Chapter 51
Soil Moisture and Precipitation: The SM2RAIN Algorithm for Rainfall Retrieval from Satellite Soil Moisture

Luca Ciabatta, Stefania Camici, Christian Massari, Paolo Filippucci, Sebastian Hahn, Wolfgang Wagner, and Luca Brocca

Abstract The standard approach for measuring instantaneous rainfall rates from space is based on the inversion of the atmospheric signals reflected or radiated by atmospheric hydrometeors, i.e., a "top-down" approach. Recently, a new "bottom-up" approach has been proposed that exploits satellite soil moisture observations for obtaining accumulated rainfall estimates. The approach, referred to as SM2RAIN, is based on the inversion of the hydrological water balance. In this chapter, after a short description of the SM2RAIN algorithm and its application to satellite soil moisture data, the two most recent satellite rainfall products obtained by the application of SM2RAIN to ESA-CCI (European Space Agency – Climate Change Initiative) and ASCAT (Advanced SCATterometer) soil moisture products are illustrated. Then, we have investigated the use of SM2RAIN-derived rainfall products, in comparison with "top-down" precipitation products, for improving flood forecasting over 600 basins in Europe. Finally, the limitations of the SM2RAIN algorithm and the future research and technological developments to address such limitations are provided.

Keywords Precipitation · Rainfall · Soil moisture · SM2RAIN · ESA-CCI · ASCAT · SMOS · AMSR · CYGNSS · TMPA · CMORPH · ERA5 reanalysis · GPCC · Floods

---

L. Ciabatta (✉) · S. Camici · C. Massari · P. Filippucci
National Research Council, Research Institute for Geo-Hydrological Protection (CNR-IRPI), Perugia, Italy
e-mail: l.ciabatta@irpi.cnr.it

S. Hahn · W. Wagner
Department of Geodesy and Geoinformation, Research Group Remote Sensing, TU Wien, Vienna, Austria

L. Brocca
Research Institute for Geo-Hydrological Protection (IRPI), National Research Council (CNR), Perugia, Italy

V. Levizzani et al. (eds.), *Satellite Precipitation Measurement*, Advances in Global Change Research 69, https://doi.org/10.1007/978-3-030-35798-6_27

51.1 Introduction

In 2013, a new "bottom-up" approach was proposed by Brocca et al. (2013) for estimating rainfall from space. Instead of considering the interaction between microwave and infrared signal with hydrometeors, as is usually done in state-of-the-art "top-down" precipitation retrieval techniques, the bottom-up approach takes advantage of the capability of spaceborne microwave sensors for measuring soil moisture. The soil is considered as a natural raingauge (Brocca et al. 2014) and from the knowledge of the variation in time of soil moisture (SM), the accumulated rainfall between two satellite overpasses is computed.

The first studies highlighting the benefit in using satellite SM measurement for improving satellite-based rainfall estimates have been carried out by Crow et al. (2009, 2011) and Pellarin et al. (2008, 2013). In these and similar more recent studies, satellite SM data have been used for correcting rainfall that employ different approaches: Kalman filtering in Crow et al. (2011), particle filtering in Wanders et al. (2015) and Román-Cascón et al. (2017), and multiplicative factors in Pellarin et al. (2013). These studies demonstrated the largest improvements in areas where satellite SM data perform well, as in Australia by using the SMOS (Soil Moisture Ocean Salinity) SM product (Brocca et al. 2016b) and in Western United States by using the AMSR (Advanced Microwave Scanning Radiometer) SM product (Crow et al. 2011).

Instead of using SM observations for rainfall correction, Brocca et al. (2013) firstly proposed the use of SM for providing direct estimates of rainfall accumulations. This method, called SM2RAIN, is based on the inversion of the soil water balance equation. That is, it estimates the rainfall by using the change in time of the amount of water stored in the soil, thus considering it "as a natural raingauge". SM2RAIN has been applied both at a local (Brocca et al. 2013, 2015) and global scale (Brocca et al. 2014, 2017; Koster et al. 2016; Ciabatta et al. 2018) with ground and satellite SM data as input with satisfactory results in terms of rainfall estimation. Recently, the use of a constellation of satellite SM products has been also investigated in India and Italy by Brocca et al. (2016a) and Tarpanelli et al. (2017), who obtained significantly improved performance with respect to the use of a single SM product. A similar approach has been also proposed by Tian et al. (2014) for estimating snowfall from snow water equivalent observations obtained by passive microwave satellite sensors.

Massari et al. (2014), in a study over a small catchment in southern France, found that the correction of rainfall through SM2RAIN provides improvement in flood modelling when compared to the use of rain gauge observations only. Similar results are obtained in Ciabatta et al. (2016) for flood simulation in four basins in Italy and by Massari et al. (2018) and Camici et al. (2018) for 15 basins in the Mediterranean area. More recently, SM2RAIN-derived rainfall datasets have been used by Abera et al. (2017) for water budget assessment in the Upper Blue Nile (Ethiopia), by Brunetti et al. (2018) for landslide prediction throughout Italy, and by Thaler et al. (2018) for crop modelling in Austria. Therefore, the SM2RAIN approach is becoming a well-established method that has been found of benefit for hydrological (floods, water resources management), hydrogeological (landslides) and agricultural applications.

Bottom-up and top-down remote sensing approaches exhibit two major differences. Firstly, top-down approaches provide instantaneous rainfall measurements from which the 3-hourly and/or daily accumulated rainfall can be estimated (Fig. 51.1 upper panel). However, if the satellite sensors do not pass over when it rains, a significant underestimation of rainfall is expected from these algorithms. Differently, the bottom-up approach is based on the estimation of accumulated rainfall between two consecutive SM measurements (Fig. 51.1 lower panel). Therefore, the method keeps track of the total rainfall fallen between satellite overpasses, with an expected higher degree of accuracy for rainfall accumulation estimates. Secondly, top-down estimates are available over land and over sea, are not significantly affected by surface conditions, and exploit a constellation of satellite sensors also specifically dedicated to rainfall measurement (e.g., Huffman et al. 2007; Hou et al. 2014). Bottom-up rainfall estimates are only available over land, and are affected by surface conditions as frozen and saturated soils, snow, and vegetation density. These two points make the two approaches highly complementary. Ciabatta et al. (2017) and Chiaravalloti et al. (2018) have already demonstrated that the integration of bottom-up and top-down approaches is able to provide highly accurate rainfall estimates, better than using either of the parent approaches alone.

