

1 Abstract

2 Characterization of the error associated to satellite rainfall estimates is a necessary
 3 component of deterministic and probabilistic frameworks involving space-born passive and
 4 active microwave measurements for applications ranging from water budget studies to
 5 forecasting natural hazards related to extreme rainfall events. We focus here on the error
 6 structure of NASA's Tropical Rainfall Measurement Mission (TRMM) Precipitation Radar
 7 (PR) quantitative precipitation estimation (QPE) at ground. The problem is addressed by
 8 comparison of PR QPEs with reference values derived from ground-based measurements
 9 using NOAA/NSSL ground radar-based National Mosaic and QPE system (NMQ/Q2). A
 10 preliminary investigation of this subject has been carried out at the PR estimation scale
 11 (instantaneous and 5 km) using a three-month data sample in the southern part of US. The
 12 primary contribution of this study is the presentation of the detailed steps required to derive
 13 a trustworthy reference rainfall dataset from Q2 at the PR pixel resolution. It relies on a bias
 14 correction and a radar quality index, both of which provide a basis to filter out the less
 15 trustworthy Q2 values. Several aspects of PR errors are revealed and quantified including
 16 sensitivity to the processing steps with the reference rainfall, comparisons of rainfall
 17 detectability and rainfall rate distributions, spatial representativeness of error, and separation
 18 of systematic biases and random errors. The methodology and framework developed herein
 19 applies more generally to rainfall rate estimates from other sensors onboard low-earth
 20 orbiting satellites such as microwave imagers and dual-wavelength radars such as with the
 21 Global Precipitation Measurement (GPM) mission.

22
 23 Key words: satellite-based rain estimation, radar, QPE, conditional bias, random error
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 2 **Toward a Framework for Systematic Error Modeling of NASA Spaceborne Radar**
 3 **with NOAA/NSSL Ground Radar-based National Mosaic QPE**

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1 Fisher 2008). It impacts rain estimates from polar-orbiting passive microwave measurements
2 and a number of satellite-based high-resolution precipitation products (Ebert *et al.* 2007;
3 Bergès *et al.* 2009; Ushio *et al.* 2006). Given the variety of potential sources of error in PR-
4 based QPE and the impact of correction algorithms, the only practical solution is to evaluate
5 PR QPE with respect to an external, independent reference rainfall data set. The reference is
6 derived from high-resolution ground validation measurements using NOAA/NSSL ground
7 radar-based National Mosaic and QPE system (NMQ; Zhang *et al.* 2011). These products
8 yield instantaneous rainfall rate products over vast regions including regions of the
9 conterminous US covered by NEXRAD data. While a number of studies have investigated
10 the quality of PR estimates in various regions of the world (e.g., Adeyama and Nakamura
11 2003; Wolff and Fisher 2008; 2009; Amitai *et al.* 2009; 2011), our aim is to perform a
12 systematic and comprehensive evaluation for regions over the southern conterminous US
13 (CONUS).

14 We will characterize errors in PR estimates at the pixel measurement scale in order to
15 minimize additional uncertainties caused by resampling. Systematic and stochastic errors of
16 PR estimates will be documented in terms of bias and spatial structure. One should note that
17 it is not possible to “validate” the PR estimates in a strict sense because independent rainfall
18 estimates with no uncertainty do not exist. Rainfall estimates from low-earth orbiting
19 satellites suffer from their poor temporal sampling (Wolff and Fisher 2008; 2009; Lin and
20 Hou 2008). Hence representative samples of direct comparisons between instantaneous
21 coincident measurements from ground and space are difficult to achieve without a sufficient
22 number of overpasses. This study uses three months (March-May 2011) of satellite
23 overpasses over the lower CONUS. The data are pixel-matched in both time and space, and
24 statistics are provided for comparing reference rain intensities to satellite-based estimates.

1 2 1. Introduction

3 Reliable quantitative information on the spatial distribution of rainfall is essential for
4 hydrologic and climatic applications, which range from real-time flood forecasting to
5 evaluation of regional and global atmospheric model simulations. Given their quasi-global
6 coverage, satellite-based quantitative rainfall estimates are becoming widely used for such
7 purposes. Converting satellite measurements into quantitative precipitation estimates poses
8 challenges. The link between the observations and surface rain rates depends on the
9 calibration and operating protocol of the instrument itself, the spatial heterogeneity of the
10 rain fields (e.g., co-existence of convective and stratiform precipitation within a single
11 instrumental field-of-view and vertical heterogeneity of rainfall), the indirect nature of the
12 measurement, and the retrieval algorithm used. As underlined by the Program to Evaluate
13 High Resolution Precipitation Products (Turk *et al.* 2008) led by the International
14 Precipitation Working Group (IPWG; see <http://www.isac.cnr.it/~ipwg/>), characterizing the
15 error structure of satellite rainfall products is recognized as a major issue for the usefulness
16 of the estimates (Yang *et al.* 2006; Zeweldi and Gebremichael 2009; Sapiano and Arkin
17 2009; Wolff and Fisher 2009). The error characterization is needed for data assimilation and
18 climate analysis (Stephens and Kummerow 2007) and more specifically over land in
19 hydrological modelling of natural hazards and budgeting water resources (Grimes and Diop
20 2003; Lebel *et al.* 2009).

21 In this study, we focus primarily on the TRMM Precipitation Radar (PR) quantitative
22 precipitation estimation (QPE) at ground. The methodology presented herein would equally
23 apply to all satellite precipitation products, in particular those onboard low-earth orbiting
24 satellites. The TRMM-PR is currently the only active instrument measuring rainfall from a
25 satellite platform conjointly with a radiometer (TMI). PR rainfall estimates are often
26 considered as a reference for TMI-based rainfall estimates (e.g., Yang *et al.* 2006; Wolff and

1 where a_i denotes a satellite pixel and N is the number of pixels covering the domain of
 2 interest. The reference data $R_{ref}(\mathbf{A})$ used to evaluate the satellite estimates should spatially
 3 match the corresponding true rainfall averaged over the same area \mathbf{A} .

4
 5 *a) original ground-based products*

6 The NOAA/NSSL National Mosaic and Quantitative Precipitation Estimation system
 7 (NMQ/Q2) (<http://nmq.ou.edu>; Zhang et al. 2011) is a set of experimental radar products
 8 comprising high resolution (0.01°, 5 min) instantaneous rainfall rate mosaics available over
 9 the CONUS. The NMQ system combines information from all ground-based radars
 10 comprising the National Weather Service's Weather Surveillance Radar – 1988 Doppler
 11 (WSR-88D) network (NEXRAD) network, mosaics reflectivity data onto a common 3D
 12 grid, estimates surface rainfall accumulations and types to arrive at accurate ground-based
 13 estimates of rainfall (Zhang et al. 2005; Lakshmanan et al. 2007; Vasiloff et al. 2007;
 14 Kitzmiller et al. 2010). Figure 1 shows an example of the CONUS coverage of Q2 rainfall at
 15 0725 UTC on 11 April 2011 highlighting several rainy systems associated with orography in
 16 the West and a wide frontal system in the central part of the domain.

17 At hourly time step Q2 adjusts radar estimates with automated rain gauge networks
 18 using a spatially variable bias multiplicative factor. A radar quality index (RQI) is produced
 19 at the (0.01°, 5min) resolution. While the true quality of the Q2 QPEs varies in space and
 20 time due to a number of complicating factors (e.g., measurements errors, non-precipitation
 21 echoes, uncertainties in Z-R relationships, variability in the vertical profile of reflectivity),
 22 the RQI represents the radar QPE uncertainty associated with VPRs (Zhang et al. 2011). The
 23 RQI field is composed of a static part relative to the radar beam sampling characteristics
 24 such as percent blockage, beam height and width and a dynamic part accounting for the
 25 freezing level height. The static part is illustrated in Fig. 1, where the reduced radar coverage

1 The quasi-instantaneous matching is performed at the scale of the PR measurement scale
 2 (4.5 x 4.5 km).

3 The PR data and steps required to refine the Q2 ground-based rainfall to arrive at the
 4 reference rainfall used for comparisons are presented in section 2. Section 3 assesses the
 5 ability of PR rain retrievals to represent the rainfall variability derived from the reference
 6 data in terms of rainfall detectability, sensitivity, and spatial structure. Section 4 provides an
 7 empirical error model of the PR estimates versus reference rainfall and segregates systematic
 8 and random error. The paper is closed with concluding remarks in section 5.

