A Rain Potential Map with High Temporal and Spatial Resolutions Retrieved from Five Geostationary Meteorological Satellites

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Abstract

In this study, we introduce a rain potential map (RPM) that globally estimates rain probabilities every hour. More specifically, we created an RPM by associating the brightness temperature (Tb) of the infrared and water vapor channels observed by five geostationary meteorological satellites (GEO) with rain probabilities observed via rain radar of the Tropical Rainfall Measuring Mission (TRMM). By using our RPM, we improved the accuracy of the Global Satellite Mapping of Precipitation (GSMaP) product, which produces global precipitation data by integrating passive microwave and infrared radiometer data. More specifically, we removed GSMaP rain areas over the ocean in which all microwave sensors were unavailable and rain probabilities according to our RPM were below 14%, which improved the “threat score” of detection in GSMaP from 0.37 to 0.41 over the ocean. Conversely, we added rain areas over land in which all microwave sensors were unavailable and rain probabilities according to our RPM were greater than 37%, which improved the “threat score” of detection from 0.27 to 0.35 over land. Given that a GSMaP “threat score” with microwave observations is approximately 0.44, our improvements here are significant.

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1. Introduction

The Global Precipitation Measurement project measures global precipitation every three hours by combining microwave radiometer observations from orbiting satellites (Hou et al. 2014); however, if a temporal resolution of one hour is required for precipitation estimations, microwave satellites cannot cover global areas. Therefore, there is a need to fill the inherent gap in the overlap of microwave satellites to estimate global precipitation with finer temporal resolutions. Global precipitation data have already been obtained in previous studies using satellite observations, e.g., the Global Precipitation Climatology Project (GPCP) primarily estimates precipitation from visible and infrared (IR) brightness temperatures (Tb) observed by geostationary meteorological satellites (GEO) using histograms that match with microwave satellites over the ocean (Adler et al. 2003).

Conversely, the Climate Prediction Center Morphing (CMORPH) technique estimates where precipitation areas observed at the previous or next time step will move by estimating cloud movement vectors from the IR Tb observations obtained from GEO data to complement precipitation detection. Consequently, rain rates are interpolated from rain propagated forward and backward in time covering periods in which all microwave sensors are unavailable (Joyce et al. 2004). Global Satellite Mapping of Precipitation (GSMaP) is essentially similar to CMORPH in terms of using movement vectors, but GSMaP employs the relationship between the rainfall rate and the IR Tb (Aonashi et al. 2009). In particular, GSMaP uses a Kalman filter by associating the rainfall rate, which is complemented with the movement vector, with the IR Tb from GEO data (Ushio et al. 2009); however, in principle, this approach for determining the destination of rain clouds cannot detect convective rainfall from storms that develop and decay between passive microwave scans. Therefore, the accuracy of GSMaP decreases when all microwave satellites are unavailable (Kubota et al. 2009). Janowiak et al. (2001) merged global GEO observations in near real-time by combining IR observations from each GEO with precipitation radar observations from the Tropical Rainfall Measuring Mission (TRMM, Kummerow et al. 1998). The use of IR Tb from GEO data improved the accuracy of GSMaP products to some extent, but other channels from GEO data have not been used much.

Given the above, in this study, we developed a rain potential map (RPM) for estimating the probabilities of rain with high temporal and spatial resolutions by associating IR and water vapor (WV) Tbs from GEO observations with precipitation radar observations from the TRMM. We used IR and WV channels given the general assumption that a deep convective cloud with rain often occurs in an area with small differences between IR and WV Tbs; this phenomenon occurs because if the top of an extremely high cloud reaches the tropopause, the difference between the IR and WV Tbs is near zero due to small contributions from the WV (Ohsawa et al. 2001). Further, Ohsawa et al. (2001) also reported that using these differences between the IR and WV Tbs was a more effective index than IR alone. As almost all GEO have sensors operating in the IR and WV channels, the above index is globally available on a long-term basis.

Finally, in this study, we attempted to modify GSMaP rain areas for which no microwave satellites are available by using the RPM. We examined to what degree GSMaP was improved by comparing our modified GSMaP with actual rainfall measurements observed by radar.

