Disaggregation of SMOS Soil Moisture over the Canadian Prairies

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Abstract- In this study, we used the Disaggregation based on Physical And Theoretical scale Change (DISPATCH) algorithm under very wet soil conditions in Western Canada for the disaggregation of coarse resolution 40-km soil moisture derived from the Soil Moisture Ocean Salinity (SMOS) satellite. The algorithm relies on the Soil Evaporative Efficiency (SEE), which was estimated using the 1-km resolution data from the MODerate resolution Imaging Spectoradiometer (MODIS). The study aimed to: (i) evaluate DISPATCH under wet soil conditions, (ii) test the linearity/non-linearity of the relationship between soil moisture and SEE, and (iii) propose a more robust procedure to calibrate the SEE model under very wet soil conditions. The disaggregated soil moisture values were compared to 0-5 cm in situ measurements and the soil moisture derived from the L-MEB (L-band Microwave Emission of the Biosphere) model from airborne brightness temperature at 1.4 GHz collected during the Canadian Experiment for Soil Moisture in 2010 (CanEx-SM10) field campaign. The results show a correlation between 0.7 and 0.8 and bias values $\sim 0 \text{ m}^3/\text{m}^3$. The DISPATCH algorithm shows better disaggregation results under very wet soil conditions when a non-linear relationship is

considered between SEE and soil moisture instead of a linear model. This is mainly due to the small variability of surface temperature inside the area covered by the SMOS pixel under very wet soil conditions, and the difficulty in accurately estimating the maximum soil temperature ($T_{s_{max}}$), which is a driving factor for SEE. A sensitivity analysis was conducted and it shows that the linear model performs well only if $T_{s_{max}}$ can be determined more accurately. The possibility to determine $T_{s_{max}}$ using high resolution MODIS data over a larger area than the SMOS pixel is examined and discussed in the paper.

Keywords: Soil moisture, SMOS, disaggregation, DISPATCH algorithm, Canex-SM10, Canada.

1. Introduction

Surface soil moisture has various potential applications such as in hydrology (Elbially et al., 2014), meteorology (Loew et al., 2013) and agriculture (Narasimhan et al., 2005). This parameter is highly variable both spatially and temporally, as the result of the heterogeneity of soil properties, topography, land cover, rainfall, and evapotranspiration. Remote sensing data can provide frequent and spatially estimates of surface soil moisture (Kerr et al., 2010; Njoku et al., 2003; Wagner et al., 2013). Results from many experimental studies suggest that the L-band in passive mode is optimal for estimating surface soil moisture, due to its greater emitting depth, its lower sensitivity to surface roughness and vegetation effects, and its independence of weather conditions (Njoku et al., 1996; Kerr et al., 2007). The Soil Moisture and Ocean Salinity (SMOS) satellite of the European Space Agency (ESA), in orbit since 2 November 2009, is the first L-band passive microwave satellite. One of its objectives is to map surface soil moisture at global

scale with accuracy better than $0.04 \text{ m}^3/\text{m}^3$ (Kerr et al., 2010). With its innovative technology based on a two-dimensional interferometric radiometer, SMOS is able to estimate soil moisture at a depth of up to 5 cm, with a repeat cycle of less than 3 days and a spatial resolution of about 40 km. This coarse spatial resolution is adequate for applications at global scale, but it is low for studies at regional and local scales that require data with a resolution of 1 to 10 km (Entekhabi et al., 2010). Spaceborne passive microwave sensors are characterized by their very low spatial resolution in general. The Advanced Microwave Scanning Radiometer - Earth Observing System (AMSR-E), has a resolution of about 60 km resolution, it is less sensitive to soil moisture than the L-band (X and C bands are the lowest frequencies used for soil moisture retrievals). As for the Soil Moisture Active and Passive (SMAP) mission, the spatial resolutions of the passive and active microwave sensors are about 40 km and 3 km, respectively (Entekhabi et al., 2010). To address the problem of scale mismatch between its large-scale passive microwave estimates and local scale applications, SMAP will also provide soil moisture products at 9 km resolution by combining L-band passive and active microwave measurements (Das et al., 2011). Alternative downscaling approaches are based on optical/thermal remotely sensed data (Chauhan et al., 2003; Merlin et al., 2008; Piles et al., 2011).

Optical/thermal satellite sensors provide data at fine spatial resolution and shorter revisit time (1 day) compared to Synthetic Aperture Radar sensors (~15 days). However, despite some potential to monitor soil moisture (Idso et al., 1975; Weidong et al., 2003), their sensitivity to other environmental factors, particularly vegetation cover and weather conditions, makes retrieving soil moisture impractical (Wang et al., 2007) from

77 optical/thermal data alone. However, their synergistic use with passive microwave
78 measurements, which are highly sensitive to soil moisture, appears as a promising
79 approach to retrieve soil moisture at finer scales. Indeed, based on the “universal
80 triangle” concept, Carlson et al. (1994) showed an empirical polynomial relationship
81 between soil moisture, soil temperature and vegetation cover. Since then, efforts are
82 being made to downscale passive microwave soil moisture estimates using
83 optical/thermal data (Chauhan et al., 2003; Merlin et al., 2008; Piles et al., 2011).
84 However, the downscaling methodologies still need to be validated for a range of hydro-
85 climatic conditions, and subsequently improved. Chauhan et al. (2003) used the universal
86 triangle concept to infer high-resolution soil moisture from coarse resolution soil
87 moisture derived from the Special Sensor Microwave Imager (SSM/I) data and optical
88 data from the Advanced Very High Resolution Radiometer (AVHRR). Later, Merlin et
89 al. (2008) improved this approach by using a semi-empirical model to express the
90 relationship between the Soil Evaporative Efficiency (SEE) and near-surface soil
91 moisture. Linear and non-linear models have been proposed to link the evaporative
92 efficiency to soil moisture. However, the performance of each type of model in the
93 disaggregation literature has not yet been extensively discussed. Other, slightly different,
94 disaggregation methods are proposed in the literature. Piles et al., (2011) and Sánchez-
95 Ruiz et al., (2014) suggested the combination of coarse resolution SMOS brightness
96 temperature with the MODIS land surface temperature and Normalized Difference
97 Vegetation Index to disaggregate SMOS soil moisture estimates at MODIS scale. A
98 correlation coefficient of up to 0.72 was found between their results and the ground truth
99 data. Rahimzadeh-Bajgiran et al. (2013) replaced the surface temperature axis in the

