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PO Box 117
221 00 Lund
+46 46-222 00 00

Disaggregation of SMOS soil moisture over West Africa using the Temperature and Vegetation Dryness Index based on SEVIRI land surface parameters

T. Tagesson^{1,2,*}, S. Horion^{1,*}, H. Nieto³, V. Zaldo Fornies¹, G. Mendiguren González^{4,5}, C. E. Bulgin⁶, D. Ghent⁷, R. Fensholt¹

¹ Department of Geosciences and Natural Resource Management (IGN), University of Copenhagen, Øster Voldgade 10, DK-1350 Copenhagen, Denmark

² Department of Physical Geography and Ecosystem Analysis, Lund University, Sölvegatan 12, SE- 223 62 Lund,

³ Efficient Use of Water in Agriculture Program, Institut de Recerca i Tecnologia Agroalimentàries (IRTA), Fruitcentre, Parc Científic i Tecnològic Agroalimentari, Lleida 25003, Spain

⁴ Department of hydrology, Geological Survey of Denmark and Greenland (GEUS), Øster Voldgade 10, DK-1350 Copenhagen, Denmark

⁵ Department of Environmental Engineering, Technical University of Denmark, 2800 Kgs. Lyngby, Denmark

⁶ Department of Meteorology, University of Reading, 3 Earley Gate, PO Box 238, Reading, United Kingdom

⁷ Space Research Centre, University of Leicester, University Road Leicester, LE1 7RH, United Kingdom

*These two authors contributed equally to this research.

⁺Corresponding author: e-mail: torbern.tagesson@ign.ku.dk; Tel. +46 704 993936

Abstract

The overarching objective of this study was to produce a disaggregated SMOS Soil Moisture (SM) product using land surface parameters from a geostationary satellite in a region covering a diverse range of ecosystem types. SEVIRI data at 15 minute temporal resolution were used to derive the Temperature and Vegetation Dryness Index (TVDI) that served as SM proxy within the disaggregation process. West Africa (3 °N 26°W; 28 °N 26°E) was selected as a case study as it presents both an important North-South climate gradient and a diverse range of ecosystem types. The main challenge was to set up a methodology applicable over a large area that overcomes the constraints of SMOS (low spatial resolution) and TVDI (requires similar atmospheric forcing and triangular shape formed when plotting morning rise temperature versus fraction of vegetation cover) in order to produce a 0.05° resolution disaggregated SMOS SM product at the sub-continental scale.

30 Consistent cloud cover appeared as one of the main constraints for deriving TVDI, especially during
31 the rainy season and in the southern parts of the region and a large adjustment window (105×105
32 SEVIRI pixels) was therefore deemed necessary. Both the original and the disaggregated SMOS SM
33 products described well the seasonal dynamics observed at six locations of *in situ* observations.
34 However, there was an overestimation in both products for sites in the humid southern regions; most
35 likely caused by the presence of forest. Both TVDI and the associated disaggregated SM product was
36 found to be highly sensitive to algorithm input parameters; especially for conditions of high fraction
37 of vegetation cover. Additionally, seasonal dynamics in TVDI did not follow the seasonal patterns of
38 SM. Still, its spatial heterogeneity was found to be a good proxy for disaggregating SMOS SM data;
39 main river networks and spatial patterns of SM extremes (i.e. droughts and floods) not seen in the
40 original SMOS SM product were revealed in the disaggregated SM product for a test case of July-
41 September 2012. The disaggregation methodology thereby successfully increased the spatial
42 resolution of SMOS SM, with potential application for local drought/flood monitoring of importance
43 for the livelihood of the population of West Africa.

44

45 **Keywords:** TVDI; SMOS; disaggregation; downscaling; soil moisture; SEVIRI; sensitivity analysis

46

47 **1. Introduction**

48 Complex interactions of energy exchange are taking place between different components of the Earth
49 system, notably between the atmosphere, hydrosphere and biosphere (Bonan 2008). A better
50 understanding of such interactions is of high societal relevance for improving assessment of carbon
51 and water fluxes as well as for preventing, monitoring and forecasting extreme events. However, it
52 implies the accurate assessment of essential climate variables, such as soil moisture (SM) that is key
53 to determining the water fluxes between the land surface and the atmosphere (Vinukollu et al. 2011).

54 Since the 1970s, data from Earth Observation (EO) satellite platforms have been used to overcome
55 the limitations of ground sensors thereby providing timely information on the spatial distribution of
56 SM. Soil moisture affects the emission and absorption of electromagnetic radiation in different
57 regions of the spectrum: 1) MicroWave (MW) backscattered or emitted energy from the ground
58 surface, particularly in the low-frequency microwave range, from 1 to 10 GHz, allows the dielectric
59 constant to be related to SM (Schmugge 1978; Stisen et al. 2008); 2) When the soil is wet the energy
60 balance of the surface is controlled by evaporation from the soil surface and vegetation transpiration
61 and lower surface temperatures are expected in wet soils than in drier soils during daytime (Schmugge
62 1978). This effect can be captured in the Thermal InfraRed (TIR) region of the electromagnetic
63 spectrum. Additionally, if multiple observations of the land surface are acquired at different times
64 throughout the day, diurnal variability in emitted radiation can be related to the soil thermal inertia (a
65 property that describes the resistance of a material to temperature change) (Wang et al. 2006) and
66 consequently serves as a good indicator of evapotranspiration and SM (Minacapilli et al. 2009; Stisen
67 et al. 2008); and 3) in the optical domain (350-2500 nm), an increase of SM produces an overall
68 decrease in albedo (Bach and Mauser 1994) and specific absorption features in the Short-Wave
69 Infrared Region (SWIR) (Sadeghi et al. 2015).

70 Each of these spectral regions have advantages and disadvantages for mapping SM (Kerr 2007;
71 Moran et al. 2004). Microwave sensors are insensitive to atmospheric disturbances, but they usually
72 require larger pixel sizes than sensors in the optical or thermal infrared domain, due to the lower
73 emitted energy in this region. This is the case for the Soil Moisture and Ocean Salinity (SMOS)
74 (average pixel size 43 km) (Kerr et al. 2012) and the Soil Moisture Active Passive (SMAP) (30km)
75 (Panciera et al. 2014) missions dedicated to monitor SM, rendering such products less suited for
76 spatially explicit studies of the hydrological cycle at the local scale. Unlike MW sensors, optical and
77 TIR sensors are greatly affected by the atmosphere, and allows a higher spatial resolution of

78 measurements. The Spinning Enhanced Visible and InfraRed Imager (SEVIRI) instrument aboard the
79 geostationary satellite Meteosat Second Generation (MSG) is an optical and TIR sensor centred over
80 Africa that scans the full Earth disk every 15 min. This high temporal resolution is a major advantage
81 since it allows estimates of soil thermal inertia (morning rise temperature; dTS) (Stisen et al. 2008)
82 and it increases the probability of obtaining cloud free observations for areas with frequent cloud
83 cover.

84 Given the advantages/disadvantages of different EO retrievals, combining high and low spatial
85 resolution data for improving the SM spatial variability has received considerable scientific attention
86 recently (Malbêteau et al. 2016; Merlin et al. 2012; Peng et al. 2017; Wang et al. 2016). Methods for
87 disaggregation of SM products can be classified into three major groups: (1) satellite based methods;
88 (2) methods using an array of geoinformation data and (3) model based methods (Peng et al. 2017).
89 Among satellite based methods, an integration of coarse spatial resolution microwave observations
90 with optical/thermal EO retrievals using a downscaling factor is most commonly used (Peng et al.
91 2017; Wang et al. 2016). One example of an optical/thermal remote sensing metric closely related to
92 SM variability is the Temperature-Vegetation Dryness Index (TVDI) (Sandholt et al. 2002) based on
93 the triangle/trapezoid (hereinafter called triangle) method, since it empirically delimits the triangle
94 formed when plotting the Land Surface Temperature (LST) or dTS versus a Vegetation Index (VI)
95 (Figure 1) (Carlson et al. 1995; Carlson et al. 1990; Moran et al. 1994; Sandholt et al. 2002; Stisen
96 et al. 2008; Sun et al. 2012; Tang and Li 2017). TVDI is most commonly calculated as:

97

$$98 \quad \text{TVDI} = \frac{\text{LST} - \text{LST}_{\min}}{\text{LST}_{\max} - \text{LST}_{\min}} \quad (1)$$

99 where LST is the LST for a given pixel; LST_{\min} is minimum LST extracted empirically from the
100 lower boundary of the triangle (the wet edge); and LST_{\max} is maximum LST extracted empirically

101 from the upper boundary of the triangle (the dry edge) for the vegetation index value of the specific
102 pixel (Figure 1) (Sandholt et al. 2002). The dry edge represents dry soils with low evaporation rates
103 causing LST to be at its maximum as a function of the vegetation fraction whereas the wet edge
104 represents wet soils where the evaporation rate occurs near its potential and thus LST is at its
105 minimum and close to the air temperature. Between these two edges, all intermediate conditions can
106 occur, and all SM conditions can consequently be represented within the LST-VI triangle space
107 (Figure 1) (Sandholt et al. 2002).

108 The triangle approach has been used in several attempts to disaggregate low spatial resolution
109 microwave SM retrievals. At a field site in the north eastern Tibetan plateau, Wang et al. (2016)
110 investigated the applicability of the TVDI for determining a downscaling factor for multiple source
111 microwave based SM data from the European Space Agency (ESA) Climate Change Initiative (CCI)
112 (Dorigo et al. 2012). At the Iberian peninsula, SMOS SM have been disaggregated using the triangle
113 technique with MODerate resolution Imaging Spectroradiometer (MODIS) LST as input data (Piles
114 et al. 2011; Piles et al. 2014), and in an attempt to overcome the issue of frequent cloud cover MSG
115 SEVIRI LST at 15-min temporal resolution was also used (Piles et al. 2016). Another common
116 approach for disaggregation of SMOS SM is to use the DisPATCH (Disaggregation based on Physical
117 And Theoretical scale CHange) model, which combines thermal and optical imagery in a contextual
118 algorithm to derive Soil Evaporative Efficiency (SEE), and then relate SEE to SM through a
119 physically based model (Djamai et al. 2015; Malbêteau et al. 2016; Merlin et al. 2010; Merlin et al.
120 2012).

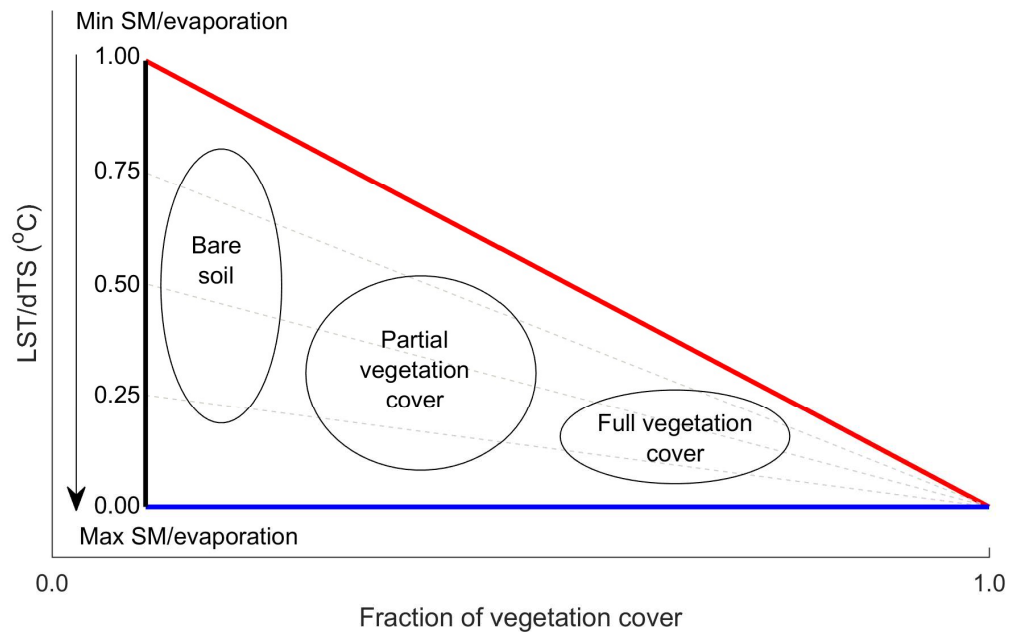
121 Several assumptions and prerequisites need to be taken into account when applying the triangle
122 method: 1) the presence of all SM and vegetation cover conditions are needed within the spatial
123 domain applied (Sandholt et al. 2002; Stisen et al. 2008); 2) the dimensions of the spatial domain
124 have to be large enough to collect a sufficient amount of LST-VI cases to adequately define the

125 triangle shape (de Tomás et al. 2014); 3) factors like land cover type and topography should be taken
126 into account to ensure the applicability of the method (Hassan et al. 2007); 4) variations in LST must
127 simply reflect variability in SM, which requires other surface properties and atmospheric forcing to
128 be homogeneous; e.g. available energy (net radiation minus ground heat flux), meteorological
129 conditions over the studied area (solar radiation, total column water vapour, air temperature, and wind
130 speed) as well as homogeneous surface roughness to ensure similar conditions affecting the turbulent
131 heat transport (Gillies and Carlson 1995; Moran et al. 1994); and 5) the strong dependence on the
132 endmembers forming the triangular shape implies that a specific TVDI is only comparable with TVDI
133 estimates derived with the same endmember values. As taken together, these preconditions are
134 difficult to fulfil over the entire triangle space (from bare soil to full vegetation cover; from humid to
135 dry conditions), which limit the applicability of the TVDI approach to localized (spatially and
136 temporally) scales (de Tomás et al. 2014; Garcia et al. 2014; Stisen et al. 2008; Tang and Li 2015) as
137 when attempting to cover larger regions there is a high risk of violating these stated preconditions.

138 Previous studies have used LST directly in the disaggregation process; however combining soil
139 thermal inertia (dTS) based on MSG SEVIRI LST at 15-min temporal resolution with the TVDI
140 approach allows for a more direct estimate of evaporative fraction (Stisen et al. 2008), which can be
141 implemented in the physically based disaggregation methodology behind DisPATCH (Merlin et al.
142 2012). The overarching objective of this study was to produce a high-resolution disaggregated SMOS
143 SM product for a region covering a diverse range of ecosystem types. We aimed at doing so by
144 disaggregation of low spatial resolution MW data (SMOS) using dTS based on higher spatial and
145 temporal resolution optical data (SEVIRI). We applied the physically based disaggregation
146 methodology behind DisPATCH (Merlin et al. 2012), thereby taking advantage of both types of EO
147 retrievals for SM assessment and accounting for their respective inherent limitations. The main
148 research questions addressed were:

149 How can TVDI derived from SEVIRI based dTS be implemented to resolve the SM spatial
150 heterogeneity within a SMOS pixel when produced at sub-continental scale over West Africa? What
151 are the methodological constraints to overcome in order to produce time series of high-resolution
152 disaggregated SMOS SM product over regions covering a wide spectrum of ecosystem types ranging
153 from desert to tropical forests?

154 To address these research questions, time series of SMOS SM and time series of LST and Fractional
155 Vegetation Cover (FVC) from the MSG SEVIRI instrument were acquired for the period 2010-2015.
156 TVDI was estimated for tile-based adjustment windows on SEVIRI dTS and FVC. The TVDI
157 estimates were incorporated into a disaggregation methodology to produce high resolution
158 disaggregated SMOS SM product for West Africa. The sensitivity of TVDI and disaggregated SMOS
159 SM to the input parameters were quantified. The original and the disaggregated SMOS SM products
160 were evaluated against *in situ* SM from sites within the International Soil Moisture Network (ISMN).
161 Finally, the spatial patterns of disaggregated SM products were evaluated for a specific case of
162 extreme SM conditions (droughts and floods) in the Sahel 2012.

