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ABSTRACT

The particle identification scheme developed by Dolan and Rutledge for X-band polarimetric radar is tested for the first time in Africa and compared with in situ measurements. The data were acquired during the Megha-Tropiques mission algorithm-validation campaign that occurred in Niger in 2010. The radar classification is compared with the in situ observations gathered by an instrumented aircraft for the 13 August 2010 squall-line case. An original approach has been developed for the radar–in situ comparison: it consists of simulating synthetic radar variables from the microphysical-probe information and comparing the two datasets in a common ‘radar space.’ The consistency between the two types of observation is good considering the differences in sampling illustrated in the paper. The time evolution of the hydrometeor types and their relative proportion in the convective and stratiform regions are analyzed. The farther away from the convection one looks, the more aggregation dominates, riming diminishes, and hydrometeors are less dense. Particle identification based on the polarimetric radar will be applied to a 5-yr African dataset in the future.

1. Introduction

Since the beginning of their application to weather radar in the 1970s (Seliga and Bringi 1976, 1978), dual-polarization techniques have contributed to improving quantitative precipitation estimation (Cifelli and Chandrasekar 2013; Ryzhkov et al. 2005) and a better analysis of physical processes inside storms (Bluestein et al. 2007; Tanamachi et al. 2012; French et al. 2014). The polarimetry-based particle identification (Hall et al. 1984; Vivekanandan et al. 1999; Zrnić et al. 2001; Lim et al. 2005; Marzano et al. 2010; Chandrasekar et al. 2013) is a method that is commonly used to synthesize the information from a variety of radar variables (reflectivities in two channels, differential reflectivity, the linear depolarization ratio when available, differential phase shift, and cross-polarization correlation coefficient) into a single piece of information: the dominant type of particle inside the radar beam. Depending on the objectives, the particle identification can be applied to filtering out nonmeteorological targets and/or to distinguish various types of hydrometeors—in particular, hail and the associated hazard (Bringi et al. 1986; Illingworth et al. 1986; Ryzhkov et al. 2005). Many case studies have been presented in which the particle identification was used, often in combination with the Doppler information, to study the microphysical and dynamical processes inside precipitating systems (Barnes and Houze 2014; Höller et al. 1994). In the paper that is presented here, radar classification of hydrometeors is applied to a very specific question: What are the characteristics of the ice-phase hydrometeors encountered in the precipitating regions of continental convective systems in the tropics?

This specific question has been raised in the framework of the Megha-Tropiques (MT) satellite mission (Roca et al. 2015; Kidd et al. 2013; http://meghatropiques.ipsl.polytechnique.fr/) dedicated to the water and energy cycle in the tropical atmosphere. Megha-Tropiques is a
member of the Global Precipitation Measurement mission (GPM; Hou et al. 2014), and one objective of MT is rainfall retrieval on the basis of passive microwave radiometry. The retrieval is based on the Bayesian Rain Retrieval Algorithm including Neural Network (BRAIN; Viltard et al. 2006) estimation algorithm. BRAIN compares the observed microwave brightness temperatures (Tbs) with a reference database of synthetic Tbs that have been obtained from microphysical profiles and a radiative transfer model. Over the continent where the lowest microwave frequencies are impacted by the surface emissivity, rainfall retrieval is based on the higher microwave frequencies, sensitive to ice scattering (Hong 2007; Johnson et al. 2012). The accuracy of the retrieval is therefore strongly dependent on 1) the physical link between the quantity of icy hydrometeors aloft and surface rain (Viltard et al. 2006) and 2) a good representation of the icy hydrometeors scattering properties in the radiative transfer model (Bauer et al. 2000; Olson et al. 2001).

To acquire quantitative information about the nature, size, and density of the hydrometeors that influence the microwave Tbs over the continent, the MT program organized a dedicated field campaign, in Niger, in August 2010. The Niamey 2010 Megha-Tropiques Ground Validation (MTGV) campaign focused on continental mesoscale convective systems (MCSs) as observed in the Sahel. An instrumented aircraft from the Service des Avions Français Instrumentés pour la Recherche Environnementale (French Service of Instrumented Aircraft for Environmental Research; SAFIRE) equipped with several microphysical probes and the 94-GHz cloud radar named Radar Aéroporté et Sol de Télédétection des Propriétés Nuageuses (RASTA; Protat et al. 2009) was stationed in Niamey for 3 weeks and flew inside 11 convective systems (Fontaine et al. 2014). Although they are extremely valuable, one limitation of airborne in situ measurements is their representativeness; only a few MCSs could be observed, and within each system the volume actually sampled is small and is limited to areas within which the aircraft can fly safely. During the MTGV campaigns the airborne observations were complemented with a ground-based dual-polarization radar to provide a more global picture of the spatio-temporal variability of hydrometeors within and between convective systems.

Previous studies that were based on cloud-resolving or conceptual models (Caniaux et al. 1994; Houze 2004; Penide et al. 2010; Schumacher and Houze 2006) and on observations (Guy et al. 2013; Evaristo et al. 2010; Bouniol et al. 2010) have given a good description of the dynamics and microphysics within continental MCSs, their convective front, the trailing stratiform region, and the anvil (Bouniol et al. 2010). The convective front is characterized by strong updrafts, high rain rates reaching 100–200 mm h\(^{-1}\), and aloft strongly rimed dense particles like graupel. The trailing stratiform region is characterized by a weaker updraft and a growth of particles by aggregation as they precipitate. On radar images the stratiform region exhibits a typical brightness band signature associated with the melting of big aggregates as they fall through the 0\(^\circ\) isotherm (see also Alcoba et al. 2016; hereinafter Part II). Evaristo et al. (2010) pointed out the presence of old dissipating convective cells associated with rimed particles even inside the stratiform region of West African MCSs. Dense particles such as graupel and aggregates that are less rimed and lighter (Hong 2007; Johnson et al. 2012; Straka et al. 2000) have very different scattering properties. Quantifying the amount of riming in different parts of MCSs would therefore be useful. This information would help to parameterize the microphysical/scattering properties of hydrometeors for a microwave rain-retrieval scheme. One way to approach this question with ground-based radar is by analyzing the radar properties of the particles as synthesized by polarimetry-based particle identification; however, the relevance/confidence level of the identification needs to be assessed first. During the African Monsoon Multidisciplinary Analysis observation campaigns (Lebel et al. 2010), several studies provided single- or dual-polarization radar observations (Guy et al. 2013; Evaristo et al. 2010) or airborne in situ observations (Bouniol et al. 2010; Frey et al. 2011) inside MCSs. During these campaigns, however, the inflight observations were not in the vicinity of polarimetric radar and the two types of measurements were not compared.