“universal triangle” space by the difference between the surface temperature and air temperature derived from the North American Regional Reanalysis (NAAR). In addition, to show improvements due to the integration of air temperature into the surface temperature/vegetation index space, these authors found that downscaling methods based on optical/thermal data led to better results for intermediate soil moisture conditions (from 0.12 to 0.22 m³/m³) than for extreme soil moisture conditions. For these cases, further studies are needed. Kim and Hogue (2012) considered various key factors providing information on relative variations in surface wetness conditions. These factors (i.e., surface temperature, vegetation indexes, and albedo) are derived from MODIS data and used as weighting parameters for downscaling the low resolution AMSR-E soil moisture. Comparing their results with those obtained from the method of Merlin et al. (2008), authors noted that both techniques significantly improve the limited spatial variability of the AMSR-E product.

DISPATCH (DISaggregation based on Physical And Theoretical scale CHange) developed by Merlin et al. (2012a) is an improved version of the algorithm by Merlin et al., (2008). DISPATCH uses a trapezoidal model instead of the “universal triangle” to account for the effect of vegetation water stress at high resolution (Moran et al. 1994) in the derivation of SEE from optical/thermal data. DISPATCH has shown good performance over semi-arid sites located in Australia (Merlin et al., 2012b) and in Spain (Merlin et al., 2013), especially if the linear model is used to express the relationship between SEE and near-surface soil moisture. However, the SEE model considered depends on “temperature end-members” which define the limits of the “universal trapezoid”, meaning soil maximum and minimum temperatures

($T_{s_{max}}, T_{s_{min}}$) and vegetation maximum and minimum temperatures ($T_{v_{max}}, T_{v_{min}}$).

The accuracy of these parameters depends on several factors such as the land cover, the meteorological conditions and the spatial variability of moisture in the study area. Thus, further studies are needed to evaluate the applicability of the DISPATCH algorithm to a wide range of surface conditions.

The objective of this research was to 1) evaluate the applicability of the DISPATCH algorithm to wet soil conditions; 2) analyze the impacts of the linearity of the relationship considered between SEE and the near surface soil moisture; and 3) propose a more robust procedure to use the relationship between SEE and near soil moisture under wet soil conditions for improved disaggregation results. The area considered experienced very wet soil conditions (above $0.15 \text{ m}^3/\text{m}^3$) during the period of this study.

2. Study area

The study area corresponds to the agricultural site considered in the framework of the SMOS validation effort in Canada. As shown in Figure 1.a, it is located in the Canadian Prairies, near Kenaston (Province of Saskatchewan, Canada), within latitudes 51.14 to 51.70 N, and longitudes 105.67 to 106.79 W. A major field campaign, named CanEx-SM10, was organized at the site from 1 to 15 June 2010 for the validation of SMOS data. Detailed information on the field protocols and the collected data (both airborne and ground-based) are available in Magagi et al., (2013), and in the dedicated website at the University of Sherbrooke in Canada (<http://pages.usherbrooke.ca/canexsm10/>).

Figure 1.b shows the topography of the site along with soil moisture measurement locations and the SMOS grid centers included in the study site and used in this paper.

Figure 1.a: Study site

Figure 1.b: Digital Elevation Model, the ground-based measurements networks and SMOS grid pixels for the Kenaston site.

3. Data description

3.1. Ground measurements

The ground measurements of soil moisture were conducted between 6 a.m. and mid-day over 60 fields. Each field was about 800 x 800 m. Using Steven's Water Hydra Probe sensors, the measurements were taken in each field, at a depth of 0-5 cm, every 100 m at 14 points distributed along two parallel transects 400 m apart. To ensure the **representativeness** of the field data, at each point, three measurements of soil moisture were taken (see the detailed protocol on the dedicated website). These field measurements were calibrated using gravimetric soil moisture samples collected for each field and on each sampling day. For comparison with the disaggregation results at a resolution of 1 km, the average soil moisture was calculated for each field. In addition to soil moisture, other variables measured during the campaign were used in this study. This includes surface roughness and soil texture information (sand and clay fractions).

Figure 2 shows the daily cumulative rainfall profile as well as the mean and the standard deviation values of the soil moisture measurements for the 60 agricultural fields during the field campaign period. The high amount of soil moisture results from the abundant rainfall during and prior to the field campaign. As a consequence, agricultural practices were delayed; the fields were almost bare and very wet (Magagi et al., 2013).

Figure 2: Temporal profile of soil moisture measurements, daily cumulative rainfall, and cloud fraction in MODIS-Aqua and MODIS-Terra acquisitions over the study site, during the CanEX-SM10 field campaign.

3.2. Airborne measurements

The L-band dual-polarized airborne brightness temperatures (1.4 GHz) were measured during the campaign at an incidence angle of 40° and a spatial resolution of approximately 2.25 km (<http://canex-sm10.espaceweb.usherbrooke.ca/>; Magagi et al., 2013). These airborne measurements were collected along 16 parallel flight lines covering the entire Kenaston site, by Environment Canada's microwave radiometer mounted on the National Research Council's (NRC) Twin-Otter aircraft at an altitude of 2341 m. Land surface infrared temperature (T_{IR}) was simultaneously measured using a thermal radiometer mounted on the aircraft. The airborne brightness temperature measurements were used in this study to estimate soil moisture at the local scale from the inversion of the L-MEB model (Wigneron et al., 2007). The retrieved soil moisture was compared to the disaggregated soil moisture values.