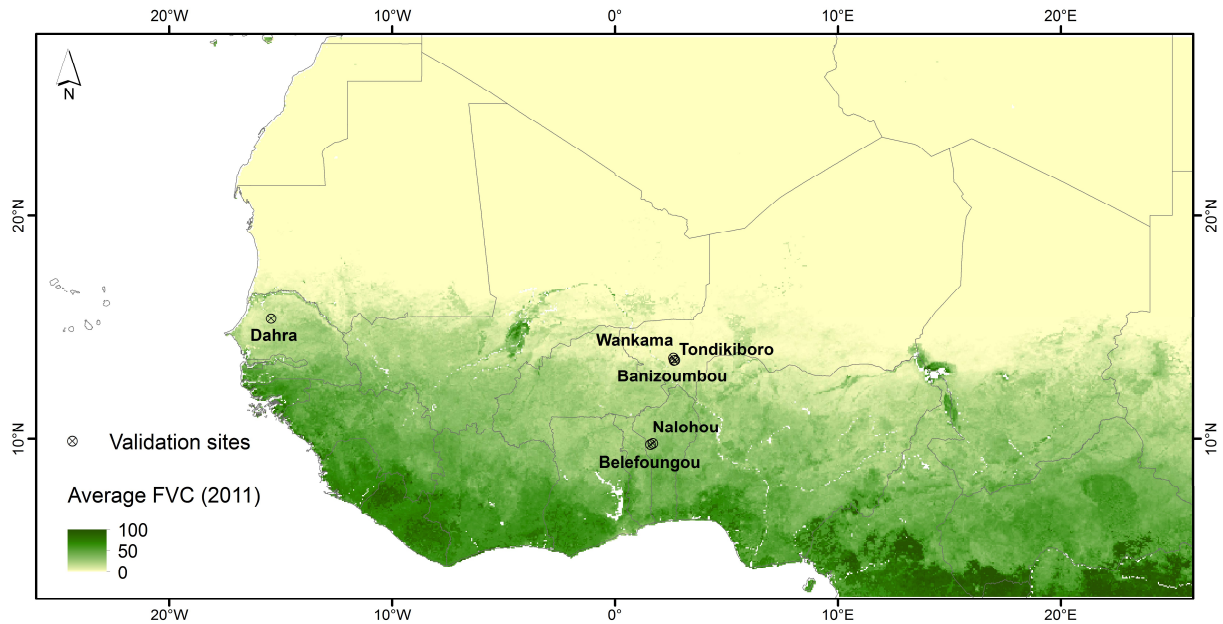


163
 164 **Figure 1.** Conceptual triangle space with the land surface temperature (LST) or morning rise
 165 temperature (dTS) on the y-axis and Fraction of Vegetation Cover (FVC) on the x-axis. The blue
 166 line is the wet edge (TVDI=0.00) and the red line is the dry edge (TVDI=1.00). The grey dotted
 167 lines are TVDI examples of 0.25, 0.50, and 0.75. The figure is adapted from Peng et al. (2017).
 168

169 **2. Materials and Methods**

170 **2.1. Study area**

171 West Africa was selected as research area for this study (Figure 2) as the climate varies from hot
 172 desert in the north to tropical forest climate in the south. The area (3 °N 26°W; 28 °N 26°E) stretches
 173 from Senegal in the west to Chad in the east. The climate is controlled by the West African Monsoon
 174 and is characterized by a north-south gradient of increasing annual precipitation. The large gradient
 175 in precipitation totals is reflected by increasing biomass from north to south as reflected in the
 176 fractional vegetation cover (Figure 2). The study area constitutes of 1.06×10^4 SMOS pixels and
 177 5.20×10^5 SEVIRI pixels.



178

179

Figure 2. Study area with the location of the *in situ* validation sites. The averaged fraction of vegetation cover (FVC) for year 2011 is used as background to illustrate the important north-south gradient in vegetation cover.

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183

184 2.2. Data collection and pre-processing

185

2.2.1 SMOS soil moisture

186

The SMOS mission includes a passive interferometric radiometer and is the first satellite mission operating at L-band (1.4 GHz). The L-band is less sensitive to green vegetation components and the SMOS multi-angular acquisition capability is additionally used to separate the soil and vegetation signal (Kerr 2007; Wigneron et al. 2007). The SMOS level 2 version-62x SM product was used in this study. We downloaded the SMOS data from 1 June 2010 until 31 December 2015 for the study area. SMOS SM is an average of SM at 0-5 cm depth. The revisiting time at the equator is every 3 days for both ascending and descending passes, which are sun synchronous at 6 am ascending and 6 pm descending. The geolocation accuracy of SMOS is 500 m. The sampling grid of the SMOS data is the Discrete Global Grid (DGG), and it has a node separation of 14.99 km. This is higher than the natural footprint size of SMOS, ranging from 30 to 90 km (average 43km) depending on viewing

195

196 angle. Data were reprojected to WGS-84 geographic coordinates using a bilinear resampling method.
197 We used a 0.35° grid (~40 km; which is close to the average natural footprint size of SMOS and is
198 easily dividable with the chosen SEVIRI pixel size) and averaged the SMOS SM estimates of the
199 DGG nodes falling within a $\pm 0.1^\circ$ area in the centre of each pixel. We only used these central nodes
200 as these are assumably least influenced by neighbouring pixels.

201 **2.2.2 Land surface temperature**

202 Land surface temperatures from SEVIRI from 1 January 2010 to 31 December 2015 were acquired
203 following the procedure described in (Nieto et al. 2011; Rasmussen et al. 2011; Stisen et al.
204 2007). SEVIRI LST fields are available every 15 minutes for the entire MSG disk centred at 0°
205 longitude and with a native pixel sampling size of 3 km. For consistency with the retrieved FVC data
206 (see below), it was resampled using nearest neighbour to a spatial resolution of 0.05° .

207 LST was calculated based on SEVIRI channels centered at 10.8 and 12 μm . The European
208 organisation for the exploitation of METeorological SATellites (EUMETSAT) NoWCasting & very
209 short range forecasting Satellite Application Facility (NWC SAF) software (version 2013) was used
210 for converting data to top-of-atmosphere (TOA) brightness temperatures. TOA brightness
211 temperatures were atmospherically corrected for surface emissivity, atmospheric attenuation along
212 the path and emissivity of downward radiation. Spectral emissivity was estimated based on soil and
213 vegetation emissivity endmember values, scaled by the Normalised Difference Vegetation Index
214 (NDVI) and a look-up table (Trigo et al. 2008). SEVIRI NDVI was calculated from daily nadir
215 Bidirectional Reflectance Distribution Function (BRDF)-adjusted reflectance corrected using the
216 Simplified Method for Atmospheric Correction (SMAC) (Proud et al. 2010). The atmospherically
217 corrected brightness temperatures were converted to LST following the generalized split window
218 proposed by Wan and Dozier (1996) for the Advanced Very High Resolution Radiometer (AVHRR)

219 and MODIS, but adapted to SEVIRI response functions (Jimenez-Munoz and Sobrino 2008; Sobrino
220 and Romaguera 2004). This data process was originally produced for (Nieto et al. 2011; Rasmussen
221 et al. 2011; Stisen et al. 2007), and just applied in this study. For a closer data description we refer to
222 these publications. Furthermore, a quality flag was produced for each LST value based on the cloud
223 mask (PGE01) derived from the NWC SAF software, and quality flags related to clouds, unreliable
224 data, sun-sensor geometry, and when the BRDF inversion failed (Proud et al. 2010; Proud et al. 2014).

225 **2.2.3 Fraction of vegetation cover**

226 Daily FVC derived from SEVIRI and distributed by the Land Surface Analysis Satellite Applications
227 Facility (LSA SAF) were provided by Instituto Português do Mar e Atmosfera (IPMA), in the
228 GLOBTEMP harmonised format (0.05° spatial resolution) for 1 January 2010 to 31 December 2015
229 (GLOBTEMP 2014; Trigo et al. 2011). The FVC accounts for the amount of vegetation distributed
230 in a horizontal perspective and is therefore an important structural property of a plant canopy, as well
231 as a crucial proxy for studies relying on the partition between soil and vegetation contribution to
232 surface emissivity and temperature. The daily FVC products are based on the k0 coefficient of a
233 BRDF model for the red (600 nm), near infrared (800nm) and shortwave infrared (1600nm) channels,
234 and is generated using an algorithm that relies on an optimised Spectral Mixture Analysis (SMA)
235 technique (García-Haro et al. 2005). The products also include quality control information that were
236 used to mask out pixels that were not reliable or relevant for this study (i.e. continental water, clouds,
237 snow, unrealistic input ranges, or failure of the algorithm).

238 **2.2.4 Surface roughness and atmospheric forcing**

239 In order to analyse the homogeneity of surface properties and atmospheric forcing in relation to the
240 use of TVDI, we downloaded ERA 5 surface solar radiation downwards (SSRD; J m^{-2} ; accumulated
241 at a 3-hour temporal resolution), forecast surface roughness (FSR; m; instantaneous at 12-hour

242 temporal resolution), total column water vapour (TCWV; kg m^{-2} ; instantaneous at 12-hour temporal
243 resolution), wind speed at 100 m height (WS; m s^{-1} ; u and v wind components instantaneous at 12-
244 hour temporal resolution), and air temperature at 975hPa level (T_{air} ; K; instantaneous at 12-hour
245 temporal resolution)) with a spatial resolution of $0.1^\circ \times 0.1^\circ$ (interpolated using a bilinear method from
246 $31 \times 31 \text{ km}$ spatial resolution) from 1 January 2010-31 December 2015 from the European Centre for
247 Medium-Range Weather Forecasts (ECMWF 2017). Collected WS and T_{air} represents conditions
248 from above the blending height, since near surface variability in these parameters is driven by local
249 meteorological conditions and is therefore allowed to be heterogeneous at the scale required for the
250 triangular shape to take form. SSRD was converted to W m^{-2} and all variables were averaged to daily
251 values.

252 **2.2.5 *In situ* soil moisture**

253 In order to validate the disaggregation methodology we collected available *in situ* measurements of
254 SM from eight sites within ISMN (Figure 2) (ISMN 2016). Available sites in West Africa with data
255 2010-2015 were from the AMMA-Catch (Niger and Benin sites) and Dahra (Senegal site) network:
256 Banizoumbou (Niger; $13.53^\circ \text{N } 2.66^\circ \text{E}$), Belefoungou-Mid (Benin; $9.80^\circ \text{N } 1.71^\circ \text{E}$), Belefoungou-
257 Top (Benin; $9.79^\circ \text{N } 1.71^\circ \text{E}$), Dahra (Senegal; $15.40^\circ \text{N } 15.43^\circ \text{E}$), Nalohou-Mid (Benin; $9.75^\circ \text{N } 1.61^\circ \text{E}$),
258 Nalohou-Top (Benin; $9.74^\circ \text{N } 1.61^\circ \text{E}$), Tondikiboro (Niger; $13.55^\circ \text{N } 2.67^\circ \text{E}$) and Wankama
259 (Niger; $13.65^\circ \text{N } 2.63^\circ \text{E}$). *In situ* SM was collected using vertical sampling at all these sites to capture
260 the rooting zone soil profile. For the best possible intercomparison with the SMOS SM soil depth
261 (average 0-5 cm), we only used data collected at the shallowest depths (0.05 m depth for all sites but
262 Nalohou-mid, where the shallowest depth was 0.10 m). The two locations of Belefoungou and
263 Nalohou were averaged before the analysis.

264 The Niger and Senegal sites are located in the Sahel region characterised by a short rainy season
265 between June and October. The Dahra field site and the Niger region receives around 400mm and
266 500mm of rain, respectively (Louvet et al. 2015; Tagesson et al. 2015). The vegetation of the Niger
267 sites are typical for cultivated areas of the Sahel, whereas the Dahra site is composed of open woody
268 savannah (Louvet et al. 2015; Tagesson et al. 2016). The Benin sites are located further south in the
269 Soudanian climate zone with an annual precipitation of ~1300mm (Louvet et al. 2015). These sites
270 are thereby characterised by significantly denser vegetation, and woody savannah and tropical forest
271 are typical of these sites (Louvet et al. 2015).

272 The *in situ* SM observations are from low density networks consisting of one or two sites per pixel
273 which introduces an uncertainty in the representativeness of the sites in relation to the validation of
274 the SM products (Peng et al. 2017). However, sensors at these sites were installed specifically for
275 satellite product evaluation, hence the location of the sites were chosen to be representative for the
276 larger area, and they have previously been used for various satellite product assessments. The *in situ*
277 SM measurements are thereby considered representative for the wider area and applicable in a
278 validation of large-scale satellite based SM estimates.

279 **2.3. Data analysis**

280 **2.3.1. Temperature and Vegetation Dryness Index (TVDI) as soil moisture proxy**

281 The TVDI was developed by Price (1990) and later improved notably by Sandholt et al. (2002) and
282 Stisen et al. (2008). It has been widely used for assessing SM and evapotranspiration (Garcia et al.
283 2014; Han et al. 2010; Jiang et al. 2008; Li et al. 2010; Li et al. 2008; Mallick et al. 2009; Patel et al.
284 2009; Wang et al. 2004). Several methodological refinements were applied in this study as compared
285 to previous approaches to make it applicable for SMOS disaggregation at the sub-continental scale:

286 (1) The dTS was used as a substitute for LST as it was demonstrated to be a strong proxy for sensible
287 heat fluxes, thereby improving the TVDI estimates as compared to those based on single (hourly or
288 daily) LST (Stisen et al. 2008). The morning rise temperature was calculated as the change (i.e. slope
289 coefficient ($^{\circ}\text{C h}^{-1}$)) in LST between sunrise and noon. A median Theil-Sen procedure was applied
290 since it is known to be robust against non-normality, heteroscedasticity, and temporal autocorrelation
291 (Alcaraz-Segura et al. 2010; Hirsch and Slack 1984; Vanbelle and Hughes 1984) and it is suggested
292 for studies of trends based on time series of data (de Beurs and Henebry 2005). Furthermore, it is
293 resistant to outliers and therefore suitable for assessing the rate of change in short or noisy time-series
294 (Eastman et al. 2009). In order to minimise cloud contamination and erroneous data in the dTS and
295 TVDI calculations, we filtered the FVC and LST data based on provided quality flags. We also
296 excluded all dTS pixels using the following criteria: 1) temporal range of daily time-series <4 hours;
297 2) sample size used in the fit < 5 cases; 3) $\text{dTS} > 10^{\circ}\text{C h}^{-1}$ and $< 0^{\circ}\text{C h}^{-1}$; and 4) poor LST vs time fit
298 ($r < 0.70$). Criteria 1 ensured that dTS was not calculated for pixels with clustered unfiltered data (i.e.
299 only available for a short window of time during the day). Criteria 2 was set in order to ensure a
300 sufficient number of observations. Criteria 3 and 4 were set to filter out observations with residual
301 clouds.

302 (2) We used the algorithm proposed by Tang et al. (2010) to estimate the dry edge (LST_{max} in
303 equation 1) due to its low sensitivity to outliers (cloud residuals). In order to determine the upper edge
304 of the triangle, we divided the dTS-FVC triangular space into bins with a FVC size of 2.5%. Each bin
305 was separated into 5 subintervals and the maximum dTS of each subinterval was extracted. All
306 subinterval maximum dTS $<$ the average ($\text{dTS}_{\text{sub_mean}}$) minus one standard deviation (δ) of these 5
307 subinterval maximum dTS were removed and a new maximum dTS was calculated and used as the
308 maximum for that specific bin. An ordinary least square linear regression was fitted through the
309 remaining maximum dTS values and their corresponding FVC bins and used as the dry edge. These

310 were the main steps in the algorithm; for a closer description we refer to Tang et al. (2010). The
311 implementation of the algorithm was slightly modified compared to the original Tang et al. (2010)
312 algorithm in that all bins to the left of the triangular maximum dTS and all dTS lower than wet edge
313 (see below) were removed before the fitting.

314 (3) The wet edge (LST_{\min} in equation 1) was calculated as the median of the 10th percentile dTS of
315 the points included in the ten 2.5% FVC bins with highest FVC values. The 10th percentile was used
316 instead of absolute minimum as it is less sensitive to outliers and therefore provides a more robust
317 assessment of the wet edge.

318 (4) The study region was separated into different tiles. The size of the tiles (i.e. the number of SEVIRI
319 pixels considered to adjust the dTS-FVC triangle for a given SMOS pixel) was set in such way that
320 it strictly coincided in location and number with a multiple of the SMOS pixel resolution. This
321 ensured that the information on spatial heterogeneity within a given SMOS pixel will be based on
322 TVDI estimates that were derived from the same triangle adjustment. In this way, a SMOS pixel
323 never over-lapped two different TVDI tiles, thereby maximizing the accuracy of the downscaling. A
324 tile size of 105×105 SEVIRI pixels was selected for the final SMOS disaggregation (see results
325 section).

326 (5) Furthermore the TVDI values were excluded based on quality of the dry edge fit ($r > -0.7$), dry
327 edge intercept values >15 and <0 , number of bins for estimating the dry edge <5 , total number of
328 points in triangle < 500 , FVC range <0.3 . These filtering criteria excluded entire 105×105 pixels-
329 tiles. With these criteria we aimed at ensuring the comparability and temporal consistency of the data,
330 having representative points over a large enough range of FVC (FVC range and number of bins),
331 excluding TVDI estimates influenced by possible residual clouds (dry edge intercept range and fit),
332 as well as having enough pixels to calculate the edges of the triangle and removal of those dates in

333 which the cloud mask reduces the number of good quality pixels available for edge definition (total
334 number of points and dry edge fit).