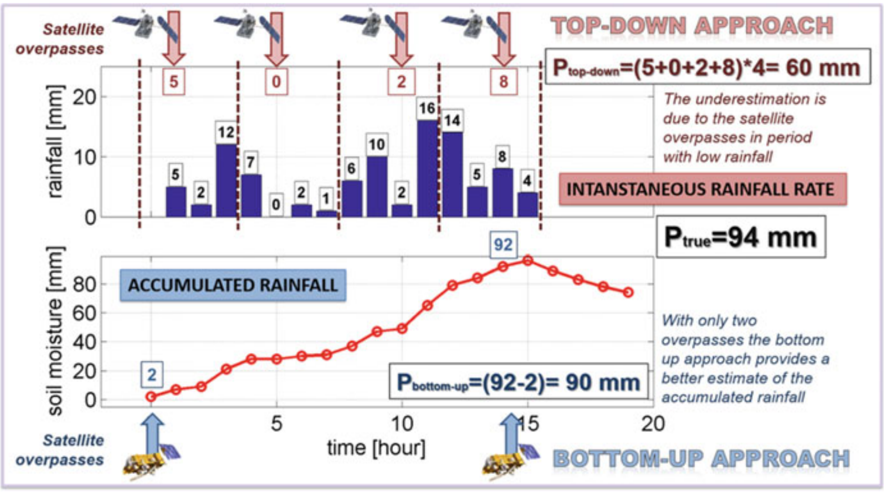

Fig. 51.1 Bottom-up vs. top-down perspective for rainfall retrieval from remote sensing assuming no error in the satellite measurements and in the retrieval algorithms. Due to the satellite overpass during low rainfall intensities, the "top down" method may fail in estimating the accumulated rainfall whereas the "bottom up" approach accurately reproduces the observations even with a lower number of overpasses

51.2 SM2RAIN Algorithm

The SM2RAIN algorithm is based on the inversion of the soil water balance equation and allows to estimate the amount of water entering into the soil by using as input SM information. SM2RAIN has been mostly used to retrieve rainfall from in situ and satellite SM data (e.g., Brocca et al. 2014, 2015, 2016a, b; Koster et al. 2016; Ciabatta et al. 2017; Massari et al. 2017a). Specifically, the soil water balance equation can be described by the following equation (over non-irrigated areas):

$$nZ\frac{dS(t)}{dt} = p(t) - g(t) - sr(t) - e(t) \tag{51.1}$$

where n [−] is the soil porosity, Z [mm] is the soil layer depth, $S(t)$ [−] is the relative saturation of the soil or relative SM, t [days] is the time, $p(t)$ [mm/day] is the rainfall rate, $g(t)$ [mm day^{-1}] is the drainage (deep percolation plus subsurface runoff) rate, $sr(t)$ [mm day^{-1}] is the surface runoff and $e(t)$ [mm day^{-1}] is the actual evapotranspiration. The drainage rate is related to the relative SM through a power law equation (Brocca et al. 2014):

$$\mathrm{g(t) = K_s S(t)}^{3+\frac{2}{\lambda}} \tag{51.2}$$

where K_s [mm day^{-1}] is the saturated hydraulic conductivity and λ [−] is the pore size distribution index. The actual evapotranspiration rate is assumed to be linearly related to potential evapotranspiration, $ET_{pot}(t)$ [mm day^{-1}]:

$$e(t) = ET_{pot}(t)S(t) \tag{51.3}$$

The potential evapotranspiration can be computed through the empirical relation of Blaney and Criddle as modified by Doorenbos and Pruitt (1977):

$$ET_{pot}(t) = K_c\{-2 + 1.26[\xi\ (0.46T_a(t) + 8.13)]\} \tag{51.4}$$

where $T_a(t)$ [°C] is the air temperature, ξ [−] is the percentage of total daytime hours for the period used (daily or monthly) out of total daytime hours of the year (365 × 12), and K_c [−] is a correction factor for taking into account the empirical nature of eq. (51.4). By assuming that the rate of surface runoff is negligible, i.e., $sr(t) = 0$ (Brocca et al. 2015), eq. (51.1) is rewritten as:

$$p(t) = Z^*\frac{dS(t)}{dt} + K_sS(t)^{3+\frac{2}{\lambda}} + ET_{pot}(t)S(t) \tag{51.5}$$

where $Z* = Zn$ [mm] represents the water capacity of the soil layer.

Therefore, eq. (51.5) is used for estimating rainfall rate from SM, $S(t)$, and air temperature, $T_a(t)$ data. Four parameters ($Z*$, K_s, λ, K_c) need to be estimated by calibration using a reference rainfall dataset; note that in previous studies the parameter K_s is defined as a and the expression $\left(3+\frac{2}{\lambda}\right)$ as b. In most of the previous applications of SM2RAIN, we have neglected the contribution of evapotranspiration (see Brocca et al. 2015 for more details) thus yielding to:

$$p(t) = Z^* \frac{dS(t)}{dt} + K_s S(t)^{3+\frac{2}{\lambda}} \tag{51.6}$$

where the knowledge of only SM observations is needed for estimating rainfall.

51.3 SM2RAIN-Derived Rainfall Products

In the last five years, we have developed and distributed several SM2RAIN-derived datasets by applying the algorithm to ASCAT (e.g., Brocca et al. 2017), SMOS (Brocca et al. 2016b), SMAP (Soil Moisture Active and Passive, Koster et al. 2016), RapidScat (Brocca et al. 2016a), AMSR (Brocca et al. 2014) and AMSR2 (Advanced Microwave Scanning Radiometer 2, Tarpanelli et al. 2017) SM products. Two of the most recent and relevant datasets are briefly illustrated below.