3.3. Satellite measurements

3.3.1. SMOS soil moisture data

Version 5.01 of SMOS soil moisture (L2 product), published on 16 March 2012, was used. Details on the SMOS soil moisture algorithm are available in Kerr et al., (2012). We performed quality control and validation of the soil moisture product for our study site (Djamai et al., 2015). Due to the well-known underestimation of SMOS soil moisture; we applied a bias correction to the data to better match ground measurements of soil moisture (Gherboudj et al., 2012; Djamai et al., 2015). Estimates of SMOS soil moisture, at both AM and PM overpasses, on 13 SMOS grid centers located over the study area were used to conduct the disaggregation (Figure 3.a).

3.3.2. MODIS optical and thermal data

The MODIS Terra and Aqua products were downloaded through the NASA Land Data Products and Services website (https://lpdaac.usgs.gov/data_access/reverb). Daily land surface temperature (LST) was extracted from MOD11A1 for Terra and MYD11A1 products for Aqua (Figure 3.b). The NDVI index was estimated daily from the red band (band 1) and the near-infrared band (band 2) provided by the MOD09GA and MYD09GA products, respectively for Terra and Aqua (Figure 3.c). Leaf Area Index (LAI) and the surface emissivity datasets were extracted from MCD15A2 and MYD11A1/EM31 MODIS products respectively. LST and NDVI data were used to downscale SMOS soil moisture estimates for both the ascending and descending overpasses, in particular for the estimation of SEE. The surface emissivity and LAI are used by the L-MEB model to invert soil moisture from airborne measurements. In

Figures 3.a and 3.b, the inverse dependence between LST and soil moisture can be clearly seen.

To take advantage of the full range of soil evaporative efficiency at 1 km, only cloud-free MODIS products could be used in the downscaling process. Thus, as indicated in Figure 2, which presents the temporal profile of the cloud fraction derived from MODIS products, only two cloud-free days were available during the CanEX-SM10 field campaign: DOY 164 and DOY 165. Despite the two days available SMOS data, this study uses a total of 13 SMOS pixels for two overpasses each day. Aircraft and ground soil moisture measurements collected over 60 sampled fields allowed statistical analyses of the results. Moreover, this dataset offers a special opportunity for the evaluation of DISPATCH under extreme soil moisture conditions, which has not previously been investigated

Figure 3: (a) SMOS derived soil moisture, (b) LST and (c) NDVI provided by MODIS/Aqua and MODIS/Terra for the Kenaston site on DOY 164 and 165.

4. Description of DISPATCH disaggregation algorithm

DISPATCH is based on the spatial relationship between the soil evaporative efficiency (SEE), derived from optical and thermal data, and the top layer soil moisture (SM) at fine scale (Merlin et al., 2012a). It involves three steps: 1) the estimation of SEE; 2) the establishment of a linking model between SEE and SM; and 3) the downscaling of SMOS soil moisture to a finer scale using Equation 1 shown below. Further details of the desegregation method can be found in Merlin et al. (2012a).

$$SM = \langle SM \rangle + \frac{\partial SM}{\partial SEE} (SEE - \langle SEE \rangle) \quad (1)$$

where SM is the disaggregated soil moisture at fine scale (1-km MODIS resolution in this study). SEE is the soil evaporative efficiency estimated using MODIS data at 1-km resolution, and $\langle SEE \rangle$ is its average value at SMOS pixel scale. $\langle SM \rangle$ is the SMOS soil moisture (40-km resolution).

SEE is estimated from MODIS optical and thermal data using the model given by Equation 2.

$$SEE = \frac{Ts_{max} - Ts}{Ts_{max} - Ts_{min}} \quad (2)$$

Ts_{max} and Ts_{min} are called “temperature end-members”. They represent the maximal and minimal soil temperatures found over the study scale. They are extrapolated from the trapezoidal model (Moran et al., 1994) given by the scatter plot of land surface temperature (LST) versus the vegetation fractional cover (f_v) derived from NDVI data. Ts is the soil skin temperature, calculated from MODIS LST and f_v as:

$$Ts = \frac{LST - f_v \cdot Tv}{1 - f_v} \quad (3)$$

where Tv is the vegetation temperature (Moran et al. 1994).

Equation 2 shows that SEE decreases with an increase in T_s as the soil loses its moisture by evaporation. Thus, it reaches its maximum value ($SEE = 1$) for $T_s = T_{s_{min}}$ and its minimum value ($SEE = 0$) at $T_s = T_{s_{max}}$.

In the literature, the relationship between SEE and near-surface soil moisture (SM) has been reported as:

A linear model (Manabe, 1969):
$$SM = SM_p \cdot SEE \quad (4)$$

SM_p is a parameter estimated by considering the SMOS pixel scale; or

A non-linear model (Merlin et al., 2013):
$$SEE = \left(\frac{SM}{SM_{sat}} \right)^p \quad (5)$$

p is a parameter estimated by considering the SMOS pixel scale, and SM_{sat} is the saturated soil moisture estimated according to Cosby et al. (1984).

5. Methodology

The application of the DISPATCH algorithm to SMOS soil moisture and the validation process for the results are schematically presented in Figure 4; details are given in sections 5.1 and 5.2. We made two assumptions in this work. The soil moisture pattern is assumed to be spatially persistent for a few hours after the SMOS overpass to overcome the mismatch between the ground soil moisture measurement time (from ~ 6 a.m. to ~ 11 a.m.) and SMOS overpass times (6 a.m./p.m.) and MODIS Aqua/Terra overpass times (1 p.m. and 10 a.m., respectively). If no rainfall occurs between the acquisition times of these measurements, the assumption is generally met. It is also assumed that the land surface temperature derived from MODIS data has a horizontal spatial correlation with the 0–5 cm soil temperature (Nishida et al., 2003) to overcome the mismatch of the soil moisture and surface temperature sensing depths.

