

# Impact of sub-pixel rainfall variability on spaceborne precipitation estimation: evaluating the TRMM 2A25 product

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Rain intensity spectra as seen by space sensors feed numerous applications at global scales ranging from water budget studies to forecasting natural hazards related to extreme rainfall events. Rainfall variability at scales finer than what is resolved by current space sensors affects their detection capabilities, the characterization of rainfall types, as well as the quantification of rainfall rates. A high-resolution surface rainfall product is used to evaluate the impact of rainfall variability within the field of view (FOV) of the Tropical Rainfall Measurement Mission (TRMM) Precipitation Radar (PR) quantitative precipitation estimation (QPE) at ground. The primary contribution of this study is to assess the impact of rainfall variability in terms of occurrence, types and rate at PR's pixel resolution on PR precipitation detection, classification and quantification. Several aspects of PR errors are revealed and quantified including sensitivity to non-uniform beam filling. While the error structure of the PR is complicated because of the interaction of these factors, simple error models are developed to describe the PR performances. The methodology and framework developed herein applies more generally to rainfall rate estimates from other sensors on board low Earth-orbiting satellites such as microwave imagers and dual-frequency radars such as with the Global Precipitation Measurement (GPM) mission.

Key Words: satellite-based rain estimation; radar; QPE; conditional bias; random error

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# 1. Introduction

In the context of changing climate, rainfall occurrence, types and intensity are becoming widely evaluated because of their impact on the energy budget and the hydrological cycle. At the global scale, only meteorological satellites provide remote-sensing observations of rainfall, essential for hydrologic and climatic applications, which range from climatic analysis (Stephens and Kummerow, 2007), budgeting water resources over land (Grimes and Diop, 2003; Lebel et al., 2009), real-time flood forecasting (Hong et al., 2007) to data assimilation and evaluation of regional and global atmospheric model simulations (Stephens and Kummerow, 2007). Rainfall fields have variability across a variety of spatial and temporal scales. Regarding measurement from remote-sensing platforms, it is important to quantitatively evaluate the following characteristics of the rainfall rate distribution at the instruments' pixel scale: occurrence and proportion of positive values, mean value, variability and types (Figure 1). The spatial heterogeneity of the rain fields within a single instrumental

field of view (e.g. beam filling, coexistence of convective and stratiform precipitation, and vertical heterogeneity of rainfall) interact with the sensitivity of the instrument itself, the indirect nature of the measurement, the spatial resolution and the retrieval algorithm used. As a consequence, satellite surface rain rate retrievals are not a simple convolution of the fine-scale rain rate distribution within the field of view of the instrument. Characterizing the error structure of satellite rainfall products is recognized as a major issue for the usefulness of the estimates (Yang et al., 2006; Turk et al., 2008; Sapiano and Arkin, 2009; Wolff and Fisher, 2009). We address these questions by evaluating how satellite surface rainfall characteristics, i.e. occurrence, type and rate, differ from a reference rainfall within the field of view. These questions address the detection, classification and quantification capabilities of such a radar sensor on board a satellite. In fact, rainfall variability at scales finer than the typical field of view of the sensors is recognized as a major source of uncertainty for rainfall estimation from space (e.g. Iguchi et al., 2009). As an example regarding rainfall detection, Lin and Hou (2012) showed



Figure 1. (a) Overpass of TRMM-PR over the conterminous U.S. at 0725 UTC on 11 April 2011. NMQ/Q2 instantaneous precipitation rates are shown; (b) zoomed area showing the variability and spatial distribution of precipitation within TRMM-PR footprints figured with circles; (c) schematic showing the variability can be addressed with the higher horizontal resolution of NMQ.

how the varying detection capabilities of space-based active and passive sensors can impact the contribution of different rain intensity categories to the total rain incidence and rain volume.

We focus primarily on the Tropical Rainfall Measurement Mission (TRMM) Precipitation Radar (PR) quantitative precipitation estimation (QPE) at ground. Iguchi et al. (2009) mentioned how difficult the non-uniform beam-filling issue is to handle in converting the PR signal into a rain rate. While the methodology presented herein would apply to all satellite precipitation products, the TRMM PR is often considered as a calibrator for other space-based passive microwave sensors such as the TRMM Microwave Imager (e.g. Yang et al., 2006; Wolff and Fisher, 2008, 2009). The combination of these sensors in a constellation collectively enables the creation of global-scale precipitation products (Ushio et al., 2006; Ebert et al., 2007; Huffman et al., 2007) and constitutes the backbone of the future Global Precipitation Measurement (GPM) mission. A number of studies have investigated the quality of PR estimates in various regions of the world (e.g. Adeyewa and Nakamura, 2003; Lin and Hou, 2008; Michaelides, 2008; Wolff and Fisher, 2008, 2009). Over the USA, Amitai et al. (2009, 2012) have compared the PR with the National Oceanic and Atmospheric Administration/National Severe Storms Laboratory (NOAA/NSSL) ground radar-based National Mosaic and QPE system (NMQ/Q2), which offers a robust set of resources for validation.

In this study, the PR QPE product is assessed over the southern conterminous USA (CONUS) with respect to the high-resolution, independent NMQ/Q2 rainfall dataset (Zhang et al., 2011a) following the methodology and framework for evaluating PR 2A25 products described in Kirstetter et al. (2012, 2013). This study is part of an effort to perform a systematic and comprehensive evaluation of PR errors by matching quasiinstantaneous data from Q2 to the  $\sim$ 5 km pixel measurement scale of PR in order to minimize uncertainties caused by resampling. Here, the finer spatial resolution of NMQ ( $\sim$ 1 km) is specifically used to characterize the rainfall sensed by the PR in terms of occurrence, type and rate. By doing so, we will also assess the impact of the small-scale variability of rainfall on the PR estimates. We evaluate the distribution or spectrum of rainfall occurrence, typology and quantity within the PR field of view (FOV) and relate these characteristics to PR rain estimates. This study used seven months (March-October 2011) of satellite

overpasses over the lower CONUS (up to latitude 36°N). Despite the seemingly short period for evaluation, the use of gridded Q2 data for reference provided a large sample size totalling 1 625 942 non-zero PR-reference pairs.

