Improvements of Rain/No-Rain Classification Methods for Microwave Radiometer over Coasts by Dynamic Surface-Type Classification

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(Manuscript received 19 June 2015, in final form 19 February 2016)

ABSTRACT

The rain/no-rain classification for the Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI) fails to detect rain over coasts, where the microwave footprint encompasses a mixture of radiometrically cold ocean and radiometrically warm land. A static land–ocean–coast mask is used to determine the surface type of each satellite footprint. The coast mask is conservatively wide to account for the largest footprints, preventing use of the more appropriate ocean or land algorithm for coastal regions.

The purpose of this paper is to develop a classification whereby the smallest region possible is defined as coast. In this endeavor, two major improvements are applied to the land–ocean–coast classification. First, the surface classification based on microwave footprints of the high frequency actually used in rain detection is employed. Second, the footprint area of the surface classification is established using an effective field-of-view size and scan geometry of the TMI. These improvements are applied to the Global Satellite Mapping of Precipitation TMI algorithm. The classification result is validated using the TRMM precipitation radar. The validation shows that these improvements lead to better rain detection in the coastal region.

1. Introduction

Global precipitation information is critical for understanding the global energy and water cycle. Since the 1970s, scientists have been developing techniques to estimate precipitation from satellite radiometric observations, which can cover most of the globe. The first techniques used visible or infrared (IR) data to infer precipitation intensity based on cloud reflectivities or cloud-top temperature (Barrett 1970). The IR technique performs poorly in estimation of warm rain systems because of the weak link between cloud properties and precipitation (Adler et al. 1993). Because microwave emission and scattering are more directly related to precipitation than cloud-top temperature, microwave radiometer (MWR) algorithms generally provide more accurate instantaneous estimates of rainfall than IR algorithms (Arkin and Ardanuy 1989; Ebert et al. 1996; Smith et al. 1998). The superior spatial and temporal sampling of geostationary IR instruments relative to MWRs on board low-Earth-orbit satellites is advantageous with respect to estimating daily and monthly rainfall. Adler et al. (1993) were the first to successfully combine the advantages of both types of instruments, by matching data from MWRs and IRs to tune the Geostationary Operational Environmental Satellite precipitation index algorithm (Arkin and Meisner 1987).

After the launch of the Tropical Rainfall Measurement Mission (TRMM) satellite (Kummerow et al. 1998), the MWR rainfall algorithms matured with the development of algorithms such as the Goddard profiling (GPROF) algorithm (Kummerow et al. 2001) and the Global Satellite Mapping of Precipitation (GSMaP) MWR algorithm (Aonashi et al. 2009). Moreover, the development of high-resolution satellite rainfall products (0.1°–0.25° latitude/longitude and 0.5–3 h) has accelerated by combining data from MWRs and IRs (see review in Gebremichael and Hossain 2010). Ebert et al. (2007) highlighted improvements in the MWR–IR combined algorithms relative to the IR-only algorithms. However, Kubota et al. (2009) showed poor performance of high-resolution satellite rainfall products over mountainous regions and coastlines, owing to problems of MWR retrievals. The performance of those retrievals over mountainous regions has been improved using topographically forced upward vertical motion (Shige
et al. 2013, 2014; Taniguchi et al. 2013; Yamamoto and Shige 2015). The problems of MWR retrievals over coastlines are associated with the rain/no-rain classification (RNC) of the algorithm, but it has not been improved.

Although RNCs have not been given as much scientific emphasis as rain-rate estimation [brightness temperature (TB)–rain-rate conversion], the success of any MWR retrieval algorithm relies on proper identification of rain pixels and the elimination of surface pixels that produce a signature similar to that of precipitation (Ferraro et al. 1998). The RNC algorithm is affected by the surface within the footprint (see review in Indu and Kumar 2014). For an ocean-only one-footprint which is radiometrically cold and homogeneous, an emission signature from raindrops across the lower-frequency spectrum is essentially used. For a land-only footprint, a scattering signature from ice crystals over the higher-frequency spectrum is used because a radiometrically warm background tends to obscure emissions from raindrops. Coastal regions include radiative contributions from both ocean and land. Because the ratio of ocean to land in a footprint varies by each footprint, a complicated assumption of surface emissivity is required. There has been relatively little work regarding RNCs over coasts compared with ocean and land. In the second WetNet Precipitation Intercomparison Project (PIP-2), most algorithms were not designed for MWR pixels over or near coastlines, so they were masked out and eliminated from rain calculation (Smith et al. 1998). One of the very first RNC algorithms for coasts was developed by Adler et al. (1994). That algorithm is based on a complicated decision tree method to isolate possible rain from similar TB signatures and is described in detail by Huffman and Adler (1993, hereafter HA93). The HA93 algorithm designed for the Special Sensor Microwave Imager (SSM/I) was implemented in GPROF and remained in use in successive GPROF versions for the TMI (Kummerow et al. 2001) and Advanced Microwave Scattering Radiometer (AMSR) for Earth Observation System (EOS; AMSR-E) (Wilheit et al. 2003), implying little work regarding RNCs over coasts.

