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► **To cite this version:**

Thierry Pellarin, Carlos Román-Cascón, Christian Baron, Rajat Bindlish, Luca Brocca, et al.. The Precipitation Inferred from Soil Moisture (PrISM) near real-time rainfall product: evaluation and comparison.. Remote Sensing, 2020, 12 (3), pp.481. 10.3390/rs12030481 . hal-02531523

**HAL Id: hal-02531523**

**<https://hal.science/hal-02531523v1>**

Submitted on 31 Dec 2020

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1 Type of the Paper (Article, Review, Communication, etc.)

# 2 The Precipitation Inferred from Soil Moisture 3 (PrISM) near real-time rainfall product: evaluation 4 and comparison

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20 Received: date; Accepted: date; Published: date

21 **Abstract:** Near real time precipitation is essential to many applications. In Africa, the lack of dense  
22 raingauge networks and ground weather radars makes the use of satellite precipitation products  
23 unavoidable. Despite major progresses in estimating precipitation rate from remote sensing  
24 measurements over the past decades, satellite precipitation products still suffer from quantitative  
25 uncertainties and biases compared to ground data. Consequently, almost all precipitation products  
26 are provided in two modes: a real-time mode (also called early-run or raw product) and a corrected  
27 mode (also called final-run, adjusted or post-processed product) in which ground precipitation  
28 measurements are integrated in algorithms to correct for bias generally at a monthly timescale. This  
29 paper describes a new methodology to provide a near-real-time precipitation product based on  
30 satellite precipitation and soil moisture measurements. Recent studies have shown that soil  
31 moisture intrinsically contains information on past precipitation and can be used to correct  
32 precipitation uncertainties. The PrISM (Precipitation inferred from Soil Moisture) methodology is  
33 presented and its performance is assessed for five in situ rainfall measurement networks located in  
34 Africa in semi-arid to wet areas: Niger, Benin, Burkina Faso, Central Africa, and East Africa. Results  
35 show that the use of SMOS soil moisture measurements in the PrISM algorithm most often improves  
36 the real-time satellite precipitation products, and provides results comparable to existing adjusted  
37 products such as TRMM-3B42, GPCP and IMERG which are available a few weeks or months after  
38 their detection.

39 **Keywords:** Precipitation; Soil moisture; Africa; satellite rainfall products; comparison

40

## 41 1. Introduction

42

43 Rainfall is a crucial resource in Africa, where large parts of the population rely on rainfed  
44 agriculture. The continent is also known for its vulnerability to rainfall variability that impacts the  
45 natural resources (water, vegetation) and subsequently the wellness of populations, in societies

46 where economy is based mainly on agriculture [1]. Knowledge on rainfall spatio-temporal  
47 distribution is essential to various applications such as water-resource and land-use management,  
48 agricultural crop yield estimates, flood nowcasting, dam management, ground-water recharge  
49 estimates and irrigation demand. Rain-gauges provide the most common and most direct  
50 measurement of point precipitation at the surface, therefore they are generally assumed as the most  
51 accurate method to measure precipitation. Unfortunately, Africa is a region where the ground-based  
52 rain-gauge network is of very low density and operational radar installations are almost non-existent  
53 [2]. Furthermore, the gauge networks have been degrading over the last few decades [3].  
54

55 In this context, satellite-based precipitation products represent an unavoidable alternative for  
56 providing precipitation knowledge in Africa. In recent decades, significant progress has been made  
57 in satellite precipitation estimation. This progress is mostly due to the introduction of new sensors  
58 (e.g. Global Precipitation Measurement Core Observatory satellite), but also to the improved sensor  
59 accuracy, and efficiency of proposed algorithms that take advantage of the many observational data  
60 (including multi-channel VIS/IR sensors, and passive microwave). Many studies have been dedicated  
61 to the evaluation of these different satellite precipitation products in Africa [4-8]. Without being  
62 exhaustive, the main conclusions of these studies can be summarized as follows: (i) the state-of-the-  
63 art products perform relatively well at monthly and decadal time steps [4, 9, 10] with a decreasing  
64 performances for finer timescales; (ii) most products satisfactorily reproduce the main features of the  
65 rainfall regime [4, 5]; (iii) real-time products exhibit moderate to high (positive or negative) biases [4]  
66 whereas adjusted or post-processed products, in which ground precipitation measurements are  
67 included in algorithms to correct bias, show lower biases, (iv) there is a clear need to improve the  
68 accuracy of satellite products in the estimation of accumulated rainfall [6, 11].  
69

70 One potential strategy for improving satellite precipitation products is to use soil moisture  
71 measurements from satellite microwave sensors. Soil moisture can be seen as the trace of  
72 precipitation, and a knowledge of the temporal and spatial variability of soil moisture could benefit  
73 to rainfall retrievals from space. Pioneer studies [12-17] exploited this signal to correct existing  
74 satellite precipitation products. Later, [18, 19] developed the SM2RAIN approach to directly derive a  
75 rainfall amount from soil moisture variations exclusively. Since 2015, these approaches were  
76 improved and applied at the global scale [20, 21] and on different locations in the US [22], in Australia  
77 [23], over selected sites [24] and in China [25]. One of the main advantages of these methodologies  
78 based on soil moisture measurement is that they can replace, in near-real-time, scaling procedures of  
79 state-of-the-art satellite precipitation and avoid significant latency for dataset availability.  
80

81 This paper aims to present the latest developments in the PrISM (Precipitation Inferred from Soil  
82 Moisture) algorithm originally developed by [17, 24]. The concept of PrISM is to use an existing real-  
83 time precipitation product and to correct it using a soil moisture information. In addition to PrISM  
84 algorithm, this paper presents an accurate evaluation of its performances for Africa, including a  
85 comparison with the performance of ten additional precipitation products at the daily time-scale. In  
86 order to improve the evaluation of the product in a region with very low rain-gauge coverage,  
87 exclusively local, national and pan-national in situ rain gauge measurements were used to assess  
88 PrISM performances and to compare with state-of-the art precipitation products. This was done to  
89 avoid traditionally used products that can be tricky at fine time scales, such as the Global  
90 Precipitation Climatology Center (GPCC [26]), the Global Precipitation Climatology Project (GPCP  
91 [27, 28]) or the Climatic Research Unit (CRU [29]). The paper is organized as follows: section 2  
92 describes the satellite and ground-based rainfall datasets, and the PrISM algorithm; section 3 presents  
93 the results and a comparison with existing rainfall products; and section 4 draws conclusions and  
94 perspectives.  
95

## 96 2. Materials and Methods

## 97                    2.1 Ground-based precipitation measurements

98

99

100            Five reference data sets based on in situ rainfall measurements are used in this study (Table 1).  
 101            The first two datasets are provided by the AMMA-CATCH Observatory in Niger and Benin [30, 31].  
 102            Both sites cover about  $1 \times 1^\circ$  and are composed of 34 gauge stations in Niger and 30 gauge stations in  
 103            Benin. A spatial interpolation (block kriging) was performed at the  $0.25 \times 0.25^\circ$  spatial resolution in  
 104            order to obtain a reference rainfall amount at the commonly used satellite spatial scale ( $0.25^\circ$ ). The  
 105            selected  $0.25^\circ$  sites in Niger and Benin are respectively centered at  $2.625^\circ\text{E}$ ;  $13.625^\circ\text{N}$  and  $1.625^\circ\text{E}$ ;  
 106             $9.625^\circ\text{N}$  (see Figure 1). The number of gauge stations that directly affect the rainfall amount at the  
 107             $0.25^\circ$  resolution are 12 in Niger and 10 in Benin. The third data set is composed of 20 in situ gauge  
 108            stations covering the whole of Burkina Faso. The dataset was provided by National Meteorological  
 109            Department of Burkina Faso. The fourth dataset is the “WaTFor” data set which documents Western  
 110            Central Africa. Built-up by [5] it contains monthly and daily in situ rainfall data collected from global  
 111            datasets, national meteorological services and monitoring projects for Cameroon, Gabon, Congo and  
 112            Central African Republic. Finally, the last data set is a gauge network composed of 78 stations  
 113            covering 7 countries in East Africa (Ethiopia, Djibouti, Somalia, Kenya, Uganda, Tanzania and  
 114            Rwanda [32]). The datasets at national scale comprise both synoptic stations (whose data are  
 115            generally incorporated in post-processed products) and independent stations.