The objective of this paper (and of Part II) is to compare the particle properties derived from the dual-polarization radar with those reported by the airborne instruments. According to BRAIN’s developers, the layer inside precipitating clouds that contributes most to the brightness temperature observed in the “scattering channels” (i.e., 80–90 GHz) is located directly above the 0\(^\circ\) isotherm and up to 3 or 4 km above it. The main focus of this work is to quantify the relative proportion of dense particles (classified as “graupel”) and lighter particles (classified as “aggregates”) in the cold precipitating layers of tropical continental MCSs. The classification is based on our X-band dual-polarization radar (Koffi et al. 2014). The comparison with the in situ data is made on the basis of the catalog of images derived from the probes and synthetic polarimetric radar variables derived from the particle information and a T-matrix scattering code (Mishchenko et al. 1996).
Section 2 describes the dataset. Section 3 compares different hydrometeor classification schemes and analyzes the sensitivity of the hydrometeor identification (HID) to uncertainty in the radar signal and the weight given to the variables. Section 4 presents the 13 August 2010 case study and the radar–in situ comparisons; section 5 analyzes the variability within the observed convective system. Section 6 summarizes the findings.

2. Dataset

The data were collected during the MT algorithm-validation campaign in Niamey, Niger, in August 2010. This prelaunch campaign (the satellite was launched in October 2011) was dedicated to validating the microphysics assumptions used in the microwave rain retrieval BRAIN (Viltard et al. 2006) for continental convective systems. An instrumented aircraft and an X-band polarimetric radar were transported to Niger for the experiment. The objectives of these combined measurements were twofold: 1) to acquire direct information on the particle size distribution and density over the limited domain sampled by the aircraft and 2) to document the spatial and temporal variability of these microphysical properties and their variations among MCSs observed by ground radar. First the consistency of the microphysical information derived by the airborne instruments and the ground radar on their common coverage must be checked. As already stated, the main concern is the scattering properties of the icy hydrometeors that have significant impact on the microwave signal received from continental tropical rainy systems: the precipitating ice above the melting level.

Eleven instrumented flights were successfully completed inside the stratiform region of squall lines, with the aircraft flying at different altitudes to document the vertical as well as horizontal variability of microphysical properties (Fontaine et al. 2014). Only one flight was close enough to the “Xport” radar to allow direct and quantitative comparison between the radar polarimetric variables and the in situ information. Figure 1 shows the ground projection of the aircraft trajectory on the 13 August flight superimposed on the radar reflectivity field. It displays the stratiform region of the MCS as observed at 1521 UTC.

a. Xport radar data

The polarimetric information is provided by the Xport X-band (9.4 GHz) polarimetric radar from the Institut de Recherche pour le Developpement (IRD). Xport is a dual-polarization radar with simultaneous (and not alternate) emission/reception of the horizontal (H) and vertical (V) polarizations. The radar characteristics are given in Table 1. During the campaign the radar was operating in Sadore (13°14′34.00″N, 2°16′27.00″E) 28 km south of the Niamey airport where the instrumented aircraft was based. The radar scanned the atmosphere by 3D sequences of 12 min with 12 PPIs as detailed in Table 1 (see also Fig. 1 of Part II). The maximum observation distance is 135 km, but the hydrometeor classification is restricted to the first 60 km of range.

As detailed in section 3, the HID is based on four polarimetric radar variables: the radar reflectivity in one polarization (here horizontal, or \( Z_H \)), the differential reflectivity \( Z_{DR} \), the specific differential phase shift \( K_{DP} \), and the cross-polarization correlation \( \rho_{hv} \).

One consequence of working at X band is that the propagation effects in rain are strong in comparison with lower frequencies. This is especially true for the heavy rainfall encountered in African squall lines. On the one hand this means that \( K_{DP} \) is 2–3 times as high as for S and C band, which is good for the HID. On the other hand the radar reflectivities in both channels suffer attenuation and need to be corrected before the HID can be applied.

The Xport data are corrected for attenuation on the basis of the well-known link between the attenuation by rain and the differential phase shift (Matrosov et al. 2009; Testud et al. 2000; Zahiri et al. 2008). The correction scheme is based on Matrosov et al. (2005) and assumes a linear relationship between the path-integrated attenuation (PIA) and the differential shift \( \varphi_{DP} \):

\[
P_{IAH} = \alpha \varphi_{DP}.
\]  

The prefactor \( \alpha \) of the relation has been estimated using the method proposed by Carey et al. (2000) as in Koffi et al. (2014). The method is based on deriving Eq. (1) as a function of \( \varphi_{DP} \). On this basis, Carey et al. (2000) showed that \( \alpha \) can be derived as the slope of the best-fitted line on a scatterplot of reflectivity versus differential phase shift. This method was applied on the whole Niamey 2010 dataset, and the value of \( \alpha \) is found to be 0.28 on average, with a small variability among storms.

The attenuation correction and the radar calibration are also verified by comparing the radar-based rainfall estimates with gauges (Koffi et al. 2014; Kacou 2014) and checking that there is no remaining range-dependent bias. The \( Z_{DR} \) is initially calibrated using vertically pointing scans for cases with no attenuation (drizzle; cloud). The consistency between the attenuation-corrected \( Z_{DR} \), or \( Z \), and \( K_{DP} \) (Koffi et al. 2014) is used as final check of the quality of the attenuation correction. We carried out some sensitivity tests that were based on a brightband model (see Part II) and the T-matrix code to check whether the attenuation-correction method adjusted in rain (lower elevation
angles) caused systematic biases when used through the bright band. The results (not shown) are that various effects within the bright band tend to cancel out and thus the overall effect is additional uncertainty (random errors) but no systematic under or overestimation. Also, given the position of the study domain (black rectangle in Fig. 1), the slant path through the bright band accounts for 2%–10% of the total path.

