On the Consequences of Resampling Microwave Radiometer Observations for Use in Retrieval Algorithms

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ABSTRACT

How to deal with the different spatial resolutions of multifrequency satellite microwave radiometer measurements is a common problem in retrievals of cloud properties and rainfall. Data convolution and deconvolution is a common approach to resampling the measurements to a single resolution. Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI) measurements are resampled to the resolution of the 19-GHz field of view for use in a multifrequency optimal estimation retrieval algorithm of cloud liquid water path, total precipitable water, and wind speed. Resampling the TMI measurements is found to have a strong influence on retrievals of cloud liquid water path and a slight influence on wind speed. Beam-filling effects in the resampled brightness temperatures are shown to be responsible for the large differences between the retrievals using the TMI native resolution and resampled brightness temperatures. Synthetic retrievals are performed to test the sensitivity of the retrieved parameters to beam-filling effects in the resampling of each of the different channels. Beam-filling effects due to the convolution of the 85-GHz channels are shown to be the largest contributor to differences in retrieved cloud liquid water path. Differences in retrieved wind speeds are found to be a combination of effects from deconvolving the 10-GHz brightness temperatures and compensation effects due to the lower liquid water path being retrieved by the high-frequency channels. The influence of beam-filling effects on daily and monthly averages of cloud liquid water path is also explored. Results show that space–time averaging of cloud liquid water path cannot fully compensate for the beam-filling effects and should be considered when using cloud liquid water path data for validation or in climate studies.

1. Introduction

Because of the single antenna used in making measurements at different microwave frequencies in many radiometers, the spatial resolution of the measurements varies with the frequency. However, the use of microwave measurements at a common resolution in multifrequency retrievals of atmospheric parameters is often desirable and sometimes necessary. Data convolution and deconvolution has a long history of use in earth sciences. Backus and Gilbert (1970, hereinafter BG) first described a technique for inverting seismic data to retrieve earth density profiles. The BG method uses a linear combination of oversampled measurements to reconstruct the measurements at a different resolution than originally sampled and has since been employed in a number of atmospheric remote sensing applications. Conrath (1972) demonstrated the application of the BG technique in the retrieval of infrared temperature profiles and ozone profiles from backscattered ultraviolet radiation (Conrath 1977). The BG method has also been applied to optical scattering measurements to retrieve both aerosol (Westwater and Cohen 1973) and cloud droplet size distributions (Post 1975). This approach was first applied to resolution modification of satellite radiometer measurements by Stogryn (1978) and is now commonly used to resample data to a common resolution.
from microwave radiometer measurements observed by satellites. The BG approach to microwave radiometer measurement enhancement takes advantage of the overlapping antenna patterns by combining nearby measurements to modify the resolution. This technique was used by Hollinger et al. (1987) to convolve Special Sensor Microwave Imager (SSM/I) measurements to the common resolution of the largest field of view (FOV) on SSM/I, the 19-GHz channel. In Robinson et al. (1992), the BG method was used to resample the SSM/I measurements to the resolution of the 37-GHz channel, while Farrar and Smith (1992) used the BG method to resample SSM/I measurements to the highest resolution FOV at 85 GHz. Long and Daum (1998) also resampled SSM/I measurements to a common high-resolution rectilinear grid for use in land surface and vegetation studies.

Retrievals of cloud water and rainfall are commonly performed both with and without resampled microwave measurements. These retrievals are often used as comparisons or validation for one another and usually try to overcome beam-filling effects (BFE) due to resolution differences by averaging the two retrievals to a common lower spatial resolution. The beam-filling effect, or the effect of partially cloud- or rain-filled FOV on the sampled microwave brightness temperatures ($T_B$), has been documented by several studies for both clouds (e.g., Melitta and Katsaros 1995; Greenwald et al. 1997, Bremen et al. 2002) and rainfall (e.g., Chiu et al. 1990; Short and North 1990; Kummerow 1998). Microwave instruments typically have large FOVs, which may contain both clear and cloudy areas. The sensor integrates over the entire scene to measure the radiance and compute the $T_B$ associated with that FOV. For an FOV with clear and cloudy areas, the radiance measured at the satellite and the resulting $T_B$ would be less than that for a completely cloud-filled scene and is known as the beam-filling effect. The BFE is caused by the nonlinear relationship between microwave $T_B$ and LWP or rain. Microwave $T_B$ are an exponential function of LWP and rain. The concave shape of the exponential relationship always causes an underestimate in the $T_B$ if the parameter is not homogeneous, which can mean either a partially cloud-filled FOV or completely cloud-filled FOV with an inhomogeneous distribution of LWP. This was demonstrated mathematically for rainfall in appendix B of Graves (1993); however, the same is true for LWP.