115

116

117

**Table 1.** Observed rainfall data sets used for evaluation.

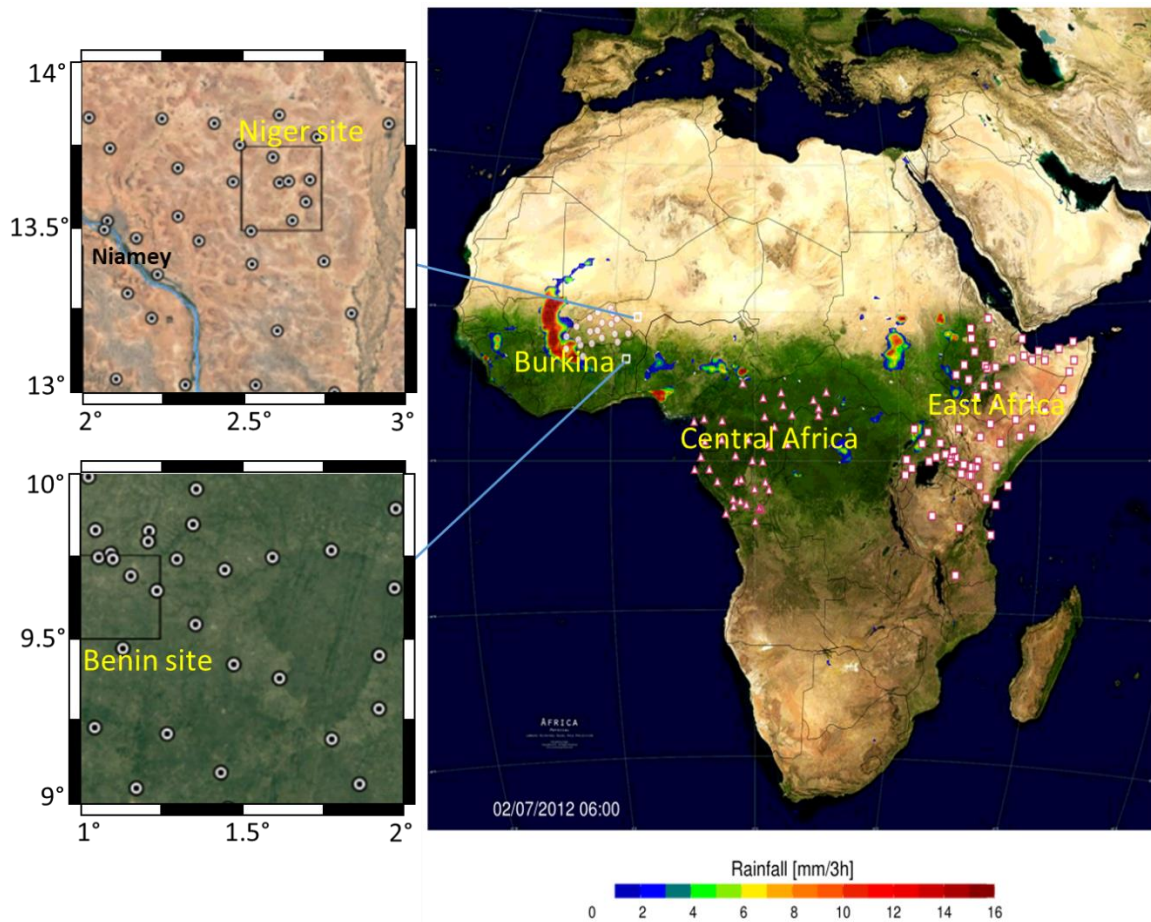
<b>Data set</b>	<b>Nb stations</b>	<b>Period</b>	<b>Time scale</b>
Niger	12	2010-2016	3h
Benin	10	2010-2016	3h
Burkina Faso	20	2010-2015	Daily
Central Africa	42	2010-2016	Daily
East Africa	78	2010-2013	Daily

118

119

120

121



122  
 123 **Figure 1:** Location of the five reference ground-based rainfall data sets: Burkina Faso (20 stations), Central Africa  
 124 (42 stations), East Africa (78 stations) and the two AMMA-CATCH sites located in Niger (region of Niamey) and  
 125 Benin (region of Nalohou). The two squares inside the two left graphs represent the two selected 0.25° pixels in  
 126 Niger and Benin. Precipitation product on top of land cover on the right map illustrates a time step (3h) of the  
 127 PrISM precipitation product (2012 July 2<sup>nd</sup> 3 to 6 am).

## 128 2.2 Satellite precipitation products

129  
 130 In addition to the PrISM product, ten existing satellite and ground-based rainfall products have  
 131 been selected for the inter-comparison (Table 2). All products are provided at the 3-hour and 0.25  
 132 degree resolution except TAMSAT (daily, 0.0375°), IMERG (half-hourly, 0.1°), SM2RAIN (daily,  
 133 0.25°), CHIRPS (daily, 0.25°) and GPCC (daily, 1°). In order to enable an inter-comparison of the  
 134 products, all the products were regrided to 0.25° spatial resolution and daily temporal resolution.  
 135 Five rainfall products (out of 10) are available in real-time and are not merged with any rain gauge  
 136 observations. The other five products are available after a latency ranging from 7 days to 2 months  
 137

138 CMORPH [33] is a rainfall estimate product based on geostationary infrared images and passive  
 139 microwave data from low earth orbiting satellites. Motion vectors are determined from half-hourly  
 140 geostationary infrared measurements, and used to propagate the estimates obtained from the  
 141 microwave data. The CMORPH rainfall product is proposed in two modes: the CMORPH-Raw  
 142 product which is not merged with any rain gauge observations and the CMORPH-Adj product which  
 143 use a monthly ground calibration procedure to remove bias and uncertainties. In this study, the 0.25°  
 144 3-hour version of the product was used.  
 145

146 TRMM 3B42 products [34] originality lies in incorporating precipitation radar and microwave  
147 measurements to better evaluate rainfall intensity. It combines these data with polar-orbiting and  
148 geostationary satellite images to obtain 3-hourly rainfall estimates at 0.25° spatial resolution. Similar  
149 to CMORPH, the TRMM 3B42 products are available in two modes: the TRMM-3B42RT product  
150 (hereafter called TRMM-Raw) available in near real-time (latency of about 7 hours) which is not  
151 merged with any raingauge observations and the TRMM-3B42 product (hereafter called TRMM-Adj)  
152 which includes GPCP monthly gauge aggregations and is available with a latency up to 6-week. The  
153 TRMM-3B42 v7 used in this study improves upon the previous ones by incorporating additional  
154 microwave and infrared data, revising the relationship between radar reflectivity and rainfall rates,  
155 and using better reference data bases for bias correction.  
156

157 The IMERG product, firstly released in early 2015 [35], is provided at 0.1°×0.1° spatial and half-  
158 hourly temporal resolutions in three modes, based on latency and accuracy: “early” (latency of 4–6 h  
159 after observation), “late” (12–18 h), and “final” (~3 months). The main difference between the early  
160 and final runs is – beyond the way the different sensor measurements are propagated in time – that  
161 the early run has a climatological rain gauge adjustment while the final run uses a month-to-month  
162 adjustment based on GPCC gauge data. In this study, we used the IMERG-Early and IMERG-Final  
163 products. The two products were upscaled to 0.25° by using a box-shaped kernel with antialiasing,  
164 which approach was found to outperform simple spatial averaging and half-hourly rainfall were  
165 accumulated to obtain a daily product [36].  
166

167 TAMSAT (Tropical Applications of Meteorology using SATellite and ground based  
168 observations) was developed at the University of Reading specifically for Africa with a spatial  
169 resolution of 0.0375°. The TAMSAT method [37–39] is based on high resolution (0.0375°) METEOSAT  
170 thermal-infrared observations for all of Africa, available from 1983 to the present and updated in  
171 near-real time (up to 7 days). Contrary to other merged products, TAMSAT does not use Global  
172 Telecommunication System (GTS) data but historical data from about 4000 stations acquired by  
173 various African agencies since the early 1990s [40]. We used the TAMSAT V3.0 version product [38]  
174 available at the daily time scale. Similar to IMERG, the product was regridded to the 0.25° spatial  
175 resolution, and is called TAMSAT\_025.  
176

