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A B S T R A C T

Correcting radiometric biases is crucial prior to the use of satellite observations in a physically based retrieval or data assimilation system. This study proposes an algorithm – RARMA (**R**adiometric **A**djustment using **R**educed **M**ajor **A**xis) for correcting the radiometric biases so that the observed radiances coincide with the simulation of a radiative transfer model. The RARMA algorithm is a static bias correction algorithm, which is developed using the reduced major axis (RMA) regression approach. NOAA's Community Radiative Transfer Model (CRTM) has been used as the basis of radiative transfer simulation for adjusting the observed radiometric biases. The algorithm is experimented and applied to the recently launched Global Precipitation Measurement (GPM) mission's GPM Microwave Imager (GMI). Experimental results demonstrate that radiometric biases are apparent in the GMI instrument. The RARMA algorithm has been able to correct such radiometric biases and a significant reduction of observation residuals is revealed while assessing the performance of the algorithm. The experiment is currently tested on clear scenes and over the ocean surface, where, surface emissivity is relatively easier to model, with the help of a microwave emissivity model (FASTEM-5).

1. Introduction

Radiometric bias correction is a term that is known as a technique to remove potential inconsistencies between the radiometric measurements and a radiative transfer model. The radiative transfer model is often used as a forward model in a number of remote sensing systems. For instance, in the physically based retrieval system, a radiative transfer model is necessary to simulate satellite brightness temperatures that also act as a forward model for the retrieval of various geophysical parameters. Remote sensing retrieval studies incorporating radiative transfer models as forward models have exclusively appeared in the literature, and thus referred therein [1,11,15,20,24,25]. On the other hand, radiative transfer model is an integral tool in the data assimilation systems. In fact, the variational data assimilation is based on unbiased observations. Nevertheless, in reality, it is impossible to find unbiased observations. The observation biases could introduce from

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a variety of sources. First of all, satellite instruments are not perfect. There could be random biases originating from the noise at the radiation detector. Nevertheless, employing some form of filtering approach can mitigate the impact of this type of biases in a data assimilation system. There is another type of bias that is systematic in nature. The systematic biases can have an adverse negative impact in a data assimilation system. This can lead to inaccurate weather forecasting. Moreover, biases can also be introduced from the radiative transfer operator itself as well as background atmospheric state vector that is used.

Bias correction is eventually the first step in a retrieval or a data assimilation process. In the past, a various form of bias correction techniques have been explored within the remote sensing community. Given examples, variational bias correction scheme is widely used in the operational data assimilation system (3DVAR/4DVAR), by a number of government agencies, including NOAA and NASA [18,26,27]. Harris and Kelly [9] have applied simple linear regression based air-mass bias correction, taking the predictors from NWP model. Fixed constant offsets based as well as geographically varying bias correction have also been reported [2].

The Global Precipitation Measurement (GPM) is an international satellite mission, designed to provide estimates of precipitation every three hours. The GPM core observatory satellite is launched in early 2014. One of the main instruments in the GPM core observatory satellite is the GPM Microwave Imager (GMI). The GPM/GMI is the successor of the Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI) [13,14,16]. Further information of the GPM satellite can be found in Islam et al. [12], Tapiador et al. [23], Hou et al. [10], among others.

In this study, we propose a novel bias correction algorithm- RARMA (**R**adiometric **A**djustment using **R**educed **M**ajor **A**xis) for the recently launched GPM/GMI instrument. The algorithm is based on the reduced major axis (RMA) regression approach. This article is structured as follows. Section 2 describes the datasets and radiative transfer model used in this study. The description of the RARMA algorithm is given in Section 3. The evaluation results from the algorithm applied to the GPM/GMI radiances are incorporated in Section 4. The conclusions are summarized in Section 5.

2. Datasets and radiative transfer model

2.1. GPM/GMI data

The GMI is a conical- scanning, microwave radiometer, operated at multi-channel frequencies. The GMI frequency ranges from 10 GHz to 183 GHz. It has a 1.2 m diameter antenna. The earth-incidence angle of the GMI is 52.8 degrees, which is identical to that of its predecessor TMI. The GMI swath covers 904 km (562 miles) on the Earth's surface. Table 1 tabulates the channel specification of the GMI instrument. Draper et al. [7] have given a comprehensive instrument overview and early on-orbit performance of the GMI.

In the present work, the calibrated brightness temperatures of the GMI instrument are used. The data are obtained from the Level 1C R data product, available at the NASA ftp site: ftp://jsimpson.pps.eosdis.nasa.gov/data/1CR.