McCollum and Ferraro (2005, hereafter MF05) made two major improvements to HA93. The first facilitated the ambiguous classification in HA93 (as a value between classes 63 and 65 in MF05) to be classified as rain, using TRMM PR data. The second was the addition of a polarization correction temperature (PCT)-based cutoff threshold for rain-possible footprints. The MF05 algorithm was implemented in GPROF for version 6 (V6) TMI products and the third release of AMSR-E in 2004, and has remained in use in GPROF for version 7 (V7) TMI products. Zagrodnik and Jiang (2013), however, showed that TMI V6 and V7 had more misses than the PR, especially over coasts. The MF05 algorithm was improved to avoid false rainfalls during winter in mid-latitude coastal areas and was implemented for GSMaP by Kubota et al. (2007). Nonetheless, as noted earlier, the RNC problem over coastlines was again identified by Kubota et al. (2009).

Wang et al. (2009) suggested that the land–ocean–coast flag designed for MWRs appears to identify too many areas as coast. Coastal area is based on a conservatively wide definition for two reasons. The first is that the size of the coast mask is based on the maximum footprint (Olson et al. 2006; Kubota et al. 2007). The size of the effective field of view (EFOV) for the MWR is related to frequency because the MWR has only one antenna. The EFOVs at higher frequencies are smaller than those at lower frequencies. Currently, the land–ocean mask is adaptable to the lowest MWR frequency. For TMI, this is 10 GHz because ocean algorithms use 10-GHz data in the TB–rain-rate conversion. The TMI TB–rain-rate conversion requires 10-GHz channel data, so higher-frequency (i.e., smaller) footprints cannot necessarily be used to execute the RNC. However, an alternative algorithm such as that developed for SSM/I that uses channels down to 19 GHz would be compatible with a higher-frequency (smaller footprint) RNC; see discussion in section 6.

The second reason is that the land–ocean–coast flag is static. Although the shape of the EFOV is an ellipse, the static flag is based on a circle with a radius corresponding to the major axis of the EFOV. The conservative definition of coast was based on a threshold applied to the distance to the nearest land if over water or to water if over land, or on the ratio of ocean to land within a true circle. The coastal area is even wider because the circle of the land–ocean classification is larger than the accurate effective antenna pattern function. The geographic database for GPROF was developed based on the minimum radius of a circle encompassing a specified minimum fraction of the surface type opposite that of the U.S. Navy $\frac{5}{16} \times \frac{5}{16}$ global “elevation” dataset (Olson et al. 2006). A $\frac{5}{16}$ grid point over land is classified as coast when water coverage is $\approx 20\%$ within a circle of 50-km radius centered on that point. A point over water is classified as coast when land coverage is $\approx 5\%$ within a circle of 30-km radius centered on that point. The land–ocean–coast flag of GSMaP TMI is gridded by 0.25° based on the TRMM Science Data and Information System (TSDIS) Toolkit, version 4.5. Thus, GSMaP coast flags are also wider than the true coast. It is possible to reduce the size of coastal areas using a land–ocean–coast flag derived from the true EFOV shape.
In our study, we used two major improvements for the land–ocean–coast classification, with the objective of classifying the smallest area possible as coast; that is, more areas are classified as ocean or land, such that the coastal area is reduced. The first improvement classifies the surface type with MWR footprints of the high frequency actually used in the RNC. The second classifies the surface type with the EFOV size and scan geometry of the sensor footprint. The land–ocean–coast flag is changed dynamically using satellite geometric data. This is to account for the actual size and geometric data of the footprint, to make the coastal area of the land–ocean–coast flag smaller.