177 The GPCC daily product is provided by the Global Precipitation Climatology Center [26], and  
178 is available since 1 January 2009 with a spatial sampling grid of 1°. GPCC is a gridded gauge-analysis  
179 product derived from quality-controlled station data (more than 85,000 different stations). This  
180 dataset is characterized by an uneven spatial distribution: some regions are characterized by dense  
181 rain gauge networks (Europe, US, China) while other regions such as Africa, Amazonia and Northern  
182 areas suffer from low density networks. To enable comparison with other products, GPCC was  
183 downscaled to 0.25° spatial resolution with a linear interpolation method.  
184

185 CHIRPS (Climate Hazards group Infrared Precipitation with Stations) dataset is a quasi-global  
186 (50°S–50°N), high resolution (0.05°), daily, pentadal, and monthly precipitation dataset [41]. CHIRPS  
187 uses the Tropical Rainfall Measuring Mission Multi-satellite Precipitation Analysis version 7 (TMPA  
188 3B42 v7) to calibrate global Cold Cloud Duration (CCD) rainfall estimates. CHIRPS incorporates  
189 station data in a two phase process. In the first phase, Meteorological Organization’s Global  
190 Telecommunication System (GTS) gauge data are incorporated and a 2-day latency product is  
191 available. In the second phase, station data are combined with monthly (and pentadal) high  
192 resolution rainfall estimates to produce a second product with a latency of about 3 weeks. The version  
193 used in this study is the second product available at the daily and 0.25 degree resolution.  
194

195 Similar to PrISM, SM2RAIN precipitation product [18, 19] takes advantage of satellite soil  
196 moisture observations to derive a precipitation product. SM2RAIN is based on the inversion of the  
197 soil water balance equation and allows to estimate the amount of water entering the soil by using as

198 input soil moisture observations from in situ or satellite sensors (e.g., [20, 42-44]. The SM2RAIN  
 199 product used in this study is the GPM+SM2RAIN precipitation dataset (hereafter called SM2RAIN)  
 200 which is based on the integration of IMERG-ER with SM2RAIN-based rainfall estimates derived from  
 201 ASCAT, SMOS and SMAP L3 soil moisture products. The merging methodology is using an Optimal  
 202 Linear Combination approach, OLI [46, 47]. This approach provides an analytically optimal linear  
 203 combination of ensemble members (precipitation products in this case) that minimizes mean square  
 204 error when compared to a reference dataset. The dataset is currently available for Africa and South  
 205 America (2015-2018), Europe, India, Contiguous United States and Australia (2015-2017) and can be  
 206 downloaded at <https://doi.org/10.5281/zenodo.3345323>.

208 Table 2. Inventory of all satellite rainfall products data sets used in the study. To enable fair comparison of all  
 209 products, each product was regridded to the 0.25° spatial resolution and daily time-scale.

Data set	Spatial Resolution	Time-scale	Period	Latency	Ground calibration
PrISM	0.25°	3-hourly	2010-present	~5 day	no
CMORPH-Raw	0.25°	3-hourly	1998-present	18 h	no
TRMM-RT	0.25°	3-hourly	1998-present	~6 h	no
IMERG-Early	0.1°	30 min	03/2015-present	~12 h	no
TAMSAT-v3.0	0.0375°	Daily	1983-present	~2 days	no
SM2RAIN	0.25°	Daily	2015-2018	~5 days	no
CHIRPS-v2.0	0.25°	Daily	1981-present	~3 weeks	yes
GPCC	1°	Daily	2009-present	15-45 days	yes
CMORPH-Adj	0.25°	3-hourly	1998-present	>1 month	yes
TRMM-3B42	0.25°	3-hourly	1998-present	>1 month	yes
IMERG-Final	0.1°	30 min	03/2015-present	>1 month	yes

210

### 211 2.3 The SMOS soil moisture dataset

212 The Soil Moisture and Ocean Salinity [48, 49] satellite was launched in November 2009 and  
 213 started delivering data on January 2010. The primary goals of this Earth Explorer mission are to  
 214 measure globally and frequently surface soil moisture over land and sea surface salinity over the  
 215 oceans. The SMOS data used in the study as the main input to the PrISM algorithm corresponds to  
 216 the CATDS level-3 soil moisture data obtained through <https://www.catds.fr> site. The SMOS-L3SM  
 217 products are in NetCDF format and were regridded from the EASE 25km grid to the 0.25°x0.25°  
 218 regular grid retained in the present study using the closest neighbor.

### 219 2.4 The PrISM methodology

220

221 The concept of the PrISM (Precipitation Inferred from Soil Moisture) methodology is to exploit  
 222 remote sensing soil moisture measurements to correct the amount of rainfall estimated by an existing  
 223 satellite rainfall product (CMORPH-Raw in this study). It makes use of a simple soil moisture /  
 224 precipitation model and an assimilation scheme.

225

#### 226 2.4.1 The API soil moisture / precipitation model

227

228 The API (Antecedent Precipitation Index) model is a simple model designed to simulate a soil  
 229 moisture dynamic based on precipitation data. The API model is defined as:

230

$$API_{(t)} = API_{(t-1)} \cdot e^{-\frac{\Delta t}{\tau}} + P_{(t)} \quad (\text{Eq.1})$$

232

233 where  $P(t)$  is the rainfall accumulation (in mm) during the period  $\Delta t$  (in h) and  $\tau$  a parameter that  
 234 describes the drying-out soil moisture velocity (in h). The API index is a simple proxy of the soil  
 235 moisture dynamic (in mm). Recently, [50] proposed a slight modification of the original API model  
 236 in order to improve its accuracy and enable the calculation of volumetric soil moisture in  $\text{m}^3/\text{m}^3$   
 237 instead of an index expressed in mm. The new version of the API model contains two modifications:  
 238 (i) it accounts for the degree of saturation of the soil before a rain event; and (ii) the soil moisture is  
 239 now limited by the saturation value. These modifications of the relationship add three parameters:  
 240  $d_{\text{soil}}$  an equivalent soil thickness (in mm),  $\theta_{\text{sat}}$  the soil moisture value at saturation (in  $\text{m}^3/\text{m}^3$ ) and  $\theta_{\text{res}}$   
 241 the residual soil moisture (in  $\text{m}^3/\text{m}^3$ ). The new version of the API model (hereafter referred as the API  
 242 model) is written:

243

$$\theta_{(t)} = (\theta_{(t-1)} - \theta_{\text{res}}) \cdot e^{-\frac{\Delta t}{\tau}} + (\theta_{\text{sat}} - (\theta_{(t-1)} - \theta_{\text{res}})) \cdot \left(1 - e^{-\frac{P(t)}{d_{\text{soil}}}}\right) + \theta_{\text{res}} \quad (\text{Eq.2})$$

245

246 where  $\theta(t)$  is the surface soil moisture in  $\text{m}^3/\text{m}^3$ ,  $\tau$  is the soil moisture drying-out velocity (in h), and  
 247  $P(t)$  is the cumulative precipitation in mm during the  $\Delta t$  period (in h). It requires the use of a  
 248 precipitation product at infra-daily resolution (3 hours or less) to determine when rainfall occurs  
 249 compared to SMOS ascending (6am) or descending (6pm) orbits. A sensitivity study was conducted  
 250 over 10 sites at the global scale [24] to derive the best 4 parameters of the API model. Authors showed  
 251 that a constant value for  $\theta_{\text{sat}} = 0.45 \text{ m}^3/\text{m}^3$  provided reliable results. On the contrary, a spatial  
 252 distribution of the  $\theta_{\text{res}}$  and  $d_{\text{soil}}$  parameters is required and as well as a spatiotemporal distribution of  
 253 the  $\tau$  parameter.

