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Multi-satellite rainfall sampling error estimates – a comparative study

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11677

Abstract

This study focus is set on quantifying sampling related uncertainty in the satellite rainfall estimates. We conduct observing system simulation experiment to estimate sampling error for various constellations of Low-Earth orbiting and geostationary satellites.

5 There are two types of microwave instruments currently available: cross track sounders and conical scanners. We evaluate the differences in sampling uncertainty for various satellite constellations that carry instruments of the common type as well as in combination with geostationary observations.

10 A precise orbital model is used to simulate realistic satellite overpasses with orbital shifts taken into account. With this model we resampled rain gauge timeseries to simulate satellites rainfall estimates free of retrieval and calibration errors. We concentrate on two regions, Germany and Benin, areas with different precipitation regimes.

15 Our results show that sampling uncertainty for all satellite constellations does not differ greatly depending on the area despite the differences in local precipitation patterns. Addition of 3 hourly geostationary observations provides equal performance improvement in Germany and Benin, reducing rainfall undersampling by 20–25 % of the total rainfall amount. Authors do not find a significant difference in rainfall sampling between conical imager and cross-track sounders.

1 Introduction

20 Accurate measurements of precipitation are equally important for the scientific and non-scientific communities. Knowledge of precipitation processes improves our understanding of the global water cycle, Earth latent heat fluxes, floods prediction. It is used as an input information for hydrological modeling as well as for agricultural management, emergency services and policy makers (Bastiaanssen et al., 2000; Hong et al., 2007; Huffman et al., 2010). A broad overview of scientific applications of precipitation products derived from satellite observations is given by Kucera et al. (2012).

11678

Currently a truly global monitoring of precipitation is only possible via satellite measurements as no dense gauge and radar network can be installed and maintained in the remote locations e.g. oceans, where precipitation can be observed only during field experiments (Klepp et al., 2010). Flying at the altitude of several hundreds or thousands of kilometers satellites are able to observe precipitation events that are otherwise not seen by in-situ instruments or not reproduced by numerical weather prediction (NWP) models (Klepp et al., 2005).

Some climatological precipitation datasets like Global Precipitation Climatology Project (GPCP) (Adler et al., 2003), TRMM Precipitation Analysis (TMPA) (Huffman et al., 2007), Climate Prediction Center Morphing Method (CMORPH) (Joyce et al., 2004) utilize all available satellite precipitation observations that require different retrieval methods while other datasets like Hamburg Ocean Atmosphere Precipitation from Space (HOAPS) (Andersson et al., 2010) or retrieval systems like Microwave Integrated Retrieval System (MIRS) (Boukabara et al., 2011) rely only on the observations conducted by the same type of instrument, loosing in the number of employed spacecrafts and coverage but gaining in the consistency of the single retrieval method.

Rainfall retrieval techniques have made a significant advancement during the recent years. Studies by Wolff and Fisher (2009) and Turk et al. (2009) show that precipitation estimates aggregated over 1 day and 1° are nearly unbiased and have root mean square error of 1 mm day^{-1} or less. Same studies indicate that on a smaller spatial and temporal scale the uncertainties are still large. There are at least two sources of uncertainties: retrieval uncertainty which exists because no retrieval method can perfectly calculate true precipitation amount, and sampling uncertainty, which appears due to the intermittent nature of the rainfall process. In this paper we concentrate only on the sampling part of the rainfall retrieval uncertainty.

Few earlier studies addressed the sampling uncertainty of satellite rainfall observations (Shin and North, 1988; Bell and Kundu, 2000; Nesbitt and Anders, 2009; Fisher and Wolff, 2010; Chambon et al., 2012). Steiner et al. (2003) and Gebremichael and Krajewski (2004) developed approaches to calculate sampling errors using the average

11679

rainfall rate, the size of the sensor footprint and the aggregation intervals as the input parameters. However they have not taken satellite flight patterns into account but used fixed sampling intervals instead. Their approach was further extended by Iida et al. (2006). It considered realistic flight patterns of DMSP, Aqua and TRMM satellites but did not consider any changes in satellite orbital parameters. As can be seen in Fig. 1 satellite orbits experience shifts of few hours during satellites lifetime. However this effect is important for the precipitation records that spread over several years. In case of a precipitation regime with strong diurnal cycle the shifts in equator crossing times may lead to biases in precipitation timeseries. Fisher and Wolff (2010) followed a different path and disaggregated the overall errors in the final monthly precipitation product onto the sampling and retrieval components using statistical decomposition method.

The aim of our study is to estimate and compare sampling uncertainty for various satellite constellations that have different orbits and different instruments on-board. This study is unique in the few following ways. We estimate sampling error for all spacecrafts that carry passive microwave rainfall sensors, as well as the combinations of satellites to match those used in various long-term precipitation products. Complete listing of satellites and instrument characteristics is presented in Table 1.

Unlike previous studies we used a realistic orbital model to compute satellite orbits or extracted subsatellite tracks from the existing records, thus our analysis provides the most realistic picture of satellite overpasses.

Finally our methodology was applied over two rain gauge networks in Benin and Germany, the areas with different precipitation regimes. Our aim is to evaluate the effect of precipitation regime on the sampling error behavior. Benin is strongly affected by the West African monsoons, where strong and short convective rainfall events are typical, while in Germany relatively weak large scale stratiform precipitation occurs more frequently throughout the year.

Usually to estimate sampling error in rainfall estimates researchers analyze two-dimensional fields of precipitation (e.g. Steiner et al., 2003; Iida et al., 2006). Instead we look at the one dimensional point measurements. Essentially, this is the worst case

11680

scenario, as the majority of the rain events are not observed simultaneously by the ground stations and satellites. Such analysis will provide the knowledge of what magnitude of the sampling error one should expect when comparing point rainfall data and satellite observations. By analyzing the point data we also avoid issues like beam
5 filling effect. And since we are interested in sampling errors differences for different satellite constellations it is not so important whether we look at two-dimensional or one-dimensional rainfall timeseries.

