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Remote Sensing of Terrestrial Rainfall From Ku-Band Scatterometers

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***Abstract*—Rainfall is the most fundamental variable of the terrestrial hydrological cycle. However, in many regions of the world, ground observations are still very scarce or even missing. Recently, a bottom-up approach, named SM2RAIN, for terrestrial rainfall estimation from satellite soil moisture (SM) products was proposed and successfully applied to C- and L-band products from scatterometers and radiometers. Thanks to the multiple Ku-band scatterometers launched in the recent years and a number of new sensors expected in the near future, accurate rainfall estimation at subdaily time scale could be obtained. We present here a first attempt to estimate terrestrial rainfall from Ku-band scatterometers using SM2RAIN. To this end, backscattering data (sigma-0) collected in central Italy from the RapidScat instrument on board the International Space Station are compared with the Advanced SCATterometer (ASCAT, C-band) SM product and *in situ* observations for assessing its sensitivity to SM variations. Then, RapidScat sigma-0 is used for rainfall retrieval and compared with ground observations over a regular grid of 15-km spacing. The 8-month period from Nov 2014 to Jun 2015 is considered. Results show a very good agreement between ASCAT SM and RapidScat SM index with a median temporal correlation coefficient *R* of ~ 0.9 and a reasonable performance ($R > 0.52$) against *in situ* data. More interestingly, the performance of RapidScat in 1-day rainfall estimation is found to be satisfactory with median *R*-values equal to ~ 0.6. These promising results highlight the large potential of using the constellation of scatterometers for providing an accurate rainfall product with high spatial-temporal resolution.**

***Index Terms*—Hydrology, radar applications, rain, soil measurements.**

I. Introduction

RAINFALL is the main driver of the hydrological cycle, and its quantification in space and time is needed for many applications, such as flood modeling [1], [2], landslide prediction [3]–[5], drought monitoring [6], and crop production [7], to cite a few.

The most common method for estimating rainfall is using rain gauges that, however, are experiencing a strong decline in the recent years and suffer from scale representative issues [8]. Due to the strong space–time variability of rainfall, ground (meteorological radar) and satellite remote sensing techniques are suitable for providing area-averaged estimates. However, being indirect measurements, both radar and remote sensing techniques are affected by large uncertainties [9]–[12], mainly in areas not covered by ground observations.

Recently, some researchers suggested to use satellite soil moisture (SM) data for correcting [1]–[16] and estimating [8], [17], [18] rainfall. Specifically, Brocca *et al.* [8] developed a bottom-up approach, named SM2RAIN, for the estimation of rainfall directly from SM measurements. SM2RAIN was successfully applied to satellite products from L- and C-band radiometers (SMOS—Soil Moisture and Ocean Salinity, AMSR-E—Advanced Microwave Scanning Radiometer Earth Observing System) and from C-band (ASCAT—Advanced SCATterometer) scatterometer [17], with the latter providing the best performance. More recently, Ciabatta *et al.* [19] demonstrated that the integration of the bottom-up and top-down (state-of-the-art products) approaches could provide a significant improvement in rainfall estimation. Despite these good results, obtaining rainfall products at high temporal resolution (daily, subdaily) through the SM2RAIN approach is still difficult if 4–8 overpasses per day of satellite observations are not available. This configuration can be achieved only by considering multiple sensors.

Currently, a constellation of scatterometers is being coordinated for the near future (next 5 years), where C- and Ku-band scatterometers are considered together (http://ceos.org/ourwork/virtual-constellations/osvw/). As shown in Fig. 1, it is foreseen that more than 8 scatterometers (starting from the end of 2015) will be in orbit at the same time thus allowing to have very frequent measurements, potentially every 2–3 h (depending on the overpass time of the different sensors). Concerning Ku-band scatterometers, Mladenova *et al.* [20] and Oveisgharan *et al.* [21] demonstrated the good sensitivity of QuikSCAT Ku-band backscattering data (sigma-0) to SM variations, with the better results over scarcely vegetated areas. Moreover, Turk *et al.* [22] have shown very recently that sigma-0 s from the Oceansat-2 Scatterometer (OSCAT) are sensitive to fallen rain and can be employed for tracking previous-time precipitation in view of improving satellite rainfall products from the Global Precipitation Mission (GPM, [12]). Notwithstanding the long-term availability of Ku-band scatterometers (e.g., QuikSCAT was launched in 1999), to our knowledge, the previously cited studies are the only ones using these measurements for detecting SM and rainfall, and only a limited number of studies have used these data in land applications (e.g., [23]).