Figure 4: Schematic diagram of the methodology

5.1. Application of DISPATCH algorithm to SMOS soil moisture

SMOS soil moisture data and cloud-free MODIS images acquired over the Kenaston site during the CanEx-SM10 field experiment were used to estimate soil moisture at 1 km scale from the DISPATCH algorithm (Merlin et al., 2012a). In total, 13 SMOS pixels, 2 acquisition times, 2 days, 2 MODIS datasets and 2 linearity modes were considered.

To generate daily SEE maps (Equation 2) using MODIS/Aqua and MODIS/Terra datasets, DISPATCH, which was developed under high spatial variability of soil moisture (Merlin et al, 2012b; 2013), is applied to CanEx-SM10's very wet soil conditions. The estimation of the "temperature end-members" was only based on the high-resolution optical/thermal data within each SMOS pixel. Thus, the scatter plots of the vegetation fractional cover f_v versus the surface temperature LST and the SEE maps were generated for each SMOS pixel.

As a second step, in order to overcome a limitation of DISPATCH encountered for very wet soil conditions: underestimation of Ts_{max} , we proposed a simple method to improve the accuracy of Ts_{max} so that it will be representative of a dry soil (water content $\approx 0 \text{ m}^3.\text{m}^3$). Thus, instead of considering each SMOS pixel independently, the estimation of the "temperature end-members" was based on the high-resolution optical/thermal data within the entire study site. Enlarging the research area allows the consideration of a wider range of surface conditions, namely dry pixels. Thus, instead of considering each SMOS pixel independently, the estimation of the "temperature end-members" was based on the high-resolution optical/thermal data encountered within the entire study site. Therefore, for each of the two MODIS datasets, a unique scatter plot of f_v /LST and a unique SEE map were produced for the entire study area (33 km x 71 km). Considering

that the grid cells of a typical global climate model are about 100 - 300 km (Salathé et al., 2010; <http://scied.ucar.edu/longcontent/climate-modeling>), we assume that the uniformity of the atmospheric forcing could be accepted like in the simulations of the Canadian Global Climate Model (CGCM) carried out on a grid of about 415 km x 415 km (Flato et al., 2000; Scinocca et al., 2008) and of the Canadian Regional Climate Model (CRCM) whose grid spacing is about ~ 50 km (Laprise, 2008).

To test the linearity of the relationship between SEE and SM (Equation 2) under very wet soil conditions, both linear and non-linear models were used in Equation 1 to generate soil moisture at 1-km scale.

5.2. Validation with ground-based data

For validation purposes, we compared the 1-km downscaled soil moisture to the ground-based soil moisture data collected during the field campaign. First, ground soil moisture data were calculated for each field as the average of the contained point measurements. Only SMOS day-time overpass data were used because of the constraints imposed by the field data acquisition times.

5.3. Comparison to L-MEB inversion

The SMOS downscaled soil moisture was also compared to the soil moisture estimated by inverting the L-MEB model. We used the L-band airborne brightness temperature (Tb_h, Tb_v) measurements. The main unknowns in the model were the soil temperature (T_s) and optical thickness (τ). T_s was estimated from Equation 6, where T_{IR} is the infrared temperature measured by the thermal radiometer mounted on board the Twin Otter aircraft, and e is the soil emissivity which was extracted from the MODIS data.

$$Ts = e.T_{IR} \quad (6)$$

τ was estimated from the MODIS LAI product according to Equation 7 (Kerr et al., 2012):

$$\tau = b_v \cdot LAI \quad (7)$$

where b_v is an empirical parameter equal to 0.06 for low vegetation.

First Tb_h , Tb_v and Ts were re-sampled to the MODIS grid (1 km x 1 km). Then, an iterative process was used to determine the soil moisture value that minimizes the root mean square error (RMSE) between the modeled and the measured brightness temperatures at H and V polarizations. Finally, the retrieved soil moisture values at 1-km resolution using L-MEB were compared to the downscaled soil moisture using the DISPATCH algorithm.

5.4. Sensitivity analysis

As described above, the disaggregation method is based on the soil evaporative efficiency, which in turn depends on temperature end-members. For wet soil conditions, the estimation of the dry edge Ts_{max} is not obvious. We conducted a sensitivity analysis to understand the effect of a small variation of Ts_{max} in the extrapolated value on the downscaled soil moisture, in order to evaluate the stability of the model under wet soil conditions. Thus, the partial derivative of the downscaling relationship (Equation 1) with respect to Ts_{max} (dSM/dTs_{max}) was computed for different soil temperatures between Ts_{min} and Ts_{max} .

6. Results

6.1. Disaggregation of SMOS soil moisture data

Soil moisture results obtained from DISPATCH downscaling algorithm (Merlin et al., 2012a) are presented and validated using ground measurements of soil moisture. Comparison of the results with L-MEB derived soil moisture using airborne data is also conducted. It is followed by a sensitivity analysis of the downscaled soil moisture to T_{Smax} .

6.1.1. Soil moisture maps

The maps of 1-km downscaled soil moisture for DOY 164 and 165 for the day-time and the night-time overpasses obtained from SMOS/MODIS (Terra and Aqua) data and the use of linear and non-linear models between SEE and SM are shown in Figure 5.a.

The results from the linear and non-linear models better captured the spatial patterns of soil moisture at fine scale (Figure 5.a) than the coarse resolution SMOS data (Figure 3.a). In accordance with the topography of the study site, very wet soils were identified in the north-eastern and the central parts of the site. The decrease in soil moisture observed from DOY 164 to DOY 165 (successive no rainy days), following a rainy period (before 164), was effectively captured by SMOS and was also reproduced at higher resolution.

