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Methodology Development for Calibration Assessment Using Quasi-Deep Convective Clouds With Application to Aqua MODIS TEB

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Abstract Deep convective clouds (DCC) are identified by using a combination of brightness temperature (BT) and visible reflectance thresholds. Moreover, it is common practice to use daytime DCC measurements for the calibration assessment of reflective solar and longwave infrared bands. The DCC cold core is suitable for the Moderate Resolution Imaging Spectroradiometer (MODIS) thermal emissive bands (TEB) calibration assessment; more specifically, for the offset effect in the quadratic calibration function. However, the reflected solar radiance in the daytime DCC measurements affects the midwave infrared bands. Thus, an assessment over low-BT measurements is not applicable to these bands. Because of this, a quasi-DCC (qDCC) technique is developed for the midwave infrared bands calibration assessment. The feasibility of using nighttime DCC measurements is demonstrated by comparing the DCC and daytime qDCC techniques. A DCC normalization method is also developed to remove the DCC fluctuation impact and enhance the accuracy. The DCC measurements’ distribution is asymmetrical for all TEB, and their BT ranges fluctuate around 20 K. An empirical model is developed and applied to normalize the measurements over DCC to a reference temperature. After the normalization, the DCC and qDCC measurements’ distributions are close to symmetrical and Gaussian in shape. These improvements are applied to the Aqua MODIS instrument. The calibration stability, noise performance, and consistency are evaluated for all Aqua MODIS TEB. Lastly, the Aqua MODIS formatter reset effect on the calibration offset bias between two mirror sides is analyzed, and a calibration coefficient correction is proposed for future calibration improvements.

1. Introduction

Deep convective clouds (DCC) are cold targets whose stable reflectance in the visible and near-infrared spectrum, combined with minimal water vapor and aerosol presence when viewed from space, makes them suitable targets for satellite sensor calibration and intercomparison (Cao et al., 2008; Doelling et al., 2010; Doelling et al., 2012; Doelling et al., 2013; Doelling et al., 2015; Doelling et al., 2004; Fougnie & Bach, 2009; Hu et al., 2004; Sohn et al., 2005). Doelling et al. (2004) used a DCC technique to evaluate the Advanced Very High Resolution Radiometer (AVHRR) calibration and gain degradation. Previous literature indicates that most of the DCC-associated studies focus on sensor intercomparison and stability assessments for the reflective solar bands. However, the lower DCC brightness temperature (BT) levels have been shown to provide an advantage when assessing the calibration of the infrared thermal emissive bands (TEB) (Chang et al., 2019). Hence, a bias model application for cold BT measurements can yield an offset correction for the Moderate Resolution Imaging Spectroradiometer (MODIS) TEB quadratic calibration algorithm.

This work presents two developed calibration assessment techniques: quasi-DCC (qDCC) and DCC normalization. These improvements are applied to the Aqua MODIS instrument. MODIS possesses 36 bands, 16 of which are bands that cover the midwave infrared (MWIR) (bands 20–25) and longwave infrared (LWIR) (bands 27–36) spectral regions. The MODIS TEB calibration is performed using its onboard blackbody (BB), whose temperature ranges from instrument ambient temperature (about 270 K) to 315 K during each warm-up/cool-down (WUCD) event. The onboard BB operates as the primary calibration source, while the space view (SV) port provides a reference for instrument background. The TEB calibration is based on a quadratic algorithm that converts the sensor digital response to radiance. This quadratic function is calibrated using the BB and applied to Earth view (EV) radiance retrievals. During nominal operation, the BB...
temperature is set to 290 and 285 K for Terra and Aqua MODIS, respectively. Due to the BB temperature range, the uncertainty of the offset in the quadratic function is large and propagates to the EV measurements, especially for those over low-BT scenes (e.g., DCC). Therefore, assessing measurements over DCC can be beneficial for corrections in the calibration algorithm.

DCC pixels are identified by using a combination of BT and visible reflectance thresholds. Hence, all DCC samples are composed of daytime measurements (Doelling et al., 2004). Because a fraction of the retrieved radiance comes from the DCC target’s solar reflectance, and the DCC thermal emission radiance is low, the MWIR bands exhibit high BT. Additionally, the solar reflectance is solar zenith angle and instrument view angle dependent. Moreover, the daytime MWIR measurements over DCC have a wide BT range, making the calibration assessment uncertainty quite large. As opposed to our previous study, this work expands the MODIS TEB calibration assessment using DCC method to the MWIR bands using nighttime measurements—where the undesired solar reflectance effects are not present (Chang et al., 2019).