2. Datasets

For our study, we used IR and WV Tbs data obtained from five GEO, the details of which are presented in Table 1. We performed data analysis covering a three-year period from January 2007 through December 2009 because there were no satellite replacements during this period. Further, we used near-surface rainfall rates determined by the TRMM Precipitation Radar (PR) (TRMM PR, 2A25, V7; Iguchi et al. 2000, 2009) as an indication of rainfall. The TRMM PR data are available from 36° south latitude to 36° north latitude. To maintain the quality of these data, we used 31 beam positions near the sub-satellite point from among all 49 beam positions on a scan.

Note that we used the GSMaP_MVK (v.5.222.1) and GSMaP_NRT products, which measure global precipitation every hour by integrating passive microwave radiometer data with IR radiometer
data. When all microwave satellites are unavailable, GSMaP_MVK estimates rainy cloud movements from IR Tb observations made by GEO to complement precipitation detection. Here, GSMaP_NRT is a near real-time version of GSMaP that utilizes only past observations, thus the accuracy of GSMaP_NRT is less than that of GSMaP_MVK (Kubota et al. 2009).

Although the TRMM Microwave Imager (TMI) is available at any time during the orbit of the TRMM, the TRMM PR cannot verify the GSMaP product data when microwave sensors are unavailable. Therefore, in this study, we created a GSMaP rain product without relying on TRMM TMI by using the GSMaP algorithm for making GSMaP_MVK (Ushio et al. 2009). Hereafter, we name the GSMaP_MVK and GSMaP_NRT products without the TRMM TMI as MVK_NOM and NRT_NOM, respectively. The GSMaP product with at least one microwave sensor available is called as GSMaP_MWR.

Finally, we used ground-based rain radar data obtained from the Japan Meteorological Agency as an indication of rainfall at mid-latitude. We averaged these data spatially from approximately 1 to 10 km, which is the same approach as that used by GSMaP. We used radar data within a radius of 200 km from each radar site to mitigate the effect of radar attenuation. If rainfall intensity was greater than 0.5 mm h\(^{-1}\), we considered that rain was present.

### 3. Results and discussion

#### 3.1 Developing the RPM

We collected simultaneous observations from the GEO and TRMM PR data for one month (i.e., July 2007) to create a lookup table for converting Tbs from GEO data into rain probabilities, which we show in Fig. 1a. Figure 1b shows sample number of the simultaneous observation. This lookup table gives the probability of detecting rain by the TRMM PR when the GEO observed particular values of IR Tb, as well as the differences between IR and WV Tbs. If the difference in observation time between the GEO and TRMM PR data was less than 10 minutes, we selected the nearest TRMM pixel to the GEO pixels as a simultaneous observation.

By using the correspondence between the Tb from the GEO and the rain probability from the TRMM PR, obtained from a similar lookup table for each month, we can immediately convert Tbs values observed via the GEO every hour into rain probabilities. From Fig. 1a, rain probabilities were clearly found to be high when the Tbs observed by the GEO were low and the difference between the IR and WV Tbs was also small. This finding is aligned with that of Ohsawa et al. (2001).

The shaded area at the bottom of Fig. 1a shows the correspondence between the IR Tb and rain probabilities calculated by using IR Tb without WV Tb. Compared with rain probabilities obtained from the lookup table with both IR and WV Tbs, the latter enables us to estimate a higher probability versus only using IR Tb for low clouds (in which Tb was higher than 240 K). The lookup table with IR and WV Tbs can be used to classify low clouds, in which Tb lies between 240 and 260 K, into the following two types: one with a probability of less than 10% and likely has no rain areas and the other with a probability between 10% and 30%. Since it was difficult to separate the above two types using only IR Tb, we showed that using WV Tb improved the accuracy of this rain/no-rain classification; thus, we constructed lookup tables for land, ocean, and coastal areas, with a land-sea mask obtained from TRMM 2A25 and re-gridded using a grid of 0.04°, which is the same as the spatial resolution of the IR Tb from the GEO data.