The method adopted to produce $K_{DP}$ for each range bin from $\varphi_{DP}$ is similar to Koffi et al. (2014): the mean slope in $\varphi_{DP}$ as a function of range is calculated over ±5 range bins around the bin of interest, using a linear fit. Only the range bins with a value of $\rho_{HV}$ above a given threshold are used for the linear fit.

b. Airborne microphysical instruments

The instrumented aircraft is SAFIRE’s Falcon 20, flying at cruising speed of 290 m s$^{-1}$. The aircraft was equipped with microphysical optical-array probes to sample frozen and liquid cloud and precipitation hydrometeors: a 2D stereo probe (2D-S) from Stratton Park Engineering Company, Inc., that acquires 2D images in the size range 10–1280 $\mu$m and the Precipitation Imaging Probe from Droplet Measurement Technologies, Inc., for images of hydrometeors in a size range of 100–6400 $\mu$m. A catalog of hydrometeor images from the probes is produced for each flight. Artifact rejection is applied on the catalog to filter splashed and shattered images on the basis of a combination of rules for inter-arrival time, size of fragments, and number of fragments in the image, and reconstruction of partial particle images is performed (Duroure et al. 1994; Fontaine et al. 2014). From the catalog, the particle maximum dimension $D_{max}$, or major axis, is extracted as the longest dimension of the axis crossing the barycenter of the particle image. The dimension of the minor axis is equal to the dimension of the axis perpendicular to the $D_{max}$ axis passing through the barycenter. Thus, the ratio of the minor axis over the major axis is identified as the aspect ratio of the particle, and the number particle size

![Fig. 1. Xport radar reflectivity field (1.12° elevation) for 1521:36 UTC 13 Aug 2010. Red line: ground projection of the instrumented-aircraft trajectory for the flight (which lasted from 1323 to 1610). The black rectangle is the ground projection of the volume used to analyze the time evolution of the microphysics (section 5), and the black point is the position of the Deberegati rain gauge (13.058°N, 2.122°E).]
distribution (PSD) is calculated as a function of $D_{\text{max}}$. The aircraft was also carrying the 94-GHz Doppler RASTA (Bouniol et al. 2008; Protat et al. 2009). Fontaine et al. (2014) have developed a method to derive the hydrometeor mass–diameter laws by combining the PSD derived from the probes and the reflectivity measured by the radar and using T-matrix simulations. The in situ information (Fontaine et al. 2014) available for this study consists of three things: The first is the PSD $N(D)$ expressed as the number of particles per volume of air and per diameter class $(\text{mm}^{-3} \cdot \text{m}^{-3})$. For this work, the PSD is based on the maximum dimension $D_{\text{max}}$ of the particles (Fontaine et al. 2014). The PSD is integrated over 10 s along the flight. The diameter increment is set to 100 $\mu$m for a size range of particle diameters ranging from 50 to 6450 $\mu$m. The second consists of the prefactor $\alpha$ and exponent $\beta$ of the density law, as defined by

$$m(D_{\text{max}}) = \alpha D_{\text{max}}^\beta,$$  \hspace{1cm} (2)

with $D_{\text{max}}$ in centimeters and $m(D_{\text{max}})$ in grams. The third is the mean aspect ratio of the particles. With the above items and a scattering code, synthetic radar variables can be simulated along the flight trajectory, as discussed in section 4.

3. Particle identification: Principle and sensitivity analysis

Distinguishing various types of hydrometeors from polarimetric radar signatures was first introduced and implemented by Straka and Zrnić (1993). One strong operational motivation for their study was to distinguish hail from rain. Following this pioneering work, many studies have demonstrated the usefulness of HID for various research and operational applications: better understanding of cloud dynamics and microphysics coupling (Rowe and Houze 2014), improvement of radar processing and elimination of nonmeteorological targets (Gourley et al. 2007; Figueras i Ventura and Tabary 2013; Al-Sakka et al. 2013), and more precise quantitative precipitation estimation (QPE; Rico-Ramirez and Cluckie 2008). Most of the work on HID has been done in the S and C bands, which are the most common frequencies for operational weather radar. However, because of the recent renewed interest in radar operating at X band for QPE (Matrosov et al. 2005; Testud et al. 2000; Koffi et al. 2014), several groups have reported HID on the basis of X-band radar (Dolan and Rutledge 2009; Marzano et al. 2010).

a. Principle

The basic principle of HID is to distinguish particles on the basis of the position in the space of the polarimetric radar variables $(Z_h, Z_{DR}, K_{DP}, \rho_{HV})$ with or without additional information (such as the air temperature profile). Different techniques have been proposed: decision tree (Höller 1995), fuzzy-logic technique (Dolan and Rutledge 2009; Zrnić et al. 2001), neural networks (Liu and Chandrasekar 2000), or Bayesian theory (Marzano et al. 2010). The choice and number of input and output variables vary a lot from author to author. Review works such as Chandrasekar et al. (2013) and Al-Sakka et al. (2013) give a good idea of the span of available methods and applications.

The HID scheme used for this study is based on Vivekanandan et al. (1999) as adapted to the X band by Dolan and Rutledge (2009). It uses a fuzzy-logic method with weighted membership beta functions (MBF) associated to each couple of input variables and hydrometeor types. The input variables are $Z_h, Z_{DR}, K_{DP}$, and $\rho_{HV}$. Nine types of hydrometeors are considered: drizzle (light rain), rain (medium or heavy), big drops, hail, wet graupel, wet aggregates or snow, dry graupel, dry aggregates or snow, and ice crystals.

The hybrid fuzzification method, in which the MBFs of the radar variables are multiplied by the MBF of the temperature, is implemented. This method gives a strong weight to the temperature, which helps in discriminating between liquid and solid particle, such as drizzle and snow (Al-Sakka et al. 2013).

Equation (3) below gives the expression of the score calculated for the hydrometeor type $i$ as a function of the MBF of the radar variables and temperature:

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**Table 1.** Xport radar characteristics.

<table>
<thead>
<tr>
<th>Radar name</th>
<th>Xport</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency</td>
<td>9.4 GHz</td>
</tr>
<tr>
<td>Polarization</td>
<td>Dual (H and V simultaneous)</td>
</tr>
<tr>
<td>Transmitted power</td>
<td>100 kW (50 kW horizontal; 50 kW vertical)</td>
</tr>
<tr>
<td>Pulse width</td>
<td>1 $\mu$m</td>
</tr>
<tr>
<td>Pulse repetition frequency</td>
<td>1 kHz</td>
</tr>
<tr>
<td>Beamwidth (3 dB)</td>
<td>1.4°</td>
</tr>
<tr>
<td>Pulse integration</td>
<td>64</td>
</tr>
<tr>
<td>Gate length</td>
<td>205 m</td>
</tr>
<tr>
<td>Polarization</td>
<td>Dual (H and V simultaneous)</td>
</tr>
<tr>
<td>Antenna scanning strategy</td>
<td>1.4°</td>
</tr>
<tr>
<td>Elev range</td>
<td>From $-0.5^\circ$ to 90.5°</td>
</tr>
<tr>
<td>Antenna dimension</td>
<td>1.8 m</td>
</tr>
<tr>
<td>Available radar variables for HID</td>
<td>$Z, Z_{DR}, K_{DP}, K_{HV}$</td>
</tr>
<tr>
<td>Antenna scanning strategy: elev of the 12 PPIs</td>
<td>1.1°, 2.6°, 5.5°, 9.5°, 15°, 31°, 1.1°, 4°, 7.5°, 12°, 21.7°, and 45°</td>
</tr>
<tr>
<td>Sequence duration</td>
<td>12 min</td>
</tr>
<tr>
<td>Distance of obs</td>
<td>Radar range: 135-km; obs restricted to 60 km for HID</td>
</tr>
</tbody>
</table>