A number of studies have illustrated the BFE in LWP retrievals using microwave satellite data. Melitta and Katsaros (1995) combined passive microwave data from SSM/I with visible and infrared data to identify the BFEs at 37 and 85 GHz. They found that with decreasing cloud fraction, lower microwave cloud liquid water path is retrieved at both 37- and 85-GHz channels. Greenwald et al. (1997) quantified the BFE at 37 GHz using independent microwave and solar reflectance retrievals of LWP and computed a 22% reduction in microwave LWP for an average cloud fraction of 73%. The reduction in retrieved microwave LWP at lower cloud fractions (i.e., more inhomogeneity) shown in these two studies is consistent with the underestimate in $T_B$ due to BFEs. These studies examining the cloud LWP BFE focused on comparing higher-resolution retrievals from an independent method, such as visible–near-infrared retrievals, with the lower-resolution microwave LWP retrieval. Comparing retrievals of the same dataset, where one is performed on the microwave measurements at their sampled native resolution and another is performed on the same data that have been resampled to a common resolution, shows that inhomogeneity effects are still very large.

In this paper, we examine the consequences of data convolution and deconvolution on an optimal estimation (OE) retrieval algorithm that uses microwave radiometer measurements to retrieve cloud LWP, wind speed, and total precipitable water (TPW). Results show that data resampling has a substantial effect on the retrieved parameters when compared with retrievals performed on microwave radiometer observations at their native resolution because of BFEs. These effects will be seen to correspond to the intrinsic variability of the parameter within the FOV and are not eliminated by averaging two retrievals performed on different resolutions to a common spatial grid.

2. Deconvolution method

The microwave radiometer dataset employed in this study is from the Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI). The TMI is a conically scanning passive microwave radiometer with nine channels, summarized in Table 1. The resolution is diffraction limited and thus ranges from roughly 60 km at 10 GHz to 7 km at 85 GHz. More information regarding the instrument characteristics can be found in Kummerow et al. (1998).

The TMI $T_B$ are deconvolved at 10 GHz and convolved at 21–85 GHz to a common FOV corresponding to the horizontally polarized 19-GHz FOV using the BG technique as applied to the SSM/I sensor by Robinson et al. (1992). The method uses the spatial overlap of the antenna gain function of adjacent pixels to reconstruct the $T_B$ as it would be observed by a radiometer with any desired gain function. In this work the desired gain function is that of the 19-GHz channel.
The data could be resampled to a higher resolution; however, the associated noise becomes larger. The enhancement of the 10-GHz channel to the 19-GHz FOV increased the noise level from 0.54 to about 1.5 K, which was deemed acceptable. Trying to increase the resolution of the 10-GHz channel to that of the 37-GHz FOV would double the noise to over 3 K, which could significantly affect the retrieval. Table 2 illustrates the noise at native resolution and when resampled to the 19-GHz FOV and the increase in noise at the low-frequency channels when resampled to the 37-GHz resolution. Besides the large increase in noise at 10 GHz that could especially affect the retrieval of wind speed, resampling to the 37-GHz FOV also greatly increases the noise at 21 GHz, which would also influence the retrieval of TPW.

The observed brightness temperature \( T_N \) for measurement \( i \) is given by

\[
T_N(i) = \int T_B(x, y) G_i(x, y) \, dx \, dy, \tag{1}
\]

where \( T_B(x, y) \) is the actual scene brightness temperature and \( G_i(x, y) \) is the antenna response function for observation \( i \). Application of the resampling method to the TMI data to compute the effective brightness temperature, \( T_{BG} \), at the resampled pixel location \((x_r, y_r)\), at the resolution of the 19-GHz channel, is constructed by using a linear combination of nearby observations. This is expressed as

\[
T_{BG}(x_r, y_r) = \sum_{i=1}^{N} a_i T_N(i) = \int \left[ \sum_{i=1}^{N} a_i G_i(x, y) \right] T_B(x, y) \, dx \, dy, \tag{2}
\]

where \( a_i \) are coefficients that must be computed for each channel and scan position. These calculations are time consuming and take days to compute even with modern computing capabilities, but because the TMI antenna patterns and scan geometry are known and fixed, the coefficients only need to be calculated once and can then simply be applied to each orbit.