254

255 The residual soil moisture is the minimal value of soil moisture on a given pixel. Based on surface  
 256 soil moisture measurements obtained over the 10 sites presented in [24], the simple following  
 257 formulation was proposed:

258

$$\theta_{\text{res}} = 0.04676 + 0.05936 (\overline{NDVI}) - 0.00136 (\overline{Tair}) \quad (\text{Eq.3})$$

260

261 with  $\overline{Tair}$  (in °C) is the annual mean 2m air temperature (source MERRA, 2013) and  $\overline{NDVI}$  is the  
 262 annual mean NDVI value provided by ESA-CCI-LC-L4-NDVI (Spot VGT, 2015). Globally, residual  
 263 soil moisture values range from 0.017 to 0.099  $\text{m}^3/\text{m}^3$  at the global scale and from 0.017 to 0.060  $\text{m}^3/\text{m}^3$   
 264 in Africa.

265

266 The  $d_{\text{soil}}$  coefficient (in mm) describes the rapidity of soil moisture wetting during a rainfall event and  
 267 is related to the soil thickness. The thinner (thicker) the soil layer, the faster (slower) the soil  
 268 wetting. Over 9 out of the 10 sites studied in [24], it was found that a  $d_{\text{soil}}$  value of 35 mm was adequate  
 269 compared to in situ soil moisture dynamic. This is consistent with soil moisture depth sensors located  
 270 at 5 cm depth. However, on the Niger site, a value of  $d_{\text{soil}}$  equal to 100 mm was required to reproduce  
 271 observed in situ soil moisture dynamics. It was concluded that this parameter can be related to the  
 272 presence/absence of vegetation. In regions without vegetation, soils are often degraded with an  
 273 impermeable crust associated with a low infiltration rate. A simple sigmoid relationship based on  
 274 mean annual NDVI (ESA-CCI-LC-L4-NDVI, 2015) was proposed in this study as :

275

$$d_{\text{soil}} = 120 - \frac{80}{1 + 178482301e^{(-100 \cdot \overline{NDVI})}} \quad (\text{Eq.4})$$

277

278 Globally,  $d_{\text{soil}}$  values range from 40 mm (almost everywhere) to 120 mm in arid and semi-arid areas.

279



280 The  $\tau$  parameter in Eq.2 describes the drying-out velocity of the surface soil moisture due to both  
 281 evapotranspiration and infiltration rate. Consequently, this parameter should depends on both soil  
 282 hydraulic properties and atmospheric forcing (air temperature, wind velocity, solar radiation). In a  
 283 first approximation, it was shown in this study that  $\tau$  value can be appropriately estimated with 30-  
 284 days smoothed air temperature ( $T_{air}$ ) using the following relationship:

$$285 \tau(t) = 400 - \left( \frac{350}{1 + e^{-0.1(T_{air} - 7.5)}} \right) \quad (\text{Eq.5})$$

287 where 30-days smoothed  $T_{air}$  values ( $^{\circ}\text{C}$ ) are obtained from MERRA-2 database (3-hours, 2013). At  
 288 the continental scale of Africa, the  $\tau$  parameter ranges from 80 h to 350 h.

#### 291 2.4.2 The CDF matching procedure

292 The PrISM methodology is based on the assimilation of the SMOS soil moisture retrievals into the  
 293 API model (Eq.2). Thus, a preliminary work consists in scaling the SMOS soil moisture retrievals to  
 294 the API simulation using a simple CDF-matching procedure. To that end, a reference rainfall dataset  
 295 was selected to provide a reference soil moisture simulation with the API model at the Africa scale.  
 296 The evaluation of two adjusted products (CMORPH-adj and TRMM-3B42) against in situ rainfall  
 297 measurements in Niger and Benin sites led to the selection of the CMORPH-Adj precipitation product  
 298 as the reference for the CDF-Matching procedure. Then, the API model (Eq. 2) was run for the whole  
 299 of Africa using CMORPH-Adj precipitation product and parameters were derived from Eq. 3, 4 and  
 300 5. Based on the obtained reference soil moisture simulation (2012), a calculation of the two linear  
 301 CDF-matching coefficients ( $p1$  and  $p2$ ) was made to scale the SMOS L3SM to the reference soil  
 302 moisture. The scaled SMOS values ( $SMOS_{CDF}$ ) are assumed to be linearly related to SMOS original  
 303 values as:

$$304 SMOS_{CDF} = p1 + p2 \cdot (SMOS) \quad (\text{Eq.6})$$

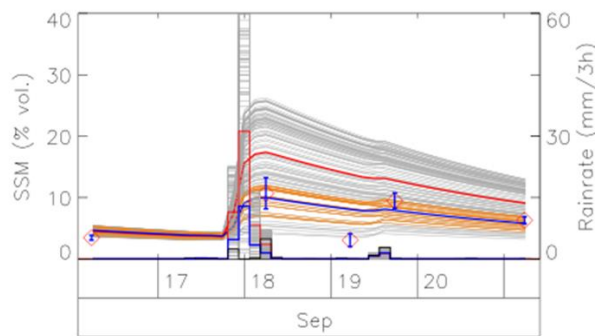
$$305 \text{with } p2 = \frac{\sigma_{SMmodel}}{\sigma_{SMsmos}} \quad \text{and} \quad p1 = \overline{SM_{model}} - p2 \cdot (\overline{SM_{smos}})$$

#### 311 2.4.3 The Particle Filter assimilation scheme

312 Among the various existing assimilation schemes, the Particle Filter (PF) is an original method  
 313 based on random stochastic perturbations of the precipitation forcing that explicitly simulates the  
 314 consequences of precipitation uncertainties in the associated soil moisture outputs [51-53]. It is  
 315 suitable for non-linear models and makes no assumption on the prior and posterior distributions of  
 316 the model states. This property of the PF makes it more suitable for this study compared to ensemble  
 317 based data assimilation approaches whose optimality and performance depend on the linearity  
 318 between input and output variables, having Gaussian distributed errors, as for example in the  
 319 Ensemble Kalman Filter [54, 55]. For a mathematical or formal description of PF, the reader should  
 320 referred to [56].

321 The concept is a pixel-based approach. An illustration of the PF assimilation method is shown  
 322 in Figure 2 (Niger site, 2015). Once there is a new SMOS soil moisture retrieval on a given pixel, an  
 323 assimilation window which contains the five last SMOS retrievals is defined. The length, i.e. the  
 324 number of SMOS retrieval within each assimilated sub-period was chosen after a sensitivity study  
 325 (not shown) and represents a compromise between too short periods (giving much weight to  
 326 individual SMOS uncertainties) and too long periods which reduce the operational interest of the  
 327 methodology. Thus, the API model is forced with the real-time satellite rainfall product (CMORPH-  
 328 Raw in this study) that we aim to correct and which is represented as red "bars" in Figure 2. The red  
 329 curve in Figure 2 represents the soil moisture simulated by the model forced with this real-time

332 satellite rainfall. Then, the real-time satellite rainfall is used to generate 100 random rainfall time  
 333 series (number tested in sensitivity experiments) using random stochastic perturbations (grey “bars”  
 334 in Figure 2). These new rainfall time series are used to force the API model (Eq.2) to obtain an  
 335 ensemble of soil moisture predictions (i.e., 100 soil moisture time series associated to 100 different  
 336 rainfall time series, grey curves in Figure 2). The random stochastic perturbations of rainfall is done  
 337 using the following simple multiplicative relationship:  $Rain(t,i) = Rain(t) * a(i)$  with  $a(i)$  a random  
 338 number between 0 and 2 for  $i=1,100$  (uniform distribution). Figure 2 clearly shows that the random  
 339 rainfall can’t exceed twice the amount of the initial rainfall. Then, the SMOS retrievals are used to  
 340 select the 30 most probable soil moisture trajectories which minimize the RMSE. Finally, the corrected  
 341 rainfall amount corresponds to the average of the 30 most probable rainfall time-series. The corrected  
 342 rainfall estimate is associated with an uncertainty calculated as the difference between the maximum  
 343 and the minimum value of the 30 most probable rainfall time-series.  
 344



345  
 346

347 **Figure 2:** Illustration of the PF assimilation scheme for the Niger site. The initial satellite precipitation rate (in  
 348 red) produces the associated soil moisture evolution (in red). Stochastic perturbations of the initial satellite  
 349 precipitation rate produce an ensemble of potential soil moisture evolutions (in grey). The SMOS retrievals (5  
 350 orange diamonds) are used to select the most probable soil moisture curves (in orange) and to calculate the  
 351 averaged soil moisture (in blue), which is associated with a specific precipitation rate (in blue). In this case, a  
 352 decrease of the initial satellite precipitation rate is proposed which is consistent with in situ precipitation  
 353 measurements (in black).