This paper is organized as follows. Background information on sampling error is given in Sect. 2. Ground observations are described in Sect. 3. Satellite constellations and their orbit modelling is presented in Sect. 4. Sampling error estimation approach is presented in Sect. 5. The results of our analysis are given in Sect. 6 and conclusions are discussed in Sect. 7.
10

2 Sampling error

Producing a precipitation climatology from observations is a complex task. Precipitation sensors and retrieval algorithms are imperfect and therefore calibration and retrieval errors are always present in the final products. Due to the discrete nature of satellite observations a third component of satellite error budget will be the sampling error. According to Roca et al. (2010) the total error budget for precipitation products can be written as:
15

$$20 S^2 = S^2_{\text{calibration}} + S^2_{\text{algorithm}} + S^2_{\text{sampling}}, \quad (1)$$

where $S^2_{\text{calibration}}$ is the calibration term, associated with the systematic errors, $S^2_{\text{algorithm}}$ is the retrieval term associated with the error in the retrieval process and S^2_{sampling} is the sampling term caused by discrete satellite observations pattern, as certainly not all rainfall events can be observed from space from LEO satellites.
25

In this study we concentrate on the sampling term of the rainfall retrievals error budget. We follow the approach used by Gebremichael and Krajewski (2004) and Iida et al.

11681

(2006) and simulate satellite precipitation timeseries using ground rain gauge observations. In order to avoid calibration and retrieval errors we do not use any satellite rainfall retrievals and resample the original rain gauge timeseries instead. For simulated satellite rainfall timeseries we chose only those gauge measurements that coincided with
5 the satellite overpasses in time and space. This way only the sampling term of the total rainfall product error budget is left:

$$S^2 = S^2_{\text{sampling}} \quad (2)$$

3 Rain gauge observations

Ideally, to resolve short scale precipitation processes ground observations made every
10 5 min or less are required. However we think that for the purpose of our research hourly resolution is sufficient.

For sampling error evaluation we obtained hourly rainfall measurements over Germany from the German Weather Service (Deutscher Wetterdienst, DWD) and over Benin from African Monsoon Multidisciplinary Analyses (AMMA) project. Summary of network characteristics is presented in Table 3, and their spatial distribution is shown in Fig. 2.
15

The 156 measurement stations in Germany belong to the DWD meteorological and climatological observation network and cover the entire country. They are evenly spread between 47 and 55° N. Selected timeseries span from January 1998 to December 2008 thus the timeseries contain over 13 million records. The station density is approximately one station per 2000 km².
20

Benin measurement network is a part of the AMMA Coupling the Tropical Atmosphere and the Hydrological Cycle (AMMA-CATCH) observing system, described in Lebel et al. (2009). It includes 52 stations equipped with tipping buckets, spread across
25 ca. 15 000 km² in the upper catchment area of the Ouémé river between 9 and 10° N. This network was set up to perform mesoscale rainfall analysis and has a density of

11682

approximately one station per 200 km^2 over a $1^\circ \times 1^\circ$ area. This dataset contains measurements made from March 2005 to September 2007.

Our main motivation for selecting these areas was the difference in precipitation regimes. As illustrated in Fig. 3 rainfall in Benin tends to be strong but infrequent. The largest contribution to the overall volume comes from the rainfall events that exceed 10 mm h^{-1} and they occur in less than 10% of all rainfall occurrences. In Germany on average the largest input comes from the light rainfall of less than 1 mm h^{-1} . It makes more than 30% of the total rainfall volume and occurs in over 70% of all precipitation events.

4 Satellite rainfall timeseries simulation

4.1 Satellite instruments

There are two types of passive microwave rainfall sensors that allow rainfall retrieval: conical imagers and cross-track sounders. Special Sensor Microwave Imager (SSM/I), Advanced Microwave Scanning Radiometer (AMSR-E) and TRMM Microwave Imager are conical scanners. Their construction allows imaging the underlying surface always with the same angle, thus their field of view remains constant. They measure the intensity of surface radiation in the window parts of spectra at the frequencies between 7 and 89 GHz. Advanced Microwave Sounding Unit B (AMSU-B) and its follow up, Microwave Humidity Sensor (MHS) are cross-track sounders. They measure radiation in the region between 89 and 190 GHz, profiling atmosphere at the different levels using channels centered at 183 GHz and measuring surface radiation in the window channels 89 and 150 GHz. Their scanning pattern is perpendicular to the spacecraft movement direction and field of view changes the further away it is from the nadir position.

Due to the limitation of MW signal strength all MW rainfall instruments are carried onboard low-Earth orbiting (LEO) satellites. Their orbit does not exceed elevation of 1000 km and their swath width lays within 700 and 2000 km. Another type of satellite

11683

information useful for rainfall retrievals is geostationary (GEO) infrared (IR) measurements. They do not suffer the same problems with sampling as with LEO satellites, as they observe almost an entire Earth hemisphere from a “fixed” position with regular frequent time intervals. But unlike MW measurements they cannot provide information for direct physical rainfall rate retrieval. Instead they provide information on the spatial distribution and physical properties of the clouds, that can be further interpreted for the rainfall retrieval. Geostationary IR measurements can be used for the rainfall retrieval standalone or they are utilized as a valuable source of supplemental information for the MW based rainfall retrievals.

4.2 Satellite constellations

Since the interest of this study is to investigate the overall sampling error for all satellites as well as the sampling error for satellite constellations that have onboard only sensors of certain type (cross-track sounders or conical scanners) we consider four constellations. Group PMS contains LEO satellites with passive microwave cross-track imagers. Group LEO includes all of the LEO satellites. Group GEO includes only a geostationary satellite. We consider the fourth constellation alone or in combination with other groups to evaluate the effect of 3 hourly GEO IR measurements on the sampling error magnitude. We chose 3 hourly GEO observation frequency as this is the frequency used in datasets like TMPA, CMORPH and others. Constellations listing is presented in Table 2. It is important to note that the number of satellites in each group changes from year to year as can be seen in Fig. 1.