Section 2 presents the MODIS TEB background and previous DCC techniques used for calibration assessments. Section 3 describes the qDCC and DCC normalization methodologies that we developed. Section 4 discusses the Aqua MODIS TEB stability trending and consistency assessments. All DCC and qDCC pixels in this work are collected monthly from MODIS Collection 6.1 (C6.1) Level-1B (L1B) data. The mission long-term trending and mirror side difference are analyzed to assess the instrument performance and identify future calibration improvements. The calibration assessment focuses on the calibration offset bias between the two mirror sides and a calibration bias correction.

2. Background

2.1. MODIS TEB Calibration

MODIS TEB include the MWIR bands 20–25 (3.8 to 4.5 μm) and LWIR bands 27–36 (6.8 to 14.2 μm) spectral regions. All the MWIR bands and LWIR bands 27–30 have 10 photovoltaic (PV) detectors, while the LWIR bands 31–36 have 10 photoconductive detectors. The TEB detectors are located on two cold focal plane assemblies (FPAs): a shortwave and MWIR FPA and a LWIR FPA. The two cold FPAs are nominally controlled on orbit at 83 K using a passive radiative cooler and a heater. The MODIS TEB calibration uses a quadratic calibration algorithm on a scan-by-scan basis for each TEB detector and side of the scan mirror. The linear coefficient of the response function is calibrated scan by scan using a two-point calibration performed via the response to the onboard BB with reference to the SV, while the nonlinear and offset terms come from a look-up table. The BB WUCD is used to characterize and update the instrument nonlinear response coefficients on orbit. The BB WUCD events are performed quarterly. During both nominal operation and WUCD events, the calibration radiance is the BB view-minus-SV view radiance. The quadratic function is also used for EV radiance retrievals. In general, the conversion from digital output to radiance is

\[ L_{\text{target}} = a_0 + b_1 dn + a_2 dn^2, \]  

where \( a_0 \) is the offset term, \( a_2 \) is the quadratic term, and \( dn \) is the digital response of the target (BB or EV) given in digital count. This function is used for the WUCD calibration to derive the \( a_0 \) and \( a_2 \) coefficients and for scan-by-scan linear coefficient calibrations during nominal operation. The MODIS instrument response changes with scan mirror angle, and this has been considered for the BB, SV, and EV radiance calculations.

The Aqua MODIS B-side electronic configuration underwent a formatter reset in January 2018. An electronic setting change can cause mirror side correlated noise and mirror side difference changes. In this instance, the formatter reset caused a few digital output number changes, and its impact is not noticeable for typical (or higher) scene radiances or temperatures. The formatter reset mirror side impact assessment using DCC reveals the effect of the event on colder targets, and a correction for this artifact is included in this manuscript.

2.2. DCC Pixel Identification

The DCC core is the most reflective portion of the cloud, thus providing stable reflectance for instrument response trending and intercomparisons. The DCC pixel identification and selection process in this work
follows that described in detail by Doelling et al. (2004). Potential DCC are identified as pixels located over the tropical domain, between latitudes 30°N and 30°S, with BT lower than 205 K at 11 μm (MODIS band 31). The visible reflectance homogeneity and infrared BTs can be used to capture the convective DCC core. Because DCC have cold anvils (clouds around the core), it is possible for nonuniform cloud pixels to be present around a DCC pixel. Hence, spatial homogeneity thresholds are used to characterize the DCC convective core only. The infrared temperature and visible reflectance (0.65 μm, MODIS band 1) standard deviations (STDs) were computed over all 3 × 3 pixel blocks surrounding each potential DCC pixel. Afterward, if the infrared temperature STD was higher than a 1 K threshold, or the reflectance STD is larger than 3%, the potential DCC pixel was discarded to remove all DCC pixels near cloud edges.

2.3. Calibration Assessment Application

The DCC convective core has been proven to contribute a few advantages for reflective solar band performance and calibration assessments; these are as follows: its steadiness, prevalence in the tropics, minimal water vapor absorption and aerosol effects when viewed from space, and large number of samples. Likewise, these features are useful for the calibration and product stability assessments of the TEB (Chang et al., 2019). As mentioned previously, the lowest BB temperature during every WUCD event fluctuates around 270 K; hence, the offset uncertainty in the nonlinear response function is affected by the WUCD temperature range. Therefore, measurements over cold targets (e.g., DCC) are unique and advantageous for the assessment of the calibration function’s offset term. However, the DCC’s high reflectance can impact the MWIR band BT measurements (Chang et al., 2019). For example, MODIS band 20 daytime DCC measurements are in the 250–280 K range. Hence, the MWIR bands produce higher BT measurements than those produced by the LWIR bands due to their solar reflectance response. In our previous work, the MODIS MWIR bands were excluded from the DCC-associated analyses. However, this manuscript focuses on the development of methodology to solve this issue for these bands.