The PR data and steps required to refine the Q2 ground-based rainfall to arrive at the reference rainfall used for comparisons are presented in section 2. Section 3 assesses the ability of PR rain retrievals to detect rainfall. Section 4 details the impact of the beam filling and rain typology on the PR rainfall classification. Section 5 addresses the aspect of rainfall quantification. The article is closed with concluding remarks in section 6.

## 2. Data sources

# 2.1. Q2-based reference rainfall and derived products

All rain fields observed coincidentally by TRMM overpasses and the Next-Generation Weather Doppler Radar (NEXRAD) radar network from March to October 2011 are collected. The NMQ-Q2 products closest in time to the TRMM satellite local overpass schedule time are used. The NOAA/NSSL National Mosaic and Quantitative Precipitation Estimation system (NMQ: http://nmq.ou.edu; Zhang et al., 2011a) is a set of experimental radar products including high-resolution (0.01°, 5 min) instantaneous rainfall-rate mosaics available over the CONUS. The NMQ system gathers information from all ground-based radars comprising the Weather Surveillance Radar-1988 Doppler (WSR-88D) network, mosaics reflectivity data onto a common three-dimensional (3D) grid, and estimates surface rainfall accumulations and types to deliver accurate ground-based estimates of rainfall (Zhang et al., 2005; Vasiloff et al., 2007). At hourly time steps, Q2 adjusts radar estimates with automated rain-gauge networks using a spatially variable bias multiplicative factor. A radar quality index (RQI) is produced to represent the radar QPE uncertainty associated with reflectivity changes with height and near the melting layer (Zhang et al., 2011b). One should note that it is not possible to 'validate' the PR estimates in a strict sense because independent rainfall estimates with no uncertainty do not exist. A number of complicating factors impact the radar QPE uncertainty, such as measurement errors, non-precipitation echoes, uncertainties in Z-R relationships, and variability in the vertical profile of reflectivity associated with range. Trustworthy values of the Q2 rainfall estimates within the satellite pixel are needed to evaluate the satellite estimates. To mitigate potential error sources affecting quantitative precipitation estimation from ground-based radars and to refine the reference dataset as much as possible, co-located rain-gauge observations were used to adjust instantaneous Q2 products (Kirstetter et al., 2012, 2013). The reference rainfall is derived from an instantaneous gauge bias-corrected Q2 product adjusted using a spatially variable multiplicative bias field. A conservative approach is followed: (i) by filtering out instances when the radar and gauge have significant quantitative disagreement (i.e. radar-rain-gauge ratios outside of the range (0.1-10), and (ii) by retaining only the best measurement conditions (i.e. no beam blockage and radar beam below the melting layer) using the RQI product as described in Kirstetter et al. (2012, 2013). One must keep in mind these improvements may not screen out all possible errors in groundbased radar estimates. Nevertheless, Chen et al. (2013) recently quantified the errors of Q2 rainfall estimates and provided uncertainty estimates of hourly rainfall products. They found that the errors depended strongly on RQI, with there being very little bias at RQI values of 1, the same threshold used in this study.

A simplified rain type classification was elaborated from the Vertically Integrated Liquid Content (VIL) derived from the Q2 3D mosaics at the original resolution (1 km, 5 min). A two-step approach similar to Steiner *et al.* (1995) was applied to identify convective areas. First the centres of convective cells are identified from the VIL map using a threshold value (5.5 kg m<sup>-2</sup>) above which it is assumed that precipitation can only result from convective processes. Then an associated convective region is identified from surrounding pixels with VIL values greater than 2 kg m<sup>-2</sup> at distances within 20 km. Pixels flagged as non-convective are designated as stratiform.

Radar observations enable a reliable evaluation of areaaveraged rainfall. The reference rainfall  $R_{ref}$  is computed from a block-Q2 rainfall pixel matching each PR pixel. All of the Q2 pixels (rainy and non-rainy) found within an approximate 2.5 km radius around the centre of the PR pixel location are considered to compute unconditional mean rain rates for the Q2 at the PR pixel scale. The number of Q2 pixels within a PR footprint used to derive the statistical characteristics of the reference rainfall tends to average about 25. Additional reference rainfall characteristics on occurrence, variability and types are derived within the FOV. Kirstetter et al. (2012) assessed the estimation reference representativeness using a standard error computed alongside the mean reference rainfall value:  $\sigma_{\text{footprint}}$ , quantifying the variability of the Q2 rainfall (at its native 1 km resolution) inside the PR footprint. It was used to select the PR-Q2 reference pairs for which the  $R_{ref}$  is trustworthy by segregating the reference pixels into 'robust' ( $R_{ref} > \sigma_{footprint}$ ) and 'non-robust' ( $R_{ref} < \sigma_{footprint}$ ) estimators (see Kirstetter et al. (2012) for more details). Later, Kirstetter et al. (2013) used  $\sigma_{\text{footprint}}$  to assess the Non-Uniform Beam Filling (NUBF) by quantifying the variability of Q2 precipitation within the PR footprint. In the present study, an extended description of the reference rainfall within the PR FOV is assessed through three products derived at the PR footprint resolution:

- (i) the rainy fraction (RF) characterizes the rainfall occurrence within the PR pixel. It represents the FOV filling with the proportion of positive Q2 values inside the PR pixel and is expressed in per cent between 0% (no rainfall within the FOV) and 100% (FOV filled);
- (ii) the quantitative variability of the Q2 values. Because  $\sigma_{\text{footprint}}$  presents some correlation with the reference rainfall rate (Ciach and Krajewski, 2006), we use the Relative Non-Uniform Beam Filling quantity as RNUBF =  $\frac{\sigma_{\text{footprint}}}{R_{\text{ref}}}$  (unitless) to assess the impact of the variability of the Q2 rain rate relative to  $R_{\text{ref}}$ ; typical values range from 0.1 (homogenous Q2 values within the FOV) to 50 (highly variable Q2 values);

