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Towards deterministic downscaling of SMOS soil moisture using MODIS derived soil evaporative efficiency

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ABSTRACT

A deterministic approach for downscaling ~40 km resolution Soil Moisture and Ocean Salinity (SMOS) observations is developed from 1 km resolution MODerate resolution Imaging Spectroradiometer (MODIS) data. To account for the lower soil moisture sensitivity of MODIS surface temperature compared to that of L-band brightness temperature, the disaggregation scale is fixed to 10 times the spatial resolution of MODIS thermal data (10 km). Four different analytic downscaling relationships are derived from MODIS and physically-based model predictions of soil evaporative efficiency. The four downscaling algorithms differ with regards to i) the assumed relationship (linear or nonlinear) between soil evaporative efficiency and near-surface soil moisture, and ii) the scale at which soil parameters are available (40 km or 10 km). The 1 km resolution airborne L-band brightness temperature from the National Airborne Field Experiment 2006 (NAFE'06) are used to generate a time series of eleven clear sky 40 km by 60 km near-surface soil moisture observations to represent SMOS pixels across the three-week experiment. The overall root mean square difference between downscaled and observed soil moisture varies between 1.4% v/v and 1.8% v/v depending on the downscaling algorithm used, with soil moisture values ranging from 0 to 15% v/v. The accuracy and robustness of the downscaling algorithms are discussed in terms of their assumptions and applicability to SMOS.

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1. Introduction

Soil moisture observations over large areas are increasingly required in a range of environmental applications including meteorology, hydrology, water resource management and climatology. Various approaches have been developed over the past two decades to infer near-surface soil moisture from remote sensing measurements of surface temperature, radar backscatter and microwave brightness temperature (e.g. Prigent et al., 2005; Crow and Zhan, 2007). The relative merit of these approaches depends on i) the strength of the physical link between the observable in the different spectral domains and soil water content, and ii) the spatial/temporal resolution that is technically achievable by the different spaceborne remote sensing systems. The physical link between L-band brightness temperature and soil moisture profile (up to 5 cm) has been shown to be stronger than at higher frequency, and more direct than with radar backscatter and with thermal data (Kerr, 2007; Wagner et al., 2007).

The Soil Moisture and Ocean Salinity (SMOS) mission (Kerr et al., 2001) is to be the first soil moisture dedicated satellite. It will use L-band radiometry to provide data of the 0–5 cm soil moisture every 3 days at 40 km resolution globally. Despite the high sensitivity of

microwave radiometers to near-surface soil moisture, their spatial resolution is about 10 to 500 times coarser than that of active microwave and optical systems. For instance, the L-band Phased Array type L-band Synthetic Aperture Radar (PALSAR) and the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) can achieve a spatial resolution of about 100 m. Note however that current and planned radar observations have repeat cycles of about 30 days with high-resolution products and about 6 days with medium-resolution products such as 1 km resolution C-band Advanced Synthetic Aperture Radar (ASAR) data. In the optical domain, high-resolution data are also currently acquired sparsely with a repeat cycle of 16 days for ASTER. In fact, only optical sensors at intermediate spatial resolution, such as the MODerate resolution Imaging Spectroradiometer (MODIS) having 1 km resolution, provide a global coverage every 1–2 days.

Given the high soil moisture sensitivity but low spatial resolution of passive microwave data, and the high spatial resolution but non-optimal soil moisture sensitivity of optical/thermal data, the combination of both types of information is expected to result in reliable soil moisture products at intermediate spatial resolution. However, such downscaling approaches need to be matured so that SMOS data can be used in the numerous applications requiring high-resolution soil moisture information. To date, disaggregation strategies based on optical data have been developed by building either stochastic (e.g.

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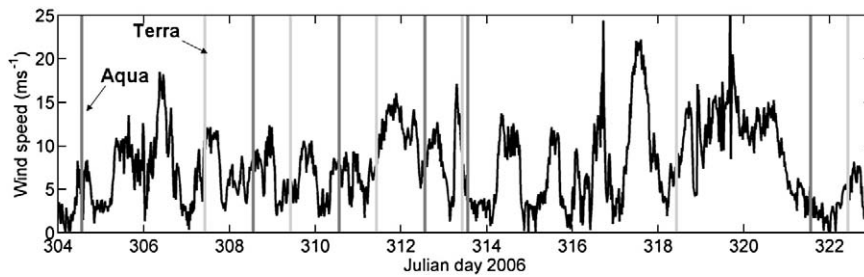


Fig. 1. Time series of wind speed monitored at Y11 in the Yanco area. The overpass time on clear sky days of MODIS/Terra (10 am) and MODIS/Aqua (1 pm) are also shown.

Chauhan et al., 2003) or deterministic (e.g. Merlin et al., 2006b) relationships between near-surface soil moisture and optical-derived soil moisture indices. While stochastic approaches have the advantage of requiring few ancillary data, they may not be valid outside the conditions used for calibration. Conversely, deterministic approaches can potentially be transferred to a wider range of conditions, but generally require a larger amount of surface parameters and micro-meteorological data which may not be available over large areas.

This paper develops a novel analytic approach for downscaling ~40 km resolution SMOS soil moisture from 1 km resolution MODIS derived and physically-based model predictions of soil evaporative efficiency (soil evaporative efficiency is defined as the ratio of the actual to potential soil evaporation). Four different downscaling algorithms are developed, differing only in i) the assumed relationship (linear or nonlinear) between soil evaporative efficiency and near-surface soil moisture and ii) the scale at which soil parameters are available (40 km or disaggregation scale). The four algorithms are tested with data from the National Airborne Field Experiment 2006 (NAFE'06, Merlin et al., 2008b). A simulated SMOS near-surface soil moisture observation is derived from the Polarimetric L-band Multi-beam Radiometer (PLMR) data acquired at 1 km resolution over the 40 by 60 km Yanco area on eleven cloud free days during the three-week campaign. Moreover, the 1 km resolution data are also used to verify downscaling results at the disaggregation scale. The downscaling algorithms are compared in terms of accuracy and robustness with the NAFE'06 data set. Their operational applicability to SMOS is also discussed.

2. Data

NAFE'06 was undertaken from 30 October to 20 November 2006 in the Murrumbidgee catchment, in southeastern Australia. A detailed description of the data set is provided in Merlin et al. (2008b) so only the pertinent details are given here. The data used in this study are composed of: the 1 km resolution PLMR data over the 40 by 60 km Yanco area, the MODIS data acquired over the Yanco area on clear sky days during the three-week experiment, and a time series of wind speed measurements at one micro-meteorological station included in the study area.

2.1. L-band derived soil moisture

During NAFE'06, L-band brightness temperature was mapped at 1 km resolution over the 40 by 60 km Yanco area on 11 days: JD 304, 306, 307, 308, 309, 311, 313, 317, 318, 320 and 322. A soil moisture product at 1 km resolution was derived over the area from PLMR data on each acquisition date (Merlin et al., submitted for publication). The error in soil moisture retrievals as compared to ground measurements aggregated to 1 km resolution was estimated to be less than 4% v/v.

Note that the presence of standing water over rice crops included in the Yanco area was not explicitly accounted for in the retrieval procedure. By doing so, all water surfaces were interpreted as bare soil with 100% moisture content. In other words, any standing water in the

1 km PLMR pixels systematically increases the retrieved soil moisture. However, this assumption is consistent with the use of MODIS surface temperature and NDVI to estimate soil evaporative efficiency (see next section).

2.2. MODIS data

The MODIS data used in the downscaling algorithms are composed of MODIS/Terra (10 am) and MODIS/Aqua (1 pm) 1 km resolution daily surface temperature, and MODIS/Terra 1 km resolution 16-day Normalized Difference Vegetation Index (NDVI). The MODIS NDVI data are from Terra only to minimize sun-glint effects occurring with Aqua reflectances at lower sun incidence angles. The 16-day NDVI product was cloud free. In between the first (Julian day JD 304) and last day (JD 322) of 1 km resolution PLMR flights over Yanco, 12 MODIS surface temperature images with less than 10% cloud cover were acquired including six aboard Terra (JD 307, 309, 311, 313, 318 and 322) and six aboard Aqua (JD 304, 308, 310, 312, 313 and 321).

2.3. Wind speed data

Wind speed was monitored at 2 m by a meteorological station near Y11 (southwestern corner of the Yanco area) continuously during NAFE'06 with a time step of 20 minutes. The time series is illustrated in Fig. 1. Note that wind speed is assumed to be uniform within the 40 by 60 km area, at the time of MODIS overpass.

3. Approach

The three general steps of the downscaling approach consist of (i) estimate soil evaporative efficiency from MODIS data (ii) link soil evaporative efficiency to near-surface soil moisture via a physically-based scaling function and (iii) build a downscaling relationship to express high-resolution near-surface soil moisture as function of SMOS-scale observation and high-resolution soil evaporative efficiency.

