Improving Cross-Track Scanning Radiometers’ Precipitation Retrieval over Ocean by Morphing

Yalei You, a Christa Peters-Lidard, b S. Joseph Munchak, c Jackson Tan, b,d Scott Braun, c Sarah Ringrud, b, William Blackwell, f John Xun Yang, a Eric Nelkin, b,g and Jun Dong a

a Cooperative Institute for Satellites Earth System Studies, Earth System Science Interdisciplinary Center, University of Maryland, College Park, College Park, Maryland
b NASA Goddard Space Flight Center, Greenbelt, Maryland
c Laboratory for Mesoscale Atmospheric Processes, NASA Goddard Space Flight Center, Greenbelt, Maryland
d Universities Space Research Association, Columbia, Maryland
e Earth System Science Interdisciplinary Center, University of Maryland, College Park, College Park, Maryland
f Lincoln Laboratory, Massachusetts Institute of Technology, Lexington, Massachusetts
g Science Systems and Applications, Inc., Lanham, Maryland

ABSTRACT: Previous studies showed that conical scanning radiometers greatly outperform cross-track scanning radiometers for precipitation retrieval over ocean. This study demonstrates a novel approach to improve precipitation rates at the cross-track scanning radiometers’ observation time by propagating the conical scanning radiometers’ retrievals to the cross-track scanning radiometers’ observation time. The improved precipitation rate is a weighted average of original cross-track radiometers’ retrievals and retrievals propagated from a conical scanning radiometer. The cross-track scanning radiometers include the Advanced Technology Microwave Sounder (ATMS) on board the SNPP satellite and four Microwave Humidity Sounders (MHSs). The conical scanning radiometers include the Advanced Microwave Scanning Radiometer 2 (AMSR2) and three Special Sensor Microwave Imager/Sounders (SSMIs), while the precipitation retrievals from the Global Precipitation Measurement (GPM) Microwave Imager (GMI) are taken as the reference. Results show that the morphed precipitation rates agree much better with the reference. The degree of improvement depends on several factors, including the propagated precipitation source, the time interval between the cross-track scanning radiometer and the conical scanning radiometer, the precipitation type (convective versus stratiform), the precipitation events’ size, and the geolocation. The study has potential to greatly improve high-impact weather systems monitoring (e.g., hurricanes) and multisatellite precipitation products. It may also enhance the usefulness of future satellite missions with cross-track scanning radiometers on board.

KEYWORDS: Precipitation; Remote sensing; Satellite observations

1. Introduction

Precipitation estimates from passive microwave radiometers are foundational for generating high-quality global precipitation datasets, including NASA’s Integrated Multisatellite Retrievals for GPM (IMERG) (Huffman et al. 2019), Climate Prediction Center’s morphing technique (CMORPH) (Xie et al. 2017), and JAXA’s Global Satellite Mapping of Precipitation (GSMaP) (Kubota et al. 2007). A common feature for all three widely used precipitation datasets is that they combine the precipitation retrievals from microwave and infrared observations. Microwave observations are more directly sensitive to precipitation hydrometeors, but come at irregular and low temporal resolution compared to infrared observations. Thus, they are propagated to a period when they are not available through motion vectors.

Passive microwave radiometers can be grouped into two categories: conical scanning radiometers and cross-track scanning radiometers. A passive microwave radiometer is considered a conical scanning radiometer when the footprint size and Earth incidence angle remain unchanged across the scan line, while a cross-track scanning radiometer has varying footprint size and Earth incidence angle across the scan line. The five conical scanning radiometers used in this study include three Special Sensor Microwave Imager/Sounder (SSMIS) on board the Defense Meteorological Satellite Program (DMSP) F16, F17, and F18 satellites, the Advanced Microwave Scanning Radiometer-2 (AMSR2) on board the Global Change Observation Mission–Water (GCOM-W1) satellite, and the Global Precipitation Measurement (GPM) Microwave Imager (GMI) on board the GPM Core Observatory satellite. The five cross-track scanning radiometers used in this study include the Microwave Humidity Sounder (MHS) on board NOAA-18, NOAA-19, MetOp-A, and MetOp-B satellites, and the Advanced Technology Microwave Sounder (ATMS) on board Suomi National Polar-Orbiting Partnership (SNPP) satellite.

Previous studies have demonstrated that conical scanning radiometers provide better precipitation retrieval performance...
relative to spaceborne radars over ocean than cross-track scanning radiometers. For example, Lin and Hou (2008) concluded that rainfall rates over the tropical ocean from conical scanning radiometers are noticeably better than those from cross-track scanning radiometers in terms of standard deviation errors using the Tropical Rainfall Measuring Mission (TRMM) Precipitation Radar (PR) as the reference. You et al. (2020a) evaluated 10 passive microwave radiometers relative to the GPM Ku-band precipitation radar (KuPR) over oceanic surfaces (65°S–65°N) and concluded that precipitation retrievals from conical scanning radiometers over ocean perform much better than those from cross-track scanning radiometers. Specifically, results showed that the correlation between the precipitation rates from cross-track scanning radiometers (ATMS and MHS) and KuPR is about 0.40. The correlation between precipitation rates from SSMIS and KuPR is 0.57. The best performance over ocean is from AMSR2, which has a correlation of 0.69 relative to KuPR. The better performance from conical scanning radiometers like SSMIS and AMSR2 results from the availability and usage of low-frequency channels over ocean, which better captures the emission signature from liquid raindrops closer to the surface. In contrast, the cross-track scanning radiometers primarily rely on ice-scattering signals, leading to a relatively poor retrieval performance. The finer footprint size of AMSR2 largely accounts for the better performance of AMSR2 than SSMIS. For more detailed discussions, the reader is referred to You et al. (2020a).