(iii) the rainfall type through a Convective Percentage Index (CPI) quantifying the volume contribution of convective rainfall to  $R_{ref}$  as follows:

$$CPI(A) = 100 \frac{\sum_{j=1}^{nconv} \omega_j Q2(a_j)}{\sum_{i=1}^{n} \omega_i Q2(a_i)} \text{ with } \omega_i = \int\limits_{\theta_{\text{mesh}}(a_i)} f^2(\theta, \theta_0) d\theta,$$
(1)

where notations, consistent with Kirstetter *et al.* (2012), have been simplified for the sake of convenience. Q2 denotes the Q2 rain rate at the original data product resolution  $(1 \text{ km}^2)$  for the mesh  $a_i$ ; *n* is the number of Q2 data points inside the PR pixel *A*; *nconv*  $\leq n$  is the number of Q2 pixels flagged as convective inside the pixel *A*; the weights  $\omega$  are derived from the two-way normalized power-gain function of the PR antenna *f* (assumed to be Gaussian) and the beam width  $\theta_0$ ; each  $\omega_i$  is computed over the domain  $\theta_{\text{mesh}}$  corresponding to the Q2 mesh  $a_i$ . It is assumed the PR resolution remains constant (circle of 5.1 km) whatever the radar beam off-nadir inclination angle. Additional research may be needed to take into account the deformation of the resolution with off-nadir angle (Takahashi *et al.*, 2006). The CPI is expressed in per cent between 0% (purely stratiform rainfall within the PR FOV) to 100% (purely convective rainfall).

#### 2.2. Precipitation radar (PR)-based rainfall

The PR measures reflectivity profiles in the Ku band. Surface rain rates are estimated over the southern USA up to a latitude of 36°N (see Figure 1, Kirstetter et al., 2012). The scan geometry and sampling rate of the PR yield footprints spaced approximately 5.1 km in the horizontal and along-track, over a 245 km wide swath. The TRMM product used in this work is the PR 2A25 product (versions 7) described in Iguchi et al. (2000, 2009) which provides 3D reflectivity and 2D rain rate fields at ground. The variable eSurfRain (estimated surface rain) was extracted from the 2A25 files as the PR surface QPE. The PR detection limit of rainfall depends primarily on the instrument sensitivity around 17 dBZ. The various conditions of filling of the FOV by rainfall may impact the detection capabilities of the PR. The 2A23 product classifies rain into stratiform and convective (Awaka et al., 2007). Our dataset includes 468 921 pixels classified as stratiform by the PR and 185 860 convective pixels. The 2A25 algorithm relies on a hybrid attenuation correction method that combines the surface reference technique and Hitschfeld-Bordan method (Iguchi et al., 2000; Meneghini et al., 2000, 2004; Takahashi et al., 2006). It uses models to describe the hydrometeor drop size distributions (DSDs), which are adjusted to match the observed Path Integrated Attenuation. The PR is a well-calibrated and very stable radar. Primary errors in rainfall retrievals have mainly been attributed to attenuation correction of the radar signal (involving the incorrect physical assumptions related to convective versus stratiform rainfall classification and assumed drop size distribution), non-uniform beam filling (NUBF) and conversion from reflectivity to rainfall intensity (Iguchi et al., 2009).

By characterizing the rainfall variability within the PR FOV and as a function of precipitating system types (convective and stratiform), we will address the impact of the NUBF and the rainfall classification. By comparing rain rates at ground, some error factors like the attenuation correction will not be assessed. Wen *et al.* (2011) addressed this topic by comparing the radar reflectivity factors at various heights.

# 2.3. Comparison samples

Figure 2(a) shows the mean reference rainfall  $R_{ref}$  as a function of the rain fraction RF and the relative NUBF (RNUBF). Because of the convolution of the rain rate spectrum by the PR antenna pattern, various types of rain rate spectra result in similar values



**Figure 2.** (a) Mean reference rainfall  $R_{ref}(mm h^{-1})$  and (b) mean reference rainfall convective volume contribution (CPI, %) as functions of the rain fraction RF and the relative non-uniform beam filling (RNUBF).

of R<sub>ref</sub>. As an example, moderate homogeneous precipitation filling the FOV (e.g. RF = 95% and RNUBF = 0.2) has the same average reference rainfall as a scene with inhomogeneous but heavy precipitation (e.g. RF = 55% and RNUBF = 2). Lighter rain rates are found for lower beam-filling conditions (RF<60%) with various quantitative variability. The highest mean rain rates are found for filled FOV and RNUBF within the interval (0.5-2). Figure 2(b) shows the reference rainfall type (CPI) as a function of the RF and RNUBF. The highest convective contributions are consistently found for higher RNUBF values (the convective rainfall is associated with higher variability) and the stratiform type rainfall is associated with lower RNUBF values. Because of the convolution of the rainfall type distribution in the FOV by the PR antenna pattern, various contributions from stratiform and convective rainfall within the FOV result in similar CPI.

# 3. Rainfall detection

Studying the impact of satellite sensor detection capabilities leads to a better understanding of the rain rate spectra as seen from space and of the climate variability of light rain (e.g. Lin and Hou, 2012). The goal here is to evaluate PR's rainfall detection capabilities and the percentage of rain occurrence and rain volume likely missed for various precipitation conditions. Lin and Hou (2012) evaluated the impact of missing light rain due to the PR's detection capabilities over the continental United States. They assumed the minimum detectable rain rate for PR is  $0.5 \text{ mm h}^{-1}$ . Using a product at 4 km horizontal and 1 h temporal resolutions, they estimated that 43% of total rain occurrence and 7% of total rain volume is below this threshold. This minimum detectable rain rate from PR is an approximation, and the capabilities vary with the horizontal variability within the field of view. Since the reference rainfall has better sensitivity than PR (Kirstetter et al., 2012, Figure 6), we focus on cases when the reference is positive.