On this basis and in view of the near future availability of a constellation of scatterometers, for the first time, we tested here the capability of sigma-0 from RapidScat for estimating both

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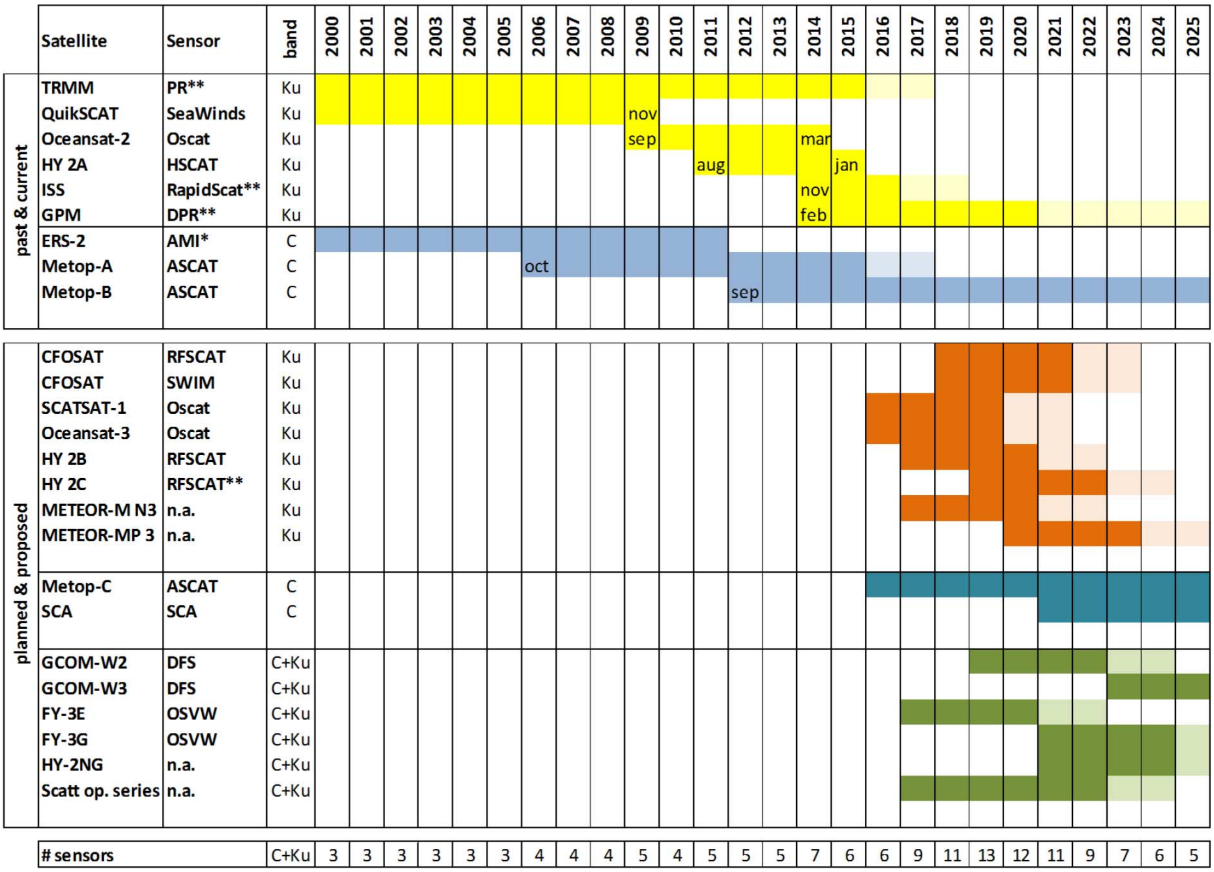

** ERS2 AMI has become a regional mission since 2000 due to a failure of the tape recorder*
*** non sun-synchronous orbits*
n.a. not available

Fig. 1. Constellation of Ku- and C-band scatterometers from 2000 and (currently) planned for next 10 years (see also http://ceos.org/ourwork/virtual-constellations/osvw/).