---
where \( i \) is the hydrometeor type, \( j \) is one of the four polarimetric variables, \( W_j \) is the weight given to the polarimetric variable, and \( T \) is temperature; \( n \) is the number of polarimetric variables and is equal to 4 here (\( Z_h, Z_{DR}, K_{DP}, \) and \( \rho_{hv} \)). The hydrometeor type with the maximum \( A \) value is considered to be the predominant type in the radar volume.

The MBFs are illustrated in Fig. 2. They are the monovariables MBF that were proposed by Dolan and Rutledge (2009) and further improved by Thompson et al. (2014). They are based on scattering simulations and a rich span of assumptions for the microphysical properties of the hydrometeors (Dolan and Rutledge 2009).

Figure 2 presents the regions where the MBF is equal to 1, for each particle type in four two-dimensional spaces defined by the radar variables and the temperature: \( Z_h-Z_{DR}, Z_h-K_{DP}, Z_h-\rho_{hv}, \) and \( Z_h-T \) (°C). None of the variable pairs enables the unambiguous distinction of all particles. The overlap between at least two particles and up to five particles is common as, for instance, for the domain limited by the reflectivity range 25–30 dBZ and the \( Z_{DR} \) range 0–1 dB. Some radar variables provide a good discrimination between two specific species. For instance, reflectivity is a good discriminating factor between snow aggregates (with a maximum of probability in the range 0–35 dBZ) and dry graupel (most probable between 25 and 45 dBZ); in their common reflectivity domain (25–35 dBZ), the larger spread of \( K_{DP} \) and \( Z_{DR} \) values can help in distinguishing the graupel. Phase shift \( K_{DP} \) is also useful to distinguish between wet graupel and wet aggregates, which occupy overlapping domains in the \( Z_h-Z_{DR} \) space. Correlation \( r_{hv} \) is a very good indicator of the wet/melting hydrometeors. The drop in \( r_{hv} \) along a vertical profile is indeed known as a good marker of the melting layer (Zrnić et al. 2001). However, \( r_{hv} \) can also diminish when the signal-to-noise ratio is low, as at the edge of storms or in case of strong attenuation, and this variable should be used with caution in classifications (Zahrai and Zrnić 1993). The weight given to each radar measurement \( [W_j \text{ in Eq. (3)}] \) is adjusted according to the confidence one has in the polarimetric variables (Dolan and Rutledge 2009).

### b. HID sensitivity analysis

As displayed in Fig. 2 and Eq. (3), the output of the HID scheme depends on the MBF of each of the measured radar variables \([Z_h, Z_{DR}, K_{DP}, \rho_{hv}, \text{ and } T(\degree C)]\) and the weights \( (W_j) \). A shift in the measured values (e.g., because of a calibration drift) or a change in the weights may result in the selection of a different type of particle. This section
analyzes the sensitivity of the HID output to the uncertainty in the observed radar variables and to the prescribed weights; this kind of analysis is seldom presented in papers reporting HID results.

To illustrate the influence of measurement uncertainty and weight values, the HID output when the radar variables are shifted or a different weight is applied are compared with a default setup. The case study is the stratiform region of the 13 August 2010 squall line (seen in Fig. 1) observed at 1606 UTC. The HID output is analyzed for the whole volume scan (12 PPIs). The analysis is restricted to a 60-km range, which gives a total of 292 radar gates. The HID is based on $Z_{hh}$, $Z_{DR}$ (both corrected for attenuation—see section 2a), $K_{DP}$, $\rho_{hv}$, and the temperature profile (provided for the day by the airplane). For the default setup, the weights given to each variable are those provided by Dolan and Rutledge (2009): $W_{Z_{hh}} = 1.5$, $W_{Z_{DR}} = 0.4$, $W_{K_{DP}} = 1.0$, and $W_{\rho_{hv}} = 0.2$.

The analysis focuses on the percentage of radar pixels with a given type of predominant hydrometeor within the volume scan. For the default setup (highlighted red rectangles on Fig. 3) these percentages are 34% of drizzle, 17.6% of rain, 3.7% of wet snow, 0.6% of wet graupel, 32.9% of snow aggregates, 8% of dry graupel, and 3% of ice crystals. Sections 3b(1) and 3b(2) illustrate the variability of these percentages when the radar signal is perturbed or the weights are changed. The analysis focuses on the respective proportions of aggregates and graupel, which is the main objective of this work.