3. Methodology Development

3.1. qDCC for TEB Assessments

As discussed in section 2, the 0.65-μm reflectance uniformity filter for DCC pixel identification restricts the calibration assessments to daytime DCC measurements. Moreover, the MWIR band daytime measurements are affected by solar reflection. This work presents an improvement to the methodology by using MODIS C6.1 L1B-derived nighttime measurements for the assessment of the TEB using band 31 as a reference. MODIS band 31 BTs and their uniformity are used for pixel identification, as described in section 2.2. Since there are no valid 0.65-μm nighttime reflectance measurements, no reflectance uniformity filter can be applied. Over the Terra and Aqua mission lifetimes, MODIS band 31 has demonstrated to be well calibrated and has shown the best accuracy and precision among all TEB (Li et al., 2013; Xiong et al., 2015). Hence, MODIS band 31’s stability has proven reliable, which made it a reference for calibration assessments. Furthermore, MODIS band 31 has also shown consistency between mirror sides and among its detectors.

The term qDCC is introduced to differentiate it from the more commonly recognized DCC. The lack of a uniformity filter using the visible band can yield DCC cores that are subsets of the qDCC pixels, \( DCC \in qDCC \), for certain time intervals. Additionally, qDCC may contain more cold pixels. Henceforth, when used as a technique, the term DCC will only refer to daytime measurements, due to reflectance usage to categorize DCC pixels. Figure 1 illustrates a flowchart to explain the validity of using nighttime qDCC for TEB assessments. The initial step is to separate daytime and nighttime qDCC. Second, the consistency between DCC and daytime qDCC is evaluated. Lastly, the daytime and nighttime qDCC are compared. Nighttime retrievals remove the solar reflectance impact on the TEB BT measurements.

Figure 2 (top left) shows the Aqua band 31 DCC, daytime qDCC, and nighttime qDCC BT histograms for January 2019, while Figure 2 (top right) displays their normalized distributions. Although the DCC and daytime qDCC counts and histograms are dissimilar, their normalized distributions are almost identical. Figure 2 also illustrates some expected differences between daytime and nighttime qDCC. Nighttime qDCC measurements shift slightly to lower BTs. The DCC and daytime qDCC distribution comparison demonstrates that their correspondent band 31 BT distributions are similar. Additional qDCC samples do not impact the overall distribution. Figure 2 (bottom) shows the average DCC, daytime qDCC, and nighttime qDCC BTs for all Aqua TEB (represented as band center wavelength) for January 2019. Nighttime qDCC...
exclude the solar reflection effect, and thus, the lower BTs come from measuring only the DCC thermal emission. Moreover, slightly higher BTs for bands 24, 30, and 34–36 may be due to the cloud top property [Seemann et al., 2003 and Baum et al., 2012]. Lower BTs provide a distinctive advantage for offset calibration assessments in the instrument response function, making the MWIR bands calibration assessment a possibility by using nighttime qDCC (Chang et al., 2019).

Figure 3 displays count histogram and normalized distribution comparisons between DCC and daytime qDCC BTs for bands 20, 28, and 34. As previously discussed in section 3.1, DCC are a subset of qDCC.

Figure 1. Flowchart to explain the DCC and qDCC pixel selection and validity of using nighttime qDCC for TEB assessments. Rectangles indicate data, and diamonds designate processing. Red and blue symbolize daytime and nighttime measurements, respectively.
However, their normalized distributions are quite similar. Nonetheless, the average qDCC BTs can be affected due to a larger sample size and an asymmetrical distribution. The long-term trending plots in Figure 4 (left column) demonstrate that the average DCC and qDCC BTs have a stable bias, as evidenced by their respective 2003–2019 time series. The long-term series linear regressions show consistent DCC and daytime qDCC changes. Conversely, daytime and nighttime qDCC (Figure 4, right column) exhibit inherent differences due to solar reflectance; this statement holds particularly true for the MWIR bands (e.g., band 20 nighttime qDCC BTs are considerably lower than their daytime qDCC counterpart). Furthermore, it is evident that solar reflectance is not as impactful for the LWIR bands, as exhibited by the parallelism in the daytime and nighttime qDCC long-term linear regressions. Change rates for all linear regressions are presented in section 4.