2.2. ECMWF analysis data

The European Centre for Medium-range Weather Forecasts (ECMWF) analysis data has been obtained from the high-resolution forecast and data assimilation of the operational runs (IFS). The data are used to feed the radiative transfer model for the purpose of simulating the brightness temperatures. The IFS system is based on a 4D-variational system. The vertical model levels are terrain-following near the surface. The product resolution is 0.125×0.125 degrees in latitude-longitude grid. A comprehensive overview of the ECMWF IFS model is accumulated in Gregory et al. [8], Barros et al. [3], and referred therein.

2.3. Radiative transfer model

The radiative transfer model used in this work is the Community Radiative Transfer Model (CRTM). The CRTM is developed by the Joint Center for Satellite Data Assimilation (JCSDA) at the NOAA. A thorough description of the CRTM model is depicted in Chen et al. [5], Chen et al. [4], Ding et al. [6], among others. It is a fast radiative transfer model for simulation of satellite radiances. In the CRTM, the radiative transfer problem is divided into various components, for instance, gaseous absorption, surface optics, and scattering components.

Table 1
The channel specification of the GMI instrument.

Channel no	Central frequency (Ghz)	Central frequency stabilization ($\pm$MHz)	Bandwidth (Mhz)	Polarization	Integration time (ms)	NEDT (K)	Antenna beamwidth @ 3 dB (°)
1	10.65	10	100	V	9.7	0.96	1.75
2	10.65	10	100	H	9.7	0.96	1.75
3	18.70	20	200	V	5.3	0.84	1.00
4	18.70	20	200	H	5.3	0.84	1.00
5	23.80	20	400	V	5.0	1.05	0.90
6	36.50	50	1000	V	5.0	0.65	0.90
7	36.5	50	1000	H	5.0	0.65	0.90
8	89.00	200	6000	V	2.2	0.57	0.40
9	89.00	200	6000	H	2.2	0.57	0.40
10	166.0	200	3000	V	3.6	1.5	0.40
11	166.0	200	3000	H	3.6	1.5	0.40
12	183.31 ± 3	200	3500	V	3.6	1.5	0.4
13	183.31 ± 7	200	4500	H	3.6	1.5	0.4

3. Rarma algorithm

The RARMA algorithm uses the reduced major axis (RMA) regression approach for adjusting radiometric biases. The RMA is Model II regression procedure [22]. It is an effective method for handling the problem of natural variability in predictor x and the response variable y. Traditional ordinary least squares (OLS) regression minimizes the sum of the squares of the errors produced. On the other hand, the RMA follows the minimization of the perpendicular distance from x and y to the best fit line. Particularly, the RMA minimizes the triangular area between each data point and the best-fit line as:

$$\frac{1}{2} \times (\Delta x \Delta y) \tag{1}$$

where, Δx and Δy denote the produced distances between the predictor variable x and response variable y during the minimization process. The slope b of the regression equation is calculated as:

$$b = \pm \sqrt{\frac{SS_y}{SS_x}} \tag{2}$$

$$b = \pm \sqrt{\frac{\sum y^2 - \frac{(\sum y)^2}{n}}{\sum x^2 - \frac{(\sum x)^2}{n}}} \tag{3}$$

where, SS_x and SS_y are the standard deviations of x and y, respectively. Similar to the OLS, the best fit line passes through the data centroid described by the sample mean. Thus, intercept a is defined as:

$$a = \bar{y} - b\bar{x} \tag{4}$$

Further to note, in the present work, the confidence interval is calculated by bootstrapping method. The bootstrap method estimates the variability of data statistics by Monte Carlo resampling. Two different procedures have been employed for the calculation of confidence intervals-the Ricker procedure [21], and Jolicoeur and Mosimann procedure [17]. Ricker procedure uses the Student t-distribution and Jolicoeur and Mosimann procedure uses the asymmetrical F distribution.