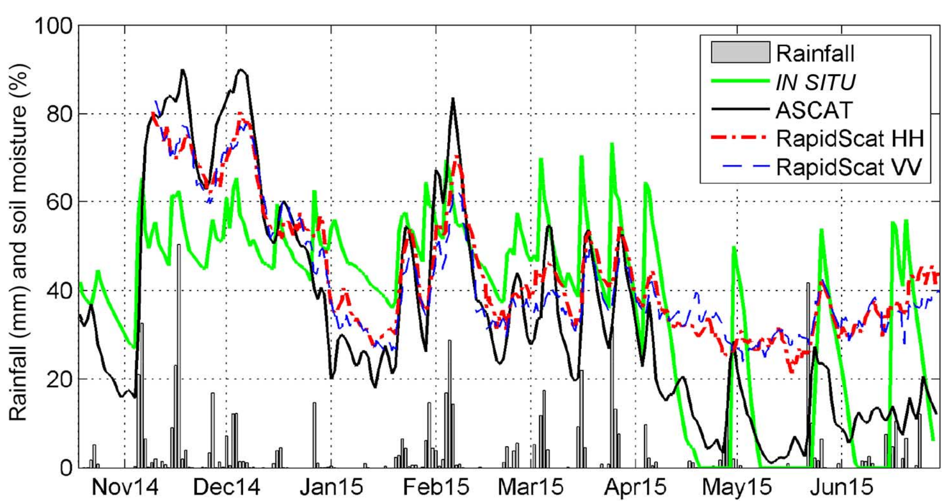

Fig. 2. Comparison of relative SM data by RapidScat (HH and VV polarizations), ASCAT, and *in situ* observations for the period November 2014–June 2015 in central Italy (lon, lat $= 12.5°, 43.0°$); daily rainfall data are also shown.

SM and rainfall (through SM2RAIN) in Umbria region (central Italy). We underline that it is the first study in which RapidScat data are used over land and, remarkably, for a new application for which Ku-band sigma-0 measurements were never used before. Specifically, the SM product obtained from ASCAT is used for analyzing the sensitivity of RapidScat to SM variations. Ground rainfall observations from a dense network of rain gauges are employed for the validation of the estimated rainfall

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data from RapidScat. Due to its recent launch, only 8-month period from November 2014 to June 2015 is investigated.

II. Study Area and Datasets

The Umbria region ($\sim$8500 km^2), located in central Italy, is considered as a case study for the high quality and quantity of rainfall (and SM) observations, the low probability of having frozen soil conditions associated with a small amount of mountainous areas. The region is characterized by a Mediterranean climate with annual rainfall ranging between 700 and 1500 mm and mean annual temperature of 13.1 °C. In the area, a dense hydrometeorological network is operating since 1990 in real time for civil protection purposes, i.e., mainly, the mitigation of the hydrogeological risks (floods and landslides). For this study, quality-checked half-hourly rainfall data from 90 rain gauges are aggregated at daily time scale in the period from November 2014 to June 2015 and interpolated (through inverse distance weighting) over a regular grid with spacing of about 15 km (53 pixels). Additionally, *in situ* SM observations at 10-cm depth (Cerbara station) are used for a qualitative assessment of ASCAT and RapidScat SM estimates.

Satellite SM data are obtained from ASCAT, which is a C-band (5.255 GHz) scatterometer currently operating on the Metop-A and Metop-B satellites. SM is retrieved from ASCAT sigma-0 using a change detection algorithm developed by Wagner *et al.* [24]. In central Italy, the ASCAT SM product is available nearly every day with a spatial resolution of 25 km (sampling of 12.5 km). The product is used here as benchmark since 1) good performances were found in the study area in the comparison between ASCAT and ground SM observations [25], and 2) it allows us to compare directly Ku-band and C-band observations that, potentially, can be merged for deriving an advanced product with higher temporal resolution.

