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Comparison of TRMM 2A25 Products Version 6 and Version 7

with NOAA/NSSL Ground Radar-based National Mosaic QPE

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1   Abstract

2   Characterization of the error associated to satellite rainfall estimates is a necessary

3   component of deterministic and probabilistic frameworks involving spaceborne 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 Tropical Rainfall Measurement Mission (TRMM) Precipitation Radar (PR)

7   quantitative precipitation estimation (QPE) at ground. The problem was addressed in a

8   previous paper by comparison of 2A25 version 6 (V6) product with reference values derived

9   from NOAA/NSSL's ground radar-based National Mosaic and QPE system (NMQ/Q2). The

10   primary contribution of this study is to compare the new 2A25 version 7 (V7) products that

11   were recently released as a replacement of V6. This new version is considered superior over

12   land areas. Several aspects of the two versions are compared and quantified including

13   rainfall rate distributions, systematic biases, and random errors. All analyses indicate V7 is

14   an improvement over V6.

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16   Key words: satellite-based rain estimation, radar, QPE, conditional bias, random error

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1. Introduction

Given their quasi-global coverage, satellite-based quantitative rainfall estimates are becoming widely used for hydrologic and climatic applications. Characterizing the error structure of satellite rainfall products is recognized as a major issue for the usefulness of the estimates (Yang et al. 2006; Zeweldi and Gebremichael 2009; Sapiano and Arkin 2009; Wolff and Fisher 2009) as underlined by the Program to Evaluate High Resolution Precipitation Products (Turk et al. 2008) led by the International Precipitation Working Group (IPWG; see http://www.isac.cnr.it/~ipwg/). In this study, we focus on the TRMM Precipitation Radar (PR) quantitative precipitation estimation (QPE) product. The TRMM-PR is currently the only active instrument dedicated to the measurement of rainfall from a satellite platform conjointly with a radiometer (TMI). PR measurements are considered as the starting point for subsequent algorithms that use microwave measurements from low-earth orbiting satellites and for combined end products that utilize data from geostationary satellites (e.g., Yang et al. 2006; Wolff and Fisher 2008, Ebert et al. 2007, Bergès et al. 2010, Ushio et al. 2006). Our aim is to compare the new PR 2A25 version 7 (V7) products that were recently released as a replacement for version 6 (V6). This new version is considered superior over land areas compared to the previous versions due to changes to the vertical profile of hydrometeor characteristics, which impacts the reflectivity-to-rainfall rate (Z-R) relationship and attenuation correction. Finally, a correction for non-uniform beam filling (NUBF) effects was reintroduced.

The methodology and framework followed here are described in a previous paper dedicated to the evaluation of 2A25 V6 (Kirstetter et al. 2012). The PR QPE product was assessed with respect to an independent reference rainfall data set derived from high-resolution measurements using NOAA/NSSL's ground radar-based National Mosaic and QPE system (NMQ/Q2; Zhang et al. 2011a). These products yield instantaneous rainfall rate

1 products over vast regions including the conterminous US (CONUS). A systematic and

2 comprehensive evaluation for regions over the southern CONUS was performed by

3 characterizing errors in PR estimates by matching quasi-instantaneous data from Q2 at the

4 ~5-km pixel measurement scale of PR in order to minimize uncertainties caused by

5 resampling. The study used three months (March-May 2011) of satellite overpasses over the

6 lower CONUS. Despite the seemingly short period for evaluation, the use of gridded Q2 data

7 for reference provided a large sample size totalling 392 713 comparisons. The exact same

8 reference dataset that was used to evaluate V6 is used in this study for V7.

9   The PR and Q2 reference data are briefly described in section 2. In section 3 we assess

10 the differences in the probability density functions (PDFs) of rain rate for 2A25 V6 and V7

11 and their ability to represent rainfall variability. A quantitative comparison of empirical error

12 models for V6 and V7 estimates versus reference rainfall is provided in section 4. The paper

13 is closed with concluding remarks in section 5.