Table 1 shows that the different downscaled soil moisture maps have a very similar spatial mean value ($\approx 0.33 \text{ m}^3/\text{m}^3$). This explains the zero biases generally found between these maps (Table 2). However, the maps derived using the linear model have higher spatial dynamics ($std \approx 0.12 \text{ m}^3/\text{m}^3$) than those derived from the non-linear model ($std \approx 0.06 \text{ m}^3/\text{m}^3$). This remark can be also noticed through the Figure 5.a.

The downscaled soil moisture maps derived from the SMOS/Aqua combination and SMOS/Terra combination show very similar spatial patterns (Figure 5.a). Table 2 presents the statistics for the two datasets: correlation coefficients from 0.72 to 0.91, RMSE values from 0.01 to 0.05 m³/m³, zero biases, and slopes varying from 0.68 to 0.88. Analyses of the spatial difference in soil moisture maps between the SMOS/Aqua combination and SMOS/Terra combination were also conducted (Figure 5.b). The results indicate that SMOS/Aqua and SMOS/Terra combinations are closer for DOY 164 compared to DOY 165 and much more for the non-linear model compared to the linear model.

High spatial correlation coefficients (R from 0.87 to 0.94, Table 2) were also obtained between the downscaled soil moisture maps using the linear and non-linear models. However, Table 2 shows higher RMSE values (~0.06 m³/m³) and lower slopes (~ 0.5) between the soil moisture maps derived from the two models, compared values found when comparing maps derived from the SMOS/Aqua and SMOS/Terra combinations. Compared to Figure 5.a, the spatial difference in soil moisture maps between the linear and non-linear models (Figure 5.c) shows the highest values over the driest and the wettest pixels.

Figure 5.a: Downscaled soil moisture provided by SMOS/Terra and SMOS/Aqua combinations, linear and non-linear models, on DOY 164 and 165, ascending (AM) and descending (PM) SMOS overpasses.

Figure 5.b: Spatial difference in soil moisture maps between SMOS/Aqua combination and SMOS/Terra combination using the linear and non-linear models.

Figure 5.c: Spatial difference in soil moisture maps between the linear and non-linear models for both SMOS/Aqua and SMOS/Terra combinations.

Table 1: Mean, standard deviation, minimum and maximum values of the downscaled soil moisture maps.

			Aqua				Terra			
Model	DOY	Time	Mean (m ³ /m ³)	Std. (m ³ /m ³)	Min (m ³ /m ³)	Max (m ³ /m ³)	Mean (m ³ /m ³)	Std. (m ³ /m ³)	Min (m ³ /m ³)	Max (m ³ /m ³)
Linear	164	AM	0.33	0.12	0.00	0.63	0.33	0.11	0.02	0.61
Linear	164	PM	0.33	0.12	0.00	0.61	0.32	0.11	0.02	0.59
Linear	165	AM	0.33	0.11	0.06	0.70	0.32	0.11	0.04	0.59
Linear	165	PM	0.34	0.12	0.06	0.74	0.33	0.12	0.04	0.62
Non-linear	164	AM	0.33	0.06	0.14	0.47	0.33	0.06	0.14	0.46
Non-linear	164	PM	0.33	0.06	0.15	0.47	0.33	0.06	0.16	0.46
Non-linear	165	AM	0.32	0.06	0.16	0.46	0.32	0.06	0.14	0.47
Non-linear	165	PM	0.33	0.06	0.13	0.46	0.33	0.06	0.08	0.47

Table 2: Correlation coefficients, RMSE, bias and slope values between the downscaled soil moisture maps estimated from (a) MODIS Aqua and MODIS Terra data using the linear and non-linear models, and (b) the linear and non-linear models for both SMOS/Aqua and SMOS/Terra combinations

(a) Aqua/Terra							(b) Linear/non-linear				
DOY	Time	Model	R	RMSE (m ³ /m ³)	Bias (m ³ /m ³)	Slope	Sensor	R	RMSE (m ³ /m ³)	Bias (m ³ /m ³)	Slope
164	AM	Linear	0.86	0.02	0.00	0.86	Aqua	0.93	0.06	0.00	0.48
164	PM	Linear	0.86	0.02	0.00	0.86	Aqua	0.94	0.06	0.00	0.51
165	AM	Linear	0.73	0.05	-0.01	0.68	Aqua	0.94	0.06	-0.01	0.50
165	PM	Linear	0.72	0.05	-0.01	0.68	Aqua	0.87	0.07	-0.01	0.47
164	AM	Non-linear	0.90	0.02	0.00	0.88	Terra	0.93	0.06	0.00	0.49
164	PM	Non-linear	0.91	0.01	0.00	0.88	Terra	0.94	0.06	0.00	0.51
165	AM	Non-linear	0.76	0.05	0.00	0.75	Terra	0.93	0.05	0.00	0.54
165	PM	Non-linear	0.80	0.04	0.00	0.76	Terra	0.88	0.06	0.00	0.50

6.1.2. Validation and comparison

The scatter plots of the downscaled soil moisture versus the ground-based soil moisture and the L-MEB derived soil moisture are presented in Figure 6 and Figure 7, respectively. They indicate that, for a given model, comparable statistical results were obtained from SMOS/Terra and SMOS/Aqua derived soil moisture maps. They show low biases for both linear and non-linear models (from -0.01 to 0.04 m³/m³) and slightly better correlation coefficients with the linear model (from 0.50 to 0.60 for ground-based

data; from 0.73 to 0.80 for L-MEB derived soil moisture) compared to the non-linear model (from 0.37 to 0.51 for ground-based data; from 0.70 to 0.78 for L-MEB derived soil moisture). The low correlation with ground-based data might be the result of the low variability of soil moisture between the measured fields or the spatial representativeness of in situ measurements at the downscaling resolution.