3.2. DCC Variation and Normalization Modeling

In this work, MODIS band 31 BTs are used as references for the stability assessment of the other bands. As shown in Figure 2, the DCC core BTs have a limited range, and its band 31 BTs can go up to 205 K. However, there is no such thing as consistent DCC at a fixed EV target. The DCC BT distribution and sample size can vary monthly and yearly. Figure 5 illustrates the band 31 monthly DCC BTs and their corresponding STDs. The month-to-month temperature variations are as high as 5 K, and the STDs range from 3.5 to 5.1 K. These fluctuations can impact the calibration assessment’s accuracy and consistency. Hence, because the MODIS band 31 BT distribution varies significantly, direct pixel-to-pixel BT comparisons between each band and band 31 are inadequate. This work provides an improved, developed method to normalize the other bands BTs to reference band 31 BTs.

Figure 6 shows the DCC BT correlation between bands 22, 28, and 35 and band 31. The LWIR bands BTs exhibit linear dependency to the band 31 BTs, while the MWIR bands exhibit nonlinear dependency. Nonetheless, all bands exhibit BTs highly correlated to those of band 31 for both the DCC and nighttime qDCC. Thus, these affinities can be used for the development of an empirical model to normalize all other bands BTs to a reference temperature (i.e. MODIS band 31 BTs) to enhance the assessment’s accuracy.
Because the band 31 BT distribution can spread out over a 20 K range, a reference temperature is defined for normalization, and the following empirical model is developed:

\[
BT_{model}(b) = c_0 + c_1(BT_{31} - BT_{31,\text{ref}}) + c_2(BT_{31} - BT_{31,\text{ref}})^2,
\]

(2)

where \(c_{0,1,2}\) are fitting coefficients and \(BT_{31,\text{ref}}\) is the reference temperature, designated as 200 K in this study. The fitting coefficients are determined from the model regression dependence (Figure 6). The \(c_0\) fitting coefficient is the band's normalized DCC BT to band 31 at the reference BT. The fitting coefficients can then be used to obtain the BT distribution after normalization as such:

\[
BT^-(b) = BT(b) - c_1(BT_{31} - BT_{31,\text{ref}}) - c_2(BT_{31} - BT_{31,\text{ref}})^2.
\]

(3)

Figure 4. (left column) DCC (red) and daytime qDCC (black) long-term trending. (right column) Nighttime (red) and daytime qDCC (black) long-term trending. Lines represent time series linear regressions.

Figure 5. (top) Aqua MODIS band 31 DCC long-term trending. Each marker symbolizes the monthly-averaged BT. (bottom) Aqua MODIS band 31 monthly DCC BT STD long-term trending.
This developed empirical model is used in section 3.3 to demonstrate the advantages of using this methodology. DCC (or qDCC) and normalized DCC (or qDCC) will be compared and discussed. Figure 7 displays the probability density function (PDF) of DCC and nighttime qDCC BTs and normalized BTs for the LWIR bands. It is evident that both the DCC and qDCC have BT ranges that spread larger than 20 K. Moreover, as was stated previously, these distributions vary with time. However, after normalization, the BT ranges become narrower—down to a few kelvin units (e.g., bands 27, 28, 32, 33, and 34). As shown in Figure 2, band 30 is also affected by the DCC BT spectrum, which explains why its BT range is 10 K even after the standardization. Nonetheless, all LWIR bands exhibit an improvement after their BTs have been normalized. Furthermore, the asymmetrical BT distribution features are drastically removed. A symmetrical distribution improves the statistical analysis' accuracy (e.g., reduces the DCC fluctuation effect) by causing instrument noise performance to dominate the distribution changes instead. Ultimately, these improvements make the noise performance trending feasible.

Figure 8 displays the PDF of nighttime qDCC and normalized nighttime qDCC application for MWIR bands 20–25 (band 21 is excluded). As was mentioned in the preceding sections, while still dependent on the band 31 BTs, the MWIR bands exhibit larger BT fluctuations than do the LWIR bands. Nonetheless, the normalization removes the band 31 BT dependency and enhances the assessment’s accuracy. Moreover, the BT distribution is smoother after the standardization. However, improvements on the BT range appear to be limited, since the distribution is not as narrow, particularly for bands 20, 22, and 23, as that of the LWIR bands.