14

15 2.   **Data sources**

16 *a) Q2-based reference rainfall*

17   All significant rain fields observed coincidentally by TRMM overpasses and the

18 NEXRAD radar network from March to May 2011 are collected. The Q2 products closest in

19 time to the TRMM satellite local overpass schedule time are used. The NOAA/NSSL

20 National Mosaic and Quantitative Precipitation Estimation system (NMQ/Q2)

21 (http://nmq.ou.edu; Zhang et al. 2011a) is a set of experimental radar-based products

22 comprising high-resolution (0.01°, 5 min) instantaneous rainfall rate mosaics available over

23 the CONUS (Zhang et al. 2005; Lakshmanan et al. 2007; Vasiloff et al. 2007; Kitzmiller et

24 al. 2010). One should note that it is not possible to "validate" the PR estimates in a strict

25 sense because independent rainfall estimates with no uncertainty do not exist. Many errors

1   affect the estimation of rainfall from ground-based radars, such as non-weather echoes,

2   NUBF, range-dependency due to Vertical Profile of Reflectivity (VPR) variability,

3   conversion of Z-to-R, and calibration of the radar signal. While several procedures are

4   already in place within the Q2 system to correct for these errors, the following post-

5   processing steps were taken to refine the reference data set as much as possible: (i) adjusting

6   instantaneous Q2 products using co-located rain gauge observations (corrects for inaccurate

7   Z-R relationship and calibration errors) and (ii) filtering data through a Radar Quality Index

8   (RQI, Zhang et al. 2011b) (eliminates overestimation in the bright band and mitigates range

9   dependency caused by VPR effects). One must keep in mind these improvements may not

10   screen out all possible errors in ground-based radar estimates. The reference rainfall R_{ref} is

11   a Q2 rainfall mean computed to match each PR pixel by considering the power density

12   function of the PR beam. A standard error is computed alongside the mean reference rainfall

13   value: $\sigma_{footprint}$, which represents the variability of the Q2 rainfall (at its native resolution)

14   inside the PR footprint and is used to select the PR-Q2 reference pairs for which the R_{ref} is

15   trustworthy (see Kirstetter et al. 2012 for more details). The reference pixels are segregated

16   into "robust" ($R_{ref} > \sigma_{footprint}$) and "non robust" ($R_{ref} < \sigma_{footprint}$) estimators. Non-robust

17   reference values are discarded for quantitative comparison. The PR rainfall statistical

18   characteristics are preserved because the product remains free of undesirable impacts caused

19   by resampling.

20

21   *b) Precipitation Radar (PR) based rainfall*

22   The PR measures reflectivity profiles at Ku band. Surface rain rates are estimated over

23   the southern US up to a latitude of 37°N (see Fig. 1, Kirstetter et al. 2012). The scan

24   geometry and sampling rate of the PR lead to footprints spaced approximately 5.1 km in the

1   horizontal and along-track, over a 245-km-wide swath. The TRMM product used in this

2   work is the PR 2A25 product (versions 6 and 7) described in Iguchi et al. (2000, 2009). The

3   2A25 algorithm relies on a hybrid attenuation correction method that combines the surface

4   reference technique and Hitschfeld-Bordan method (Iguchi et al. 2000; Meneghini et al.

5   2000, 2004). Retrieval errors of the algorithm have mainly been attributed to the uncertainty

6   of the assumed drop size distribution (DSD), incorrect physical assumptions (freezing level

7   height, hydrometeor temperatures) and NUBF effects (Iguchi et al. 2009). Some of the

8   weaknesses in performance with V6 (i.e., underestimation of rain-rates) over land compared

9   to over sea previously reported (Wolff and Fisher 2008; Iguchi et al. 2009) are expected to

10   improve as Z-R relationships over land were recalibrated and the NUBF correction, which

11   was abandoned in V6, was re-introduced in the new V7 product.

12

13   **3.   Rainfall data analysis**

14   *a) Probability distributions by occurrence and by rain volume*

15   Hereafter, the PR rain estimates are the conditional ones (non-zero rainfall) coincident

16   and collocated with non-zero Q2 reference estimates. In addition, the "robust" ($R_{ref} >$

17    $\sigma_{footprint}$) rain rates dataset is used as reference. Two PDFs for PR versus Q2 reference

18   rainfall are computed and shown in Fig. 1: (i) the PDF by occurrence (PDF_c) and (ii) the

19   PDF by rain volume (PDF_v) (Wolff and Fisher 2009; Amitai et al. 2009, 2011; Kirstetter et

20   al. 2012). The PDF_c provides statistical information on the rain rate distribution and

21   highlights the estimates' sensitivity as a function of rain rate. The PDF_v represents the

22   relative contribution of each rain rate bin to the total rainfall volume.