Because conical scanning radiometers demonstrate better performance than cross-track scanning radiometers, the objective of this study is to improve cross-track scanning radiometer precipitation retrievals by propagating the precipitation rates from close-in-time conical scanning radiometers to the times of cross-track scanning radiometer observations. Then we obtain weighted-average precipitation rates by combining the propagated precipitation rates from conical scanning radiometers with the original cross-track scanning radiometer precipitation rates at the cross-track scanning radiometer observation time. Hereafter, we use “morphing/morped/morph” to represent both the precipitation propagation via motion vectors and the precipitation combination by weighted-average.

The morphing technique was pioneered by Joyce et al. (2004) at the NOAA Climate Prediction Center as the key component of the CMORPH precipitation product. Other infrared and microwave merged precipitation products including IMERG (Huffman et al. 2019) and GSMaP (Kubota et al. 2007; Ushio et al. 2009) later adopted this concept due to its effectiveness in improving precipitation-estimate performance. At the core of the morphing technique is the concept of propagating the high-quality passive microwave precipitation rates to a time when no passive microwave observations are available using motion vectors, derived either from geostationary infrared (IR) brightness temperatures (TB) (Joyce et al. 2004) or total precipitable water vapor from numerical models (Tan et al. 2019).

The key innovation in this study is the improvement of cross-track scanning radiometer precipitation rates at the cross-track scanning radiometer observation time by using information from preceding or succeeding conical scanning radiometer precipitation rates in a 3-h time window. In contrast to the morphing schemes in IMERG, CMORPH, and GSMaP, the instantaneous passive microwave precipitation is not merged with precipitation propagated from other times, so the cross-track scanning radiometer retrievals do not leverage information from conical scanning radiometer retrievals within similar time windows (3 h). In addition, the precipitation motion vector in this study is derived directly from the precipitation rate field (more details in the methodology section).

The study is organized as follows. Section 2 describes the passive microwave precipitation datasets from 10 radiometers. Section 3 details the necessary steps to generate the improved cross-track scanning radiometer precipitation rates via the morphing technique and the precipitation weighted averaging scheme. The results are presented in section 4 beginning with two case studies and later showing the overall performance for all five cross-track scanning radiometers. Section 5 highlights the precipitation field improvements for a hurricane case study using the morphing schemes. Finally, we present the conclusions and future work in section 6.

2. Datasets

This study primarily uses the precipitation estimates from 10 radiometers, including GMI, SSMIS on board F16, F17, and F18; AMSR2 on board GCOM-W1; MHS on board NOAA-18, NOAA-19, MetOp-A, MetOp-B; and ATMS on board SNPP. As mentioned previously, the first five sensors are conical scanning radiometers and the rest are cross-track scanning radiometers.

All precipitation rates for these 10 sensors are from the latest climate version of the Goddard profiling algorithm (GPROF V05; Kummerow et al. 2015). GPROF classifies the surface into 14 types and only retrievals over oceanic surfaces are used in this study, because no clear advantage is observed from conical scanning radiometer precipitation retrievals over land (You et al. 2020a). For convenience, these sensors are referred to as AMSR2, GMI, F16-SSMIS, F17-SSMIS, F18-SSMIS, NOAA18-MHS, NOAA19-MHS, MetOpA-MHS, MetOpB-MHS, and ATMS. From now on, we use these abbreviations to represent either the sensors themselves or the GPROF retrieved precipitation rates from these sensors, depending on the context of the discussion.

We use precipitation rates from all 10 radiometers from March 2014 (just after launch of the GPM satellite) to August 2020 except for NOAA18-MHS, which stopped functioning in October 2018. In the validation process, KuPR precipitation rates (latest version, V06) in the same period (i.e., from March 2014 to August 2020) are used as an independent reference to assess the precipitation estimate improvements for cross-track scanning radiometers. In addition, the precipitation type information is also extracted from KuPR dataset to analyze the varying degree of improvements for convective and stratiform precipitation systems. We do not use KuPR in the morphing process because of the limited spatial overlaps between KuPR and the cross-track scanning radiometers due to its narrow
swath width (i.e., ~245 km from KuPR versus ~2500 km from ATMS and MHS).

3. Methodology

The objective of this study is to improve the precipitation rates at the cross-track scanning radiometer observation time, by combining the propagated precipitation rates from conical scanning radiometers and the original cross-track scanning radiometer precipitation rate. To assess improvements, we primarily use GMI as the reference. We compare the original cross-track scanning radiometer precipitation rates and the morphed precipitation rates at the cross-track scanning radiometer observation time against GMI-derived precipitation rates. Ideally, we would choose other observations as the reference (e.g., rain gauges), so that we can also use the GMI retrieval in the morphing process. However, traditional precipitation rate observations from surface radar or gauges are rarely available over ocean, especially on the global scale.

In the following discussions, we choose to use NOAA19-MHS as an example to explain how the morphing concept is implemented. The same procedure is equally applicable to the other four cross-track scanning radiometers.