The RapidScat scatterometer (http://winds.jpl.nasa.gov/missions/RapidScat/) is a swift and cost-effective replacement for the National Aeronautics and Space Administration (NASA) QuikSCAT satellite mounted on the International Space Station. The instrument is a conically scanning pencil-beam scatterometer (Ku-band, 13.4 GHz) with two "spot" beams on the ground: a horizontal polarization beam (HH) and a vertical polarization beam (VV) at incidence angles of $49°$ and $56°$, respectively. Due to the conical scanning, a measurement is generally viewed when looking forward (fore) and a second time when looking backward (aft). As such, up to four measurement classes (called "beam") emerge for each sampling point, i.e., HH fore, HH aft, VV fore, and VV aft. For this study, sigma-0s from fore and aft beams are averaged together. Therefore, HH and VV polarization data are extracted and regridded over a regular grid with spacing of about 15 km using the nearest neighboring method and selecting the 8 measurements nearest to the centroid of each grid point (53 pixels).

III. Methods

In the following, the procedure used for retrieving a SM index and, then, rainfall from RapidScat sigma-0 is outlined. We note that the SM retrieval algorithm is taken as simple as possible as our purpose is to demonstrate the sensitivity of the signal seen from RapidScat to SM and not to develop a retrieval algorithm. The latter will be the object of future investigations that will exploit the multiple incidence angles and polarizations of Ku-band scatterometers.

According to Mladenova *et al.* [20], sigma-0 measurements from QuikSCAT were found linearly related to change in SM. Moreover, as for each polarization, the incidence angle of RapidScat is constant, the normalization of sigma-0 with respect to incidence angle, as performed in the ASCAT change detection algorithm, is not needed. Therefore, a simple approach for deriving a SM index from RapidScat is normalizing the log-scale sigma-0 between its maximum and minimum values for each pixel. Here, a linear normalization approach is used. However, due to the limited time length of the availability of sigma-0 from RapidScat, the minimum and maximum values are expected to be not representative of dry and saturated conditions. Therefore, the linear normalization is carried out by considering the maximum and minimum SM values obtained from ASCAT (9-year data period) in the same period of observation of the two sensors. For each pixel, the normalization is not made between zero and one but between the maximum and minimum SM values given by ASCAT.

The SM2RAIN method is based on the inversion of the water balance equation and, by assuming that during rainfall, the surface runoff and the evapotranspiration rates are negligible, the rainfall rate *p(t)* is obtained as

$$p\left(t\right) = Z^{*} \frac{ds\left(t\right)}{dt} + as(t)^{b} \tag{1}$$

where *s(t)* is the relative SM, *Z** is the soil water capacity, and *a* and *b* are the two parameters of the drainage rate (more details can be found in [17] and [18]). In this study, the SM2RAIN algorithm is applied to RapidScat SM data using the same approach as described in [19]. Specifically, the calibration of SM2RAIN parameter values is performed pixel by pixel. No validation periods are considered due to the limited period in which RapidScat measurements are available. Indeed, we would like to remark that the main purpose of this letter is to make the scientific community aware of the possibility of using Ku-band sigma-0 to estimate rainfall, and that multiple Ku-band scatterometers—that will be available in the near future—may constitute a new and independent source of terrestrial rainfall measure worldwide. Since backscatter measurements are characterized by considerable high frequency noise, the exponential filter proposed by [24] is firstly applied to RapidScat SM data and the calibration of the T-parameter (characteristic time length) is performed together with SM2RAIN parameters. The minimization of the root-mean-square error (RMSE) for 1-day rainfall is considered as objective function, and as performance scores, we used the latter and the correlation coefficient R.

IV. Results

As a first step, SM time series obtained from RapidScat, expressed in relative terms between 0% and 100%, are

TABLE I
MAIN STATISTICS, FOR THE WHOLE UMBRIA REGION TERRITORY, OF THE PERFORMANCE OF RAPIDSCAT IN ESTIMATING SOIL MOISTURE AND RAINFALL