23   Compared to Q2's reference PDF_c, both 2A25 versions tend to overestimate light rain

24   rates (~[0.3-0.5] mm h^{-1}) and demonstrate poor detection of the lightest rain rates (below

25   ~0.3 mm h^{-1}). A possible explanation is the edges of rain areas might be only partially

1 detected by PR because they are associated with low rain rates and intermittency (Kirstetter

2 et al. 2012). The detectability issue is related to the sensitivity of PR and is thus not readily

3 correctable with an update to the processing algorithm. However, it is noted that the mode of

4 V7's PDF_c is shifted towards higher values than V6's and is more consistent with the mode

5 of the reference PDF_c. In examining the rain rate distributions by volume, we see the modes

6 of PDF_v for both V6 and V7 are shifted toward lower rain rates compared to the reference's

7 mode (~60 mm h^{-1}), which agrees with the results found in Amitai et al. (2006, 2009). This

8 has been attributed to high rainfall rates (> 10 mm h^{-1}), which are likely underestimated by

9 PR due to one or more of the following reasons: insufficient correction due to attenuation

10 losses, NUBF effects, and inaccurate conversion from Z-to-R (Wolff and Fisher 2008). V7

11 presents a PDF_v in better agreement with the reference than V6. The mode of the PDF_v has

12 increased from 18 to 25 mm h^{-1}, indicating a positive impact from the NUBF correction

13 and/or Z-R improvements over land.

14

15 *b) Correlations and biases*

16   Density-colored scatterplots of PR versus reference rainfall are presented for the two

17 versions of 2A25 in Fig. 2. Improvements (i.e., increases) in V7 are evident particularly for

18 reference rainfall values > 30 mm h^{-1}. In addition, the underestimation from V6 at lighter

19 rain rates (< 1 mm h^{-1}) has now been mitigated in V7. We also provide common comparison

20 metrics in Table 1. A rainy pixel is included in the statistics if both PR and the reference are

21 non-zero. The V6 and V7 estimates are both subjected to the same discrepancies in

22 spatiotemporal matching with the Q2 reference, which is a source for differences on a point-

23 to-point comparison basis, so their relative differences can be directly attributed to

24 algorithms themselves. PR underestimates the mean reference rainfall values in both

25 versions. However, the V7 products are less biased (-18%) than the prior version (-23%),

1   showing a positive impact of the new processing (i.e., recalibrated Z-R relationship over

2   land and NUBF correction). The correlation coefficients between both versions of PR

3   rainfall and Q2 reference estimates are moderate, but we note the correlation with V7 has

4   improved. Increasing both the bias and the correlation of the 2A25 products is a significant

5   achievement. In fact, it is generally recognized that it is difficult to improve one of these

6   statistics without the expense of the other (Ciach et al. 2000). The correction of the largely

7   underestimated rain rates in going from V6 to V7 (see Fig. 2) certainly contributes to this

8   improvement.

9

10   *c) Error models*

11   The uncertainties associated with satellite estimates of rainfall include systematic errors

12   as well as random effects from several sources (Yang et al. 2006; Kirstetter et al. 2011). In a

13   similar manner with Kirstetter et al. (2012), the departures of PR estimates from the Q2

14   reference values are analyzed in this section on a point-to-point basis. With the true rainfall

15   being unknown, the residuals are defined as the difference between the reference rainfall

16   (R_{ref}) and the satellite estimates (R): $\varepsilon = (R - R_{ref})$. Only pairs for which R_{ref} and R are

17   both nonzero are considered in the calculations. The sets of ε distributions are studied using

18   the generalized additive models for location, scale, and shape (GAMLSS) technique (Rigby

19   and Stasinopoulos 2001, 2005; Akantziliotou et al. 2002; Stasinopoulos and Rigby 2007).

20   R_{ref} is considered as the main driving (explanatory) variable conditioning the departures of

21   PR estimates from reference values and we use the reverse Gumbel distribution

22   ($f(\varepsilon) = \frac{1}{\sigma}\left[-\left(\frac{\varepsilon-\mu}{\sigma}\right) - \exp\left\{-\left(\frac{\varepsilon-\mu}{\sigma}\right)\right\}\right]$) to model the conditional residual distributions,

23   where the location μ (mean of the residual population) is to be linked to systematic errors

24   and σ (the standard deviation) is representative of random errors.