Because the antenna temperature measurement uncertainties are assumed to be uncorrelated, standard propagation of errors provides the variance in the deconvolved \( T_B \) as

\[
e^2 = (\Delta T_{\text{rms}})^2 \sum_{i=1}^{N} a_i^2, \tag{3}
\]

where \( \Delta T_{\text{rms}} \) is the uncertainty in the observed antenna temperatures. Because of this inherent uncertainty, this technique requires a balance between resolution enhancement and amplification of noise. Therefore, following Robinson et al. (1992) we minimize the function

\[
Q = Q_0 \cos(\gamma) + e^2 w \sin(\gamma), \tag{4}
\]

where the first term on the right-hand side represents resolution enhancement and the second term represents the propagation of noise. The weighting between these terms is given by \( \gamma \), which may vary between 0° and 90°. Here \( w \) is a scale factor (K^{-2}) used to make the two terms on the right-hand side of Eq. (4) dimensionally and numerically similar. We use an order-of-magnitude estimate for \( w \) based on the computed values of \( Q_0 \), and in this work the constant value of \( w = 10^{-12} \text{ K}^{-2} \) is found to be appropriate. As discussed by Stogryn (1978), the exact value of \( w \) chosen does not change the physical content of the theory.

### Table 1. TMI instrument characteristics.

<table>
<thead>
<tr>
<th>Channel</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency (GHz)</td>
<td>10.65</td>
<td>10.65</td>
<td>19.35</td>
<td>19.35</td>
<td>21.3</td>
<td>37.0</td>
<td>37.0</td>
<td>85.5</td>
<td>85.5</td>
</tr>
<tr>
<td>Polarization</td>
<td>V</td>
<td>H</td>
<td>V</td>
<td>H</td>
<td>V</td>
<td>V</td>
<td>H</td>
<td>V</td>
<td>H</td>
</tr>
<tr>
<td>FOV down track (km)</td>
<td>59.0</td>
<td>60.1</td>
<td>30.5</td>
<td>30.1</td>
<td>27.2</td>
<td>16.0</td>
<td>16.0</td>
<td>6.7</td>
<td>6.9</td>
</tr>
<tr>
<td>FOV cross track (km)</td>
<td>35.7</td>
<td>36.4</td>
<td>18.4</td>
<td>18.2</td>
<td>16.5</td>
<td>9.7</td>
<td>9.7</td>
<td>4.1</td>
<td>4.2</td>
</tr>
</tbody>
</table>

### Table 2. Noise values \( e \) at native resolution and computed for TMI \( T_B \) resampled to the 19- and 37-GHz FOVs.

<table>
<thead>
<tr>
<th>Channel</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency (GHz)</td>
<td>10.65</td>
<td>10.65</td>
<td>19.35</td>
<td>19.35</td>
<td>21.3</td>
<td>37.0</td>
<td>37.0</td>
<td>85.5</td>
<td>85.5</td>
</tr>
<tr>
<td>Polarization</td>
<td>V</td>
<td>H</td>
<td>V</td>
<td>H</td>
<td>V</td>
<td>V</td>
<td>H</td>
<td>V</td>
<td>H</td>
</tr>
<tr>
<td>Native resolution</td>
<td>0.63</td>
<td>0.54</td>
<td>0.50</td>
<td>0.47</td>
<td>0.71</td>
<td>0.36</td>
<td>0.31</td>
<td>0.52</td>
<td>0.93</td>
</tr>
<tr>
<td>Resampled to 19-GHz FOV</td>
<td>1.61</td>
<td>1.59</td>
<td>0.50</td>
<td>0.47</td>
<td>0.47</td>
<td>0.12</td>
<td>0.11</td>
<td>0.09</td>
<td>0.16</td>
</tr>
<tr>
<td>Resampled to 37-GHz FOV</td>
<td>3.0</td>
<td>3.0</td>
<td>2.5</td>
<td>2.4</td>
<td>2.4</td>
<td>0.36</td>
<td>0.31</td>
<td>0.2</td>
<td>0.3</td>
</tr>
</tbody>
</table>
In the case of the 21-, 37-, and 85-GHz channels, the resolution is being degraded to that of the 19-GHz FOV. This is an averaging process, which naturally reduces error. As a result, amplification of noise is not a concern and we set \( \gamma = 0 \) when computing the convolution coefficients for these channels. In the case of the 10-GHz channels, the resolution is enhanced and proper care must be taken to choose \( \gamma \) carefully so as to minimize the amplification of noise. The choice of \( \gamma \) is not independent from our choice of \( w \). Because we are using a very small value for \( w \), we must choose a relatively large value of \( \gamma \). It should be noted that the opposite is true in Robinson et al. (1992). Because they chose a relatively large value for \( \gamma \), they are able to choose a very small value for \( w \) because they are using a large value of \( \gamma \) acceptable. Through trial and error we find an appropriate value of \( \gamma \) to be 85°, which heavily emphasizes the minimization of noise amplification while matching the resolution to 19-GHz FOV. Table 3 shows the weighting coefficients, \( a \), error variance, \( e^2 \), and noise values \( e \) for the center TMI pixel as a function of tested \( \gamma \) values for the resolution enhancement from 10 to 19 GHz with \( w = 10^{-12} \text{ K}^{-2} \). This table illustrates the necessity of using a large value for \( \gamma \) to reduce the noise at 10 GHz to an acceptable level.