2. Data

The analysis presented herein is based on observations from the TMI because the location and time of its observation are similar to the PR. The TMI is one of five sensors aboard the TRMM satellite, which was launched into low-Earth orbit in November 1997 to provide data on the characteristics of precipitation in the tropics and subtropics (35°S–35°N). The PR is a single-frequency (13.8 GHz) electronically scanning radar (Kozu et al. 2001; Kummerow et al. 1998). The PR’s 215-km-wide swath is centered within the TMI’s 760-km swath. The TRMM orbit was originally 350-km altitude. The orbit was boosted from 350 to 403 km in August 2001 (Shimizu et al. 2009). The boost increased the swath width and footprints for all sensors on the satellite. We used a postboost EFOV size 1.15 (∼403/350) times larger than the preboost EFOV size. The algorithm retrieves estimates of rain from the TMI level 1 raw and calibrated radiance products (1B11). We defined surface type based on latitude, longitude, and local azimuth angle from TMI 1B11. PR 2A25, version 7 (Iguchi et al. 2009), was used as a reference for validation. Because signals of an active microwave sensor are not degraded, there is no rain/no-rain flag, so the rain footprint is reclassified from coast to ocean. If the surface is covered entirely by land, then the footprint from GPROF used herein is larger than 0.5 mm h⁻¹.

The dynamic surface flag method we developed requires high-resolution gridded land–ocean data. Here, we used high-resolution geographic data (0.0833°) that were developed and used for the Global Precipitation Measurement dual-frequency precipitation radar (DPR), level 1B (the DPR land–ocean flag). The data are derived from the flags mainly using the Shuttle Radar Topography Mission water body data, which provide land–ocean flags for all TMI coverage.

Because the PR swath is coincident with TMI observations, global validation of TMI was performed with all swath data over 4 months. The validation scores show the RNC characteristics of GSMaP and GPROF, as well as improvement produced by the dynamic surface flag method. We used a dynamic surface flag in the GSMaP TMI algorithm for rain detection.

3. Method

MWR algorithms, such as GPROF and GSMaP, switch rain retrieval algorithms depending on the surface flag. RNC methods of GSMaP are switched between the ocean, land, and coast algorithms. The GPROF algorithm uses an RNC method for land and coast only. Surface flags for GPROF and GSMaP are gridded by latitude and longitude (the static surface flag). The definition of coast is based on a threshold applied to distance to the nearest land (if over water) or to water (if over land). The threshold is based on the major axis of the largest footprint, that is, the 10-GHz EFOV. Although 10 GHz is useful for estimating heavy rain, the signal is less important for the RNC. Furthermore, the true footprint shape is an ellipse, which means that the surface flag has a drawback in that large areas may be classified as coast, preventing use of the more appropriate ocean or land algorithms.

We changed the land–ocean–coast flag according to the lowest-frequency EFOV used in the ocean RNC algorithm (if over ocean) or land RNC algorithm (if over land), depending on the high-resolution geographic database and satellite geometric data. The coastal area was thereby minimized as much as possible. Figure 1 shows a schematic image of the creation of the dynamic surface flag method. The satellite geometric data include latitude, longitude, and local azimuth angle. Latitude and longitude indicate the center of the footprint ellipse, and the local azimuth angle is the orientation of the major axis of the footprint ellipse from north. Axis lengths of the ellipse were determined by the EFOV size. The location and the orientation determine the boundary of the EFOV. The surface type within the footprint is derived from the high-resolution geographic data. If the surface is covered entirely by ocean (Fig. 1a), then the footprint is reclassified from coast to ocean. If the surface is covered entirely by land, then the footprint is
reclassified from coast to land. If the surface is a mixture of other surface types (Fig. 1b), then the footprint remains classified as coast.

We used the dynamic surface flag method in the GSMaP TMI algorithm. The EFOV size is frequency dependent. Thus, we used the maximum size of EFOV with the lowest frequency used in the RNC method. Table 1 shows the TMI specifications (Kummerow et al. 1998) and frequencies used in the RNC algorithm of GSMaP (Aonashi et al. 2009; Kida et al. 2009; Seto et al. 2005, 2008; Kubota et al. 2007). All channels measure radiation that is polarized vertically (V) and horizontally (H) (expressed as equivalent blackbody temperatures, TB), except for the 21.3-GHz channel, which measures only vertically polarized radiance. Frequencies used in the algorithm for detecting rain over land are 21.3 and 85 GHz (Seto et al. 2005, 2008). The lowest frequency used in the GSMaP RNC algorithm over land is 21.3 GHz (Table 1). The 21.3-GHz TB is used for estimation of background temperature under no-rain conditions. Therefore, when land surface fills the 21.3-GHz footprint, the dynamic surface flag method sets the land flag.