335 **2.3.2. Fulfilment of the preconditions of spatial dimensions and homogeneity**

336 Surface properties (FSR) and atmospheric forcing (SSRD, TCWV, WS, T_{air}) should be homogenous
337 within the triangular space for the dTS variability to accurately reflect SM variation. To test for
338 homogeneous surface properties and atmospheric forcing within different sized tiles, we ran a three-
339 step procedure. Firstly, FSR, SSRD, TCWV, WS, and T_{air} data were filtered based on the criteria
340 described under point 1 in subsection 2.3.1. Secondly, we estimated the dynamic range of daily
341 averages of FSR, SSRD, TCWV, WS, and T_{air} by taking the difference between the 95th and the 5th
342 percentile for different tile sizes covering the Dahra and the Nalohou field sites. These 2 sites were
343 assumed to be representative for the dry and wet parts of the study area, respectively. The 95th and
344 the 5th percentile were used to avoid influence from outliers. The analysis of data range as a function
345 of tile sizes started from 1×1 SEVIRI pixels with an increment of 1 pixels up until 200×200 SEVIRI
346 pixels. Finally, percentiles (from 1 to the 100th in steps of 1) from the full time-series were calculated
347 for each analysed tile size. This was done to analyse the fraction of the time series affected by
348 heterogeneity in FSR, SSRD, TCWV, WS, and T_{air} for the different tile sizes tested.

349 Thereafter, to test the fulfilment of the stated precondition that the spatial dimensions was large
350 enough to capture a sufficient amount of dTS-FVC cases for the triangular shape to take form, we ran
351 the TVDI analysis for the Dahra and the Nalohou field sites using different tile sizes. The analysis
352 started from 5×5 SMOS pixels (35×35 SEVIRI pixels) with an increment of 5 SMOS pixels to 25×25
353 SMOS pixels (175×175 SEVIRI pixels). The forming of the triangular shape are dependent on a
354 sufficient number of points included in the triangle, the quality of the dry edge (r), and the dynamic

355 range in FVC. To analyse the effect of tile size we estimated percentiles (from 1 to the 100th in steps
356 of 1) of these parameters from the full time-series for each tile size analysed.

357 **2.3.3. Gap-filling of TVDI**

358 The calculated time-series of TVDI was gap-filled using two different approaches: (1) the excluded
359 105×105 SEVIRI pixels-tiles were filled by using the non-filtered tile nearest in time. This secures
360 gap-filling of the tiles excluded based on the TVDI statistics according section 2.3.1 above. (2)
361 Remaining excluded pixels were filled using long-term average calculated as follow:

$$362 \text{TVDI}_{j,t} = \frac{\overline{\text{TVDI}}_j}{\langle \text{TVDI} \rangle_{105}} \langle \text{TVDI} \rangle_t \quad (2)$$

363 where $\text{TVDI}_{j,t}$ is the TVDI at pixel (j) in a specific point in time (t) which is needing to be gap-filled;
364 $\overline{\text{TVDI}}_j$ is the TVDI for the pixel (j) averaged for the entire time-series; $\langle \text{TVDI} \rangle_{105}$ is the TVDI averaged
365 for the 105×105 pixels-tile for the point in time which needs to be gap-filled; and $\langle \text{TVDI} \rangle_{105}$ is the
366 TVDI averaged for the 105×105 pixels-tile and averaged for the entire time series. This second gap-
367 filling procedure fills pixels that were excluded based on quality flags of the input data (excluded dTS
368 and FVC data).

369

370 **2.3.4. Disaggregation methodology**

371 The SMOS SM was disaggregated following the methodology in Merlin et al. (2012) where spatial
372 heterogeneity in surface SM within the SMOS pixel is linked with a heterogeneity in the soil
373 evaporative efficiency (SEE). Merlin et al. (2012) chose SEE as high resolution data within the
374 disaggregation methodology because of the strong correlation to surface SM (Anderson et al. 2007)
375 and its stability during daytime under clear skies (Crago and Brutsaert 1996). The disaggregation
376 relationship is expressed as:

377 $SM_{\text{disaggregated}} = SM_{\text{SMOS}} + \frac{\partial SM_{\text{model}}}{\partial SEE} (SEE_{\text{SEVIRI}} - \langle SEE_{\text{SEVIRI}} \rangle_{\text{SMOS}})$ (3)

378 where $SM_{\text{disaggregated}}$ is the high-resolution SM product disaggregated from the original SMOS data
 379 (SM_{SMOS}); $\frac{\partial SM_{\text{model}}}{\partial SEE}$ is the partial derivative of modelled SM on SEE; SEE_{SEVIRI} is high-resolution
 380 SEE based on SEVIRI input data; and $\langle SEE_{\text{SEVIRI}} \rangle_{\text{SMOS}}$ is SEE averaged at SMOS scale.

381 Merlin et al. (2010) tested the accuracy and robustness of the aggregation methodology using different
 382 formulations for modelling SEE. They concluded that the formulation of Noilhan and Planton (1989)
 383 was the most applicable when conditions for soil properties were unknown:

384 $SEE_{\text{model}} = \frac{1}{2} - \frac{1}{2} \cos\left(\pi \times \frac{SM}{SM_p}\right)$ (4)

385 where SEE_{model} is modelled SEE, and SM_p is a soil parameter in SM unit. In Merlin et al. (2012) SM_p
 386 was estimated by inverting Equation 4 at SMOS resolution:

387 $SM_p = \frac{\pi \times SM_{\text{SMOS}}}{\arccos(1 - 2\langle SEE_{\text{SEVIRI}} \rangle_{\text{SMOS}})}$ (5)

388 By inverting equation 5, we got a model for estimating SM based on SEE:

389 $SM_{\text{model}} = \frac{SM_p}{\pi} \arccos(1 - 2SEE)$ (6)

390 Then, by taking the partial derivative of SM on SEE in equation 6, we get:

391 $\frac{\partial SM_{\text{model}}}{\partial SEE} = \frac{2\left(\frac{SM_p}{\pi}\right)}{\sqrt{1 - (1 - 2SEE)^2}}$ (7)

392 Merlin et al. (2012) showed a linear relationship between SEE and surface soil temperature using a
 393 physically based dual source energy budget model (Kustas and Norman 1999) and a synthetic data
 394 set. Given that TVDI was based on soil thermal inertia (dTS), it should be a strong proxy of the non-
 395 evaporative fraction, and SEE then equals (1-TVDI). For a description of the mathematical derivation

396 of equations 5 and 7; we refer to Appendix A. For a mathematical derivation showing that (1-TVDI)
 397 equals SEE in the way it is implemented in the DisPATCH methodology, we refer to Appendix B.
 398 Finally, equation 7 was inserted into equation 3 and by setting SEE to (1-TVDI), we obtained a
 399 disaggregation model directly based on TVDI.

$$400 \quad SM_{\text{disaggregated}} = SM_{\text{SMOS}} + \frac{2 \left(\frac{SM_{\text{SMOS}}}{\arccos(1-2\langle(1-TVDI)\rangle_{\text{SMOS}})} \right)}{\sqrt{1-(1-2\langle(1-TVDI)\rangle_{\text{SMOS}})^2}} ((1-TVDI) - \langle(1-TVDI)\rangle_{\text{SMOS}}) \quad (8)$$

401 **2.3.5. Sensitivity of TVDI and disaggregated SMOS soil moisture to input data**

402 We analysed the sensitivity of TVDI to its input parameters using a synthetic data set with dTS
 403 varying from 0 to 10, and FVC varying from 0 to 1.0. TVDI was estimated by setting the wet edge to
 404 0, dry edge intercept to 10, and dry edge slope to 0.1 dTS 0.01FVC⁻¹. We changed one input parameter
 405 at the time with ±10% of the total range included in the triangle at steps of 0.1% and recalculated
 406 TVDI. The input parameters changed included dTS (±1°C), FVC (±0.10), wet edge (±1°C), dry edge
 407 intercept (±1°C), and dry edge slope (±0.1°C 0.01FVC⁻¹). The sensitivity of TVDI to the parameters
 408 was quantified by fitting an ordinary least square linear regression between recalculated TVDI and
 409 % error for each dTS-FVC combination.

410 To quantify the sensitivity of disaggregated SMOS SM to errors in TVDI, we disaggregated SMOS
 411 SM using equation 8 with SMOS SM varying from 0 to 100%, TVDI varying from 0.0 to 1.0, and
 412 mean TVDI for each SMOS pixel ($\langle(1-TVDI)\rangle_{\text{SMOS}}$) set to 0.25, 0.50 and 0.75. We changed TVDI with
 413 ±0.1 at steps of 0.01 and repeated the disaggregation procedure. The sensitivity of disaggregated
 414 SMOS SM to errors in TVDI was quantified by fitting an ordinary least square linear regression
 415 between disaggregated SMOS SM and the TVDI error for each SMOS SM, TVDI, and
 416 ($\langle(1-TVDI)\rangle_{\text{SMOS}}$) combination.

417 **2.3.6. Evaluation of soil moisture products**

418 We evaluated both the original and the disaggregated SMOS SM using the *in situ* based SM data sets
419 from ISMN as independent data. The agreements between SMOS based SM and the *in situ* SM were
420 quantified as the root mean square error (RMSE), the product-*in situ* ratio, and by goodness-of-fit
421 when an ordinary least-square linear regression was fitted between SMOS based SM and daily *in situ*
422 SM estimates. Spatial patterns of the disaggregated SMOS SM over West Africa were also evaluated
423 for a specific case of extreme SM conditions (i.e. drought and flood). Monthly anomalies of SM were
424 estimated by subtracting the 2010-2015 climatology from the monthly average SM. July to September
425 (JAS) 2012 was selected as test case because both heavy rainfall events and dry conditions
426 corresponding to the ending of the long-lasting drought of 2011-2012 were registered during that
427 period (de Robert 2012; FEWSNET 2012a, b). Beside JAS also corresponds to growing season
428 months in most West Africa, which makes it an interesting case for evaluating potential monitoring
429 products of hydrological extremes from a food security and disaster management point of view.

430 **3. Results**

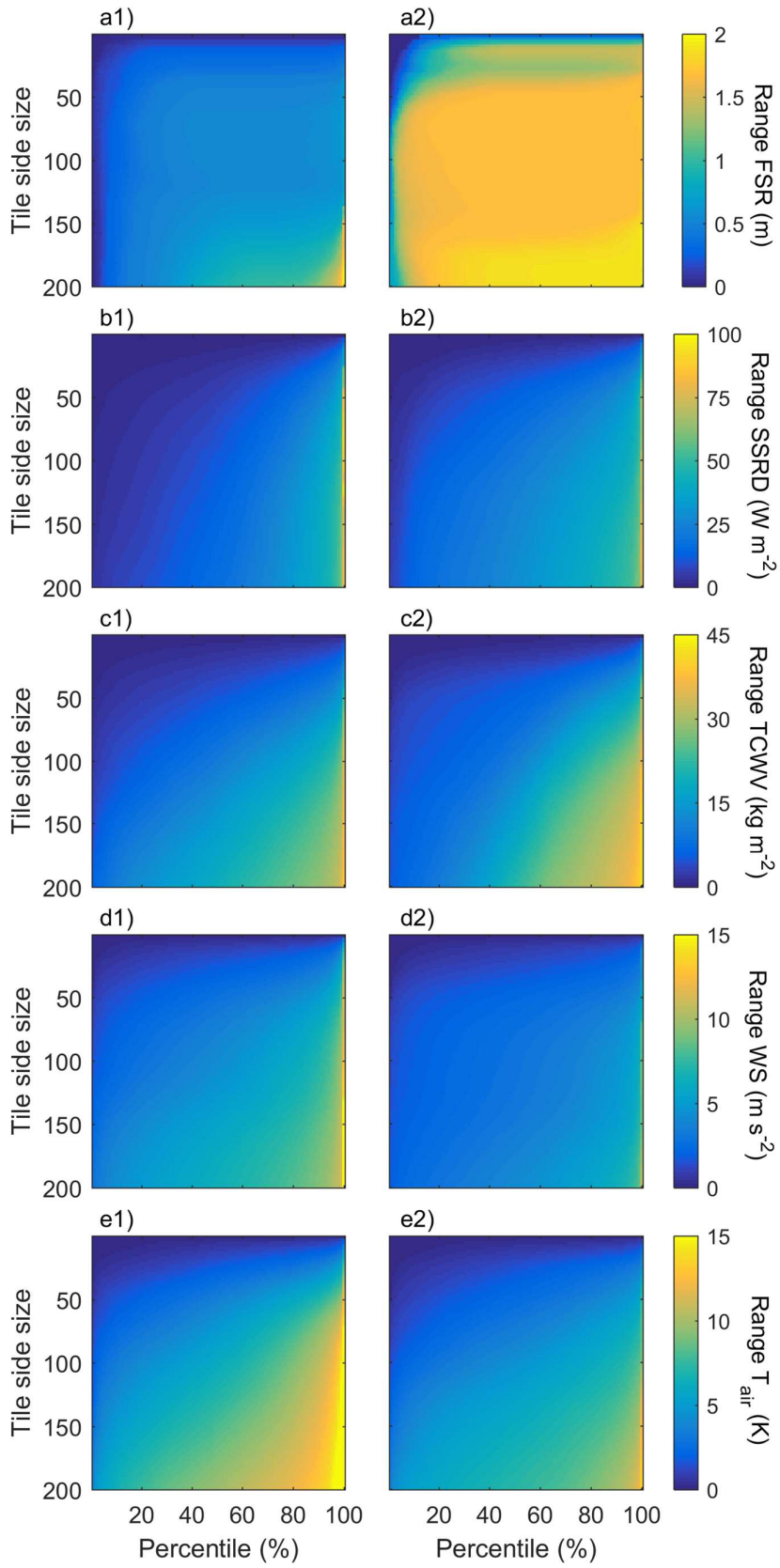
431 **3.1 Tile size selection and spatio-temporal variability of TVDI**

432 The dynamic range of the parameters affecting available energy within the triangular space differs
433 slightly in their relation to tile size. The dynamic range in FSR was relatively stable over a large
434 spectrum of tile sizes. It was found to increase rapidly to a value close to the maximum where after it
435 remained stable (at ~ 0.5 and ~ 1.6 m for Dahra and Nalohou, respectively) up to a tile size of \sim
436 160×160 SEVIRI pixels (Figure 3 a). The dynamic range in SSRD, TCWV, WS and T_{air} increased
437 more continuously with tile size (Figure 3b and 3c). Up until a tile size of 100×100 SEVIRI pixels,
438 daily averaged SSRD was $< 30 \text{ W m}^{-2}$ for $\sim 85\%$ and $\sim 75\%$ of the time series, and daily averaged WS
439 was $< 6 \text{ m s}^{-1}$ for $\sim 80\%$ and $\sim 98\%$ of the time series for Dahra and Nalohou, respectively, (Figure 3 b

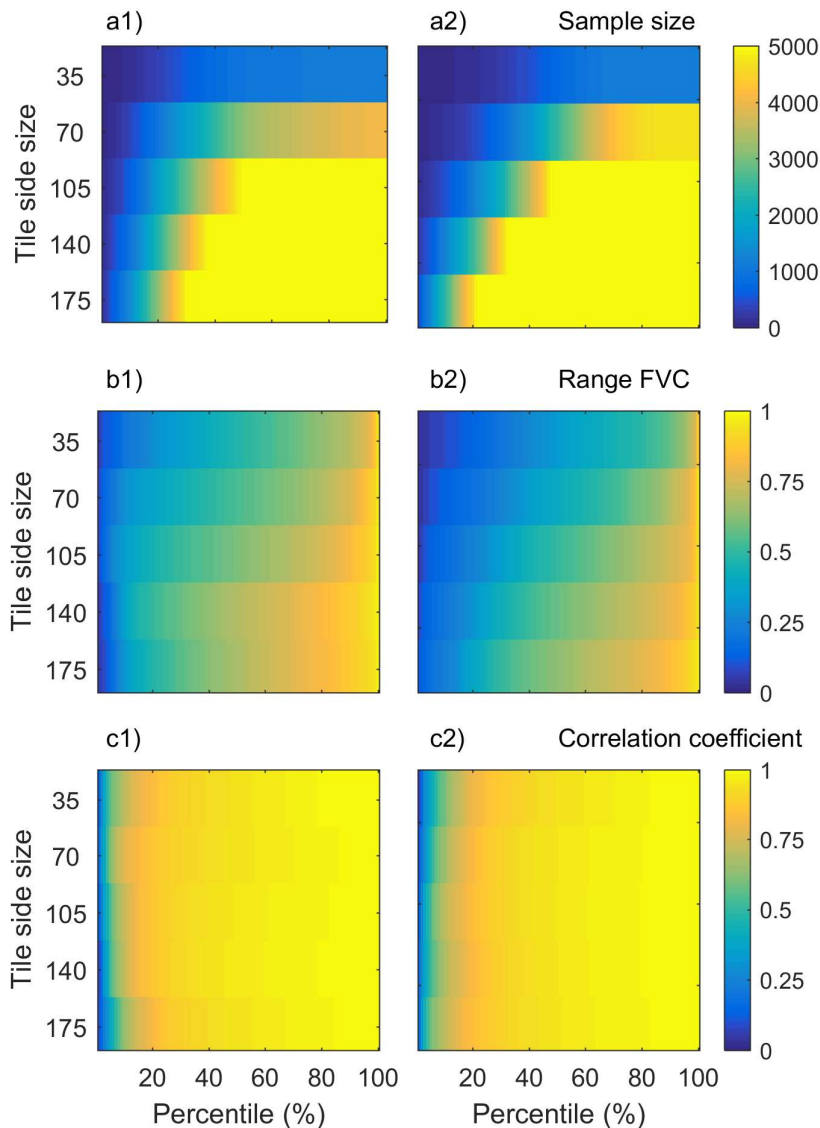
440 and 3d). Total column water vapour (TCWV) and T_{air} were more strongly affected by tile size with a
441 larger fraction of the time series having a large dynamic range (Figure 3c and 3e).