51.3.1 SM2RAIN-CCI

The SM2RAIN-CCI rainfall product has been developed in Ciabatta et al. (2018) and relies on the application of SM2RAIN to ESA-CCI (European Space Agency – Climate Change Initiative) SM product. The product is freely available at https://doi.org/10.5281/zenodo.846260 (last accessed 28 Oct. 2018) and is expected to be updated every year with the most recent ESA CCI SM dataset. The current version of the product is available from 1998 to 2015 (18 years), and it provides daily rainfall estimates over land sampled at 0.25-degree resolution. Ciabatta et al. (2018) have described in full details the procedure used for producing the SM2RAIN-CCI rainfall product. Moreover, the assessment of the product with global scale gauge-based rainfall products has been carried out, also in comparison with other satellite-based rainfall datasets, e.g., TMPA (Tropical Rainfall Measuring Mission Multi-satellite Precipitation Analysis) and CMORPH (Climate Prediction Center MORPHing). Results show good performance over Africa, Brazil, western US, India and Australia, in terms of both Pearson's correlation, R, and mean annual rainfall estimation.

51.3.2 SM2RAIN-ASCAT

The most recent product we have developed is based on the application of SM2RAIN to ASCAT SM (Wagner et al. 2013) product at full resolution (12.5 km sampling). In previous studies, the ASCAT SM product has been aggregated at 1° and 0.5° resolution in order to facilitate the computations. Recently, under the EUMETSAT (European Organisation for the Exploitation of Meteorological Satellites) project "Global-SM2RAIN", a full investigation of the capability of ASCAT SM product to provide rainfall estimates is being investigated. The current version of the rainfall product is available from 2007 to 2017 (11 years) at daily temporal resolution and sampled on an irregular grid with spacing of 12.5 km. The dataset is freely available and can be obtained by contacting the authors. A first assessment of the product is carried out by aggregating the data at 1-degree resolution and by comparing the data with gauge-based rainfall dataset from GPCC (Global Precipitation Climatology Center). The latter represents an independent dataset as SM2RAIN parameters have been calibrated on ERA5 reanalysis rainfall

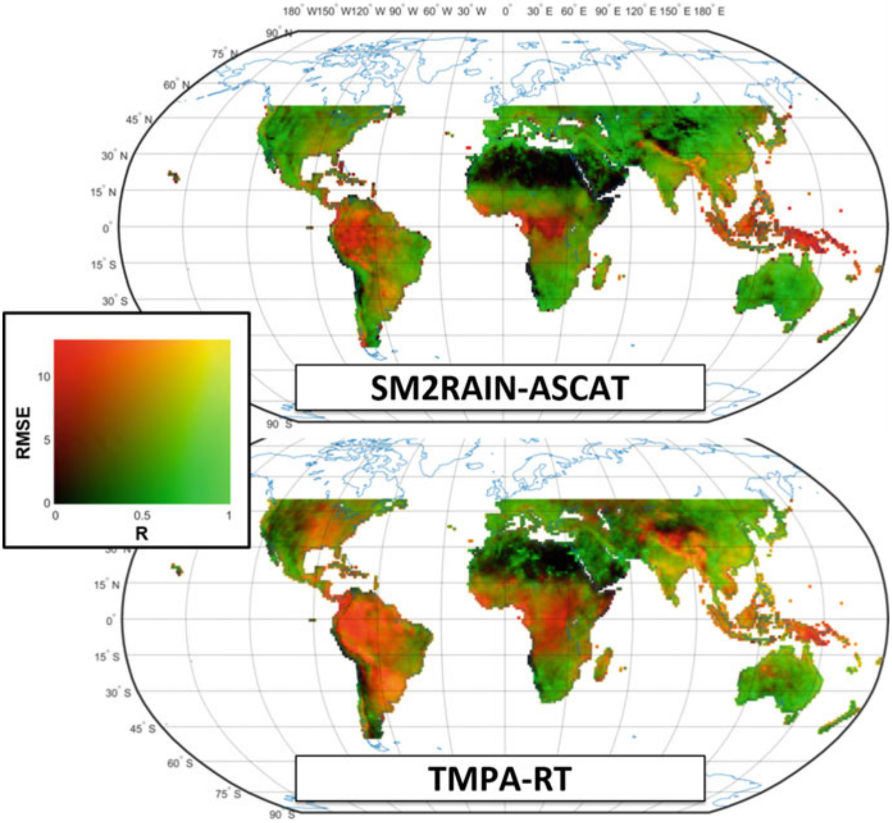

Fig. 51.2 Comparison in terms of Pearson's correlation, R, and root mean square error, RMSE, between SM2RAIN-ASCAT and TMPA-RT satellite-based rainfall products as compared with GPCC gauge-based dataset used as benchmark. The analysis is carried out at 1-day and 1° temporal spatial resolution. The maps clearly show the differences in the accuracy of the two products, with SM2RAIN-ASCAT performing well in the eastern US, Brazil, the Sahel, south-eastern Asia and Australia (green colors)

(from ECMWF). Figure 51.2 shows the results of the assessment for both SM2RAIN-ASCAT and TMPA-RT product for the period 2007–2017 at daily time scale. Maps show the results both in term of R and root mean square error, RMSE. Except tropical forests, Sahara Desert and high mountains (e.g., Himalaya), the SM2RAIN performs well with median R and RMSE equal to 0.51 and 3.89 mm day^{-1}, respectively. The accuracy of TMPA-RT is lower than SM2RAIN-ASCAT (median R/RMSE = 0.44/5.63 mm day^{-1}), particularly in eastern US, Brazil, the Sahel, south-eastern Asia and Australia. In these regions, we expect larger benefits in using SM2RAIN-ASCAT rainfall product for hydrological and climate applications.

51.4 Flood Modelling in Europe Through SM2RAIN-Derived Rainfall Products

The capability of SM2RAIN to keep track of the amount of water falling into the soil makes the derived rainfall products particularly useful for hydrological applications in which the accurate estimation of accumulated rainfall is needed, i.e. in cases where the accumulated rainfall amounts are more important than the knowledge of instantaneous rainfall rates. We have used SM2RAIN-ASCAT rainfall product, in combination with TMPA-RT and CMORPH, for flood simulations throughout Europe and the main results of this analysis are described here.