4.3 Satellite overpasses simulation

In this study we do not use any real satellite data except for the satellite position information that is required for further simulating of satellite precipitation timeseries. We use either subsatellite tracks extracted from the satellite records or simulate satellite tracks

11684

using the Simplified General Perturbations Model 4 (SGP4) described by Vallado et al. (2006). SGP4 is a fully analytical model used to calculate satellite orbital state vectors relative to the Earth-centered inertial coordinate system. It propagates satellite orbits taking into account perturbations caused by Earth's uneven gravitational field, atmospheric drag, solar and lunar gravitational forces as well as solar radiation field. It applies to satellites with an orbital period of less than 225 min. To compute satellite orbits we used PREDICT software written by Magliacane (2012), with the SGP4 model in its core. The advantage of PREDICT is that since it relies on a fully analytical orbital model satellite tracks prediction is very fast and can be done on any personal computer.

10 An example of modeled subsatellite tracks for all LEO satellites considered in this study is illustrated in Fig. 4.

Satellites measurements are not continuous and cannot cover precipitation diurnal cycle completely but observe precipitation with regular time intervals. If the satellite orbital parameters changed then additional biases would be introduced. As illustrated in Fig. 1, satellite orbit may experience shifts of several hours changing the observing time, which may change the mean observed rainfall rates. To account for this effect we either used a high precision orbital model or used geolocation information extracted from the existed satellite records.

To calculate satellite tracks with high accuracy one needs to provide PREDICT with an up-to-date two-line elements (TLE) file, that contains parameters describing an orbit of the specific satellite in a certain moment of time. Accuracy of the computed orbits depends on the time interval between the date of creation of the TLE file and the date the orbit is calculated for. According to Dong and Chang-yin (2010) positional errors for satellites orbiting at the altitude between 400 and 1200 km 1 day prediction lay within 6–7 km range. This accuracy order is even higher than required by our experiment setup.

TLE files for research and operational satellites are released daily by the North American Aerospace Defense Command (NORAD). We obtained TLE files for all satellites considered in this study from Celestrak database (<http://celestrak.com>), except for

11685

DMSP satellites. Since the year 2000 NORAD stopped public TLE release for DMSP satellites. We obtained DMSP geolocation information extracted from DMSP records by Climate Monitoring Satellite Application Facility (CM-SAF).

5 Sampling error estimation

5 After simulating satellite rainfall timeseries we estimate satellite performance by comparing constructed rainfall aggregates to the true rainfall aggregates. Like in Iida et al. (2006) we use three parameters: root mean square error, RMSE, bias, BIAS and sampling error, SE which is a ratio of RMSE to the mean true rainfall rate $\overline{R_t}$.

RMSE is presented as:

$$10 \text{ RMSE} = \sqrt{\langle (R_s - R_t)^2 \rangle}, \quad (3)$$

where R_s stands for the estimated satellite rainfall rate, R_t stands for the true rainfall rate and $\langle \rangle$ indicates averaging across time axis. We emphasize that R_s is not a value retrieved from real satellite observations, but is a sum of the hourly precipitation rates at each gauge location taken if a satellite overpass occurs during this time. R_t in turn is the sum of actual observations over the considered period (from 3 h to 1 month) taken without considering any satellite overpasses.

BIAS is the difference between mean true rainfall rate $\overline{R_t}$ and mean satellite rainfall estimate $\overline{R_s}$:

$$15 \text{ BIAS} = \overline{R_t} - \overline{R_s} \quad (4)$$

20 Sampling error, SE is defined as a ratio of root mean square error, RMSE to the true rainfall rate $\overline{R_t}$:

$$\text{SE} = 100 \times \text{RMSE} / \overline{R_t}. \quad (5)$$

11686

We estimate sampling error at five time scales: 3 h, 1 day, 7 days, 15 days and 30 days. Sampling intervals were chosen in accordance to their appearance in precipitation climatologies like TMPA or CMORPH. In this paper we concentrate on the results computed for the entire year, though we estimated sampling error for each of the four seasons of the year as well.

The analysis workflow goes as follows: (1) satellite tracks were either computed using Predict software or extracted from the satellite geolocation information, (2) satellite rainfall timeseries were created by resampling rain gauge timeseries according to the satellite overpasses for every location, (3) resulting rainfall timeseries were compared to the original rain gauge records. All timeseries vectors are combined into one. No spatial averaging or interpolation is performed.

6 Results

The sampling related uncertainty is estimated for various combinations of aggregation intervals and satellite constellations for Germany and Benin based on 10 yr (Germany) and 3 yr (Benin) long rainfall gauge timeseries. Total sampling error and annual bias are outlined in Sect. 6.1. Differences in diurnal cycle coverage are described in Sect. 6.2. Comparison of sampling error for various constellations are given in Sect. 6.3.

6.1 Mean annual rainfall

As illustrated in Fig. 6 by employing all available satellite observations we are able to observe not more than 56 % of the total rainfall volume. Surprisingly, despite variations in the rainfall regime, the difference in rainfall sampling between Germany and Benin is marginal, and does not exceed 5 % for any satellite constellation.

PMS constellation performs slightly better in both areas, over Germany the amount of rainfall records exceeds PMI observations by 11 %. This effect is more obvious over midlatitude areas than close to equator, in Benin this difference is 7 %. This advantage

11687

in sampling can be explained by the sensors wider field of view, therefore the time gap between observations is smaller and diurnal cycle is covered more evenly.

Combination of GEO and LEO observations provides significant improvement, reducing the mean annual bias by 22 % over Germany and 21 % over Benin. 3 hourly GEO observations alone will cover only 33 % to 35 % of total rainfall volume. Therefore we confirm that it is highly recommended to use a combination of GEO and LEO observations.

Using GEO with only one sensor type, PMS or PMI will increase bias by 7 to 13 % over Germany and 7 to 12 % over Benin.

