Retrieval of Parameters of a Horizontal Hydrometeor Distribution Within the Field of View of a Satellite Microwave Radiometer

Boris Z. Petrenko, Member, IEEE

Abstract—The information about variations in a small-scale horizontal hydrometeor distribution (HHD) within the microwave radiometers field of view (FOV) is necessary to subdue “beamfilling” errors in rainfall retrieval. The present study substantiates the potentiality and the method of the determination of some HHD parameters along with a footprint-averaged rainfall from spectral/polarization microwave radiometer measurements. HHD parameters selected for the retrieval provide an effective description of the HHD, and at the same time their variations are detectable and distinguishable from radiometer measurements. In addition, availability of the HHD parameters allows the interpretation of the procedure of screening rainless footprints as a detection of the rainfall signal on the background of the retrieval errors. The method is tested for available hydrometeor profile simulation and demonstrated with the example of tropical rainfall measuring mission microwave imager (TRMM TMI) measurements processing.

Index Terms—Inverse problems, microwave radiometry, rain.

I. INTRODUCTION

TROPICAL precipitation significantly contributes to the energy exchange in the ocean–atmosphere system by transferring latent heat from the ocean to the atmosphere. The development of reliable methods for remote sensing of precipitation is important for better understanding of global climate and weather processes. Due to a strongly pronounced dependency of the thermal microwave outgoing radiation on basic rainfall parameters, satellite microwave radiometry has been recognized as one of the most effective tools for remote studies of rainfall. The most serious shortcoming of the microwave radiometers from this standpoint is that the diffraction on the receiving antenna prevents a reduction of a field of view (FOV) size to a typical size of a convective rain cell. The Special Sensor Microwave/Imager (SSM/I) [1] has FOV sizes in different channels of 13–70 km and the Tropical Rainfall Measuring Mission Microwave Imager (TRMM TMI) [2] has FOV sizes of 4–60 km. Since the horizontal scale of convective rainfall inhomogeneities is of one to several kilometers [3], a horizontal hydrometeor distribution (HHD) within the radiometer’s FOV is often nonuniform, especially for channels having operating frequencies of 37 GHz and less and sensitive to the emission of the rainy atmosphere. Due to the nonlinearity of the rainfall/radiative relationship HHD variations strongly affect measured microwave radiation [4], [5], and, if not properly accounted for, they cause “beamfilling” errors, which make one of major contributions to rainfall retrieval errors [6], [7].

Several approaches have been proposed to alleviate the beamfilling errors. A chance to reduce the effective FOV size in low frequency radiometer channels at the expense of a spatial sampling redundancy was examined in [8]–[10]. Unfortunately, this redundancy has been unable to allow necessary reduction of the FOV without substantial amplification of the measurement noise. Other approaches involved a priori predetermination of the HHD through a certain average “beamfilling correction” of the initially homogeneous radiative transfer model [5], [11] or simulation of the HHD with cloud dynamical models [12], [13]. Those approaches also have turned out to be insufficiently effective because of too large variability of the real HHD [7].

The alternative to a priori HHD predetermination is to retrieve it from measurements along with the FOV-averaged rainfall. Since impacts of the HHD and the FOV-averaged rainfall on measured brightness temperatures are comparable even for relatively small rain rates [6], this alternative seems reasonable. This concept has been embodied in the beamfilling algorithm (BFA) [14]. The BFA represents the radiometer’s FOV as a mosaic of several horizontally homogeneous domains with one of a priori predetermined vertical hydrometeor profiles occurring in each domain and retrieves “beamfilling coefficients,” reflecting the contribution of each domain to the measured brightness temperature. Since those contributions depend on relative FOV fractions occupied by domains, one can expect that some meaningful HHD signatures can be derived from the beamfilling coefficients. The goal of the present study is to examine this opportunity and to estimate a possible accuracy of HHD parameter retrieval.