Statistics	Soil moisture		Rainfall			
			1-Day		5-Day	
	R	RMSE [-]	R	RMSE [mm]	R	RMSE [mm]
HH polarization						
Mean	0.86	0.15	0.58	5.06	0.76	12.41
Median	0.90	0.14	0.58	5.05	0.75	12.69
Maximum	0.95	0.25	0.73	5.67	0.89	14.62
Minimum	0.60	0.11	0.42	4.19	0.62	8.53
90° percentile	0.94	0.19	0.67	5.35	0.87	14.15
10° percentile	0.69	0.12	0.50	4.70	0.66	10.17
VV polarization						
Mean	0.86	0.16	0.62	4.84	0.80	11.73
Median	0.89	0.16	0.65	4.78	0.80	11.42
Maximum	0.93	0.24	0.77	5.94	0.89	15.55
Minimum	0.63	0.11	0.35	4.04	0.61	9.24
90° percentile	0.92	0.22	0.71	5.53	0.88	13.85
10° percentile	0.73	0.13	0.44	4.33	0.71	9.56

Soil moisture data are compared with the ASCAT soil moisture product (note that data are filtered with t-values equal to 4 and 2 days for RapidScat and ASCAT, respectively).
Rainfall estimates are compared with ground observation for 1-day and 5-day accumulated values.

compared with ground rainfall, ground SM, and satellite SM data from ASCAT. Fig. 2 shows the SM timeseries from RapidScat, ASCAT, and ground observations for the pixel including the *in situ* station (longitude, latitude $= 12.5°$, $43.0°$). For reducing noise, SM data from RapidScat and ASCAT are filtered using a T-value equal to 4 and 2 days, respectively. The higher T-value for RapidScat is selected due to the thinner soil depth sensed at Ku-band with respect to C-band, thus requiring higher T-values. By a simple visual inspection of Fig. 2, it is evident the strong agreement between RapidScat and ASCAT SM time series except for the period from April to June 2015 likely due to the vegetation effect that is correctly removed in the ASCAT SM retrieval algorithm and not for RapidScat. For better investigating this aspect, we analyzed the monthly–$0.1°$ resolution—leaf area index (LAI) values in the study area from October 2014 to June 2015 using the MOD15 product from moderate resolution imaging spectroradiometer [26]. A clear increase of the mean LAI values from $\sim 1\ \mathrm{m}^2/\mathrm{m}^2$ in the winter period to $\sim 3\ \mathrm{m}^2/\mathrm{m}^2$ in May and June 2015 is observed, which explains the lower agreement between RapidScat and ASCAT toward the end of the period. In addition, the pattern obtained from the RapidScat data acquired in the two polarizations HH and VV is very similar. The sensitivity of RapidScat-implied SM to rainfall is evident with significant positive variations associated with each rainfall event. The quantitative comparison between RapidScat and ASCAT filtered SM data is reported in Table I in which the statistics of the temporal R- and RMSE-values for each grid point are reported. As it can be seen, an overall good agreement is obtained with median R-values equal to ~ 0.89 and RMSE lower than 0.25 (in relative terms). The comparison with *in situ* observations also provides satisfactory results (considering the differences in the spatial scale and soil layer depth between *in situ* and satellite data). The temporal R-values are equal to 0.62 (0.52) and 0.71 for RapidScat HH (VV) polarization and ASCAT, respectively. The corresponding RMSEs are equal to 0.33 (the same value for both the polarizations) and 0.17 for RapidScat and ASCAT, respectively. As mentioned above, the good agreement here obtained for RapidScat is favored from the analysis period (winter and spring) in which vegetation density is quite low.

Based on the good performance in reproducing SM data, RapidScat data are then employed for rainfall estimation over the entire Umbria region. Specifically, as mentioned above, the SM2RAIN parameter values plus the T-value of the exponential filter (not a constant as in the ASCAT vs RapidScat comparison) are calibrated point by point in order to minimize the RMSE between observed and estimated rainfalls. Note that the calibration carried out point by point is not strictly required for obtaining reasonable rainfall estimation since an alternative calibration using constant parameter values (not shown) provided similar performance scores. However, to be more realistic, we preferred to allow parameters to vary in space.