6.2 Diurnal cycle coverage

We analyzed how well the precipitation diurnal cycle is covered during the summer months (June–August) of the year 2006. We picked that season because it is the time with the rainfall of the highest intensity in both areas and because during the year 2006 the equal number of PMS and PMI satellites are available simultaneously: NOAA-15, 16, 17 and 18, and DMSP F-13, F-14, F-15 and the AQUA satellite. Over both areas PMS provides consistently more uniform coverage of the diurnal cycle, that is probably due to its wide swath angle so there is more overlap between two successive orbital passes. However it lacks observations during the evening hours between 8 and 10 p.m. LT (local time). PMI observations have clear peaks in the evening hours that partly coincide with the summer evening rainfall peaks. The evening maximum in Benin (5–6 p.m. LT) is not captured well by neither of the constellations including GEO. Also the gaps during 2 and 5–6 a.m. contribute significantly to the rainfall underestimation by the satellites.

6.3 Sampling error

Figure 8 displays the total sampling error for both study areas for various satellite constellations. The major difference between Germany and Benin is apparent on the

11688

subdaily and daily scale. The sampling error value for a constellation that includes all satellites (black line on the Fig. 8 reaches 230% in Germany and almost 386% in Benin. By aggregating rainfall in time the error is significantly reduced and falls down to 70–55% (Germany) and 76–61% (Benin) on a weekly and monthly time scale. The large difference between sampling error values on a subdaily scale in Germany and Benin can be explained by the rainfall regime differences described in Sect. 3. PMS and PMI constellations perform very similar, the sampling error difference on various timescale lays within 10–15% interval with PMS having slightly smaller values. Addition of geostationary information provides significant improvement over single sensor constellations (PMI, PMS or Geo). The difference between the sampling error values for all satellites constellation (Leo + Geo) and Geo combined with either PMS or PMI constellations lays within 20–40% for the subdaily scale and falls down to 10–15% on a monthly scale for both areas, Germany and Benin. Full bias, RMSE and sampling error values are described in Tables 4 and 5.

7 Conclusions

Satellite rainfall estimates have been made using a comprehensive orbit modelling approach that accounts for changes in satellite orbital parameters. The performance of simulated satellite rainfall estimates was analyzed through a comparison to ground-based observations in different geographical locations. The findings of this study are:

- The overall sampling error in Germany and Benin varies significantly on the subdaily scale, but not so much if rainfall estimates are aggregated on longer timescales. Due to the differences in the rainfall regime satellite sampling error in Germany on 3 hourly time scale is 150% smaller than in Benin. But on the longer timescales the sampling error values become relatively close and drop down to 55–60% for both study areas.

11689

- Addition of 3 hourly geostationary information to PMS and PMI observations reduces rainfall underestimation by 20–25% of the total rainfall amount in both study areas. Undersampling of 3 hourly geostationary measurements is similar to that of PMS and PMI observations combined.
- The difference in rainfall events coverage between NOAA (PMS) and DMSP (PMI) based satellite constellations is relatively small, being 10% of the true mean annual rainfall amount at most. When either of the LEO constellation (PMS or PMI) is combined with GEO observations the performance is relatively close to the constellation that includes all available satellite information.

The found overall sampling error values are very large, however it should be noted that we have done a point-wise analysis for a set of individual stations which is the “worst-case” scenario for such type of analysis. Using spatial fields instead of point data would allow to see the rainfall events otherwise not seen by the rain gauges. As shown in previous studies, like Gebremichael and Krajewski (2004), the magnitude of the sampling error drops significantly with enlarging the area of analysis.

Rainfall rate retrieval methods are not the same for the data that comes from cross-track sounders and conical imagers. However when one has to choose which type of observations to use, PMI or PMS, then sampling error should not be the primary concern as these constellations do not outperform each other by more than 10% of the total annual rainfall amount. It is recommended to include geostationary observations if possible.

An interesting finding is that there is no significant differences in sampling error between Germany and Benin on the timescales longer than one day. This may suggest that no special regionalization is required when building up a global precipitation climatology using satellite information.

In this study we estimated the overall sampling error for the various constellations of LEO and GEO satellites with the precipitation sensors onboard, but did not do a

11690

detailed analysis of satellite orbital parameters. Further research may address the effect of satellite orbital drift on the precipitation timeseries.