To check the significance of the correlation coefficients found between the soil moisture datasets, the Pearson H_0 statistical test was applied. The null hypothesis “ H_0 : X and Y are linked (X and Y are the two soil moisture datasets)” was considered with different thresholds. The results indicated that the correlation between the downscaled soil moisture and L-MEB derived soil moisture was significant at $p < 0.05$. But the correlation between the downscaled soil moisture and the ground-based measurements was significant only when $p < 0.10$.

In terms of RMSE, the downscaled soil moisture data resulting from the non-linear model (RMSE $\approx 0.04 \text{ m}^3/\text{m}^3$, compared to both ground-based data and L-MEB derived soil moisture) are more accurate than those from the linear model (RMSE $\approx 0.08 \text{ m}^3/\text{m}^3$). Furthermore, in contrast to the non-linear model, both Figures 6 and 7 show that the downscaled soil moisture values resulting from the linear model vary over a broader range (from about 0 to $0.50 \text{ m}^3/\text{m}^3$) compared to the ground-based data (0.25 to $0.45 \text{ m}^3/\text{m}^3$) and the L-MEB derived soil moisture (0.18 to $0.5 \text{ m}^3/\text{m}^3$). As a consequence, a slope varying from about 1.4 to 1.9 was observed for the scatter plots using the linear model, while it was close to 1 (about 0.6 to 0.9) for the non-linear model.

These results indicate that under very wet soil conditions, the non-linear model leads to better results than the linear model. This may be due to the fact that the estimated Ts_{max}

could be lower than its real value, given the difficulty of finding a dry surface inside the SMOS pixel to calibrate it properly. Consequently, the linear model linearly stretches the soil moisture values over a wider range than in reality, thus giving scatter plots characterized by pronounced slopes (> 1.4) as shown in Figures 6 and 7. The non-linear model is able to compensate for systematic underestimation of Ts_{max} under generally wet conditions within the SMOS pixel. To further investigate the role of Ts_{max} on the downscaled soil moisture, a sensitivity analysis was conducted.

Figure 6: Day-time downscaled soil moisture compared to in situ soil moisture.

Figure 7: Day-time downscaled soil moisture compared to L-MEB derived soil moisture.

6.1.3. Sensitivity study

Figure 8 presents dSM/dT_{smax} as a function of T_{smax} for two selected SMOS pixels located within the study site. The vertical bold and dotted lines (not presented when lower than the origin of the x axis) represent respectively the extrapolated T_{smax} and T_{smin} values (Section 6.1.1), referred here as $T_{smax-mod}$ and $T_{smin-mod}$. Results show that the sensitivity of the downscaled soil moisture to T_{smax} decreases with an increase of $T_{smax} - T_{smin}$ and is highly related to the model used to express the relationship between SEE and SM.

For the linear model, the sensitivity is higher than $0.10 \frac{m^3}{m^3} / K$ for a value of $T_{smax-mod}$ close to $T_{smin-mod}$ (DGG ID: 147227); it becomes lower ($< 0.04 \frac{m^3}{m^3} / K$) otherwise (DGG ID: 147225). For the non-linear model, the downscaled soil moisture was more

stable as a function of $T_{s_{max}}$. The sensitivity is about $0.05 \frac{m^3}{m^3} / K$ for a value of $T_{s_{max-mod}}$ close to $T_{s_{min-mod}}$, and about $0.01 \frac{m^3}{m^3} / K$ otherwise.

Figure 8: The sensitivity of downscaled soil moisture to $T_{s_{max}}$

Under conditions of low spatial variability of soil moisture, these results showed that the downscaled soil moisture is significantly sensitive to $T_{s_{max}}$, and much more so using the linear model. Subsequently, we presented the possibility of improving the estimated $T_{s_{max}}$ using the neighboring soil conditions. The idea is to determine the $T_{s_{max}}$ value more representative of a dry soil (water content $\approx 0 \text{ m}^3/\text{m}^3$) in order to reduce the dependence of the downscaled soil moisture on $T_{s_{max}}$.

6.2. Improvement of $T_{s_{max}}$

Here, we proposed to improve the already estimated $T_{s_{max}}$ value (Section 5.1). Soil moisture results obtained from DISPATCH downscaling algorithm using the improved $T_{s_{max}}$ value are presented and validated with ground measurements of soil moisture. Comparison of the results with L-MEB derived soil moisture using airborne

data is also conducted. It is followed by a sensitivity analysis to evaluate the stability of the downscaled soil moisture to the improved value of TS_{max} .

6.2.1. Soil moisture maps

The maps of 1-km downscaled soil moisture using the improved value of TS_{max} are shown in Figure 9.a. The same observations previously made (Section 6.1.1) can be repeated here for the spatial distribution of soil moisture (Figure 9.a and Table 3) and the statistics between the different maps (Table 4). Nevertheless, although Tables 1 and 3 show a similar spatial average for the downscaled soil moisture maps ($\approx 0.33 \text{ m}^3/\text{m}^3$), lower spatial variability are observed in Figure 9.a compared to Figure 5.a (in Table 3, $\text{std} \leq 0.07 \text{ m}^3/\text{m}^3$ and $\text{std} \leq 0.03 \text{ m}^3/\text{m}^3$, respectively for the linear and non-linear models). As for the spatial difference in soil moisture maps, obtained from SMOS/Aqua and SMOS/Terra combinations and from the linear and non-linear models, the same observations previously made for Figures 5.b and 5.c can also be repeated (Figures 9.b and 9.c). However, lower linear/non-linear differences were noted for DOY 165 compared to DOY 164, especially for maps derived from the SMOS/Aqua combination.