Fig. 3(a) and (b) shows the map of the temporal R-value for the comparison of RapidScat rainfall data with observations at daily time scale and for HH and VV polarizations. The statistics of the performance scores are given in Table I. Unexpectedly, the performance for 1-day temporal resolution is quite good with median R equal to 0.58 and 0.65 for HH and VV polarizations, respectively. If compared with results given in [19], who estimated rainfall from ASCAT throughout Italy and found 1-day R equal to ~ 0.44, then the local performance here is much better. This improvement can be attributed to the short period (8 months vs 2 years), the lower topographic complexity (e.g., not including Alps and Gran Sasso), and the noise filtering applied in this study. Indeed, by performing the same analysis with ASCAT SM data (not detailed here for brevity), a median R-value equal to 0.69 is obtained. As expected, the performance scores increase for the estimation of

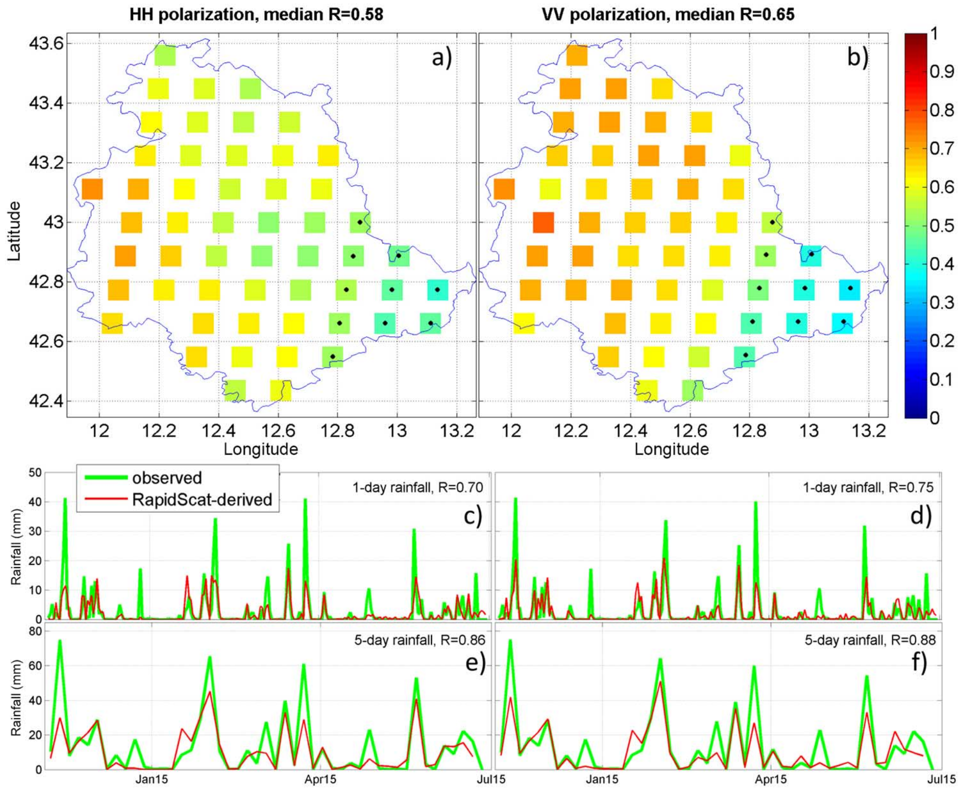

Fig. 3. Top panels [(a) and (b)]: map of the correlation coefficient between observed and estimated 1-day rainfalls from RapidScat for HH (a) and VV (b) polarizations. The dotted pixels are excluded from the spatial average in the bottom panels (see text for details). Bottom panels [(c)–(f)]: time series of spatially averaged observed and RapidScat-derived rainfall data cumulated over (c) and (d) 1 day and (e) and (f) 5 day for (c) and (e) HH and (d) and (f) VV polarizations in the period November 2014–June 2015 (R: correlation coefficient).

5-day rainfall, with R-values ranging between 0.61 and 0.89 and median RMSE less than 12.69 mm. By analyzing the spatial pattern of R-values shown in Fig. 3(a) and (b), worse performance is obtained, as expected, in the south-eastern part of the region characterized by complex topography and denser vegetation (similar results, not shown, are obtained in terms of SM reproduction).