3.1. MODIS-derived soil evaporative efficiency

The fine-scale information used in the downscaling procedure is the soil evaporative efficiency derived from MODIS surface temperature and MODIS NDVI. The rationale for choosing soil evaporative efficiency as fine-scale information is based on the strong correlation with near-surface soil moisture (Anderson et al., 2007) and its relative stability during daytime on clear sky days (Shuttleworth et al., 1989; Nichols and Cuenca, 1993; Crago and Brutsaert, 1996). The soil evaporative efficiency β is estimated as in Nishida et al. (2003).

$$\beta_{\text{MODIS}} = \frac{T_{\text{max}} - T_{\text{MODIS}}}{T_{\text{max}} - T_{\text{min}}} \quad (1)$$

with T_{max} being the soil temperature at minimum soil moisture, T_{min} the soil temperature at maximum soil moisture, and T_{MODIS} the soil

t1.1 **Table 1**
t1.2 Model parameters

t1.3 Parameter	Value	Unit	Source
θ_{c0}	2.5	% v/v	Default value estimated from Komatsu (2003)
γ	100	s m ⁻¹	Default value estimated from Komatsu (2003)
z_{0m}	0.005	m	Typical value for bare soil Liu et al. (2007)
t1.7 NDVI _{min}	0.22	—	Estimated from NDVI image
t1.8 NDVI _{max}	0.60	—	Estimated from NDVI image

166 skin temperature derived from MODIS data at the time of interest.
167 Using the triangle approach (Price, 1980; Carlson et al., 1995), T_{MODIS}
168 can be expressed as

$$169 T_{MODIS} = \frac{T_{surf, MODIS} - f_{veg} T_{veg}}{1 - f_{veg}} \quad (2)$$

170 with $T_{surf, MODIS}$ being the MODIS surface skin temperature, T_{veg} the
171 vegetation skin temperature and f_{veg} the vegetational fraction cover.
172 Herein, T_{MODIS} is defined as the temperature of the bare soil when
173 vegetation temperature T_{veg} is assumed to be uniform within the
174 SMOS pixel. In this formulation of soil evaporative efficiency, the
175 impact of spatially variable root-zone soil moisture on T_{veg} is not
176 accounted for. Note that β varies between 0 and 1 when $f_{veg} < 1$ and is
177 not defined when $f_{veg} = 1$. Cover fraction is computed as

$$180 f_{veg} = \frac{NDVI_{MODIS} - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \quad (3)$$

181 with $NDVI_{MODIS}$ being the MODIS observed NDVI, and $NDVI_{min}$ and
182 $NDVI_{max}$ the minimum and maximum NDVI values for a particular
183 scene.

184 Five parameters are needed to compute soil evaporative efficiency
185 from MODIS data: $NDVI_{min}$, $NDVI_{max}$, T_{veg} , T_{min} and T_{max} . While $NDVI_{min}$
186 and $NDVI_{max}$ are assumed to be constant within the Yanco area during
187 NAFE'06, T_{veg} , T_{min} and T_{max} are assumed to be uniform within the Yanco
188 area, but vary in time. Parameters $NDVI_{min}$ and $NDVI_{max}$ are determined
189 from the 16-day NDVI product within the SMOS pixel. Vegetation
190 temperature T_{veg} is estimated at the time of overpass (10 am or 1 pm) as
191 the minimum temperature reached at maximum NDVI ($f_{veg} = 1$).
192 Minimum temperature T_{min} can be estimated either over fully vegetated
193 pixels by assuming $T_{min} \sim T_{veg}$ or over water bodies as the minimum
194 temperature reached at minimum NDVI. Parameter T_{max} is the value
195 extrapolated along the dry edge of the triangle. As the impact of root-
196 zone soil moisture on T_{veg} is neglected, the dry edge is interpreted as the
197 1 km pixels with dry soils in the near-surface. Note that the accuracy in
198 extrapolating T_{max} depends on moisture conditions within the study
199 area; it is optimum in dry conditions and is expected to be relatively
200 low in uniformly wet conditions.

201 3.2. Scaling function

202 Although evaporative fraction has been shown to be relatively
203 constant between 10 am and 1 pm (MODIS overpass times), several
204 studies have indicated that it cannot be considered as completely
205 independent from atmospheric conditions (Lhomme and Elguero,
206 1999; Gentine et al., 2007). Moreover, in constant soil moisture and
207 atmospheric conditions, soil evaporative efficiency may significantly
208 vary with soil type (Komatsu, 2003). To account for these temporal
209 (atmospheric) and spatial (atmospheric and soil properties) effects,
210 the MODIS-derived β computed from Eq. (1) is explicitly linked to
211 near-surface soil moisture θ by the following model from Komatsu
212 (2003)

$$214 \beta_{model} = 1 - \exp(-\theta/\theta_c) \quad (4)$$

with $\theta_c = \theta_{c0}(1 + \gamma/r_{ah})$, θ_{c0} (% v/v) and γ (s m⁻¹) being two soil-
215 dependent parameters and r_{ah} (s m⁻¹) the aerodynamic resistance
216 over bare soil, given the soil roughness z_{0m} (see Table 1) and the wind
217 speed u at a reference height (2 m in our case). Komatsu's model was
218 validated over bare soil for the very top soil layer (1 mm). The
219 empirical parameter θ_{c0} (typical range 1–4% v/v) controls the soil
220 capacity to retain moisture in optimal evaporative conditions i.e.
221 when wind speed is zero or r_{ah} is infinite. In other words, the higher
222 θ_{c0} , the slower the soil dries.

223 By inverting the soil evaporative efficiency model from Eq. (4), one
224 obtains:

$$\theta_{model} = -\theta_c \ln(1 - \beta) \quad (5) \quad 225$$

226 This model provides an estimate of the slope of the correlation
227 between near-surface soil moisture and soil evaporative efficiency,
228 $\partial\theta_{model}/\partial\beta = \theta_c/(1 - \beta)$ and an estimate of the “non-linearity” of this
229 correlation, $\partial^2\theta_{model}/\partial\beta^2 = \theta_c/(1 - \beta)^2$. Note that the non-linearity of θ_{model}
230 is a decreasing function of near-surface soil moisture and is maximum at
231 $\beta = 0$.

232 3.3. Downscaling relationships

233 The physically-based model of Eq. (4) is used to derive four
234 deterministic relationships between downscaled soil moisture, simulated
235 SMOS observations, and MODIS-derived soil evaporative efficiency.

236 3.3.1. Linear approximation

237 A downscaling relationship is derived by writing the first-order
238 Taylor series approximation of the downscaled soil moisture θ at the
239 SMOS-scale observation θ_{SMOS}

$$\theta = \theta_{SMOS} + \left(\frac{\partial\theta}{\partial\beta}\right) \Delta\beta_{MODIS} \quad (6) \quad 240$$

241 with $\Delta\beta_{MODIS}$ being the difference between MODIS-derived soil
242 evaporative efficiency and its integrated value at the SMOS scale. As in
243 the recent study of Merlin et al. (2008a), the function $f_1 = \partial\theta/\partial\beta$ is used to
244 convert β variations into soil moisture variations about the low-
245 resolution observation. The main difference here is that this function
246 f_1 depends on soil type, wind speed, and SMOS-scale near-surface soil
247 moisture. In Merlin et al. (2008a), the function f_1 was assumed to be
248 constant and was estimated during a training period. Herein, the simple
249 model of Eq. (4) requiring two soil parameters (θ_{c0} and γ) and wind speed
250 is used to describe explicitly the variability of the relationship between
251 soil evaporative efficiency and near-surface soil moisture for different
252 soils, wind speed and moisture conditions at the SMOS scale. Note that
253 Eq. (6) relies on the assumption that the 0–1 mm soil moisture
254 (as described by MODIS evaporative efficiency) and the 0–5 cm soil
255 moisture (as derived from PLMR brightness temperature) have the same
256 spatial variability about the mean within the SMOS pixel.

257 By replacing f_1 by its analytical expression, the downscaling
258 relationship of Eq. (6) becomes

$$\theta = \theta_{SMOS} + \theta_c \frac{\Delta\beta_{MODIS}}{1 - \beta_{SMOS}} \quad (7) \quad 262$$

263 with $\beta_{SMOS} = \int \partial\beta/\partial\theta d\theta$ the integral of β at the SMOS scale. Eq. (7) can
264 be simplified as

$$\theta = \theta_{SMOS} + \theta_c SMP_{MODIS} \quad (8) \quad 265$$

266 with SMP_{MODIS} a soil moisture proxy defined as

$$SMP_{MODIS} = \frac{\Delta\beta_{MODIS}}{1 - \beta_{SMOS}} \quad (9) \quad 267$$

271 By assuming that (i) T_{\max} and T_{\min} are mostly uniform within the
 272 SMOS pixel and (ii) the integral $T_{\text{SMOS}} = \int_{\lambda} T / \partial \theta \, d\theta$ is approximately
 273 equal to the areal average of T_{MODIS} , SMP can be computed as

$$274 \text{ SMP}_{\text{MODIS}} = \frac{T_{\text{SMOS}} - T_{\text{MODIS}}}{T_{\text{MODIS}} - T_{\min}} \quad (10)$$

275
 276 The major advantage of this formulation over Eq. (9) is that SMP
 277 does not depend on the soil temperature at minimum soil moisture
 278 T_{\max} .