From the analysis of the results, it appears that the use of the improved value of TS_{max} does not modify the spatial pattern of soil moisture over the study site (i.e., the location of the wettest and driest pixels); it only changes the absolute value of soil moisture at fine scale.

Figure 9.a: Downscaled soil moisture from the use of the improved value of Ts_{max} , SMOS/Aqua and SMOS/Terra combinations, linear and non-linear models, day-time and night-time SMOS overpasses on DOY 164 and 165.

Figure 9.b: Spatial difference in soil moisture maps between SMOS/Aqua combination and SMOS/Terra combination from the use of the linear and non-linear models and the improved value of Ts_{max} .

Figure 9.c: Spatial difference in soil moisture maps between the linear and non-linear models for both SMOS/Aqua and SMOS/Terra combinations and the use of the improved value of Ts_{max} .

Table 3: Mean, standard deviation, minimum and maximum values of the downscaled soil moisture maps using the improved value of Ts_{max} .

Model	DOY	Time	Aqua				Terra			
			Mean (m ³ /m ³)	Std. (m ³ /m ³)	Min (m ³ /m ³)	Max (m ³ /m ³)	Mean (m ³ /m ³)	Std. (m ³ /m ³)	Min (m ³ /m ³)	Max (m ³ /m ³)
Linear	164	AM	0.33	0.07	0.14	0.50	0.33	0.06	0.15	0.48
Linear	164	PM	0.32	0.07	0.15	0.49	0.32	0.06	0.16	0.48
Linear	165	AM	0.32	0.03	0.25	0.42	0.31	0.04	0.20	0.43
Linear	165	PM	0.32	0.04	0.23	0.45	0.32	0.04	0.19	0.45
Non-linear	164	AM	0.33	0.02	0.25	0.39	0.33	0.02	0.25	0.38
Non-linear	164	PM	0.32	0.02	0.25	0.38	0.32	0.02	0.26	0.38
Non-linear	165	AM	0.32	0.02	0.26	0.38	0.31	0.02	0.25	0.36
Non-linear	165	PM	0.32	0.03	0.23	0.40	0.32	0.03	0.22	0.37

Table 4: Correlation coefficients, RMSE, bias and slope values between the downscaled soil moisture maps estimated from the use of the improved value of Ts_{max} and (a) MODIS Aqua and MODIS Terra data using the linear and the -linear models, and (b) the linear and non-linear models for both SMOS/Aqua and SMOS/Terra combinations.

(a) Aqua/Terra							(b) Linear/non-linear				
DOY	Time	Model	R	RMSE (m ³ /m ³)	Bias (m ³ /m ³)	Slope	Sensor	R	RMSE (m ³ /m ³)	Bias (m ³ /m ³)	Slope
164	AM	Linear	0.85	0.04	0.00	0.75	Aqua	0.94	0.05	0.00	0.31
164	PM	Linear	0.86	0.03	0.00	0.76	Aqua	0.98	0.04	0.00	0.34
165	AM	Linear	0.64	0.04	0.00	0.69	Aqua	0.99	0.01	0.00	0.73
165	PM	Linear	0.62	0.04	0.00	0.73	Aqua	0.98	0.01	0.00	0.79
164	AM	Non-linear	0.89	0.01	0.00	0.86	Terra	0.94	0.04	0.00	0.34
164	PM	Non-linear	0.88	0.01	0.00	0.82	Terra	0.98	0.04	0.00	0.36
165	AM	Non-linear	0.67	0.02	0.00	0.48	Terra	0.96	0.02	0.00	0.41
165	PM	Non-linear	0.84	0.02	0.00	0.73	Terra	0.85	0.03	0.00	0.49

6.2.2. Validation and comparison

Figures 10 and 11 present the scatter plots of the downscaled soil moisture versus the ground-based soil moisture and the L-MEB derived soil moisture, respectively. They show low biases for both the linear and non-linear models (from -0.01 to 0.01 m³/m³), comparable RMSE values (from 0.03 to 0.05 m³/m³), slightly better correlation coefficients with the linear model and better correlation between the downscaled results

525 and the L-MEB derived soil moisture (R from 0.49 to 0.79) than the ground data (R from
526 0.30 to 0.52).

527 However, compared to the results shown in Figures 6 and 7, the range of the downscaled
528 soil moisture is narrower (Figures 10 and 11). For the linear model, it is similar to that of
529 the ground data, except for SMOS/Aqua derived soil moisture on DOY 165. As a result,
530 using the improved TS_{max} value under very wet soil conditions leads to a slope varying
531 from 0.6 to 1, with the linear model. For the non-linear model, weak results are obtained
532 (slopes from 0.2 to 0.3), in contrast to the results previously found (Section 6.1.2).

Figure 10: Day-time downscaled soil moisture compared to in situ soil moisture.

Figure 11: Day-time downscaled soil moisture compared to L-MEB derived soil moisture.

In summary, the results show that under very wet soil conditions the non-linear model between SEE and SM provides better downscaled soil moisture from DISPATCH as used by Merlin et al. (2012b). By improving the estimation of Ts_{max} , the linear model between SEE and SM performs better. A sensitivity analysis was conducted to evaluate the stability of the downscaling method by using the improved value of Ts_{max} .