1

2   For a given conditional distribution of the response variable ε, the conditional quantiles

3   can be expressed as a function of R_{ref}. Figure 3 shows the residuals as a function of R_{ref} as

4   well as the fitted GAMLSS model for the two 2A25 versions. The conditional PDFs of

5   residuals ε present a high conditional shift from the 0 line and a high conditional spread.

6   Note that for $R_{ref} > \sim 50$mm h^{-1}, the model is quite undetermined because of the lack of

7   observed residuals. Both 2A25 versions present a tendency to underestimate high rain rates

8   (negative median of residuals); V6 underestimates $R_{ref} = 20$ mm h^{-1} with an occurrence of

9   80% and with a representative bias of -7 mm h^{-1} while V7 underestimates the same reference

10   value with an occurrence of 75% and with a representative bias of -6 mm h^{-1}. There is an

11   improvement with V7, but the remaining bias is likely to be due to an inaccurate Z-R

12   relationship, NUBF effects and/or insufficient correction of PR attenuation losses at heavier

13   rain rates.

14   We consider the conditional median of the residuals to compare the systematic error

15   component for V6 and V7 as well as the interquantile (90%-10%) value to assess the random

16   part of the error. Figure 4 shows the conditional biases and random errors of both versions of

17   2A25 relative to the Q2 reference dataset. The underestimation with V6 and V7 over a large

18   range of rain rates induces a global negative bias, which was evident in Table 1. The

19   conditional biases of both versions relative to the reference are quite similar but with a slight

20   improvement in V7. The random error increases consistently with R_{ref} for both products.

21   The random part of error for V7 is greater than V6, suggesting that other factors in addition

22   to R_{ref} could be considered to properly model the random error of V7 rain rate estimates.

23

24   **4.   Conclusions**

1   A three-month dataset of gauge-adjusted, quality-filtered surface rainfall estimates from

2   the NEXRAD-based Q2 has been used to compare and contrast PR-based 2A25 rainfall

3   estimates from the older V6 algorithm and the newly released version (V7). V7 includes

4   improvements in attenuation correction of the radar signal, a recalibrated Z-R equation for

5   use over land areas, and a correction for NUBF effects was reintroduced. The comparisons

6   have been performed at the PR-pixel resolution over the lower CONUS using a framework

7   proposed in Kirstetter et al. (2012). Our analyses indicate that the bias of the rain rate

8   estimates from V7 has been improved from a prior underestimation bias of -23% (from V6)

9   to -18%. Moreover, this improvement in reducing bias is accompanied by an increase in the

10   correlation coefficient from a prior value of 0.64 to 0.68; simultaneous improvement in both

11   error metrics is quite challenging and was found to be a result of simultaneously correcting

12   overestimation at lighter rain rates (< 10 mm hr^{-1}) and underestimation at high rain rates ($>$

13   30 mm hr^{-1}). The former correction is most likely a result of the recalibration of the Z-R

14   equation over land while the latter is likely a result from the NUBF correction; NUBF is

15   known to cause underestimation at high rain rates (Iguchi et al. 2009).

16   A statistical error model was developed for both versions of PR algorithms to separate

17   conditional biases and random errors as a function of reference rainfall rate. The PR

18   residuals are confirmed to be quite large even with the newer V7 due to the aforementioned

19   combination of error factors. Presently, the error model only considers rainfall rate of the

20   reference as the dominant factor. A more robust error model will include the primary,

21   identifiable error sources in PR rainfall estimates. Future work will evaluate and quantify the

22   relative contributions of PR rainfall estimation errors linked to additional factors such as

23   rainfall type, off-nadir angle, NUBF, attenuation, as well as influence of the underlying

24   terrain.

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1

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2 **Table captions**

3

4 Table 1. Performance criteria values for PR estimates: mean, standard deviation, mean

5 relative error (MRE) and correlation (R) with respect to references. Only the reliable Q2 data