First, we find coincident precipitation event observations from NOAA19-MHS and GMI. We define coincident observations as pixels from NOAA19 and GPM that are separated by less than 5 min (earlier or later) and 5 km. The GMI precipitation rate is used as the reference to evaluate the morphing results. A precipitation event is defined as “connected precipitating pixels” in each swath. That is, we find pixels with precipitation intensity greater than 0 being connected if their edges or corners touch. Two adjoining pixels are part of the same event if they are both on and are connected along the horizontal, vertical, or diagonal direction.

Second, the precipitation events from NOAA19-MHS and GMI are both mapped to a 0.1° latitude/longitude grid box, which is how these level-2 precipitation rates are incorporated into IMERG (Huffman et al. 2019). The purpose of this gridding is to compute the spatial correlation between NOAA19-MHS and the conical scanning radiometer closest to NOAA19-MHS in a 3-h window. For events observed by NOAA19-MHS, but not observed by the conical scanning radiometers in a ±3-h window, the NOAA19-MHS retrievals remain unchanged. To compute the motion vector accurately, we make sure that both GMI and NOAA19-MHS have at least 50 precipitating grid boxes. In this step, we also obtain the central latitude and longitude of each precipitation event by averaging all latitude/longitude values for each event.

Third, we check whether there are overpasses in the same region (±15° from the central latitude and longitude) in a ±3-h window from four conical scanning radiometers (i.e., three SSMISs and AMSR2). We intentionally select a large region to include all possible overpasses from the conical scanning radiometers. In this selected region (±15° from the central latitude and longitude), there may exist several precipitation events, which are all considered as one single event in the motion vector computation. If there are multiple overpasses from these four conical scanning radiometers, we only select the conical scanning radiometer closest in time to NOAA19-MHS.

Fourth, the precipitation field from the selected conical scanning radiometer is also mapped to the 0.1° grid. Similar to the approach for cross-track scanning radiometers, we only choose events that have at least 50 precipitating grid boxes from the conical scanning radiometer to ensure the accuracy of the motion vector computation.

Fifth, we compute the motion vector using the gridded data from the selected conical scanning radiometer and the NOAA19-MHS using the method of Joyce et al. (2004) by shifting the conical scanning radiometer’s precipitation field in the latitudinal and longitudinal directions. We propagate the precipitation rates from the selected conical scanning radiometer to the cross-track scanning radiometer observation time with the spatial offset that gives maximum correlation between the shifted conical scanning radiometer precipitation field and the NOAA19-MHS precipitation field. Note that this computation of motion vector and propagation of precipitation are different from those in IMERG, CMORPH, and GSMaP in that the motion vectors are computed from the instantaneous PMW precipitation itself rather than from an ancillary field (e.g., IR TB).

Sixth, a combined precipitation rate is calculated using a weighted average of the precipitation rates from the conical scanning radiometer and NOAA19-MHS and assigning equal weights (i.e., 0.5). That is, the morphed precipitation rate at the NOAA19-MHS observation time is an average of the rates from the morphed conical scanning radiometer product and NOAA19-MHS.

Finally, we compute statistics for both the original NOAA19-MHS and the morphed precipitation rates at the NOAA19-MHS observation time relative to GMI precipitation rates at the 0.1° resolution. These statistical metrics include correlation, root-mean-square error (RMSE), and bias.

4. Results

a. Retrieval performance against GMI

In You et al. (2020a), we evaluated the precipitation retrieval performance of the previously mentioned radiometers except GMI relative to KuPR, showing that conical scanning radiometers outperform cross-track scanning radiometers. In this study, we use GMI as the reference due to its much wider swath coverage compared with KuPR (i.e., 245 km from KuPR versus 885 km from GMI). The wider GMI swath ensures that there are enough overlapping samples between GMI and the five cross-track scanning radiometers. Therefore, we first assess these sensors’ precipitation retrieval performance against GMI.

Figure 1 shows the correlation between the coincident observations (<5 min and <5 km) from GMI and the other nine sensors. Similar to the previous results against KuPR (You et al. 2020a), these results show that conical scanning radiometers (SSMISs and AMSR2) outperform cross-track scanning radiometers (MHSs and ATMS). In addition, AMSR2 performs better than the SSMISs due to its finer footprint size. The correlation values are different from those
relative to KuPR (see Fig. 5a in You et al. 2020a). For example, the correlation between cross-track scanning radiometers and KuPR is about 0.40, while these values are close to 0.55 when using GMI as the reference (Fig. 1). However, the most important feature is that the rank of these nine sensors does not change, regardless of using KuPR or GMI as the reference.

Because of the superior precipitation retrieval performance from conical scanning radiometers, the objective of this study is to borrow information from conical scanning radiometers to improve the precipitation rates at the cross-track scanning radiometer observation time using the morphing technique.

### b. Two case studies

This section shows two cases to demonstrate how and why we would like to morph the precipitation rates from conical scanning radiometers to the cross-track scanning radiometer observation time. Both case studies use NOAA19-MHS as a representative cross-track scanning radiometer. The retrieval from AMSR2 and F16-SSMIS are morphed to the time of the NOAA19-MHS observation.