442 Both the sample size and the FVC range increased strongly with tile size (Figure 4). Using the defined
443 filtering criteria for the sample size (>500) it can be seen that 40%, 22%, 11%, 4%, and 1% of the
444 time series for Nalohou and 26%, 12%, 8%, 5%, and 3% of the time series for Dahra would be rejected
445 for the different tested tile sizes (with increased tile size order). Tile size is thereby a trade-off between
446 having a large enough sample size allowing for a sufficient amount of dTS-FVC cases, but keeping
447 it as small as possible not to induce uncertainty caused by heterogeneity in the available energy within
448 the triangular space. Reaching a sufficient number of points was challenging during the rainy season,
449 especially in the Southern parts of the study area due to the low number of eligible dTS/FVC pixels
450 (e.g. cloud-free data and good dTS fits) (Figure 5a). As a compromise, when enlarging the tile size
451 to 105 x 105 SEVIRI pixels, more pixels passed the filtering criteria (Figure 5c), and this tile size was
452 chosen for the final analysis.

453



455 **Figure 3.** Dynamic range in surface properties and atmospheric forcing influencing the homogeneity
 456 of available energy within the triangular space. Influence of tile size (y-axis) on the percentiles of the
 457 time series (x-axis) of the dynamic range in daily averaged a) forecast surface roughness (FSR) (m);
 458 b), surface solar radiation downwards (SSRD) ($W\ m^{-2}$); c) total column water vapour (TCWV) (kg
 459 m^{-2}); d) wind speed at 100 m height (WS) ($m\ s^{-1}$); and e) air temperature at the 975 hPa level (T_{air})
 460 (K) for 1) the Dahra and 2) the Nalohou field sites. The percentiles on the x-axis gives an indication
 461 of the fraction of the time series for a given tile size having a dynamic range smaller than the value
 462 shown by the colour. For the z-axis, dark blue indicates high homogeneity (i.e. small dynamic range)
 463 in surface properties or atmospheric forcing, whereas yellow indicates low homogeneity.



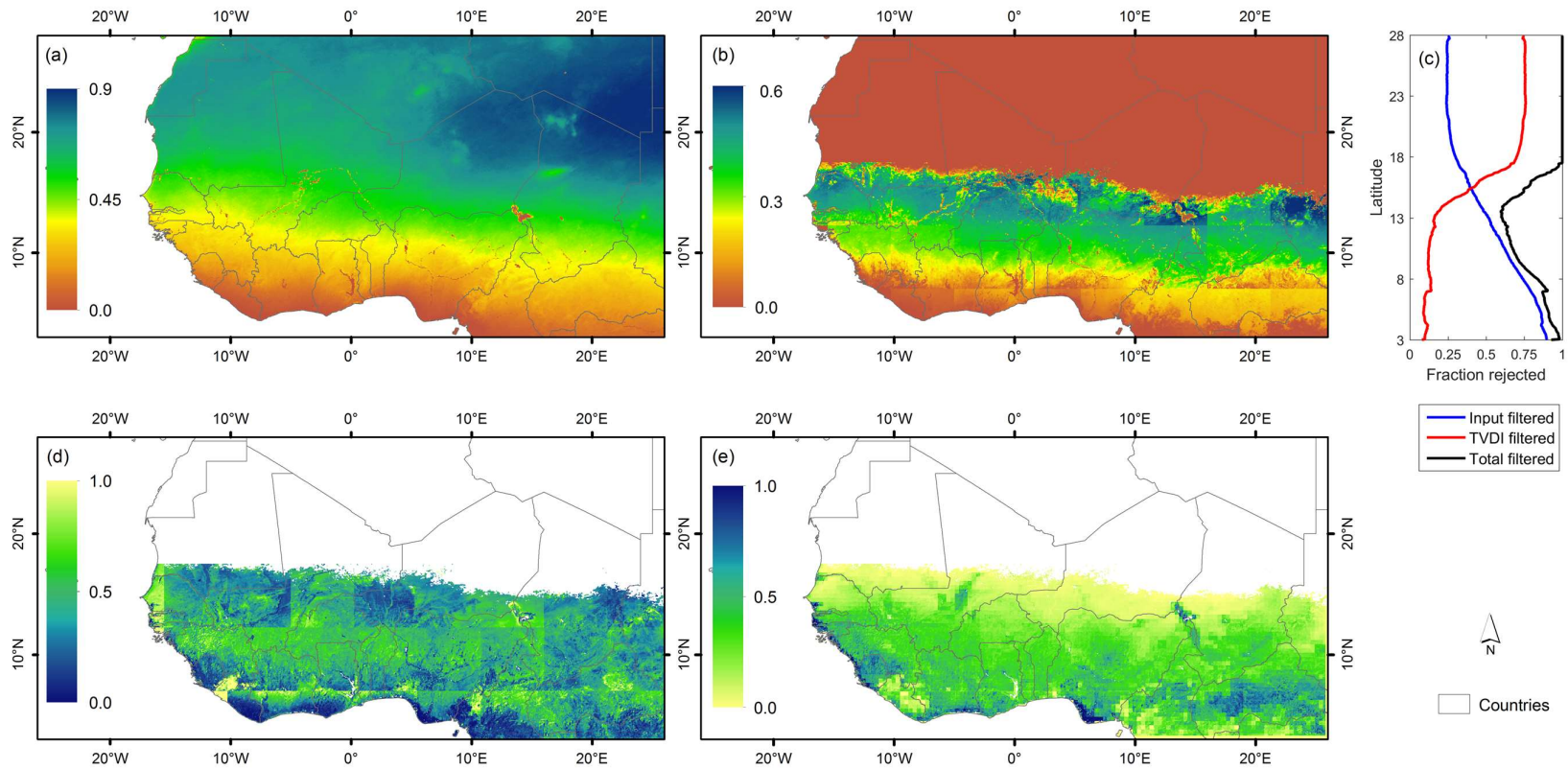
464

465 **Figure 4.** Influence of tile size (y-axis) on the percentiles of the time series (x-axis) of the parameters
466 influencing the triangular shape. a) Number of points including in the triangle (N); b) range in fraction
467 of vegetation cover (FVC); and c) correlation coefficient of the dry edge slope (r) for 1) the Dahra
468 and, 2) the Nalohou field sites. The percentiles on the x-axis gives an indication of the fraction of the
469 time-series for a given tile size having a range smaller than the value shown by the colour.

470

471 It can be seen that the amount of unfiltered input data (dTS and FVC) increased substantially with
472 latitude (Figure 5a); the further south the higher the fraction of cloud cover and an almost linear loss
473 of data is observed southwards from 20°N (Figure 5c). The amount of data excluded based on TVDI
474 tile statistics had the opposite pattern; at the border between the Sahel and the Sahara the FVC range
475 required for the triangular shape to take form starts to be too low (around 15°N) and above 17.5°N
476 no TVDI retrievals are obtained (Figure 5c). As a result, the largest amount of eligible data for
477 calculating TVDI was observed in the central part of the study area at ~13.5°N. In the spatial pattern
478 of the average TVDI for the entire study period, clear borders between the different tiles can be seen
479 (Figure 5d). However, when combining TVDI with SMOS SM using the disaggregation
480 methodology, the blocky structure disappears and SM heterogeneity across the study area is revealed
481 (Figure 5e; cf subsection 3.3 below).

482



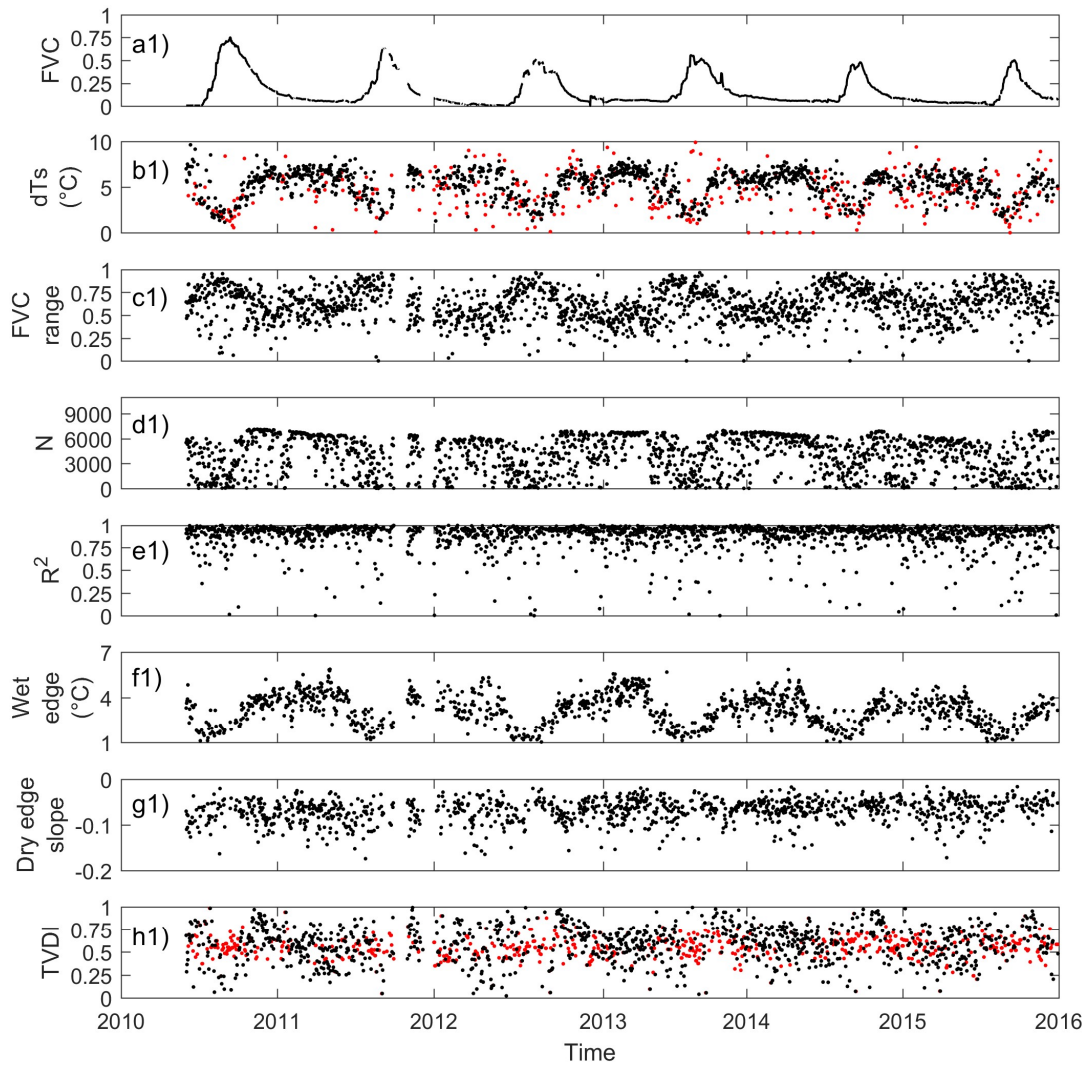
483

484 **Figure 5.** (a) Fraction of data coverage for the input data (dTS and FVC) used in the TVDI calculations; (b) fraction of data coverage for
 485 the TVDI calculations when TVDI was filtered based on both TVDI tile statistics and quality flags in input data. (c) Average data exclusion
 486 fraction depending on latitude; blue is the fraction of rejected input data, red is the fraction rejected in relation to the TVDI calculation, and
 487 black is the total rejected fraction. Included are also: (d) average TVDI for the entire study period; and (e) disaggregated SMOS SM
 488 averaged for the entire study period.

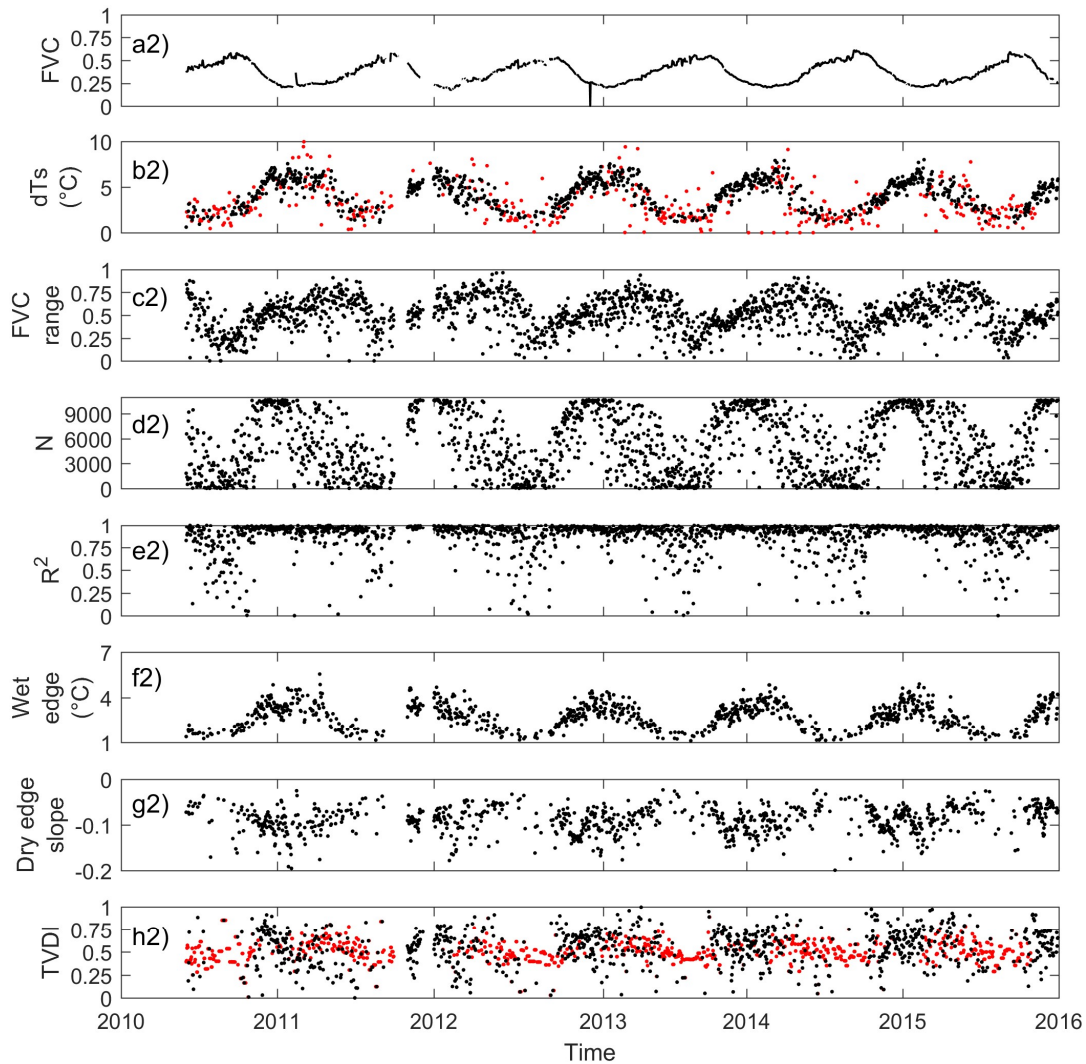
489

490 Clear seasonality was observed in the FVC and dTS time series for the pixels covering the Dahra and
491 the Nalohou field sites (Figure 6a,b,) whereas TVDI did not exhibit any sign of seasonal patterns and
492 had a relatively large variability (Figure 6h). The FVC range observed in the adjustment window
493 varied a lot throughout the year at the semi-arid Sahelian site; even though no clear seasonality was
494 detected (Figure 6c1). For the southern humid Soudanian savanna site, FVC was also highly variable,
495 but with a clear seasonality decreasing the FVC range during the rainy season (Figure 6c2). This was
496 most likely caused by an increased vegetation cover throughout the tile during this part of the
497 year. The coefficient of determination (R^2) of the dry edge fit remained high the entire year (> 0.75),
498 but a larger variability was observed during the rainy season (Figure 6e).