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References

- Adler, R. F., Huffman, G. J., Chang, A., Ferraro, R., Xie, P. P., Janowiak, J., Rudolf, B., Schneider, U., Curtis, S., Bolvin, D., Gruber, A., Susskind, J., Arkin, P., and Nelkin, E.: The version-2 Global Precipitation Climatology Project (GPCP) monthly precipitation analysis (1979–present), *J. Hydrometeorol.*, 4, 1147–1167, 2003. 11679
- Andersson, A., Fennig, K., Klepp, C., Bakan, S., Graßl, H., and Schulz, J.: The Hamburg Ocean Atmosphere Parameters and Fluxes from Satellite Data – HOAPS-3, *Earth Syst. Sci. Data*, 2, 215–234, doi:10.5194/essd-2-215-2010, 2010. 11679
- Bastiaanssen, W. G., Molden, D. J., and Makin, I. W.: Remote sensing for irrigated agriculture: examples from research and possible applications, *Agr. Water Manage.*, 46, 137–155, 2000. 11678
- Bell, T. L. and Kundu, P. K.: Dependence of satellite sampling error on monthly averaged rain rates: comparison of simple models and recent studies, *J. Climate*, 13, 449–462, 2000. 11679
- Boukabara, S.-A., Garrett, K., Chen, W., Iturbide-Sanchez, F., Grassotti, C., Kongoli, C., Chen, R., Liu, Q., Yan, B., Weng, F., Ferraro, R., Kleespies, T. J., and Meng, H.: MiRS: an all-weather 1DVAR satellite data assimilation and retrieval system, 11th Specialist Meeting on Microwave Radiometry and Remote Sensing Applications (MicroRad 2010), Washington, DC, 1–4 March 2010, *IEEE T. Geosci. Remote*, 49, 3249–3272, doi:10.1109/TGRS.2011.2158438, 2011. 11679
- Chambon, P., Jobard, I., Roca, R., and Viltard, N.: An investigation of the error budget of tropical rainfall accumulation derived from merged passive microwave and infrared satellite measurements, *Q. J. Roy. Meteorol. Soc.*, doi:10.1002/qj.1907, in press, 2012. 11679
- Dong, W. and Chang-Yin, Z.: An accuracy analysis of the SGP4/SDP4 model, *Chin. Astronom. Astrophys.*, 34, 69–76, 2010. 11685
- Fisher, B. and Wolff, D. B.: Satellite sampling and retrieval errors in regional monthly rain estimates from TMI, AMSR-E, SSM/I, AMSU-B, and the TRMM PR, *J. Appl. Meteorol. Climatol.*, 50, 994–1023, doi:10.1175/2010JAMC2487.1, 2010. 11679, 11680
- Gebremichael, M. and Krajewski, W. F.: Modeling distribution of temporal sampling errors in area-time-averaged rainfall estimates, *Atmos. Res.*, 73, 243–259, doi:10.1016/j.atmosres.2004.11.004, 2004. 11679, 11681, 11690
- Hong, Y., Adler, R., Negri, A., and Huffman, G.: Flood and landslide applications of near real-time satellite rainfall products, *Nat. Hazards*, 43, 285–294, doi:10.1007/s11069-006-9106-x, 2007. 11678
- Huffman, G., Bolvin, D., Nelkin, E., Wolff, D., Adler, R., Gu, G., Hong, Y., Bowman, K., and Stocker, E.: The TRMM multisatellite precipitation analysis (TMPA): quasi-global, multiyear, combined-sensor precipitation estimates at fine scales, *J. Hydrometeorol.*, 8, 38–55, 2007. 11679
- Huffman, G. J., Adler, R. F., Bolvin, D. T., and Nelkin, E. J.: The TRMM Multi-Satellite Precipitation Analysis (TMPA), in: *Satellite Rainfall Applications for Surface Hydrology*, edited by: Gebremichael, M. and Hossain, F., Springer, The Netherlands, doi:10.1007/978-90-481-2915-7, 3–22, 2010. 11678
- Iida, Y., Okamoto, K., Ushio, T., and Oki, R.: Simulation of sampling error of average rainfall rates in space and time by five satellites using radar-AMeDAS composites, *Geophys. Res. Lett.*, 33, L01816, doi:10.1175/BAMS-D-11-00171.1, 2006. 11680, 11681, 11686
- Joyce, R., Janowiak, J. E., Arkin, P. A., and Xie, P.: CMORPH: a method that produces global precipitation estimates from passive microwave and infrared data at high spatial and temporal resolution, *J. Hydrometeorol.*, 5, 487–503, 2004. 11679
- Klepp, C., Bakan, S., and Graßl, H.: Missing North Atlantic cyclonic precipitation in ECMWF numerical weather prediction and ERA-40 data detected through the satellite climatology HOAPS II, *Meteorol. Z.*, 14, 809–821, doi:10.1127/0941-2948/2005/0088, 2005. 11679

- Klepp, C., Bumke, K., Bakan, S., and Bauer, P.: Ground validation of oceanic snowfall detection in satellite climatologies during LOFZY, *Tellus A*, 62, 469–480, doi:10.1111/j.1600-0870.2010.00459.x, 2010. 11679
- Kucera, P. A., Ebert, B., Turk, F. J., Levizzani, V., Kirschbaum, D., Tapiador, F., Xian, P., Loew, A., and Borsche, M.: Precipitation from space: advancing earth system sciences, *B. Am. Meteorol. Soc.*, doi:10.1175/BAMS-D-11-00171.1, in press, 2012. 11678
- Lebel, T., Cappelaere, B., Galle, S., Hanan, N., Kergoat, L., Levis, S., Vieux, B., Descroix, L., Gosset, M., Mougin, E., Peugeot, C., and Seguis, L.: AMMA-CATCH studies in the Sahelian region of West-Africa: an overview, *J. Hydrol.*, 375, 3–13, 2009. 11682
- Magliacane, J. A.: PREDICT software, available at: <http://www.qsl.net/kd2bd/predict.html>, last access: 11 September 2012. 11685
- Nesbitt, S. W. and Anders, A. M.: Very high resolution precipitation climatologies from the tropical rainfall measuring mission precipitation radar, *Geophys. Res. Lett.*, 36, 1–5, doi:10.1029/2009GL038026, 2009. 11679
- Roca, R., Chambon, P., Jobard, I., Kirstetter, P.-E., Gosset, M., and Bergès, J. C.: Comparing satellite and surface rainfall products over West Africa at meteorologically relevant scales during the AMMA campaign using error estimates, *J. Appl. Meteorol. Climatol.*, 49, 715–731, doi:10.1175/2009JAMC2318.1, 2010. 11681
- Shin, K.-S. and North, G. R.: Sampling error study for rainfall estimate by satellite using a stochastic model, *J. Appl. Meteorol. Climatol.*, 27, 1218–1231, 1988. 11679
- Steiner, M., Bell, T. L., Zhang, Y., and Wood, E. F.: Comparison of two methods for estimating the sampling-related uncertainty of satellite rainfall averages based on a large radar dataset, *J. Climate*, 16, 3759, doi:10.1175/1520-0442(2003)016<3759:COTMFE>2.0.CO;2, 2003. 11679, 11680
- Turk, F., Sohn, B.-J., Oh, H.-J., Ebert, E., Levizzani, V., and Smith, E.: Validating a rapid-update satellite precipitation analysis across telescoping space and time scales, *Meteorol. Atmos. Phys.*, 105, 99–108, doi:10.1007/s00703-009-0037-4, 2009. 11679
- Vallado, D. A., Crawford, P., Hujsak, R., and Kelso, T.: Revisiting spacetrack report #3, in: *AIAA/AAS Astrodynamics Specialist Conference*, AIAA, Keystone, CO, USA, 92 pp., 2006. 11685
- Wolff, D. B. and Fisher, B. L.: Assessing the relative performance of microwave-based satellite rain-rate retrievals using TRMM ground validation data, *J. Appl. Meteorol. Clim.*, 48, 1069–1099, doi:10.1175/2008JAMC2127.1, 2009. 11679

11693

Table 1. Microwave instrument characteristics.