In the first case, a precipitation event is observed by AMSR2 at 1440 UTC (Fig. 2a), NOAA19-MHS at 1518 UTC (Fig. 2b), and GMI at 1515 UTC (Fig. 2c) 11 February 2015 over the ocean southeast of Australia. The purple cross indicates the central longitude and latitude of the precipitation event computed from NOAA19-MHS. As defined earlier, the GMI and NOAA19-MHS observations are less than 5 min away and are considered coincidental. Clearly, NOAA19-MHS underestimates the precipitation intensities close to the event center (indicated by the purple cross) compared with GMI, while the AMSR2 precipitation intensities (38 min preceding the NOAA19-MHS observation time) is much closer to the GMI precipitation intensities. Therefore, we would like to morph AMSR2’s precipitation rates to the NOAA19-MHS observation time.

Using the steps outlined in section 3, we compute the morphed NOAA19-MHS by averaging the precipitation rates morphed from AMSR2 and the original NOAA19-MHS precipitation rates, shown in Fig. 3d. We grid the data into 0.1° resolution to compute the motion vector and the comparison has also been done at this resolution. Comparing with the original NOAA19-MHS (Fig. 3b), the morphed NOAA19-MHS (Fig. 3d) values agree better with GMI (Fig. 3c), especially in the area indicated by the black box (cf. Figs. 3b,d) where regions of heavy precipitation have expanded to be more consistent with GMI. More importantly, the widespread precipitation intensities near 2 mm h$^{-1}$ are largely mitigated in this region. The improvement is even more clearly demonstrated by scatterplots (cf. Figs. 4a,b). All statistical metrics are greatly improved for this case with the correlation increased from 0.52 to 0.82 and RMSE reduced from 1.39 to 0.98 mm h$^{-1}$.
Figures 5 and 6 demonstrate another case over the Pacific Ocean near the lower Baja California Peninsula. This precipitation event was observed by F17-SSMIS at 1440 UTC (Fig. 5a), NOAA19-MHS at 1407 UTC (Fig. 5b), and GMI at 1409 UTC (Fig. 5c) 29 August 2020. For this case, we morph the F17-SSMIS precipitation rate backward to the NOAA19-MHS observation time. From the spatial distribution in Fig. 6b, NOAA19-MHS largely misses the heavy precipitation over the region indicated by the black box, while this heavy precipitation, indicated by GMI (Fig. 6c) almost simultaneously and by F17-SSMIS (Fig. 6a) at 33 min later, is better captured by the morphed NOAA19-MHS (Fig. 6d). The scatterplot further confirms the better performance of the morphing technique, indicated by the more skillful statistical metrics (cf. Figs. 4c,d).

c. Overall performance for all cross-track scanning radiometers

We apply the morphing technique and the weighting scheme to all five cross-track scanning radiometers. Figure 7 shows the density scatterplots between precipitation rates from GMI and from each cross-track scanning radiometer, as well as between precipitation rates from GMI and the morphed precipitation rates at the cross-track scanning radiometer observation time. The morphed precipitation rates are computed as the average of the precipitation rates morphed from a conical scanning radiometer and the original cross-track scanning radiometer precipitation rates. Statistical metrics and the total sample size are listed in Table 1, and only the correlation is labeled on each subplot due to the limited space.

It is immediately clear that the morphed precipitation rates for the cross-track scanning radiometers are better correlated with those from GMI (Fig. 7) than the original cross-track scanning radiometer-only estimates. Particularly, the double peak issues (around 1 mm h\(^{-1}\) and 4 mm h\(^{-1}\) on the y axis) evident over all cross-track scanning radiometer retrievals, noticed by You et al. (2020a), are mostly resolved when using the morphed precipitation rates (e.g., cf. Figs. 7a,b for NOAA19-MHS). However, the degree of correlation improvement differs for different cross-track scanning radiometers. Specifically, the correlation improves the most for ATMS from 0.53 for the original ATMS precipitation rates to 0.72 for the morphed precipitation rates. For NOAA19-MHS and NOAA18-MHS, the correlation increases from 0.51 to 0.65 and from 0.53 to 0.66, respectively. For both MetOpA-MHS and MetOpB-MHS, the correlation shows the least improvements from 0.55 to 0.60 and from 0.53 to 0.59, respectively.

Using KuPR precipitation rates as another validation reference further corroborates the precipitation rate improvements for cross-track scanning radiometers. Figure 8 shows the scatterplots between KuPR and original cross-track scanning radiometer precipitation rates, and between KuPR and morphed cross-track scanning radiometer precipitation rates. The numerical values of the statistical metrics differ from using GMI as the reference. For example, the correlation increases from 0.38 (Fig. 8a) to 0.49 (Fig. 8b) for NOAA19-MHS relative to KuPR, while these values are 0.51 (Fig. 7a) and 0.65 (Fig. 7b) when using GMI as the reference. However, the performance enhancements via the morphing technique are clearly evident.
for all cross-track scanning radiometers (Fig. 8). Only the correlation is labeled on Fig. 8 due to the limited space. The other two statistical metrics (RMSE and bias) have similar features with those shown in Table 1 when using GMI as the reference.

The improved correlation between the precipitation rates from GMI and the morphed precipitation rates is further demonstrated by the correlation time series for NOAA19-MHS and ATMS. We select NOAA19-MHS and ATMS since both have enough samples to compute correlations each month from March 2014 to August 2020. Figure 9a shows the monthly correlation time series between the precipitation rates from GMI and the original NOAA19-MHS precipitation rates (red curve), and between the precipitation rates from GMI and the morphed NOAA19-MHS precipitation rates (blue curve). The morphed precipitation rates consistently correlate better with the reference from March 2014 to August 2020, except for December 2019. For ATMS, the morphed precipitation rates exhibit better correlation in all months from March 2014 to August 2020 (Fig. 9b).

d. Factors affecting the degree of improvements

This section first discusses the varying degree of improvements dependent on the different precipitation sources from conical scanning radiometers and the time interval by comparing the improvements among these five cross-track scanning radiometers. Then, we further analyze the degree of improvements conditioned on geolocation, precipitation type (convective versus stratiform), and precipitation events’ size by using NOAA19-MHS retrievals as an example.