Overall, a near-Gaussian distribution for all the TEB is a significant enhancement. The asymmetrical features of the original DCC samples are due to the asymmetrical distribution of the band 31 BTs. More importantly, the near-Gaussian BT distribution indicates that the random BT fluctuation of the DCC samples (using the fixed band 31 BT reference) and instrument measurement uncertainty dominate the DCC uncertainty. Since the DCC are stable targets, their distribution width can be used to assess instrument measurement uncertainty changes over time. All data presented in this work are derivatives of the MODIS C6.1 L1B product. Over the Aqua mission’s life span, a few MODIS TEB detectors have been identified as noisy. Naturally, these can have an effect on the noise performance. Hence, a noise performance assessment can be a helpful, telling piece when evaluating instrument performance.

### 3.3. Modeling Development

The MODIS TEB use a quadratic function to describe the instrument’s response (shown in equation ((1))). During nominal operation, the uncertainty of the offset \(a_0\) and quadratic \(a_2\) terms propagates to the linear coefficient calculation throughout its calibration, along with the BB emissivity uncertainty and temperature measurement error:

\[
\frac{\Delta b_1}{b_1} = \Delta \varepsilon_{BB} + \left[ \frac{dL(T)}{dT} \right]_{T=T_{BB}} \frac{\Delta T_{BB}}{L_{BB}} - \frac{\Delta a_0}{L_{BB} b_1^2} - \frac{\Delta a_2}{b_1^2}. \tag{4}
\]

Using a simplification of the EV retrieval equation, \(\Delta \varepsilon_{BB}^{eff} = \Delta \varepsilon_{BB} + \left[ \frac{dL(T)}{dT} \right]_{T=T_{BB}}\), the impact on the EV radiance retrieval is...
Figure 7. The PDF of DCC and nighttime qDCC BTs and normalized BTs for the LWIR bands. Red is for DCC, and blue is for nighttime qDCC. The narrower PDF is after normalization.

Figure 8. The PDF of nighttime qDCC BTs (blue line) and the normalized BTs (red dotted line) for the MWIR bands.
The calibration offset bias dominates and affects cold (low EV radiance) target retrievals. Hence, the offset uncertainty impact is modeled by

\[
\Delta L_{EV} = \Delta L_{BB} + (L_{BB} - L_{EV}) \left( \frac{\Delta a_0}{L_{EV}} - \frac{\Delta a_2}{b_1} \right),
\]

(5)

When dealing with cold targets (e.g., DCC), the offset bias between mirror sides can be estimated using

\[
\Delta a_0 = \frac{\Delta L_{DCC}}{L_{BB} - L_{DCC}},
\]

(6)

where \( L_{DCC} \) is the DCC radiance and \( \Delta L_{DCC} \) is the radiance measurement bias between the mirror sides. Moreover, the offset bias error impact on warm targets can be evaluated as

\[
\frac{\Delta L_{EV}}{L_{EV}} = \left( \frac{\Delta L_{DCC}}{L_{DCC}} \right) \left( \frac{L_{BB} - L_{EV}}{L_{BB} - L_{DCC}} \right) \left( \frac{L_{DCC}}{L_{EV}} \right).
\]

(8)

Equations (7) and (8) are used in the calibration assessment in section 4.3.

4. Application to TEB Calibration Assessments

4.1. Stability Assessment

The Aqua MODIS stability assessment is performed using the qDCC and DCC long-term trending for all TEB and the LWIR bands, respectively. Figure 9 demonstrates how using normalized qDCC measurements improves the evaluation’s accuracy and illustrates the (left) qDCC and (right) normalized qDCC long-term trending, respectively, for bands 22, 25, 28, and 32. It is evident that the qDCC BT fluctuations are significantly removed after normalization (band 31 reference BT = 200 K); this is congruent with the results shown in Figures 7 and 8. Table 1 lists the Aqua MODIS TEB stability assessment change rates and uncertainties, while Figure 10 illustrates these results. These metrics indicate that using DCC (as opposed to qDCC) produces slightly better values for the LWIR bands. Furthermore, the normalization improves the assessment’s accuracy. For bands 22 and 23, the qDCC standardization produces smaller change rates than without it. Based on the analysis in section 3.2, the normalization can reduce the fluctuation and seasonal oscillation effects, all the while providing more accurate results.