499



500



501
 502 **Figure 6.** Time series of the input parameters, extracts from the TVDI calculation tiles, and final
 503 TVDI estimates for (1) Dahra and (2) Nalohou: (a.) fraction of vegetation cover (FVC); (b) unfiltered
 504 (red) and filtered (black) morning rise temperature (dTs); (c) range of FVC in the TVDI tiles; (d)
 505 total number of points included in the triangle (N); (e) coefficient of determination (R^2) for the dry
 506 edge fit; (f) wet edge; and (g) dry edge slope. Included are also (h) filtered (black) and gap-filled (red)
 507 TVDI estimates (black).

508

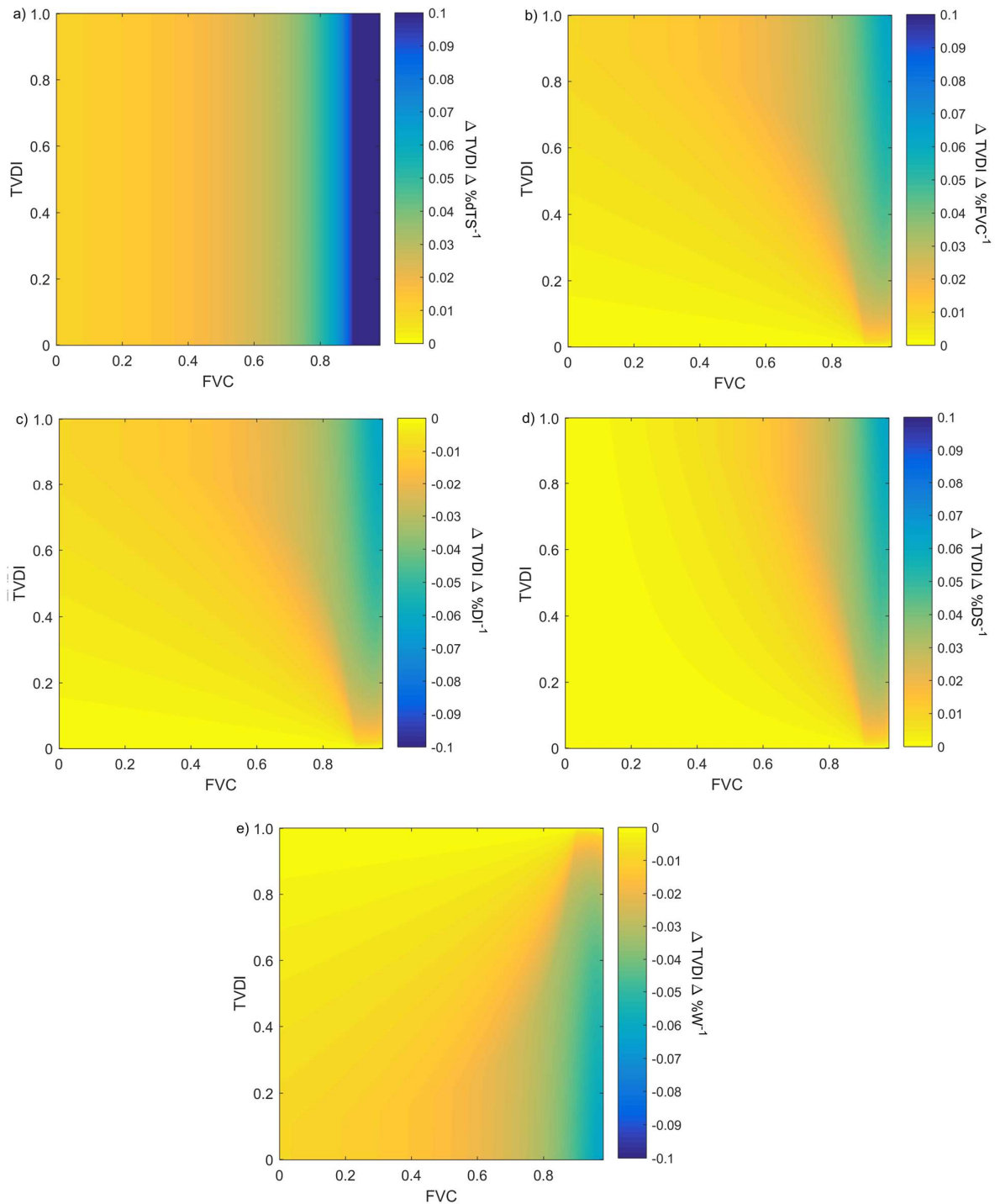
509 **3.2. Sensitivity of TVDI and soil moisture to input parameters**

510 The sensitivity analysis of TVDI indicated that sensitivity is strongly dependent on the pixel location
511 within the triangular space. Errors in the input parameters have a very strong impact on the estimated
512 TVDI at the peak of the triangle (upper part of the FVC range) whereas TVDI is less affected close
513 to the vertical catheter of the triangle (lower part of the FVC range) (Figure 7). The reason for this is
514 the small dTS range at the peak of the triangle, resulting in a large sensitivity. An error in the input
515 dTS data have the same impact throughout the entire TVDI range (Figure 7a). As expected, TVDI
516 values close to the dry edge (TVDI=1.0) are more sensitive to errors in the FVC, the dry edge slope
517 and the dry edge intercept (Figure 7b-d) than TVDI values close to the wet edge (Figure 7e). The
518 opposite is the case close to the wet edge (TVDI=0.0) where TVDI values are insensitive to errors in
519 the above mentioned parameters (FVC, the dry edge slope and intercept) but more sensitive to an
520 error in the wet edge.

521 For low SMOS SM values, disaggregated SM remain low throughout the entire TVDI range (Figure
522 8 a1-c1) and the disaggregation procedure is thereby rather insensitive to errors in TVDI for this
523 SMOS SM region (Figure 8 a2-c2). However, as SMOS SM increases the range in disaggregated SM
524 start to range from 0-100% (Figure 8 a1-c1), with implications for the sensitivity of the disaggregation
525 procedure. The effect of a change in TVDI is strongest for combinations of low SMOS SM and low
526 TVDI and high SMOS SM and high TVDI (seen in the colour change of Figure 8 a1- c1). For
527 example, when $\langle(TVDI)\rangle_{SMOS}$ is set to 0.75 disaggregated SM goes from 0 to 100%Vol with a TVDI
528 change from 1.0 to 0.8 (Figure 8c1). This pattern is also visible in the sensitivity of disaggregated
529 SMOS SM to TVDI (Figure 8c2). The most sensitive parts of the triangular space for the
530 disaggregation procedure are thereby close to the wet and dry edges where TVDI approaches 0.0 and
531 1.0, respectively.

532

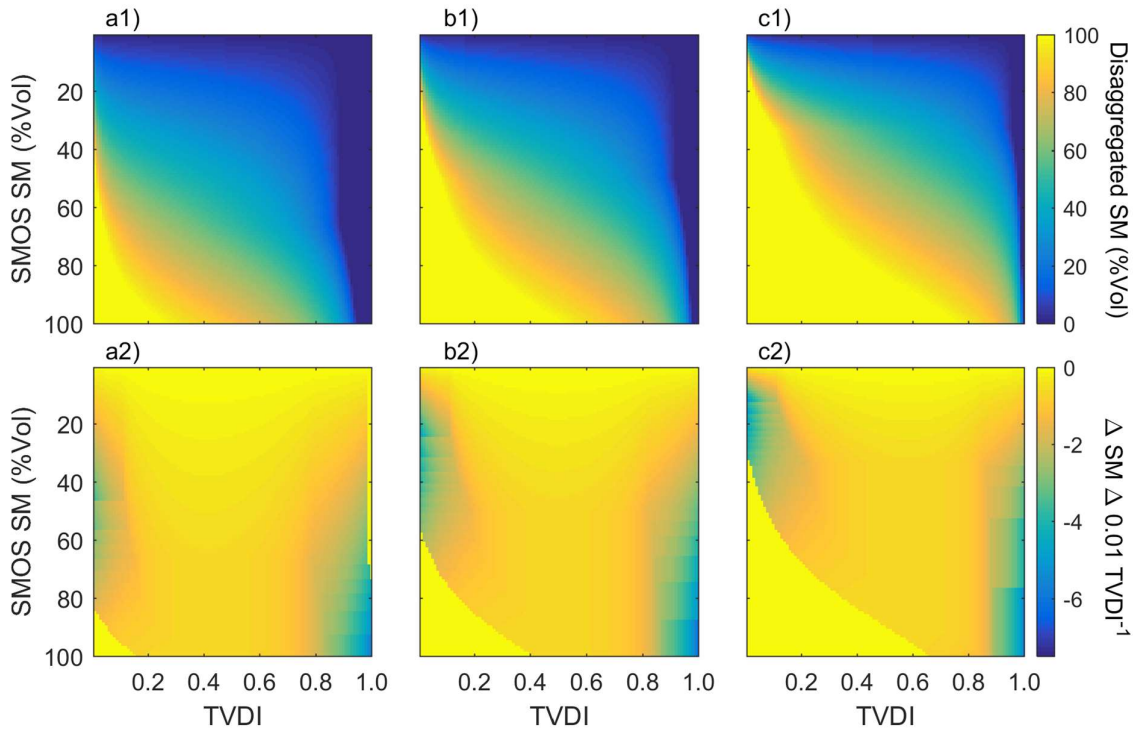
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534

535 **Figure 7.** Sensitivity of TVDI to input data and equation parameters: a) morning rise temperature
 536 (dTS; °C); b) fraction of vegetation cover (FVC); c) dry edge intercept (DI); d) dry edge slope (DS);
 537 and e) wet edge (W). The % for the temperatures (dTS, DI, and W) and the FVC is a % change in

538 relation to the range of the triangle. During the analysis we changed one parameter at the time and
 539 the rest remained stable.
 540



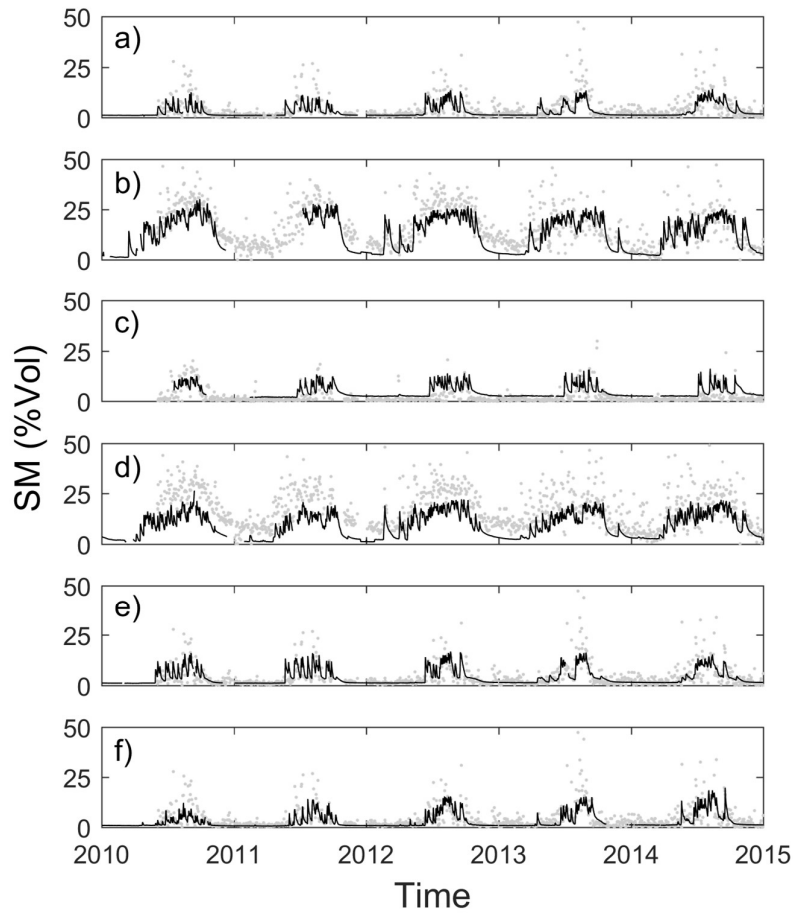
541

542 **Figure 8.** Sensitivity of disaggregated SMOS soil moisture (SM; %Vol) to changes in TVDI.
 543 Average TVDI in equation 8 was set to a) 0.25, b) 0.50 and c) 0.75. First row (1) shows the actual
 544 disaggregated SM for each original SMOS SM -TVDI case and second row (2) shows the changes in
 545 disaggregated SM for each 0.01 error in TVDI for each SM -TVDI case.
 546

547 3.3. Evaluation of the SMOS soil moisture products

548 The original SM product from SMOS generally describes the seasonal dynamics well for the 6 sites
 549 (Figure 9). The SMOS SM were on average 8.41%Vol whereas *in situ* SM was on average 6.33%Vol
 550 and it can be seen that SMOS SM is overestimated at some of the sites (Belefoungou and Nalohou).
 551 This overestimation generated a relatively high RMSE (6.26%Vol) between SMOS SM and *in situ*
 552 SM (Table 1). The sites with the highest overestimation are located in the southern humid parts of the
 553 study area (Figure 9). The linear function fitted between SMOS SM and *in situ* SM also indicated a

554 general overestimation by SMOS, but high SMOS SM has an even higher overestimation (Figure 10;
555 Table 1; slope: 1.26; intercept: 0.77; R^2 : 0.73).



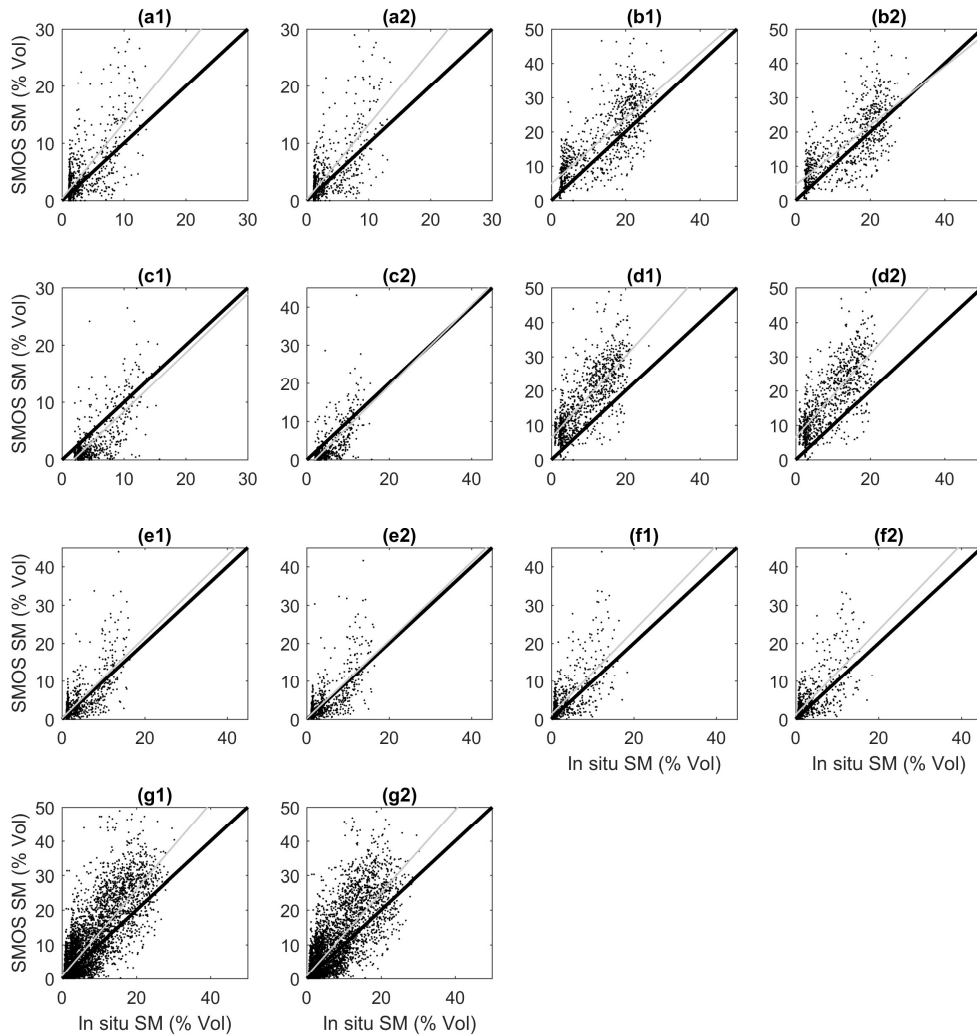
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557

558 **Figure 9.** Time series of *in situ* measured soil moisture (SM (%Vol)) (thin black line) and Soil
559 moisture and Ocean Salinity (SMOS) SM (grey dots) for: a) Banizoumbou; b) Belefoungou; c) Dahra;
560 d) Nalohou e) Tondikiboro; and f) Wankama. The location of the different sites is shown in Figure 2.