# 3.1. Modelling the rainfall detection by the PR

Satellite rainfall retrievals are often characterized by a rainfall threshold, under which the detection capabilities degrade (Petty, 1995, 1997; Lin and Hou, 2008, 2012; Berg *et al.*, 2010). It is commonly noted that PR misses weaker echoes probably due to its sensitivity (Schumacher and Houze, 2000). We assess here the threshold detection model because of the significant impact of the rainfall variability within the FOV on the PR detection capability. In the ideal case, the distributions of detected and missed reference rainfall would have no overlap, and the threshold would take on

a value between the two distributions. In reality, the distributions overlap.

Figure 3(a) shows the cumulative distributions of rain occurrence and volume as functions of the rain intensity. Light precipitation dominates the rain intensity spectra in terms of the fraction of rain occurrence with 78% of reference rainfall less than 1 mm h<sup>-1</sup>, while the fraction of intermediate rain intensity  $(1 \text{ mm } h^{-1} < R_{\text{ref}} < 10 \text{ mm} h^{-1})$  is 19%, and the fraction of the heavy rain intensities ( $R_{\text{ref}} > 10 \text{ mm} h^{-1}$ ) is only 3%. If the PR detection threshold is 0.5 mm h<sup>-1</sup> then it misses 68% of the rain occurrence. Intermediate and heavy rain intensities dominate the total rainfall volume. Although heavy rainfall occurs less frequently than light rain intensities, its contribution is as much as 58%, with 35% for intermediate rain intensities and only 7% for light rain intensities. Figure 3(a) depicts the behaviour of the probability of detection (POD) of the PR as a function of the reference rain rate. The POD improves with rain rate with a sharp increase between 0.1 and 1.5 mm h<sup>-1</sup>. Yet the POD is neither null for low rain rates nor equal to unity for high rain rates, and the transition between the two sills is not a step function. In finding a reference rainfall threshold defining the detection capabilities of the PR, there is a trade-off between increasing the percentage of correct detections and minimizing misses. We use the Heidke Skill Score (HSS: Wolff and Fisher, 2009; Wilks, 2011) to quantify the accuracy of precipitation detection relative to random chance at a given rainfall rate. Maximizing the HSS enables us to identify the threshold and to evaluate this model: 1 indicates a perfect delineation between PR detection above some threshold and missed precipitation below it; 0 indicates no skill (the detected occurrence of precipitation is the same as the PR without correlation); negative values indicate a model no better than random guess. The HSS is defined as (Brier and Allen, 1951):

$$HSS = \frac{2(hc - fm)}{f^2 + m^2 + 2hc + (f + m)(h + c)},$$
 (2)

where *h*, *m*, *f* and *c* are the hits, misses, false detections and correct rejections (as defined in Kirstetter *et al.*, 2012).

Figure 3(b) shows the HSS score computed for various rain rate thresholds over the entire dataset. The maximum occurs at 0.53 mm h<sup>-1</sup>, a value very close to the 0.5 mm h<sup>-1</sup> threshold assumed by Lin and Hou (2012). Using this value we evaluate the error as given in the contingency table (Table 1). The difference between the actual (see Kirstetter *et al.* (2012) for discussion on the contingency results) and modelled proportions of detected rain occurrence is small (2%). However, differences in rainfall intensities are more significant with an 18% overestimation of the



**Figure 3.** (a) Probability of detection of the reference rainfall by the PR (\_\_\_) as a function of the reference rain intensity (mm  $h^{-1}$ ). The accumulated fractions of rain occurrence (\_ \_\_) and volume (\_\_\_) are plotted in grey. (b) Heidke Skill Score for the PR as a function of the reference rain intensity. The dashed line marks the threshold (0.53 mm  $h^{-1}$ ) identified by the maximum of the HSS score.

Table 1. Contingency table for PR detection of rainfall relative to the reference.

PR estimates		Number of data samples	Percentage (%)	Mean rainfall value	Missed volume (%
>0.	Actual	530 261	33	4.33/4.61	-
	Model	486 524	31	-/5.43	
=0.	Actual	1 059 111	67	0.0/0.29	11.4
	Model	1 102 848	69	-/0.10	4.1

The results are provided for the actual and modelled (section 3) contingency values. Mean rainfall values associated to the contingency for PR/reference are provided as well as the proportion of missed volume of rainfall by PR relative to the reference.

mean reference rainfall value and 65% underestimation of mean missed reference rainfall. Because the PR consistently detects higher rain rate and misses lighter rain intensities relative to the reference (Kirstetter *et al.*, 2012), these discrepancies are mitigated in terms of total missed volume. Yet, the threshold model underestimates the missed rainfall volume by 7.3%. These findings are consistent with those of Lin and Hou (2012), but the missed occurrence and volume of rainfall are greater here.

The difference between the actual and modelled detected rainfall suggests that the rain intensity is not the only factor driving the detection capabilities of PR. The same reference rain rate can be characterized by various conditions of rain occurrence and quantitative variability (cf. Figure 2). Hereafter, we quantitatively examine the characteristics of the reference rainfall at fine spatial scale within the PR FOV and evaluate how they impact the PR detection performance.