9
 10 **2. Data sources**

11
 12 One of the first challenges encountered is the lack of knowledge about the true averaged
 13 rainfall for the spatial domains considered. One wants to compare instantaneous satellite
 14 rainfall estimates $R(\mathbf{A})$ with reference rainfall $R_{ref}(\mathbf{A})$ for a spatial domain \mathbf{A} (which may
 15 be a satellite mesh, watershed, etc.) to characterize the accuracy of the satellite QPEs. The
 16 true (and unknown) area-averaged rainfall accumulation, denoted $R_{true}(\mathbf{A})$ is written as:

$$17 \quad R_{true}(\mathbf{A}) = \frac{1}{A} \iint R(\underline{x}) d\underline{x} \quad (1)$$

18 where \underline{x} is the location vector. The reference rainfall $R_{ref}(\mathbf{A})$ is a proxy of $R_{true}(\mathbf{A})$. The
 19 final products of the satellite data processing are gridded rainfall fields. Satellite QPEs may
 20 then be written as:

$$21 \quad R(\mathbf{A}) = \frac{1}{N} \sum_{i=1}^N R(a_i) \quad (2)$$

1 difference of the temporal resolution between the hourly adjustment factors applied
 2 downscale to 5-min Q2 rainrates. Nevertheless, they provide the best possible reference at
 3 the scale of PR in terms of sampling conditions and unbiased estimates.

4
 5 *b) Q2-based reference rainfall*

6 In the current study, all significant rain fields observed coincidentally by TRMM
 7 overpasses and the NEXRAD radar network from March to May 2011 are collected. The Q2
 8 products closest in time to the TRMM satellite local overpass schedule time are used. To
 9 compute the reference rainfall, a block-Q2 rainfall pixel is computed to match each PR pixel
 10 in case of TRMM overpasses in a similar manner to Kirstetter *et al.* (2010, 2011).

11 Although the quantitative interpretation of the weather radar signal in terms of rainfall
 12 may be complex, radars enable a reliable evaluation of area-averaged rainfall estimates. The
 13 spatial variability of rainfall at small scales and the resolution difference between radar and
 14 PR footprint (as much as 2 orders of magnitude in area) may cause significant discrepancies
 15 in the statistical sampling properties and adds statistical noise in the comparison (see e.g.
 16 Ciach and Krajewski (1999) for a similar issue when comparing point-measurement
 17 raingauge to area-rainfall radar data). In order to estimate PR-pixel-averaged ground rainfall
 18 accumulation (and the associated sampling errors), a weighted mean estimator is considered
 19 to determine the reference rainfall $R_{ref}(A)$ over the PR footprint A from Q2 products. As
 20 the representativeness of the rainfall sampled by PR is related to the characteristics of the
 21 radar beam, the weighting function is given by the PR beam pattern inside a PR footprint.
 22 The reference rainfall is therefore:

23
$$R_{ref}(A) = \frac{1}{\sum_{i=1}^n \omega_i} \sum_{i=1}^n \omega_i Q2(a_i) \quad \text{with } \omega_i = \int_{\theta_{min}(a_i)} f^2(\theta, \theta_0) d\theta \quad (3)$$

1 in the western part of US results in lower RQI values. The dynamic part causes the RQI
 2 values to decrease in cool season months when the freezing level is lower and the radar
 3 samples the melting layer and the ice phase at closer range and to increase in the warm
 4 season when the freezing level is at higher altitudes. This is illustrated in Fig. 1 where the
 5 freezing level is lower behind a cold frontal system, which deteriorates the already limited
 6 coverage in the western part of the CONUS.

7 The original Q2 products utilized in this study are (i) the radar-only instantaneous rain-
 8 rate national mosaic updated every 5min, (ii) the radar-only rain-rate national mosaic at
 9 hourly time step, (iii) the hourly raingauge-corrected national mosaic product and (iv) the
 10 RQI. The primary Q2 product used for comparison with PR is the radar-only instantaneous
 11 rainrate mosaic. Current Q2 radar products do not include an instantaneous gauge-adjusted
 12 rainrate mosaic. For this study and similarly to Amitai *et al.* (2009; 2011), a second
 13 reference rainfall was derived from the bias-corrected Q2 product by using the hourly gauge-
 14 adjusted and the hourly radar-only products. Pixel-by-pixel hourly (multiplicative)
 15 adjustment factors are calculated and applied to the radar-only instantaneous product.
 16 Extreme adjustment factors (outside the [0,1-10] range) are discarded and no comparison is
 17 performed with PR for the corresponding Q2 values. Thus, the gauge-adjustment also serves
 18 as a data quality control procedure. A subsequent reference is derived from the bias-
 19 corrected Q2 product filtered using the RQI index. Only the rainrates associated with the
 20 best RQI values (i.e., equal to 1) were retained. This selection insures that only Q2 estimates
 21 presenting the best measurements conditions (i.e., no beam blockage and radar beam below
 22 the melting level of rainfall) are retained.

23 One should note these incremental improvements of the Q2 products may not screen out
 24 all possible errors in ground-based radar estimates. In particular, the gauge-adjustment may
 25 suffer from representativeness errors from scarce raingauge network density and from the

1 to the PR resolution preserves the statistical characteristics of the PR product including the
 2 total rainfall amount, the total rainy area, and the PDF shapes. All of these properties may
 3 therefore be compared to the reference at once.

4 Figure 1 shows an example of continuous mapping of the weighted mean estimator for
 5 the reference rainfall $R_{ref}(A)$. The estimator is a smoother of the original Q2 rain field. The
 6 maximum of the rainfall rate decreases from 145 mm h⁻¹ to 130 mm h⁻¹. The total rainfall
 7 area increases, mainly at the edges of the rainfield. In order to avoid a contamination of the
 8 PR-reference comparison by the uncertainty on the ground reference, the reference pixels
 9 were segregated into “robust” ($R_{ref} > \sigma_{footprint}$) and “non robust” ($R_{ref} < \sigma_{footprint}$)
 10 estimators. This procedure illustrated in Fig. 1 filters out the reference values at the edges of
 11 the rain fields. Non-robust reference values are discarded for quantitative comparison. The
 12 robustness check is applied to the three Q2 products considered for reference (native Q2,
 13 bias corrected Q2, RQI+bias corrected Q2). As an example for the “RQI+bias corrected Q2”
 14 the averaged relative error (σ_{ref}/R_{ref}) of the reference decreases from 832% to 16%. The
 15 ratio of the mean error to the standard deviation of the reference ($\sigma_{ref}/\sigma(R_{ref})$) decreases
 16 slightly from 5.6% to 5.4%. This method of reference selection therefore increases the
 17 reliability and representativeness of the block-Q2 values that constitute our ground
 18 reference.