354 The process is repeated when a new SMOS measurement is available. Consequently, each  
 355 rainfall event is considered 4 times (a period of 5 successive SMOS measurements provides 4  
 356 intervals) and the final rainfall rate correction is the averaged value of the 4 proposed corrected  
 357 rainfall rates.  
 358

359 As the method is based on a modification of the precipitation rate of an existing product, it is  
 360 not possible to create any rain event. It is also difficult to completely remove an existing rain event  
 361 even if it is possible to significantly reduce it. Therefore, the method has a low impact on scores  
 362 usually used in satellite precipitation product comparisons such as probability of detection (POD)  
 363 and false-alarm ratio (FAR).

### 364 3. Results

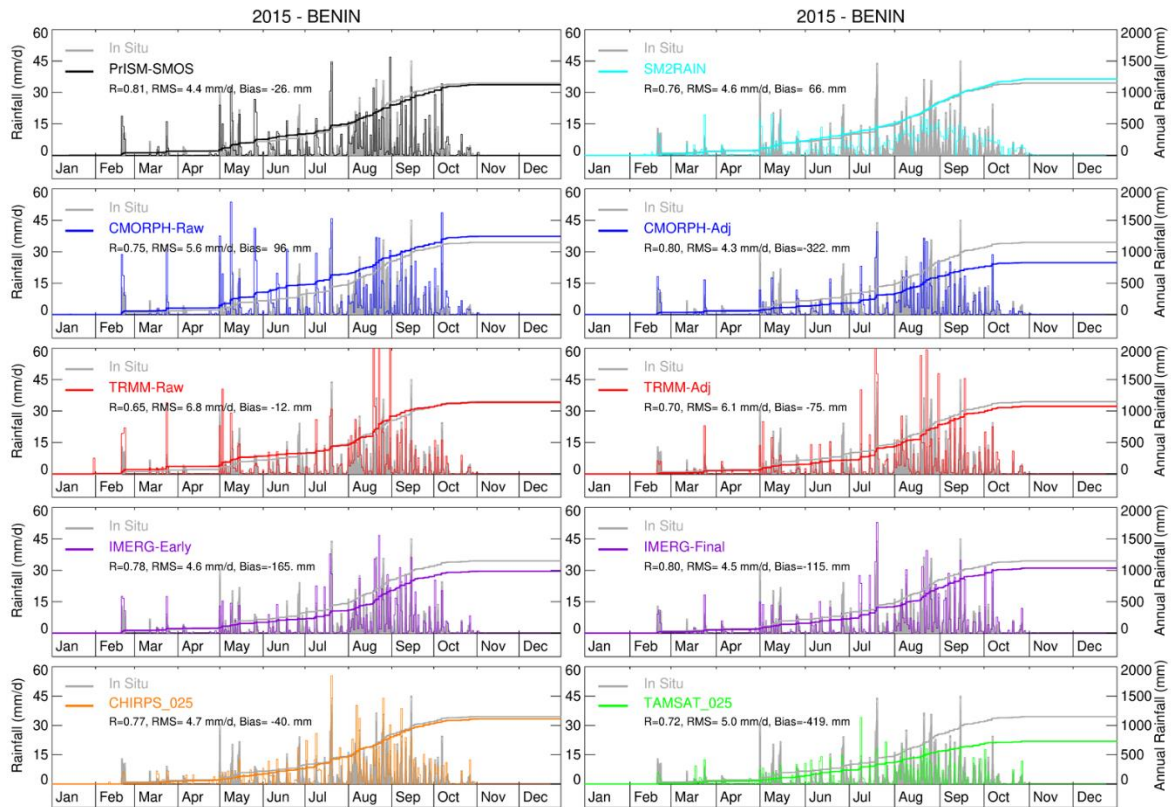
365 To enable fair comparison between satellite precipitation products, all products listed in Table 2  
 366 were regridded to the  $0.25^\circ$  resolution and daily time-scale. At this spatial scale, a direct comparison  
 367 with a single raingauge station can be distrusted due to the large spatial scale difference. Thus, we  
 368 conducted a two-step assessment methodology. First, an accurate assessment was performed on two  
 369 sites where 10 to 12 raingauge stations are located within the same pixel of  $0.25^\circ$  (i.e. about  $25 \times 25$   
 370  $\text{km}^2$ ) belonging to the AMMA-CATCH Observatory in Niger and Benin. As stated in section 2.1, the  
 371 use of dense networks of rain gauges allows an accurate estimate of the precipitation rate at this scale.

372 In a second step, a direct, less relevant comparison between satellite (0.25°) and individual rainfall  
373 station was done and results were analyzed at the network scale, i.e. Burkina Faso (20 stations),  
374 Central Africa (42 stations) and East Africa (78 stations).

### 375 3.1. Assessment at the local scale (Niger and Benin)

376 The eleven selected precipitation products were compared to ground-based precipitation  
377 measurements using commonly used statistical scores: the Pearson correlation (R), the Root Mean  
378 Square Error (RMSE in mm/day) and the annual bias (in mm). Null values were accounted for in the  
379 scores calculation and the comparison was performed at the daily time scale and at the 0.25° spatial  
380 resolution. As the ground-based precipitation datasets (Niger and Benin) are available at the hourly  
381 time scale whereas some satellite products are provided at the daily time scale, the matching of the  
382 two time-series was carefully checked to avoid the known ambiguity between a 6am-6am day  
383 (commonly used in precipitation measurements) and a 0-24h day. Lastly, we also examine the  
384 number of rainy days (cumulative daily rainfall > 1 mm) compared to in situ measurements.  
385

386 Results are presented for illustrative purposes for the Benin site (2015) in Figure 3. Statistical  
387 scores (R, RMSE and annual bias) are plotted in each graph and are also reported in Table 3. Overall,  
388 all products capture relatively well the temporal dynamics of precipitation with a rather high  
389 correlation coefficient ( $R > 0.70$  except for TRMM-Raw ( $R = 0.65$ ) and GPCC ( $R = 0.42$ ) reported only in  
390 Table 3). Best performances in term of correlation are obtained by PrISM ( $R = 0.81$ ), CMORPH-Adj,  
391 IMERG-Final ( $R = 0.80$ ), IMERG-Early ( $R = 0.78$ ) and CHIRPS ( $R = 0.77$ ). Regarding RMSE, best  
392 performances are obtained by CMORPH-Adj, PrISM, IMERG-Final and SM2RAIN and IMERG-Early  
393 with RMSE values equal to 4.3, 4.4, 4.5 and 4.6 mm/day respectively. Lowest performances are  
394 obtained by TRMM-Raw and GPCC with 6.8 mm/day. Regarding bias score, four products obtained  
395 annual cumulative precipitation values very close to the observation (1150 mm): TRMM-Raw (1138  
396 mm, -1%), PrISM (1124 mm, -2.3%), CHIRPS (1110 mm, -4.3%) and SM2RAIN (1216 mm, +5.7%). On  
397 the contrary, TAMSAT\_025 strongly underestimates the annual precipitation with an estimation of  
398 only 731 mm (-36%). Surprisingly, the three adjusted products (CMORPH-Adj, TRMM-Adj and  
399 IMERG-Final) provide moderate to strong underestimated precipitation (respectively 828 mm (-28%),  
400 1075 mm (-6.5%) and 1035 mm (-10%) compared to in situ precipitation measurements. Similarly,  
401 GPCC exhibits moderate underestimation (1013 mm, -12%). Only the CMORPH-Raw product shows  
402 an overestimation of the annual rainfall with 1246 mm (+8%) in Benin in 2015. Lastly, Table 3 includes  
403 the difference in term of annual rainy days. In the Benin site, 103 rainy days (> 1mm) were observed  
404 in 2015. Table 3 shows that CHIRPS, GPCC and SM2RAIN tends to overestimate this number (112,  
405 135 and 168 days respectively) whereas PrISM and CMORPH-Raw provides similar number of rainy  
406 days (101 and 102 days respectively). All other precipitation products exhibit a slight underestimation  
407 (from 88 to 94 days).  
408