Figure 10 shows the contribution of the different conical scanning radiometers to the morphing process for each cross-track scanning radiometer’s precipitation estimate. For ATMS, almost all the morphed precipitation rates are from AMSR2
Specifically, there are 1,554 events in which GMI and ATMS observe these events coincident with other conical scanning radiometers in a ±3 h window. Out of these 1554 events, 1495 (1495/1554 = 96.2%) events are observed by AMSR2, and the remaining 49 are observed by F16-SSMIS. As shown in Fig. 1, AMSR2 has the best correlation with GMI due to the availability/usage of low-frequency channels (compared with MHSs and ATMS) and the finer footprint size. Additionally, almost all the time intervals between AMSR2 and ATMS are less than 60 min (Fig. 10i). Because of these two factors, the morphed ATMS precipitation events show the largest correlation improvements compared with the original ATMS precipitation rates (Table 1). The shorter time difference between ATMS and AMSR2 occurs because the orbits of the SNPP and GCOM-W1 satellites are relatively close in time to each other. For example, the local equator crossing time (ECT) difference from SNPP and GCOM-W1 is only about 7 min apart (Fig. 11). Keep in mind that Fig. 11 shows ECT at the nadir pixel. Near the edge of the swath, the time difference between ATMS and AMSR2 can be as large as ~1 h depending on latitudes.

Compared with the morphed precipitation rates for ATMS, there is a substantial increase in precipitation rates from

![Fig. 5](image-url)

**Fig. 5.** (a) The precipitation event observed by F17-SSMIS at 1440 UTC 29 Aug 2020 over the Pacific Ocean near the lower California peninsula (orbit number: 71308). (b) As in (a), but the event is observed by NOAA19-MHS at 1407 UTC (orbit number: 59571). (c) As in (a), but the event is observed by GMI at 1409 UTC (orbit number: 36945). Black curves in each plot represent the GMI swath boundaries.

![Fig. 6](image-url)

**Fig. 6.** (a)–(c) Panels correspond to original precipitation rates in Fig. 5, except that precipitation rates are gridded into 0.1° boxes; (d) the morphed precipitation rates by averaging original NOAA19-MHS precipitation rates in (b) and propagated precipitation rates from F17-SSMIS in (a).
SSMISs that are morphed to the observation times of NOAA19-MHS (Fig. 10a) and NOAA18-MHS (Fig. 10c). Also, the time difference between the conical scanning radiometers and NOAA19-MHS (Fig. 10b) and NOAA18-MHS (Fig. 10d) are relatively larger than those for ATMS (cf. Figs. 10b and 10j, cf. Figs. 10d and 10j). Because SSMISs have smaller correlation with GMI than AMSR2 combined with larger time differences between conical scanning radiometers and NOAA18-MHS and NOAA-19 MHS, the correlation improvements are not as large as seen for ATMS.

Although the morphed precipitation rates for MetOpA-MHS and MetOpB-MHS also come from SSMISs on board

Table 1. Correlation, root-mean-square-error (RMSE), and bias between the precipitation rates from GMI and the original cross-track scanning radiometer precipitation rates, and between the precipitation rates from GMI and the morphed cross-track scanning radiometer precipitation rates. The five cross-track scanning radiometers include four MHSs onboard NOAA-19, NOAA-18, MetOp-A, and MetOp-B, and ATMS onboard SNPP. The degree of the improvement is grouped into three categories: ATMS, MHSs onboard NOAA-19 and NOAA-18, and MHSs onboard MetOp-A and MetOp-B (see contexts for more details). The sample size of precipitating grids (0.1°) is listed in the last column. Data for 10 sensors are from March 2014 (just after launch of the GPM satellite) to August 2020 except for NOAA18-MHS, which stopped functioning in October 2018. Correlation increases for all five cross-track scanning radiometers are significant at the 95% level.

