for each case the estimated uncertainty in disaggregated 912
 soil moisture (computed as the standard deviation of the disag- 913
 gregation output ensemble) against the subpixel variability of 914
 1-km resolution *in situ* measurements (computed as the stan- 915
 dard deviation of the *in situ* measurements made within 916
 1-km pixels). The data corresponding to DoY 51 are plotted 917
 separately because of the time gap between HDAS/SMOS 918
 (DoY 51) and MODIS (DoY 54) collection time. It is interest- 919
 ing to observe that the estimated uncertainty in disaggregated 920
 soil moisture is closely related to the observed subpixel vari- 921
 ability of *in situ* measurements. Hence, $\sigma_{SM,1\text{ km}}$ could be used 922
 as a proxy for representing the soil moisture variability at scales 923
 finer than 1-km resolution. Concerning the data on DoY 51, the 924
 linear regression is clearly off the 1:1 line. This is consistent 925
 with a decrease of the spatial variability in soil moisture during 926
 a dry down period [43]. In particular, the spatial variability 927
 in soil moisture is expected to be lower on DoY 54 than on 928
 DoY 51. 929

The correlation between the estimated uncertainty in disag- 930
 gregated soil moisture and the subpixel soil moisture variability 931
 makes an additional link between DisPATCH output and assim- 932
 ilation schemes into hydrological models. A number of optimal 933
 assimilation methodologies have been developed to combine 934
 model predictions with remote sensing observations. However, 935
 any so-called optimal assimilation technique stops being opti- 936
 mal if the uncertainty in remotely sensed data is unknown or 937
 estimated with a large uncertainty. In the perspective of assim- 938
 ilating disaggregated SMOS data into land surface models, one 939
 should keep in mind that the error information on observable 940
 variables is as crucial as the observations themselves, e.g., [44]. 941

V. SUMMARY AND CONCLUSION 942

DisPATCH is an algorithm dedicated to the disaggregation of 943
 soil moisture observations using high-resolution soil tempera- 944
 ture data. It converts soil temperature fields into soil moisture 945
 fields given a semi-empirical soil evaporative efficiency model 946

TABLE V

DISPATCH IS RUN IN THE ZONE A ONLY MODE, AND STATISTICAL RESULTS ARE LISTED IN TERMS OF ROOT MEAN SQUARE DIFFERENCE (RMSD), MEAN DIFFERENCE (BIAS), CORRELATION COEFFICIENT (R), AND SLOPE OF THE LINEAR REGRESSION BETWEEN 1-KM RESOLUTION DISAGGREGATED SMOS SOIL MOISTURE AND 1-KM AGGREGATED *In Situ* MEASUREMENTS. THE RESULTS OBTAINED USING THE RADIANCE-DERIVED LAND SURFACE TEMPERATURE DATA (RAD MODE) AND USING THE OFFICIAL MODIS LAND SURFACE TEMPERATURE DATA (LST MODE IN PARENTHESIS) ARE COMPARED. THE MEAN AND STANDARD DEVIATION OF GROUND MEASUREMENTS ($\langle SM_{HDAS} \rangle$ AND σ_{HDAS}), THE NUMBER OF CONSIDERED 1-KM PIXELS AND STATISTICAL SIGNIFICANCE (P-VALUE) ARE ALSO LISTED FOR EACH DATE-FARM UNIT