19
 20 *c) Precipitation Radar (PR) based rainfall*

21 The PR measures reflectivity profiles at Ku band. Surface rain rates are estimated over
 22 the southern US up to a latitude of 37°N (Fig. 1). Artifacts such as contamination by surface
 23 backscatter, attenuation and extinction of the signal, brightband effects and accuracy of the
 24 Z-R relationship (Wolff and Fisher, 2008) must be accounted for. In the present study, the

1 where notations have been simplified for the sake of convenience. Q2 denotes the Q2 rain
 2 rate product for the mesh a_i . The value $R_{ref}(A)$ depends on the number n of Q2 meshes
 3 inside the PR footprint; the weights ω_i are derived from the two-way normalized power-gain
 4 function of the radar antenna f (assumed to be Gaussian) and the beamwidth θ_0 ; each ω_i is
 5 computed over the domain θ_{mesh} corresponding to the Q2 mesh a_i . It is assumed the PR
 6 footprint remains constant (circle of approximately 5km) whatever the radar beam off-nadir
 7 inclination angle. Additional research may be needed to take into account the deformation of
 8 the footprint with off-nadir angle (Takahashi et al, 2006).

9 Two weighted standard errors are computed with the reference rainfall. The first one is
 10 the weighted sample standard deviation, which represents the variability of the Q2 rainfall
 11 (at native resolution) inside the PR footprint:

$$12 \quad \sigma_{footprint} = \sqrt{\frac{V_1}{V_1^2 - V_2} \sum_{i=1}^n \omega_i (Q2(a_i) - R_{ref}(A))^2} \quad \text{with} \quad V_1 = \sum_{i=1}^n \omega_i \quad V_2 = \sum_{i=1}^n \omega_i^2 \quad (4)$$

13 It is used to select the PR-reference pairs for which the $R_{ref}(A)$ is trustworthy. The second
 14 one is the standard deviation relative to the weighted mean $R_{ref}(A)$:

$$15 \quad \sigma_{ref} = \sqrt{\frac{V_2}{V_1} \sum_{i=1}^n (Q2(a_i) - R_{ref}(A))^2} \quad (5)$$

16 It allows us to assess the $R_{ref}(A)$ estimation quality.

17 Matching PR and $R_{ref}(A)$ estimates only exist at locations where both the PR and
 18 ground radars have taken actual observations. This technique averages the minimum number
 19 of Q2 meshes needed to produce spatially coincident sample $R_{ref}(A)$ estimates. The
 20 advantages of the current technique over gridded approaches are that there is no
 21 interpolation, extrapolation, smoothing or oversampling of PR data. Bringing the Q2 product

1 deviation from the 1:1 degree line compared to the whole distribution. The reference
2 distributions are fairly stable given the different censoring levels with the mean of the PR-
3 resampled distributions being within 7% of the one for the whole dataset. We may therefore
4 consider each reference dataset to be quite representative of the corresponding whole rainfall
5 distribution.

6 Similarly we compared the different PR datasets to assess the impact of censoring on
7 their representativeness. Figure 4 shows quantile-quantile plots between (i) the complete
8 (“Native”) PR data set (x-axis) and (ii) the censored subsets according to the “Bias
9 corrected” and “Bias+RQI corrected” samples. Table 3 provides values of the conditional
10 mean and standard deviation for each set. The different PR rainfall distributions do not show
11 a clear deviation from the 1:1 degree line compared to the “Native” PR rainfall distribution.
12 The means and standard deviations of the “Bias corrected”-censored and “Bias+RQI
13 corrected”-censored distributions are less than 1% and around 10% higher respectively. We
14 may therefore consider the representativeness of each PR dataset, following censoring steps,
15 to be quite comparable to each other.

17 3. Rainfall data analysis

19 This section reviews the ability of PR rain retrievals to represent the rainfall variability
20 derived from the Q2 data. First, contingency tables provide information on the reference
21 rainfall reliability and on the influence of PR sensitivity to detect rainfall occurrence. The
22 PDF of rainfall estimates provide in-depth information on the sensor’s global ability to
23 capture rain regimes given the influence of its sensitivity and the attenuation of the radar
24 signal. Another feature to compare is the spatial structure of rainfall fields.

1 surface rain rate at each PR footprint location is a standard TRMM product (2A25 v6)
2 described in Iguchi *et al.* (2000). The scan geometry and sampling rate of the PR lead to
3 footprints spaced approximately 4.3 km cross and along-track (5.1 after TRMM boost), over
4 a 215-km-wide swath. The minimum theoretical detectable rain rate by the PR is fixed by its
5 sensitivity and is about 17 dBZ, or $\sim 0.5 \text{ mm h}^{-1}$.

7 d) Comparison samples

8 Several factors including rainfall intermittency, discrete temporal sampling of TRMM
9 and censoring of reference values for required quality reduce the number of comparison
10 samples for reference and PR estimates over the comparison period. Table 1 provides the
11 number of these samples for the reference values, inclusive and exclusive of non-rainy
12 pixels. The comparison sample sizes in Table 1 are primarily driven by the number of rain
13 events and the overpass frequency of TRMM, then by the censoring of reference values. The
14 quality control in the bias adjustment discarded 26% of original Q2 values and an additional
15 34% were filtered using RQI. Note that after two levels of processing and censoring, the
16 comparison sample size for the “RQI+bias corrected Q2” remains significant at 393 347.
17 This is credited to the large number of samples offered by the high-resolution, gridded Q2
18 product.

19 To assess the representativeness of our spatially and temporally limited samples, we
20 compared the statistics of the reference rainfall resampled to the PR-pixel resolution with
21 respect to the whole reference dataset (CONUS-wide below 38°N which don't necessary
22 match a TRMM overpass). Figure 3 shows quantile-quantile plots between (i) the whole
23 reference data set (x-axis) and (ii) the subset of pixels that matched to PR-pixel resolution
24 for the different reference datasets. Table 2 provides values of the conditional mean and
25 standard deviation. The PR-resampled reference rainfall distribution does not show a clear

1 volume. Note the lowest values (less than 8%) are obtained with the “Bias+RQI corrected
2 Q2” reference.

3 The impact of the reference rainfall on the contingency scores is shown in Figure 5.
4 Contingency values are used to compute probability of detection (POD), false alarm rates
5 (FAR), and critical success index (CSI). Scores are generally better for the robust reference
6 than for the non-robust one. Within this category CSI shows a general increase with
7 sequential Q2 data quality steps, while the FAR shows the lowest values with additional
8 processing of the Q2 reference. A general convergence between the Q2 reference and PR
9 estimates is therefore acknowledged as a function of the reference accuracy.

10 Considering that 80% of the reference rain rates that are not detected by the PR are lower
11 than 0.3 mm.h^{-1} , the sensitivity of PR is close to this value. The misses are probably
12 associated with high intermittency and/or the “rain/no rain” limits of rain fields. These
13 features are missed by the PR because the rainrates are close to the detection threshold. This
14 suggests that the PR can indeed capture the main rain regions but loses the weaker echoes
15 (Schumacher and Houze 2000), probably due to its sensitivity.

17 *b) Probability distributions by occurrence and rain volume*

18 Hereafter, the PR rain estimates are the conditional ones (positive rainfall) coincident
19 and collocated with nonzero reference estimates. Two PDFs for PR versus reference rainfall
20 are computed and shown in Fig. 6: (i) the PDF by occurrence (PDF_c) and (ii) the PDF by
21 rain volume (PDF_v) (Wolff and Fisher, 2009; Amitai *et al.*, 2009-2011). The PDF_c provides
22 statistical information on the rain rate distribution and highlights the estimate’s sensitivity as
23 a function of rainrate; it is computed as a ratio between the number of the rainrates inside
24 each bin and the total number of rainrates. The PDF_v represents the relative contribution of
25 each rainrate bin to the total rainfall volume; it is computed as a ratio between the sum of the

1 *a) Contingency tables*

2 Table 4 shows the contingency tables for PR rain/no rain occurrence relative to the
3 references with percentile of hits (H; both Q2 and PR detect rain), misses (M; PR does not
4 detect rain while Q2 does), false alarms (F; PR detects rain while Q2 does not), and correct
5 rejections (C; both Q2 and PR do not detect rain). The reference data are separated into three
6 sub-samples: the non-robust set ($R_{ref} < \sigma_{\text{footprint}}$, see section 2b), the robust set ($R_{ref} >$
7 $\sigma_{\text{footprint}}$) and the “whole” Q2 set. Reference null values are considered as robust. All
8 coincident and collocated PR values are considered and sorted according to the reference
9 samples. Table 5 provides the mean rainfall values according to the same contingency tables
10 with PR on the left hand side of the “/” sign and the reference on the right hand side.