561

562



563

564 **Figure 10.** Relationship between *in situ* and both original (1) and disaggregated (2) Soil Moisture
 565 and Ocean Salinity (SMOS) soil moisture (SM; %Vol) for the pixels used in the evaluation of the
 566 disaggregation methodology. The subplots are: a) Banizoumbou; b) Belefoungou; c) Dahra; d)
 567 Nalohou; e) Tondikiboro; f) Wankama; and g) all sites combined. The grey line is the ordinary least
 568 square linear regression and the black line is the one-to-one ratio. Statistics of the slopes are given in
 569 Table 1. The location of the sites can be seen in figure 2.

570

571

572

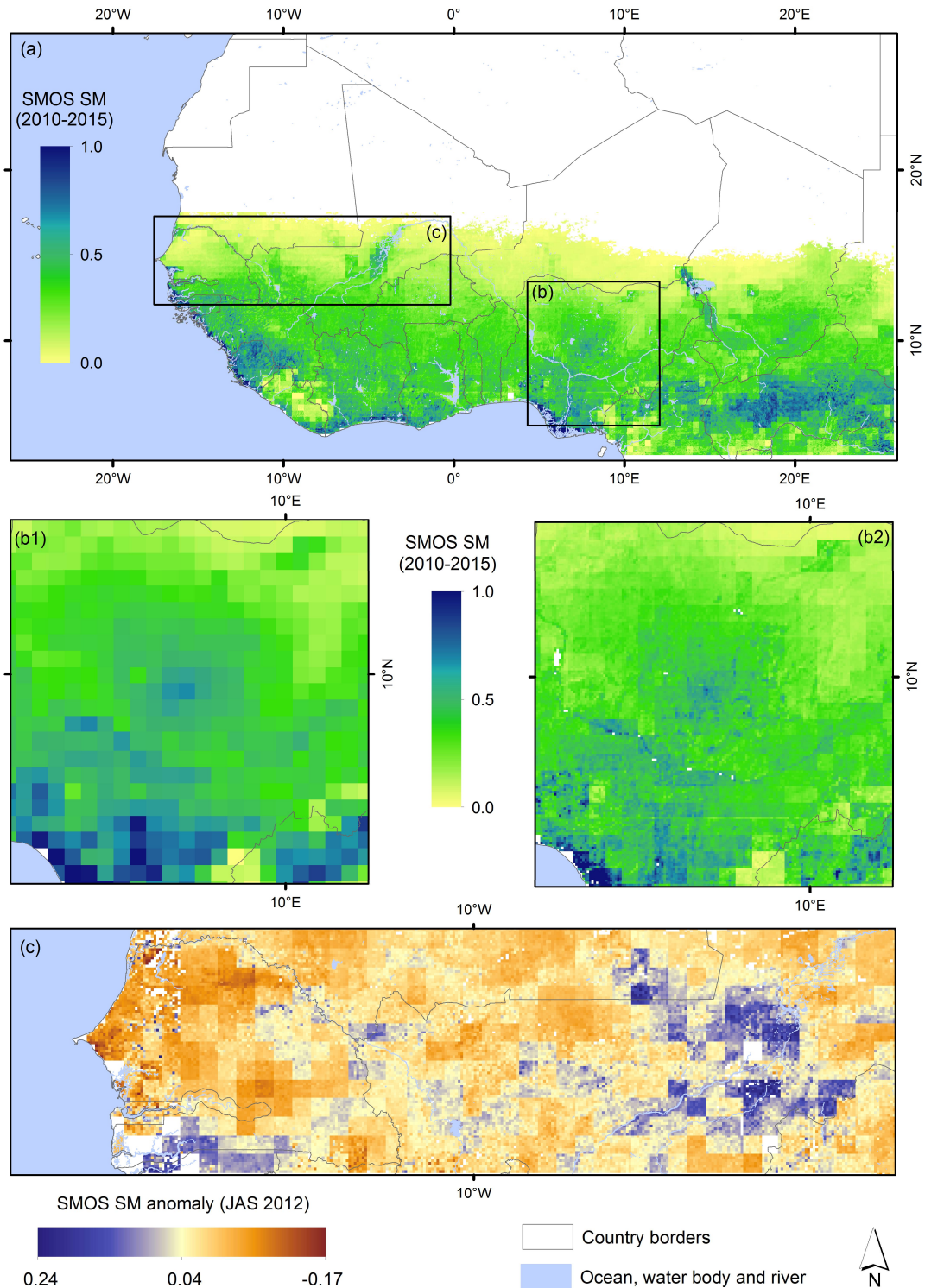
573 **Table 1.** Comparative statistics for the *in situ* validation of the original SMOS and disaggregated SMOS soil moisture. The ratio was the
 574 product-*in-situ* ratio and it was calculated as original and disaggregated SMOS SM divided by the *in situ* measurements. The analysis was
 575 conducted for individual sites and with all data combined.

Validation site	Original SMOS						Disaggregated SMOS					
	Slope	Intercept (%Vol)	R2	Mean bias (%Vol)	Ratio	RMSE (%Vol)	Slope	Intercept (%Vol)	R2	Mean bias (%Vol)	Ratio	RMSE (%Vol)
Banizoumbou (BAN)	1.32	0.35	0.58	-1.36	1.44	4.45	1.30	0.19	0.59	-1.13	1.36	4.18
Belefontou (BEL)	0.95	4.87	0.71	-4.19	1.25	7.81	0.86	4.57	0.67	-2.77	1.10	6.93
Dahra (DAH)	1.03	-1.88	0.58	1.76	0.59	3.21	1.06	-2.03	0.55	1.74	0.59	3.42
Nalohou (NAL)	1.19	6.35	0.68	-8.13	1.80	10.21	1.22	6.44	0.66	-8.39	1.76	10.61
Tondikiboro (TON)	1.07	0.22	0.61	-0.49	1.13	4.03	1.03	0.17	0.61	-0.28	1.07	3.87
Wankama (WAN)	1.11	1.16	0.59	-1.5	1.45	4.41	1.12	1.10	0.59	-1.47	1.43	4.36
All	1.26	0.77	0.73	-2.38	1.33	6.26	1.21	0.86	0.69	-2.09	1.25	6.13

576

577 In order to compare the original SMOS SM with the disaggregated SMOS SM, we filtered the SM
578 products (original and disaggregated SMOS SM) so that only days included in both time-series were
579 included in the evaluation (Figure 10). Disaggregated SMOS SM had a slightly lower correlation than
580 original SMOS SM to *in situ* SM (Figure 10; R^2 in Table 1). However, disaggregated SMOS had a
581 lower bias, a ratio closer to 1.0, a lower RMSE, and it was slightly closer to the one-to-one ratio (slope
582 1.21 and 1.26) (Table 1, Figure 10). The largest discrepancy between SMOS SM and the *in situ* SM
583 was seen for the sites in the southern part of the study area (Belefoungou and Nalohou; Table 1,
584 Figure 10). These are the sites generating the high SMOS SM in the low *in situ* SM region of Figure
585 10g. These high SMOS SM values were mainly from the dry season when *in situ* SM was relatively
586 low (Figure 9b, d).

587 Spatial patterns of disaggregated and original SMOS SM were also evaluated for the entire West
588 Africa (Figure 11). Major river networks (e.g. Niger, Senegal, Hadejia, etc.) are visible in the
589 disaggregated product whereas they are not on the original product (Figure 11b). To assess the
590 potential of the disaggregated SM products for monitoring climate extremes, SM anomalies were
591 estimated for the period July to September (JAS; growing season months in most of West Africa)
592 2012 (Figure 11c). Both cases of drought and flooding were observed during that period in West
593 Africa, and negative SM anomalies are seen in most Senegal and Mali, whereas large patterns of
594 positive SM anomalies are observed in Central Mali (Figure 11c).



595

596 **Figure 11.** SM 2010-2015 average derived from the disaggregated SMOS product over West Africa
 597 (a). Main river networks were not visible in the original (non-disaggregated) products (b1), whereas
 598 they became apparent after disaggregation (b2). SM extremes (flood and drought) were also captured
 599 for the test case of JAS 2012 (c). Filtered and no data are represented in white. The blocky structure
 600 observed in the disaggregated products are caused by the original SMOS pixel resolution.

601

602 **4. Discussion**

603 The use of a higher spatial resolution SM proxy to disaggregate SMOS SM is of high interest as there
604 is a stringent mismatch between the spatial scale at which SM information is provided (e.g. ~ 40 km
605 for SMOS) and the scale of the studied process (Collow et al. 2012). Besides the question of the
606 representability of *in situ* measurements for validating such coarse dataset has often been raised
607 (Dorigo et al. 2015), suggesting that the development of a disaggregated product would grant a more
608 accurate *in situ* validation (Malbêteau et al. 2016). However, if a systematic bias is present in the
609 original SMOS SM (such as seen for the southern sites (Figure 9), seen in the blocky structure of the
610 final disaggregated product (Figure 5e and Figure 11), and as reported by Collow et al. (2012)), the
611 uncertainty will propagate during the disaggregation process, regardless of the quality of the
612 information used for the disaggregation. One large source of uncertainty for SMOS SM is the
613 presence of forest, being the most likely explanation to the systematic bias in the southern sites
614 (Leroux et al. 2013). The disaggregation of SMOS using TVDI as input data improved the
615 relationship for most sites, suggesting that the TVDI spatial heterogeneity is adequately capturing
616 SM heterogeneity within each SMOS pixel.

617 One of the major challenges here was to produce a time series of TVDI estimates at sub-continental
618 scale in order to best serve the disaggregation process. Commonly TVDI has been used to evaluate
619 SM or evapotranspiration conditions over regions of limited spatial extent (i.e. hydrological basin,
620 sub-national administrative entities, etc.) (de Tomás et al. 2014; Garcia et al. 2014; Stisen et al. 2008).
621 Here TVDI was estimated using a tile approach of 105 by 105 SEVIRI pixels. By fitting TVDI for
622 such tiles the impact of heterogeneous atmospheric and surface condition were alleviated as much as
623 possible and at the same time made TVDI applicable across the subcontinental study area.

624 It is important to note that TVDI values can only be compared within a given tile (Figure 5d). The
625 exact TVDI value estimated for a certain pixel depends on the location of the wet and dry edge and a
626 specific TVDI value will not represent similar local hydrological conditions when fitted over a tile
627 covering humid tropical forest as over a tile covering semi-arid savanna. Besides, TVDI is not only
628 affected by the exact region used for fitting the triangle, but the size of the tile also has a strong
629 influence (Long et al. 2012). With an increase in tile size more humid and dry conditions are included
630 in the triangular space and the wet and dry edge thereby moves up- and down-wards, respectively,
631 with a strong impact on the TVDI estimates (Figure 7) (Long et al. 2012). Additionally, a small tile
632 size causes large uncertainties in the calculation of the wet and dry edges due to the low number of
633 available pixels (Figure 4) (de Tomás et al. 2014), whereas a large tile size induce uncertainty in
634 relation to heterogeneity of surface roughness and atmospheric forcing (Figure 3). As a compromise
635 we used a relatively large tile size as this was deemed necessary to fulfil the requirements of sufficient
636 amount of data-points for TVDI calculations within parts of the study region (Figure 5c).

637 It is not only challenging to compare TVDI values originating from different tiles but also values
638 derived at the same location but under different meteorological conditions. Indeed, short-term
639 variability in meteorological parameters (e.g. rainfall, temperature, incoming radiation, wind, cloud
640 cover) is likely to impact the temporal variability in TVDI. If we hypothesize that SM temporal
641 variability can be captured by TVDI time series, rainy season TVDI should be substantially lower
642 than dry season TVDI. As this pattern is not observed (Figure 6), it leads to the questioning of the
643 applicability of TVDI as proxy for monitoring the SM temporal variability. This finding however do
644 not disqualify TVDI as proxy for assessing the spatial variability of SM within a given tile. Here the
645 tile size was set so that a SMOS pixel is never overlapping two different tiles; and each pixel only
646 uses the TVDI heterogeneity within a tile and at a certain point in time for disaggregation of SMOS
647 SM. Future research related to the improvement of the temporal patterns of TVDI could possibly

648 focus on the use of the newly launched geostationary satellite GOES-R with 1-km spatial resolution
649 which will improve the ability to acquire pure pixels for a comparable smaller area or by using data
650 from constellations of polar orbiting sensors (e.g. MODIS, VIIRS and Sentinel-3) ensuring higher
651 spatial resolution in combination with an adequate temporal resolution.

652 The TVDI retrievals were found to be very sensitive to errors in the input parameters at the upper
653 range of FVC, challenging the applicability of the TVDI approach for the high FVC regions needed
654 to shape the triangular space. Indeed, it has previously been shown that DisPATCH in the form that
655 it was implemented in this study performs better over semi-arid areas than over temperate zones
656 (Malbêteau et al. 2016). It has also been found that the triangular method underestimates
657 evapotranspiration because the surface temperature of empirically retrieved dry and wet edges are
658 usually under- and overestimated, respectively (Tang and Li 2015). In reality, the evapotranspiration
659 and SM should reach a minimum and maximum level at surface temperatures higher than and lower
660 than what the actual observations show (Tang and Li 2015). This is specifically the case for the upper
661 part of the FVC range (Tang et al. 2010). Incorporating a theoretical dry and wet edge higher and
662 lower than the actual measured level would decrease the sensitivity of the disaggregated product to
663 the input parameters, given that the wet and dry edge would be displaced from the observed values.
664 Tang and Li (2017) developed a physically based model for estimates of endmembers of a trapezoid
665 for evapotranspiration estimates based on both data from earth observation and *in situ* measurements
666 (meteorology, incoming short and longwave radiation, and vegetation height). It is possible that this
667 approach could be adjusted and applied to earth observation and gridded meteorological and
668 vegetation data for estimating endmembers giving such theoretical dry and wet edges. Possibly, this
669 would also result in larger temporal (seasonal) dynamics in TVDI since high FVC observations (i.e.
670 growing season conditions) would be more influenced than low FVC observations (dry season
671 conditions).

672 Despite these inherent limitations of the TVDI approach, TVDI is found to be a valuable approach
673 for the purpose of disaggregating SM of a SMOS pixel as implemented here. The accuracy of the
674 disaggregated products (RMSE 3.4-10.6 %Vol) were at a similar level as previously published
675 disaggregated SMOS SM products (RMSE varying between 3-11 %Vol) for a range of vegetation
676 types covered here (semi-arid woody savannah, cultivated semi-arid regions, humid woody savannah
677 and tropical forest) (Djamai et al. 2015; Malbêteau et al. 2016; Merlin et al. 2013; Peng et al. 2017;
678 Piles et al. 2016; Piles et al. 2014). Increased details related to major river networks confirms that the
679 disaggregation method driven by the TVDI spatial heterogeneity was successful in improving the
680 spatial representation of the hydrological landscape over West Africa (Figure 11). SM extremes were
681 depicted adequately for the test case of JAS 2012 that coincided with a complex food security crisis
682 in the Sahel. During that year, late, erratic rainfall, together with high food prices and chronic poverty
683 pushed more than 19 million people into food insecurity in the Sahel (de Robert 2012). In August
684 countries already affected by the drought were then hit by heavy rainfall (e.g. in Central Mali, and in
685 several regions in Niger and Nigeria) causing flooding, destroyed infrastructure and damaged crop
686 fields (FEWSNET 2012a, b). Despite the relatively short length of available time series (max. 5
687 years), seasonal anomalies derived from the disaggregated SM product proved to be an adequate tool
688 to identify both areas affected by extreme high and low SM content. Further investigations should
689 focus on the evaluation of potential monitoring and early warning products at monthly or lower time
690 scale derived from the disaggregated product.