The following feature of the proposed approach should be emphasized. The input data for the BFA are the brightness temperatures, measured on radiometer’s operating frequencies and polarizations and brought to a common FOV, as it is planned to do with the data of the future AQUA advanced microwave scanning radiometer (AMSR) [15]. The current version of the BFA does not exploit the information about small-scale brightness temperatures variability, which may be available from the high-frequency channels, having a better horizontal resolution. This means that the HHD is determined from spectral/polarization signatures only. This makes the BFA opposite to the approach [15], [16], which exploits horizontal variations in brightness temperatures at a single frequency 85 GHz to determine...
some specific HHD characteristics, such as fractions of stratiform and convective precipitation within the FOV. It is quite likely that the future HHD retrieval algorithm will take into account both spectral/polarization and spatial signatures of measurements.

II. DETERMINATION OF THE BEAMFILLING COEFFICIENTS

The details of the BFA have been expounded in [14]. Here, we mention only those BFA features, which are necessary for understanding of the further discussion. The antenna temperature \( T_a(r_0) \) measured by the microwave radiometer is a linear convolution of the brightness temperature \( T_B(r) \), with the antenna gain function \( \gamma(r, r_0) \)

\[
T_a(r_0) = \int_{A_0} \gamma(r, r_0) T_B(r) \, da, \quad \int_{A_0} \gamma(r, r_0) \, da = 1 \tag{1}
\]

where

- \( r_0 \) — antenna boresight;
- \( r \) — vector under which the brightness temperature \( T_B(r) \) is observed;
- \( da \) — element of a scene \( A_0 \), whose contribution to \( T_a(r_0) \) is essential.

Assuming that antenna temperatures, measured in \( M \) radiometer channels, have been brought to the common FOV, the BFA approximates the three-dimensional (3-D) hydrometeor distribution within this FOV with a composition of \( N \) horizontally homogeneous domains, with vertical hydrometeor profiles and outgoing brightness temperatures known for each domain.

With this approximation, the measured \( M \)-vector of antenna temperatures \( \mathbf{T}_A \) is expressed by a weighted sum of domain’s brightness temperatures

\[
\mathbf{T}_A = \sum_{i=1}^{N} c_i \mathbf{T}_i, \tag{2a}
\]

\[
\sum_{i=1}^{N} c_i = 1, \quad c_i > 0, \quad i = 1, 2, \ldots, N \tag{2b}
\]

where

- \( \mathbf{T}_i = \Psi(x_i) \) — domains’ brightness temperature vectors;
- \( \Psi \) — \( M \)-dimensional radiative transfer model function of the domain’s geophysical vector \( x_i \);
- \( c_i \) — beamfilling coefficients.

The linear set of (2a) is solved in terms of \( N \) beamfilling coefficients taking into account the restrictions (2b).

To ensure nonsingularity of (2a), the vectors \( \mathbf{T}_i, \quad i = 1, 2, \ldots, N, \) should be linearly independent, with the total amount of domains \( N \) not exceeding the number of radiometer channels \( M \), \( N \leq M \). On the other hand, \( \mathbf{T}_i \) should be selected in such a way that their linear combination can approximate any measured \( \mathbf{T}_a \). This means that vectors \( \mathbf{T}_i, \quad i = 1, 2, \ldots, N, \) form a basis in the \( M \)-dimensional space and can be referred to as “basic” vectors. The procedure of selecting \( \mathbf{T}_i \) and corresponding \( x_i \) from a simulated hydrometeor/radiative database has been described in [14].

III. BEAMFILLING COEFFICIENTS AND THE HHD SIGNATURES

According to (1) and (2), the beamfilling coefficients reflect the contribution of each domain to \( T_a \). These contributions depend both on areas, covered by domains, and, through the antenna gain function, on the locations of the domains within the FOV. As it will be shown in this section, a set of retrieved beamfilling coefficients coupled with a priori domains’ hydrometeor profiles provides the approximation of one-dimensional HHD in terms of “effective” relative FOV fractions, occupied with a given value of hydrometeor parameter. This allows estimation of HHD parameters through the beamfilling coefficients. For example, the FOV-averaged rainfall rate can be estimated as follows:

\[
W_{\text{FOV}} = \sum_{i=1}^{N} c_i R_i \tag{3}
\]

where \( R_i, \quad i = 1, 2, \ldots, N, \) are domains’ rainfall rates. The estimate of the RMS deviation of the rainfall rate throughout the FOV is

\[
S_{\text{FOV}} = \left[ \sum_{i=1}^{N} c_i (R_i - R_{\text{FOV}})^2 \right]^{1/2}. \tag{4}
\]