11 The false detections (M + F) of PR are mainly associated with the non-robust reference
12 data; more than 80% for all “non-robust sets”, while around 50% are improperly classified
13 when using the “valid” reference data set. The Misses (M) are the main contributors to the
14 false detection population (i.e., approximately 85% for the “whole” data set). These Misses
15 of PR are coincident with low reference values (less than 0.15 mm h^{-1} for the non-robust set
16 for all references; see Table 5). By comparison, the correct detections (H + C) of PR are
17 mainly associated with the robust reference set from 45% to 52%. For the same robust
18 reference sets, the Hits of PR are coincident with the higher reference values with mean
19 rainfall rates more than 6 mm h^{-1} . One should note for all references that (i) the mean PR (F)
20 values are significantly lower than the PR (H) values, and (ii) the mean reference (M) values
21 are significantly lower than the mean reference (H) values. Finally both mean reference and
22 PR values are higher for the robust Q2 set than for the non-robust Q2 set. Table 6 shows the
23 discarded rain volumes in question; the Misses of PR represent less than 12% of the
24 reference rainfall volume, while False Alarms represent less than 16% of the PR rainfall

1 simple function, we use a normalized variogram, which represents the spatial correlation of
 2 the rain field (Journel and Huijbregts 1978; Lebel *et al.* 1987; Kirstetter *et al.* 2010; 2011).
 3 An appropriate model is fit to the empirical normalized variogram. Among the set of
 4 classical models, the exponential model was found most suitable. It is expressed as:

$$\gamma(h) = C_0 + (C - C_0) \left(1 - \exp\left(-\frac{h}{d}\right) \right) \quad (6)$$

6 where the three parameters are the nugget (C_0), the sill (C) and the variogram range
 7 parameter (d). The exponential model reaches its sill asymptotically as $h \rightarrow \infty$. The
 8 "effective range" corresponds to the mean decorrelation distance of the estimates. It is the
 9 distance where the variogram reaches 95% of its maximum and corresponds to $3d$ for the
 10 exponential model. The nugget parameter can be used to describe a possible discontinuity of
 11 the variogram at the origin which may be due to (i) the process variability at scales poorly
 12 resolved by the observation system and/or (ii) measurement errors. In the following, these
 13 parameters are used to characterize the structure of rainfall.

14 Spatially normalized variograms of references and PR estimates are displayed in Fig. 7.
 15 Table 7 summarizes the parameters of these variograms. The variogram ranges of PR are
 16 quite similar to the three references' (approximately 18km). The nugget values, however, are
 17 more distinct. While it is $\sim 32\%$ for the Q2 references, it is significantly higher for PR
 18 (approximately 45% of the sill). These decorrelations of spatial structure at short
 19 interdistances suggest the resolution of the PR measurements may be limited when sampling
 20 the variability of small, disorganized rainfall structures associated with localized convection.
 21 The smaller reference nugget is an indication of the better sampling of the rain field by the
 22 reference rainfall, an issue previously discussed in section 2b. The comparatively higher
 23 nugget with PR may be caused by the rain intermittency, contamination by surface
 24 backscatter, attenuation of the signal, brightband effects or inaccuracy of the Z-R

1 rainrates inside each bin and the total sum of rainrates. It is therefore an important
 2 characteristic of the instantaneous products from the perspective of building merged rainfall
 3 accumulations; it enables a comparison of PDFs based on estimates derived from
 4 instruments characterized by different detection limits (in particular at weak intensities).

5 The rainrates of PR exhibit similar PDF_c for all references. Compared to references'
 6 PDF_c, PR tends to overestimate light rain rates ($\sim[0.3-0.5]$ mm h⁻¹). But, PR demonstrates
 7 poor detection of the lightest rain rates (below ~ 0.3 mm h⁻¹) compared to the two bias
 8 corrected references. This is coherent with the concept of rain area "edges" that might be
 9 only partially detected by PR, resulting in misses associated with low rain rates (see previous
 10 section). PR PDF_c presents similar features with references for rain rates $> \sim 1$ mm h⁻¹. One
 11 may note the improved convergence between PR and reference rainfall PDF_c in the rain rates
 12 interval $[0.5-1.0]$ mm h⁻¹ with the sequential Q2 data quality steps.

13 Despite the low occurrence of relatively high rain rates (> 10 mm.h⁻¹), their contribution
 14 to the total rainfall volume is significant (greater than 60 %). As a consequence, the mode of
 15 PDF_v for PR is shifted toward lower rainrates (~ 18 mm h⁻¹) compared to the reference's
 16 mode (~ 60 mm h⁻¹), in agreement with the results found in Amitai *et al.* (2006, 2009). This
 17 is attributed to high rainfall rates (> 10 mm.h⁻¹), which are evidently underestimated by PR
 18 because insufficient correction due to attenuation losses as suggested by Wolff and Fisher
 19 (2008) for the 2A25 version 6.

20

21 c) Space structure of estimated rainfall fields

22 For hydrological applications, the total amount of water over a basin as well as the
 23 location and spatial correlation within the catchment might be important. It is therefore
 24 relevant to assess the ability of space-based estimates to retrieve the spatial structure of
 25 rainfall fields as seen by the reference. In order to describe the structure by a relatively

1 the radar). The gauge-based bias correction of the native Q2 product decreases the mean
2 reference values, so the negative bias of PR is apparently improved. The additional RQI
3 filtering removes the underestimation of Q2 at far range so the bias of PR is degraded. The
4 reference shows higher standard deviation than the PR in coherence with the PDF features
5 presented in section 3b.

6 The correlation coefficients between PR and Q2 reference estimates are moderate
7 (around 0.6). One could note the best correlation between the two sensors is achieved with
8 the “Bias+RQI corrected” reference. The differences between the two products on a point-
9 to-point comparison basis can be attributed to sample volume discrepancies, timing and
10 navigation mismatches and the uncertainties in the respective rainfall estimates. The
11 significantly greater nugget in the PR variogram than in the reference variogram is also an
12 indication of the greater level of noise in the PR rain field spatial structure, which may limit
13 the correlation between the two series on a point-to-point comparison.

15 *b) error model*

16 The departures of PR estimates from the references are analyzed in this section on a
17 point-to-point basis. The uncertainties associated with satellite estimates of rainfall include
18 systematic errors as well as random effects from several sources (Yang *et al.*, 2006;
19 Kirstetter *et al.*, 2011). There is a fundamental issue in segregating the proportion of the
20 scatter due to purely random error and the proportion due to conditional biases of the PR
21 estimates that may be either positive or negative, producing additional scatter.

22 With the true rainfall being unknown, the residuals are defined as the difference
23 $\epsilon = (R - R_{ref})$ between the reference rainfall (R_{ref}) and the satellite estimates (R). Only
24 pairs for which R_{ref} and R are both nonzero are considered in the calculations in order to
25 emphasize the PR ability to quantify precipitation where it is raining. The sets of ϵ

1 relationship. An interesting feature is that both sensors present a slightly decreasing nugget
2 with the sequential Q2 data quality steps. This feature could be attributed to the censoring of
3 the reference, which filters out complicated sampling situations for the ground-based radars.