6 are kept (see section 2.b) for references.
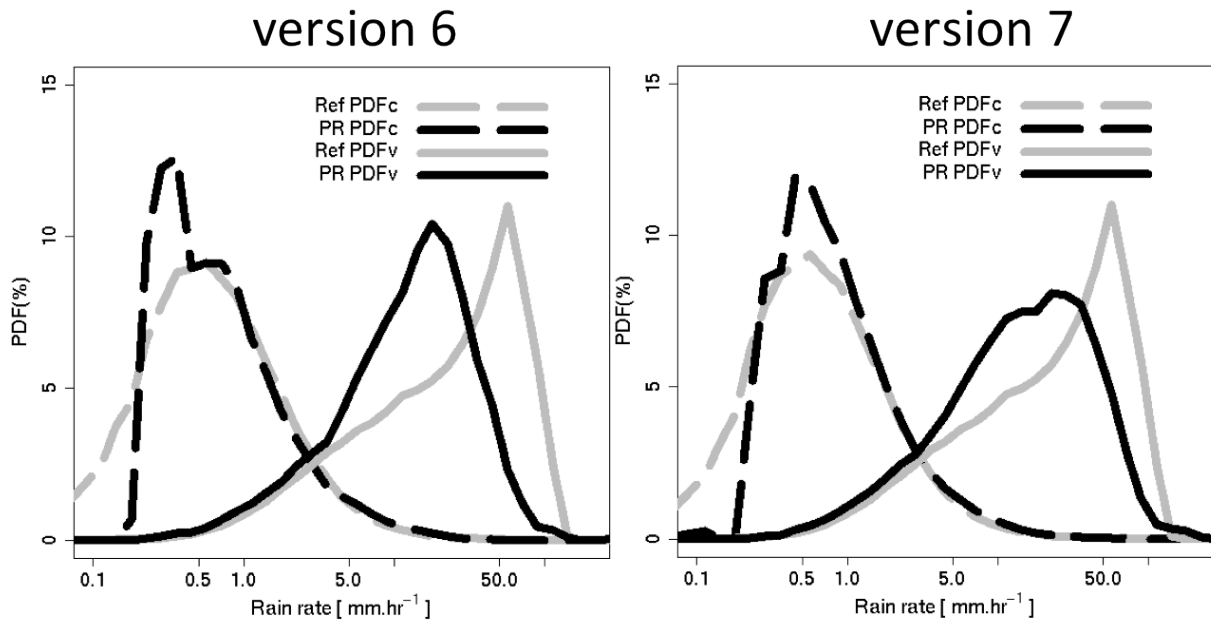
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2 **Figure captions**

3

4 <u>Figure 1:</u> Probability distributions of rain rates for the reference rainfall (grey) and for PR

5 rainfall V6 (left) and V7 (right). The "robust" reference rain rates are used. The solid and

6 dashed-dotted lines represent the distribution by volume PDF_v and the distribution by

7 occurrence PDF_c respectively, while the grey and black lines represent the distributions for

8 references and PR respectively. Note that the x-axis is in log-scale.

9 <u>Figure 2:</u> Scatterplots of 2A25-V6 (left) and 2A25-V7 (right) versus reference rainfall

10 (mm.h^{-1}). The first bisectors (solid lines) are displayed.

11 <u>Figure 3:</u> PR residuals represented versus reference (top) and the corresponding GAM model

12 fitted and represented by [5, 10, 20, 30, 40, 50, 60, 70, 80, 90, 95] conditional quantile lines

13 (bottom) for 2A25-V6 (left) and 2A25-V7 (right). The dotted lines represent the cumulative

14 distribution function of the reference rainfall.

15 <u>Figure 4:</u> Conditional bias (median) of residuals (left) and conditional random error

16 (interquantile 90%-10%) of residuals (right) for 2A25-V6 (blue) and 2A25-V7 (red) as a

17 function of reference rainfall.

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4 TABLE 1. Performance criteria values for PR estimates: mean, standard deviation, mean

5 relative error (MRE) and correlation (R) with respect to references. Only the reliable Q2 data

6 are kept (see section 2.b) for references.

PR -2A25	Reference	Version 6	Version 7
Mean	7.27	5.60	5.97
standard deviation	13.76	8.26	9.8
MRE / reference (%)	-	-23 %	-18 %
Correlation / reference	-	0.64	0.68