The RNC algorithm of the GSMaP used for rain detection over the ocean has two stages (Kida et al. 2009). Frequencies used in the first stage (denoted by 1 in Table 1) are 37 and 85 GHz. Frequencies used in the second stage (denoted by 2 in Table 1) are 10, 19, and 37 GHz. In the first stage, the deep-rain pixels are determined by the PCT of 85 GHz (PCT85) and the shallow-rain pixels by the 37-GHz emission signature. However, the scattering signature of 85 GHz used in the first stage indicates ice cloud, so there is not necessarily precipitation under the cloud. In the second stage, emission signatures of 10, 19, and 37 GHz were used to remove no-rain pixels under ice cloud. When ocean surface filled the low-frequency footprint, the dynamic surface flag method set the ocean flag. The lower-frequency (10 and 19 GHz) signatures were used when the footprints were filled by ocean surface. Therefore, if ocean surface filled the 10-GHz footprint, then the dynamic surface flag method set the ocean flag to use the emission signatures. The lower-frequency (10 and 19 GHz) signatures were used when the footprints were filled by ocean surface. Therefore, if ocean surface filled the 10-GHz footprint, then the dynamic surface flag method set the ocean flag to use the 10-, 19-, and 37-GHz emission signatures. If ocean surface filled the 19-GHz footprint, then that method set the ocean flag to use the 19- and 37-GHz emission signatures. If ocean surface filled the 37-GHz footprint, then that method set the ocean flag to use the 37-GHz emission signatures.

For other conditions within the footprints, that method sets the coast flag. The frequencies used in the algorithm for rain detection over the coast are 19, 21.3,
37, and 85 GHz (McCollum and Ferraro 2005; Kubota et al. 2007). The following section presents RNC results of the original GSMaP algorithm (GSMaP1) and the dynamic surface flag method (GSMaP2).

### 4. Case studies

We describe two case studies in this section. The first case was an organized rain system offshore of the Mississippi River delta (box 1 in Fig. 2) on 10 October 2009. In this case, the dynamic surface flag method reclassified the original “coast” flagged pixels as ocean, considering the actual size and geometry of footprints of the high frequency used in the RNC. The second case was the edge of a large rain system in the Gulf of California on 14 January 2004 (box 2 in Fig. 2). In this case, the dynamic surface flag method reclassified the original coast flagged pixels as ocean or land.

In the first case, the PR detected an organized rain system with rain rate $\geq 20$ mm h$^{-1}$ from 30.2°N, 87.6°W to 28.1°N, 90.4°W in Fig. 3a. The colored points in Figs. 3b–d show validation for GPROF, GSMaP1, and GSMaP2, respectively. We defined the pixels within a circle of 4-km radius centered on the PR raining pixel as actual rain pixels. For validation of GSMaP1 and GSMaP2, actual PR rain pixels were defined using the rain-certain flag of the PR 2A25 data. GPROF does not identify pixels as rain/no rain; validation matched the retrieved GPROF rain $\approx 0.5$ mm h$^{-1}$ and rain-rate PR $\approx 0.5$ mm h$^{-1}$. Red, yellow, blue, and gray points indicate hits, misses, false alarms, and zeroes, respectively. A hit...
TABLE 2. Validation scores of RNC of GPROF, GSMaP1, and GSMaP2 with PR, for the first case shown in Fig. 3.

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<th>GPROF</th>
<th>GSMaP1</th>
<th>GSMaP2</th>
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<tbody>
<tr>
<td>POD</td>
<td>0.336</td>
<td>0.274</td>
<td>0.423</td>
</tr>
<tr>
<td>FAR</td>
<td>0.409</td>
<td>0.167</td>
<td>0.211</td>
</tr>
<tr>
<td>FB</td>
<td>0.567</td>
<td>0.329</td>
<td>0.535</td>
</tr>
<tr>
<td>ETS</td>
<td>0.204</td>
<td>0.211</td>
<td>0.314</td>
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As shown in Fig. 3b, the GPROF detected only part of the rainband near the coast (Fig. 3b). Although the algorithm detected rain pixels offshore, there were many false alarm pixels. GPROF had higher POD and FB but also the highest FAR (Table 2), implying many false alarm pixels. Many such pixels produced the smallest ETS (0.204). Figure 3c shows that GSMaP1 detected rain pixels of the rainband near the coast in similar locations as GPROF but fewer false alarm pixels offshore. The ETS (0.211) of GSMaP1 is slightly better than that of GPROF. In contrast, GSMaP2 detected most parts of the rainband over the ocean near coastline (Fig. 3d). Although the GSMaP2 algorithm had a few false pixels, the POD (0.423) of the GSMaP2 is the best of the algorithms. Accordingly, GSMaP2 had the highest ETS (0.314).