We chose to use an 11 \( \times \) 11 array of pixels surrounding the pixel to be deconvoluted leading to a value of \( N = 121 \). Table 4 shows the weighting coefficients \( a \), error variance \( e^2 \), noise values \( e \), and \( Q_0 \), which provides a measure of the resolution enhancement, for the center TMI pixel as a function of tested \( N \) values. From this table, it is clear that a minimum of a 5 \( \times \) 5 array of surrounding pixels is required to reduce the noise, but the resolution enhancement continues to increase as \( N \) increases. The choice of 11 \( \times \) 11 surrounding pixels is somewhat subjective, but the convergence of \( Q_0 \) suggests that increasing \( N \) beyond our chosen value is likely unnecessary.

After minimizing Eq. (4) to solve for the coefficients, \( a_n \), they are applied to each TMI pixel to calculate \( T_{BG} \). These resampled TMI \( T_{\theta S} \) are then used as input to the OE retrieval algorithm described briefly in the following section and the resultant changes in retrieved quantities due to deconvolution and their associated BFEs are analyzed.

### Table 3. Weighting coefficient, error variance, and noise values as a function of \( \gamma \) when \( w = 10^{-12} \text{ K}^{-2} \).

<table>
<thead>
<tr>
<th>( \gamma )</th>
<th>( a^2 )</th>
<th>( e^2 )</th>
<th>( e )</th>
</tr>
</thead>
<tbody>
<tr>
<td>50°</td>
<td>33.6</td>
<td>13.4</td>
<td>3.6</td>
</tr>
<tr>
<td>70°</td>
<td>18.6</td>
<td>7.4</td>
<td>2.7</td>
</tr>
<tr>
<td>80°</td>
<td>11.0</td>
<td>4.4</td>
<td>2.1</td>
</tr>
<tr>
<td>85°</td>
<td>6.5</td>
<td>2.6</td>
<td>1.6</td>
</tr>
</tbody>
</table>

### Table 4. Weighting coefficient, error variance, noise values, and \( Q_0 \) as a function of \( N \).

<table>
<thead>
<tr>
<th>( N )</th>
<th>( a^2 )</th>
<th>( e^2 )</th>
<th>( e )</th>
<th>( Q_0 (10^{-10}) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>3 ( \times ) 3</td>
<td>13.4</td>
<td>5.3</td>
<td>2.3</td>
<td>1.48</td>
</tr>
<tr>
<td>5 ( \times ) 5</td>
<td>5.4</td>
<td>2.1</td>
<td>1.5</td>
<td>1.25</td>
</tr>
<tr>
<td>7 ( \times ) 7</td>
<td>6.8</td>
<td>2.7</td>
<td>1.6</td>
<td>0.97</td>
</tr>
<tr>
<td>9 ( \times ) 9</td>
<td>6.4</td>
<td>2.5</td>
<td>1.6</td>
<td>0.86</td>
</tr>
<tr>
<td>11 ( \times ) 11</td>
<td>6.5</td>
<td>2.6</td>
<td>1.6</td>
<td>0.82</td>
</tr>
</tbody>
</table>

### 3. Retrieval and results

The algorithm used in this paper to illustrate the effects of data resampling was first developed by Elsaesser and Kummerow (2008) for the retrieval of nonraining parameters over oceans and used passive microwave radiometer observations at their native resolution. Further development of this algorithm attempted to address scene inhomogeneities by accounting for both clear and cloudy areas within the TMI footprints by calculating cloud fraction from visible and infrared datasets. To define a cloud fraction over a given area required that the microwave measurements at the different frequencies be resampled to a common resolution. The BG method was applied to deconvolve and convolve the data to the resolution of the 19-GHz FOV as discussed in the previous section and the retrieval was run on both the native resolution TMI measurements and the resampled TMI measurements. The differences between the retrievals are examined and the BFEs are assessed.