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Figure 1: Probability distributions of rain rates for the reference rainfall (grey) and for PR rainfall V6 (left) and V7 (right). The "robust" reference rain rates are used. The solid and dashed-dotted lines represent the distribution by volume PDF_v 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.
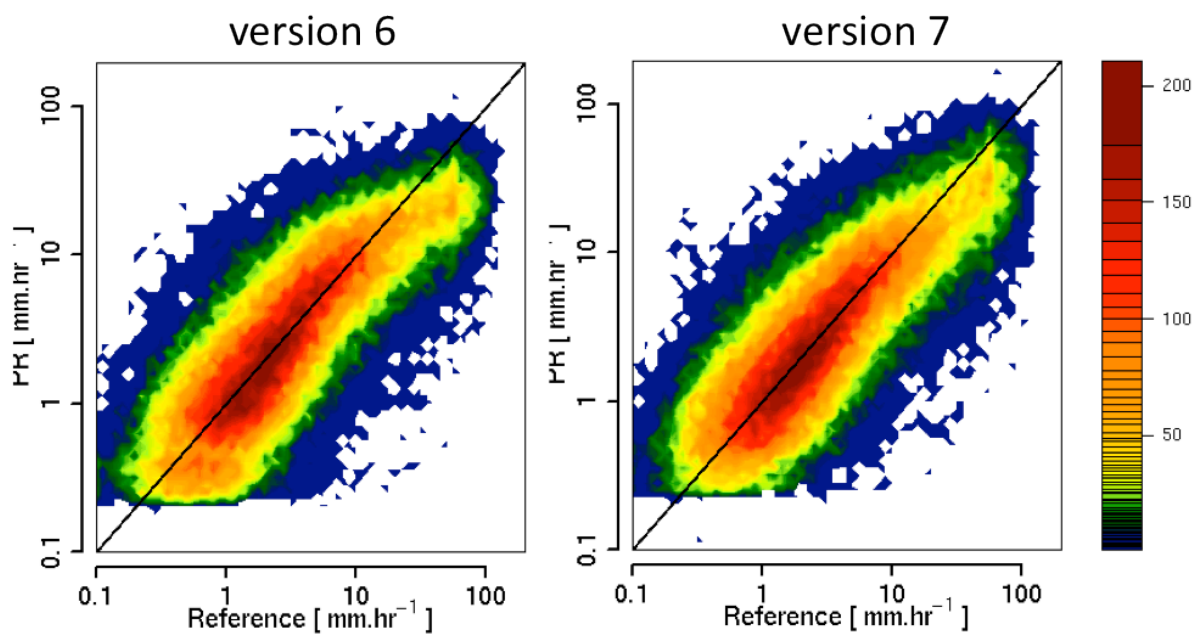
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Figure 2: Scatterplots of 2A25-V6 (left) and 2A25-V7 (right) versus reference rainfall (mm.h^{-1}). The first bisectors (solid lines) are displayed.
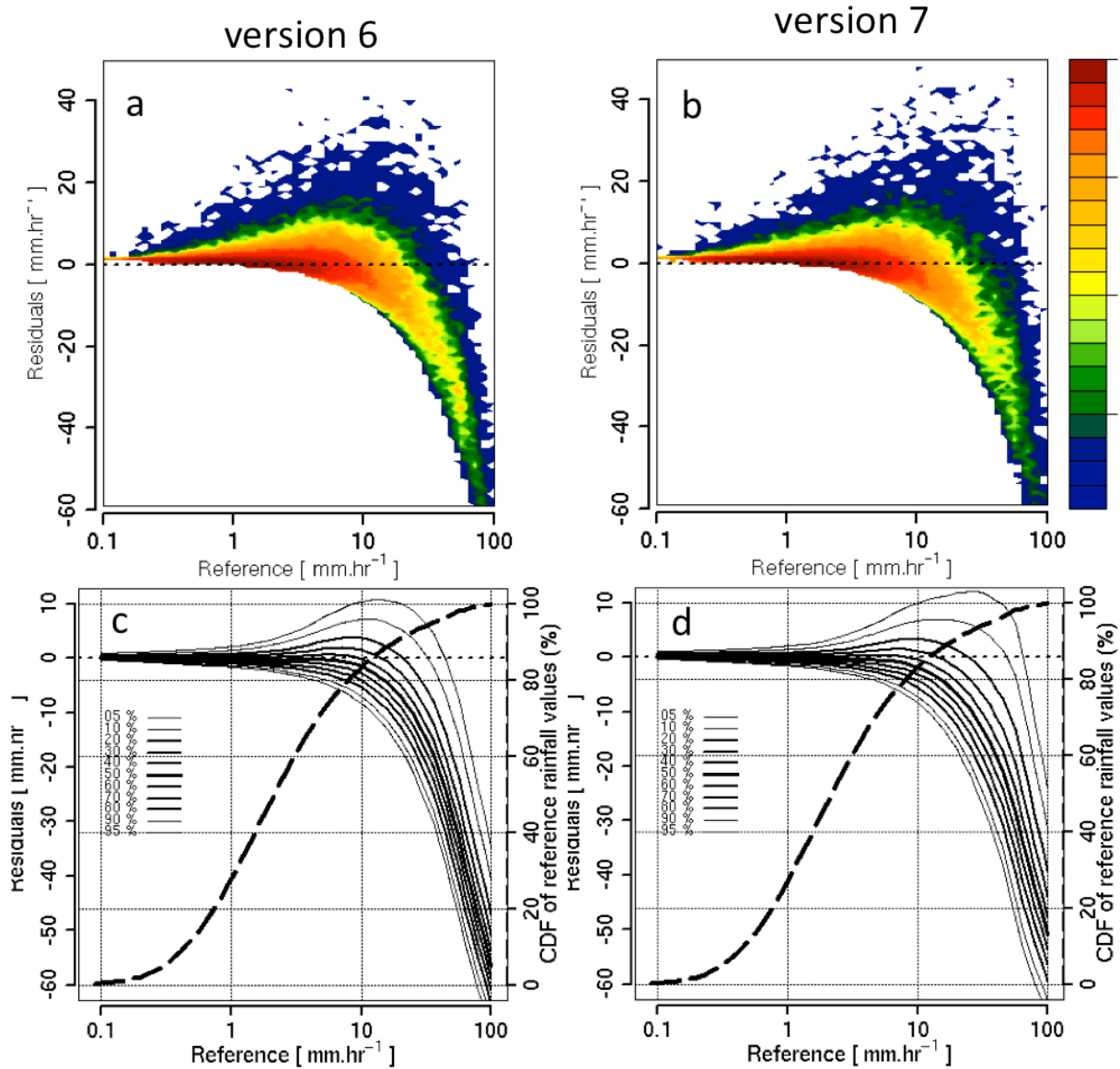