279 **3.3.2. Second-order correction**

280 A second downscaling relationship is derived by adding the term in
 281 β^2 in the Taylor series expansion:

$$282 \theta = \theta_{\text{SMOS}} + \left(\frac{\partial \theta}{\partial \beta} \right) \Delta \beta_{\text{MODIS}} + \frac{1}{2} \left(\frac{\partial^2 \theta}{\partial \beta^2} \right) \Delta \beta_{\text{MODIS}}^2 \quad (11)$$

283
 284 Note that f_1 is now θ -dependent. In particular, the second
 285 derivative $\partial^2 \theta / \partial \beta^2$ specifically accounts for the non-linear relationship
 286 between soil evaporative efficiency and near-surface soil moisture at
 287 about θ_{SMOS} .

288 By replacing the first and second derivatives with their analytical
 289 expression, the downscaling relationship of Eq. (11) becomes

$$290 \theta = \theta_{\text{SMOS}} + \theta_c \left[\frac{\Delta \beta_{\text{MODIS}}}{1 - \beta_{\text{SMOS}}} + \frac{\Delta \beta_{\text{MODIS}}^2}{2(1 - \beta_{\text{SMOS}})^2} \right] \quad (12)$$

291 and after simplification
 292

$$293 \theta = \theta_{\text{SMOS}} + \theta_c \left(\text{SMP}_{\text{MODIS}} + \frac{1}{2} \text{SMP}_{\text{MODIS}}^2 \right) \quad (13)$$

294 with $\text{SMP}_{\text{MODIS}}$ defined as in Eq. (10).

295 **3.3.3. Downscaling relationships**

296 Four downscaling relationships are derived from Eqs. (8) and (13).
 297 They differ with regards to their degree of complexity by assuming a
 298 linear (or non-linear) relationship between soil evaporative efficiency

and near-surface soil moisture, and by using soil parameter θ_c
 299 estimated at low- (or high-) resolution: 300

• Downscaling scheme D1 is based on the linear approximation
 301 between β and θ , and assumes θ_c is uniform: 302

$$303 \text{ D1} : \theta = \theta_{\text{SMOS}} + \theta_{c,\text{SMOS}} \text{SMP}_{\text{MODIS}} \quad (14)$$

• Downscaling scheme D2 includes a second-order correction in
 305 $\text{SMP}_{\text{MODIS}}^2$, and assumes θ_c is uniform: 306

$$307 \text{ D2} : \theta = \theta_{\text{SMOS}} + \theta_{c,\text{SMOS}} \left(\text{SMP}_{\text{MODIS}} + \frac{1}{2} \text{SMP}_{\text{MODIS}}^2 \right) \quad (15)$$

• Downscaling scheme D1' is based on the linear approximation
 309 between β and θ , and accounts for the variability of θ_c at the
 310 downscaling resolution: 311

$$312 \text{ D1}' : \theta = \theta_{\text{SMOS}} + \theta_{c,\text{MODIS}} \text{SMP}_{\text{MODIS}} \quad (16)$$

• Downscaling scheme D2' includes a second-order correction in
 314 $\text{SMP}_{\text{MODIS}}^2$, and accounts for the variability of θ_c at the scale of the
 315 downscaling resolution: 316

$$317 \text{ D2}' : \theta = \theta_{\text{SMOS}} + \theta_{c,\text{MODIS}} \left(\text{SMP}_{\text{MODIS}} + \frac{1}{2} \text{SMP}_{\text{MODIS}}^2 \right) \quad (17)$$

Note that the difference between D1 and D1' and likewise the
 319 difference between D2 and D2' is simply the spatial scale at which soil
 320 parameters are estimated. 321

322 **4. Application**

The four downscaling algorithms of Eqs. (14)–(17) are tested with
 323 the NAFE'06 data set. The “goodness” of the disaggregation process is
 324 measured by two estimators: the root mean square difference and the
 325 correlation coefficient between 10 km resolution disaggregated soil
 326 moisture and 10 km resolution L-band retrieval. 327

328 **4.1. Validation approach**

The approach for verification of downscaling results is illustrated
 329 in Fig. 2. The 1 km resolution L-band derived soil moisture is 330

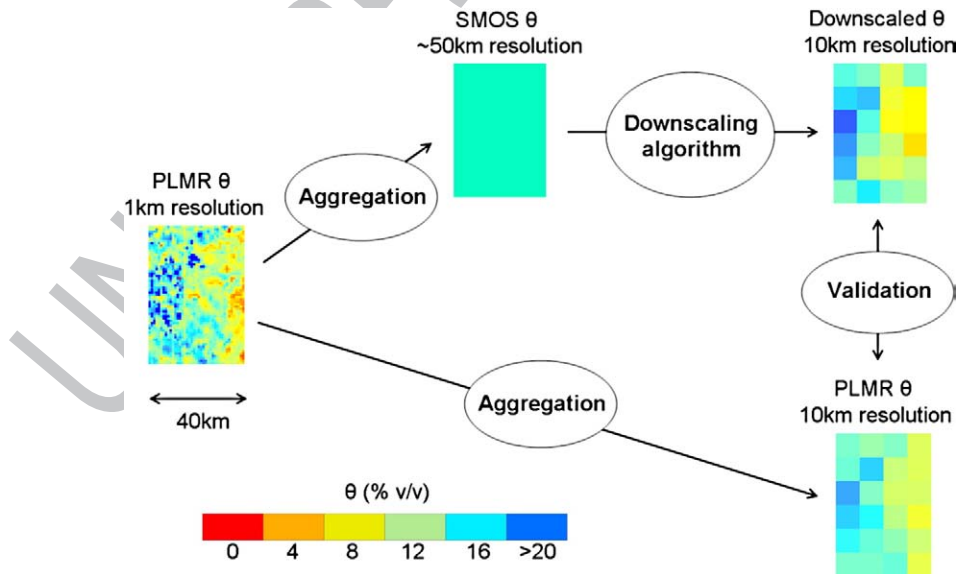


Fig. 2. Schematic diagram of the validation approach. Downscaling results are validated at 10 km resolution to account for the lower sensitivity (relative to PLMR data) of MODIS surface temperature to near-surface soil moisture.

t2.1 **Table 2**
 List of the acquisition date of MODIS data, satellite platform (Aqua/1 pm and Terra/
 10 am), minimum soil temperature T_{min} , wind speed u , SMOS-scale soil moisture θ_{SMOS} ,
 and its variability (standard deviation) at 1 km resolution σ_{SMOS}

Day	Satellite	T_{min} °C	u ms^{-1}	θ_{SMOS} (σ_{SMOS}) % v/v
304	Aqua	37	6	4.4 (4.9)
307	Terra	28	10	16.6 (5.4)
308	Aqua	37	5	11.0 (4.6)
309	Terra	35	8	6.5 (4.6)
310	Aqua	38	8	5.4 (4.5) ^a
311	Terra	33	9	4.2 (4.4)
312	Aqua	35	7	4.0 (4.3) ^a
313	Terra	32	8	3.8 (4.3)
313	Aqua	39	4	3.8 (4.3)
318	Terra	27	6	11.3 (3.8)
321	Aqua	37	5	8.0 (4.6) ^a
322	Terra	37	6	5.4 (4.7)
All ^b	Terra	33	7	6.2 (4.4)
All	Aqua	37	6	6.1 (4.5)

t2.19 ^a Interpolated between dates.
 t2.20 ^b All dates except 307.

aggregated over the 40 by 60 km Yanco area to generate a ~40 km resolution SMOS type soil moisture observation on each PLMR flight day. The time series of θ_{SMOS} and its sub-pixel variability at 1 km resolution σ_{SMOS} are presented in Table 2. The simulated SMOS resolution observation ranges from 4 to 17% v/v with a spatial variability at 1 km resolution of about 5% v/v. These coarse observations are next disaggregated at higher spatial resolution using 1 km resolution daily MODIS-derived SMP. The L-band derived soil moisture product is then used to verify downscaling results at the disaggregation scale.