Resampling the TMI data to the resolution of the 19-GHz FOV had a larger impact on the retrieval than expected. Figures 1a–d are a comparison of the TMI OE retrieval parameters at the native resolution of each TMI channel and the TMI OE retrieval resampled to the resolution of the 19-GHz channel for 3 months of data (December 2005–February 2006) in the tropical western Pacific at 30°S–30°N, 130°E–170°W. Figures 1a and 1b show that resampling the data has little effect on the retrieved TPW, however it results in a decrease in the retrieved LWP of about 30%. As shown in Fig. 1c, the wind speed from the retrieval with the resampled data tends to consistently be 1 m s\(^{-1}\) higher up to wind speeds of about 10 m s\(^{-1}\) and up to 2 m s\(^{-1}\) lower for wind speeds of 20 m s\(^{-1}\). Though the scale of LWP in Fig. 1a extends to 600 g m\(^{-2}\) to illustrate that the LWP difference increases as LWP increases, it should be noted that the majority of the clouds have LWP values below 200 g m\(^{-2}\). A useful diagnostic that results from OE retrievals is the \( \chi^2 \) statistic shown in Fig. 1d. The \( \chi^2 \) value indicates how well the simulated \( T_{BG} \) in the forward model of the retrieval algorithm match the observed \( T_{\theta S} \), therefore larger values of \( \chi^2 \) suggest a poorer fit between simulated and measured \( T_{\theta S} \) than low values of \( \chi^2 \). One of the benefits
of using resampled \( T_B \)s over native \( T_B \)s in the retrieval is the lowering of the \( \chi^2 \) statistic, shown in Fig. 1d, indicating that the resampled data result in a better fit retrieval solution than the native resolution retrieval. This is another example of scene inhomogeneity effects, since at the native resolution of the TMI dataset, the channels are sampling different scenes.

Because the resolution of the 21-GHz channel is very similar to that of the 19-GHz FOV, the 21-GHz convolved \( T_B \)s are almost the same as their native resolution \( T_B \)s. Since the 21-GHz channel is most sensitive to atmospheric water vapor, this means that TPW is relatively insensitive to resampling. Therefore, only the differences in the retrieved LWP and wind speeds are examined as a function of the cloud fraction within the 19-GHz FOV. Figure 2 shows LWP and winds retrieved with native resolution and resampled TMI \( T_B \)s for different cloud fraction bins: 100% cloudy, greater than 75% cloudy, 50%−75% cloudy, 25%−50% cloudy, and less than 25% cloudy. This figure illustrates that as cloud fraction decreases, the systematic differences between the two retrievals increase. At cloud fractions greater than 75% the bias between the two retrievals ranges from 10% at low LWPs up to 35% at very high LWPs. For the lowest cloud fractions, the range in the bias is much larger, from 10% at low LWPs to almost 60% at high LWPs. The bias in the wind speed does not seem to be as large of a function of cloud fraction as the LWP, especially for wind speeds below 10 m s\(^{-1}\). At the highest wind speeds, the bias does slightly increase with cloud fraction.

Figure 3 summarizes the difference in retrieved LWP and winds using native and resampled \( T_B \)s as a function of cloud fraction. The retrieval algorithm in this study uses both the 37- and 85-GHz channels to retrieve LWP, but the results in Fig. 3 are similar to those shown by Melitta and Katsaros (1995). The difference between the retrievals increases with decreasing cloud fraction and between 70% and 75% cloudy, we find a reduction in cloud LWP for resampled \( T_B \) retrievals of 20%, almost identical to that found by Greenwald et al. (1997). Above about 80% cloud fraction, the difference between retrieved LWP decreases substantially. As suggested in Fig. 2, above cloud fractions of about 40%, the difference between the retrievals of wind speed does not substantially change with cloud fraction, with the native resolution \( T_B \)s retrieving about 20% lower wind speed than the deconvolved \( T_B \)s.

While there will still be scene inhomogeneities within the resampled data, by limiting the sample to only 100%
cloud fraction, we have at least reduced the effects of sampling a combination of clear and cloudy scenes, although the cloud fraction effects are not fully accounted for in the nonresampled retrieval. Because the cloud fractions were calculated for the resampled data, the clouds are only guaranteed to completely fill the 19-GHz footprint. It is likely that some of the observed differences can be attributed to the clouds not completely filling the large 10-GHz footprint, which may explain some of the 10% difference in Fig. 3 at 100% cloudy. Another factor contributing to the differences at 100% cloudy is the distribution of LWP within the FOV. Even at 100% cloud fraction, variability of LWP within the FOV will affect the retrieved results. These retrievals would only be expected to be the same if the cloud completely filled the 10-GHz footprint and the LWP was homogeneous across the entire scene.

4. Synthetic tests

While we assume that beam-filling effects are responsible for these results, we test the effects of the BG algorithm in a more controlled environment. A set of synthetic cloud scenes for a range of cloud LWP from 75 to 400 g m$^{-2}$ is created. Each scene is 200 km $\times$ 200 km at a resolution of 1 km $\times$ 1 km and contains from 10% to 75% cloud coverage, where the cloud locations in the scene are chosen by a random number generator. Because the locations of the clouds are chosen randomly, the cloud fraction of the entire scene is not necessarily representative of the scene sampled for our retrieval. Clouds are created to be 25 km $\times$ 25 km and each cloud within the scene is randomly populated with LWP values that return the chosen mean cloud LWP (75, 100, 200, 300, or 400 g m$^{-2}$) with a standard deviation of 30%. Despite the fact that the clouds are originally 25 km $\times$ 25 km, because of the random selection of the locations, clouds often merge to create a scene with a population of cloud sizes.