Fig. 3(c)–(f) shows the observed and estimated time series of rainfall averaged over the whole study area, but excluding the "complicated" 10 pixels in south-eastern part of the region [Fig. 3(a) and (b)], for 1-day and 5-day accumulations and for HH and VV polarizations. As expected, the spatially averaging further improves the agreement between satellite and observed rainfall data with R-values for HH (VV) polarization equal to 0.70 (0.75) and 0.86 (0.88) for 1-day and 5-day cumulated rainfalls, respectively. Overall, VV polarization is found to perform better than HH polarization, in accordance with [20], even though it is well known that the SM signal should be stronger in the HH-polarized data (as we obtained in the comparison with *in situ* observations). This aspect needs an in-depth analysis that will be carried out in future studies in which the performance of the two polarizations in areas characterized by different soils, vegetations, and climate conditions will be analyzed.

V. Conclusion

Results obtained in this study with Ku-band scatterometer data, along with those already published in [17] and [19] with C-band sigma-0 observations, have very interesting and exciting implications for remote sensing of rainfall over land. The performance obtained using RapidScat data in rainfall retrievals [Fig. 3] is found satisfactory and very similar to those of ASCAT, despite the substantial increase in the electromagnetic frequency. The low vegetation density in the study period might be surely responsible for the good performance obtained, and it will be further investigated. Moreover, by working on polarization and incidence angle differences, it is expected that SM retrieval from Ku-band scatterometers will be improved.

In the near future, the merging of Ku- and C-band scatterometer data is expected to be achievable thus increasing the number of satellite sensors that can be employed in this application [Fig. 1]. Consequently, the application of SM2RAIN to these observations will provide a rainfall estimate with finer spatial ($\sim$10 km) and temporal ($\sim$4 hours) resolution. In addition, if SM products from C- and L-band radiometers would be included, the use of the bottom-up approach could become quickly a well-established technique for estimating terrestrial rainfall on a global scale.

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References

[1] B. Wake, "Flooding costs," *Nat. Clim. Change*, vol. 3, p. 778, 2013.

[2] C. Massari, L. Brocca, A. Tarpanelli, and T. Moramarco, "Data assimilation of satellite soil moisture into rainfall-runoff modelling: A complex recipe?," *Remote Sens.*, vol. 7, no. 9, pp. 11403–11433, 2015.

[3] Y. Hong, R. F. Adler, and G. J. Huffman, "An experimental global prediction system for rainfall triggered landslides using satellite remote sensing and geospatial datasets," *IEEE Trans. Geosci. Remote Sens.*, vol. 45, no. 6, pp. 1671–1680, Jun. 2007.

[4] F. Guzzetti, S. Peruccacci, M. Rossi, and C. P. Stark, "The rainfall intensity-duration control of shallow landslides and debris flows: An update," *Landslides*, vol. 5, no. 1, pp. 3–17, 2008.

[5] L. Brocca, F. Ponziani, T. Moramarco, F. Melone, N. Berni, and W. Wagner, "Improving landslide forecasting using ASCAT-derived soil moisture data: A case study of the Torgiovannetto landslide in central Italy," *Remote Sens.*, vol. 4, no. 5, pp. 1232–1244, 2012.

[6] K. E. Trenberth *et al.*, "Global warming and changes in drought," *Nat. Clim. Change*, vol. 4, no. 1, pp. 17–22, 2014.

[7] J. Ramarohetra, B. Sultan, C. Baron, T. Gaiser, and M. Gosset, "How satellite rainfall estimate errors may impact rainfed cereal yield simulation in West Africa," *Agric. For. Meteorol.*, vol. 180, pp. 118–131, 2013.

[8] L. Brocca, F. Melone, T. Moramarco, and W. Wagner, "A new method for rainfall estimation through soil moisture observations," *Geophys. Res. Lett.*, vol. 40, no. 5, pp. 853–858, 2013.

[9] M. Borga, "Accuracy of radar rainfall estimates for streamflow simulation," *J. Hydrol.*, vol. 267, no. 1, pp. 26–39, 2002.

[10] G. Villarini and W. F. Krajewski, "Sensitivity studies of the models of radar-rainfall uncertainties," *J. Appl. Meteorol. Climatol.*, vol. 49, pp. 288–309, 2010.