51.4.1 In Situ and Satellite Datasets

To perform a robust assessment of satellite-based rainfall products for flood modelling, a dataset of 600 basins throughout Europe has been compiled. For each basin, daily river discharge observations for a period of at least 1 year (average length of 5.6 years) between 2007 and 2013 are available. Daily precipitation and air temperature observations have been collected from in situ stations by using the E-OBS (Haylock et al. 2008) dataset. Three different satellite-based rainfall datasets have been used including: SM2RAIN-ASCAT, TMPA-RT and CMORPH (Joyce et al. 2004) real time versions. Additionally, the combination of TMPA-RT (and CMORPH) with SM2RAIN-ASCAT following the same merging approach proposed in Ciabatta et al. (2016) has been implemented. Therefore, for each basin, six river discharge simulations have been carried out, i.e., by using as precipitation input: (1) E-OBS, (2) CMORPH, (3) TMPA-RT, (4) SM2RAIN-ASCAT, (5) SM2RAIN-ASCAT+ CMORPH, and (6) SM2RAIN-ASCAT+ TMPA-RT.

51.4.2 MISDc Rainfall-Runoff Modelling

MISDc (Modello Idrologico Semi-Distribuito in continuo) is a continuous rainfall-runoff model developed by Brocca et al. (2011) for the operational forecasting of flood events in central Italy. In this chapter, a two-layer version of the model is used. With respect to the previous version, it includes a snow module and a different infiltration equation. The model uses as input daily rainfall and air temperature data and simulates the temporal evolution of river discharge and SM for a surface and a root-zone soil layer. Water is extracted from the first layer by evapotranspiration, which is calculated by a linear function between the potential evaporation and SM. A non-linear relation is used for computing the percolation from the surface to the root zone layer. The rainfall excess is calculated by a power law relationship as a function of the first layer SM while base flow is a non-linear function of the SM of the second layer. Full details on model equations are given in Brocca et al. (2011) and recent applications can be found in Camici et al. (2018) and Massari et al. (2018).

51.4.3 Results

The use of satellite-based rainfall products for flood modelling requires some pre-processing steps. We have employed the same approach as in Camici et al. (2018) in which MISDc model has been recalibrated in each simulation by maximizing the Kling-Gupta Efficiency (KGE, Gupta et al. 2009) with respect to observed daily discharge. The calibration of the merged products, i.e., SM2RAIN-ASCAT+ CMORPH and SM2RAIN-ASCAT+TMPA-RT, has been also carried out to maximize KGE. Therefore, for each rainfall product and basin, MISDc parameter values are calibrated and a validation period is not considered in this analysis. Certainly, this procedure does not allow for the evaluation of the satellite rainfall product in an operational context, but here we want to assess the best information that can be extracted from each product by using the maximum length of the available data.

The results in terms of KGE for all basins and products are shown in Fig. 51.3 as boxplots. As expected, very good performances are obtained with raingauge observations from E-OBS with a mean KGE equal to 0.77. Among the three satellite single rainfall products, SM2RAIN-ASCAT provides the best scores (mean KGE = 0.67) followed by TMPA-RT (mean KGE = 0.57), and CMORPH (mean KGE only 0.31). The percentages of basins in which SM2RAIN-ASCAT, TMPA-RT, and CMORPH provide the best KGE are equal to 77%, 21% and 4%, respectively. The integration of SM2RAIN-ASCAT with TMPA-RT and CMORPH provides improved performance close to the ones obtained with E-OBS. Specifically, for 27% (24%) of basins SM2RAIN-ASCAT+TMPA-RT (SM2RAIN-ASCAT +CMORPH) shows better results than E-OBS. It should be underlined that such satellite rainfall products are potentially available in near real-time, thus representing an important new data source for flood forecasting in Europe.

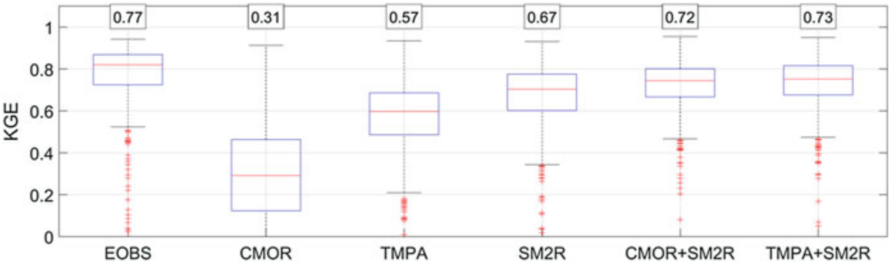

Fig. 51.3 Boxplot of KGE for the six investigated rainfall products and for the 600 basins. For each box, the red line represents the median values and the blue box represents the 25th and 75th percentile, the black dotted whiskers extend to the most extreme data points and cross symbols represent outliers. The numbers in the top boxes indicate the mean value for each rainfall product. The integration of SM2RAIN-ASCAT (SM2R) with TMPA-RT (TMPA) and CMORPH (CMOR) provides the best performance close to the ones obtained with high-quality raingauge observations (EOBS)