For each 1 km $\times$ 1 km pixel in the scene, we then run the forward model used in our retrieval with a prescribed 8 m s$^{-1}$ wind speed, TPW value of 24 mm, and SST of 293 K, along with either zero LWP if the pixel is clear sky or their assigned cloud LWP value, to calculate the associated microwave $T_{\mu}$ at each channel. The $T_{\mu}$ for each frequency are then sampled in the center of the
scene at both the resolution of each microwave channel as observed by the TMI and at the resolution of the 19-GHz FOV as would be calculated from the BG deconvolution algorithm. Using these $T_B$s, the OE retrieval algorithm is run and the results are compared. Histograms of the frequency of LWP values retrieved at their native resolution and at their resampled resolution are plotted in Fig. 4, as well as the “truth” for mean LWP assigned for the calculation of the microwave $T_B$s. For the synthetic resampled LWP retrievals, the histogram shifts to the left toward lower values and the mean LWP retrieved for all scenes is about 33% higher in the native resolution retrievals. Similar to the actual data, the synthetic results show that the retrieval using resampled $T_B$s on average underestimates LWP and retrieves approximately 15% higher retrieved wind speed relative to the native resolution retrieval. Figure 4 also shows that the histogram and mean LWP of resampled retrievals are more representative of the true mean LWP within the FOV than the native resolution retrieved LWP. It should be noted that in the actual data, we are only comparing resampled to native resolution retrievals. The actual data show that the resampled $T_B$s underestimate LWP relative to the native resolution $T_B$s, but not necessarily the truth. We have defined truth as the mean LWP of all of the 1-km assigned pixels within the 19-GHz FOV, which includes a combination of clear and clouds. Therefore, when the data are resampled to the common resolution of the 19-GHz FOV, the BFEs reduce the $T_B$s and retrieved LWP, yielding a result closer to the truth than the native resolution retrieval.

To illustrate the effects of beam filling on cloud LWP, we compare the difference in retrieved results with the difference in cloud fraction of the 85-GHz FOV at its native resolution and cloud fraction at the resampled 19-GHz FOV in Fig. 5. This figure shows that the percent difference in cloud LWP is strongly correlated with the difference in cloud fraction between the smaller 85-GHz and larger 19-GHz FOV sizes. Also, the majority of the points are located at positive cloud fraction differences, indicating that when cloud fraction is high for the smaller footprints, there is a tendency to move toward lower cloud fraction when resampled to the larger 19-GHz FOV. The likely explanation for this is that as the size of the FOV increases, there is a higher likelihood of viewing some clear area within the scene. The reduction in retrieved LWP as the FOV size increases is due to the nonlinear nature between the $T_B$s and LWP that was previously described and is shown for the 85-GHz horizontally and vertically polarized channels in Fig. 6. This bias in retrieved LWP is similar to the bias with FOV size shown by Graves (1993) and Ha and North (1995) for rainfall retrievals.

While these synthetic results clearly illustrate that BFEs are driving the differences between the native resolution and resampled retrievals, it is not yet clear which channels are most responsible for these differences. To
examine this, we ran several tests by substituting the 10-GHz deconvolved TBs and 37- and 85-GHz convolved TBs individually and in combination into the synthetic scenes where all other channels are run with their native TMI resolution TBs. We omit the 19- and 21-GHz tests because the 19-GHz native resolution and convolved TBs are the same and the TBs at 21 GHz are so close that it makes no difference in the retrieved parameters.

In the first test, we substitute only the 10-GHz deconvolved TB in the retrieval. For reference, Figs. 7a and 7b are the synthetic retrieval results with all the channels sampled at either their native resolution or deconvolved resolution. The deconvolved LWP and wind speed results are plotted against the native resolution results with the deconvolved 10-GHz TB substitution in Figs. 8a and 8b. From these results, it is obvious that the 10-GHz channel provides little information for the cloud LWP. While it may be difficult to discern from Figs. 7b and 8b, the 10-GHz TB substitution results in an increase in the mean wind speed from 7.2 to 7.5 m s$^{-1}$ and also reduces the scatter with the standard deviation decreasing from 0.54 to 0.47 m s$^{-1}$. This suggests that the resampling of the low-frequency channel is driving some of the change in retrieved wind speed, which is expected. In the second and third tests we substitute the 37- and 85-GHz convolved TBs with the other channels at their native resolutions. The 37- and 85-GHz results are shown in Figs. 8c,d and 8e,f, respectively. It is clear that the resampling of the high-frequency channels is responsible for the lower LWP being retrieved, though neither channel alone fully explains the discrepancy observed in Fig. 7a. It is interesting to note the effect that resampling the 85-GHz channel has on the wind speed retrieval, which suggests that some of the increased wind speed in retrievals using convolved TBs is actually a compensating effect that is produced as a by-product of retrieving the lower LWP. At 37 and 85 GHz, the wind speed signal is relatively small compared to the sensitivity to cloud water. After the convolution, the error bounds on the 85-GHz channels are very small compared to noise at 10 GHz, which is most sensitive to the wind speed. To converge on a solution, the OE algorithm must find a solution for the three parameters that matches the observed TBs within the bounds of the measurement noise at all channels. This means that because of the sensitivity to LWP and low noise at the high-frequency channels the retrieval must find a solution for LWP that matches the observed TBs very well. However, the low sensitivity of the high-frequency channels to the wind speed combined with the larger error bounds at 10 GHz means that the retrieval has more room to adjust the wind speed. This is most likely the reason that the reduction in LWP when using the resampled 85-GHz TBs results in increased retrieved wind speed.