691 Overall it can be concluded that the disaggregation methodology successfully increased the spatial
692 resolution of SMOS SM and that the disaggregated products can potentially be applied to local SM
693 monitoring for drought/flood risks which is of significant importance for the livelihood of the
694 population in West Africa. Initiatives such as the one set by the European Space Agency (ESA) Data
695 User Element (DUE) GlobTemperature Project that aims at producing and distributing high quality,

696 consistent LST dataset are of high value for climate and hydrological studies, especially in remote
697 areas with low density *in situ* SM networks. Further research effort should therefore continue the
698 development and distribution of very high temporal time series of LST that are essential for specific
699 activities related to the better understanding of the hydrological cycle, the monitoring, forecasting
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711 drivers and impacts on livelihoods..

712

713 **References**

714 Alcaraz-Segura, D., Liras, E., Tabik, S., Paruelo, J., & Cabello, J., 2010. Evaluating the Consistency
715 of the 1982-1999 NDVI Trends in the Iberian Peninsula across Four Time-series Derived from the
716 AVHRR Sensor: LTDR, GIMMS, FASIR, and PAL-II. *Sensors* 10, 1291-1314

717

718 Anderson, M.C., Norman, J.M., Mecikalski, J.R., Otkin, J.A., & Kustas, W.P., 2007. A
719 climatological study of evapotranspiration and moisture stress across the continental United States
720 based on thermal remote sensing: 2. Surface moisture climatology. *J. Geophys. Res. -Atmos.* 112,
721 n/a-n/a

722

723 Bach, H., & Mauser, W., 1994. Modelling and model verification of the spectral reflectance of soils
724 under varying moisture conditions, *Proceedings of IGARSS '94 - 1994 IEEE International*
725 *Geoscience and Remote Sensing Symposium*, Pasadena, CA, USA

726

727 Bonan, G., 2008. *Ecological Climatology: Concepts and Applications*. Cambridge University Press,
728 New York

729

730 Carlson, T.N., Gillies, R.R., & Schmugge, T.J., 1995. An Interpretation of Methodologies for
731 Indirect Measurement of Soil-Water Content. *Agric. For. Meteorol.* 77, 191-205

732

733 Carlson, T.N., Perry, E.M., & Schmugge, T.J., 1990. Remote Estimation of Soil-Moisture
734 Availability and Fractional Vegetation Cover for Agricultural Fields. *Agric. For. Meteorol.* 52, 45-
735 69

736

737 Collow, T.W., Robock, A., Basara, J.B., & Illston, B.G., 2012. Evaluation of SMOS retrievals of
738 soil moisture over the central United States with currently available in situ observations. *J.*
739 *Geophys. Res.-Atmos.* 117

740

741 Crago, R., & Brutsaert, W., 1996. Daytime evaporation and the self-preservation of the evaporative
742 fraction and the Bowen ratio. *J. Hydrol.* 178, 241-255

743

744 de Beurs, K.M., & Henebry, G.M., 2005. A statistical framework for the analysis of long image
745 time series. *Int. J. Remote Sens.* 26, 1551-1573

746

747 de Robert, G., 2012. Sahel Food Crisis 2012 - A Cyclical or Exceptional Crisis?, Rome, FAO
748 report, pp. 6

749

750 de Tomás, A., Nieto, H., Guzinski, R., Salas, J., Sandholt, I., & Berliner, P., 2014. Validation and
751 scale dependencies of the triangle method for the evaporative fraction estimation over
752 heterogeneous areas. *Remote Sens. Environ.* 152, 493-511

753

754 Djamai, N., Magagi, R., Goita, K., Merlin, O., Kerr, Y., & Walker, A., 2015. Disaggregation of
755 SMOS soil moisture over the Canadian Prairies. *Remote Sens. Environ.* 170, 255-268

756

757 Dorigo, W.A., Gruber, A., De Jeu, R.A.M., Wagner, W., Stacke, T., Loew, A., Albergel, C.,
758 Brocca, L., Chung, D., Parinussa, R.M., & Kidd, R., 2015. Evaluation of the ESA CCI soil moisture
759 product using ground-based observations. *Remote Sens. Environ.* 162, 380-395

760

761 Eastman, R., Sangermano, F., Ghimire, B., Zhu, H., Chen, H., Neeti, N., Cai, Y., Machado, E.A., &
762 Crema, S.C., 2009. Seasonal trend analysis of image time series. *Int. J. Remote Sens.* 30, 2721-2726

763
764 ECMWF, 2017. ERA5.
765 [https://software.ecmwf.int/wiki/display/CKB/How+to+download+ERA5+data+via+the+ECMWF+](https://software.ecmwf.int/wiki/display/CKB/How+to+download+ERA5+data+via+the+ECMWF+Web+API)
766 [Web+API](https://software.ecmwf.int/wiki/display/CKB/How+to+download+ERA5+data+via+the+ECMWF+Web+API) (accesssed 18-09-2017),

767
768 FEWSNET, 2012a. Mali Food Security Outlook update. www.fews.net/mali (accesssed 03-05-
769 2017),

770
771 FEWSNET, 2012b. West Africa Food Security Outlook Update. [http://www.fews.net/west-](http://www.fews.net/west-africa/food-security-outlook-update/september-2012)
772 [africa/food-security-outlook-update/september-2012](http://www.fews.net/west-africa/food-security-outlook-update/september-2012) (accesssed 03-05-2017),

773
774 García-Haro, F.J., Sommer, S., & Kemper, T., 2005. A new tool for variable multiple endmember
775 spectral mixture analysis (VMESMA). *Int. J. Remote Sens.* 26, 2135-2162

776
777 Garcia, M., Fernández, N., Villagarcía, L., Domingo, F., Puigdefábregas, J., & Sandholt, I., 2014.
778 Accuracy of the Temperature–Vegetation Dryness Index using MODIS under water-limited vs.
779 energy-limited evapotranspiration conditions. *Remote Sens. Environ.* 149, 100-117

780
781 Gillies, R.R., & Carlson, T.N., 1995. Thermal Remote-Sensing of Surface Soil-Water Content with
782 Partial Vegetation Cover for Incorporation into Climate-Models. *J. Appl. Meteorol.* 34, 745-756

783
784 GLOBTEMP, 2014. GLOBTEMPERATURE- an ESA DUE initiative. <http://globtemperature.info/>
785 (accesssed 2017-10-16),

786
787 Han, Y., Wang, Y.Q., & Zhao, Y.S., 2010. Estimating Soil Moisture Conditions of the Greater
788 Changbai Mountains by Land Surface Temperature and NDVI. *IEEE T. Geosci. Remote Sens.* 48,
789 2509-2515

790
791 Hassan, Q.K., Bourque, C.P.A., Meng, F.R., & Cox, R.M., 2007. A wetness index using terrain-
792 corrected surface temperature and normalized difference vegetation index derived from standard
793 MODIS products: An evaluation of its use in a humid forest-dominated region of eastern Canada.
794 *Sensors* 7, 2028-2048

795
796 Hirsch, R.M., & Slack, J.R., 1984. A Nonparametric Trend Test for Seasonal Data with Serial
797 Dependence. *Water Resour. Res.* 20, 727-732

798
799 ISMN, 2016. The International Soil Moisture Network. <https://ismn.geo.tuwien.ac.at/> (accesssed
800 14-02-2016),

801

802 Jiang, Z.Y., Huete, A.R., Didan, K., & Miura, T., 2008. Development of a two-band enhanced
803 vegetation index without a blue band. *Remote Sens. Environ.* 112, 3833-3845

804

805 Jimenez-Munoz, J.C., & Sobrino, J.A., 2008. Split-Window Coefficients for Land Surface
806 Temperature Retrieval From Low-Resolution Thermal Infrared Sensors. *IEEE Geosci. Remote*
807 *Sens. Lett.* 5, 806-809

808

809 Kerr, Y.H., 2007. Soil moisture from space: Where are we? *Hydrogeol. J.* 15, 117-120

810

811 Kerr, Y.H., Font, J., Martin-Neira, M., & Mecklenburg, S., 2012. Introduction to the Special Issue
812 on the ESA's Soil Moisture and Ocean Salinity Mission (SMOS)-Instrument Performance and First
813 Results. *IEEE T. Geosci. Remote Sens.* 50, 1351-1353

814

815 Kustas, W.P., & Norman, J.M., 1999. Evaluation of soil and vegetation heat flux predictions using a
816 simple two-source model with radiometric temperatures for partial canopy cover. *Agric. For.*
817 *Meteorol.* 94, 13-29

818

819 Leroux, D.J., Kerr, Y.H., Richaume, P., & Fieuzal, R., 2013. Spatial distribution and possible
820 sources of SMOS errors at the global scale. *Remote Sens. Environ.* 133, 240-250

821

822 Li, H.J., Li, C.Q., Lin, Y., & Lei, Y.P., 2010. Surface temperature correction in TVDI to evaluate
823 soil moisture over a large area. *J. Food Agric. Environ.* 8, 1141-1145

824

825 Li, Z.G., Wang, Y.L., Zhou, Q.B., Wu, J.S., Peng, J., & Chang, H.F., 2008. Spatiotemporal
826 variability of land surface moisture based on vegetation and temperature characteristics in Northern
827 Shaanxi Loess Plateau, China. *J. Arid Environ.* 72, 974-985

828

829 Long, D., Singh, V.P., & Scanlon, B.R., 2012. Deriving theoretical boundaries to address scale
830 dependencies of triangle models for evapotranspiration estimation. *J. Geophys. Res. -Atmos.* 117,
831 D05113

832

833 Louvet, S., Pellarin, T., al Bitar, A., Cappelaere, B., Galle, S., Grippa, M., Gruhier, C., Kerr, Y.,
834 Lebel, T., Mialon, A., Mougin, E., Quantin, G., Richaume, P., & de Rosnay, P., 2015. SMOS soil
835 moisture product evaluation over West-Africa from local to regional scale. *Remote Sens. Environ.*
836 156, 383-394

837

838 Malbêteau, Y., Merlin, O., Molero, B., Rüdiger, C., & Bacon, S., 2016. DisPATCH as a tool to
839 evaluate coarse-scale remotely sensed soil moisture using localized in situ measurements:
840 Application to SMOS and AMSR-E data in Southeastern Australia. *Int. J. Appl. Earth Obs. Geoinf.*
841 45, 221-234

842
843 Mallick, K., Bhattacharya, B.K., & Patel, N.K., 2009. Estimating volumetric surface moisture
844 content for cropped soils using a soil wetness index based on surface temperature and NDVI. *Agric.*
845 *For. Meteorol.* 149, 1327-1342

846
847 Merlin, O., Al Bitar, A., Walker, J.P., & Kerr, Y., 2010. An improved algorithm for disaggregating
848 microwave-derived soil moisture based on red, near-infrared and thermal-infrared data. *Remote*
849 *Sens. Environ.* 114, 2305-2316

850
851 Merlin, O., Escorihuela, M.J., Mayoral, M.A., Hagolle, O., Al Bitar, A., & Kerr, Y., 2013. Self-
852 calibrated evaporation-based disaggregation of SMOS soil moisture: An evaluation study at 3km
853 and 100m resolution in Catalunya, Spain. *Remote Sens. Environ.* 130, 25-38

854
855 Merlin, O., Rudiger, C., Al Bitar, A., Richaume, P., Walker, J.P., & Kerr, Y.H., 2012.
856 Disaggregation of SMOS Soil Moisture in Southeastern Australia. *IEEE T. Geosci. Remote Sens.*
857 50, 1556-1571

858
859 Minacapilli, M., Iovino, M., & Blanda, F., 2009. High resolution remote estimation of soil surface
860 water content by a thermal inertia approach. *J. Hydrol.* 379, 229-238

861
862 Moran, M.S., Clarke, T.R., Inoue, Y., & Vidal, A., 1994. Estimating Crop Water-Deficit Using the
863 Relation between Surface-Air Temperature and Spectral Vegetation Index. *Remote Sens. Environ.*
864 49, 246-263

865
866 Moran, M.S., Peters-Lidard, C.D., Watts, J.M., & McElroy, S., 2004. Estimating soil moisture at
867 the watershed scale with satellite-based radar and land surface models. *Can. J. Remote Sens.* 30,
868 805-826

869
870 Nieto, H., Sandholt, I., Aguado, I., Chuvieco, E., & Stisen, S., 2011. Air temperature estimation
871 with MSG-SEVIRI data: Calibration and validation of the TVX algorithm for the Iberian Peninsula.
872 *Remote Sens. Environ.* 115, 107-116

873
874 Noilhan, J., & Planton, S., 1989. A Simple Parameterization of Land Surface Processes for
875 Meteorological Models. *Monthly Weather Review* 117, 536-549

876
877 Panciera, R., Walker, J.P., Jackson, T.J., Gray, D.A., Tanase, M.A., Ryu, D., Moneris, A., Yardley,
878 H., Rudiger, C., Wu, X.L., Gao, Y., & Hacker, J.M., 2014. The Soil Moisture Active Passive
879 Experiments (SMAPEX): Toward Soil Moisture Retrieval From the SMAP Mission. *IEEE T.*
880 *Geosci. Remote Sens.* 52, 490-507

881

882 Patel, N.R., Anapashsha, R., Kumar, S., Saha, S.K., & Dadhwal, V.K., 2009. Assessing potential of
883 MODIS derived temperature/vegetation condition index (TVDI) to infer soil moisture status. *Int. J.*
884 *Remote Sens.* 30, 23-39

885

886 Peng, J., Loew, A., Merlin, O., & Verhoest, N.E.C., 2017. A review of spatial downscaling of
887 satellite remotely sensed soil moisture. *Reviews of Geophysics* 55, 341-366

888

889 Piles, M., Petropoulos, G.P., Sánchez, N., González-Zamora, Á., & Ireland, G., 2016. Towards
890 improved spatio-temporal resolution soil moisture retrievals from the synergy of SMOS and MSG
891 SEVIRI spaceborne observations. *Remote Sens. Environ.* 180, 403-417

892

893 Piles, M., Sánchez, N., Vall-llossera, M., Camps, A., Martínez-Fernández, J., Martínez, J., &
894 González-Gambau, V., 2014. A Downscaling Approach for SMOS Land Observations: Evaluation
895 of High-Resolution Soil Moisture Maps Over the Iberian Peninsula. *IEEE J. Sel. Top. Appl.* 7,
896 3845-3857

897

898 Price, J.C., 1990. Using Spatial Context in Satellite Data to Infer Regional Scale
899 Evapotranspiration. *IEEE T. Geosci. Remote Sens.* 28, 940-948

900

901 Proud, S.R., Rasmussen, M.O., Fensholt, R., Sandholt, I., Shisanya, C., Mutero, W., Mbow, C., &
902 Anyamba, A., 2010. Improving the SMAC atmospheric correction code by analysis of Meteosat
903 Second Generation NDVI and surface reflectance data. *Remote Sens. Environ.* 114, 1687-1698

904

905 Proud, S.R., Zhang, Q., Schaaf, C., Fensholt, R., Rasmussen, M.O., Shisanya, C., Mutero, W.,
906 Mbow, C., Anyamba, A., Pak, E., & Sandholt, I., 2014. The Normalization of Surface Anisotropy
907 Effects Present in SEVIRI Reflectances by Using the MODIS BRDF Method. *IEEE T. Geosci.*
908 *Remote Sens.* 52, 6026-6039

909

910 Rasmussen, M.O., Gottsche, F.M., Olesen, F.S., & Sandholt, I., 2011. Directional Effects on Land
911 Surface Temperature Estimation From Meteosat Second Generation for Savanna Landscapes. *IEEE*
912 *T. Geosci. Remote Sens.* 49, 4458-4468

913

914 Sadeghi, M., Jones, S.B., & Philpot, W.D., 2015. A linear physically-based model for remote
915 sensing of soil moisture using short wave infrared bands. *Remote Sens. Environ.* 164, 66-76

916

917 Sandholt, I., Rasmussen, K., & Andersen, J., 2002. A simple interpretation of the surface
918 temperature/vegetation index space for assessment of surface moisture status. *Remote Sens.*
919 *Environ.* 79, 213-224

920

921 Schmugge, T., 1978. Remote-Sensing of Surface Soil-Moisture. *J. Appl. Meteorol.* 17, 1549-1557

922
923 Sobrino, J.A., & Romaguera, M., 2004. Land surface temperature retrieval from MSG1-SEVIRI
924 data. *Remote Sens. Environ.* 92, 247-254