\( W_{\text{FOV}} \) and \( S_{\text{FOV}} \) for rainfall rate \( R \) and rainwater integral \( RWI \) have been used for HHD description in [6] and later in [14]. However, those parameters seem to be unable to provide the complete description of the HHD for the following reasons. First, the HHD of the most important rainfall parameters including \( R \) and \( RWI \) are essentially non-Gaussian, for the reason alone that those parameters are always nonnegative. This means that their HHD can not be completely described with the first and the second moments. In addition, as it will be shown later, \( W_{\text{FOV}} \) and \( S_{\text{FOV}} \) can be strongly correlated, and, hence, once \( W_{\text{FOV}} \) is known, the estimate of \( S_{\text{FOV}} \) does not carry much independent information. In this study, we introduce another description of the HHD based on the special sampling of the cumulative function of the HHD. All the considerations in this section will be made for the rainfall rate \( R \), however they are applicable to any other rainfall parameter.

The initial HHD approximation \( F(z) \) can be obtained from the set of the beamfilling coefficients \( c_1, c_2, \ldots, c_N \), and domains’ rain rates \( R_1, R_2, \ldots, R_N \) as follows. Let \( N \) domains be arranged and numbered in the order of increasing \( R \), \( R_1 \leq R_2 \leq \cdots \leq R_N \). A staircase monotonically increasing function \( F(\zeta) \) is defined on the interval \( 0 < z \leq 1 \)

\[
F(z) = R_K, \quad \sum_{i=0}^{K-1} c_i < z \leq \sum_{i=1}^{K} c_i, \quad K = 1, \ldots, N. \tag{5}
\]

It is assumed in (5) that \( c_0 = 0 \). The beamfilling coefficients \( c_i, \quad i = 1, 2, \ldots, N \) are not exactly equal to the geometric portions of the whole FOV area, occupied by the domains. According to (1) and (2), \( c_i \) rather reflects the contribution of \( \mathbf{T}_i \) to \( \mathbf{T}_C \) taking into account both the domain’s area \( A_i \) and the
antenna gain function. In view of that, the variable \( z \) in (5) is interpreted as the “effective” fraction of the FOV

\[
\bar{z} = \int_\mathbb{A} \gamma(\mathbf{r}, \mathbf{R}_0) \, da,
\]

\[
\sum_{i=0}^{K-1} A_i < \bar{z} \leq \sum_{i=1}^{K} A_i, \quad K = 1, \ldots, N
\]

\( A_0 = 0, 0 \leq z \leq 1. \) Since \( F(z) \) is always positive and monotonic, the cumulative function

\[
G(z) = \int_0^z F(x) \, dx \tag{6}
\]
is also monotonically increasing, with the slope of \( G(z) \) increasing when \( z \) growing from 0 to 1. \( G(z) \) is equal to the least quantity, which can be obtained by integrating \( R \) over any \( z \) fraction of the FOV. The minimum average of \( R \) over any positive FOV fraction \( z = G(z)/z \), and the FOV-averaged mean of \( R \), \( W_{\text{FOV}} = G(1) \). In order to separate HHD variations from \( W_{\text{FOV}} \) variations, a normalized cumulative function is introduced

\[
H(z) = G(z)/G(1) \tag{7}
\]
assuming that \( G(1) > 0 \). The continuous function \( H(z) \), \( 0 \leq z \leq 1 \), along with \( G(1) \) completely determines the retrieved HHD. However, for practical purposes it is more convenient to characterize the HHD with a finite set of discrete parameters. Because of a high variability of the HHD, any set of \( H(z) \) values sampled at \( n \) fixed \( z \) values \( z_1, z_2, \ldots, z_n \), does not provide an equally effective description of any possible HHD. The quasiuniform HHD can be characterized by values of \( H(z) \), sampled at several equidistant \( z \) values. However, if the HHD is essentially inhomogeneous, uneven sampling of \( H(z) \) is required. The more universal description of the HHD is provided by another function \( \bar{z}(\alpha) \), closely related with \( H(z) \). Let \( \bar{z}(\alpha) \) be equal to \( z \) value at which

\[
H(z) = \alpha, \quad 0 < \alpha \leq 1. \tag{8}
\]