Because the normalization removes the DCC sample’s fluctuation effect and makes the results more reliable, the change rates are computed using the DCC and qDCC BTs after these have been normalized. MODIS band 29 exhibits the largest change rate (approximately 0.05 K/year upward). MODIS band 30 shows a downward trend of 0.035 K/year, while bands 27 and 28 display decreasing 0.013 K/year change rates. MODIS MWIR bands 20, 22, and 23 have downward change rates that range from 0.03 to 0.04 K/year. All other bands appear to be quite stable, and most of them exhibit change rates within their respective uncertainties.

As demonstrated in section 3.2, the MODIS band 31 DCC BT distribution varies monthly and induces asymmetrical artifacts to all TEB. Moreover, the monthly STD is significantly affected by these asymmetrical features. Hence, by normalizing the DCC data, its distribution becomes symmetrical and near-Gaussian, thus reducing the DCC fluctuation effect and, in turn, the measurement uncertainty (specifically for the LWIR bands). These improvements make using the DCC STD measurements for instrument performance assessment feasible.

Figure 11 illustrates the qDCC and normalized qDCC BT STD long-term trending for bands 22, 25, 28, and 32. The linear regressions can be used to evaluate STD changes from the mission beginning. Table 2 lists the DCC BT STD change rates and uncertainties for all Aqua MODIS TEB. Results indicate that the Aqua MODIS TEB performance is quite stable, except for band 29, due to a few detectors flagged as noisy. The downward BT STD trends for bands 24, 25, and 27 imply their performance improved slightly. Moreover, the Aqua MODIS bands 24 and 25 change rates are within their uncertainties.
4.2. Mirror Side Consistency Assessment

Consistency between the 2 mirror sides and 10 detectors is important for the MODIS image quality and calibration assessments. The offset term, sensitive to cold target (e.g., DCC) measurements, in the instrument response function is also mirror side and detector dependent. The Aqua MODIS LWIR bands BT mirror side differences were analyzed using DCC measurements, and a calibration model was developed by Chang et al. (2019) to fix a calibration offset error that produces large mirror side differences at low BT scenes. Hence, the qDCC availability provides a previously inexistent alternative to analyze mirror side differences at low BTs.

![Figure 9](image-url)

**Figure 9.** Demonstration of the calibration assessment accuracy enhancements using normalized qDCC. The (left) qDCC and (right) normalized qDCC long-term trending for bands 22, 25, 28, and 32. Markers represent monthly-averaged qDCC BTs and lines are the linear regressions of the times series.

### Table 1

*Aqua MODIS TEB Stability Assessment Results Using DCC, qDCC, Normalized DCC, and Normalized qDCC Techniques*

| B | qDCC BT (K) | DCC | Normalized DCC | qDCC | Normalized qDCC |
|---|-------------|-----|----------------|------|-----------------|
|   | Change rate | Rate uncertainty | Change rate | Rate uncertainty | Change rate | Rate uncertainty | Change rate | Rate uncertainty |
| 20 | 204.97      | 201.20 | -0.29          | 0.017 | 0.003           | -0.041 | 0.006            | -0.030 | 0.007            |
| 22 | 205.46      | 201.46 | -0.025         | 0.016 | 0.007           | -0.047 | 0.010            | -0.038 | 0.005            |
| 23 | 205.83      | 202.87 | -0.006         | 0.021 | 0.004           | 0.000  | 0.019            | 0.000  | 0.010            |
| 24 | 211.31      | 210.30 | 0.040          | 0.015 | 0.004           | 0.001  | 0.019            | 0.000  | 0.010            |
| 25 | 205.15      | 219.79 | -0.003         | 0.014 | 0.007           | 0.032  | 0.017            | 0.048  | 0.002            |
| 27 | 201.20      | 201.66 | 0.008          | 0.018 | 0.004           | -0.003 | 0.014            | 0.008  | 0.003            |
| 28 | 201.46      | 201.16 | 0.006          | 0.021 | 0.004           | -0.008 | 0.020            | 0.008  | 0.003            |
| 29 | 205.46      | 201.66 | -0.006         | 0.022 | 0.004           | -0.008 | 0.026            | 0.003  | 0.006            |
| 30 | 201.46      | 201.66 | 0.008          | 0.018 | 0.004           | -0.008 | 0.020            | 0.004  | 0.003            |
| 31 | 201.30      | 201.66 | -0.006         | 0.021 | 0.005           | -0.007 | 0.022            | 0.005  | 0.004            |
| 32 | 205.07      | 206.08 | 0.006          | 0.022 | 0.004           | -0.008 | 0.026            | 0.003  | 0.006            |