In this study, the disaggregation scale is 10 km. Consequently, the MODIS-derived soil temperature is aggregated from 1 km to 10 km to derive SMP at 10 km resolution. There are several rationales for

aggregating MODIS-derived soil temperature. First, the aggregation of MODIS derived SMP to 10 km is expected to increase the sensitivity of SMP to near-surface soil moisture (the sensitivity of surface temperature to near-surface soil moisture is relatively low compared to that of L-band brightness temperature). Second, the aggregation limits the errors on downscaled results associated with the presence of clouds in surface temperature images and with the re-sampling strategy that is required for comparison with gridded PLMR data. Third, meteorological forcing (wind speed notably) reacts to the surface heterogeneity in an organized manner at scales larger than 1 km (Shuttleworth et al., 1997).

The four algorithms of Eqs. (14)–(17) are applied to 12 MODIS surface temperature images and downscaling results are compared to the PLMR retrieval aggregated to 10 km resolution on the same grid as MODIS derived SMP. For the three MODIS overpass days (JD 310, 312, and 321) on which no PLMR flight was undertaken, PLMR data are interpolated between dates by averaging soil moisture products obtained on the day before and day after. The interpolation is valid because no rainfall occurred during the period.

4.2. MODIS derived SMP

All downscaling relationships in (14)–(17) are based on the MODIS derived SMP computed from the soil temperature T_{MODIS} and the minimum soil temperature T_{min} . The MODIS-derived soil temperature is computed by estimating T_{veg} for each MODIS surface temperature image. Fig. 3 presents the triangles obtained by plotting 1 km resolution MODIS surface temperature (Terra or Aqua) against 1 km resolution NDVI (16-day product from Terra platform). The vegetation temperature is estimated as the minimum surface temperature reached at maximum NDVI (0.6). The MODIS-derived SMP is then computed by estimating T_{min} for each MODIS surface temperature image. In practice, the minimum soil temperature is approximated to the vegetation temperature

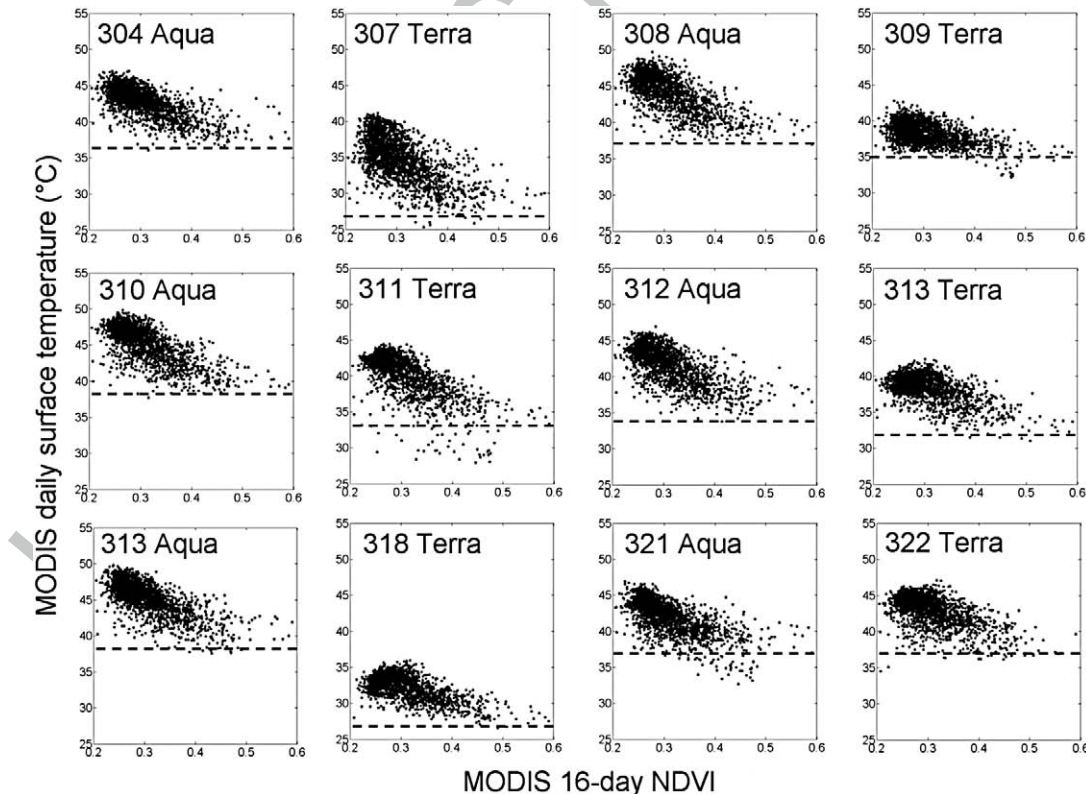


Fig. 3. MODIS daily surface temperature versus MODIS 16-day NDVI. The minimum soil temperature (and vegetation temperature) is represented in dash line.

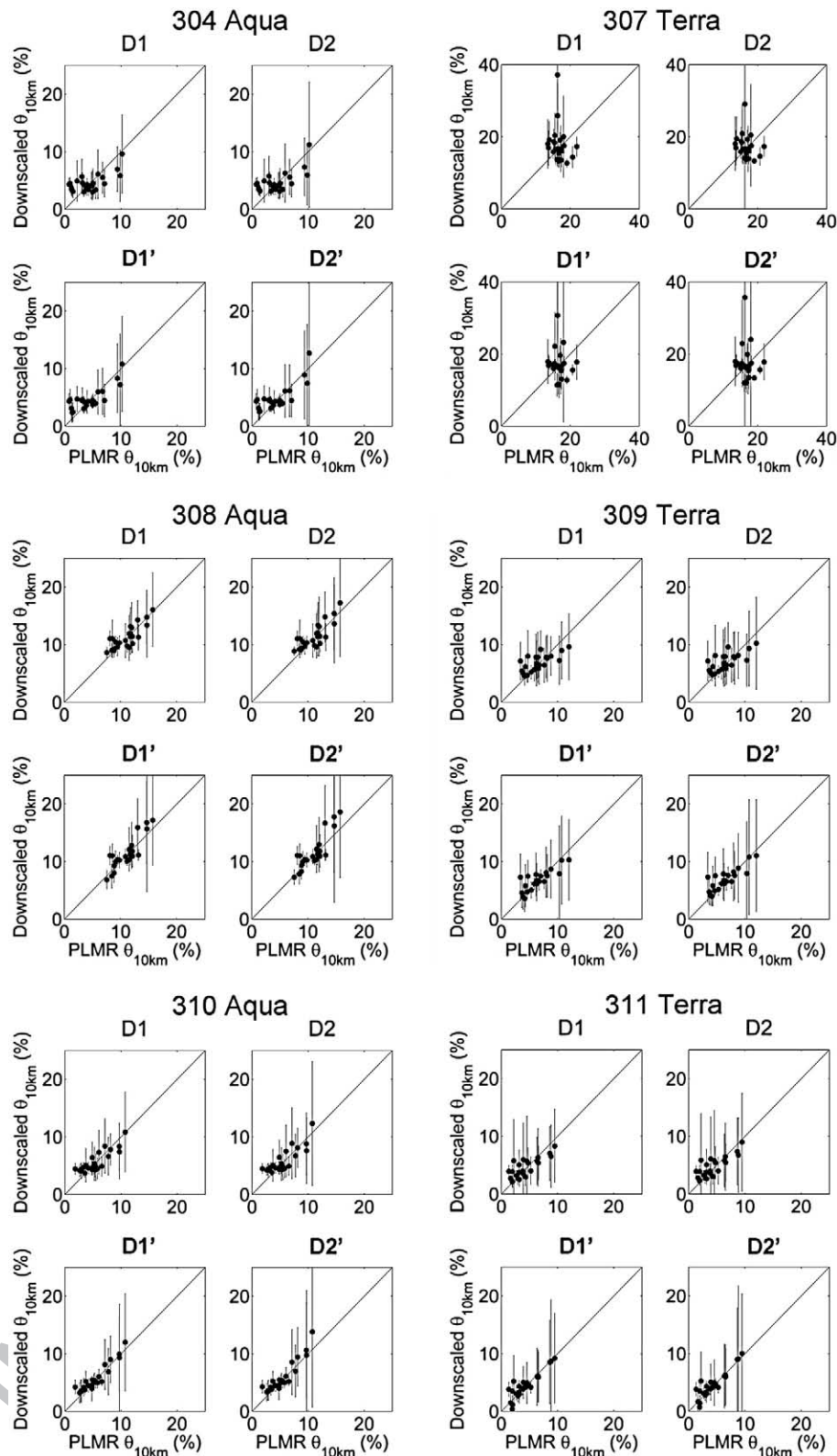


Fig. 4. Downscaled versus PLMR derived soil moisture for each clear sky MODIS surface temperature image between JD 304 and 311. Results include the downscaled soil moisture at 10 km resolution (circles), and its sub-pixel variability (error bars).