In other words, \( \bar{z}(\alpha) \) represents the FOV fraction, over which \( G(z) \) accounts for \( \alpha \) fraction of the whole-FOV integral \( G(1) \). A set of values of \( \bar{z}(\alpha) \), taken at \( n \) fixed \( \alpha \) values, \( 0 < \alpha_i < 1 \), provide a unique sampling of each possible \( H(z) \) even though \( \alpha_i, i = 1, 2, \ldots, n \), are constant.

The relationship between \( \bar{z}(\alpha_1) \) and \( \bar{z}(\alpha_2) \): \( \alpha_1 < \alpha_2 \), characterizes the variability of \( H \) within the \( 1 - \bar{z}(\alpha_1) \) FOV fraction, covered with the greatest \( R \) values. The behavior of \( H(z) \) for the cases of uniform and nonuniform HHD on the interval \( \bar{z}(\alpha_1) < z < 1 \) is shown in Fig. 1. It follows from (8) that \( H(\bar{z}(\alpha_1)) = \bar{z}_1 \) and \( H(1) = 1 \). According to (7), a slope of \( H(z) \) is equal to \( F(z)/W_{\text{FOV}} \). If \( F(z) \) is constant on this interval, the slope \( \beta(\alpha_1) \) is also constant, with \( H(\xi) \) linearly growing from \( \alpha_1 \) to 1

\[
H(\xi) = \alpha_1 + \beta(\alpha_1)[\bar{z} - \bar{z}(\alpha_1)],
\]

\[
\beta(\alpha_1) = (1 - \alpha_1)/(1 - \bar{z}(\alpha_1)). \tag{9}
\]

Otherwise, if \( F(z) \) is nonuniform, the slope of \( H(z) \) is monotonically growing on the interval \( \bar{z}(\alpha_1) < z < 1 \). The more nonuniform \( F(z) \), the greater is \( \bar{z}(\alpha_2) \), approaching its upper limit of 1 with increasing excess of \( F(1) \) over \( F(\bar{z}(\alpha_1)) \). Given \( \bar{z}(\alpha_1) \), the lower limit \( \bar{z}_{\min}(\alpha_1, \alpha_2) \) of \( \bar{z}(\alpha_2) \) is found by replacing \( H(z) \) with \( \alpha_2 \) in the left-hand side of (9) and solving the resulting equation in terms of \( z \)

\[
\bar{z}_{\min}(\alpha_1, \alpha_2) = \bar{z}(\alpha_1) + (\alpha_2 - \alpha_1)/\beta(\alpha_1). \tag{10}
\]

Based on the above consideration, the following measure can be used to characterize the uniformity of the HHD within the \( 1 - \bar{z}(\alpha_1) \) fraction of the FOV, covered with the biggest \( R \) values:

\[
d(\alpha_1, \alpha_2) = [\bar{z}(\alpha_2) - \bar{z}_{\min}(\alpha_1, \alpha_2)]=[1 - \bar{z}(\alpha_1, \alpha_2)]. \tag{11}
\]

\( d(\alpha_1, \alpha_2) = 0 \) if \( F(z) \) is constant between \( \bar{z}(\alpha_1) \) and 1, and \( d(\alpha_1, \alpha_2) \) tends to 1 in the most inhomogeneous case.

Based on the above consideration, we have used in this study the following parameters to characterize the HHD of \( R \) and \( \bar{R}_{\text{VI}} \):

\[
W_{\text{FOV}} = G(1) \quad \text{integral of the rainfall parameter over the whole FOV}
\]
 \( z(0.01) \) maximum fraction of the FOV, covered by only 1% of \( W_{\text{FOV}} \) (practically, \( z(0.01) \) determines the rainless fraction of the FOV); measure of the nonuniformity of the HHD over the rainy FOV fraction;

In general, more detailed HHD characterization may require sampling \( z(\alpha) \) and \( d(\alpha_1, \alpha_2) \) at \( \alpha \) values other than 0.01 and 0.5. The problem of the optimal HHD parameters selection is to be studied yet.