1) UNCERTAINTIES IN RADAR VARIABLES

Random and systematic errors impact the radar variables (Lee 2007; Smith and Krajewski 1991). For instance, biases due to miscalibration or to a non-perfect correction of the attenuation may affect the reflectivities (both $Z_{hh}$ and $Z_{DR}$) and shift the value of their MBFs, $\rho_{hv}$ may be reduced because of a low signal-to-noise ratio in the case of strong attenuation, and the uncertainty in $K_{DP}$ is brought about by the noise in the measured differential phase shift and various effects like nonuniform beamfilling or the impact of the scattering phase shift (Anagnostou et al. 2004). A negative or positive bias was introduced into the variables, one at a time, before applying the HID. The amplitude of the signal offset varies by $\pm 3$ dB (in steps of 0.25) for $Z_{hh}$, $\pm 1$ dB (in steps of 0.25) for $Z_{DR}$, $\pm 1.5^\circ$ km$^{-1}$ (in steps of 0.01$^\circ$ km$^{-1}$) for $K_{DP}$, and from 0 to $-0.1$ (in steps of 0.01) for $\rho_{hv}$. The impact on the HID results is quantified in Fig. 3.
As expected from the shape of the MBF patterns (Fig. 2), a positive bias in \( Z_h \) enhances the proportion of particles associated with strong reflectivities (below the 0°C level, rain at the expense of drizzle; above the bright band, dense graupel at the expense of less reflexive aggregates). For a positive bias of 3 dB, the respective percentages of graupel and aggregates become 13.1% and 28.4% instead of 8% and 32.9% for the default setup. On the contrary, a negative bias enhances the apparent proportion of aggregate (36%) and reduces further the amount of graupel (3.8%). The uncertainty in the polarimetric variables \( Z_{DR} \) and \( \rho_{hv} \) has less impact on the proportion of graupel versus aggregates but tends to modify the amounts of wet particles that have a strong polarimetric signature. According to Fig. 2, wet snow is very probable while aggregates and graupel are not, for high value of \( Z_{DR} \) and for low values of \( K_{DP} \). These sensitivity results are obviously very dependent on the way that the various particles were modeled in the numerical database used to derive the MBFs. An important result for our focus is that the relative quantities of graupel/aggregates are very robust to the radar variable uncertainty. The higher sensitivity is associated with \( Z_h \), which is logical given the shape of the aggregates and graupel MBF in Fig. 2 and also given the strong weight given to \( Z_h \). Within the offset range \( \pm 1.5 \text{ dB} \), the percentage of graupel varies from 5.6% to 10.7% and the percentage of aggregate varies from 30.5% to 34.8%. In this example, aggregates remain dominant over graupel, whatever the bias may be.

A similar test (not shown) was carried to check the sensitivity to the height of the 0°C isotherm. Given an error up to \( \pm 750 \text{ m} \) (\( \pm 3 \text{ radar bins} \)), the relative proportion of aggregates versus graupel changed from 77% aggregate and 23% graupel to 82% and 18%, respectively.

2) WEIGHT OF THE POLARIMETRIC VARIABLES

Adjusting the weight \( [W_j \text{ in Eq. (3)}] \) is a way to limit the impact of variables that are not “trusted.” According to Vivekanandan et al. (1999), the weights are determined subjectively on the basis of the accuracy of the variables and the discrimination skill they provide. At S band, Vivekanandan et al. set the weights of three of the variables (\( Z_{hv}, Z_{DR}, \) and \( T \)) to 2 times as high as the weights of \( K_{DP} \) and \( \rho_{hv} \). For X band, Dolan and Rutledge (2009) chose a low weight for \( Z_{DR} \) (0.4) to limit the impact of this variable’s uncertainty on the HID results; the weight on \( \rho_{hv} \) was also low (0.2), and the weight on \( K_{DP} \) was kept high (1.0 while \( Z_h \) is 1.5) because this variable is better measured at X band than at S or C band. The work presented here uses by default the weights proposed by Dolan and Rutledge (2009).

To test the sensitivity of the HID to the weights given to each radar variable, we vary them one at a time, in the range from 0.1 to 2.0 by step of 0.1. The impact on the HID results is quantified in Fig. 4.

The sensitivity to the weight of \( Z_h \) is very low when the weight varies in the range 1–2. When the weight of \( Z_h \) is below 1, the effect is strong—in particular, on the respective amounts of retrieved aggregates/graupel. The same effect is also noticed when the weight on \( K_{DP} \) is increased. These results are in agreement with Fig. 2: graupel is probable for a larger range of \( K_{DP} \) values than aggregates; when more weight is given to \( K_{DP} \) then graupel is favored relative to aggregates by the HID scheme. A similar reasoning explains the enhanced percentage of hail when the weight of \( Z_h \) is reduced and/or the weight of \( K_{DP} \) is increased.

The \( Z_{DR} \) weight has a weak impact on the HID result. The impact on the particles above the freezing level is unnoticeable; for weights above 1, the ratio of rain over drizzle increases slightly.

Changes in the \( \rho_{hv} \) weight within the range 0–1 have no significant impact on the HID. Only a slight decrease in graupel and an equivalent increase in wet particles are noticeable when the weight goes from 0.1 to 1. Above 1, the changes are most significant, with a noticeable increase in hail.

In conclusion, the HID is robust to a moderate change in the weights of the variables. Except for extreme, low values of the \( Z_h \) weight or extreme, high values of \( \rho_{hv} \) weight, the proportions of the various particles are stable.

4. Radar in situ comparisons

Comparing airborne and ground radar information is not a trivial exercise because the sampling modes of both instruments are very different. The radar acquires 3D scans inside the precipitating systems with a typical revisit of a given pixel every 10 min (the duration of a 12-PPI sequence). The aircraft acquires information along a line (the trajectory) at high speed (290 m s\(^{-1}\)) with an acquisition sampling rate of 1 s. A radar pixel represents a volume of a few hundred to a few thousand meters cubed, whereas sampling volume for the airborne probes is typically \( \sim 1 \text{ m}^3 \). However, many authors have shown some agreement between radar ground observations and in situ probe measurements (e.g., Liu and Chandrasekar 2000; Loney et al. 2002; Aydin and Singh 2004; Lim et al. 2005). They used images from an onboard optical sensor to compare and/or validate HID obtained from ground radar measurements. El Magd et al. (2000) compare polarimetric ground radar measurements (\( Z_h, Z_{DR}, \) and linear depolarization ratio)
and synthetic ones in hail and graupel storm environments. To compute the synthetic radar variables, the PSD is extracted from in situ high-volume particle sample images, and density and canting angle are adjusted to match with the observations. In Liu and Chandrasekar (2000), radar data from different storms feed a fuzzy-logic and neuro-fuzzy network to classify hydrometeors. The results are compared with in situ observations from the T-28 aircraft and show good agreement, with a weak impact of the radar measurement errors. Lim et al. (2005) used in situ data from the T-28 aircraft collected during the Severe Thunderstorm Electrification and Precipitation Study (STEPS) campaign with particle-discrimination results obtained from dual-polarization radar measurements at the Colorado State University–University of Chicago–Illinois State Water Survey (CSU–CHILL) facility. By introducing a new “height” MBF, linked to the height of the melting layer, they show the ability of the HID algorithm to identify raindrops and a mixture of rain and hail above the 0°C isotherm.