In order to develop the RARMA model, the CRTM has been applied on the ECMWF analyzed field to compute the GPM/GMI satellite brightness temperatures at each channel. Nevertheless, ECMWF analysis data is a $0.125° \times 0.125°$ resolution product (6 h temporal resolution). Therefore, it has been necessary to interpolate the ECMWF analysis fields to the GMI footprint, in both time and space. This is done by

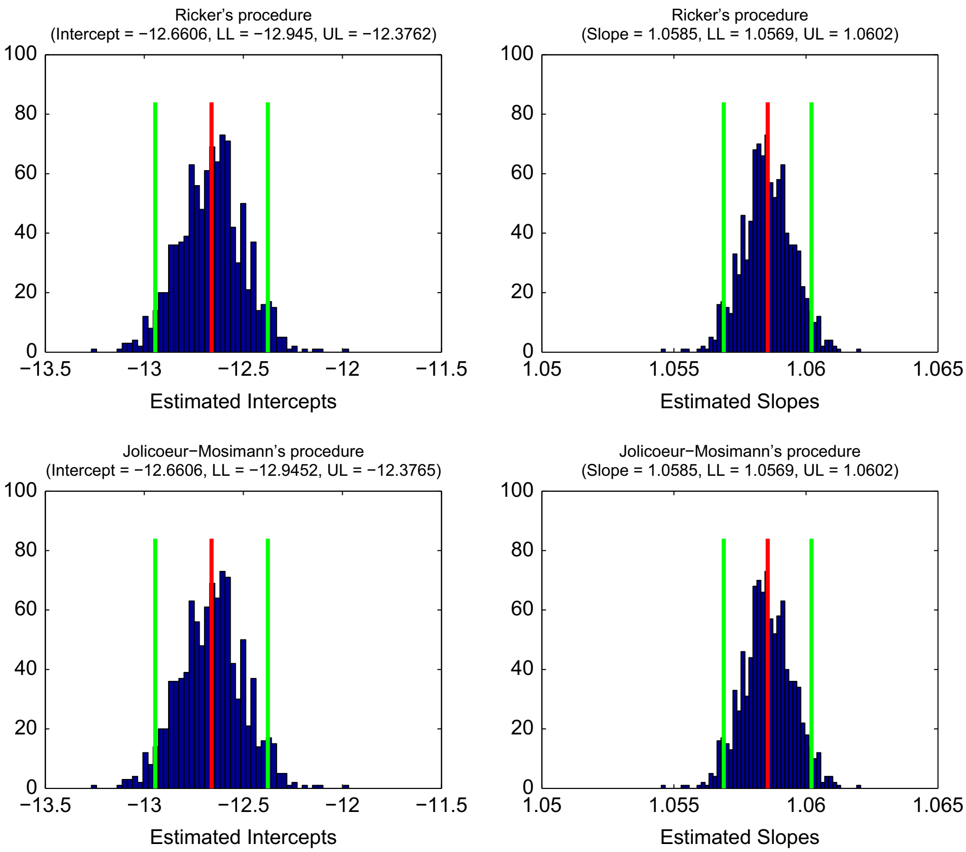

Fig. 1. The histogram plots of estimated intercepts and slopes from the bootstrap reduced major axis regression.

employing a simple interpolation scheme that interpolates the ECMWF atmospheric and surface analysis fields in time and space to the exact location of the GMI radiometric measurements. One should also remember that emissivity is very difficult to model over non-ocean surface. Particularly, the radiometric simulation for surface sensitive channels can be highly erratic due to the challenge associated with modeling accurate emissivity by a radiative transfer model. Therefore, our study is exclusively limited to the ocean surface. The FASTEM emissivity model (version 5) has been employed to compute the emissivity over the ocean surface. The description of the FASTEM model is well described in Liu et al. [19]. Briefly speaking, the model computes the emissivity as a function of frequency, viewing angle, surface temperature, and surface winds. Necessary input parameters have been taken from the ECMWF analysis fields. Furthermore, precipitation scenes have been avoided to develop the RARMA algorithm. Additional precaution has