5 **4. Quantitative error modelling**

7 *a) Correlations and biases*

8 Scatterplots of PR versus reference rainfall are presented for the three sets of Q2
9 reference in Fig. 8. Classical performance criteria of satellite-based rainfall estimation
10 compared to reference values are listed in Table 8: correlation coefficient and mean relative
11 error (MRE), expressed in percentage and defined as $MRE = (PR_mean -$
12 $Ref_mean)/Ref_mean$. The comparisons between the PR and reference estimates are
13 assessed on a point-to-point basis. A rainy pixel is included in the statistics if both PR and
14 the reference are nonzero to emphasize the PR ability to quantify precipitation when it is
15 raining. This is particularly significant given the significant misses of PR.

16 The two sensors present coherent mean and standard deviation values as long as the
17 representativeness of the comparison samples are kept in mind. As expected, the means of
18 the three PR sets are quite similar. In all cases the PR underestimates the reference mean
19 values by ~17%. This is once again attributed to the significant underestimation of the higher
20 rainrates in the 2A25-v6 products, presumably due to attenuation losses. The variations of
21 the reference mean for the three sets explain in large part the variations in the apparent bias
22 of PR relative to the reference. The native reference set is affected by (i) a global
23 overestimation of rain rates, which could be due to the inaccuracy of the Z-R relationship
24 and (ii) an underestimation of rain rates linked to partial beam blockage and vertical profile
25 of reflectivity effects (i.e., overshooting above the melting layer by the radar beam far from

Several two-parameter density functions (log normal, normal, reverse gumbel, logistic, gamma, etc.) have been tested to fit the data. The distributions of residuals (not shown here) were generally found to be unimodal and asymmetric. The goodness-of-fit on the whole dataset has been checked by investigating the Akaike information criteria (AIC) for the each semi-parametric density fits. The reverse Gumbel distribution $(f(\varepsilon) \frac{1}{\sigma} \left[1 - \left(\frac{\varepsilon - \mu}{\sigma} \right) - \exp \left\{ - \left(\frac{\varepsilon - \mu}{\sigma} \right) \right\} \right])$, where μ is the mean and σ the standard deviation of the residual population) was found to be the most appropriate. Figure 9 shows the residuals as a function of R_{ref} as well as the fitted GAM model for PR in the representative case of the "Bias+RQI corrected" reference. The conditional PDF of residuals ε present a high conditional shift versus the 0 line and a high conditional spread. Note that for $R_{ref} > \sim 50 \text{ mm.h}^{-1}$, the model is quite undetermined because of the lack of observed residuals. All models show that PR present a tendency to overestimate light rain rates (the median of residuals is positive) and underestimate higher rain rates (negative median of residuals): e.g. PR underestimates $R_{ref} = 20 \text{ mm.h}^{-1}$ rain rates with an occurrence of 70% and with a representative bias of -7 mm.h^{-1} and underestimates $R_{ref} = 40 \text{ mm.h}^{-1}$ with an occurrence of 92% and with a representative bias of -24 mm.h^{-1} . This is likely to be once again due to the insufficient correction of PR attenuation for heavier rain rates.

In case of a non-symmetric density for residuals or in case of extreme values, the median is preferred to the expectation for a better representativeness of the systematic component of the residuals. The systematic error component (i.e. conditional bias) is therefore described by the conditional median of these distributions. For the same reason we consider the interquartile (q90-q10) value to assess the random part of the error. It is computed after having applied the error separation variance correction to the conditional standard deviation

distributions are studied using the generalized additive models for location, scale and shape (GAMLSS, Rigby and Stasinopoulos 2005) technique. As a preliminary step, R_{ref} is considered as the main driving (explanatory) variable conditioning the departures of PR estimates from references.

Generalized linear models for location, scale and shape aim at modeling the parameters of a response variable's distribution. Two main assumptions are made: (1) the response variable ε is a random variable following a known parametric distribution with density $f(\varepsilon | \mu, \sigma)$ conditional on the parameters (μ, σ) ; (2) the observations ε are mutually independent given the parameter vectors (μ, σ) . Each parameter is modeled as a function of R_{ref} (the explanatory variable) using monotonic (linear/non-linear or smooth) link functions. More details are provided by Rigby and Stasinopoulos (2001, 2005), Akantziliotou, Rigby, and Stasinopoulos (2002) and Stasinopoulos and Rigby (2007). A wide variety of distributional forms are available, but for the sake of simplicity and to distinguish between systematic and random errors, a number of conditional densities with the first two moments (the location μ - mean, to be linked on to systematic errors - and the scale σ - standard deviation representative of random errors) as parameters are considered here. For a given conditional distribution of the response variable, the conditional quantiles can be expressed as a function of the location and scale. GAMLSS is best fitted using the package gamlss in R (Stasinopoulos and Rigby 2007). The rainfall trends for each parameter are fitted using locally weighted scatterplot smoothing (loess), which are more flexible than polynomials or fractional polynomials for modelling complex nonlinear relationships. It is a polynomial curve determined by R_{ref} , which is fitted locally by weighted polynomial regression, giving more weight to points near the point whose response is being estimated and less weight to points further away (see Cleveland, Grosse, and Shyu 1993).

1 conditional bias is less significant), which could be seen as a sign of a better convergence
 2 between PR estimates and this Q2 reference. This is confirmed when considering the random
 3 part of error. The “Bias+RQI corrected” curve shows the lowest random errors up to $R_{ref} =$
 4 4 mm h^{-1} (more than 65% of the reference rain rates are under this value). The random error
 5 increases consistently with R_{ref} . It is systematically higher for the “Bias corrected” than for
 6 the “Native” reference, a result consistent when applying a bias correction (Ciach *et al.*
 7 2000). It represents a significant part of error, suggesting that other factors than R_{ref} could
 8 be considered to evaluate the error of PR rain rate estimates at ground.

10 5. Conclusions

11
 12 In preparation for NASA’s future Global Precipitation Measurement (GPM) mission, a
 13 three-month data sample of TRMM-PR-based rainfall products have been compared to
 14 surface rainfall derived from Q2 over the lower conterminous US. The major advantage of
 15 the Q2 ground-based reference dataset is its resolution in both time and space commensurate
 16 with rainfall estimates derived from sensors onboard low-earth-orbiting satellites. The
 17 comparisons have been performed at the PR-pixel resolution. A framework is proposed
 18 herein to address methodological issues so as to provide a preliminary version of an error
 19 model for satellite QPEs. The error model is empirically derived and is thus prone to be
 20 specific to the dataset considered and the PR/Q2 data processing implemented. However, the
 21 results show similarities with previous rainfall comparisons over West Africa (Benin and
 22 Niger) and thus give credence to the developed framework (Kirstetter *et al.* 2011). Results
 23 from the error model presented herein provide insights into the most significant

1 σ extracted from the GAM model. The error separation variance concept (Ciach and
 2 Krajewski, 1999; Teo and Grimes, 2007; Kirstetter *et al.* 2010) makes it possible to evaluate
 3 the variance of the PR with respect to the true unknown rainfall. We assume the errors on the
 4 reference rainfall and on the PR estimates to be uncorrelated. Introducing the true rainfall
 5 R_{true} in the expression of the variance of the residuals between the PR and reference values
 6 leads to (see Kirstetter *et al.* 2010 for details):

$$7 \quad \sigma(R^* - R_{true}) = \sqrt{\text{var}(\epsilon) - \sigma_{ref}^2} \quad (7)$$

8 Fortunately as can be seen in Figure 10, the reference estimation standard deviations are
 9 lower than the standard deviations of the PR-reference residuals, indicating the reference
 10 values to be comparatively reliable to evaluate PR. The standard deviation of the PR
 11 residuals with respect to the true rainfall is significantly reduced compared with the PR-
 12 reference residual standard deviation. One may note the standard deviations increase up to a
 13 reference value ($\sim 50 \text{ mm.h}^{-1}$) beyond which we believe sampling issues lead to a
 14 stabilisation or a decrease of the standard deviations. We therefore apply the modelling up to
 15 this limit only. As $\sim 98\%$ of the reference values are under his limit, this choice won’t lead to
 16 any significant lack of representativeness.