376 $T_{\min} = T_{\text{veg}}$. One physical explanation behind this is that both
 377 vegetation temperature and the soil temperature at saturation are
 378 in first approximation close to the air temperature. Note that on
 379 JD 311 and 321, the surface temperature of some pixels is below the
 380 vegetation temperature. This can be explained by the presence

of small clouds on the images and/or a de-coupling between
 381 soil skin temperature with evaporation. However, this effect
 382 was relatively small, and did not appear on the other days.
 383 Parameter T_{\min} is listed in Table 2 for each of the 12 MODIS surface
 384 temperature images. 385

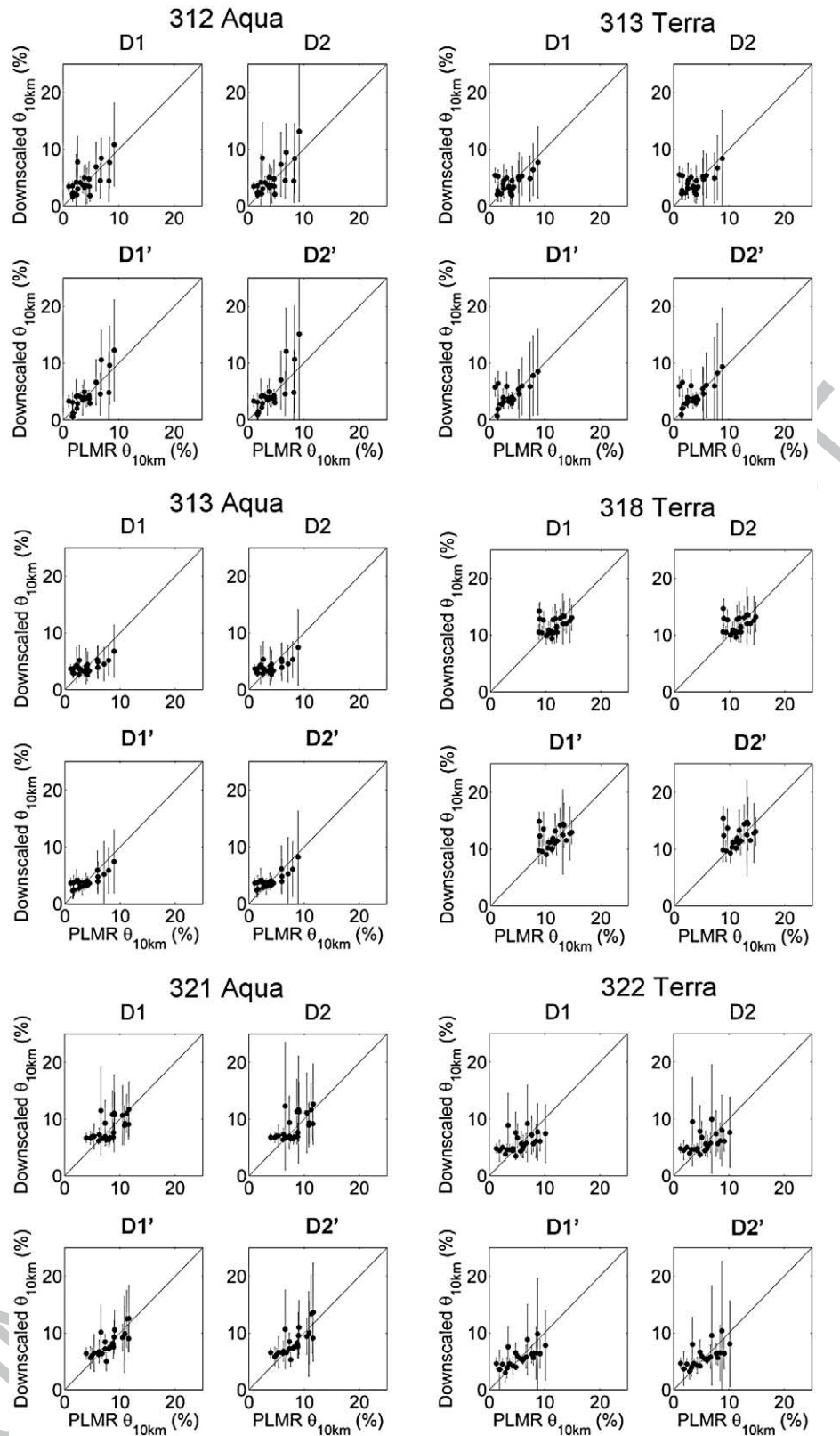


Fig. 5. As for Fig. Fig. 4 but between JD 312 and 322.

386 4.3. Downscaling with D1 and D2 (uniform θ_c)

387 Downscaling schemes D1 and D2 are applied to the NAFE'06 data
 388 set. In Eqs. (14) and (15), parameter $\theta_{c,SMOS}$ is evaluated by estimating
 389 θ_{c0} and γ when the soil type is not known. In Komatsu (2003), θ_{c0}

varied from 1 % v/v for sand to 4 % v/v for agricultural (clay) soil, and γ 390
 varied from 85 to 115 $s\ m^{-1}$. Herein, default values are fixed to 391
 $\theta_{c0}=2.5\%$ v/v and $\gamma=100\ s\ m^{-1}$. 392

Downscaling results are presented in Figs. 4 and 5 for each MODIS 393
 image separately. The data points represent the 10 km resolution 394

Table 3
List of the acquisition date of MODIS data, satellite platform (Aqua/1 pm and Terra/10 am), root mean square error (RMSE) on the 10 km resolution downscaled soil moisture θ , and the correlation coefficient R^2 between 10 km resolution downscaled and PLMR derived soil moisture

Day	Satellite	RMSE on $\theta_{10\text{ km}}$				Correlation coefficient r^2			
		D1	D2	D1'	D2'	D1	D2	D1'	D2'
		% v/v	% v/v	% v/v	% v/v				
304	Aqua	2.0	2.0	1.6	1.7	0.67	0.67	0.81	0.79
307	Terra	5.7	8.6	7.0	11	-0.18	-0.13	-0.08	-0.07
308	Aqua	1.3	1.4	1.4	1.6	0.82	0.82	0.86	0.85
309	Terra	1.6	1.6	1.3	1.3	0.69	0.70	0.82	0.84
310	Aqua	1.3 ^a	1.5 ^a	0.85 ^a	1.1 ^a	0.85 ^a	0.84 ^a	0.93 ^a	0.92 ^a
311	Terra	1.4	1.4	1.0	1.0	0.79	0.80	0.90	0.91
312	Aqua	1.8 ^a	2.1 ^a	1.6 ^a	2.1 ^a	0.68 ^a	0.68 ^a	0.81 ^a	0.80 ^a
313	Terra	1.6	1.6	1.6	1.7	0.62	0.64	0.68	0.69
314	Aqua	1.6	1.6	1.3	1.2	0.70	0.71	0.85	0.84
318	Terra	1.8	1.9	1.9	2.0	0.29	0.27	0.35	0.33
321	Aqua	1.9 ^a	2.0 ^a	1.4 ^a	1.6 ^a	0.61 ^a	0.60 ^a	0.77 ^a	0.75 ^a
322	Terra	2.2	2.3	1.8	1.8	0.47	0.43	0.68	0.64
All ^b	Terra	1.7	1.8	1.5	1.6	0.57	0.57	0.68	0.68
All	Aqua	1.6	1.7	1.4	1.6	0.72	0.72	0.84	0.83

^a PLMR data interpolated between dates.
^b All dates except 307.

downscaled soil moisture $\theta_{10\text{ km}}$ and the errorbars represent the 1 km variability in 10 km fields $\sigma_{10\text{ km}}$, computed as the standard deviation of downscaled θ at 1 km resolution. Quantitative results in terms of root mean square error (RMSE) and correlation coefficient with L-band derived soil moisture are presented in Table 3. The downscaled soil moisture is generally in good agreement with PLMR retrieval with an overall RMSE of 1.7% v/v and 1.8% v/v for D1 and D2 respectively, and an overall correlation coefficient of about 0.7 for both schemes.

On JD 307 however, the correlation coefficient is negative (-0.2) for both D1 and D2 and the RMSE is 6% v/v and 8% v/v for D1 and D2 respectively. In particular, the RMSE is higher in both cases than the variability of 1 km resolution L-band derived soil moisture within the SMOS pixel ($\sigma_{\text{SMOS}}=5\%$ v/v), which means that the ~40 km resolution observation is a better estimate of near-surface soil moisture than the downscaled one at scales ranging from 1 km to 40 km. Those poor results are probably due to the poor estimates of L-band derived soil moisture on this particular day. The relationship between MODIS surface temperature and NDVI in Fig. 3 obtained on JD307 is consistent with that obtained on the other days. Consequently, MODIS surface temperature on JD307 can reliably be used to derive SMP. The point is that the MODIS surface temperature image on JD 307 is the only image available that directly follows one of the two major rainfall events of NAFE'06. In particular, the rainfall event during the night of JD 306–307 might be the cause of a temporary change in vegetation water content or possibly intercepted water (Merlin et al., 2008b), resulting in an unreliable L-band derived soil moisture product. Independently from the impact of canopy water storage on microwave soil moisture retrieval, one should note that the disaggregation approaches will not operate well in very wet conditions, under which surface skin temperature is generally decoupled from soil moisture levels. This decoupling is due to a switch from moisture-limited (dry) to energy-limited (wet) conditions.