![Fig. 5. Difference in the 85-GHz FOV cloud fraction and the 19-GHz FOV cloud fraction plotted against the percent difference in native-resolution LWP retrieval and deconvolved LWP retrieval.](image)

![Fig. 6. Cloud LWP and (a) 85-GHz horizontal polarization TBs and (b) 85-GHz vertical polarization TBs.](image)
In the next test, we substitute both the 37- and 85-GHz convolved $T_B$s with the results shown in Figs. 9a and 9b. The LWP retrieval now retrieves the same solution as that with all of the channels resampled to the 19-GHz FOV and shows that the decrease in retrieved LWP using convolved $T_B$s is fully explained by the high-frequency channels. The 37- and 85-GHz channels are both being resampled to a resolution lower than their native resolution. While it is clearly scene dependent as shown by the scatter, Fig. 5 showed that on average, moving from a higher resolution to lower resolution tends to reduce the cloud fraction, which lowers the emission signature and $T_B$s and thus, the retrieved LWP. These results also show that the difference in retrieved wind speed with resampled data cannot be fully explained by compensating effects within the retrieval. The final test (shown in Figs. 9c,d), which adds the deconvolved 10-GHz $T_B$s to the previous test, yields the same results as the retrieval run using all resampled $T_B$s. It also supports our previous test result that the high-frequency channels are solely responsible for the decreased LWP and that the increased wind speed is a combination of compensating effects from the reduced LWP retrieved from the combination of convolved 37- and 85-GHz $T_B$s and the increase in speed due to the deconvolution of the 10-GHz channels.

To verify our tests on the real data, the OE retrieval algorithm was run with combinations of native resolution and resampled TMI $T_B$s as in the fourth and fifth tests on our synthetic scene. While not shown here, the retrievals from the TMI data reproduced the results of our tests. Degrading the resolution of the 37- and 85-GHz frequencies resulted in consistently lower retrieved LWP with a compensating increase in wind speed. Enhancing the resolution of the 10-GHz frequencies did increase the wind speeds even more for wind speeds below 8 m s$^{-1}$, as in our synthetic tests; however, above 8 m s$^{-1}$ the addition of the resampled 10-GHz data tended to decrease the wind speed.

As mentioned in the introduction, when comparing parameters that are retrieved at different resolutions, many users try to overcome resolution effects and BFEs by averaging the retrieved products, like LWP, to the lower-resolution product or to a common resolution. Figure 10a shows the LWP from our two retrievals, one at the native TMI resolution and the other at the 19-GHz FOV resolution, averaged onto a 1° × 1° grid for each swath. Averaging should account for spatial resolution differences, but any residual differences should be due to BFEs in the retrievals. While the bias is not as large as that shown in Fig. 1, these results show that a significant bias of about 20% still exists between the LWP even after averaging. Greenwald et al. (1997) pointed out that BFEs are less of an issue when averaged over monthly time scales for large grid boxes. The resampled and native TMI resolution retrievals were averaged on a 1° × 1° grid for a month of data and plotted in Fig. 10b. While even more differences are resolved by such large space–time averaging, a residual bias of about 10% still exists. Again, because of the nonlinear nature of the relationship between $T_B$s and LWP, averaging in radiance space is not comparable to averaging in parameter space and cannot account for the BFEs even in retrievals performed on the same dataset at different resolutions. These effects become very important in work that uses retrievals of LWP in climate studies or in tuning model parameters to reproduce observational results.