IV. TESTING WITH SIMULATED DATA

An accuracy of the HHD parameter determination was tested with the TOGA3 cloud model simulations. The TOGA3 dataset has been generated with the use of the Goddard Cloud Ensemble Model [18], the radiative transfer model [19] and
Fig. 2. Scatterplots of $W_{\text{FOV}}$ and HHD parameters, calculated for $RWI$ from the initial high-resolution dataset for low-resolution FOV. (a) $S_{\text{FOV}}$ versus $W_{\text{FOV}}$; (b) $z(0.01)$ versus $W_{\text{FOV}}$; (c) $d(0.01, 0.5)$ versus $W_{\text{FOV}}$; (d) $d(0.01, 0.5)$ versus $z(0.01)$.

<table>
<thead>
<tr>
<th>HHD parameters</th>
<th>Rainfall rate</th>
<th>Rain water integral</th>
</tr>
</thead>
<tbody>
<tr>
<td>$W_{\text{FOV}}$ and $S_{\text{FOV}}$</td>
<td>0.891</td>
<td>0.800</td>
</tr>
<tr>
<td>$W_{\text{FOV}}$ and $z(0.01)$</td>
<td>-0.132</td>
<td>-0.117</td>
</tr>
<tr>
<td>$W_{\text{FOV}}$ and $d(0.01, 0.5)$</td>
<td>-0.341</td>
<td>-0.226</td>
</tr>
<tr>
<td>$z(0.01)$ and $d(0.01, 0.5)$</td>
<td>0.267</td>
<td>0.245</td>
</tr>
</tbody>
</table>

3-D hydrometeor distributions, derived from radar soundings during the Tropical Oceans Global Atmosphere-Coupled Ocean-Atmosphere Response Experiment (TOGA COARE). TOGA3 dataset includes simulations of a squall line over the ocean with a 3-km resolution on a 384 km × 384 km domain (128 × 128 pixels). It includes 16 subsets, assuming four different sea surface temperatures (SSTs): 288 K, 292 K, 296 K, and 300 K, and four surface wind speed values: 0 m/s, 6 m/s, 12 m/s, and 18 m/s. Simulations involved horizontal distributions of surface rain rate and vertical profiles of relative humidity, cloud liquid water, rain liquid water, snow, cloud ice, graupel, and hail in 28 atmospheric layers at six temporal stages of a cloudy system’s development. More detailed descriptions of the TOGA3 simulations can be found in [6], [12], [13].

When simulating satellite radiometer measurements, initial high-resolution TOGA3 hydrometeor profiles and brightness temperatures were averaged over square areas of 24 × 24 km² (8 × 8 pixels). This procedure was performed for all the TRMM TMI channels. The TRMM TMI radiometer [2] observes the Earth’s surface under the incidence angle of 52.8° in nine channels with the horizontal resolution of 35–60 km at 10.65 GHz ($V, H$), 18–30 km at 19.35 GHz ($V, H$), 16–27 km at 21.3 GHz ($V$), 10–16 km at 37 GHz ($V, H$), and 4–7 km at 85.5 GHz ($V, H$). During averaging, the aforementioned HHD signatures for $R$ and $RWI$ were calculated from the distribution of high-resolution hydrometeor profiles for each simulated radiometer’s FOV. The resulting set of low-resolution hydrometeor profiles and brightness temperatures included 24 576 samples, taking into account 256 samples for each of six temporal stages, four SST values, and four wind speeds.
Bases of brightness temperature vectors were constructed from the TOGA3 high-resolution dataset with the procedure described in [14]. One basis has been formed separately for each SST and wind speed value, which resulted in 16 bases in total. While retrieval, the beamfilling coefficients were being estimated subsequently with each of 16 bases, and the accuracy of approximation of the measured antenna temperature vector \( T_A \) with each basis was assessed. According to [14], the estimate of beamfilling coefficients in a given basis was taken as the final one if the accuracy of the \( T_A \) approximation in this basis was the best one among all 16 bases.