<table>
<thead>
<tr>
<th></th>
<th>Correlation</th>
<th>RMSE (mm h⁻¹)</th>
<th>Bias (%)</th>
<th>Sample size</th>
</tr>
</thead>
<tbody>
<tr>
<td>NOAA19-MHS original</td>
<td>0.51</td>
<td>2.64</td>
<td>-15.23</td>
<td>486 606</td>
</tr>
<tr>
<td>NOAA19-MHS morphed</td>
<td>0.65</td>
<td>2.45</td>
<td>-13.44</td>
<td>486 606</td>
</tr>
<tr>
<td>NOAA18-MHS original</td>
<td>0.53</td>
<td>2.82</td>
<td>-16.83</td>
<td>302 527</td>
</tr>
<tr>
<td>NOAA18-MHS morphed</td>
<td>0.66</td>
<td>2.66</td>
<td>-17.70</td>
<td>302 527</td>
</tr>
<tr>
<td>MetOpA-MHS original</td>
<td>0.55</td>
<td>2.96</td>
<td>-18.06</td>
<td>221 869</td>
</tr>
<tr>
<td>MetOpA-MHS morphed</td>
<td>0.60</td>
<td>3.04</td>
<td>-19.63</td>
<td>221 869</td>
</tr>
<tr>
<td>MetOpB-MHS original</td>
<td>0.53</td>
<td>2.71</td>
<td>-16.94</td>
<td>227 126</td>
</tr>
<tr>
<td>MetOpB-MHS morphed</td>
<td>0.59</td>
<td>2.81</td>
<td>-18.71</td>
<td>227 126</td>
</tr>
<tr>
<td>ATMS original</td>
<td>0.53</td>
<td>2.49</td>
<td>-12.27</td>
<td>613 913</td>
</tr>
<tr>
<td>ATMS morphed</td>
<td>0.72</td>
<td>2.08</td>
<td>-7.84</td>
<td>613 913</td>
</tr>
</tbody>
</table>
F17 and F18, and AMSR2, the time differences between these conical scanning radiometers and MetOpA-MHS and MetOpB-MHS are much longer (Figs. 10f,h), frequently larger than 90 min. This leads to decreased morphing performance because events observed by MetOpA-MHS and MetOpB-MHS may diverge as they evolve compared with the conical scanning radiometer observations. Again, the longer time differences between MetOpA-MHS and MetOpB-MHS and conical scanning radiometers (AMSR2 and three SSMIs) are well explained by their orbital time feature on Fig. 11. Because the local crossing time from MetOpA-MHS and MetOpB-MHS are relatively stable (Fig. 11 blue and purple dashed lines), they have fewer opportunities to intersect with conical scanning radiometers with smaller time differences.

In terms of the RMSE and bias, the morphed precipitation rates for ATMS, NOAA18-MHS, and NOAA19-MHS have better performance, with the largest improvements from ATMS since almost all the morphed precipitation is from AMSR2 (Table 1). For MetOpA-MHS and MetOpB-MHS, RMSE and bias slightly degrade after the morphing. Further analyses show that the morphed precipitation indeed improves greatly for light precipitation intensities (cf. Figs. 7e and 7f, cf. Figs. 7g and 7h). However, for heavy rainfall (>32 mm h⁻¹), the morphed precipitation rates become smaller than the

**Fig. 8.** As in Fig. 7, but using KuPR precipitation rates as the reference.

**Fig. 9.** (a) Monthly correlation coefficients between GMI precipitation rates and original NOAA19-MHS precipitation rates, and between GMI precipitation rates and morphed NOAA19-MHS precipitation rates. (b) As in (a), but for SNPP-ATMS.
original retrieval results, which contributes to the slightly degraded performance of the overall statistical metrics from the morphed precipitation rates for MetOpA-MHS and MetOpB-MHS.

To further analyze the degree of improvements, we compare the NOAA19-MHS retrievals over tropics ($20^\circ S$–$20^\circ N$) and midlatitudes ($60^\circ S$–$40^\circ S$, $40^\circ S$–$60^\circ N$), shown from Figs. 12a–d. It is immediately clear that the degree of improvements for the morphed precipitation rates over midlatitudes is larger than those over the tropics. Specifically, the correlation increases from 0.49 to 0.69 over midlatitudes (cf. Figs. 12c and 12d), while it only increases from 0.53 to 0.60 over tropics (cf. Figs. 12a and 12b).

Over tropics, there are more convective precipitation systems than over midlatitudes, which most likely contributes to the smaller degree of improvements over tropics since convective systems evolve more in a short time scale relative to the stratiform systems. To corroborate this point, we use KuPR as the reference and group the NOAA19-MHS retrievals into convective and stratiform systems. It is worth mentioning that the convective/stratiform indexes are extracted from KuPR precipitation dataset. As expected, the performance improvements are larger for stratiform precipitation systems than those from convective systems, indicating by a larger correlation increase from 0.37 (Fig. 12g) to 0.49 (Fig. 12h) for stratiform, while the correlation only improves slightly from 0.53 (Fig. 12e) to 0.56 (Fig. 12f) for convective.

Next, we analyze the degree of the improvements conditioned on the precipitation events’ size, shown in Figs. 12i–l. The precipitation event is considered a “large” system when the number of precipitating grid boxes is greater than 600, while it is considered a “small” event when the precipitating boxes are less than 200. The correlation increases from 0.51 (Fig. 12k) to 0.70 (Fig. 12l) for the large precipitation systems, while it increases from 0.49 (Fig. 12i) to 0.59 (Fig. 12j) for small

![Fig. 10](image_url)  
(a) The histogram of the number of events where precipitation rates are morphed from different conical scanning radiometers to NOAA19-MHS. Due to the space limit, the satellite name without the radiometer name is labeled on the x axis. (b) The time difference between NOAA19-MHS events and events at the conical scanning radiometers’ observation time. (c),(e),(g),(i) As in (a), but for NOAA18-MHS, MetOpA-MHS, MetOpB-MHS, and SNPP-ATMS, respectively. (d),(f),(h),(j) As in (b), but for NOAA18-MHS, MetOpA-MHS, MetOpB-MHS, and SNPP-ATMS, respectively.

![Fig. 11](image_url)  
FIG. 11. Local equator crossing times for nine satellites, including NOAA-19, NOAA-18, MetOp-A, MetOp-B, SNPP, F16, F17, F18, and GCOM-W1. Keep in mind that these times are near nadir. GPM is a non-sun-synchronous satellite, meaning that it can overpass a location at any local time.
precipitation systems. Obviously, the degree of improvements is greater for the large precipitation systems than that for small systems. This improvement discrepancy between large and small systems is also likely related to the stratiform and convective precipitation systems.