17 Figure 10 shows the conditional biases and random errors of PR relative to the three Q2
 18 references. The global bias (see previous section and Table 8) of PR results from a balance
 19 between overestimation of light rainrates and underestimation of high rainrates. The
 20 underestimation is more frequent, inducing a global negative bias. The conditional biases of
 21 PR relative to the references are quite similar. Note the “Bias corrected” conditional bias is
 22 shifted to the right compared to the “Native” one, so overestimation of light rainrates is more
 23 significant and the underestimation of higher rainrates less pronounced, consistently with the
 24 reduced negative global bias for this specific reference (see Table 8). Note also the negative
 25 slope of the “Bias+RQI corrected” conditional bias is lower than for the two other (the

1 other sensors onboard low-earth-orbiting satellites (i.e., TMI, AMSR-E, SSMI, MADRAS).
2 This framework will also be applied to GPM rainfall estimates following its launch in 2013.
3 Another important issue to study is how the various error sources in PR, which is often used
4 as a calibrator, propagate when merging with geostationary infrared data for a number of
5 satellite-based, high-resolution precipitation products.

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1 characteristics of PR rainfall retrieval errors that need to be taken into account when such
2 data are used in applications.

3 A consistent result noted throughout each analysis was the increased consistency
4 between PR and the Q2 reference following sequential data quality control steps including
5 bias correction using rain gauges and filtering using the radar quality index (RQI) product.
6 This finding, alone, highlights the importance of matching the scales and refining the
7 accuracy of the reference dataset as much as possible before reaching meaningful
8 conclusions about the PR accuracy.

9 Different error sources were identified and quantified for PR rainrate estimates. The
10 most significant error is most likely due to the attenuation of the PR radar signal. It is not yet
11 known if this error is due to inadequate correction for attenuation losses or complete loss of
12 the signal. Segregating rain from no-rain boundaries is also a driving contributor to the PR
13 rainrate errors, probably linked to the lack of sensitivity in the most inhomogeneous and
14 light parts of the edges of rainy regions. Nevertheless, the variogram analysis showed that
15 the PR adequately represents the spatial structure of the rain fields. The scatterplots revealed
16 PR-estimated rainrates are only moderately correlated (Pearson correlation coefficient of
17 0.6) to the best reference rainfall on a point-to-point basis.

18 The statistical model developed here quantifies the relation between instantaneous PR
19 rainfall and the corresponding reference rainfall. It consists of a deterministic additive
20 function and a random uncertainty component, both conditioned on given reference values.
21 The contribution of systematic PR errors is confirmed to be quite large due to the
22 aforementioned signal attenuation issue.

23 In terms of perspectives, the relative contributions of errors linked to rainfall type and
24 off-nadir angle need to be evaluated, as well as influence of the underlying terrain. The same
25 framework and reference rainfall datasets can be readily applied to rainfall retrievals from

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2 **Table captions**
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4 Table 1. Comparison samples for different reference datasets.
5 Table 2. Conditional mean and standard deviation of “whole” and “PR-resampled”
6 references datasets.
7 Table 3. Conditional mean and standard deviation of PR estimates for different references.
8 Table 4. Contingency table for PR relative to the three references. The results are provided
9 for robust / non robust reference data according to a criterion based on the variability of the
10 Q2 rainfall (at native resolution) inside the PR footprint ($R_{ref} > \sigma_{footprint}$).
11 Table 5. Mean rainfall values associated to the contingency table for PR / references.
12 Table 6. Discarded rain volumes from PR due to misses relative to references and rain
13 volume implied in the false alarms relative to robust references.
14 Table 7. Parameters of the normalized variograms (exponential model) for references and
15 PR. The “effective range” values are indicated. The nugget is expressed as a percentage of
16 the normalised sill.
17 Table 8. Performance criteria values for PR estimates: mean, standard deviation, mean
18 relative error (MRE) and correlation (R) with respect to references. Only the reliable Q2 data
19 are kept (see section 2.b) for references.
20

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1 Figure 8: Scattergraphs of PR versus native (a), bias corrected (b) and Bias+RQI
2 corrected(c) reference rainfall (mm h^{-1}). The first bisectors (solid lines) are displayed.
3 Figure 9: PR residuals represented versus “Bias+RQI corrected” reference (left) and the
4 GAM model fitted is represented by [5, 10, 20, 30, 40, 50, 60, 70, 80, 90, 95] conditional
5 quantile lines (right).
6 Figure 10: Standard deviation of PR-reference residuals (dashed line), estimated standard
7 deviation of the reference rainfall (dotted line) and standard deviation of PR-true rainfall
8 residuals (solid line) as functions of the “Bias+RQI corrected” reference. The vertical line
9 (50 mm.h^{-1}) indicates the limit of the good sampling conditions.
10 Figure 11: Conditional bias (median) of residuals (left) and conditional random error
11 (interquantile 90%-10%) of residuals (right) for PR as a function of “Native” (dotted line),
12 “Bias corrected” (dotted line) and “Bias+RQI corrected” references.

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2 **Figure captions**

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4 Figure 1: Map of CONUS area with NMQ/Q2 instantaneous rainrates at 0725 UTC on 07
5 April 2011. The red area shows the good quality radar coverage corresponding to Radar
6 Quality Index equal to 1. The shaded area is not sampled by the TRMM-PR.

7 Figure 2: Maps of instantaneous rainrates at 0725 UTC on 07 April 2011: the NMQ-Q2
8 product (top left), the equivalent reference rainfall R_{ref} (top right), the “robust” reference set
9 (bottom left) and the “non robust” reference set (bottom right).

10 Figure 3: Quantile-quantile plots for reference “PR-sampled” and “Whole” rainfall
11 distribution comparison, for native (a), bias corrected (b) and Bias+RQI corrected (c)
12 references. The positions of 10, 50 and 95 percentiles are showed for each distribution.

13 Figure 4: Quantile-quantile plots for reference “PR-sampled” and “Whole” rainfall
14 distribution comparison, for native (a), bias corrected (b) and Bias+RQI corrected (c)
15 references. The positions of 10, 50 and 95 percentiles are showed for each distribution.

16 Figure 5: Critical success index (CSI), probability of detection (POD) and false alarm rates
17 (FAR), and for the three references and partitioned as a function of robustness.

18 Figure 6: Probability distributions of rain rates the PR rainfall and for the native (a), bias
19 corrected (b) and Bias+RQI corrected (c) reference rainfall. The solid and dashed-dotted
20 lines represent the distribution by volume PDF, and the distribution by occurrence PDF_c
21 respectively, while the grey and black lines represent the distributions for references and PR
22 respectively. Note that the x-axis is in log-scale.

23 Figure 7: Spatial variograms for reference (left) and PR (right) for the native (top), bias
24 corrected (middle) and Bias+RQI corrected (bottom) reference. The empirical variograms
25 are plotted with crosses, and the models fitted are represented by the thick black lines.

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TABLE 4. Contingency table for PR relative to the three references. The results are provided for robust / non robust reference data according to a criterion based on the variability of the Q2 rainfall (at native resolution) inside the PR footprint ($R_{ref} > \sigma_{\text{footprint}}$).

PR Estimates		Native Q2		
		> 0.	= 0.	Σ estimates
> 0.	whole set	26 %	6 %	320715
	robust	45 %	15 %	251175
	non robust	12 %	0 %	69540
=0.	whole set	67 %	0. %	664220
	robust	40 %	0. %	167986
	non robust	88 %	0. %	496234
Σ reference	whole set	921758	63177	984935
	robust	355984	63177	419161
	non robust	545774	0	565774

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TABLE 1. Comparison samples for different reference datasets.

	Including non-rainy (0 mm h ⁻¹)	Rainy only
Native Q2	35 349 900	984 598
Bias corrected Q2	35 342 653	723 495
Bias+RQI corrected Q2	35 342 653	393 347

TABLE 2. Conditional mean and standard deviation of “whole” and “PR-resampled” references datasets.