Fig. 2 exhibits scatterplots between \( W_{\text{FOV}} \), \( S_{\text{FOV}} \), \( z(0.01) \), and \( d(0.01, 0.5) \), calculated for \( RIWI \) from the initial high-resolution dataset for low-resolution FOV. Only those FOV were taken into account, for which the FOV-average \( RIWI \) exceeded 0.1 kg/m² and the FOV-average \( R \) exceeded 1 mm/h. The correlation coefficients between the \( W_{\text{FOV}} \) and the horizontal structure parameters are given in Table I both for \( R \) and \( RIWI \). It is evident from the Fig. 2 and Table I, that the \( S_{\text{FOV}} \) is strongly correlated with \( W_{\text{FOV}} \) both for \( R \) and \( RIWI \). On the other hand, the correlation coefficients between the \( W_{\text{FOV}} \), \( z(0.01) \), and \( d(0.01, 0.5) \) are quite low. This means that parameters \( z(0.01) \) and \( d(0.01, 0.5) \) are more suitable for HHHD description than \( S_{\text{FOV}} \).

Fig. 3 demonstrates ranges of variations within the TOGA3 simulation, RMS retrieval error and retrieval bias of \( z(0.01) \) and \( d(0.01, 0.5) \) as functions of retrieved values of \( R \) and \( RIWI \). The remarkable bias of estimates is clearly seen at lower values of \( R \) and \( RIWI \). This bias is caused by the fact that when \( W_{\text{FOV}} \) is small enough, the BFA approximates the HHD with a small number of domains corresponding to less hydrometeor parameter values. The reduction of the number of domains affects the quality of the HHD approximation. The same, but less pronounced, effect takes place at the greatest values \( W_{\text{FOV}} \). It can be seen also from the Fig. 3 that the RMS retrieval errors of \( d(0.01, 0.5) \) at the greatest values of \( R \) and \( RIWI \) become equal or even exceed the true ranges of \( d(0.01, 0.5) \) variations within the TOGA3 simulation. However, we suggest that in reality the range of \( d(0.01, 0.5) \) variations, characterizing the nonuniformity of the rainfall, can be much wider than in this simulation. This is confirmed by the fact that the width of a TOGA3 simulated squall line, containing the bulk of cumulus cloudiness, is only several kilometers, whereas real cumulus cloudy systems may reach several tens of kilometers in diameter. At any rate, the simulation gives a hope to estimate the \( RIWI \)-free FOV fraction with accuracy better than 0.1 and \( RIWI \) nonuniformity, \( d(0.01, 0.5) \), with accuracy better than 0.2 if the retrieved \( RIWI \) is greater than 0.8 kg/m². The accuracy of the rainless FOV fraction is better than 0.15–0.2 and the accuracy of \( R \) nonuniformity is better than 0.2 if the retrieved rainfall rate is greater than 5 mm/h.

V. APPLICATION TO TMI DATA-SCREENING RAINLESS FOV

TRMM TMI measurements were downloaded from the GSFC TRMM database along with retrievals made with the Goddard profiling algorithm (GPROF). The GPROF [12], [13] is a TRMM TMI rainfall algorithm that retrieves FOV-averaged rainfall parameters by weighted averaging of simulated low-resolution database profiles with weights, depending on differences between simulated and measured brightness temperatures. Since the GPROF exploits the same TOGA database as one used by the BFA to construct brightness temperature bases, the difference between FOV-averaged retrievals with the BFA and the GPROF reflects features of the algorithms themselves rather than differences in radiative transfer models or in a priori information. For a more detailed comparison of the BFA and the GPROF, see [14]. A routine processing of TRMM TMI data does not involve the procedure of bringing measurements to a common horizontal resolution. For this reason, the technique [20] was applied to bring both TRMM measurements and GPROF data to a common footprint with the diameter of 25 km. Since this technique does not take into account the real antenna gain functions for the radiometer’s channels, it may introduce additional noise, especially in 10.65-GHz channels having a worse horizontal resolution than a common one.