409  
 410 **Figure 3 :** Example of comparison between in situ precipitation measurements (Benin 0.25° site, 2015, in grey)  
 411 and the ten precipitation products (PrISM, SM2RAIN, CMORPH (Raw and Adj), TRMM (Raw and Adj), IMERG  
 412 (Early and Final), CHIRPS-025 and TAMSAT-025). Bars show daily rainfall amounts (left axis), curves show  
 413 cumulative rainfall (right axis). Statistical scores are reported in Table 3.  
 414

415 The same analysis was conducted for the Niger site in 2015. Graphics are shown in  
 416 supplementary materiel (Figure S1) and the statistical scores are reported in Table 3. Similarly, the  
 417 CMORPH-Adj and PrISM products obtain good performances in term of correlation ( $R=0.82$  and  
 418  $R=0.81$  respectively) and GPCC obtains the lower score ( $R=0.33$ ) probably due to the low density of  
 419 gauges in the Niger region and its original spatial resolution of  $1^\circ$ . Regarding the RMSE scores, best  
 420 performances are obtained by PrISM, TAMSAT-025, CHIRPS, TRMM-Adj, SM2RAIN, CMORPH-Adj  
 421 and IMERG-Final (from 3.7 mm/day to 4.6 mm/day). Conversely, CMORPH-Raw and TRMM-Raw  
 422 products obtain lower RMSE scores (6.7 and 6.9 mm/day). In term of annual bias, four products  
 423 obtained annual cumulative precipitation values quite close to the observation (601 mm): TRMM-Adj  
 424 (602 mm), IMERG-Final (547 mm, -9%), PrISM (669 mm, +11%) and IMERG-Early (687 mm, +14%).  
 425 On the contrary, CMORPH-Raw and TRMM-Raw strongly overestimate annual precipitation (1052  
 426 mm, +75% and 1090 mm, +81% respectively). Other products obtain intermediate annual bias (see  
 427 Table 3). Regarding the number of rainy days in Niger (43 days from in situ measurements), best  
 428 performances were obtained by SM2RAIN, TAMSAT\_025 and CMORPH-Adj (48, 50 and 51 days  
 429 respectively) whereas GPCC still provides an overestimated number of rainy days (71 days). Other  
 430 products, PrISM included, provide a slight overestimation of the number of rainy days compared to  
 431 observations (from 52 to 57 days).

432  
 433 **Table 3.** Statistical scores (R, RMSE, annual bias and nb of rainy days) between in situ precipitations  
 434 measurements (Benin and Niger, 2015) and the eleven precipitation products. Bold values indicate the best  
 435 performances. There are 103 rainy days in Benin and 43 rainy days in Niger in 2015.

2015	Benin 0.25° (1150 mm, 103 rainy days)	Niger 0.25° (601 mm, 43 rainy days)
------	---------------------------------------	-------------------------------------

	R	RMSE (mm/d)	Bias (mm)	Rainy days (>1mm/d)	R	RMSE (mm/d)	Bias (mm)	Rainy days (>1mm/d)
PrISM	<b>0.81</b>	<b>4.4</b>	<b>-26</b>	<b>101</b>	<b>0.81</b>	<b>3.7</b>	<b>+68</b>	55
CMORPH-Raw	0.75	5.6	+96	<b>102</b>	<b>0.80</b>	6.7	+451	56
TRMM-Raw	0.65	6.8	<b>-12</b>	94	0.75	6.9	+489	54
IMERG-Early	<b>0.78</b>	<b>4.6</b>	-165	90	0.63	5.3	<b>+86</b>	57
TAMSAT-025	0.72	5.0	-419	92	0.77	<b>3.9</b>	-169	<b>50</b>
SM2RAIN	<b>0.76</b>	<b>4.6</b>	<b>+66</b>	168	0.74	<b>4.1</b>	-203	<b>48</b>
CHIRPS	<b>0.77</b>	<b>4.7</b>	<b>-40</b>	112	0.70	<b>4.3</b>	-138	55
GPCC	0.42	6.8	-137	135	0.33	5.9	-147	71
CMORPH-Adj	<b>0.80</b>	<b>4.3</b>	-322	88	<b>0.82</b>	<b>4.3</b>	+152	<b>51</b>
TRMM-Adj	0.70	6.1	<b>-75</b>	92	0.75	<b>4.1</b>	<b>+1</b>	53
IMERG-Final	<b>0.80</b>	<b>4.5</b>	-115	94	0.66	<b>4.6</b>	<b>-54</b>	52

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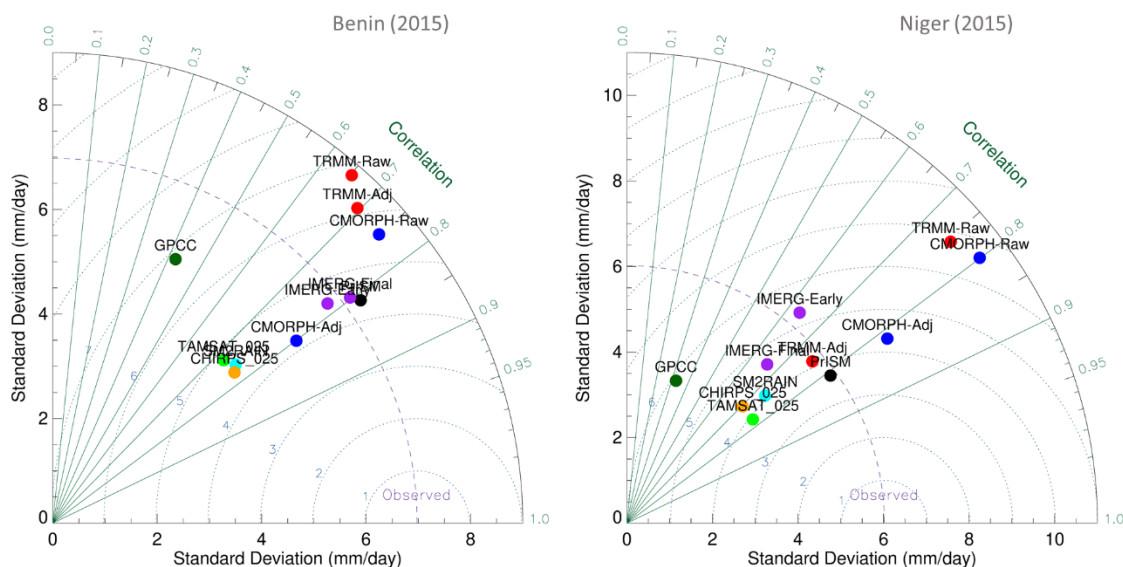
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Figure 4 shows the Taylor diagrams [57] in Benin and Niger sites daily precipitation in 2015. Taylor diagram enables a visual comparative assessment of the different precipitation products quantifying the degree of correspondence between the estimated and observed precipitation in terms of three statistics: the Pearson correlation coefficient, the root-mean-square error (RMSE), and the standard deviation. Correlation scores are plotted as the radial lines, and the linear distance of a point to the Observed point indicates the RMSE from in situ measurements. For instance, the GPCC point for Benin site is close to the 0.4 radial line ( $R=0.42$  in Table 3) and close to the “7” dotted circle ( $RMSE=6.8$  mm/days). Graphically, the best products are those closest to the “Observed” point and to the dashed curve which indicates the same amplitude of the variations. In Benin (2015), those best products are the two IMERG products and the PrISM product. For Niger (2015), PrISM and TRMM-Adj perform better than the other ones.