6.2.3. Sensitivity study

Figure 12 presents dSM/dTs_{max} as a function of Ts_{max} for the two selected SMOS pixels located within the study site. The vertical bold line represents the extrapolated Ts_{max} value (Section 6.2.1) referred here as $Ts_{max-mod}$. Since $Ts_{min-mod}$ is lower than the origin of the x axis, it is not presented in Figure 12. Results show that the downscaled soil moisture varies very slightly as a function of Ts_{max} , for

550 both the linear and non-linear models. In fact, a variation of 1 K in $T_{s_{max}}$, from
 551 $T_{s_{max-mod}}$ (red axis), generates a variation of the downscaled soil moisture lower than
 552 $0.03 \frac{m^3}{m^3}$ and $0.01 \frac{m^3}{m^3}$ for the linear and the non-linear models, respectively. By comparing
 553 Figures 12 and 8, it can be seen that the downscaled soil moisture results obtained using
 554 the improved value of $T_{s_{max}}$ are less affected by $T_{s_{max}}$ than those obtained with
 555 DISPATCH as used in Merlin et al. (2012b). The proposed method allows searching for
 556 $T_{s_{max}}$ in a wider area, and appears as an interesting way to reduce the impact of its
 557 uncertainty on the disaggregation process.

Figure 12: Sensitivity of the downscaled soil moisture to the improved $T_{s_{max}}$.

7. Discussion and conclusion

562 DISPATCH, a physically-based downscaling algorithm, was used in this paper to
 563 downscale the 40-km resolution SMOS soil moisture estimates over the agricultural site
 564 of the CanEx-SM10 field campaign. The algorithm relies on the spatial link between the
 565 optical/thermal derived Soil Evaporative Efficiency and near-surface soil moisture. Since
 566 DISPATCH provided good results over semi-arid areas (Merlin et al., 2012b; Merlin et

al., 2013), the objective of the present work was to evaluate its applicability for other soil moisture conditions, in particular the very wet conditions encountered during CanEx-SM10. This study also tested the suitability of using the linear or non-linear relationship between the Soil Evaporative Efficiency derived from MODIS data and the near-surface soil moisture for very wet soils. For validation purposes, the downscaled results were compared to ground measured soil moisture and to the inverted soil moisture from the L-MEB algorithm applied to L-band airborne passive microwave data.

The results show that under wet soil conditions, the non-linear model between SEE and SM provides better downscaled soil moisture from the DISPATCH algorithm. This is in contrast with the results found by Merlin et al. (2012b) for semi-arid areas, where the linear model performed better. For wet soil conditions, the spatial variability of soil moisture is low. The contrast between the minimum and maximum soil temperatures required in the estimation of SEE becomes weaker. Indeed, because of the difficulty in finding a dry surface inside the SMOS pixel, $T_{s_{max}}$ is underestimated. The linear model tends to linearly stretch the narrow range of soil moisture values observed within the low resolution pixel. As a result, pronounced slopes (> 1.4) were found between the downscaled and ground-based or L-MEB derived soil moisture, in contrast to the slope close to 1 found with the non-linear model. Indeed, for very wet soil conditions characterized by low spatial variability, the non-linear model is able to artificially compensate for systematic underestimation of $T_{s_{max}}$ and produce better results. Furthermore, the downscaling results were found to be very sensitive to $T_{s_{max}}$ particularly with the linear model. Therefore, under wet soil conditions characterized by

low spatial variability of soil moisture, the results obtained in this paper recommend the use of the non-linear model in the DISPATCH downscaling algorithm.

For wet soil conditions, the estimation of the TS_{max} value is critical for the downscaling process. Different approaches can be suggested to optimize the accuracy of TS_{max} to make it more representative of a dry pixel (water content $\approx 0 \text{ m}^3.\text{m}^3$) for the same surface and atmospheric conditions. An extrapolation of TS_{max} from a previous dry condition encountered in the same SMOS pixel or even considering an average value representative of each period of the year could be an alternative. But, it is limited by the difficulty in satisfying the uniformity of the atmospheric forcing conditions necessary for the application of the DISPATCH downscaling method. As for the use of a land surface model to estimate TS_{max} , it requires a considerable number of accurate ground-based datasets, which are not always available. However, under very wet soil conditions, extrapolating TS_{max} from the neighboring dry surface is less cumbersome and could be efficient. Over an area larger than the SMOS pixel, the spatial variability of soil moisture should be greater, and drier soils may be encountered. This increases the possibility of obtaining better estimates of TS_{max} . Therefore, we proposed to extrapolate the temperature end-members from high-resolution optical data within the entire Kenaston site instead of the SMOS pixel. This resulted in a higher value of TS_{max} , which should be more representative of a dry soil condition. Consequently, the results obtained from the linear model performed better at fine scale than those gained from the non-linear model, both in terms of correlation and slope with the ground data and the L-MEB inverted soil moisture. Moreover, the results of the downscaling process become quasi-invariant when the estimated TS_{max} is equal to or greater than to the improved value.

In examining the results, we found lower correlations and slopes when the SMOS/Aqua combination is compared to L-MEB derived soil moisture for DOY 165. The difference with the results from SMOS/Terra can be attributed to the substantial incidence angle of the Aqua instrument ($\theta > 60^\circ$) compared to Terra (θ between 20° and 40°). The study also showed that SMOS/Aqua and SMOS/Terra downscaled soil moisture maps are very similar. This is important since the combination of MODIS Terra and MODIS Aqua products (surface temperature and NDVI) could be used to minimize the data gaps due to cloud cover. Good correlation ($R > 0.85$) is also found between the downscaled soil moisture from the linear and non-linear models.

It is important to note that extending the search area is a trade-off between capturing enough variability in soil moisture and meeting the condition of relatively uniform atmospheric conditions. Thus, future studies are needed to develop methods that define the smallest, sufficient spatial extent to calibrate Ts_{max} (and may be Ts_{min} in case of a dry soil), and the maximum spatial extent in which the atmospheric conditions could be considered uniform.

Finally, this paper shows the importance of using the appropriate linear or non-linear model between the soil evaporative efficiency and the near surface soil moisture when using the DISPATCH algorithm to downscale coarse resolution SMOS soil moisture. Cloud free conditions are a limitation of the daily applicability of the DISPATCH downscaling algorithm, compared to passive/active microwave combination, which is independent of the atmospheric conditions. Our future work will consider cloudy situations.

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