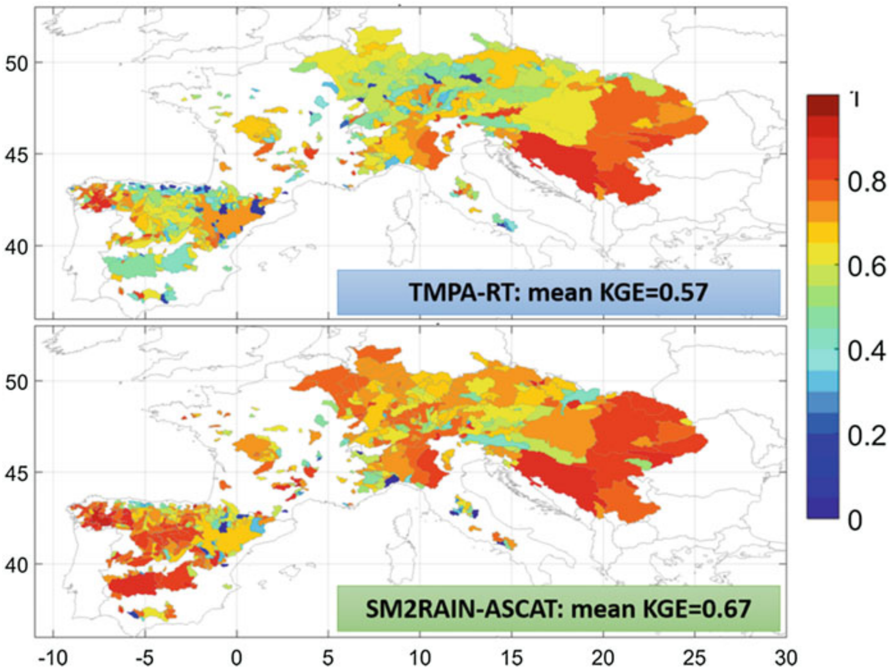

Fig. 51.4 Spatial distribution of KGE performance for TMPA-RT and SM2RAIN-ASCAT rainfall products over 600 basins in Europe. Red colours mean high KGE values and, hence, better performances. Overall, SM2RAIN-ASCAT is performing better over 77% of basins with TMPA-RT showing better results over some basins in Italy (mainly close to the western Alps), in central France and in South-Eastern Europe (Balkans)

To visualize the spatial distribution of the performances, Fig. 51.4 shows the KGE values for each basin and the two satellite products TMPA-RT and SM2RAIN-ASCAT as coloured polygons by mapping from the larger to the smaller basins (to visualize all basins and avoid overlapping). Overall, SM2RAIN-ASCAT is performing better than TMPA-RT over Central Europe and Spain while TMPA-RT is better over some basins in Italy (mainly close to the western Alps), in central France and in south-eastern Europe (Balkans).

As an example, Fig. 51.5 shows the simulation of river discharge for four randomly selected basins (Rhine at Köln, Danube at Pfelling, Duero at Almazan,

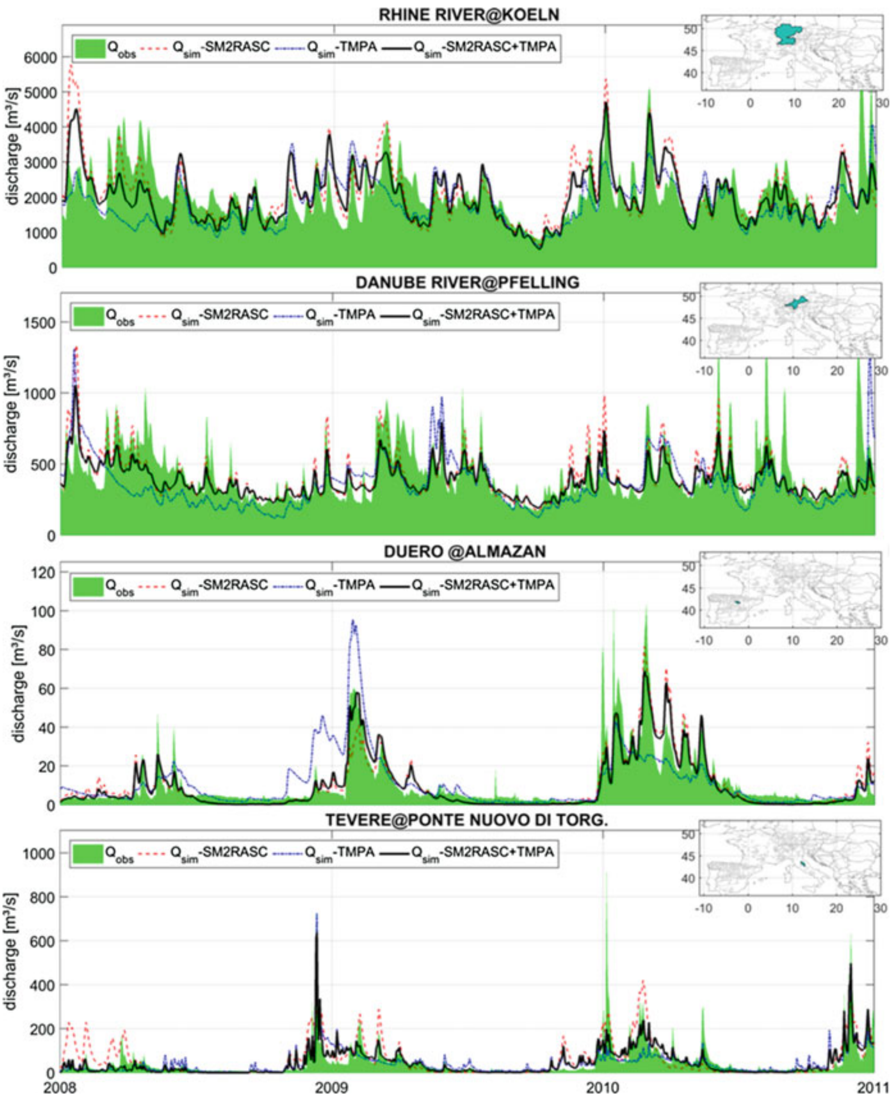

Fig. 51.5 Simulation of 3-year discharge at four basins across Europe by using SM2RAIN-ASCAT (red line), TMPA-RT (blue line) and SM2RAIN-ASCAT+TMPA-RT (black line) as input rainfall. The comparison with in situ discharge (green area) clearly underlined the benefit of integrating top-down and bottom-up approaches for flood simulation with a better reproduction of both high and low flows

Tevere at Ponte Nuovo di Torgiano) using SM2RAIN-ASCAT, TMPA-RT and TMPA-RT + SM2RAIN-ASCAT as input. The results highlight that the integration of top-down and bottom-up approaches is highly beneficial for reproducing river discharge observations in Europe, both for high and low flows. A nice example is visible for the Duero river at Almazan where the integrated product corrects the overestimation of TMPA-RT at the beginning of 2009 and the underestimation in 2010.