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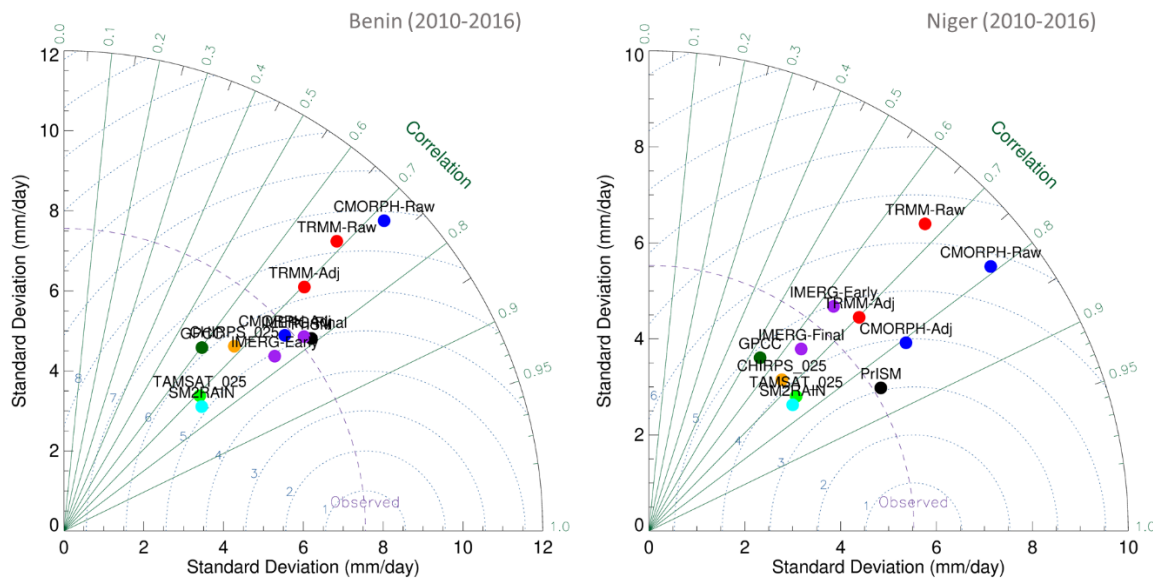
**Figure 4:** Taylor diagrams for the Benin (left) and Niger (right) 0.25° sites for the year 2015 for the 11 precipitation products. Color dots refer to the different products (blue=CMORPH, red=TRMM, purple=IMERG, green=TAMSAT\_025, cyan=SM2RAIN, orange=CHIRPS, dark green=GPCC and black=PrISM). Statistical scores are given in Table 3.

454

455

Lastly, the Taylor diagrams were plotted for the whole period (2010-2016, instead of 2015) except for the two IMERG and SM2RAIN precipitation products that start in March 2014 and are then

456 considered only for 2015-2016 period. Figure 5 reveals some slight differences compared to Figure 4  
 457 but leads to similar conclusions. Globally, when a product is provided in two versions, e.g. raw and  
 458 adjusted, the adjusted product performs better. The “raw” version of TRMM and CMORPH are  
 459 located far away from their adjusted versions. The PrISM product was found to be among the best  
 460 products for the Benin site and provides the best performance for the Niger site. TAMSAT\_025 and  
 461 SM2RAIN have similar scores and perform better for the Niger site but their standard-deviations are  
 462 much lower than in the observation.  
 463  
 464



465  
 466 **Figure 5:** Taylor diagrams for the Benin (left) and Niger (right) 0.25° sites and the 2010-2016 period (except for  
 467 IMERG, 2015-2016) and the 11 precipitation products. Color dots refer to the different products (blue=CMORPH,  
 468 red=TRMM, purple=IMERG, green=TAMSAT\_025, cyan=SM2RAIN, orange=GPCP and black=PrISM).

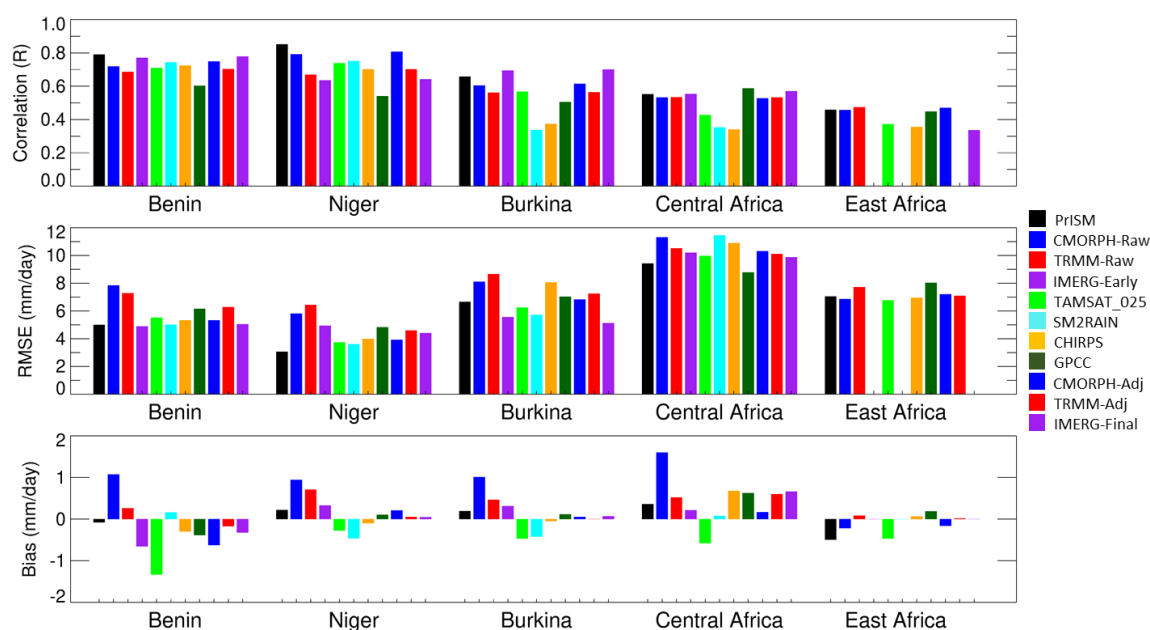
469

### 470 3.2. Assessment at the regional scale

471 At the regional scale, scores were calculated using individual raingauge stations compared to  
 472 0.25° precipitation products. Scores were calculated at the daily time scale based on the whole  
 473 available period (see Table 1). Then, the median value of all individual scores (R, RMSE and bias) was  
 474 calculated. Results are presented separately for the three raingauge networks (Burkina Faso, Central  
 475 Africa and East Africa) in Figure 6. Results obtained for Benin and Niger are also reported in Figure  
 476 6 for comparison. Note that the two IMERG products were not considered for East Africa because the  
 477 ground rainfall measurements were not available after 2013.  
 478

479 Results show globally that the correlation score is slightly lower for Burkina, Central Africa and  
 480 East Africa compared to Benin and Niger. Similarly, the corresponding RMSE are respectively greater  
 481 (worse) for these three networks. On the other hand, the biases are in the same order of magnitude  
 482 in the five regions. In all regions, PrISM shows good performances according to the 3 scores and is  
 483 among the best products together with the two IMERG products. It can be observed that PrISM  
 484 systematically outperforms CMORPH-Raw in term of RMSE (except in East Africa where it is slightly  
 485 less performant). But the improvement in term of correlation is more modest. CMORPH and TRMM,  
 486 in their adjusted or raw versions, show similar performances in terms of correlation but provide  
 487 generally much better results in term of RMSE and biases for their adjusted versions. SM2RAIN and  
 488 CHIRPS products show lower correlation and higher RMSE scores for Burkina-Faso and Central  
 489 Africa but presents a low bias for all regions. Although its biases are small, GPCP, as expected from

490 its low original resolution, generally shows relatively low performances, except in Central Africa.  
 491 Finally, TAMSAT\_025 globally tends to underestimate the rainfall rate but shows relatively good  
 492 correlation and RMSE scores.  
 493



494 **Figure 6:** Statistical scores (R, RMSE and bias) for the five regions (Benin, Niger, Burkina-Faso, Central Africa  
 495 and East Africa) and for the 11 precipitation products. The temporal period depends on the satellite product and  
 496 in situ availabilities.  
 497

#### 498 4. Limitation of the PrISM methodology

499  
 500 One limitation of the methodology is that it is not able to create a rain event. This is clearly shown  
 501 in Table 3 where the number of rainy days (> 1 mm) does not change much between the CMORPH-  
 502 Raw product and the PrISM product. Therefore, it is necessary to use an initial precipitation product  
 503 that overestimates the number of events since the PrISM algorithm is able to reduce the amount of  
 504 rainfall.  
 505