	PR resampled dataset		Whole reference data set	
	Mean	St. dev.	Mean	St. dev.
Native Q2	1.64	6.55	1.57	6.30
Bias corrected Q2	2.00	6.99	1.95	6.84
Bias + RQI correctd Q2	1.98	7.26	2.13	7.37

TABLE 3. Conditional mean and standard deviation of PR estimates for different references.

	Mean	Standard deviation
Native Q2	4.21	6.91
Bias corrected Q2	4.24	6.94
Bias+RQI corrected Q2	4.65	7.47

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2 TABLE 5. Mean rainfall values associated to the contingency table for PR / references.

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PR Estimates		Native Q2	
		> 0.	= 0.
> 0.	whole set	4.65 / 5.06	2.41 / 0.00
	robust	5.07 / 6.21	2.41 / 0.00
	non robust	3.51 / 1.97	-
=0.	whole set	0.00 / 0.31	-
	robust	0.00 / 0.92	-
	non robust	0.00 / 0.10	-

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PR Estimates		Bias corrected Q2	
		> 0.	= 0.
> 0.	whole set	4.83 / 4.71	2.28 / 0.00
	robust	5.38 / 6.07	2.28 / 0.00
	non robust	3.61 / 1.73	-
=0.	whole set	0.00 / 0.38	-
	robust	0.00 / 1.05	-
	non robust	0.00 / 0.14	-

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PR Estimates		Bias corrected Q2		
		> 0.	= 0.	Σ estimates
> 0.	whole set	34 %	10 %	316941
	robust	48 %	21 %	240223
	non robust	20 %	0 %	76260
=0.	whole set	56 %	0 %	406610
	robust	31 %	0 %	108218
	non robust	80 %	0 %	298392
Σ reference	whole set	650567	72984	723551
	robust	275915	72526	348441
	non robust	374652	0	374652

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PR Estimates		Bias+RQI corrected Q2		
		> 0.	= 0.	Σ estimates
> 0.	whole set	32 %	3 %	137978
	robust	52 %	7 %	94533
	non robust	18 %	0 %	43178
=0.	whole set	65 %	0 %	254921
	robust	41 %	0 %	64620
	non robust	81 %	0 %	190301
Σ reference	whole set	380087	12812	392899
	robust	146608	12545	159153
	non robust	233479	0	233479

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TABLE 7. Parameters of the normalized variograms (exponential model) for references and PR. The “effective range” values are indicated. The nugget is expressed as a percentage of the normalised sill.

	Reference		PR	
	Nugget (% sill)	Range (km)	Nugget (% sill)	Range (km)
Native	34 %	17	48 %	16
Bias corrected	32 %	15	48 %	16
Bias+RQI corrected	31.5 %	15.5	45 %	15

TABLE 8. Performance criteria values for PR estimates: mean, standard deviation, mean relative error (MRE) and correlation (R) with respect to references. Only the reliable Q2 data are kept (see section 2.b) for references.

PR	Native		Bias corrected		Bias+RQI corrected	
	Reference	PR	Reference	PR	Reference	PR
Mean	6.20	5.07	6.07	5.38	7.27	5.6
standard deviation	12.53	7.80	12.04	8.03	13.76	8.26
MRE / reference (%)	-	-18 %	-	-11 %	-	-23 %
Correlation / reference	-	0.61	-	0.6	-	0.64

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PR Estimates		Bias+RQI corrected Q2	
		> 0.	= 0.
> 0.	whole set	4.92 / 5.45	2.07 / 0.00
	robust	5.60 / 7.27	2.07 / 0.00
	non robust	3.63 / 2.01	-
=0.	whole set	0.00 / 0.28	-
	robust	0.00 / 0.74	-
	non robust	0.00 / 0.12	-

TABLE 6. Discarded rain volumes from PR due to misses relative to references and rain volume implied in the false alarms relative to robust references.

	Native Q2	Bias corrected Q2	Bias + RQI correctd Q2
Excess of rain volume implied in False Alarms	13.70 %	15.45 %	5.36 %
Discarded rain volume due to Misses	11.70 %	10.07 %	7.46 %

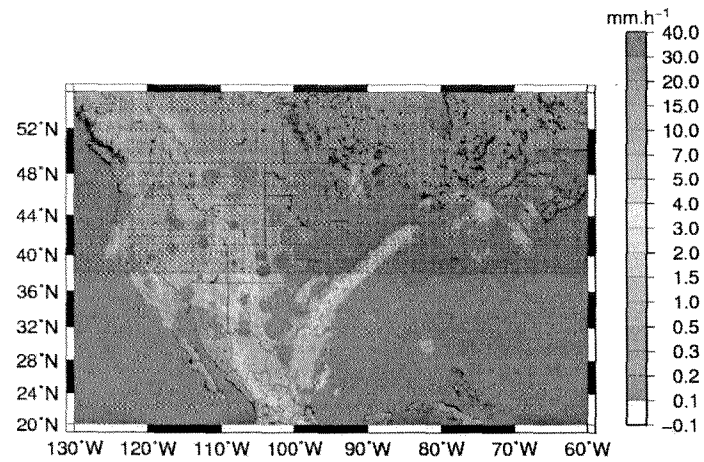


Figure 1: Map of CONUS area with NMQ/Q2 instantaneous rainrates at 0725 UTC on 07 April 2011. The red area shows the good quality radar coverage corresponding to Radar Quality Index equal to 1. The shaded area is not sampled by the TRMM-PR.

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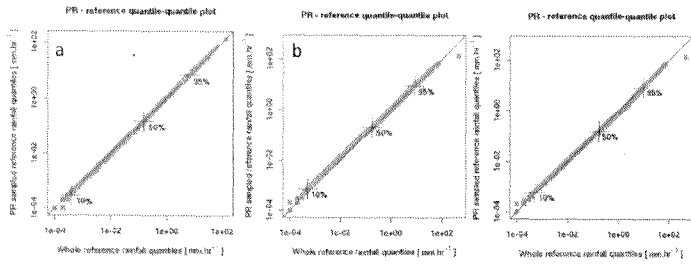


Figure 3: Quantile-quantile plots for reference “PR-sampled” and “Whole” rainfall distribution comparison, for native (a), bias corrected (b) and Bias+RQI corrected (c) references. The positions of 10, 50 and 95 percentiles are showed for each distribution.

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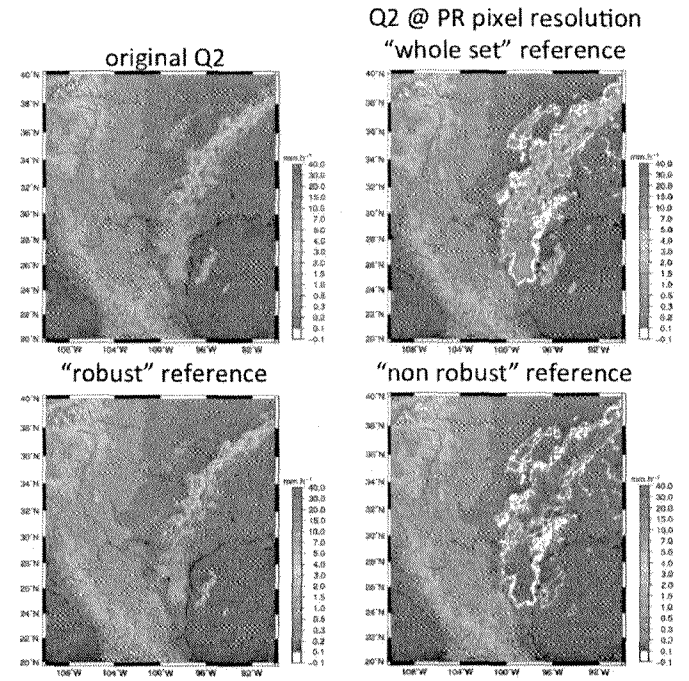


Figure 2: Maps of instantaneous rainrates at 0725 UTC on 07 April 2011: the NMQ-Q2 product (top left), the equivalent reference rainfall R_{ref} (top right), the “robust” reference set (bottom left) and the “non robust” reference set (bottom right).