# 3.2. Impact of rainfall variability at fine spatial scale on detection

The impact of rainfall variability within the PR field of view is assessed with the rain fraction (occurrence variability of rainfall) and the RNUBF (quantitative variability of rainfall). Kirstetter *et al.* (2012) characterized the PR detection performances by using contingency tables and by simply separating the reference dataset into 'robust' ( $R_{ref} > \sigma_{footprint}$ , i.e. RNUBF<1) and 'non-robust' ( $R_{ref} < \sigma_{footprint}$ , i.e. RNUBF>1). We extend this analysis by separating the reference data into various sub-samples according to the rain fraction and RNUBF in order to provide in-depth insight into the PR detection capabilities for various conditions. All coincident and collocated satellite values are considered and sorted according to the reference samples. PR sampled robust rainfall only 33% of the time (80% of total volume of rainfall). The PR FOV is 80% filled only 26% of the time (84% of total

volume of rainfall). Situations where the FOV filling is low and/or the variability of the rainfall is high occur frequently and require a detailed assessment. Figure 4 shows the behaviour of the probability of detection (POD) (Figure 4(b)), the mean missed reference rainfall (Figure 4(c)) and the missed volume of rainfall (Figure 4(d)) by the PR relative to the reference as a function of the RF and the RNUBF. Various conditions lead to equivalent detection performances by the PR. The POD increases: (i) with higher RNUBF values, and (ii) with high rainfall filling of the PR pixel. More specifically, the highest POD (>90%) are found for the conditions (RNUBF>1, RF>90%), and 90% of rainfall is properly detected for RF>95%. A significant filling of the FOV (70%) is required to detect rainfall and a high quantitative variability (RNUBF>1) has a positive impact from the PR perspective. The detection capabilities degrade significantly (i.e. POD<50%) for RF<40%. Misses are associated with high inhomogeneity and/or the 'rain/no rain' limits of rain fields. There are two regimes describing the dependency of the POD on rainfall variability:

- (i) For a given rain filling condition of the FOV, the POD is mainly driven by the RNUBF for RNUBF values lower than  $\sim$ 2. As an example with a FOV filled at 70%, only 20% of the reference rainfall is properly classified for RNUBF = 0.3 whereas 80% is detected for RNUBF = 2. This rate remains roughly constant for RNUBF>2, which coincides with decreasing  $R_{ref}$  as functions of RNUBF (see Figure 2) and does not support the threshold model for detection.
- (ii) For RNUBF values greater than ~2, the POD is mainly driven by the RF. For such conditions the filling of the FOV is a significant driver for the detection performances of the PR.

The missed volume of rainfall is closely related to the POD. Higher proportions of missed rainfall are noted at lower RNUBF and RF values, ranging from 10% (RF>80%, RNUBF>0.5) to 70% (RF<20%). The two regimes already noticed for the POD are more clearly separated for the missed volume of rainfall. The RNUBF influence is strongly mitigated when values exceed 1. By comparison, the missed volume passes from 80 to 20% for RNUBF increasing from 0.2 to 1, respectively. One should note that for all conditions of RNUBF and RF, the mean reference values are lower when PR missed them than when they were detected (compare Figures 2(a) and 4(c)). Both present the same patterns according to the RF and the RNUBF with higher values for higher rain fraction and present a maximum around RNUBF = 1.

To evaluate the threshold model (section 3.1), Figure 4(e) shows the plots of the identified (maximum) HSS values and the

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**Figure 4.** (a) Number of data samples, (b) probability (%) of rain detection by the PR, (c) mean missed reference rainfall (mm  $h^{-1}$ ), (d) missed volume of rainfall (%), (e) Heidke Skill Score and (f) corresponding detection threshold of the PR (mm  $h^{-1}$ ) as functions of the rain fraction RF (%) and the RNUBF.

corresponding reference rainfall threshold value as functions of the RF and the RNUBF. The HSS values are generally greater than 0, showing the threshold model is better than simple random guess. Yet the accuracy of the threshold model seems to vary with the rainfall variability characteristics within the FOV. The highest scores are found for RF values close to the maximum and for lower RNUBF values; the threshold model is consistent when the PR

FOV is uniformly filled by rainfall (both according to occurrence and quantitative aspects). The lowest scores are found when the FOV is nearly empty and the quantitative variability is high. It is worth noticing that accuracy of the threshold model quickly drops for higher RNUBF whatever the RF value. This is particularly true around RF = 100% and RNUBF = 1, which corresponds to the highest mean reference rainfall values (see Figure 2). The identified detection thresholds are also structured according to the RF and RNUBF. For RF<60%, detection threshold values range from 0.2 to 0.6 mm h<sup>-1</sup>. These low values are expected considering the smoothing effect of the antenna pattern on an FOV partially filled. For RF>60%, detection threshold values range from 0.5 to 0.8 mm h<sup>-1</sup>. These detection thresholds are higher than the average value 0.53 mm h<sup>-1</sup> for conditions associated with significant contribution to the total volume of rainfall. This explains why the unique threshold model discussed in the previous section underestimates the missed rainfall volume. The rainfall variability at fine spatial scale within the PR FOV impacts the PR detection performance.

# 4. Rainfall classification

Precipitation classifications from satellite algorithms have profound impacts on the accuracy of the quantitative retrievals. Stratiform and convective clouds have significantly different vertical heating and moistening profiles. The classification drives the vertical model of rainfall used to correct for the attenuation of the radar signal, to estimate the vertical profile of reflectivity, and the rainfall rate at ground (Iguchi et al., 2009). Classification of precipitation type from non-polarimetric active remote sensing relies partly on subjective analysis based on interpretation of precipitation spatial variability. We investigate relevant factors (occurrence, type and rate of rain within the PR FOV) driving the convergence or divergence of the PR classification relative to the reference. PR's rainfall classification capabilities, the conditions driving potential misclassification, and the proportion of rain likely to be misclassified have been largely unknown. We address these questions focusing on cases when both the PR and the reference rainfall are positive, so that precipitation detectability is not a factor.