506 The PrISM algorithm was also found to be more efficient when the initial rainfall product  
 507 overestimates the annual rainfall amount. This is particularly true in East Africa where the CMORPH-  
 508 Raw showed a negative annual bias (see Figure 6) and the PrISM algorithm was not able to correct  
 509 for that underestimation. On the contrary, on the other 4 sites, the CMORPH-Raw showed positive  
 510 annual biases which are suitably corrected by PrISM. The reason for this behavior is that a 10 mm  
 511 rain event (for instance) can easily be reduced to 1 mm, but the PrISM algorithm can't propose a  
 512 correction greater than 20 mm (correction factor ranging between 0 and 2). Consequently, it is easier  
 513 to reduce the rainfall amount than to increase it.  
 514

515 The satisfactory results of the PrISM methodology in Central Africa are a pleasant surprise since  
 516 the SMOS soil moisture retrievals under dense forest are expected to be inaccurate. The explanation  
 517 of this results is partly due to the large overestimation of the CMORPH-Raw product in Central  
 518 Africa. The PrISM methodology leads to reduce the rainfall amount of most events and, mechanically,  
 519 RMSE is reduced as well as the annual bias. Overall, the effect of vegetation cover on the performance  
 520 of the PrISM algorithm is difficult to evaluate. Indeed, areas of dense vegetation are at the same time  
 521 areas where the SMOS signal can be inaccurate but also areas of heavy precipitation with a high  
 522 potential for improvement. PrISM performances are similar in Niger (low vegetation) and in Benin

523 (medium vegetation), and the PrISM performances in Central Africa are better than in East Africa (in  
524 term of correlation and bias correction).

#### 525 4. Summary and next step

526

527 This study presents the PrISM algorithm and its evaluation over 5 regions in Africa. PrISM  
528 algorithm uses knowledge of soil water content (provided by SMOS soil moisture measurements) to  
529 adjust the precipitation rate of an existing satellite product (CMORPH-raw in this study). To assess  
530 the benefit of the proposed methodology, PrISM was compared against ten state-of-the-art satellite  
531 and ground-based rainfall products for five rain gauge networks located in semi-arid to wet areas in  
532 Africa.

533

534 PrISM was found to generally outperform all real-time products (CMORPH-Raw, TRMM-Raw,  
535 IMERG-Early, TAMSAT\_025 and SM2RAIN), especially when considering areas where there exists a  
536 dense network of rain gauge stations as a reference data set. It showed same or even better  
537 performances than adjusted or post-processed products. The main contribution of PrISM is that it  
538 greatly decreases RMSE values and reduces the bias values compared with the original CMORPH-  
539 Raw product. Results in term of correlations are more modest. This result is quite important for many  
540 applications that require real-time information on precipitation such as crop yield estimates, flood  
541 nowcasting, dam management, ground-water recharge estimates and irrigation demand over large  
542 areas.

543

544 Future studies will be designed to apply PrISM algorithm to other satellite soil moisture dataset  
545 such as SMAP, ASCAT or SMOS-IC. At the moment, PrISM product is available on the ftp site:  
546 [ftp://ftp.ifremer.fr/Land\\_products/L4\\_PrISM/Africa/](ftp://ftp.ifremer.fr/Land_products/L4_PrISM/Africa/) and can be downloaded at  
547 <https://doi.org/10.5281/zenodo.3565610> at an annual latency. The near-real-time version of the  
548 product will shortly be available on the external ERDDAP of IGE in Grenoble: [http://osug-smos-  
549 rea.osug.fr:8081/erddap/index.html](http://osug-smos-rea.osug.fr:8081/erddap/index.html).

550 **Supplementary Materials:** The following are available online at [www.mdpi.com/xxx/s1](http://www.mdpi.com/xxx/s1), Figure S1: Comparison  
551 between in situ precipitation measurements (Niger 0.25° site, 2015, in grey) and the ten precipitation products  
552 (PrISM, CMORPH (Raw and Adj), TRMM (Raw and Adj), IMERG (Early and Final), TAMSAT-025, CHIRPS and  
553 SM2RAIN). Statistical scores are reported in Table 3.

554 **Author Contributions:** T. P. proposed the idea, carried out the experimental design, analyzed the data, and  
555 wrote the paper. C. R.-C. and B. P. participated to the PrIMS algorithm development and validation, C. B, P. C.,  
556 N. P. and G.P. provide in situ rainfall data; G. Q. help in the visualization, L. B. and C. M. provide SM2RAIN  
557 product and contribute to the writing of the paper. Y. K. contribute to the original idea and to the writing of the  
558 paper.

559 **Funding:** This research was funded by ESA, grant number ESA/AO/1-7875/14/I-NC (4000114738/15/I-SBO). This  
560 research also benefits from TOSCA (CNES, Centre national d'études spatiales, France).

561 **Acknowledgments:** The authors would like to thank University of Douala, University of Bangui, University  
562 Omar-Bongo in Libreville, University of Liège, CIRAD Montpellier for providing precipitation data in Central  
563 Africa, and National Meteorological Department of Burkina Faso.

564

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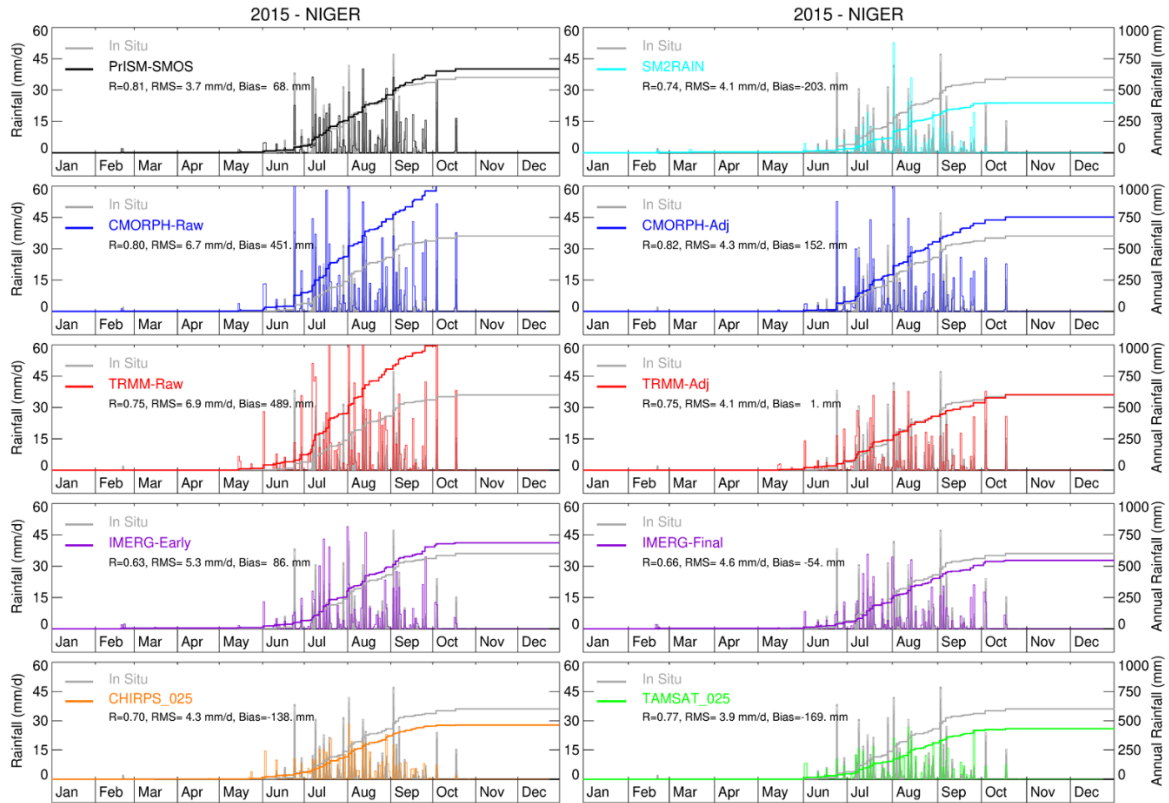
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734 **Figure S1:** Example of comparison between in situ precipitation measurements (Niger 0.25° site, 2015, in grey)  
 735 and the ten precipitation products (PrISM, SM2RAIN, CMORPH (Raw and Adj), TRMM (Raw and Adj), IMERG  
 736 (Early and Final), CHIRPS-025 and TAMSAT-025). Statistical scores are reported in **Table 3**.

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