The comparison between schemes D1 and D2 shows that better results in terms of RMSE and correlation coefficient are generally obtained with the linear approximation (D1). The inclusion of a second-order correction slightly deteriorates the results. It is argued that the aggregation of the MODIS derived soil temperature and L-band derived soil moisture from 1 km to 10 km tends to “linearize” the relationship between soil evaporative efficiency and soil moisture. The aggregation to 10 km makes the linear approximation approach more valid than the second-order correction one. Moreover, the simple model of Eq. (4) does not represent the saturation of soil evaporative

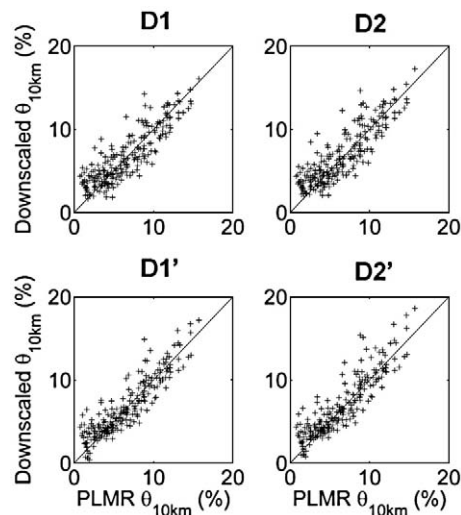


Fig. 6. Downscaling results at 10 km resolution obtained on all acquisition dates except JD 307.

efficiency at very low soil moisture values as modelled in Sellers et al. (1992). This saturation is visible in Fig. 6 for soil moisture values below 5% v/v.

4.4. Downscaling with D1' and D2' (spatially variable θ_c)

The variability of soil type within the SMOS pixel is now accounted for in the disaggregation scheme. Soil parameter θ_c is first fitted with MODIS SMP and PLMR soil moisture retrieval during a calibration period JD 304–311. The $\theta_{c,\text{MODIS}}$ values at 10 km resolution are then used in the application of downscaling schemes D1' and D2' to the whole period JD 304–322.

Parameter θ_c is a function of two soil-dependent parameters θ_{c0} and γ . In Komatsu (2003), γ and θ_{c0} were estimated for three different substrates (sand, agricultural soil, and cornstarch). In that study, most of the variability in θ_c was attributed to θ_{c0} (1% v/v for sand and 4% v/v for clay), while γ remained relatively constant. To simplify our analysis, parameter γ is thus fixed to a constant, estimated from the average of the values in Komatsu (2003) ($\gamma=100\text{ s m}^{-1}$). This approximation is consistent with the relatively high uncertainty in wind speed associated with the extrapolation of point-measurements (meteorological station) to the 40 by 60 km Yanco area.

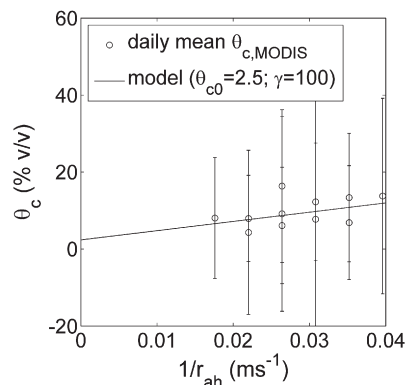


Fig. 7. Areal average (circle) and spatial variability (error bar) within the SMOS pixel of MODIS retrieved $\theta_{c,\text{MODIS}}$ versus $1/r_{ah}$. The aerodynamic resistance r_{ah} was computed from ground-based measurements of wind speed. Modelled θ_c is also plotted for comparison.

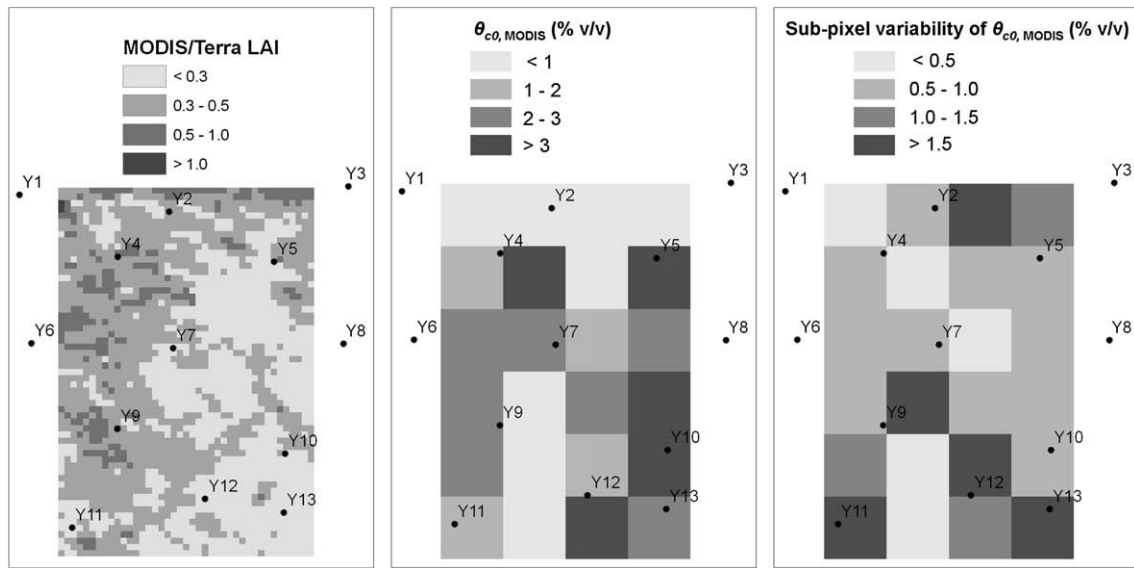


Fig. 8. Map over the 40 by 60 km Yanco area of 1 km resolution MODIS/Terra LAI (left), the retrieved 10 km resolution $\theta_{c0, MODIS}$ (centre) and its sub-pixel variability (right).

Given downscaling scheme D1 was found to be more accurate than downscaling scheme D2, Eq. (16) is used to estimate parameter $\theta_{c, MODIS}$:

$$\theta_{c, MODIS} = \frac{\theta_{PLMR} - \theta_{SMOS}}{SMP_{MODIS}} \quad (18)$$

from L-band derived soil moisture θ_{PLMR} and MODIS derived SMP using the five first clear sky MODIS images of NAFE'06, on JD 304, 308, 309, 310 and 311. Fig. 7 plots the areal average of 10 km resolution $\theta_{c, MODIS}$ as function of $1/r_{ah}$ (r_{ah} is computed from ground-based observation of wind speed). It appears that the model with default parameters $\gamma = 100 \text{ s m}^{-1}$ and $\theta_{c0} = 2.5\% \text{ v/v}$ fits relatively well the observed mean $\theta_{c, MODIS}$, which justifies the assumptions made previously. A variation of 0.02 ms^{-1} in $1/r_{ah}$ (equivalent to 4.5 ms^{-1} in wind speed) induces an increase of 5% v/v in θ_c . For a given day, the spatial variability of θ_c within the SMOS pixel is about three times larger (~15% v/v).

By fixing the value of γ to 100 s m^{-1} , one is able to estimate $\theta_{c0, MODIS}$ with Eq. (18) from fitted $\theta_{c, MODIS}$ and ground observations of r_{ah}

$$\theta_{c0, MODIS} = \frac{\theta_{c, MODIS}}{1 + \gamma/r_{ah}} \quad (19)$$

The soil parameter $\theta_{c0, MODIS}$ is retrieved at 10 km resolution over the Yanco area and its sub-spatial variability (standard deviation) are mapped in Fig. 8. The spatial variability of $\theta_{c0, MODIS}$ is linked to soil type distribution. The soil in the near-surface over Yanco has a high clay content in the CIA (left part of the image) near Y9 and along the Yanco Creek (right part of the image) from Y5 to Y12, and a high sand content in the north of the Yanco area around Y2 (Hornbuckle and Christen, 1999; Merlin et al., 2007). To determine whether the retrieved θ_{c0} compensates for possible errors in MODIS derived soil temperature retrievals, it is correlated with MODIS NDVI at 10 km resolution. The correlation coefficient is 0.0004, which indicates that the retrieved θ_{c0} is mainly dependent on soil properties, and not on vegetation cover.