DoY/Farm	$\langle SM_{HDAS} \rangle$ (m^3/m^3)	σ_{HDAS} (m^3/m^3)	Number of 1 km pixels	RMSD* (m^3/m^3)	Bias* (m^3/m^3)	R [†] (-)	Slope [†] (-)	p-value (-)
28/F05	0.04	0.02	7 (7)	0.04 (0.04)	-0.04 (-0.04)	- (-)	- (-)	0.72 (0.80)
30/F07	0.02	0.03	8 (8)	0.02 (0.02)	-0.02 (-0.02)	- (-0.70)	- (-0.08)	0.20 (0.05)
30/F08	0.03	0.02	7 (7)	0.02 (0.02)	-0.02 (-0.02)	- (-0.95)	- (-0.03)	0.11 (0.001)
46/F15	0.29	0.05	8 (8)	0.09 (0.09)	0.09 (0.08)	- (0.66)	- (1.4)	0.13 (0.07)
46/F16	0.34	0.06	3 (2)	0.07 (0.14)	-0.06 (-0.12)	- (-)	- (-)	0.96 (-)
49/F17	0.21	0.06	8 (8)	0.02 (0.04)	0.02 (-0.02)	0.79 (-)	0.71 (-)	0.02 (0.64)
49/F18	0.25	0.07	1 (0)	- (-)	- (-)	- (-)	- (-)	0.20 (0.20)
49/F20	0.20	0.09	4 (4)	0.05 (0.02)	0.05 (0.01)	0.98 (0.92)	1.1 (0.42)	0.02 (0.08)
51/F19	0.24	0.08	0 (1)	- (-)	- (-)	- (-)	- (-)	0.19 (0.19)
51/F20	0.20	0.10	6 (6)	0.09 (0.09)	-0.09 (-0.09)	- (-)	- (-)	0.70 (0.45)
AACES-1 mean [‡]	0.21 (0.25)	0.08 (0.07)	6 (6)	0.04 (0.06)	0.04 (0.05)	0.89 (0.79)	0.91 (0.91)	0.02 (0.08)
254/F09	0.33	0.07	4 (7)	0.05 (0.12)	-0.03 (-0.02)	- (-)	- (-)	0.70 (0.30)
256/F07	0.36	0.10	8 (4)	0.12 (0.15)	-0.10 (-0.13)	- (-)	- (-)	0.13 (0.43)
264/F13	0.30	0.07	8 (7)	0.14 (0.17)	-0.13 (-0.14)	- (-)	- (-)	0.64 (0.86)
265/F15	0.25	0.06	2 (2)	0.26 (0.30)	0.26 (0.30)	- (-)	- (-)	- (-)
267/F09	0.21	0.07	8 (9)	0.15 (0.15)	-0.15 (-0.15)	- (-)	- (-)	0.77 (0.85)
AACES-2 mean [‡]	-	-	- (-)	- (-)	- (-)	- (-)	- (-)	>0.10 (>0.10)

* RMSD and bias values are computed if the number of 1 km pixels > 1.

† R and slope values are reported if p-value < 0.10.

‡ the mean values computed for AACES-1 and AACES-2 include only statistically significant (p-value < 0.10) results and discard extensive dry days DoY 28-30.

947 and a first-order Taylor series expansion around the field-mean
948 soil moisture. In this study, the disaggregation approach is ap-
949 plied to 40-km resolution version-4 SMOS level-2 soil moisture
950 using 1-km resolution MODIS data. The objective is to test
951 DisPATCH under different surface and atmospheric conditions
952 using the very intensive ground measurements collected in
953 southeastern Australia during the 2010 summer and winter
954 AACES campaigns. Those measurements are aggregated at
955 the downscaling resolution (1 km) and subsequently compared
956 to the disaggregated SMOS soil moisture. Over the study
957 area, climatic (evaporative demand), meteorologic (presence
958 of clouds), and vegetation (cover and water status) conditions
959 are strong constraints on disaggregation results. The quality
960 of disaggregation products varies greatly according to season:
961 while the correlation coefficient between disaggregated and
962 *in situ* soil moisture is 0.7 during the summer AACES, it
963 is about zero during the winter AACES, consistent with a
964 weaker coupling between evaporation and surface moisture
965 in temperate than in semi-arid climate. Moreover, vegetation
966 cover prevents the soil temperature to be retrieved from thermal
967 infrared data and the vegetation water stress may increase the
968 remotely sensed land surface temperature independent of near-
969 surface soil moisture. By separating the 1-km pixels where
970 MODIS temperature is mainly controlled by soil evaporation,

from those where MODIS temperature is controlled by both 971
soil evaporation and vegetation transpiration, the correlation 972
coefficient between disaggregated and *in situ* soil moisture is 973
increased from 0.70 to 0.85 during the summer AACES cam- 974
paign. Also, cloud cover totally obscures the surface during rain 975
events, and on clear sky days, the water vapor in the atmosphere 976
significantly affects the quality of land surface temperature 977
data. It is found that the 5-km resolution atmospheric correction 978
of the official MODIS temperature data has significant impact 979
on DisPATCH output. An alternative atmospheric correction at 980
40-km resolution increases the correlation coefficient between 981
disaggregated and *in situ* soil moisture from 0.72 to 0.82 during 982
the summer AACES. 983