Satellite	Instrument	Frequency range (GHz)	Swath width (km)
NOAA-15	AMSU-B	89–183	2343
NOAA-16	AMSU-B	89–183	2343
NOAA-17	AMSU-B	89–183	2343
NOAA-18	MHS	89–190	2343
NOAA-19	MHS	89–190	2343
MetOp-A	MHS	89–190	2343
DMSP F-14	SSM/I	19–85.5	1400
DMSP F-15	SSM/I	19–85.5	1400
DMSP F-16	SSM/I	19–85.5	1400
TRMM	TMI	10–85.5	760
Aqua	AMSRE	6.9–89	1445

11694

Table 2. Satellites constellations.

Constellation	NOAA	MetOp-A	DMSP	AQUA	TRMM	GEO
PMS	x	x				
PMI			x	x	x	
LEO	x	x	x	x	x	
GEO						x

11695

Table 3. Characteristics of the rain gauge networks.

Name	Localization	Area	Gauges	Observation period
Ouémé	9.0–10.0° N, 1.5–2.8° E	15 400 km ²	60	1998–2008
DWD	47.4–55.01° N, 6.09–14.94° E	357 021 km ²	156	2005–2007

11696

Table 4. Total sampling error, RMSE and bias values for Germany.

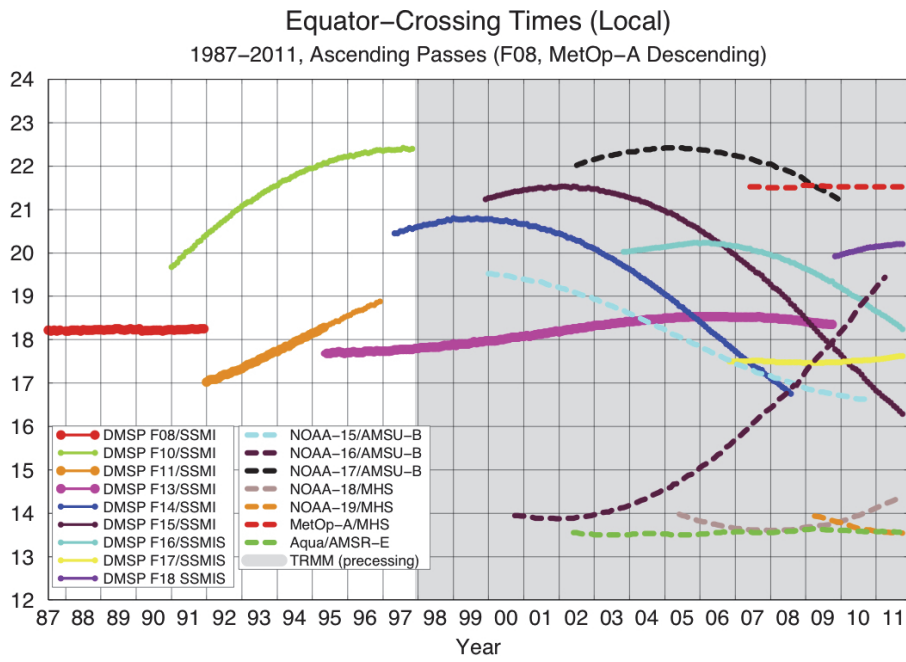
Aggregation time interval	Bias, mm	RMSE, mm	Sampling error, %
3 h	-0.13	0.68	231
1 day	-1.05	2.74	116
7 days	-7.35	11.43	69
15 days	-15.68	21.36	60
30 days	-31.18	38.81	55

11697

Table 5. Total sampling error, RMSE and bias values for Ouémé.

Aggregation time interval	Bias, mm	RMSE, mm	Sampling error, %
3 h	-0.22	1.97	386
1 day	-1.75	6.12	150
7 days	-12.05	21.04	76
15 days	-25.26	38.44	66
30 days	-47.99	67.80	61

11698



Thickest lines denote GPCP calibrator.

Image by Eric Nelkin (SSAI), 27 October 2011, NASA/Goddard Space Flight Center, Greenbelt, MD.

Fig. 1. Equator crossing times of LEO satellites (Figure produced by Eric Nelkin, NASA/Goddard Space Flight Center, source: http://precip.gsfc.nasa.gov/times_allsat.jpg, included with the permission from the author).

11699

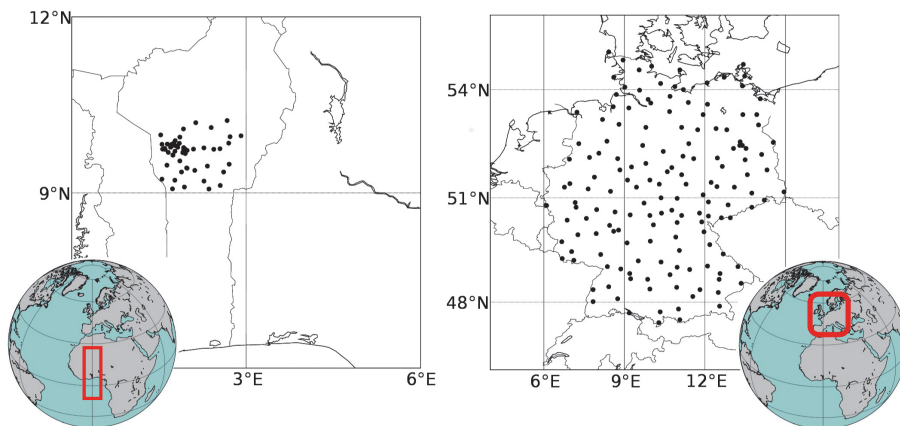


Fig. 2. AMMA–CATCH Ouémé (left panel) and DWD rain gauge networks.