# 4.1. Convective detection

The PR classification is a binary decision (i.e. either convective or stratiform), while the ground reference provides a volume contribution of convective rainfall varying continuously from 0% (purely stratiform reference rainfall) to 100% (purely convective reference rainfall). In a similar way to the rainfall detection, we separated the reference rainfall into purely stratiform (59% of the data sample) and convective when the convective volume contribution is positive. Table 2 shows the contingency table for the PR classification relative to the reference with percentile of hits (h: both reference and PR detect convective activity), misses (m: 2A25 classifies as stratiform while the reference classifies as convective), false alarms (f: 2A25 classifies as convective while the reference does not), and correct rejection (c: both 2A25 and the reference classifies as stratiform). Again, all coincident and collocated PR values are considered and sorted according to the reference sample. As the false detections (m + f) have a rate of 24%, it can be concluded that the PR classification generally agrees with the reference. The misses are the main contributors to this population (i.e. 70% of this population). Table 3 provides the mean rainfall values and the classified rainfall volumes according to the same contingency tables with PR on the left-hand side of the '/' sign and the reference on the right-hand side. As we expect, the convective rain rates are higher than the stratiform ones for both PR and reference. The convective rainfall missed by PR relative to the reference is consistently associated with lower PR (and reference) rain rates than when properly classified. Regarding the rain volumes in question, one can say that PR and the reference conjointly detect convective rainfall volume (90% for PR, 80% for the reference). The largest discrepancies are noted for the conjoint stratiform detection with the PR properly classifying echoes nearly 90% of the stratiform reference rainfall volume, but underestimating the volume in question by  $\sim 26\%$ . Nearly 40% of PR's stratiform rainfall volume is classified as convective by the reference. The discrepancies in rainfall volume are much less

Table 2. Contingency table for PR rainfall classification relative to the reference.

PR estimates		Reference	
	Convective	Stratiform	Number of data samples
Convective	24%	7.2%	164 960
Stratiform	16.8%	52%	363 435
Number of data samples	215 494	312 901	528 395

Table 3. Contingency table for PR classification of rainfall relative to the reference.

PR	classification/ reference	Number of data samples	Percentage (%)	$\begin{array}{l} Mean\ rainfall\\ value\ (mm\ h^{-1}) \end{array}$	(Mis)classified volume (%)
C/C	Actual	126 886	24	10.8/12.1	90/80
	Model	175 394	33.2	10.6/10.6	100/96.1
S/C	Actual	88 608	16.8	3.4/4.4	39/20
	Model	40 100	7.6	1.9/1.9	12.9/3.9
C/S	Actual	38 074	7.2	4.1/1.8	10/13
	Model	0	0	_	_
S/S	Actual	274 827	52	1.7/1.6	61/87
	Model	312 901	59.2	1.6/1.6	86.9/100

The results are provided for the actual and modelled (section 4) classification contingency. Mean rainfall values associated to the contingency for PR/reference are provided as well as the proportion of classified volume of rainfall by PR relative to the reference.

significant regarding convective reference classified as stratiform by the PR.

Figure 5 provides an in-depth view of the 2A25 classification by showing the proportion of convective classification as a function of the variability within the PR field of view (rain fraction and RNUBF) for both sensors. The reference classification is regularly distributed and depends primarily on the RNUBF with values ranging from  $\sim$ 3% to more than 95%. This is expected since the convective rainfall involves more quantitative variability than the stratiform rainfall. The 2A25 classification shows different patterns than the reference. There is less dependence on RNUBF, and the proportion of convective detection does not exceed 85%. While the classification dependence on the RNUBF shows the same trend as the reference for RF>50%, the 2A25 classification shows two detection maxima for extreme RNUBF values in the domain RF<50%. More investigation is necessary to identify the reason why the PR is prone to detect convective activity under these last conditions.

Hits, misses, false alarms and correct rejection for PR's detection of convective rainfall are computed and plotted as functions of the rainfall variability within the PR field of view in Figure 5. Both products classify convective rainfall consistently at higher RNUBF values; stratiform classification by both sensors typically occurs at lower RNUBF values. Misses are not as prevalent but tend to occur at higher RNUBF values. False alarms are mainly associated with low filling of the FOV and low RNUBF values. To summarize, the 2A25 classification differs from the reference mainly for extreme rainfall variability (i.e. low filling of the FOV and high quantitative variability). Because the 2A23 classification algorithm is based on a characterization of horizontal and vertical variability of reflectivity, these cases are certainly difficult to resolve from the PR perspective.

Grey lines in Figure 6(a) show the cumulative distributions of CPI occurrence and according convective volume contribution as functions of the CPI. The CPI is quite evenly distributed with light convective contribution (CPI<25%) representing 30% of the population, the fraction of intermediate convective contribution (25% < CPI < 75%) being  $\sim 30\%$ , and the fraction of the significantly convective reference rainfall (CPI>75%) is 40%. The last class dominates the total convective rainfall volume with a contribution of more than 90%. Figure 6(a) also depicts the probability of detection (POD) of the PR as a

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**Figure 5.** (a) Proportion (%) of convective detection by the reference and (b) by the PR, (c) proportion of conjoint convective classification by the PR and reference, (d) PR-convective and reference-stratiform classification, (e) PR-stratiform and reference-convective classification and (f) conjoint stratiform classification as functions of the rain fraction RF (%) and the RNUBF. The colour table is the same for (a,b) and for (c-f).

function of the convective volume contribution to the reference rainfall. The POD improves with CPI with a sharp increase from 13% to nearly 40% at light CPI values, then increases more slowly yet regularly with the convective contribution to reach  $\sim$ 80% for a purely convective reference rainfall. The PR shows consistent classification performances relative to the reference. Yet the POD is neither null for light CPI nor equal to unity for high CPI values, and the transition

between the two sills is not a step function as would be the case for a perfect classification of rainfall relative to the reference. In finding a reference rainfall threshold defining the classification capabilities of the PR, there is a trade-off between increasing the percentage of convective and stratiform classification. Similarly with the detection aspect, we evaluate hereafter the convective contribution threshold describing the stratiform/convective separation by the PR.



**Figure 6.** (a) Proportion (%) of convective detection by the PR as a function of the reference rainfall convective volume contribution (%). The proportion of convective contribution by occurrence  $(\_\_\_]$  and volume  $(\_\_\_]$  are figured in grey. (b) Heidke Skill Score and (c) corresponding classification threshold (%) of the PR as functions of the rain fraction RF (%) and the relative non-uniform beam filling RNUBF.