Note. Change rate and uncertainty units are K/year.
for the MWIR bands. Figure 12 illustrates the qDCC BT mirror side differences for bands 20 to 25 and 27 to 30 over the entire Aqua mission (July 2002 to September 2019). Since the seasonal fluctuations do not have significant impacts on month-to-month mirror side differences, the normalization is not applied. The MODIS PV LWIR bands 27–30 results are consistent with those using DCC. Moreover, the MODIS photoconductive LWIR bands do not exhibit significant mirror side differences. Conversely, the MWIR bands display significant mirror side differences at low BTs. The BT mirror side difference changes after January 2018 are due to an Aqua formatter reset. During 2002, there were multiple configuration changes, which caused the mirror side difference change. All TEB (except band 21) have smaller mirror side relative biases after the event. The mirror side difference, calibration coefficient relative bias, and impact on the EV scenes are presented and discussed in the next section.

4.3. Calibration Assessment

The model presented in section 3.3 can be used to assess the instrument's mirror side differences. Applying equation (6), the relative difference between the two mirror sides, \( \frac{L_{ \text{ms} }^{\text{EV}} - L_{ \text{ms} }^{\text{EV}}}{L_{ \text{ms} }^{\text{EV}}} \), is modeled as

![Figure 10. Aqua TEB stability assessment using DCC [blue], qDCC [yellow], normalized DCC [red], and normalized qDCC [green] techniques.](image)

![Figure 11. DCC BT STD enhancements and their impacts on long-term trending for bands 22, 25, 28, and 32. Markers represent monthly-averaged qDCC BTs, and lines are the linear regressions of the times series.](image)
where $\Delta L_{ms}^{2} - ms_{1}^{EV} = \frac{1}{L_{EV}} - \frac{1}{L_{BB}} \Delta a_{0}^{ms_{2} - ms_{1}}$, and $\Delta a_{0}^{ms_{2} - ms_{1}} = \Delta a_{0}^{ms_{2}} - \Delta a_{0}^{ms_{1}}$ are the mirror side differences. Moreover, the offset bias between mirror sides can be estimated using

$$
\Delta a_{0}^{ms_{2} - ms_{1}} = \frac{\Delta L_{ms}^{2} - ms_{1}^{EV}}{L_{BB} - L_{DCC}}.
$$

Lastly, the offset bias impact on EV retrievals can be modeled using equation (8).

Figure 13 displays the mirror side biases calculated using the model described anteriorly for MWIR bands 20 to 25 and LWIR bands 27 to 30. The squares represent DCC results, and the lines define the model. Diamonds and triangles describe the Dome Concordia (Dome-C) results (Shrestha et al., 2018), while asterisks and crosses depict the ocean scenes (Díaz et al., 2019). Blue and red markers and lines construe the results before and after the Aqua MODIS formatter reset in January 2018. The DCC and model results agree quite well for Dome-C and the ocean scenes for most bands (except band 29). Band 29 exhibits the largest measurement uncertainty due to the detectors being flagged as noisy detectors. The band 21 mirror side difference was analyzed as well. Band 21 uses a linear calibration algorithm without an offset term. However, an offset equal to zero might not be able to catch low-BT biases or mirror side bias changes before and after the formatter reset. These results were validated using Dome-C and ocean targets.

### Table 2

| Band | STD change rate | Rate uncertainty |
|------|----------------|-----------------|
| 20   | 0.011          | 0.004           |
| 22   | 0.016          | 0.005           |
| 23   | 0.015          | 0.004           |
| 24   | −0.001         | 0.001           |
| 25   | −0.002         | 0.002           |
| 27   | −0.015         | 0.003           |
| 28   | 0.003          | 0.001           |
| 29   | 0.043          | 0.002           |
| 30   | 0.000          | 0.001           |
| 32   | 0.007          | 0.001           |
| 33   | 0.006          | 0.001           |
| 34   | 0.005          | 0.001           |
| 35   | 0.004          | 0.001           |
| 36   | 0.004          | 0.001           |

Note. Change rate and uncertainty units are K/year.

Figure 12. Quasi-DCC BT mirror side-relative biases for all MODIS PV bands over the entire mission (July 2002 to September 2019). The vertical dashed lines represent the Aqua formatter reset (January 2018).
As mentioned previously, due to the limited WUCD BB temperature range, the offset uncertainty is large and affects the measurements over low-BT EV scenes. The formatter setting also affects the mirror side response and thus the offset difference between the two mirror sides. The results using DCC, as well as the modeling of the offset bias, are useful for calibration algorithm improvements. The appropriate approach to improve the calibration for Aqua MODIS TEB is currently under investigation.