Here, the comparisons are limited to the 13 August flight—the only flight for which the trajectory was close enough to the Xport radar. On 13 August 2010 around 0700 UTC, convective cells are initiated close to Sokoto, Nigeria (12.54°N, 5.34°E), and quickly organize in a squall line. A convective front followed up by a large stratiform region moves westward. The average speed of the MCS over the 20 h of its life is 63 km h⁻¹. The MCS reaches the Xport radar site at 1237 UTC, approximately at 40% of its life cycle, as based on the Tracking of Organized Convection Algorithm through a 3D Segmentation (TOOCAN) tracking-data analysis (Fiolleau and Roca 2013). At 1411 UTC, the MCS front observed by the radar is 280 km wide and is oriented northeast–southwest. Xport data are recorded from 1200 to 1700 UTC. Measurements on board the F20 aircraft last from 1320 to 1610 UTC.

a. Radar pixel–aircraft collocation

The aircraft position is specified in longitude, latitude, and altitude every second. The GPS units on the radar and the aircraft ensure the time synchronization. To compare the two datasets, the aircraft GPS positions are transformed into the radar coordinate system (azimuth, elevation, and range). The aircraft-probe information is averaged for 10 s. The time and position of the nearest radar pixel are first determined; because of the sampling differences, an exact collocation is not guaranteed. This is illustrated in Fig. 5, which shows the time and space distance between the airborne sample and the radar closest pixel, for every 10 s along the 13 August flight. The red curve in the left panel of Fig. 5 shows the exact altitude of the aircraft, and the blue curve is the altitude.
of the radar pixel that is the closest from the trajectory at that time. The light blue lines represent the radar beamwidth (1.4°).

The right panel in Fig. 5 shows the spatial (in black) collocation error between the aircraft and the closest radar pixel. The spatial error between the aircraft’s position and the closest radar pixel center accounts for the position difference along the three radar coordinates (elevation, azimuth, and range). The time collocation error (in red) is the difference between the aircraft-probe acquisition time and the radar pixel acquisition time (each radial is time stamped). The typical order of magnitude of this collocation error is the kilometer and the minute, which is acceptable for studying relatively slow variations of the microphysical properties, as expected in the stratiform region. It is noticeable that, “thanks to” these collocation errors, no radar pixel is contaminated by the aircraft radar echo.

The radar variables ($Z_h$, $Z_{DR}$, $K_{DP}$, and $\rho_{hv}$) of the closest pixel for every 10-s-average aircraft position are presented in Fig. 6, together with their variance (calculated over 10 samples). The colors represent the hydrometeor type identified by the HID scheme for each pixel. Figure 6e shows the distance between the studied pixel and the radar location.

In the presence of dry aggregates, snow, or graupel above the melting layer, $\rho_{hv}$ is expected to be close to unity (Dolan and Rutledge 2009; Matrosov et al. 2009). In the bright band, $\rho_{hv}$ is expected to drop because of the tumbling of particles as they melt. In practice, $\rho_{hv}$ can also drop when the signal-to-noise ratio is too low and/or when the radar beamfilling is not uniform. This variable is a good indicator of signal quality. Many observations show the degradation of $\rho_{hv}$ as well as an increase in noise in $Z_{DR}$ and $K_{DP}$ when the distance from the radar increases. This is visible in Fig. 6 for radar ranges beyond 60 km. The periods during which the aircraft is more than 60 km away from the radar have therefore been excluded from the comparisons and are gray shaded in Fig. 6. Between 1435 and 1448 UTC, the aircraft is flying near and below the freezing level. This period is also excluded because the information needed to simulate radar variables from the airborne probes (see details below in section 4b) is not provided for the melting particles.

b. Comparison in the polarimetric variable space

An original approach has been developed to compare the radar measurements and the aircraft data: it consists of simulating synthetic radar variables from the in situ information and then comparing the radar-observed and simulated polarimetric signatures along the flight. In a second step, the HID scheme is run on the synthetic variables and compared with the radar HID results.

THE SYNTHETIC DATASET

From the analysis of the airborne particle imagers and radar, Fontaine et al. (2014) have computed the 10-s average of the PSD and the particle axis ratio. This information is used with a T-matrix scattering code (Mishchenko et al. 1996) to simulate what an X-band radar should observe if the beam were uniformly filled with the observed particles. For the simulations, the particles are assumed to be oblate.

As in Part II, the mass–diameter law proposed by Fontaine et al. (2014) and introduced in Eq. (2) is used to set the relative proportion of ice and air in the hydrometeors and to calculate the refractive index needed for
the scattering simulations. The exponent $\beta$ of the mass–diameter relationship has been set to 2.28, which is the mean value of $\beta$ for the 11 flights of the Niamey 2010 experiment.

On the basis of the values reported during the flights, the prefactor $\alpha$ was allowed to vary and was set to three different values: 0.006, 0.01, and 0.015. These three values are representative of the three quartiles of $\alpha$ distribution among the flights (Fontaine et al. 2014). The bulk density of a particle as function of its maximum dimension $D_{\text{max}}$ (i.e., here, the major axis $b$ of the ellipsoid) is computed with the following formula (see the appendix of Part II for details):

$$\rho_{\text{ice}} = \frac{b}{\alpha} \frac{6}{\pi} \alpha D_{\text{max}}^{\beta-3},$$

with $D_{\text{max}}$ in centimeters and $\rho_{\text{ice}}$ in grams per centimeter cubed. Also, the axis ratio $a/b$ is set to an averaged value of 0.6 as proposed by Fontaine et al. (2014). The temperature is set to $-10^\circ$C. The wavelength is the same as Xport: 3.2 cm. The canting-angle distribution is Gaussian, with a mean angle equal to 0" and a standard deviation equal to 0.1. The antenna elevation is set to 30°. The resulting $Z_h$, $Z_{\text{DR}}$, and $K_{\text{DP}}$ are computed, and then the HID is run on these synthetic variables.