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Figure 3: PR residuals represented versus reference (top) and the corresponding GAM model fitted and represented by [5, 10, 20, 30, 40, 50, 60, 70, 80, 90, 95] conditional quantile lines (bottom) for 2A25-V6 (left) and 2A25-V7 (right). The dotted lines represent the cumulative distribution function of the reference rainfall.
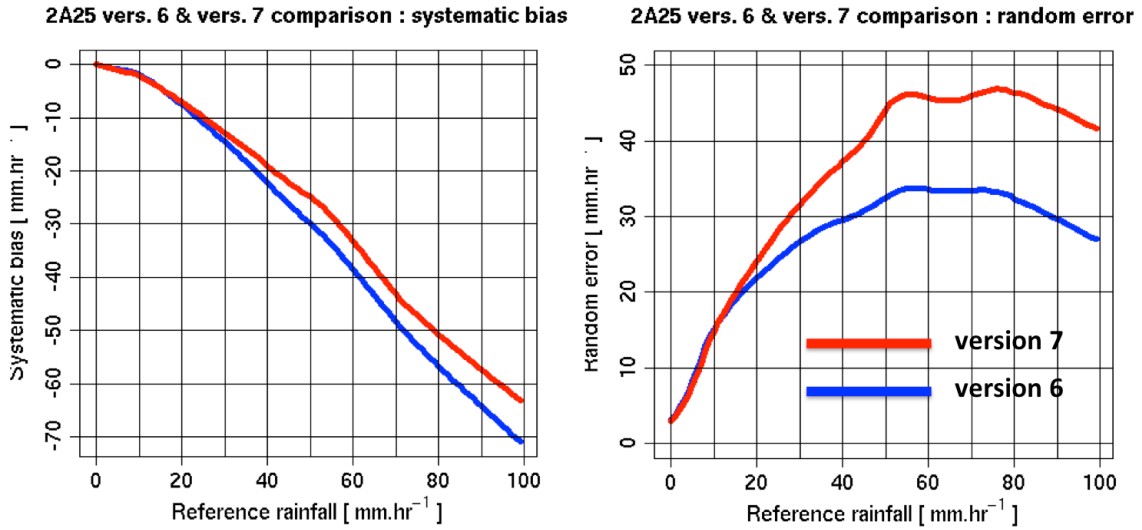
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Figure 4: Conditional bias (median) of residuals (left) and conditional random error (interquantile 90%-10%) of residuals (right) for 2A25-V6 (blue) and 2A25-V7 (red) as a function of reference rainfall.

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