The downscaling schemes D1' and D2' are then applied to the NAFE'06 data set using the soil parameter $\theta_{c0, MODIS}$ retrieved from JD 304–311. Downscaling results are presented in Figs. 4 and 5 for each MODIS image separately. Quantitative results in terms of RMSE and correlation coefficient with L-band derived soil moisture are listed in Table 3, showing that the inclusion of a spatially variable θ_c in the

downscaling relationship significantly increases the accuracy of the disaggregation. The overall RMSE on the downscaled θ is decreased from 1.7% to 1.4% v/v with the linear approximation, and from 1.7% to 1.6% v/v with the second-order correction. The overall correlation coefficient is increased from 0.65 to 0.76 with the linear approximation and from 0.64 to 0.75 with the second-order correction. These improvements justify the relative complexity of D1' compared to D1. However, the second-order correction in β^2 of D2 and D2' does not improve the downscaling approach with this data set (and the β model used).

4.5. Uncertainties in fractional vegetation cover

The performance of disaggregation approaches depends on fractional vegetation cover estimates. The uncertainties in f_{veg} can be associated with uncertainties in $NDVI_{min}$ and $NDVI_{max}$. The NDVI value at full vegetation cover $NDVI_{max}$ is not very accurate in the low-covered NAFE'06 area, and the value for $NDVI_{min}$ (0.22) does not probably correspond to pixels with 100% bare soil. To assess the impact of uncertainties in fractional vegetation cover on disaggregation results, a sensitivity analysis was conducted by adding a bias of ± 0.1 to $NDVI_{min}$ and $NDVI_{max}$. Results in terms of RMSE on disaggregated soil moisture are presented in Table 4 for downscaling algorithms D1 and D1'. When looking at the results for D1, a bias on

Table 4 Sensitivity of the disaggregation algorithms D1 and D1' to a bias of ± 0.1 on extreme NDVI values

Bias (Δ)	RMSE (% v/v) on	
	θ_{D1}	$\theta_{D1'}$
0	1.69	1.45
0	1.70	1.43
0	1.75	1.44
+0.1	2.03	1.41
+0.1	2.03	1.41
+0.1	2.03	1.41
-0.1	1.84	1.43
-0.1	1.73	1.46
-0.1	2.14	1.43

The RMSE on disaggregated soil moisture is computed from data including all days except JD 307.

516 NDVI_{min} has in general more impact than a bias on NDVI_{max}. This was
 517 expected as most pixels are in the lower range of NDVI values. In the
 518 worst case (negative bias on both NDVI_{min} and NDVI_{max}), the over-
 519 RMSE on disaggregated soil moisture is estimated as 2.1% v/v, which is
 520 relatively small compared to the range of variation of 10 km resolution
 521 soil moisture (0–15% v/v). When looking at the results for D1', it is
 522 apparent that a bias on vegetation fraction estimates has almost no
 523 effect on disaggregation results. In fact, the errors associated with an
 524 under(or over)estimation of f_{veg} is compensated by the calibration of
 525 θ_{co} . Consequently, the sensitivity study indicates that the impact of
 526 uncertainties in extreme NDVI values is relatively small, and can be
 527 corrected by a calibration strategy. Moreover, it should be noted that
 528 the accuracy of NDVI_{max} can potentially be improved by combining the
 529 maximum NDVI value observed within the study area with the value
 530 extrapolated along the dry edge of the temperature-NDVI triangle.

531 4.6. Observation time

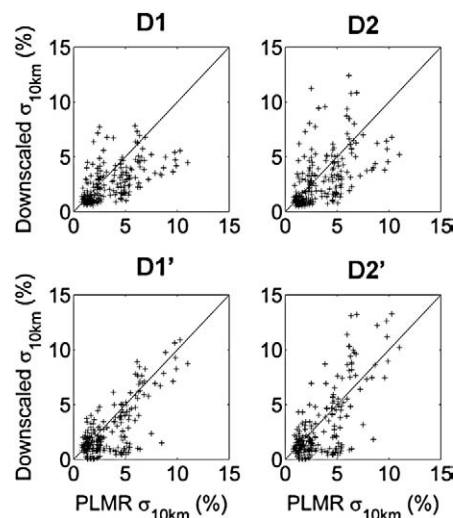
532 The disaggregation results obtained separately with MODIS aboard
 533 Terra (10 am) and MODIS aboard Aqua (1 pm) are compared in Table 3.
 534 While the RMSE is about the same with Terra and with Aqua for all
 535 downscaling schemes, the mean correlation coefficient between the
 536 downscaled and PLMR derived soil moisture varies between 0.57 and
 537 0.68 with Terra data and between 0.72 and 0.84 with Aqua data
 538 depending on the downscaling scheme. The downscaling approaches
 539 appear to be generally more robust with Aqua than with Terra, despite
 540 the interpolation of PLMR data on three days out of the six clear sky
 541 images (JD 310, 312 and 321). Actually, the acquisition time of surface
 542 temperature is an important requirement for β estimation, as the
 543 evaporation process directly depends on incoming solar radiation.
 544 These results confirm that the coupling between optical derived β and
 545 near-surface soil moisture is generally stronger at 1 pm than at 10 am.

546 4.7. Noise-level reduction at 10 km resolution

547 In the disaggregation approaches, the MODIS soil temperature was
 548 aggregated from 1 to 10 km to reduce the noise-level in data. The aim
 549 here is to verify the noise reduction at 10 km resolution under certain
 550 conditions. Table 5 lists the 10 km variability in the SMOS pixel and the
 551 1 km variability in 10 km fields of successively, NDVI, soil skin
 552 temperature, SMP, disaggregated soil moisture (scheme D1'), and
 553 PLMR derived soil moisture. When looking at the dry down period JD
 554 308–310 following the first rainfall event, it appears that the 1 km
 555 variability of SMP increases on JD 309 from 0.23–0.24 to 0.38, while
 556 the 10 km resolution variability is constant at 0.18–0.19. By assuming the
 557 spatial variability of soil moisture generally decreases with the
 558 mean during a dry down period (Teuling et al., 2007), it can be

551 **Table 5**
 552 10 km variability in the SMOS pixel and 1 km variability in 10 km fields of successively,
 553 NDVI, soil temperature, SMP (Soil Moisture Proxy), disaggregated soil moisture (scheme
 554 D1') and PLMR derived soil moisture

		10 km variability in the SMOS pixel (1 km variability in 10 km fields)					
		σ_{NDVI}	$\sigma_{T_{MODIS}}$	$\sigma_{SMP_{MODIS}}$	$\sigma_{\theta_{D1'}}$	$\sigma_{\theta_{PLMR}}$	
Day	Satellite	$\%$	K	$\%$	% v/v	% v/v	
556	304	Aqua	0.033 (0.041)	1.0 (1.6)	0.17 (0.25)	1.9 (2.3)	2.7 (3.2)
557	307	Terra	idem	2.2 (2.3)	0.39 (0.36)	6.5 (5.4)	2.0 (4.7)
558	308	Aqua	idem	1.5 (1.9)	0.18 (0.23)	2.7 (2.6)	2.2 (3.7)
559	309	Terra	idem	0.76 (1.4)	0.18 (0.38)	1.7 (3.0)	2.3 (3.4)
560	310	Aqua	idem	1.4 (1.9)	0.19 (0.24)	2.3 (2.4)	2.4 (3.3)
561	311	Terra	idem	1.3 (2.0)	0.14 (0.25)	2.2 (2.8)	2.3 (3.1)
562	312	Aqua	idem	1.7 (1.9)	0.24 (0.26)	2.9 (2.5)	2.3 (3.1)
563	313	Terra	idem	1.1 (1.6)	0.14 (0.21)	1.9 (2.4)	2.1 (2.9)
564	313	Aqua	idem	1.1 (1.8)	0.15 (0.26)	1.2 (1.7)	2.1 (2.9)
565	318	Terra	idem	1.0 (1.4)	0.15 (0.23)	1.7 (2.2)	1.7 (3.2)
566	321	Aqua	idem	1.5 (1.7)	0.26 (0.34)	2.0 (2.3)	2.3 (3.3)
567	322	Terra	idem	1.2 (1.7)	0.18 (0.26)	1.7 (2.3)	2.4 (3.4)



568 **Fig. 9.** 1 km variability in 10 km fields ($\sigma_{10\text{ km}}$) of downscaled soil moisture versus the
 569 $\sigma_{10\text{ km}}$ of PLMR derived soil moisture (for all acquisition dates except JD 307).

568 concluded that i) the noise-level in SMP observation is higher on JD
 569 309 than on the other days, and ii) the aggregation to 10 km reduces
 570 significantly random errors at 1 km resolution. Note that the higher
 571 uncertainty in SMP on JD 309 is probably due to the observation time:
 572 the data on JD 309 were acquired at 10 am aboard Terra, while the data
 573 on JD 308 and 310 were acquired at 1 pm aboard Aqua.