Usually, rainfall algorithms involve special procedures to screen out rainless FOV prior to the rainfall retrieval itself [21], [22]. Screening procedures are intended to prevent a misdetection of a rainfall over vast rainless areas, which can essentially distort results of time/space averaging of a rainfall. Typically, screening procedures exploit spectral and (or) polarization differences between rainy and rainless areas. The BFA allows the consideration of the screening problem as the detection of a rainfall signal on the background of retrieval noise. In terms of the BFA, a zero value of the retrieved \( W_{\text{FOV}} \) means that rainless domains occupy the whole FOV area. Retrieval errors, caused by the different factors, result in the misdetection of a small fraction of the rainless FOV, covered by domains...
with nonzero rainfall. Therefore, the detector of rainfall can be constructed by assigning a threshold \( z^T \), denoting the maximum \( 1 - z^T \) FOV fraction, covered by positive rainfall, with which a given FOV is still considered as “rainless.” In the present study, the above criterion took the following form: the FOV was considered as rainless if \( H(z^T) < 0.01 \), otherwise, the FOV was considered as rainy.

The threshold value \( z^T \) was determined from the following consideration. The value of \( R \), averaged along a prolonged part of a satellite orbit, \( R_{AV}(z^T) \), depends on \( z^T \) in the following way:

\[
R_{AV}(z^T) = \frac{\sum_{n=1}^{L} R_{FOV,n} \delta_n(z^T)}{L}
\]

where \( L \) is the total number of FOV within the observed area, \( R_{FOV,n} \) is the retrieved FOV-averaged rainfall for the FOV \( n \), \( \delta_n(z^T) = 1 \) if \( H(z^T) > 0.01 \), and \( \delta_n(z^T) = 0 \) if \( H(z^T) \leq 0.01 \). Fig. 4 shows area-averaged means of \( R \) and \( RWI \), for the part of a TRMM TMI swath, shown in Fig. 6(a), as functions of the threshold \( z^T \). The relatively slow increase of \( R_{AV}(z^T) \) on the interval \( 0 < z^T < 0.85 \) is caused by accounting for new FOV, located in the vicinity of the main cloudy system and having smaller fractions, covered by the rainfall. After \( z^T \approx 0.85 \), \( R_{AV}(z^T) \) both for \( R \) and \( RWI \) grow much more rapidly due to accounting for numerous rainless FOV contaminated with retrieval errors. This behavior of \( R_{AV}(z^T) \) is quite similar for all considered TMI soundings. Based on the above consideration, the threshold to cut off the retrieval noise \( z^T \) has been set at 0.85. Table II shows that the screening procedure, described above, performs quite similar to one used by the GPROF. The areas, where only one of the two algorithms detected positive values, add a little to area-averaged means. In the case of the BFA, those additions are of 1.3% for \( RWI \) and of 1.2% for \( R \). In the case of the GPROF, they are of 4.0% and 2.8%, respectively. The largest discrepancy between the area-averaged parameters is caused by peculiarities of the algorithms themselves. The difference between the area-averaged parameters, determined by BFA and the GPROF, is of 30% for \( RWI \) and 18% for \( R \). Fig. 5 represents a scatterplot of area-averaged rainfall rates, retrieved with the GPROF and the BFA over 70 TMI swath fragments with observations of rainy cloudiness over the Atlantic and Pacific oceans. A quite good coincidence between estimates made with the two algorithms confirms the effectiveness of the above screening procedure based on the HHD retrieval.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>BFA retrieval over the area where the GPROF indicates zero parameter values</th>
<th>GPROF retrieval over the area where the BFA indicates zero parameter values</th>
<th>BFA and GPROF retrievals over the area, where both algorithms indicate non-zero parameter values</th>
</tr>
</thead>
<tbody>
<tr>
<td>RWI</td>
<td>0.001 kg/m²</td>
<td>0.004 kg/m²</td>
<td>BFA: 0.073 kg/m² GPROF: 0.097 kg/m²</td>
</tr>
<tr>
<td>R</td>
<td>0.005 mm/h</td>
<td>0.014 mm/h</td>
<td>BFA: 0.414 mm/h GPROF: 0.488 mm/h</td>
</tr>
</tbody>
</table>