11700

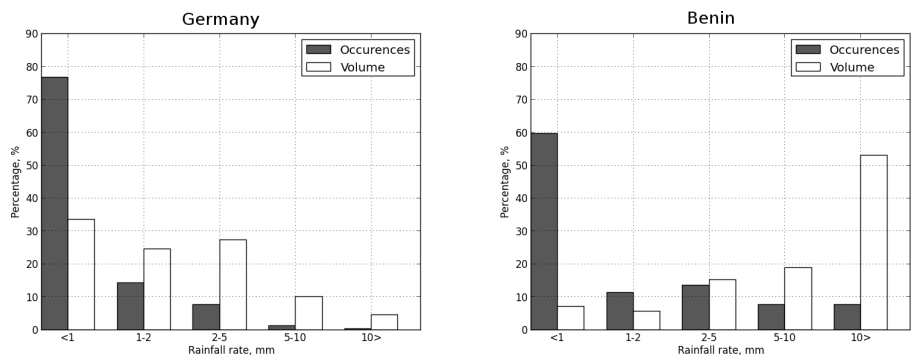


Fig. 3. Occurrences and volume of different intensity rainfall events as a fractional part of total event numbers and total rainfall volume in Germany (left panel) and Benin.

11701

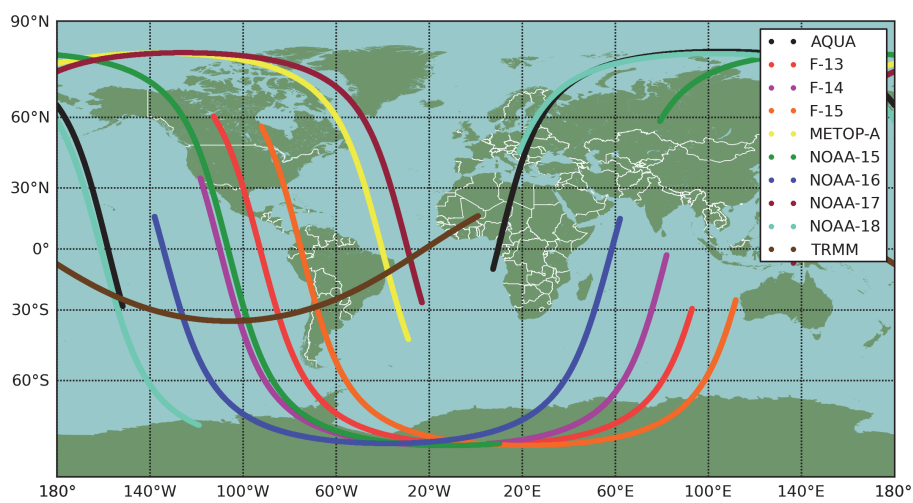


Fig. 4. Example of modelled satellite subtracks, 1 h coverage.

11702

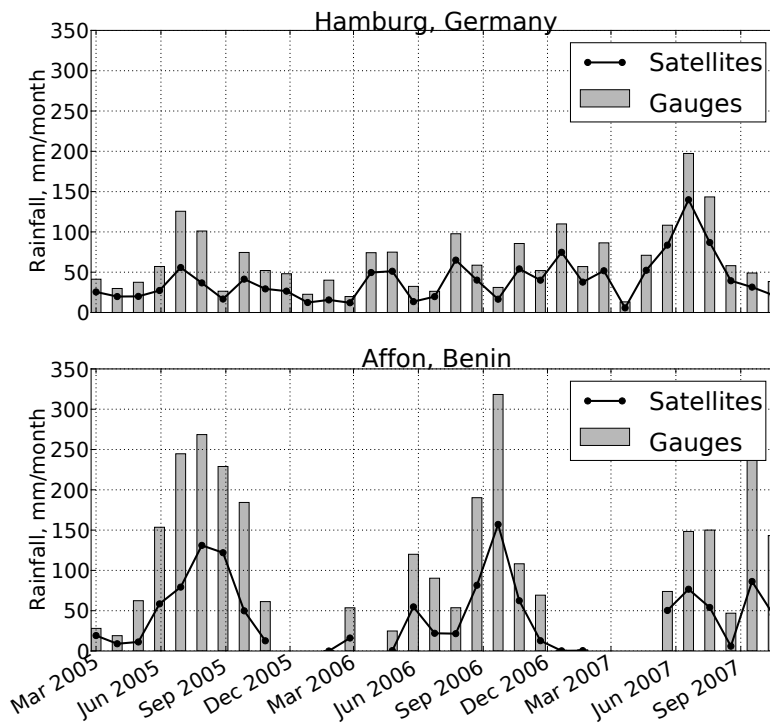


Fig. 5. An example of rain gauge and satellite monthly rainfall timeseries for Hamburg, Germany (upper panel), and Affon, Benin.