GPROF land–ocean–coast flags, static 0.25° gridded land–ocean–coast flags of GSMaP1, and the dynamic surface flag of GSMaP2 are shown for the first case in Fig. 4, with the high-resolution surface flag as reference. The dynamic surface flag method (GSMaP2) delineated coastlines more accurately than the other surface flags (GSMaP1 and GPROF), taking into account actual size and geometry of footprints of the high frequency used in the RNC. The RNC of GPROF using the ocean flag showed rain detection, although few footprints had ocean flags (Figs. 3b and 4b). GPROF missed the PR-derived rain pixels over the coast. GSMaP1 detected PR-derived rain with the ocean RNC algorithm around 29.5°N, 88°W and 28.5°N, 90.1°W (Figs. 3c and 4c). In contrast, GSMaP2 correctly detected more rain pixels (Fig. 3d). GSMaP2 converted a wide coastal flag to
ocean flag, except for islands and the coast (Fig. 4d). Locations of the rain pixels of GSMaP2 (Fig. 3d) are in good agreement with rain observed by the PR.

Figure 5 shows TBs and PCTs for case 1. The TBs of 10 GHz (TB10V) do not clearly indicate a rain signal (Fig. 5a), but TBs of 19 GHz (TB19V) and 37 GHz (TB37V) from 30°N, 87.6°W to 28.5°N, 90.3°W are higher than for the surrounding ocean (Figs. 5b and 5c). PCT of 37 GHz (PCT37) and PCT85 decreased within the same area (Figs. 5d and 5e). The area of TB increase and reduced PCT corresponds to rain observed by the PR. Thus, the ocean algorithm can detect organized rain systems near coastline.

Figure 6 shows the rain rate from the PR and RNC of the MWR algorithm for the second case. There are several rain pixels of PR (Fig. 6a). However, a few rain pixels of PR were weak (<0.5 mm h⁻¹). Thus, a few pixels were classified as no precipitation in the GPROF validation (Fig. 6b). GPROF land–ocean–coast flags, static 0.25° gridded land–ocean–coast flags of GSMaP1, and the dynamic surface flag of GSMaP2 are shown for the second case in Fig. 7, with the high-resolution surface flag for reference. GPROF and GSMaP1 classified most areas as coast (Figs. 7b and 7c). GSMaP2 reclassified coast in GSMaP1 as ocean, taking into account the actual size and geometry of footprints of the high frequency used in the RNC (Fig. 7d). The POD, FAR, FB, and ETS of each algorithm are summarized in Table 3. The smallest FAR (0.109) indicates that GPROF detected a few false rain pixels on the edge of rain (Fig. 6b). However, the lowest POD (0.561) and lowest FB (0.629) reveal numerous missed pixels. Missed rain pixels over the coast gave a smaller ETS (0.443). Although POD (0.682) indicates the GSMaP1 algorithm detected more pixels than the GPROF algorithm, it had many false rain pixels over land and it missed rain pixels near islands in the Gulf of California (Fig. 6c). These missed pixels produced the highest FAR (0.288) and

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**Figure 5.** As in Fig. 3, but TMI observation TBs and PCTs for the first case: (a)–(c) 10-, 19-, and 37-GHz TBs, respectively, showing vertical polarization; and (d),(e) 37- and 85-GHz PCTs, respectively.
smallest ETS (0.395). Although GSMaP2 had some false rain pixels on the edges of rain areas, its FAR (0.213) indicates decreased false rain pixels over that of GSMaP1. The FB of GSMaP2 was similar to that of GSMaP1. POD and FAR were improved over those of GSMaP1. Thus, the dynamic surface flag produced a higher ETS (0.485).

GSMaP2 improved the RNC of GSMaP1 in three areas (boxes A, B, and C in Fig. 6d). First, near Tiburón Island in the Gulf of California (around 28°N, 112°W), GSMaP2 detected the rainband over the ocean (box A in Fig. 6d). Although false pixels were near rain pixels in the boxes, the ocean algorithm improves rain detection. Second, GSMaP1 classified false rain over the Baja California Peninsula, but GSMaP2 reduced this false rain (box B in Fig. 6d). Third, the GSMaP2 classification reduced false rain over the peninsula (box C in Fig. 6d).

The ocean algorithm of GSMaP2 detected rain pixels near islands in the gulf (box A in Figs. 6c and 6d). TB10V did not show rain signals in the gulf (box A in Fig. 8a). TB37V increased in the gulf (box A in Fig. 8c). The GSMaP ocean algorithm detected rain pixels from the TB37V over the ocean, near the coastline.