VI. APPLICATION TO TMI DATA-RETRIEVAL OF THE HHD PARAMETERS

The example of the retrieved distributions of the \( W_{FOV} \), \( z(0.01) \), \( d(0.01, 0.5) \), and \( S_{FOV} \) of the rainfall rate over the area of the hurricane Karl (Atlantic Ocean, Orbit 4776, September 26, 1998) is shown in Fig. 6(a)–(d). The distributions of the HHD parameters reveal some physically meaningful features. As it could be expected, the greatest values of the rainless footprint fraction \( z(0.01) \) take place at the boundaries of the cloudy system. The greatest values of the rainfall nonuniformity \( d(0.01, 0.5) \) are not collocated with the maximums of \( W_{FOV} \), but rather they surround those maximums and are collocated with the maximums of the horizontal gradients of \( W_{FOV} \).
At the same time, at the areas where $W_{\text{FOV}} < 5$ mm/h, the estimated values of $d(0.01, 0.5)$ are relatively low due to the bias of the estimate discussed in Section IV. The distribution of $W_{\text{FOV}}$ much better coincides with the distribution of $S_{\text{FOV}}$ than with $d(0.01, 0.5)$, including the closer coincidence of maximums of $W_{\text{FOV}}$ and $S_{\text{FOV}}$. The correlation coefficients between the HHD parameters for $R$ and $RWI$ are shown in the Table III. To avoid accounting for strongly biased HHD parameter estimates, according to Section IV, in the case of $R$ correlation coefficients were calculated only for those FOV, where the retrieved $W_{\text{FOV}}$ exceeded 5 mm/h. Similarly, in the case of $RWI$, only those FOV were taken into account where the retrieved $W_{\text{FOV}}$ exceeded 0.8 kg/m$^2$. According to Table III, the correlation coefficients between $W_{\text{FOV}}$, $z(0.01)$ and $d(0.01, 0.5)$ are quite low and do not exceed 0.5, confirming that those parameters really carry the independent information about the HHD. At the same time, the estimate of $S_{\text{FOV}}$ is strongly correlated with $W_{\text{FOV}}$ and $d(0.01, 0.5)$. This means that $S_{\text{FOV}}$ estimate adds a little to the information carried by the parameters $W_{\text{FOV}}$, $z(0.01)$, and $d(0.01, 0.5)$.

### VII. Conclusions

The BFA provides estimates of FOV-averaged rainfall parameters, comparable with ones made with the GPROF algorithm, and at the same time it is capable of providing additional information about the small-scale HHD within the FOV. Testing the BFA for both TOGA3 simulations and TMI data confirms that
the BFA allows distinguishing at least two additional HHD parameters, characterizing the relative FOV fraction, covered with the rainfall (or, conversely, rainless FOV fraction) and the horizontal rainfall nonuniformity within the rainy FOV fraction. It has been shown also that those parameters provide more effective description of the HHD structure than such parameter as the horizontal RMS deviation of the rainfall. Since the HHD signatures are derived from the same data, which are used for the rainfall parameter retrieval, they are those characteristics whose variations directly affect radiometer measurements and cause the beamfilling errors. Therefore, the method described above can be used for collecting the HHD statistics, necessary for building models of beamfilling errors, which is recognized as one of main goals of the validation activity within the framework of such satellite missions as TRMM and AQUA [7].

The availability of the HHD signatures makes it possible to interpret the problem of screening rainless FOV as a problem of the detection of the rainfall signal on the background of the retrieval noise. This concept of the screening procedure is quite different from other known screening procedures. The performance of the BFA screening procedure has been shown to be close to one used within the framework of the GPROF.

Finally, it should be noted that the proposed approach to the HHD retrieval is quite formal and general. All the physical specificity of a concrete remote sensing problem is accounted for by the procedure of selecting basic brightness temperature vectors and associated environmental parameters, which is performed off-line prior to on-line data processing. Once this procedure has been accomplished, the same BFA software can be applied to other remote sensing problems, where the beamfilling effect is essential.

ACKNOWLEDGMENT

The author would like to thank C. Kummerow and E. Nelkin of NASA/GSFC, who kindly provided him with databases of hydrometeor/radiative simulations and R. Spencer of NASA/MSFC for the useful discussion of some issues, related to this study. The anonymous reviewers have made helpful remarks, which have allowed the essential improvement of the manuscript.

REFERENCES