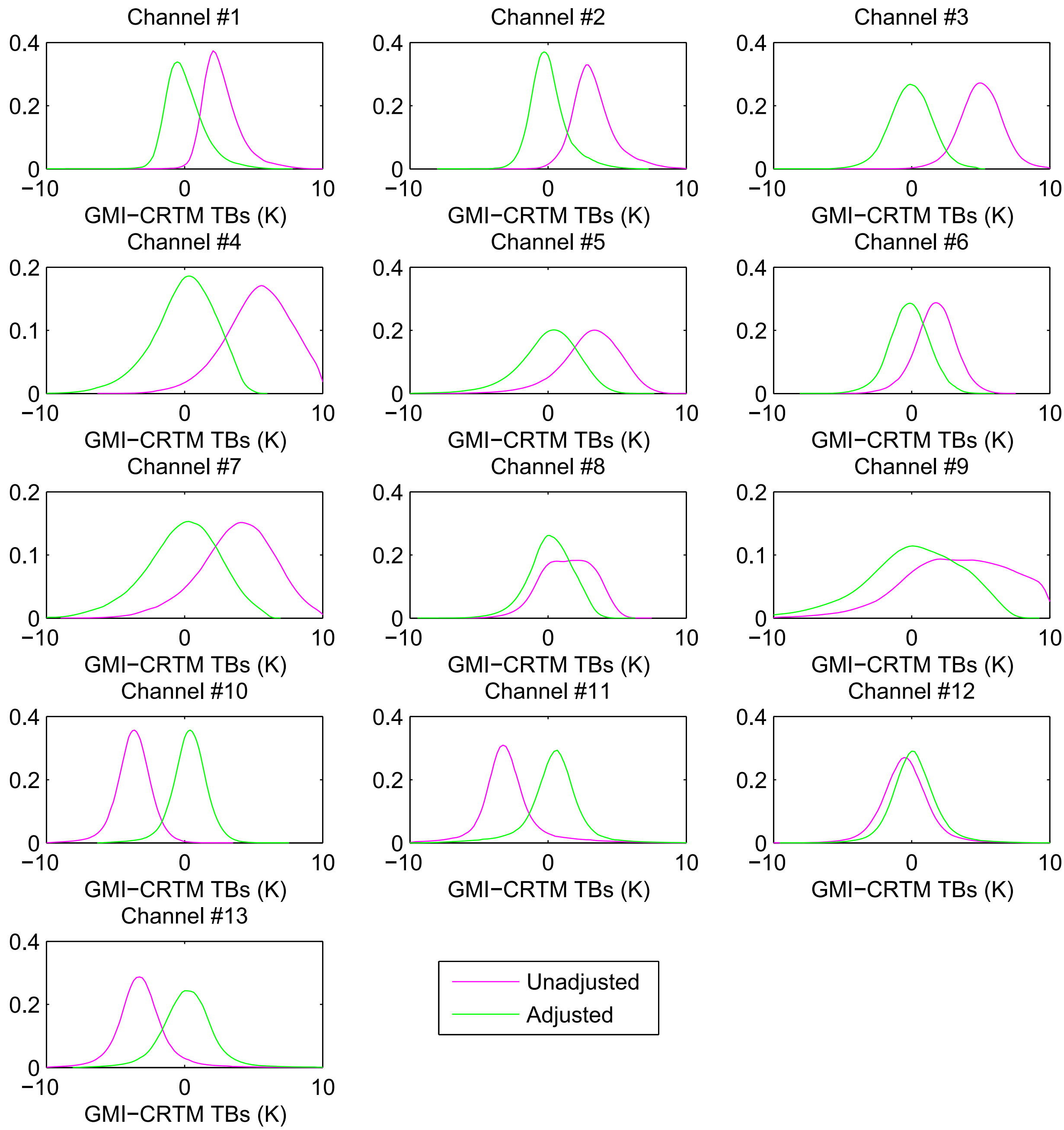

Fig. 2. Probability density functions of GMI observed minus CRTM computed radiances (in K) before (unadjusted) and after (adjusted) applying the RARMA algorithm.

been taken to limit the study region within ± 40 degrees latitude to avoid sea ice scenes. A reasonable number of orbital cases have been included in the year of 2014 for the development of the RARMA algorithm. Independent of the development database, a validation database has been created to assess the performance of the RARMA. In the latter section, we will be presenting the results revealed from the RARMA algorithm applied to the validation database.

4. Bias correction results

Prior to providing the bias correction results, we demonstrate the histogram plots of estimated intercepts and slopes from the bootstrap Model II regression (Fig. 1).

Table 2
Mean radiance departures (in K) for unadjusted and adjusted radiometric measurements.

Channel No.	Unadjusted	Adjusted (RARMA)
1	2.67	0.03
2	3.26	0.04
3	5.02	−0.06
4	5.33	−0.05
5	3.07	0.03
6	1.71	−0.14
7	3.79	−0.16
8	1.43	0.16
9	3.37	0.10
10	−3.71	0.34
11	−2.90	0.41
12	−0.45	0.20
13	−3.10	0.22

The histograms for both procedures are presented (Ricker's and Jolicoeur and Mosimann's) in the figure. Confidence lower and upper limits are also shown. It can be seen that the estimated intercepts and slopes for both procedures are identical.