The land algorithm of GSMaP2 eliminated the false rain classified by the coast algorithm of GSMaP1 in boxes B and C in Fig. 6d. The coast algorithm of GSMaP is based on McCollum and Ferraro (2005) (Kubota et al. 2007), which has “TB21V \geq 269.1 \text{K}” as a rain criterion in a decision tree identifying possible coastal rain, where TB21V is TB of 21.3 GHz. TB21V are \( \geq 269.1 \text{K} \) in boxes B and C in Fig. 9b. Hence, the coast algorithm classified the PCT85 signatures in the boxes as rain.

GSMaP2 reclassified wide surfaces as land in boxes B and C in Fig. 7d. The land algorithm of GSMaP mainly uses the TB85V scattering signal. TB85V depression is in no-rain pixels (boxes B and C in Fig. 9a). The land algorithm assumes that the TB21V for a rain pixel is less than the no-rain value (Seto et al. 2005, 2008). The GSMaP RNC algorithm over land estimates the no-rain condition threshold from the TB21V via the following equation (Seto et al. 2005, 2008):

\[
\text{TB85V}_{\text{no-rain}} = a + b \times \text{TB21V}. \quad (1)
\]

In the above-mentioned equation, the no-rain subscript indicates that TB is estimated for the assumed no-rain condition. The parameters \(a\) and \(b\) are linear regression variables in the least squares error method, and the linear regression is a relationship between TB21V and TB85V under the no-rain condition. These variables are altered by land surface conditions. It is seen that there are TB21V depressions in boxes B and C in Fig. 9a. These depressions caused the TB85V no-rain threshold to decrease. The estimated no-rain threshold is lower than the observed TB85Vs in the boxes, and the land algorithm classified pixels with low TB85V values as no
rain. The land algorithm eliminated false rain pixels of GSMaP1 in boxes B and C in Fig. 6d.

Although GSMaP2 detected a few pixels, there are false alarm pixels around 26.5°N, 114°W (box D in Fig. 6d). On the other hand, the TB19V and TB37V increased in the box. There are several rain pixels of PR in the box, but these were weak (<0.5 mm h⁻¹). Thus, the pixels were also classified as no precipitation by GPROF (Fig. 6b). A hot signature of emission channels (TB19V and TB37V) and a cold signature of a scattering channel (PCT85) were wider than PR rain pixels (Figs. 8b, 8c, and 8e). PR sometimes missed light rainfall (<1.0 mm h⁻¹) (Berg et al. 2010), so there may be weak rain that PR could not detect in the box.

The first case shows GSMaP2 improvement of near-coast rain. The second case shows GSMaP2 improvement of rain detection over land and bay. Although one area (box D) in the second case is degraded, the ETS is improved by the dynamic surface flag.

5. Global validation

In this section, we present the global validation of the rain classification results using PR 2A25, version 7, as reference data. This is to show the RNC characteristics of GSMaP1 and GPROF, and those produced by the dynamic surface flag method (GSMaP2). The geographic area of validation is 38°N–38°S, 180°W–180°E, the same as the coverage of PR. The global validation was performed with all swath data over 4 months—January, April, July, and October 2009. The number of pixels varied over the coast (19,895,925), land (60,723,212), and ocean (180,908,736) backgrounds. The number of pixels over the coast exceeded 19 million, which was adequate for statistical analysis. Because this paper focuses on surface classification for RNC in coastal areas, the different numbers of pixels cited above do not affect the discussion.

Table 4 compares GSMaP1 and GSMaP2 scores. The ETS show that the land algorithm was poorer than the ocean algorithm and that the coast algorithm had the worst performance in GSMaP1. Although the POD over land is higher than over ocean, the FAR over land is greatest. The FB over land is 1.14 and so false pixels over land led to lower ETS. GSMaP1 had the lowest FAR over the coast but also the lowest POD (0.484) and lowest FB (0.571) there. This is

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<tr>
<td>ETS</td>
<td>0.443</td>
<td>0.395</td>
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because too few rain pixels were detected by GSMaP1 over the coast.

Table 5 shows the validation scores of GPROF. We executed the validation using two definitions of the PR rain footprint. In the first validation, PR rain footprints were defined using the rain-certain flag of the PR 2A25 data. In the second validation, the footprints were defined by rain rate $\geq 0.5 \text{ mm h}^{-1}$. The results of that validation are given in parentheses. The ETS of the first validation is better than that of the second validation over ocean and land, and is similar to that of the second validation over coast. Because the first validation is consistent with the validation of Table 4, the validation between GPROF rain and the PR certain-rain flag is discussed below.