Figure 7a shows the radar variables simulated along the flight trajectory superimposed with Xport observations for the closest pixels. In Fig. 7a, the radar simulations are based on the mean aspect ratio of 0.6 derived by Fontaine et al. (2014) for the Niamey dataset. This value is also in agreement with the one proposed by Hogan et al. (2012) to model the 94-GHz radar properties of ice cloud particles. In Fig. 7a, the simulated reflectivities with the median value of the prefactor $\alpha$ (0.01) are in good agreement with the observed reflectivities. With the lowest prefactor ($\alpha = 0.006$), $Z_h$ is underestimated by $\sim 3\text{ dBZ}$, and in a
similar way the highest prefactor (0.015) leads to overestimating by \( \sim 3 \) dBZ. The simulated \( Z_{\text{DR}} \) values are below the observations. The underestimation is \( \sim 0.1 \) dB for the median density (\( \alpha = 0.01 \)) and less than 0.05 dB for the highest density. The simulated \( Z_{\text{DR}} \) is also much less variable than the observed \( Z_{\text{DR}} \); the measurement noise and the additional uncertainty brought by the attenuation correction may explain the observed \( Z_{\text{DR}} \) variability. The \( K_{\text{DP}} \) simulation is most sensitive to the density. The agreement for the median density (\( \alpha = 0.01 \)) is acceptable but with a slight overestimation (by \( \sim 0.2 \) dB km\(^{-1} \) on average). With the highest density (\( \alpha = 0.015 \)), \( K_{\text{DP}} \) is frequently above 1° km\(^{-1} \) and sometimes up to 2° km\(^{-1} \), whereas the maximum observed value is 0.6° km\(^{-1} \). (As for \( Z_h \), the agreement in terms of temporal variability is good.)

Figure 7b displays the HID results for the three sets of synthetic radar variables and the Xport observations from Fig. 7a. The HID results obtained with the median prefactor simulation (\( \alpha = 0.01 \)) are very close to the Xport HID. The proportion between aggregates (the predominant particles) and dry graupel is very similar. Despite the differences discussed above between the observed and simulated values of \( K_{\text{DP}} \) and \( Z_{\text{DR}} \), the agreement between the in situ and radar observations in the HID “space” is good. This is consistent with the sensitivity analysis presented in section 3b(2) and Fig. 3: differences of a few tens of decibels in \( Z_{\text{DR}} \) and up to 1° km\(^{-1} \) in \( K_{\text{DP}} \) have a small effect on the HID outcome and on the derived proportions of graupel and aggregates. What weights the HID most is the reflectivity \( Z_h \), which is simulated well with the median density assumption (\( \alpha = 0.01 \)).
Despite the good agreement of the above simulation in terms of HID, it is worth investigating the differences between the simulated and observed $K_{DP}$ and $Z_{DR}$. The sensitivity to the assumption of a fixed aspect ratio ($a/b = 0.6$) whatever the particle size may be is explored in Fig. 7. Figures 7c and 7d are similar to Figs. 7a and 7b, but this time the aspect ratio is set to 0.9 for the smallest (and thus denser) particles and to 0.52 for particles above 0.95 mm. The outcome in terms of HID (Fig. 7d) is unchanged, but the agreement for $K_{DP}$ and $Z_{DR}$ (Fig. 7c) is better. Because $Z_{DR}$ is sensitive to the largest particles in the spectrum, $Z_{DR}$ values increase with the new assumption; because the weight of small particles is important in $K_{DP}$, the assumption of spherical particles below 0.95 mm decreases $K_{DP}$. More-complex assumptions on the relationship between aspect ratio and size (such as polynomial functions) did not lead to significant differences or improvement. Investigating further the aspect ratio of the observed particles on the basis of in situ observations (probes and RASTA) and polarimetric radar is beyond the scope of this paper but should be carried out in the future.

c. Radar classifications versus in situ catalog

The hydrometeors identified by the radar can also be compared with the classification that is based on the visual analysis of the airborne-imager catalog. This is a qualitative comparison that is based on human expertise. The particles can be identified visually by their shape—irregular or circular—and by their apparent compactness (C. Duroyre 2014, personal communication).

An example of such a comparison is presented in Fig. 8. The displayed sequence was recorded between 1425 and 1535 UTC 13 August as the aircraft made a small excursion through and below the bright band. The sequence is interesting because many types of particles,
aggregates, graupel, melting particles, and drops were sampled (Fig. 8a).

Figures 8a1–a3 illustrate the difficulty and the limits of the classification exercise. The images in Figs. 8a1 and 8a3 were acquired at the same altitude—around 6 km—before (Fig. 8a1) and after (Fig. 8a3) the aircraft crossed the melting layer (as seen in Fig. 8a2). These two images are representative of the type of hydrometeors encountered at this altitude during the 13 August and all 2010 flights (Fontaine et al. 2014): they appear to be some kind of hybrid between aggregates and graupel and are essentially rimed aggregates with various degrees of riming. Such particles are not explicitly represented in the database used for the radar classification. Depending on their size and degree of riming, the particles are expected to be picked up as aggregates (for the lighter ones) or graupel (for the denser, more rimed ones). The visual analysis reveals that slightly more unrimed and very irregular aggregates are present in Fig. 8a3 than in Fig. 8a1.

From the 2D images and on the basis of statistical analysis of geometric measures (area and perimeter of each particle), Durose et al. (1994) derived information about the growth mode of the particles. They use for this purpose the “roughness” exponent, which links the surface area and the perimeter of a population of ice particles. When the particles grow “like spheres” the roughness exponent is close to 0.5—for more-complex particles, the roughness exponent is higher (and the upper limit would be 1 for particles that grow “like lines”; Bouniol et al. 2010). A rugosity index can be derived as the ratio of the roughness exponent to the roughness exponent of a spherical particle (0.5). The rugosity index is close to 1 for spherical particles (small drops, graupel) and closer to 2 for more-complex particles (dendrites). Figure 8c (right axis) shows the time evolution of the rugosity index along the flight.

Note that the rugosity index is computed from the images via an automated algorithm and is averaged over 10 s. The differences between the two time periods are consistent with the radar classification, which detects...
more graupel in the first period and more aggregates in the last one. In addition to the most probable particle detected by the HID (Fig. 8b) for each 10-s interval, Fig. 8c indicates the percentage of pixels that are in agreement inside the 10-s sample. It is an indicator of the robustness of the classification.

Close to Fig. 8a1, around 1430–1435 UTC, the radar classifies graupel with a high degree of confidence (71% of the 10-s samples identify graupel as the dominant particle, and for 32% of them 100% of the pixels in the sample agree; for the rest about 28% of the pixels select aggregates and 1% select wet snow). Close to Fig. 8a3, at 1531 UTC, aggregates are picked up as the dominant particle for 100% of the pixels.

At the time of Fig. 8a2 when the aircraft crosses the bright band, the radar HID is in very good agreement with the aircraft observations. The radar depicts a mixture of particles, with a clear transition from a majority of graupel to a majority of wet hydrometeors and then rain at the lowest altitude and back through melting and then graupel again. In the bright band, the variability within the 10-s samples is high (low percentage in Fig. 8c) as depicted also in Fig. 8a2.