574 4.8. Robustness at 10 km resolution

575 The robustness of the downscaling schemes is assessed by plotting
 576 in Fig. 9 the 1 km variability in 10 km fields ($\sigma_{10\text{ km}}$) of downscaled soil
 577 moisture versus the $\sigma_{10\text{ km}}$ of PLMR derived soil moisture. The RMSE
 578 (and correlation coefficient) is 1.9% (0.61), 2.1% (0.58), 1.8% (0.73), and
 579 2.1% v/v (0.72) for D1, D2, D1', and D2' respectively. Results indicate
 580 that D1' is the most stable of the four approaches. Moreover, the RMSE
 581 on the $\sigma_{10\text{ km}}$ of downscaled soil moisture (1.8% v/v for D1') is about
 582 twice as small as the mean $\sigma_{10\text{ km}}$ of PLMR derived soil moisture (3.4%
 583 v/v). This means that the spatial variability of near-surface soil
 584 moisture is relatively well represented below the scale of 10 km. The
 585 scale of the disaggregation algorithm could therefore be improved to a
 586 resolution higher than 10 km. However, further studies are needed
 587 to estimate quantitatively an “optimal” downscaling resolution in
 588 between the MODIS resolution (1 km) and 10 km.

589 5. Discussion

590 Comparison of the algorithms using soil properties at SMOS scale
 591 θ_{cSMOS} and at the disaggregation scale θ_{cMODIS} shows that parameter
 592 θ_c is the most important parameter to be estimated at both high-
 593 and low-resolution. The application of the methodology to SMOS would
 594 therefore require estimating θ_c over large areas. Given the correlation
 595 between θ_c and sand/clay fraction (Komatsu, 2003), this parameter
 596 could possibly be derived from existing soil maps. However, soil
 597 maps of the first cm of soil are not available globally and consequently
 598 a more robust approach is to estimate θ_c from remote sensing
 599 observations. One way to do this would be to use the temporal
 600 behaviour of near-surface soil moisture observation as an index of
 601 soil evaporative rate: for a given surface area with approximately the
 602 same amount of precipitation, the faster the soil dries, the higher θ_c is.
 603 An iterative procedure on θ_{cMODIS} is proposed. First, the SMOS-scale
 604 θ_{cSMOS} is estimated from a time series of SMOS observation θ_{SMOS} and
 605 SMOS-scale β_{SMOS} . Next, θ_{cMODIS} is initialized $\theta_{cMODIS} = \theta_{cSMOS}$, and is
 606 retrieved at improved spatial resolution (10 km or higher), by
 607 iteratively (i) downscaling θ_{SMOS} and (ii) evaluating θ_{cMODIS} from the

599 downscaled θ and measured β_{MODIS} (in Eq. (18)). Such a downscaling/
600 assimilation coupling scheme would combine the spatial pattern
601 search (downscaling) and the temporal dynamics search (assimila-
602 tion) in an optimal manner (Merlin et al., 2006a).

603 The main limitation of the general downscaling approach outlined
604 in this paper is the derivation of accurate SMP (or soil evaporative
605 efficiency) estimates. For NAFE'06, the LAI ranged from 0 to 1.5 at 1 km
606 resolution, resulting in relatively low fractional vegetation covers.
607 It should be noted that the uncertainty in soil skin temperature
608 retrievals increases with LAI, and the retrieval will not be feasible over
609 fully vegetated pixels. Also, the formulation of the fractional
610 vegetation cover f_{veg} as a linear function of NDVI in Eq. (3) could be
611 improved (Baret et al., 2007). A second limitation of the method is
612 estimation of the minimum soil temperature T_{min} , as it partly depends
613 on a subjective interpretation of the triangle. As depicted by Carlson
614 (2007) “the most severe limitation of the triangle method is that
615 identification of the triangular shape in the pixel distribution requires
616 a flat surface and a large number of pixels over an area with a wide
617 range of soil wetness and fractional vegetation cover”. However, the
618 downscaling approach differs from the traditional triangle analysis as
619 it does not require estimating the maximum soil temperature T_{max} . As
620 T_{max} can be largely uncertain, especially after a rainfall event when the
621 soil is wet everywhere in the SMOS pixel, the use of SMP (instead of
622 soil evaporative efficiency) represents a key step in the downscaling
623 procedures. One drawback of the use of SMP is that the denominator
624 ($T_{\text{MODIS}} - T_{\text{min}}$) is subject to numerical instabilities when the MODIS
625 derived soil temperature is close to the minimum soil temperature.

626 6. Summary and conclusions

627 A deterministic approach for downscaling ~40 km resolution
628 SMOS soil moisture observations was developed from 1 km resolution
629 MODIS data. To account for the lower soil moisture sensitivity of
630 MODIS surface temperature compared to L-band brightness tempera-
631 ture, the downscaling scale was fixed to 10 times (10 km) the spatial
632 resolution of MODIS thermal data (1 km). The three general steps of
633 the downscaling procedure were (i) estimate soil evaporative
634 efficiency from MODIS data (ii) link soil evaporative efficiency to
635 near-surface soil moisture via a physically-based scaling function and
636 (iii) build a downscaling relationship to express high-resolution near-
637 surface soil moisture as function of SMOS type observation and high-
638 resolution soil evaporative efficiency. This innovative approach was
639 able to account for spatial variations in soil type and temporal
640 variations in wind speed and near-soil moisture across the SMOS
641 pixels. Four different downscaling algorithms were proposed. They
642 differed only with regards to i) the assumed relationship (linear or
643 nonlinear) between soil evaporative efficiency and near-surface soil
644 moisture, and ii) the scale at which soil parameters (θ_c) were available
645 (40 km or 10 km).

646 The four downscaling algorithms have been tested using the
647 NAFE'06 data set. The 1 km resolution L-band derived soil moisture
648 was aggregated over the Yanco area to generate a time series of coarse-
649 scale (~40 km) near-surface soil moisture observations. The simulated
650 SMOS soil moisture was then disaggregated by the different down-
651 scaling algorithms. The disaggregation results obtained at 10 km
652 resolution from twelve MODIS surface temperature images (six aboard
653 Terra and six aboard Aqua) were compared with the L-band derived
654 soil moisture aggregated to 10 km.

655 The overall root mean square difference between downscaled and
656 L-band derived soil moisture was better than 1.8% v/v with soil
657 moisture values ranging from 0 to 15% v/v. The consistency between
658 downscaled and L-band derived soil moisture was also demonstrated
659 at the 1 km scale. The overall RMSE on sub-pixel variability (standard
660 deviation within 10 km resolution pixels) of downscaled soil moisture
661 was better than 2.1% v/v with a variability ranging from 0 to 12% v/v. In
662 all cases, the correlation coefficient between downscaled and L-band

663 derived soil moisture (and its sub-pixel variability) was better
664 than 0.6. These results illustrated the remarkable robustness of the
665 four different algorithms at 10 km resolution across the three-week
666 experiment. It was found that results are more accurate
667 with MODIS/Aqua than with MODIS/Terra data, due to the stronger
668 coupling between β and near-surface soil moisture at 1 pm than at
669 10 am.

670 The comparison of the linear and non-linear algorithms showed
671 that better results were generally obtained with the linear approx-
672 imation. It was argued that the aggregation from 1 km to 10 km of
673 MODIS-derived soil temperature and L-band derived soil moisture
674 tends to “linearize” the correlation between soil evaporative efficiency
675 and near-surface soil moisture around the SMOS observation.
676 However, as the soil moisture variability over the study area was
677 mainly due to irrigation at scales smaller than 1 km, it is not possible
678 to generalize this finding to SMOS pixels with a stronger heterogeneity
679 at 10 km resolution, for which the impact of the non-linearity of β
680 would be higher.

681 The comparison of the algorithms using soil properties at the
682 SMOS scale $\theta_{c,\text{SMOS}}$ and at the disaggregation scale $\theta_{c,\text{MODIS}}$ showed
683 that θ_c is the most important parameter to be estimated at both high-
684 and low-resolution. The knowledge of θ_c at 10 km resolution made the
685 overall RMSE on downscaled soil moisture decrease from 1.7% v/v to
686 1.3% v/v, and the mean correlation coefficient increase from 0.7 to 0.8.

687 The application to SMOS data would imply coupling the disag-
688 gregation approach with an assimilation scheme in order to retrieve
689 soil parameters (e.g. θ_c) at the disaggregation scale. Further testing
690 will be needed to assess the applicability of such an approach in a
691 wider range of surface conditions, especially over higher vegetation
692 covers. Also, studies evaluating the relative sensitivity of L-band
693 observations and soil moisture proxies (such as soil evaporative
694 efficiency) are needed to determine optimal disaggregation scales in
695 terms of downscaling accuracy.

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