#### 3.2 Global RPM

Figure 2 shows a snapshot of the RPM at 03:00 UTC on July 1 2007. Before the Tbs from the GEO were converted into rain probabilities, those from the five GEO were combined to provide a global and seamless estimate. During the combination process, we first needed to remove the viewing angle dependence from the GEO observations (Joyce et al. 2001); a problem that becomes apparent with GEO observations at large viewing angles. Here, at the edge of the area of observation of the given GEO, the GEO tends to overestimate the optical thickness of the clouds, thus underestimating the IR and WV Tbs by observing the clouds diagonally. Joyce et al. (2001) noted that two adjacent GEO observed a cloud at the sub-satellite point of one GEO from two different angles, i.e., the vertical and diagonal angles. Therefore, they collected simultaneous observations from adjacent GEO for approximately one year to construct a lookup table that relates the viewing angle to the rate of decrease of the IR Tb for removing this dependence on the viewing angle. Using the same approach, we constructed the above lookup table from our own GEO data and removed the viewing angle dependence to produce global

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**Table 1. Details of GEO.**

| Satellite       | MSG-2 | Meteosat-7 | MTSAT-1R | GOES-11 | GOES-12 |
|-----------------|-------|------------|----------|---------|---------|
| Subsatellite point longitude | 0°E   | 57.5°E     | 140°E    | 135°W   | 60°W    |
| IR channel (µm) | 9.8−11.8 | 10.5−11.5  | 10.3−11.3| 10.2−11.2| 10.2−11.2|
| WV channel (µm) | 5.35−7.15 | 5.7−7.1    | 6.5−7.0  | 6.5−7.0  | 5.8−7.3  |

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Fig. 1. Example lookup table over the ocean on July 2007 for converting Tb from GEO data into rain probabilities. The horizontal and vertical axes indicate the IR and IR minus WV Tbs, respectively, observed by the GEO. In Fig. 1a, the colors indicate the probabilities of rain calculated from TRMM PR observations, and the bottom color bar indicates the probability of rain in the same way as the above lookup table, but instead uses only IR Tb. In Fig. 1b, the colors indicate number of samples.
GEO datasets.

Finally, we constructed a global RPM from global GEO data, as mentioned in Section 3.1. The RPM provides rain probabilities at high temporal and spatial resolutions (i.e., hourly and 0.04°, respectively) without microwave sensors and, in contrast to GSMaP, is therefore available regardless of surface conditions, i.e., our mapping is applicable for conditions of land, ocean, and coast.

3.3 Improving GSMaP rain estimates via our RPM

Using our constructed RPM, we attempted to improve the detection accuracy of GSMaP by modifying its rain areas. First, to investigate which features of the rain/no-rain classification using GSMaP need improvement, we compared rain estimates from GSMaP with actual rain measurements at ground level near Japan, as shown in Fig. 3. Compared with the rain area obtained from

Fig. 2. Snapshot of the global RPM. Yellow dots represent sub-satellite points of the GEO, while dashed lines indicate the northern and southern limits of the TRMM observing area.

Fig. 3. (a) Rain intensity measures obtained from ground-based radar; hatching denotes areas in which a microwave satellite was available. (b) Rain intensity measures obtained from GSMaP_MVK. (c) Rain probabilities obtained from our RPM. The white lines indicate contours of the 14% optimum cut-off value for our RPM. (d) Comparison of rain/no-rain classification between GSMaP_MVK and ground-based radar; here, yellow, blue, red, and gray colors indicate hits, misses, false alarms, and zeroes, respectively. (e) Same as (d), but the GSMaP_MVK rain area was modified using our RPM.
ground-based radar shown in Fig. 3a, we observe in Fig. 3b that the rain area from MVK_NOM tended to overestimate.

Further, Fig. 3d shows an evaluation of the accuracy of the rain/no-rain classification via GSMaP_MVK by comparing its data with those from ground-based radar that serves as an indicator of actual rain. In the figure, the yellow, blue, red, and gray colors indicate hits, misses, false alarms, and zeroes, respectively. A hit indicates that both ground-based radar and GSMaP correctly detected rain. A miss indicates that ground-based radar observed rain, but GSMaP did not. A false alarm indicates that GSMaP classified the area as rain, but ground-based radar classified it as no rain. Finally, a zero indicates that both ground-based radar and GSMaP classified the area as no rain.

Further, the hatched areas of Fig. 3d show the areas in which at least one microwave sensor was available. In these hatched areas, most of the results were hits, and the accuracy of the rain/no-rain classification by GSMaP was high; however, in the unhatched areas, the number of false alarms increased and GSMaP tended to overestimate rain areas. To confirm whether this was a general tendency or not, we investigated a global evaluation of GSMaP using the TRMM PR from 2007 through 2009, as shown in Fig. 4. Since the TRMM PR was available only from 36° south latitude to 36° north latitude, our evaluation was limited to the same area.