51.5 Limitations and Future Directions

In the previous paragraphs, and in the studies mentioned in the introduction, we have shown the good capability of SM2RAIN method to reproduce accumulated rainfall, with good performance when the rainfall product is applied in hydrological applications. However, we are also aware of the limitations of the method. Indeed, SM2RAIN may fail in reproducing rainfall when the soil is close to saturation (e.g., Brocca et al. 2013; Koster et al. 2016) and if the temporal resolution of the data is too coarse (e.g., > 2–3 days, see Brocca et al. 2016b). Moreover, the method is dependent on the accuracy of the original satellite SM dataset used as input. Therefore, high errors are expected over mountainous, urbanized and highly vegetated areas and during frozen/snow soil conditions (Brocca et al. 2014, 2017). The most important issue in using satellite surface SM data (layer depth < 5 cm) for rainfall estimation is due to the high temporal frequency fluctuations of satellite SM signals (due to noise and not to rainfall) that, when positive, are interpreted as rainfall by the SM2RAIN algorithm.

The SM2RAIN algorithm has been developed quite recently and a number of future steps is needed to fully exploit its potential for rainfall estimation. Two different kinds of development are envisaged: technological and methodological. For the technological developments, three future directions are foreseen:

1. An operational rainfall product from the SM2RAIN algorithm still has to be provided. Under the EUMETSAT H-SAF (Satellite Application Facility on Support to Operational Hydrology and Water Management, http://hsaf.meteoam.it, last accessed 28 Oct. 2018) project, an operational product integrating bottom-up and top-down approaches is being developed, and it is expected to be delivered in 2019. A comprehensive assessment of the product accuracy in time and space will be carried out, which will provide the estimation of rainfall uncertainty.
2. The integration of different satellite SM products, as initially demonstrated in Tarpanelli et al. (2017) for producing a higher quality rainfall product through SM2RAIN, is being investigated under the ESA SMOS+rainfall project.
3. The most recent satellite SM products characterized by higher spatial resolution are also being analysed to highlight the potential of obtaining high-resolution (1 km) rainfall products from space. Specifically, SM2RAIN has been applied to

the integration of ASCAT and Sentinel-1 SM product, i.e., SCATSAR, in Bauer-Marschallinger et al. (2018) for the Italian territory. Moreover, the application of SM2RAIN to NASA's Cyclone Global Navigation Satellite System (CYGNSS) SM products as obtained by Chew and Small (2018) is being investigated due to the low cost and high temporal frequency of the satellite SM product obtained through CYGNSS.

For the methodological developments, four future directions are foreseen:

1. The loss function in eq. (51.6) has been kept as simple as possible in all previous applications of SM2RAIN. However, as suggested in Koster et al. (2018), the use of a more complex loss function, taking into account of the evapotranspiration component, and fully exploiting the drying rate of SM time series, is expected to provide more robust and accurate results. More specifically, the analysis of the SM recession rate would allow the model to directly obtain the loss function and its parameterization from SM observations only, thus potentially enabling the derivation of a self-calibrated SM2RAIN formulation that does not need rainfall observations for its calibration.
2. The calibration of SM2RAIN parameter values is usually carried out pixel-by-pixel, thus not considering the space component. We want to develop more elaborated calibration procedures exploiting the expected continuity in space of rainfall and soil parameters, thus obtaining a more robust parameterization. The analysis of the temporal variability of model parameter values is also foreseen.
3. The integration between bottom-up and top-down approaches have been carried out by considering a simple linear weighting (e.g., Ciabatta et al. 2016; Brocca et al. 2016b). Even though the linear weighting has been found successful in obtaining a higher quality rainfall product, it does not consider the different error behavior of the two approaches. For instance, we are aware of the errors of SM2RAIN approach as a function of land cover and time (e.g., at saturation), and similar for the top-down approaches. We have recently developed a more elaborated merging technique that considers the time and space variability of the errors in the two approaches, under a Bayesian framework. First results have shown to be promising (Maggioni et al. 2017), and further investigations are being carried out.
4. The reduction of the noise in the SM signal is found to be mandatory to obtain reliable rainfall estimates. The current SM2RAIN approach considers the application of the exponential filter (Wagner et al. 1999), which may fail to correctly reproduce the timing of rainfall. More specific filters, such as those based on wavelet (e.g., Massari et al. 2017b), should be tested for improving the reduction of noise in SM signal and thus obtaining more accurate rainfall estimates.

For each of the points above, specific studies have been already started, or are going to be started in the future. Finally, we expect to apply SM2RAIN-derived rainfall in more applications over large areas and longer time periods to properly assess its potential. Apart from flood prediction, as shown in this chapter, SM2RAIN-derived rainfall is being applied for landslide prediction (Brunetti et al.

2018), water management (Abera et al. 2017), crop prediction (Thaler et al. 2018), and new applications such as bird migration and disease prevention.

Acknowledgements The authors gratefully acknowledge support from the EUMETSAT through the "Satellite Application Facility on Support to Operational Hydrology and Water Management (H SAF)" CDOP3 (EUM/C/85/16/DOC/15) and the Global SM2RAIN project (contract no. EUM/CO/17/4600001981/BBo), and from the ESA through SMOS+rainfall project (contract no. 4000114738/15/I-SBo) and the Climate Change Initiative, CCI (contract no. 4000104814/11/I-NB).

References

Abera, W., Formetta, G., Brocca, L., & Rigon, R. (2017). Modeling the water budget of the Upper Blue Nile basin using the JGrass-NewAge model system and satellite data. *Hydrology and Earth System Sciences, 21*, 3145–3165. https://doi.org/10.5194/hess-21-3145-2017.

Bauer-Marschallinger, B., Paulik, C., Hochstöger, S., Mistelbauer, T., Modanesi, S., Ciabatta, L., Massari, C., Brocca, L., & Wagner, W. (2018). Soil moisture from fusion of scatterometer and SAR: Closing the scale gap with temporal filtering. *Remote Sensing, 10*(7), 1030. https://doi.org/10.3390/rs10071030.

Brocca, L., Melone, F., & Moramarco, T. (2011). Distributed rainfall-runoff modelling for flood frequency estimation and flood forecasting. *Hydrological Processes, 25*(18), 2801–2813. https://doi.org/10.1002/hyp.8042.