These above analyses indicate that a varying weight scheme under different conditions (e.g., different time intervals, different precipitation events' size, etc.) may further improve the morphed precipitation performance. Further analyses show that the statistical metrics (correlation, RMSE, and bias) vary very little by changing the weight uniformly from 0.5 for the propagated conical scanning radiometers' precipitation intensity to 0.25 or 0.75. For example, the correlation between GMI precipitation rates and morphed NOAA19-MHS precipitation rates only changes from 0.65 with a weight of 0.5 (the current scheme) to 0.67 with a weight of 0.75. However, the correlation improves from 0.65 to 0.73 by using weight of 0.75 when the morphed precipitation rates are from AMSR2 and the time interval between NOAA19 and GCOM-W1 is less than 30 min. Future work seeks to apply a varying weight scheme by considering the aforementioned factors (e.g., time interval and propagated precipitation source)

e. Value of the original sounder retrieval

As shown by previous analyses, the morphed precipitation rates at the cross-track scanning radiometer time better correlate with GMI precipitation rates. This brings the question of the value of the original cross-track scanning radiometer precipitation estimates at the cross-track scanning radiometer observation time. In other words, can propagated precipitation rates from conical scanning radiometers replace cross-track scanning radiometer retrievals completely at the cross-track scanning radiometer observation time (i.e., assigning the zero weight to the cross-track scanning radiometer retrieval)?

To illustrate this issue, we use NOAA19-MHS as a representative cross-track scanning radiometer. Analyses show that the precipitation rates propagating from conical scanning radiometers often have smaller correlation coefficient and larger RMSE value relative to the reference (GMI precipitation rates) than the morphed precipitation rates at the cross-track scanning radiometer time. For example, the correlation and RMSE from the propagated-conical scanning radiometers' precipitation rates for NOAA19-MHS are 0.61 and 2.76 mm h$^{-1}$, which are noticeably worse than statistics from the morphed NOAA19-MHS (0.65 and 2.45 mm h$^{-1}$, second row in Table 1). Figure 13 clearly demonstrates the larger RMSE from the propagated-conical scanning radiometers' precipitation rates (cf. Figs. 13b,c). In terms of the bias, the larger positive and negative values from morphed-conical scanning radiometer precipitation rates tend to cancel out each other, leading to a
relative smaller bias. For example, the bias for morphed-conical scanning radiometer precipitation rates for NOAA19-MHS is $-11.68\%$, which is better than the value from morphed NOAA19-MHS precipitation rates ($-13.44\%$, second row in Table 1).

To conclude, the original cross-track scanning radiometer retrievals contain valuable information and cannot be replaced completely by propagated precipitation rates from conical scanning radiometers. It is the combination of the original cross-track scanning radiometer retrievals and the morphed precipitation rates from conical scanning radiometers that provides the optimal precipitation estimates at the cross-track scanning radiometer observations time. Additionally, our approach does not change cross-track scanning radiometers’ precipitation detection result (i.e., precipitating versus non-precipitating) at the cross-track scanning radiometer observation time.

5. Discussions with respect to Hurricane Celia

In this section, we focus on a case study for Hurricane Celia over the eastern Pacific to highlight the potential usefulness of this work. AMSR2, NOAA19-MHS, and GMI observed Celia at 2133 UTC 11 July 2016 (Fig. 14a), at 2304 UTC 11 July 2016 (Fig. 14b), and at 0015 UTC 12 July 2016 (Fig. 14c), respectively. Compared with the precipitation fields from both AMSR2 (Fig. 14a) and GMI (Fig. 14c), the precipitation field from NOAA19-MHS (Fig. 14b) clearly misses the inner rainbands close to the hurricane center just outside of the eyewall and underestimates the rainfall in the large outer rainband on the east side of the storm.

The second row of Fig. 14 shows the IMERG final product with 0.1° resolution at the corresponding half hours of AMSR2, NOAA19-MHS, and GMI. When there are passive microwave retrievals in the corresponding half-hour, the IMERG final product primarily uses the individual microwave retrieval result. Therefore, the IMERG final product (second row of Fig. 14) is almost identical to those from the passive microwave retrievals (first row of Fig. 14). The consequences of the IMERG approach are that the inner rainbands disappear and then reappear and outer rainband rainfall shifts from heavy to lighter back to heavy rainfall rates, particularly due east of the center.

As a proof of concept of the new approach, we propagate the AMSR2 precipitation rates forward to the NOAA19-MHS observation time, using the motion vectors derived from AMSR2 and NOAA19-MHS precipitation rates. The morphed NOAA19-MHS precipitation rates are shown in Fig. 14h. We can clearly observe the rainbands near the hurricane center after the morphing (cf. Figs. 14b,h). Additionally, the rainband is also clearly noticeable when morphing GMI precipitation rates backward to the NOAA19-MHS observation time (not shown). For this case, it seems that we should morph both GMI and AMSR2 to the NOAA19-MHS observation time since NOAA19-MHS is relatively close to both AMSR2 (91 min ahead) and GMI (71 min after). It is unclear how many cases exist where two conical scanning radiometers are close to a cross-track scanning radiometer, although further investigation of these conjunctions is beyond the scope of this study.