In Fig. 2, we provide the bias correction results by applying the RARMA algorithm for the 13 GMI channels. The results are shown in the form of biases (GMI-CRTM TBs) before (unadjusted) and after (adjusted) applying the RARMA algorithm. The bias histograms seem to appear more similar to a Gaussian distribution in the figure. Eventually, bias exists for all of the GMI channels. Comparatively, a small bias is seen on channel 12, which is in the water vapor absorption line (183.31 ± 3 GHz). One can see that the peak of the distribution for all channels has come closer to zero after applying the RARMA algorithm. This figure should be accompanied with Table 2, which tabulates the resulting mean radiance departures before and after applying the radiometric adjustment procedure. Computed biases seem to vary from one channel to another, which is to be expected. Up to ~5 K bias is observed in some channels, more specifically in channels 3 and 4 (18 GHz). Nevertheless, after applying the RARMA algorithm, a significant bias reduction has been possible. This is evident for all the channels. Given example, the radiance departures for channels 3 and 4 have been reduced to 0.04 and −0.06 K from 3.26 and 5.02 K, respectively.

Finally, in Fig. 3, we demonstrate an example illustrating the spatial distribution of GMI minus CRTM computed TBs before and after applying the radiometric adjustment procedure on channel 1. Notable radiometric

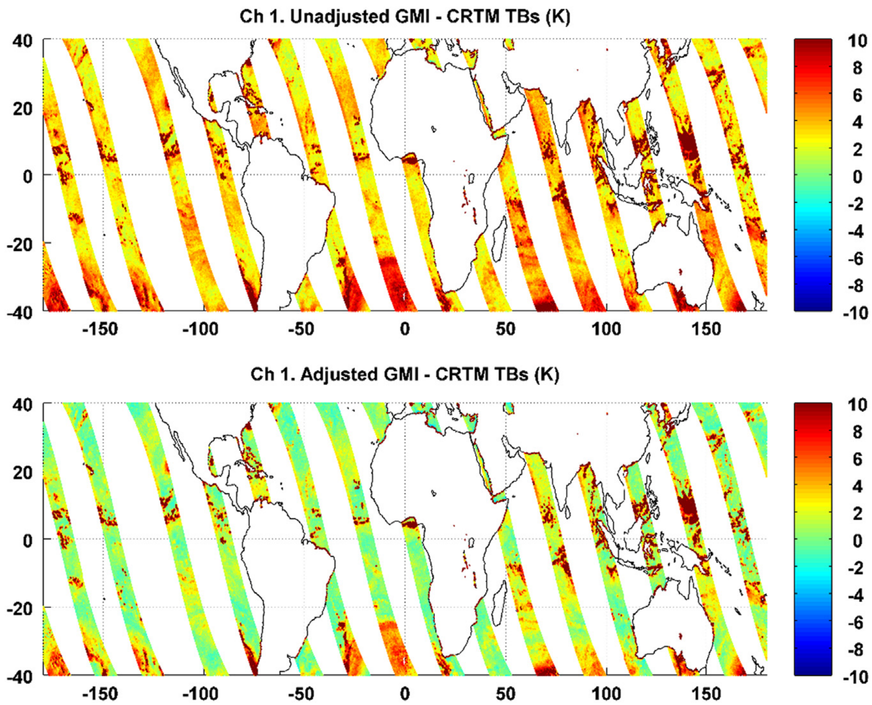

Fig. 3. Spatial distribution of GMI observed minus CRTM computed radiances (in K) before (unadjusted) and after (adjusted) applying the RARMA algorithm.

biases have been observed across the globe (±40 degrees) on this day. From the figure, it is evident that after applying the RARMA algorithm, such radiometric biases have been significantly reduced.

5. Conclusions

Radiometric biases are well-known setback in satellite retrieval and data assimilation systems, thus requires a bias correction step. In this effort, a radiometric bias correction algorithm, named as RARMA, is presented. RARMA uses a model II regression method, more particularly, reduced major axis (RMA) regression approach to correct the radiometric biases. The CRTM has been used as the radiative transfer model for simulating the brightness temperatures on GMI frequencies. The RARMA algorithm seems to be performing well for correcting the radiometric biases.

It must be stressed that the proposed bias correction is a static scheme. That means the coefficients are fixed at this time. Nevertheless, the satellite may decay over the time, thus could impact on the sensor calibration. It will be interesting to look in the near future, how the revealed coefficients perform for correcting the radiometric biases. Most likely, the RARMA coefficients need to be updated. Another option can be the use of an adaptive scheme, where the coefficients will be updated regularly prior to the retrieval and assimilation runs.

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