Altogether, and given the difficulties in such a comparison exercise, the agreement between the radar classification and the image catalog is very satisfactory, both in terms of the dominant type of particle and in terms of variability/mixture of particles depicted within each 10-s sample. The subjective/visual analysis in section 4b and the objective method based on simulations that is presented in section 4a give encouraging results and confirm the interest—and also the quantitative limits—of the HID to get some insight on the type of hydrometeors and how their proportion may vary. The next section applies the HID scheme to analyze the evolution of hydrometeor typology inside a typical West African squall line.

5. The hydrometeor distribution and its time evolution inside the 13 August 2010 squall line

This section analyzes the percentage of the different types of particles at several altitudes within the precipitation and their distribution in time as the convective front moves westward from the radar. The HID is run for every full 3D scan (12 min) within a vertical column situated 20 km west of the radar. The ground projection of the column is rectangular, 1 km × 120 km with a north–south orientation (black box in Fig. 1). The convective and stratiform regions have first been differentiated on the basis of the vertical profile of reflectivity and horizontal gradients, as explained in Part II. The convective part passed over the sampled area from 1250 to 1320 UTC; it was followed by a long-lasting stratiform region that was observed until 1645 UTC.

The time evolution of the percentage of each hydrometeor is displayed in Fig. 9. The statistics are computed for three particular layers: the liquid precipitation level at 0–3 km, the melting layer at 4–5 km, and the icy precipitation region above the bright band at 6–8 km. As discussed in the introduction, the latter level is representative of the area within the system that needs to be documented for a passive microwave rain-retrieval algorithm.

Figures 9a–f summarize the differences in hydrometeor content between the convective and the stratiform region. As expected, the convective part is dominated by heavier rain than the stratiform region, and a few occurrences of big drops are detected in the former. The melting particles are, in majority, wet graupel in the convective region and wet snow (melting aggregates) in the stratiform region. Above the melting layer, graupel are dominant in the convective part (with, however, a nonnegligible amount of aggregates being detected) while aggregates are dominant in the stratiform region. The differences are consistent with what is expected from theory and what has been observed by previous authors (Bouniol et al. 2010; Cetrone and Houze 2009).

The time series (Figs. 9g–i) provides more details on these changes and reveals a gradual change in the composition as the front moves away. The gradual inversion of the graupel/aggregate proportion in the 6–8-km level is of special interest for our focus. This layer is initially dominated by graupel in the convective cell (until 1320 UTC), and then their population decreases sharply as the transition and finally the stratiform regions are sampled. The evolution from 1400 to 1630 UTC while the stratiform region is well established is interesting and confirms what has been noticed by Alcoba et al. (Part II) using the vertical profile of reflectivity: the hydrometeors tend to become less dense as the front moves away. This could be interpreted as less riming occurring, the old decaying cells (Evaristo et al. 2010) having vanished and less updraft being present, and more classical stratiform processes dominated by aggregation being the main source of precipitation growth.

6. Conclusions

The particle identification scheme developed by Dolan and Rutledge (2009) for X-band polarimetric radar has been evaluated for the first time in an African convective system and compared with in situ measurements. The dataset was acquired as part of the Megha-Tropiques satellite prelaunch validation campaign in
Niamey. The campaign focused on documenting the microphysical properties of the icy precipitating hydrometeors that influence the passive microwave signal used for rain retrieval in the continental tropics. The output of radar classification is compared with the in situ observations made by an instrumented aircraft. The comparisons are carried out for the 13 August 2010 squall line, the only flight case for which the aircraft trajectory was close enough to the radar to ensure the quality of the radar signal and subsequent classification. The aircraft flew inside the stratiform region of the squall line during 2 h, sampling the hydrometeors close to the convective front initially and then farther away as the system was moving westward.

An original approach has been presented to compare the radar measurements and the aircraft data: it consists of simulating synthetic radar variables from the in situ information, applying the HID scheme on the synthetic and observed radar variables, and comparing the two datasets in a common “radar space.” The simulated and observed radar reflectivities $Z_H$ are in good agreement when the mean aspect ratio (0.6) proposed by Fontaine et al. (2014) and the median value of the density law are used. For the polarimetric variables ($K_{DP}$ and $Z_{DR}$) better agreement is obtained when the aspect ratio varies with size, showing that further investigation on the actual particle shape would be interesting. The consistency between the two types of observation in terms of dominant hydrometeor type is very good, whatever the shape assumption may be. This is remarkable given the differences in sampling, as illustrated in section 4. In addition the sensitivity analysis shows that the HID output is robust to the amount of radar signal uncertainty expected at reasonable range (typically within 60 km) and to moderate changes in the HID-scheme setting.

The time evolution in the percentage of the various hydrometeor types appears to be realistic. The comparison between the radar-detected hydrometeors and the direct information from the airborne 2D imagers reveals that the relative proportion of graupel/aggregates seen by the radar along the flight varies in conformity with the decrease of density or increase in rugosity seen by the probes. The differences depicted by the radar between the convective and stratiform region are in conformity with what is expected from our knowledge of precipitation processes. The evolution of the hydrometeor density within the stratiform region, as the convective front moves away, is also compatible with our understanding and previous observations in squall lines. The farther away from the convection one looks, the more dominating is aggregation and the less apparent is riming, which is compatible with what was found in Part II on the basis of the vertical profile of reflectivity analysis. These results suggest that, although the radar HID does not provide precise quantitative information on the particle size distribution and density law, the retrieved proportion of hydrometeors and their space/time evolution within and between storms is valuable information that can be inferred. The relative proportion of aggregate/graupel is found to be an interesting proxy to analyze the variability of hydrometeor
density in the ice-phase precipitating layers that contribute to the microwave-scattering channels.

Following this validation, the short-term perspective is to apply the particle identification to the whole dataset that was gathered in Africa with the Xport polarimetric radar: 2 years in Benin, 1 year in Niger, and 2 years in Burkina Faso. One objective in the framework of the MT validation effort is to analyze how the hydrometeor density changes according to the distance to convection, the life stage of the storms, or other storm or environment characteristics. Comparison of the HID with other sources of information on the microphysics, such as the analysis that is based on the vertical profile of reflectivity that is presented in Part II or observations from spaceborne radars, is also considered. The microphysical information that was gathered during the MT campaigns in Africa is currently being implemented in the rain-retrieval algorithms; the next step will be to check the final results in terms of rainfall estimation by comparing the satellite estimates with the rain fields derived from the Xport radar in Niamey in 2010, but also in Ouagadougou, Burkina Faso, in 2012 and 2013.

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