11703

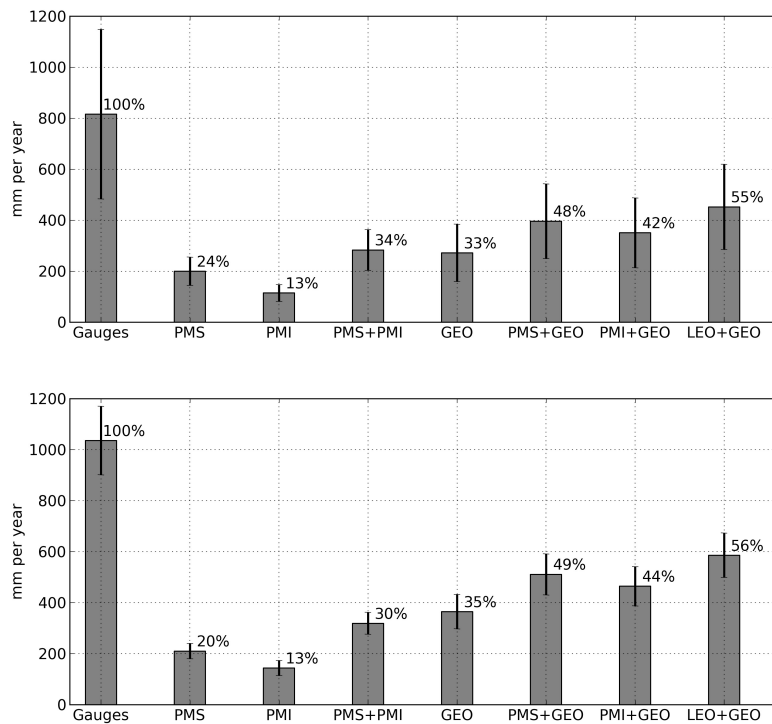


Fig. 6. Mean annual rainfall volume recorded by the rain gauges and simulated satellite observations in Germany (top panel) and Ouémé site, Benin. Thin vertical error bars indicate standard deviation.

11704

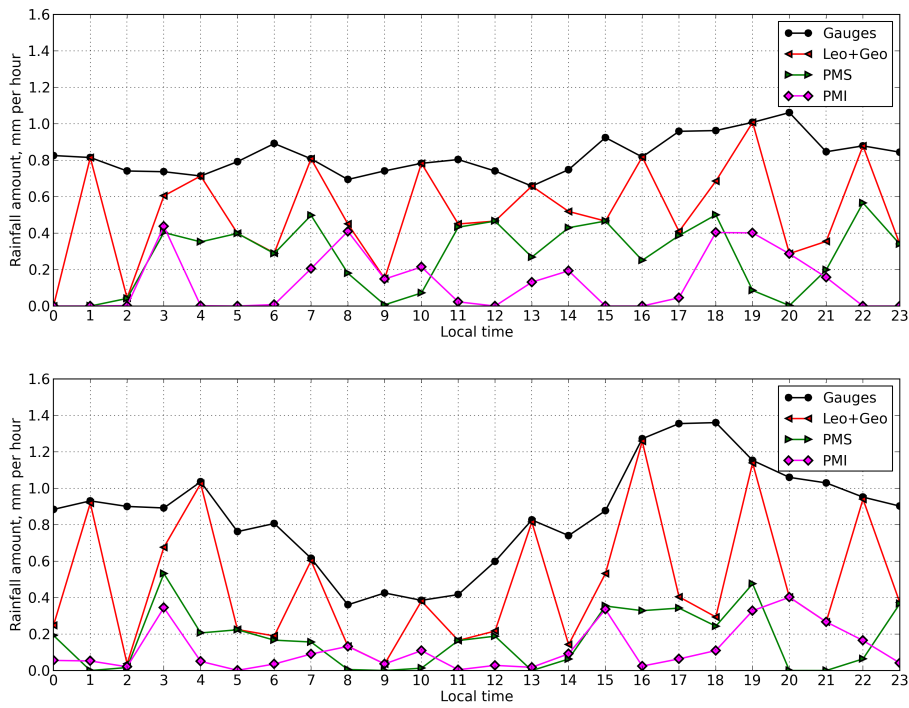


Fig. 7. Precipitation diurnal cycle (mean daily rainfall amount) observed by rain gauges and satellites over Germany (top panel) and Ouémé site, Benin, during the summer season (June–August) 2006.

11705

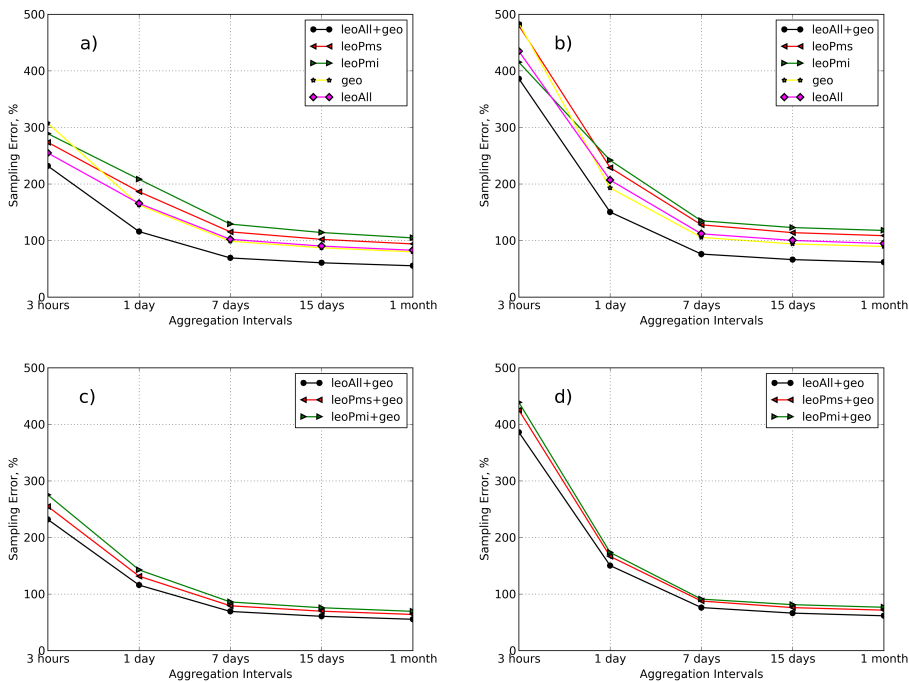


Fig. 8. Total sampling error for Germany (a, c) and Ouémé site (b, d). Upper panels show sampling error values for all major satellite constellations separately and for a combination of all satellites. Lower panels demonstrate the performance of imagers and sounders combined with geostationary observations against a combination of all satellites.

11706