We used the following performance indices calculated from comparisons of GSMaP rain with radar rain: threat score \([TS = H/(H + FA + M)]\), probability of detection \([POD = H/(H + M)]\), false alarm rate \([FAR = FA/(H + FA)]\), and bias score \([BS = (H + FA)/(H + M)]\). Here \(H\) indicates the number of hits, \(M\) indicates the number of misses, and \(FA\) indicates the number of false alarms. We classified cases in which the observed rain rate was greater than 0.5 mm h\(^{-1}\) as having rain. The deep blue bars in Fig. 4 indicate the verification scores of the rain/no-rain classification performed by the original GSMaP. We observe that the BS for MVK_NOM over the ocean was greater than 1.5; further, MVK_NOM overestimated rain areas. On the other hand, the TS of MVK_NOM was lower than that of GSMaP_MWR.

Next, we attempted to remove rain areas overestimated by MVK_NOM in Fig. 3 by focusing on areas in which the values obtained from our RPM were lower than a predefined threshold. To decide the optimum threshold here, we executed parameter sweep applications, as shown in Fig. 5. The figure shows the variations in each verification score as rain areas indicated by GSMaP, which are then removed if the RPM shows a lower probability than the cut-off value. We also observe that the FAR and POD values decreased as the cut-off value for the RPM increased; however, the rate of decrease of the FAR was higher than that of the POD when the cut-off value for the RPM was small, thus the TS for the modified GSMaP_MVK product over the ocean was optimal when the cut-off value for the RPM was 14%.

The blue line in Fig. 5 indicates the result of a similar parameter sweep, but in this case, the RPM was constructed using Tb with only IR. Here, the TS for the modified GSMaP did not increase as compared to that of the original MVK_NOM. Figure 3e is the same as Fig. 3d, but the rain area indicated by MVK_NOM in which the probability value from the RPM was equal to or less than 14% was removed. It is shown in Fig. 3e that the red area, which indicates false alarms of MVK_NOM, is significantly reduced.

To confirm whether the improvement achieved above was general or not, we investigated a global evaluation of the GSMaP with our RPM. The green bars in Fig. 4 show improvements in verification scores after modifying the rain/no-rain classification by GSMaP using the RPM. The BS for MVK_NOM greatly decreased, and the TS for the detection of rain by MVK_NOM increased from 0.37 to 0.41 over the ocean, as summarized in Table 2. Here, the TS for GSMaP with microwave observations was 0.44, thus the observed improvements were certainly significant and valuable.

On the other hand, we also observe from Fig. 4 that the BS for GSMaP_NRT was much less than 1.0, and that NRT_NOM under-
estimated rain areas over land. Further, the TS for NRT_NOM was much less than that for GSMaP_MVK. Therefore, we examined the addition of rain areas where rain probabilities obtained from our RPM exceeded 37%. As a result, the TS for the GSMaP_NRT product over land also increased from 0.27 to 0.35; however, if we attempt to add rain areas using our RPM, we first need to obtain rainfall rate information from another source because it is difficult to estimate rainfall rates by IR Tb from GEO data alone.

4. Summary

In this study, we developed an RPM that is able to estimate the global probability of rain with high temporal resolution by combining IR and WV Tbs observations from five GEO, complementing the Tbs information with rain information observed by rain radar. We found that rain areas in MVK NOM were overestimated over the ocean, while those of NRT_NOM were underestimated over land and coasts. Therefore, we modified these rain areas by using our RPM. As a result, we reduced the overestimation of rain areas over the ocean and the underestimation of rain areas over land with the TS values increasing from 0.37 to 0.41 and from 0.27 to 0.35, respectively. The TS for GSMaP was 0.44 when microwave sensors were available, thus the accuracy of the GSMaP estimates were significantly improved by our RPM.

For future work, we plan to construct an RPM for mid-latitude regions when data is fully accumulated from the Global Precipitation Measurement core satellite with dual-frequency precipitation radar and an orbital inclination of 65°. We also plan to verify regional, seasonal, and latitudinal dependencies of our RPM to cover the entire global area.

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