Because IMERG primarily uses the microwave retrieval results when they are available in the corresponding half hour, improving the cross-track scanning radiometer retrieval results has great potential to directly improve the IMERG dataset, as shown in the Hurricane Celia case. Work is underway to test this scheme in the IMERG framework.

6. Conclusions

Previous studies demonstrated that over ocean, retrieved precipitation from conical scanning radiometers is of higher quality compared to the more indirect retrievals from cross-track scanning radiometers. Therefore, the objective of this study is to improve the cross-track scanning radiometer retrieval results by morphing the precipitation rates from conical scanning radiometers to the cross-track scanning radiometer observation time.

This study demonstrates the morphing concept using precipitation rates from 10 radiometers, including five cross-track scanning radiometers (MHSs on board NOAA-18, NOAA-19, MetOp-A, and MetOp-B, and ATMS on board SNPP) and five conical scanning radiometers (GMI, AMSR2, and three SSMIs on board F16, F17, and F18). For evaluation purpose,
we use GMI precipitation rates as the reference. We propagate the precipitation rates from each conical scanning radiometer (i.e., any of AMSR2 and three SSMISs) to the cross-track scanning radiometer observation time when a cross-track scanning radiometer and a conical scanning radiometer are within a $\pm 3$-h time window.

The results show that the morphed precipitation rates are better correlated with the reference for all five cross-track scanning radiometers. It is found that the following two factors significantly affect the degree of improvements, including 1) which conical scanning radiometer is selected to propagate its precipitation rates to the cross-track scanning radiometer observation time, and 2) the time interval between the cross-track scanning radiometer and the conical scanning radiometer. The largest improvement is observed for the morphed ATMS precipitation rates with the correlation increasing from 0.53 to 0.72 because almost all the morphed precipitation rates are from AMSR2 in a 60-min window. The AMSR2 has the best correlation with GMI due to the availability of its low-frequency channels (compared with cross-track scanning radiometers) and its much finer footprint size. Further analyses show that the degree of improvements is also affected by the geolocation, the precipitation type (convective versus stratiform), and the precipitation events’ size. In this study, the morphed precipitation rates at the cross-track scanning radiometer observation time are computed by averaging the original cross-track scanning radiometer precipitation rates and the propagated precipitation rates from conical scanning radiometers. It is possible that future investigations could determine an optimal weighting scheme depending on the time differences as well as the error characteristics of the sensors and precipitation regimes.

The results also suggest that the conical scanning radiometers’ precipitation rates should be kept in the system so that they can be propagated into the cross-track scanning radiometers’ time. In the same sense, future work also seeks to propagate the precipitation rates from AMSR2 and GMI to SSMISs’ observation time. Essentially, we plan to develop a hierarchical morphing scheme in the future. That is, AMSR2 and GMI precipitation rates are first propagated to SSMISs’ observation time. Then, conical scanning radiometers’ precipitation rates are propagated to cross-track scanning radiometers’ observation time.

This study has the potential to significantly improve level-3 merged precipitation products (e.g., IMERG, CMORPH, and GSMaP) over ocean, as highlighted by the Hurricane Celia case. Currently, the level-2 swath retrieval results remain
unchanged when incorporated into the level-3 merged products. By improving the level-2 cross-track scanning radiometer results, the performance of the level-3 products is expected to improve accordingly. This study also highlights the importance of exploiting temporal information by connecting the passive microwave radiometers in the GPM constellation. In our previous work (You et al. 2017, 2018, 2020b, 2021; Turk et al. 2021), we exploited the temporal information from the microwave TB and emissivity perspectives. This study demonstrates another method for applying temporal information through morphing precipitation fields. This work also highlights the need of maintaining a constellation of conical scanning radiometers into the future, considering their much better precipitation retrieval performance over ocean than cross-track scanning radiometers.

This work will enhance the utility of future satellite missions with cross-track scanning radiometers for precipitation measurement. For example, the upcoming Time-Resolved Observations of Precipitation Structure and Storm Intensity with a Constellation of Smallsats (TROPICS) mission comprises six CubeSats cross-track scanning radiometers qualitatively similar to MHS (Blackwell et al. 2018), two in each of three orbital planes in a 30°-inclined orbit. As a result, the TROPICS measurement swaths will cross all of the operational conical scanning radiometer sensors (GMI, AMSR2, and SSMIS), providing more frequent opportunities for cross-track and conical scanning radiometer match-ups. Our precipitation morphing scheme thus represents a promising approach for combining these high-temporal-resolution cross-track scanning radiometer observations with the existing conical scanning radiometers to provide better precipitation estimates at the cross-track scanning radiometer observation times and potentially improves integration of TROPICS precipitation estimates into a merged satellite product such as IMERG.

Acknowledgments. Satellite data are downloaded from NASA Precipitation Processing System (PPS) website (https://storm.pps.eosdis.nasa.gov/storm/). We thank Dr. Ping Ping Xie for the discussions of the morphing concept. This work is supported by the NASA Grant 80NSSC20K0903 from the Weather and Atmospheric Dynamics program and NASA’s Precipitation Measurement Missions Program science team via the Internal Scientist Funding Model awarded to Drs. Peters-Lidard and Munchak, which are all under the management of Dr. Gail Skofronick-Jackson. Y.Y. also would like to acknowledge the financial support from NOAA Grant NA19NES4320002 (Cooperative Institute for Satellite Earth System Studies-CICESS) at the University of Maryland/ESSIC.

REFERENCES