The GPROF scores show characteristics similar to those of GSMaP1. The ETS of the ocean algorithm is better than that of the land algorithm. However, those ETS indicate that the performance of the coast algorithm was the poorest in the GPROF algorithm. The POD of GPROF (0.629) is slightly smaller than that of GSMaP1 (0.665) over the ocean, whereas the FAR of GPROF (0.306) is slightly higher than that of GSMaP1 (0.289). Therefore, the ETS of GSMaP1 was better than GPROF over the ocean. The ETS of GPROF (0.453) is smaller than that of GSMaP1 (0.491) over land. The POD and FAR of GPROF are less than those of GSMaP1, and the FB is less than 1. This is because too few rain pixels were detected by GPROF over land. The GPROF coast algorithm exhibits smaller POD and larger FAR values than GSMaP1, and the GPROF coast algorithm performed worse than that of the GSMaP1. Although the FAR of GSMaP2 is higher than that of GSMaP1, the other scores of GSMaP2 were better than GSMaP1. The dynamic surface flag improved the ETS from 0.431 to 0.492 and improved the FB from 0.571 to 0.822. The ETS of GSMaP2 over the coast exceeds that of GSMaP1 over land. The coast validations of both
GSMaP2 and GPROF, presented in Tables 4 and 5, were performed with the coast flag of GSMaP1, so GSMaP2 included ocean, land, and coast flags. The improvement suggests that the original coast surface included pixels suitable for both the land and ocean algorithms.

The coast flag covered 7.52% of all GSMaP1 TMI pixel flags in the global validation data. GSMaP2 reclassified some of the original coast flags as either ocean or land flags. In the GSMaP2 algorithm, 49.5% of the coast flags were reclassified as ocean flags and 16.5% of the coast flags were reclassified as land flags. In GSMaP2, the number of coast flags was reduced to 35% that of GSMaP1, so the coast flags of GSMaP2 covered 2.46% of all pixel flags.

6. Discussion

In the GSMaP TMI algorithm, rain rate is retrieved using four frequency signals—10, 19, 37, and 85 GHz. The dynamic surface flag method selected either the ocean or the coast algorithm by surface using a 37-GHz footprint. The GSMaP TMI ocean algorithm (TB–rain-rate conversion) assumes that the background is cold ocean and so one method must avoid signals from areas near the coastline that are mixed with land. Figure 10 shows locations in the ocean footprint and surface flags in the case studies (described in section 4). Light blue (ocean 0) indicates ocean algorithm regions. The scan geometry expands the ocean flag to near the coastline (Figs. 10a and 4d) and bay (Figs. 10b and 7d). Yellow (ocean 1) indicates areas where the surface in the 10-GHz footprint is a mixture of ocean and land, but where the surface in higher-frequency footprints is deemed as ocean. Red indicates areas where the surfaces in the 10- and 19-GHz footprints are a mixture of ocean and land, but where the surface in higher-frequency footprints is regarded as ocean. The figure shows that the ocean algorithm can be applied to a wide area of the original coastal area (light-blue area), but that the coast algorithm (yellow and red areas) is required near the coastline.

For example, the SSM/I algorithm can be used in TB–rain-rate conversion using only higher frequency. The SSM/I aboard Defense Meteorological Satellite Program satellites has been operational since 1987. The SSM/I is a seven-channel, four-frequency (19, 21, 37, and 86 GHz), conically scanning radiometer that has proven itself stable and well calibrated. The retrieval algorithm for 19, 37, and 85 GHz has been well developed for the SSM/I. Three emission signals (10, 19, and 37 GHz) and scattering signals (85 GHz) are used in the TMI algorithm over the ocean. The addition of the 10-GHz channel to the TMI retrievals removes most of the underestimation at low rain rates, as well as the underestimation of heavy rain. It slightly improves the

TABLE 4. Verification scores of RNC of GSMaP algorithms with PR. The validation result was from January, April, July, and October 2009. Surface flags are the same as those of GSMaP1. GSMaP1 and GSMaP2 indicate the coastal region.