Brocca, L., Melone, F., Moramarco, T., & Wagner, W. (2013). A new method for rainfall estimation through soil moisture observations. *Geophysical Research Letters, 40*(5), 853–858. https://doi.org/10.1002/grl.50173.

Brocca, L., Ciabatta, L., Massari, C., Moramarco, T., Hahn, S., Hasenauer, S., Kidd, R., Dorigo, W., Wagner, W., & Levizzani, V. (2014). Soil as a natural rain gauge: Estimating global rainfall from satellite soil moisture data. *Journal of Geophysical Research, 119*(9), 5128–5141. https://doi.org/10.1002/2014JD021489.

Brocca, L., Massari, C., Ciabatta, L., Moramarco, T., Penna, D., Zuecco, G., Pianezzola, L., Borga, M., Matgen, P., & Martínez-Fernández, J. (2015). Rainfall estimation from in situ soil moisture observations at several sites in Europe: An evaluation of SM2RAIN algorithm. *Journal of Hydrology and Hydromechanics, 63*(3), 201–209. https://doi.org/10.1515/johh-2015-0016.

Brocca, L., Massari, C., Ciabatta, L., Wagner, W., & Stoffelen, A. (2016a). Remote sensing of terrestrial rainfall from Ku-band scatterometers. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 9*(1), 533–539. https://doi.org/10.1109/JSTARS.2015.2508065.

Brocca, L., Pellarin, T., Crow, W. T., Ciabatta, L., Massari, C., Ryu, D., Su, C.-H., Rudiger, C., & Kerr, Y. (2016b). Rainfall estimation by inverting SMOS soil moisture estimates: A comparison of different methods over Australia. *Journal of Geophysical Research, 121*(20), 12062–12079. https://doi.org/10.1002/2016JD025382.

Brocca, L., Crow, W. T., Ciabatta, L., Massari, C., de Rosnay, P., Enenkel, M., Hahn, S., Amarnath, G., Camici, S., Tarpanelli, A., & Wagner, W. (2017). A review of the applications of ASCAT soil moisture products. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 10*(5), 2285–2306. https://doi.org/10.1109/JSTARS.2017.2651140.

Brunetti, M. T., Melillo, M., Peruccacci, S., Ciabatta, L., & Brocca, L. (2018). How far are we from the use of satellite rainfall products in landslide forecasting? *Remote Sensing of Environment, 210*, 65–75. https://doi.org/10.1016/j.rse.2018.03.016.

Camici, S., Ciabatta, L., Massari, C., & Brocca, L. (2018). How reliable are satellite precipitation estimates for driving hydrological models: A verification study over the Mediterranean area. *Journal of Hydrology, 563*, 950–961. https://doi.org/10.1016/j.jhydrol.2018.06.067.

Chiaravalloti, F., Brocca, L., Procopio, A., Massari, C., & Gabriele, S. (2018). Assessment of GPM and SM2RAIN-ASCAT rainfall products over complex terrain in southern Italy. *Atmospheric Research, 206*, 64–74. https://doi.org/10.1016/j.atmosres.2018.02.019.

Ciabatta, L., Brocca, L., Massari, C., Moramarco, T., Gabellani, S., Puca, S., & Wagner, W. (2016). Rainfall-runoff modelling by using SM2RAIN-derived and state-of-the-art satellite rainfall products over Italy. *International Journal of Applied Earth Observation and Geoinformation, 48*, 163–173. https://doi.org/10.1016/j.jag.2015.10.004.

Ciabatta, L., Marra, A. C., Panegrossi, G., Casella, D., Sanò, P., Dietrich, S., Massari, C., & Brocca, L. (2017). Daily precipitation estimation through different microwave sensors: Verification study over Italy. *Journal of Hydrology, 545*, 436–450. https://doi.org/10.1016/j.jhydrol.2016.12.057.

Ciabatta, L., Massari, C., Brocca, L., Gruber, A., Reimer, C., Hahn, S., Paulik, C., Dorigo, W., Kidd, R., & Wagner, W. (2018). SM2RAIN-CCI: A new global long-term rainfall data set derived from ESA CCI soil moisture. *Earth System Science Data, 10*, 267–280. https://doi.org/10.5194/essd-10-267-2018.

Chew, C. C., & Small, E. E. (2018). Soil moisture sensing using spaceborne GNSS reflections: Comparison of CYGNSS reflectivity to SMAP soil moisture. *Geophysical Research Letters, 45* (9), 4049–4057. https://doi.org/10.1029/2018GL077905.

Crow, W. T., Huffman, G. J., Bindlish, R., & Jackson, T. J. (2009). Improving satellite-based rainfall accumulation estimates using spaceborne surface soil moisture retrievals. *Journal of Hydrometeorology, 10*(1), 199–212. https://doi.org/10.1175/2008JHM986.1.

Crow, W. T., van Den Berg, M. J., Huffman, G. J., & Pellarin, T. (2011). Correcting rainfall using satellite-based surface soil moisture retrievals: The Soil Moisture Analysis Rainfall Tool (SMART). *Water Resources Research, 47*(8), W08521. https://doi.org/10.1029/2011WR010576.

Doorenbos, J., & Pruitt, W. O. (1977). *Background and development of methods to predict reference crop evapotranspiration (ETo)*. FAO Irrigation and Drainage Paper No. 24, 108–119. Available at http://www.fao.org/3/a-f2430e.pdf, last accessed 29 Nov 2018.

Gupta, H. V., Kling, H., Yilmaz, K. K., & Martinez, G. F. (2009). Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. *Journal of Hydrology, 377*(1), 80–91. https://doi.org/10.1016/j.jhydrol.2009.08.003.

Haylock, M. R., Hofstra, N., Klein Tank, A. M. G., Klok, E. J., Jones, P. D., & New, M. (2008). A European daily high-resolution gridded data set of surface temperature and precipitation for 1950-2006. *Journal of Geophysical Research, 113*(D20). https://doi.org/10.1029/2008JD010201.

Hou, A. Y., Kakar, R. K., Neeck, S., Azarbarzin, A. A., Kummerow, C. D., Kojima, M., Oki, R., Nakamura, K., & Iguchi, T. (2014). The global precipitation measurement mission. *Bulletin of the American Meteorological Society, 95*, 701–722. https://doi.org/10.1175/BAMS-D-13-00164.1.