925
926 Stisen, S., Sandholt, I., Norgaard, A., Fensholt, R., & Jensen, K.H., 2008. Combining the triangle
927 method with thermal inertia to estimate regional evapotranspiration - Applied to MSG-SEVIRI data
928 in the Senegal River basin. *Remote Sens. Environ.* 112, 1242-1255

929
930 Stisen, S., Sandholt, I., Nørgaard, A., Fensholt, R., & Eklundh, L., 2007. Estimation of diurnal air
931 temperature using MSG SEVIRI data in West Africa. *Remote Sens. Environ.* 110, 262-274

932
933 Sun, L., Sun, R., Li, X.W., Liang, S.L., & Zhang, R.H., 2012. Monitoring surface soil moisture
934 status based on remotely sensed surface temperature and vegetation index information. *Agric. For.*
935 *Meteorol.* 166, 175-187

936
937 Tagesson, T., Fensholt, R., Cappelaere, B., Mougin, E., Horion, S., Kergoat, L., Nieto, H.,
938 Ehammer, A., Demarty, J., & Ardö, J., 2016. Spatiotemporal variability in carbon exchange fluxes
939 across the Sahel *Agric. For. Meteorol.* 226–227, 108-118

940
941 Tagesson, T., Fensholt, R., Guiro, I., Rasmussen, M.O., Huber, S., Mbow, C., Garcia, M., Horion,
942 S., Sandholt, I., Rasmussen, B.H., Göttsche, F.M., Ridler, M.-E., Olén, N., Olsen, J.L., Ehammer,
943 A., Madsen, M., Olesen, F.S., & Ardö, J., 2015. Ecosystem properties of semi-arid savanna
944 grassland in West Africa and its relationship to environmental variability. *Global Change Biol.* 21,
945 250-264

946
947 Tang, R., & Li, Z.-L., 2015. Evaluation of two end-member-based models for regional land surface
948 evapotranspiration estimation from MODIS data. *Agric. For. Meteorol.* 202, 69-82

949
950 Tang, R., & Li, Z.L., 2017. An End-Member-Based Two-Source Approach for Estimating Land
951 Surface Evapotranspiration From Remote Sensing Data. *IEEE T. Geosci. Remote Sens.* PP, 1-15

952
953 Tang, R.L., Li, Z.L., & Tang, B.H., 2010. An application of the T-s-VI triangle method with
954 enhanced edges determination for evapotranspiration estimation from MODIS data in and semi-
955 arid regions: Implementation and validation. *Remote Sens. Environ.* 114, 540-551

956
957 Trigo, I.F., Dacamara, C.C., Viterbo, P., Roujean, J.-L., Olesen, F., Barroso, C., Camacho-de-Coca,
958 F., Carrer, D., Freitas, S.C., García-Haro, J., Geiger, B., Gellens-Meulenberghs, F., Ghilain, N.,
959 Meliá, J., Pessanha, L., Siljamo, N., & Arboleda, A., 2011. The Satellite Application Facility for
960 Land Surface Analysis. *Int. J. Remote Sens.* 32, 2725-2744

961

962 Trigo, I.F., Peres, L.F., DaCamara, C.C., & Freitas, S.C., 2008. Thermal Land Surface Emissivity
963 Retrieved From SEVIRI/Meteosat. *IEEE T. Geosci. Remote Sens.* 46, 307-315

964
965 Vanbelle, G., & Hughes, J.P., 1984. Nonparametric-Tests for Trend in Water-Quality. *Water*
966 *Resour. Res.* 20, 127-136

967
968 Vinukollu, R.K., Wood, E.F., Ferguson, C.R., & Fisher, J.B., 2011. Global estimates of
969 evapotranspiration for climate studies using multi-sensor remote sensing data: Evaluation of three
970 process-based approaches. *Remote Sens. Environ.* 115, 801-823

971
972 Wan, Z.M., & Dozier, J., 1996. A generalized split-window algorithm for retrieving land-surface
973 temperature from space. *IEEE T. Geosci. Remote Sens.* 34, 892-905

974
975 Wang, C.Y., Qi, S.H., Niu, Z., & Wang, J.B., 2004. Evaluating soil moisture status in China using
976 the temperature-vegetation dryness index (TVDI). *Can. J. Remote Sens.* 30, 671-679

977
978 Wang, J., Ling, Z., Wang, Y., & Zeng, H., 2016. Improving spatial representation of soil moisture
979 by integration of microwave observations and the temperature–vegetation–drought index derived
980 from MODIS products. *ISPRS Journal of Photogrammetry and Remote Sensing* 113, 144-154

981
982 Wang, K.C., Li, Z.Q., & Cribb, M., 2006. Estimation of evaporative fraction from a combination of
983 day and night land surface temperatures and NDVI: A new method to determine the Priestley-
984 Taylor parameter. *Remote Sens. Environ.* 102, 293-305

985
986 Wigneron, J.P., Kerr, Y., Waldteufel, P., Saleh, K., Escorihuela, M.J., Richaume, P., Ferrazzoli, P.,
987 de Rosnay, P., Gurney, R., Calvet, J.C., Grant, J.P., Guglielmetti, M., Hornbuckle, B., Mätzler, C.,
988 Pellarin, T., & Schwank, M., 2007. L-band Microwave Emission of the Biosphere (L-MEB) Model:
989 Description and calibration against experimental data sets over crop fields. *Remote Sens. Environ.*
990 107, 639-655

991

992 **Appendix A. Mathematical derivations of Equation 5 and 7**

993 **Equation 5 was derived from equation 4:**

994
$$SEE_{\text{model}} = \frac{1}{2} - \frac{1}{2} \cos \left(\pi \times \frac{SM}{SM_p} \right) \quad (4)$$

995 Multiply both sides with -2:

996 $-2SEE_{\text{model}} = -1 + \cos\left(\pi \times \frac{SM}{SM_p}\right)$

997 Add 1 to both sides:

998 $1 - 2SEE_{\text{model}} = \cos\left(\pi \times \frac{SM}{SM_p}\right)$

999 Multiply both sides with arccos:

1000 $\arccos(1 - 2SEE_{\text{model}}) = \pi \times \frac{SM}{SM_p}$

1001 Put SM_p on the left side and put $\arccos(1 - 2SEE_{\text{model}})$ in the denominator on the right side and
 1002 equation 5 is derived:

1003 $SM_p = \frac{\pi \times SM_{SMOS}}{\arccos(1 - 2(SEE_{SEVIRI})_{SMOS})}$ (5)

1004 **Equation 7 was derived by taking the derivative of equation 6:**

1005

1006 $SM_{\text{model}} = \frac{SM_p}{\pi} \arccos(1 - 2SEE)$ (6)

1007 The derivative of $\arccos(x)$ is:

1008 $\frac{\partial \arccos(x)}{\partial x} = -\frac{1}{\sqrt{1-x^2}}$

1009 Then, by setting $x=(1-2SEE)$ and taking the derivative of x we get:

1010 $\frac{\partial S_{\text{model}}}{\partial x} = -\frac{SM_p}{\pi \sqrt{1-x^2}}$

1011 Then by taking the derivative of SEE on x we get:

$$1012 \quad \frac{\partial x}{\partial SEE} = -2$$

1013 Then by multiplying both sides with the derivative of SEE on x we get:

$$1014 \quad \frac{\partial SM_{model}}{\partial x} \times \frac{\partial x}{\partial SEE} = -\frac{\frac{SM_p}{\pi}}{\sqrt{1-x^2}} \times -2 \quad \Rightarrow \quad \frac{\partial SM_{model}}{\partial SEE} = \frac{2\left(\frac{SM_p}{\pi}\right)}{\sqrt{1-x^2}}$$

1015 Finally, by setting $x = (1-2SEE)$ equation 7 is derived:

$$1016 \quad \frac{\partial SM_{model}}{\partial SEE} = \frac{2\left(\frac{SM_p}{\pi}\right)}{\sqrt{1-(1-2SEE)^2}}$$

1017

1018 **Appendix B. Mathematical derivations indicating that TVDI is a proxy of SEE**

1019 According Merlin et al. (2012) SEE can be calculated as:

$$1020 \quad SEE = \frac{T_{soil_max} - T_{soil}}{T_{soil_max} - T_{soil_min}} \quad (B1)$$

1021 where T_{soil} is the soil temperature; T_{soil_min} is minimum T_{soil} ; and T_{soil_max} is maximum T_{soil} .

1022 Soil temperature and T_{soil_max} can be calculated as (Merlin et al. 2010; Merlin et al. 2012):

$$1023 \quad T_{soil} = \frac{LST - (FVC \times T_{vegetation})}{1 - (FVC \times T_{vegetation})}$$

$$1024 \quad T_{soil_max} = \frac{LST_{max} - (FVC \times T_{vegetation})}{1 - (FVC \times T_{vegetation})}$$

1025 If we put these two into equation B1; we get:

$$1026 \quad SEE = \frac{\frac{LST_{max} - (FVC \times T_{vegetation})}{(1-FVC)} - \frac{LST - (FVC \times T_{vegetation})}{(1-FVC)}}{\frac{LST_{max} - (FVC \times T_{vegetation})}{(1-FVC)} - T_{soil_min}} \quad \Rightarrow$$

$$1027 \quad SEE = \frac{\frac{LST_{max} - (FVC \times T_{vegetation})}{(1-FVC)} - \frac{LST - (FVC \times T_{vegetation})}{(1-FVC)}}{\frac{LST_{max} - (FVC \times T_{vegetation})}{(1-FVC)} - \frac{T_{soil_min}(1-FVC)}{(1-FVC)}} \quad \Rightarrow$$

$$1028 \quad SEE = \frac{LST_{max} - (FVC \times T_{vegetation}) - LST + (FVC \times T_{vegetation})}{LST_{max} - (FVC \times T_{vegetation}) - T_{soil_min}(1-FVC)} \quad \Rightarrow$$

1029 $SEE = \frac{LST_{\max} - LST}{LST_{\max} - (FVC \times T_{\text{vegetation}}) - T_{\text{soil_min}}(1 - FVC)} \Rightarrow$

1030 $SEE = \frac{LST_{\max} - LST}{LST_{\max} - (FVC \times T_{\text{vegetation}}) - T_{\text{soil_min}} + (FVC \times T_{\text{soil_min}})}$

1031 Given that vegetation temperature ($T_{\text{vegetation}}$) is approximately the same as minimum soil
 1032 temperature ($T_{\text{soil_min}}$) (Merlin et al. 2010), and that $T_{\text{soil_min}}$ can be estimated as minimum LST within
 1033 a window tile (the wet edge) (Merlin et al. 2010) this leads us to:

1034

1035 $SEE \approx \frac{LST_{\max} - LST}{LST_{\max} - T_{\text{soil_min}}} \approx \frac{LST_{\max} - LST}{LST_{\max} - LST_{\min}} = (1 - TVDI)$

1036

1037 **Figure Captions**

1038 **Figure 1.** Conceptual triangle space with the land surface temperature (LST) or morning rise
1039 temperature (dT_S) on the y-axis and Fraction of Vegetation Cover (FVC) on the x-axis. The blue
1040 line is the wet edge (TVDI=0.00) and the red line is the dry edge (TVDI=1.00). The grey dotted
1041 lines are TVDI examples of 0.25, 0.50, and 0.75. The figure is adapted from Peng et al. (2017).

1042

1043

1044 **Figure 2.** Study area with the location of the *in situ* validation sites. The averaged fraction of
1045 vegetation cover (FVC) for year 2011 is used as background to illustrate the important north-south
1046 gradient in vegetation cover.

1047

1048

1049 **Figure 3.** Dynamic range in surface properties and atmospheric forcing influencing the homogeneity
1050 of available energy within the triangular space. Influence of tile size (y-axis) on the percentiles of the
1051 time series (x-axis) of the dynamic range in daily averaged a) forecast surface roughness (FSR) (m);
1052 b), surface solar radiation downwards (SSRD) ($W\ m^{-2}$); c) total column water vapour (TCWV) (kg
1053 m^{-2}); d) wind speed at 100 m height (WS) ($m\ s^{-1}$); and e) air temperature at the 975 hPa level (T_{air})
1054 (K) for 1) the Dahra and 2) the Nalohou field sites. The percentiles on the x-axis gives an indication
1055 of the fraction of the time series for a given tile size having a dynamic range smaller than the value
1056 shown by the colour. For the z-axis, dark blue indicates high homogeneity (i.e. small dynamic range)
1057 in surface properties or atmospheric forcing, whereas yellow indicates low homogeneity.

1058

1059 **Figure 4.** Influence of tile size (y-axis) on the percentiles of the time series (x-axis) of the parameters
1060 influencing the triangular shape. a) Number of points including in the triangle (N); b) range in fraction
1061 of vegetation cover (FVC); and c) correlation coefficient of the dry edge slope (r) for 1) the Dahra
1062 and, 2) the Nalohou field sites. The percentiles on the x-axis gives an indication of the fraction of the
1063 time-series for a given tile size having a range smaller than the value shown by the colour.

1064

1065 **Figure 5.** (a) Fraction of data coverage for the input data (dT_S and FVC) used in the TVDI
1066 calculations; (b) fraction of data coverage for the TVDI calculations when TVDI was filtered based
1067 on both TVDI tile statistics and quality flags in input data. (c) Average data exclusion fraction
1068 depending on latitude; blue is the fraction of rejected input data, red is the fraction rejected in
1069 relation to the TVDI calculation, and black is the total rejected fraction. Included are also: (d)
1070 average TVDI for the entire study period; and (e) disaggregated SMOS SM averaged for the entire
1071 study period.

1072

1073 **Figure 6.** Time series of the input parameters, extracts from the TVDI calculation tiles, and final
1074 TVDI estimates for (1) Dahra and (2) Nalohou: (a.) fraction of vegetation cover (FVC); (b) unfiltered
1075 (red) and filtered (black) morning rise temperature (dT_S); (c) range of FVC in the TVDI tiles; (d)

1076 total number of points included in the triangle (N); (e) coefficient of determination (R^2) for the dry
1077 edge fit; (f) wet edge; and (g) dry edge slope. Included are also (h) filtered (black) and gap-filled (red)
1078 TVDI estimates (black).

1079
1080 **Figure 7.** Sensitivity of TVDI to input data and equation parameters: a) morning rise temperature
1081 (dT_S; °C); b) fraction of vegetation cover (FVC); c) dry edge intercept (DI); d) dry edge slope (DS);
1082 and e) wet edge (W). The % for the temperatures (dT_S, DI, and W) and the FVC is a % change in
1083 relation to the range of the triangle. During the analysis we changed one parameter at the time and
1084 the rest remained stable.

1085

1086 **Figure 8.** Sensitivity of disaggregated SMOS soil moisture (SM; %Vol) to changes in TVDI.
1087 Average TVDI in equation 8 was set to a) 0.25, b) 0.50 and c) 0.75. First row (1) shows the actual
1088 disaggregated SM for each original SMOS SM -TVDI case and second row (2) shows the changes in
1089 disaggregated SM for each 0.01 error in TVDI for each SM -TVDI case.

1090

1091 **Figure 9.** Time series of *in situ* measured soil moisture (SM (%Vol)) (thin black line) and Soil
1092 moisture and Ocean Salinity (SMOS) SM (grey dots) for: a) Banizoumbou; b) Belefoungou; c) Dahra;
1093 d) Nalohou e) Tondikiboro; and f) Wankama. The location of the different sites is shown in Figure 2.

1094

1095 **Figure 10.** Relationship between *in situ* and both original (1) and disaggregated (2) Soil Moisture
1096 and Ocean Salinity (SMOS) soil moisture (SM; %Vol) for the pixels used in the evaluation of the
1097 disaggregation methodology. The subplots are: a) Banizoumbou; b) Belefoungou; c) Dahra; d)
1098 Nalohou; e) Tondikiboro; f) Wankama; and g) all sites combined. The grey line is the ordinary least
1099 square linear regression and the black line is the one-to-one ratio. Statistics of the slopes are given in
1100 Table 1. The location of the sites can be seen in figure 2.

1101

1102 **Figure 11.** SM 2010-2015 average derived from the disaggregated SMOS product over West Africa
1103 (a). Main river networks were not visible in the original (non-disaggregated) products (b1), whereas
1104 they became apparent after disaggregation (b2). SM extremes (flood and drought) were also captured
1105 for the test case of JAS 2012 (c). Filtered and no data are represented in white. The blocky structure
1106 observed in the disaggregated products are caused by the original SMOS pixel resolution.

1107