The above limitations must be kept in mind when using 984
DisPATCH as a tool for validating SMOS soil moisture. Over 985
semi-arid areas, disaggregation can solve the extent mismatch 986
between the 40-km resolution SMOS data and localized *in situ* 987
measurements. However, the validation of SMOS using Dis- 988
PATCH requires separation of the errors associated with SMOS 989
data and the errors associated with DisPATCH. As SMOS data 990
are an input to DisPATCH, the errors in DisPATCH are also 991
linked to the uncertainty in SMOS soil moisture. Nevertheless, 992
one way to identify the error sources specifically attributed 993
to DisPATCH is to analyze the spatial correlation between 994

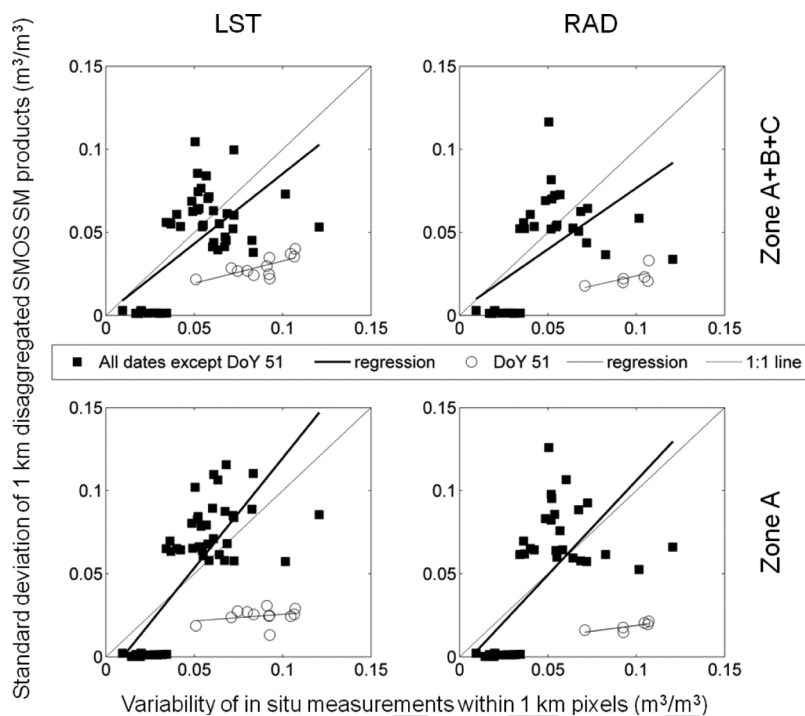


Fig. 10. Estimated uncertainty in disaggregated soil moisture ($\sigma_{SM, 1 km}$) versus subpixel variability of 1 km resolution *in situ* measurements for DisPATCH run in LST or RAD mode and Zone A+B+C or Zone A only mode.

995 disaggregated SMOS data and the *in situ* measurements made
 996 at a distance larger than the downscaling resolution (1 km with
 997 MODIS data) and smaller than the SMOS data sampling length
 998 (15 km).

999 Based on the results obtained using the AACES *in situ*
 1000 measurements, several improvements of DisPATCH can be
 1001 suggested:

- 1002 • Use of the MODIS land surface temperature quality index
 1003 to select the SMOS pixels with the highest MODIS data
 1004 quality.
- 1005 • Correcting the MODIS land surface temperature for topog-
 1006 raphy and illumination effects [45]. Within a 40-km
 1007 SMOS resolution pixel, the elevation range may be very
 1008 significant and thus induce a variability in land sur-
 1009 face temperature that is not attributed to surface soil
 1010 moisture.
- 1011 • Use of ancillary air temperature data to constrain the
 1012 estimation of end-members. The unstressed vegetation
 1013 temperature $T_{v,min}$ could be set to the air temperature
 1014 instead of the minimum MODIS land surface temperature.
 1015 This would make the estimation of $T_{v,min}$ less dependent
 1016 on the representativeness of the surface conditions met
 1017 within the SMOS pixel [24].
- 1018 • Accounting for the dependency of soil evaporative effi-
 1019 ciency to potential evaporation, by replacing the model in
 1020 [26] with the model in [38].
- 1021 • Estimating an optimal downscaling resolution for each
 1022 season: as the sensitivity of soil evaporative efficiency to
 1023 soil moisture is lower in the winter months than in the sum-
 1024 mer months, aggregating DisPATCH output may improve
 1025 the quality of disaggregation products at the expense of
 1026 spatial resolution [17].

A robust disaggregation methodology of SMOS soil moisture
 at 1-km resolution, which would provide both disaggregated
 soil moisture and its uncertainty at 1-km resolution is a crucial
 step toward the application of SMOS data to hydrological
 studies.

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