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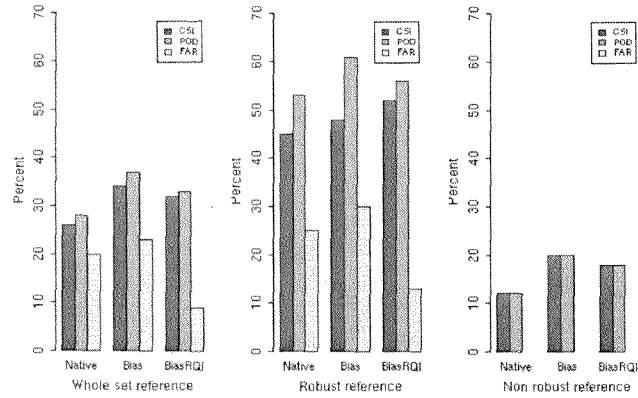


Figure 5: Critical success index (CSI), probability of detection (POD) and false alarm rates (FAR), and for the three references and partitioned as a function of robustness.

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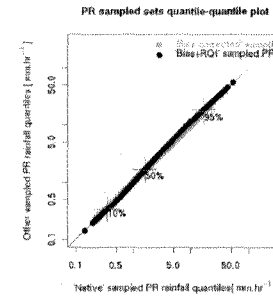


Figure 4: Quantile-quantile plots for reference "PR-sampled" and "Whole" rainfall distribution comparison, for native (a), bias corrected (b) and Bias+RQI corrected (c) references. The positions of 10, 50 and 95 percentiles are showed for each distribution.

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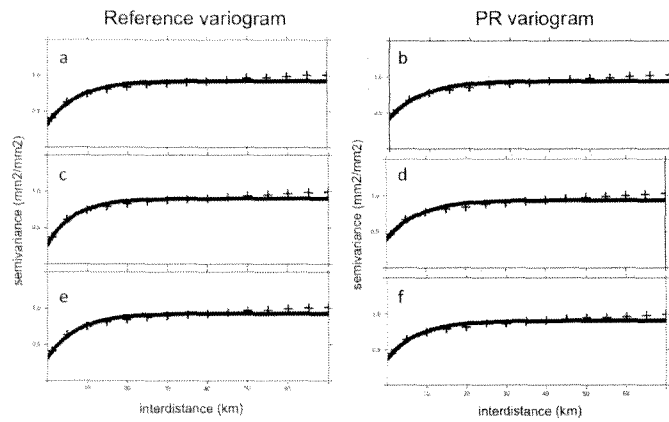


Figure 7: Spatial variograms for reference (left) and PR (right) for the native (top), bias corrected (middle) and Bias+RQI corrected (bottom) reference. The empirical variograms are plotted with crosses, and the models fitted are represented by the thick black lines.

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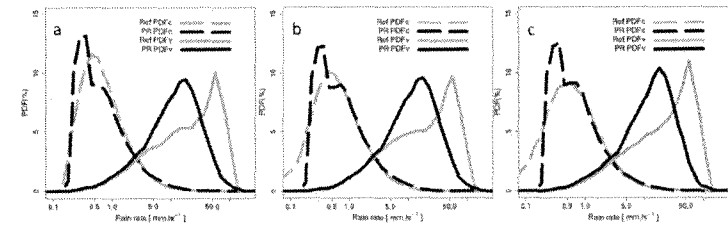


Figure 6: Probability distributions of rain rates the PR rainfall and for the native (a), bias corrected (b) and Bias+RQI corrected (c) reference rainfall. The solid and dashed-dotted lines represent the distribution by volume PDF, and the distribution by occurrence PDF_c respectively, while the grey and black lines represent the distributions for references and PR respectively. Note that the x-axis is in log-scale.

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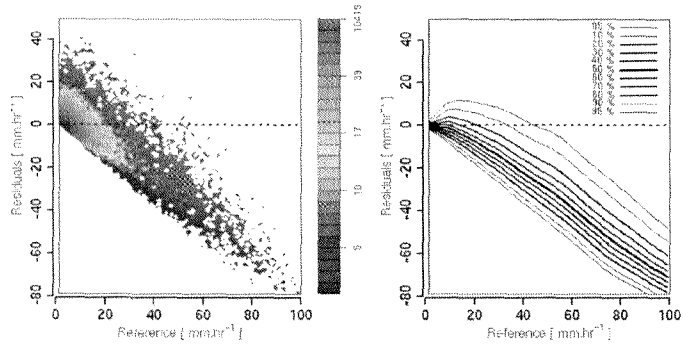


Figure 9: PR residuals represented versus "Bias+RQI corrected" reference (left) and the GAM model fitted is represented by [5, 10, 20, 30, 40, 50, 60, 70, 80, 90, 95] conditional quantile lines (right).

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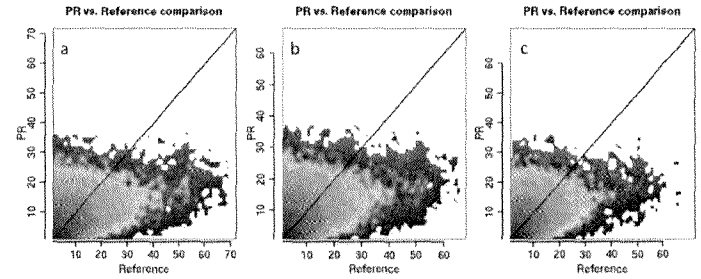


Figure 8: Scatterplots of PR versus native (a), bias corrected (b) and Bias+RQI corrected(c) reference rainfall (mm.h^{-1}). The first bisectors (solid lines) are displayed.

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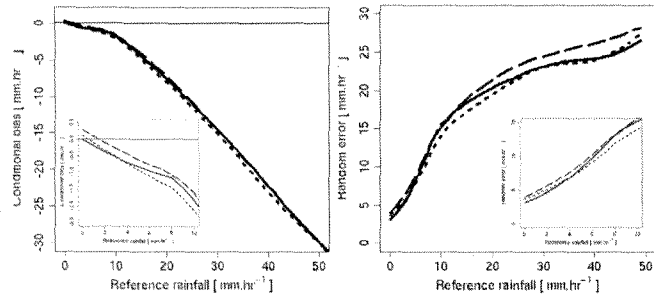


Figure 11: Conditional bias (median) of residuals (left) and conditional random error (interquartile 90%-10%) of residuals (right) for PR as a function of "Native" (dotted line), "Bias corrected" (dotted line) and "Bias+RQI corrected" references.

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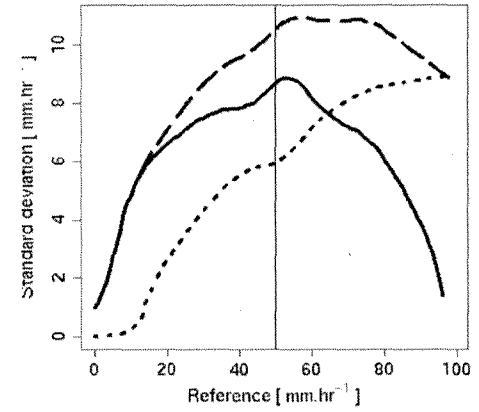


Figure 10: Standard deviation of PR-reference residuals (dashed line), estimated standard deviation of the reference rainfall (dotted line) and standard deviation of PR-true rainfall residuals (solid line) as functions of the "Bias+RQI corrected" reference. The vertical line (50 mm.h⁻¹) indicates the limit of the good sampling conditions.

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