# 4.2. Modelling the rainfall classification by the PR

We use the Heidke Skill Score to quantify the accuracy of precipitation classification (stratiform vs. convective) relative to random chance at a given reference convective contribution. By computing the HSS score for various CPI thresholds over the entire dataset, a maximum value (HSS = 0.56) is found for CPI = 6%; this indicates the 2A25 product presents overall agreement with the independent classification provided by the reference. Assuming this value, we evaluate the discrepancies with the actual classification as given in Table 3. The difference between the actual and modelled proportions of classified rainfall underestimates the wrong classifications (m + f) by 16.4%, especially the misses. While presenting overall similar features, differences in rainfall intensities are also significant especially in case of misses (1.9 mm h<sup>-1</sup> for the modelled convective reference rate misclassified as stratiform by the PR while 4.4 mm  $h^{-1}$  is the actual value). The model is close to the actual values when it comes to the conjoint stratiform classification with values close to  $1.6 \text{ mm h}^{-1}$ . The model overestimates the conjoint convective and stratiform classification volumes and underestimates the rainfall volumes implied in misses.

Rain fraction (%)

The difference between the actual and modelled classified rainfall suggests that the CPI is not the only factor driving the detection capabilities of the PR. Hereafter we quantitatively examine the characteristics of the reference rainfall at fine space scale within the PR FOV (cf. Figures 2 and 3) and evaluate how they impact the PR classification performances.

Rain fraction (%)

Figure 6(b,c) show plots of the maximum HSS and of the corresponding optimum CPI threshold value as functions of the RF and the RNUBF. The positive HSS values indicate that the threshold model is better than random guess, but its accuracy varies with the rainfall variability characteristics within the FOV. The highest scores are found for the highest RF and lowest RNUBF values: this model is consistently all the more accurate when the PR FOV is uniformly filled by rainfall (both occurrence and quantitative aspects), which are better conditions for applying the PR classification algorithm. The model accuracy quickly drops for higher quantitative variability and RF>50%. This confirms that the characterization of horizontal variability of reflectivity is difficult at scales finer than the FOV. The lowest scores are found when the FOV is nearly empty. That is consistent with the convective false alarms noticed previously. It seems the limits of the classification capabilities of the PR are reached for these conditions.

The identified classification thresholds are structured according to the RF and RNUBF. Lower threshold values (<10%) are coincident with RF<80% and higher values ranging from 20 to 90% are found for RF>80%. It is probably easier to detect convective activity in case of isolated convective cells. The contribution is more difficult to distinguish when embedded into stratiform rainfall type. This is confirmed when considering the dependence of the threshold on the RNUBF. For RF>80%



Figure 7. (a-d) Reference (left) and PR (right) rainfall rate distributions (mm h<sup>-1</sup>) as functions of the reference rainfall volume convective contribution (%) for the PR stratiform (top) and convective (second row) classifications. The thick black line represents the median (50% quantile), the dark grey-shaded region represents the area between the 25 and 75% quantiles, the light grey-shaded region represents the area between the 10 and 90% quantiles. (e,f) Conditional bias of the PR relative to the reference as a function of the reference rainfall volume convective contribution for the PR (e) stratiform and (f) convective classifications. The grey lines figure the conditional mean reference (plain) and PR (dotted) rainfall.

(<80%), the threshold values are higher for lower (higher) RNUBF.

#### **Rainfall quantification** 5.

The last section addresses the dependencies of the PR rainfall rates on rainfall variability and classification. We address these questions focusing on cases when both the PR and the reference the reference and PR rainfall rate distributions as functions

rainfall are positive, so as to remove any discrepancies related to detectability.

# 5.1. Influence of the rainfall classification

The 2A25 algorithm uses different Z-R relationships in the convective/stratiform profiling components. Figure 7 shows



Figure 8. (a) Mean reference, (b) PR rainfalls (mm  $h^{-1}$ ) and (c) bias (%) of the PR relative to the reference as functions of the rain fraction RF (%) and the RNUBF. The colour table is the same for (a,b).

of the convective contribution, CPI. All coincident and collocated PR values are considered and sorted according to the reference sample. The dataset is also separated according to the PR rain type classification. Figure 7(a-d) show a shift toward higher rainfall rates as CPI increases, as we would expect. This shift is most pronounced for PR and reference rain rates with PR-indicated convective echoes (Figure 7(c,d)). Despite these consistencies, we note rain rate distributions indicating higher rainfall rates for the reference compared to those of PR (i.e. Figure 7(a) compared to (b), and (c) compared to (d)). The dynamic ranges of rain rate distribution are greater for the reference than for the PR, especially for the PR convective type (see Figure 7(c)). Such differences, which will undoubtedly result in some bias, could be related to the 2A25 Z-R relationships. It is worth noting that the spread of the PR convective rain rate distribution in Figure 7(d) is greater than for the stratiform PR rainfall whatever the convective contribution. Such a feature does not apply to the reference rainfall, and potentially indicates uncertainties in quantifying the 2A25 convective rainfall.

The rain type impacts the bias of the PR relative to the reference. Figure 7(e,f) show the mean rainfall rates and the PR biases as a function of the CPI. The conditional biases are very distinct according to the PR rainfall types. The PR convective systematic biases present a shift towards higher values compared to stratiform biases. Biases cover a much broader range for the PR convective type (from -50 to 200%) than for the stratiform type (from -50 to 10%). They are both decreasing functions of

the convective contribution CPI, with overestimation at values <20% and underestimation for convective contribution >90%. Apparently, both stratiform and convective profiling algorithms in 2A25 lack sufficient dynamics to deal with extreme rainfall amounts. However, the behaviour of the bias for convective and stratiform PR types decreases at a quasi-linear rate with increasing CPI, and thus provides opportunities for correction using the ground reference. Biases are consistently distributed with the PR classification, with the stratiform algorithm presenting relatively limited biases for light CPI values (biases within 10% for CPI<40%) and the convective algorithm having limited biases for high CPI values (biases within 50% for CPI>70%).