<table>
<thead>
<tr>
<th></th>
<th>Coast</th>
<th>Ocean</th>
<th>Land</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GSMaP1</td>
<td>GSMaP2</td>
<td>GSMaP1</td>
</tr>
<tr>
<td>POD</td>
<td>0.484</td>
<td>0.614</td>
<td>0.665</td>
</tr>
<tr>
<td>FAR</td>
<td>0.152</td>
<td>0.253</td>
<td>0.289</td>
</tr>
<tr>
<td>FB</td>
<td>0.571</td>
<td>0.822</td>
<td>0.934</td>
</tr>
<tr>
<td>ETS</td>
<td>0.431</td>
<td>0.492</td>
<td>0.507</td>
</tr>
</tbody>
</table>

TABLE 5. GPROF vs PR validation results. Results match the retrieved GPROF rain ≥ 0.5 mm h⁻¹ or higher, and footprints defined using the rain-certain flag of PR 2A25 data. Numbers in parentheses are the same as before, but the PR rain–no rain threshold is 0.5 mm h⁻¹.

<table>
<thead>
<tr>
<th></th>
<th>Coast</th>
<th>Ocean</th>
<th>Land</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GSMaP1</td>
<td>GSMaP2</td>
<td>GSMaP1</td>
</tr>
<tr>
<td>POD</td>
<td>0.357 (0.373)</td>
<td>0.629 (0.650)</td>
<td>0.562 (0.583)</td>
</tr>
<tr>
<td>FAR</td>
<td>0.167 (0.223)</td>
<td>0.306 (0.350)</td>
<td>0.276 (0.329)</td>
</tr>
<tr>
<td>FB</td>
<td>0.428 (0.480)</td>
<td>0.905 (1.00)</td>
<td>0.776 (0.868)</td>
</tr>
<tr>
<td>ETS</td>
<td>0.321 (0.325)</td>
<td>0.475 (0.465)</td>
<td>0.453 (0.444)</td>
</tr>
</tbody>
</table>
root-mean-square error and correlation of rain because of poor spatial resolution (Kummerow et al. 1996). The 10-GHz channel is less important in the estimation of small and isolated rain areas. Thus, the SSM/I algorithm can be used for 19-GHz ocean footprints (yellow area in Fig. 10). It is also possible that the 37- and 85-GHz retrieval land algorithms can be used for 37- and 85-GHz ocean signatures (red area in Fig. 10) (Aonashi et al. 2009).

The dynamic surface flag method requires only a high-resolution geographic database and satellite geometric data. Thus, a similar method could be applied to other MWR sensors, for example, AMSR-E (Kawanishi et al. 2003), the Advanced Microwave Scanning Radiometer 2 (AMSR2) (Shimoda 2010), and the Global Precipitation Measurement Microwave Imager (GMI) (Hou et al. 2014).

7. Conclusions

The RNC for the MWR algorithms over coasts misses rain more frequently than over either land or ocean. The difficulty for the coast algorithms is caused by the mixing of radiometrically hot (land) and cold (ocean) areas within the footprint. In this study, we developed a dynamic surface flag method for the MWR RNC algorithms. The method optimizes the surface flag for the RNC algorithm, the observation location of the footprint, and the sensor scan geometry. The method uses adapted and optimized flags based on the size of the EFOV and geolocation data. Therefore, a coast footprint of dynamic surface flags is an area with only mixed ocean and land surfaces. The method classifies land–ocean–coast flags such that the smallest region possible is defined as coast.

The study used the dynamic surface flag method for the GSMaP TMI algorithm, and PR-derived rain was used as reference for validation. The surface in the TMI footprint of the original coast flag included land, ocean, and coast. Validation scores for the current coast algorithm were the poorest among the surface algorithms investigated. Two case studies illustrated the improved agreement between the PR and GSMaP2, relative to GSMaP1 and GPROF. The global validation demonstrated that the method enhanced the RNC. The method reduces the difficulty and complexity associated with the coast algorithm. The method limits the coastal region to areas of mixed ocean and land within the maximum footprint of the RNC algorithm. This results in the land and ocean algorithms being used over wider areas than with the original conservative land–ocean–coast flag. The dynamic surface flag method reduced the coast flag from 7.52% to 2.46% in applications to 4-month TMI data. We applied either the land or the ocean algorithm to about two-thirds of the original coastal area, which improved the RNC.

The dynamic surface flag method reduced the coast flag area in our study, but improvement of the coast RNC algorithm is also important. Consideration of the fraction of water within a footprint (Bennartz 1999) might improve the detection and retrieval of rain by the coast algorithm.

Acknowledgments. This study was supported by the Earth Observation Research Center, Japan Aerospace Exploration Agency (JAXA). The high-resolution geographic data were provided by JAXA. The authors thank Dr. T. Kubota and Dr. S. Kida for discussions and comments. The authors thank three anonymous reviewers for their constructive comments, which improved the clarity of the paper.
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