Huffman, G. J., Bolvin, D. T., Nelkin, E. J., Wolff, D. B., Adler, R. F., Gu, G., Hong, Y., Bowman, K. P., & Stocker, E. F. (2007). The TRMM Multisatellite Precipitation Analysis (TMPA): Quasi-global, multiyear, combined-sensor precipitation estimates at fine scales. *Journal of Hydrometeorology, 8*(1), 38–55. https://doi.org/10.1175/JHM560.1.

Joyce, R. J., Janowiak, J. E., Arkin, P. A., & Xie, P. (2004). CMORPH: A method that produces global precipitation estimates from passive microwave and infrared data at high spatial and temporal resolution. *Journal of Hydrometeorology, 5*, 487–503. https://doi.org/10.1175/1525-7541(2004)005<0487:CAMTPG>2.0.CO;2.

Koster, R. D., Brocca, L., Crow, W. T., Burgin, M. S., & De Lannoy, G. J. M. (2016). Precipitation estimation using L-band and C-band soil moisture retrievals. *Water Resources Research, 52*(9), 7213–7225. https://doi.org/10.1002/2016WR019024.

Koster, R. D., Crow, W. T., Reichle, R. H., & Mahanama, S. P. (2018). Estimating basin-scale water budgets with SMAP soil moisture data. *Water Resources Research, 54*, 4228–4244. https://doi.org/10.1029/2018WR022669.

Maggioni, V., Massari, C., Barbetta, S., Camici, S., & Brocca, L. (2017). Merging satellite precipitation products for improved streamflow simulations. *AGU Fall Meeting 2017*, abstract #H54F-03.

Massari, C., Brocca, L., Moramarco, T., Tramblay, Y., & Didon Lescot, J.-F. (2014). Potential of soil moisture observations in flood modelling: Estimating initial conditions and correcting rainfall. *Advances in Water Resources, 74*, 44–53. https://doi.org/10.1016/j.advwatres.2014.08.004.

Massari, C., Crow, W. T., & Brocca, L. (2017a). An assessment of the accuracy of global rainfall estimates without ground-based observations. *Hydrology and Earth System Sciences, 21*, 4347–4361. https://doi.org/10.5194/hess-21-4347-2017.

Massari, C., Su, C.-H., Brocca, L., Sang, Y. F., Ciabatta, L., Ryu, D., & Wagner, W. (2017b). Near real time de-noising of satellite-based soil moisture retrievals: An intercomparison among three different techniques. *Remote Sensing of Environment, 198*, 17–29. https://doi.org/10.1016/j.rse.2017.05.037.

Massari, C., Camici, S., Ciabatta, L., & Brocca, L. (2018). Exploiting satellite-based surface soil moisture for flood forecasting in the Mediterranean area: State update versus rainfall correction. *Remote Sensing, 10*(2), 292. https://doi.org/10.3390/rs10020292.

Pellarin, T., Ali, A., Chopin, F., Jobard, I., & Bergès, J. C. (2008). Using spaceborne surface soil moisture to constrain satellite precipitation estimates over West Africa. *Geophysical Research Letters, 35*(2). https://doi.org/10.1029/2007GL032243.

Pellarin, T., Louvet, S., Gruhier, C., Quantin, G., & Legout, C. (2013). A simple and effective method for correcting soil moisture and precipitation estimates using AMSR-E measurements. *Remote Sensing of Environment, 136*, 28–36. https://doi.org/10.1016/j.rse.2013.04.011.

Román-Cascón, C., Pellarin, T., Gibon, F., Brocca, L., Cosme, E., Crow, W. T., Fernández, D., Kerr, Y., & Massari, C. (2017). Correcting satellite-based precipitation products through SMOS soil moisture data assimilation in two land-surface models of different complexity: API and SURFEX. *Remote Sensing of Environment, 200*, 295–310. https://doi.org/10.1016/j.rse.2017.08.022.

Tarpanelli, A., Massari, C., Ciabatta, L., Filippucci, P., Amarnath, G., & Brocca, L. (2017). Exploiting a constellation of satellite soil moisture sensors for accurate rainfall estimation. *Advances in Water Resources, 108*, 249–255. https://doi.org/10.1016/j.advwatres.2017.08.010.

Thaler, S., Brocca, L., Ciabatta, L., Eitzinger, J., Hahn, S., & Wagner, W. (2018). Effects of different spatial precipitation input data on crop model outputs under a Central European climate. *Atmosphere, 9*(8), 290. https://doi.org/10.3390/atmos9080290.

Tian, Y., Liu, Y., Arsenault, K. R., & Behrangi, A. (2014). A new approach to satellite-based estimation of precipitation over snow cover. *International Journal of Remote Sensing, 35*(13), 4940–4951. https://doi.org/10.1080/01431161.2014.930208.

Wagner, W., Lemoine, G., & Rott, H. (1999). A method for estimating soil moisture from ERS scatterometer and soil data. *Remote Sensing of Environment, 70*(2), 191–207. https://doi.org/10.1016/S0034-4257(99)00036-X.

Wagner, W., Hahn, S., Kidd, R., Melzer, T., Bartalis, Z., Hasenauer, S., Figa-Saldaña, J., de Rosnay, P., Jann, A., Schneider, S., Komma, J., Kubu, G., Brugger, K., Aubrecht, C., Züger, J., Gangkofner, U., Kienberger, S., Brocca, L., Wang, Y., Blöschl, G., Eitzinger, J., Steinnocher, K., Zeil, P., & Rubel, F. (2013). The ASCAT soil moisture product: A review of its specifications, validation results, and emerging applications. *Meteorologische Zeitschrift, 22*(1), 5–33. https://doi.org/10.1127/0941-2948/2013/0399.

Wanders, N., Pan, M., & Wood, E. F. (2015). Correction of real-time satellite precipitation with multi-sensor satellite observations of land surface variables. *Remote Sensing of Environment, 160*, 206–221. https://doi.org/10.1016/j.rse.2015.01.016.