#### 5.2. Influence of the rainfall variability at fine scales

Figure 8 provides an in-depth view of the 2A25 rainfall rate quantification relative to the reference. The mean rainfall values by both sensors are computed as a function of the variability within the PR field of view. The reference rain rates are regularly distributed along the RNUBF and RF with values ranging from 0.01 mm h<sup>-1</sup> to more than 10 mm h<sup>-1</sup> (Figure 8(a)). Maximum rainfall rates occur where RF ~ 100% and RNUBF ~ 0.5. The 2A25 rainfall rate quantification plot in Figure 8(b) shows different patterns than the reference. Lower gradients are noted with values ranging from 1 to 7 mm h<sup>-1</sup>. A maximum is found for RF ~ 100% and RNUBF ~ 1. This shift of the 2A25 maximum toward higher quantitative variability relative



**Figure 9.** Bias (%) of the PR relative to the reference as a function of the rain fraction RF (%) and the relative non-uniform beam filling (RNUBF) for conjoint convective classification by (a) PR and the reference, (b) PR-convective and reference-stratiform classifications, (c) PR-stratiform and reference-convective classifications, and (d) stratiform classifications by both PR and reference. The colour table is the same for all panels.

to the reference may result from the NUBF correction scheme applied in version 7 of the 2A25 algorithm. The bias of the PR relative to the reference in Figure 8(c) is organized with highest underestimation (-30%) around RF  $\sim 100\%$  and RNUBF  $\sim 0.5$ . More generally, the PR underestimates relative to the reference for RF>80% and RNUBF<1. For lower FOV-filling conditions and higher quantitative variability, 2A25 overestimates relative to the reference with bias values exceeding 1000%. In these conditions the rain rates are low and the NUBF correction is almost non-existent in the 2A25 algorithm.

The bias plot in Figure 8(c) is broken down into contingency categories for convective classification in Figure 9. When both reference and PR detect convection, the bias primarily depends on the RNUBF as depicted with near-horizontal contour lines of the bias (Figure 9(a)). There is overestimation by PR relative to the reference for RNUBF>1 and underestimation otherwise. This feature is more pronounced when PR misses convection, for which the RNUBF value separating over- and underestimation is  $\sim$ 2. The 2A25 product overestimates for nearly all conditions of rainfall variability in cases of falsely detected convection relative to the reference (Figure 9(b)). When both the reference and PR classify stratiform rainfall, PR underestimates rainfall rates relative to the reference only for high filling conditions of the FOV (RF > 90%) (Figure 9(d)). The bias gradients are organized along the RNUBF axis for lower filling conditions of the FOV and along the RF axis for higher filling conditions. In convective rainfall, the quantitative variability inside the PR FOV plays a significant role in addition to the Z-R relationship (section 5.1).

# 6. Conclusions

Satellite surface rain rate estimates are affected by rainfall variability at finer scales than those resolved by space sensors and the retrieval algorithms in terms of detection capabilities, characterization of rainfall types, and quantification of rainfall rates. A 7-month data sample of TRMM-PR-based rainfall products was analysed using gauge-adjusted and quality-filtered surface rainfall estimates derived from NMQ/Q2. Several highresolution Q2 products were used to characterize the reference rainfall in terms of occurrence, types and rate at PR's pixel resolution to evaluate the PR detection, classification and quantification performances. Primary errors due to incorrect physical assumptions related to convective versus stratiform rainfall classification, non-uniform beam filling (NUBF) and conversion from reflectivity to rainfall intensity have been investigated. While the error structure of the PR is complicated because of the interaction of these factors, simple empirical threshold models regarding PR detection and rainfall classification were discussed.

Segregating rain from no-rain transition is a driving contributor to the PR rain rate errors, probably linked to the lack of sensitivity in the most inhomogeneous and light parts of the edges of rainy regions, although the PR captures the major part of the rainfall volume. Rainfall detection capabilities vary with the horizontal variability within the field of view (non-uniform beam filling). The PR detects rainfall when the rain amount is high enough (0.53 mm h<sup>-1</sup>) and the FOV is significantly filled with rainfall (at least 70%). By utilizing reference rainfall rates at scales

below the pixel resolution of PR, we have determined that simple rain rate threshold-based detection models are not accurate in case of high rainfall variability, and caution is recommended when using them for evaluating the PR detection performances. The PR classification generally agrees with the reference. Misclassification may have a huge impact on the estimated rainfall volume, with nearly 40% of PR's stratiform rainfall volume classified as convective by the reference. The PR classification is generally consistent with the rainfall quantitative variability within the FOV. However, misclassification is shown to occur with variability of the rainfall within the FOV not resolved by the 2A23 algorithm, with false convective detection associated with low filling of the FOV and low RNUBF values. Regarding quantification, significant error is most likely due to a combination of inaccurate Z-Rrelationship, non-uniform beam filling and/or attenuation of the PR radar signal. Both stratiform and convective profiling algorithms in 2A25 seem to be lacking sufficient dynamics to deal with extreme rainfall amounts. However, the bias for convective and stratiform PR types decreases at a quasi-linear rate with increasing CPI, and thus provides opportunities for correction using the ground reference. For correcting PR stratiform and convective rainfall rates, we suggest matching the PR PDFs in Figure 7(b,d) with those associated to the reference values in Figure 7(a,c), respectively. For lower FOV-filling conditions and higher quantitative variability, 2A25 overestimates relative to the reference and underestimates otherwise. Results from the conditioned error features presented herein provide insights into the most significant characteristics of PR rainfall retrieval errors that need to be taken into account when such data are used in applications.

Future works will address the relative contributions of errors linked to off-nadir angle and the underlying terrain. The same framework and reference rainfall datasets can be readily applied to rainfall retrievals from other sensors on board low Earth-orbiting satellites (i.e. TMI, AMSR-E, SSMI, MADRAS). This framework will also be applied to GPM rainfall estimates following its launch in 2014. Another important issue to study is how the various error sources in PR propagate in a number of satellite-based, highresolution precipitation products when calibrating geostationary infrared-based precipitation estimates.

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