[11] E. E. Ebert, J. Janowiak, and C. Kidd, "Comparison of near real time precipitation estimates from satellite observations and numerical models," *Bull. Amer. Meteorol. Soc.*, vol. 88, pp. 47–64, 2007.

[12] A. Y. Hou *et al.*, "The Global Precipitation Measurement (GPM) mission," *Bull. Amer. Meteorol. Soc.*, vol. 95, pp. 701–722, 2014.

[13] W. T. Crow, M. J. van Den Berg, G. F. Huffman, and T. Pellarin, "Correcting rainfall using satellite-based surface soil moisture retrievals: The Soil Moisture Analysis Rainfall Tool (SMART)," *Water Resour. Res.*, vol. 47, p. W08521, 2011.

[14] F. Chen, W. T. Crow, and T. H. Holmes, "Improving long-term, retrospective precipitation datasets using satellite-based surface soil moisture retrievals and the soil moisture analysis rainfall tool," *J. Appl. Remote Sens.*, vol. 6, no. 1, p. 063604, 2012.

[15] T. Pellarin, S. Louvet, C. Gruhier, G. Quantin, and C. Legout, "A simple and effective method for correcting soil moisture and precipitation estimates using AMSR-E measurements," *Remote Sens. Environ.*, vol. 136, pp. 28–36, 2013.

[16] N. Wanders, M. Pan, and E. F. Wood, "Correction of real-time satellite precipitation with multi-sensor satellite observations of land surface variables," *Remote Sens. Environ.*, vol. 160, pp. 206–221, 2015.

[17] L. Brocca *et al.*, "Soil as a natural rain gauge: Estimating global rainfall from satellite soil moisture data," *J. Geophys. Res. Atmos.*, vol. 119, no. 9, pp. 5128–5141, 2014.

[18] L. Brocca *et al.*, "Rainfall estimation from in situ soil moisture observations at several sites in Europe: An evaluation of SM2RAIN algorithm," *J. Hydrol. Hydromech.*, vol. 63, no. 3, pp. 201–209, 2015.

[19] L. Ciabatta *et al.*, "Integration of satellite soil moisture and rainfall observations over the Italian territory," *J. Hydrometeorol.*, vol. 16, no. 3, pp. 1341–1355, 2015.

[20] I. Mladenova, V. Lakshmi, J. P. Walker, D. G. Long, and R. D. Jeu, "An assessment of QuikSCAT Ku-band scatterometer data for soil moisture sensitivity," *IEEE Geosci. Remote Sens. Lett.*, vol. 6, no. 4, pp. 640–643, Oct. 2009.

[21] S. Oveisgharan, Z. Haddad, J. Turk, L. Li, and E. Rodriguez, "Soil moisture and vegetation water content retrieval using QuikSCAT data," in *AGU Spring Meeting Abstr.*, vol. 1, 2013, p. 02.

[22] F. J. Turk, R. Sikhakolli, P. Kirstetter, and S. L. Durden, "Exploiting over-land Oceansat-2 scatterometer observations to capture short-period time-integrated precipitation," *J. Hydrometeorol.*, vol. 16, pp. 2519–2535, 2015.

[23] C. Prigent, F. Aires, C. Jimenez, F. Papa, and J. Roger, "Multiangle backscattering observations of continental surfaces in Ku-Band (13 GHz) from satellites: Understanding the signals, particularly in arid regions," *IEEE Trans. Geosci. Remote Sens.*, vol. 53, no. 3, pp. 1364–1373, Mar. 2015.

[24] W. Wagner, G. Lemoine, and H. Rott, "A method for estimating soil moisture from ERS scatterometer and soil data," *Remote Sens. Environ.*, vol. 70, no. 2, pp. 191–207, 1999.

[25] L. Brocca *et al.*, Soil moisture estimation through ASCAT and AMSR-E sensors: An intercomparison and validation study across Europe," *Remote Sens. Environ.*, vol. 115, pp. 3390–3408, 2011.

[26] Y. Knyazikhin *et al.* (1999). *MODIS Leaf Area Index (LAI) and Fraction of Photosynthetically Active Radiation Absorbed by Vegetation (FPAR) Product (MOD15) Algorithm Theoretical Basis Document* [Online]. Available: http://eospso.gsfc.nasa.gov/atbd/modistables.html

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