5. Retrieval without 85-GHz channels

Since microwave retrievals of LWP are based on the emission from cloud water and the effects due to a scattering increase with frequency, many microwave retrievals of LWP do not use the 85-GHz channels. The synthetic retrieval results showed that much of the difference in retrieved LWP between native resolution and
resampled data can be attributed to the 85-GHz frequency. Figure 11a shows the results from the OE retrieval for LWP using native TMI resolution and resampled \( T_B \)s without the 85-GHz channels. For values of LWP below 200 g m\(^{-2}\), the two retrievals agree very well, but above that the resampled \( T_B \)s retrieve up to 20% lower LWP. Figure 11b shows the results for the synthetic scenes retrieved without the 85-GHz channels. Like the real data, the synthetic results show pretty good agreement for lower LWPs, but the differences increase up to about 25% as the LWP increases. These differences are smaller than that shown for the retrieval using 85 GHz because the relationships between LWP and \( T_B \)s at the lower frequencies are not as nonlinear, so the BFEs are not as large. However, because the 37-GHz channel is being resampled to a larger FOV, some BFEs remain.

6. Discussion

Data convolution and deconvolution algorithms are commonly used to overcome the resolution differences inherent in satellite passive microwave remote sensing. We tested the effects of data resampling in an OE microwave retrieval of LWP, TPW, and wind speed and found that beam-filling effects are substantial. Retrievals performed with TMI data as well as synthetic scenes show differences between retrieved LWP with native resolution and resampled \( T_B \)s up to about 30%, although this increases with decreasing cloud fraction and increasing LWP. Differences in the cloud fraction between the 85-GHz FOV and the resampled 19-GHz FOV are found to be highly related to the differences in retrieved LWP. Synthetic results show that convolving the 37- and 85-GHz channels to a lower resolution is
responsible for the general decrease in LWP in the resampled retrievals, although the 85-GHz channels are the largest contributor. Synthetic results also indicate that the differences in wind speed retrieved with native resolution $T_B$'s and resampled $T_B$'s are due to a combination of deconvolving the 10-GHz channels and compensating effects of retrieving lower LWP solutions driven by the higher-frequency channels. Retrievals performed without the 85-GHz channels show that using resampled data still results in lower retrieved LWP than the native resolution data due to BFEs, although the differences are about 10% smaller than retrievals with the 85-GHz channels.

The results from this study suggest that an understanding of the issues that arise from data resampling is absolutely imperative when it comes to evaluating parameters retrieved from microwave datasets. As they are intended, convolution and deconvolution algorithms allow the same scene to be sampled from each of the microwave channels, however, because of the beam-filling effects due to sub-FOV inhomogeneities in many of the properties that are often retrieved, such as cloud water and rainfall, the resultant retrieved quantity is strongly influenced by whether or not the retrieval algorithm developer has chosen to resample the input data. Since clouds and rain are not uniform in nature,

\[ \text{FIG. 9. Deconvolved retrievals of (left) LWP and (right) wind plotted against retrievals of LWP using native-resolution} \ T_B \text{'s with (a),(b) 37- and 85-GHz and (c),(d) 10-, 37-, and 85-GHz deconvolved} \ T_B \text{substitutions.} \]

\[ \text{FIG. 10. The} \ 1^\circ \times 1^\circ \text{LWP (g m}^{-2}\text{)} \text{retrieved with native-resolution TMI} \ T_B \text{'s plotted against} \ 1^\circ \times 1^\circ \text{LWP retrieved with deconvolved TMI} \ T_B \text{substitutions averaged for (a) each swath and (b) monthly.} \]
convolution of the high-frequency microwave channels to a lower resolution increases BFEs and tends toward reducing cloud emission signatures and retrieved cloud LWP.

The results from this work also show that the common technique of averaging inhomogeneous retrieved parameters from different resolution datasets to a common lower resolution may reduce some of the spatial resolution effects, but they cannot fully account for the beam-filling effects. This stems from the nonlinearities in the relationship between microwave $T_B$ and LWP and has significant implications for climate studies using these datasets. This paper serves as a reminder that choices made on input data resolution strongly influence retrieval results and that intercomparison of averaged retrieved properties that are not homogeneous does not eliminate beam-filling errors. For users of passive microwave cloud and precipitation datasets, the work in this study shows the effects that data resampling and beam-filling effects may have on retrieval products. It also emphasizes the importance of understanding these effects before undertaking any study utilizing the plethora of available microwave cloud and precipitation retrieval products.

This study shows that to retrieve an LWP that is representative of the cloud only and does not suffer from clear sky BFEs, the fractional coverage of cloud within the FOV must be taken into account. To apply what we have learned from this study on the effects of resampling, the resampled TMI data will be matched to the much higher-resolution Visible Infrared Scanner (VIRS) data from TRMM. Using a simple visible and infrared cloud masking technique, we can calculate the cloud fraction within each TMI FOV. Within the framework of the OE retrieval, the clear and cloudy $T_{BS}$ can then be computed in the forward model and weighted by the clear and cloud fractions, thus allowing the retrieval of a cloud-only LWP. The implementation of this work is discussed in Rapp et al. (2009).

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