5. Summary

The DCC cores are one of the coldest and most consistent calibration targets and thus are suitable for MODIS LWIR bands calibration assessments (e.g., offset effect in the quadratic calibration algorithm). However,
solar reflected radiance impedes the MWIR bands calibration assessments using DCC. Hence, a quasi-DCC technique was developed to allow the calibration assessment of these MODIS bands. Moreover, a DCC normalization method was also developed to remove the DCC BT fluctuation impact and enhance the assessment accuracy. In order to do this, an empirical model was developed and applied to normalize the DCC BTs to a well-calibrated reference band. Both the DCC and qDCC BT distributions became close to symmetrical and Gaussian-shaped after the normalization. This methodology was employed on the Aqua MODIS instrument TEB. The calibration stability and consistency were assessed for all bands. Moreover, the Aqua MODIS formatter reset effect on the calibration offset bias between mirror sides was analyzed, and a calibration correction is proposed to improve future Collections.

References

Baum, B. A., Paul Menzel, W., Frey, R. A., Tobin, D. C., Holz, R. E., & Ackerman, S. A. (2012). MODIS cloud-top property refinements for Collection 6. *Journal of Applied Meteorology and Climatology*, 51(6), 1145–1163.

Cao, C., Xiong, X., Wu, A., & Xu, X. (2008). Assessing the consistency of AVHRR and MODIS L1B reflectance for generating Fundamental Climate Data Records. *Journal of Geophysical Research*, 113, D09114. https://doi.org/10.1029/2007JD009363

Chang, T., Xiong, X., & Shrestha, A. (2019). Assessment of MODIS TEB calibration performance using deep convective clouds, in Proc. SPIE, Earth Observing Systems IX.

Díaz, C., Xiong, X., & Wu, A. (2019). MODIS thermal emissive bands calibration stability using in-situ ocean targets and remotely-sensed SST retrievals provided by the group for high resolution sea surface temperature, Proc. SPIE 11014, Ocean Sensing and Monitoring XI, 110140P.

Doelling, D.R., Hong, G., Morstad, D., Bhart, R., Gopalans, A., & Xiong, X. (2010). The characterization of deep convective cloud albedo as a calibration target using MODIS reflectances, in Proc. SPIE, Earth Observing Missions and Sensors: Development, Implementation, and Characterization, vol. 7862, 78620F-1 to 78620F-10.

Doelling, D. R., Lukashin, C., Minnis, P., Scarino, B., & Morstad, D. (2012). Spectral reflectance corrections for satellite intercalibrations using SCIAMACHY data. *IEEE Transactions on Geoscience and Remote Sensing*, 9(1), 119–123.

Doelling, D. R., Morstad, D., Scarino, B. R., Bhart, R., & Gopalans, A. (2013). The characterization of deep convective clouds as an invariant calibration target and as a visible calibration technique. *IEEE Transactions on Geoscience and Remote Sensing*, 51(3), 1147–1150.

Doelling, D. R., Nguyen, L., Minnis, P. (2004). On the use of deep convective clouds to calibrate AVHRR data, in Proc. SPIE, Earth Observing Systems IX, pp. 281–299.

Doelling, D. R., Wu, A., Xiong, X., Scarino, B., Haney, C. O., Morstad, D., & Gopalans, A. (2015). The radiometric stability and scaling of Collection 6 Terra- and Aqua-MODIS VIS, NIR, and SWIR spectral bands. *IEEE Transactions on Geoscience and Remote Sensing*, 53(8), 4520–4535.

Fougne, B., & Bach, R. (2009). Monitoring of radiometric sensitivity changes of space sensors using deep convective clouds: Operational application to PARASOL. *IEEE Transactions on Geoscience and Remote Sensing*, 47(3), 851–861.

Hv, Y., Wielicki, B., Yang, P., Stockhouse, P., Lin, B., & Young, D. (2004). Application of deep convective cloud albedo observations to satellite-based study of terrestrial atmosphere: Monitoring stability of space-borne measurements and assessing absorption anomaly. *IEEE Transactions on Geoscience and Remote Sensing*, 42(11), 2594–2599.

Li, Y., Wu, A., & Xiong, X. (2013). Evaluating calibration of MODIS thermal emissive bands using infrared atmospheric sounding interferometer measurements, Proc. of SPIE Vol. 8724. https://doi.org/10.1117/12.2016621

Seemann, S. W., Li, J., Gurnley, L. E., Strabala, K. I., & Menzel, W. P. (2003). "Operational retrieval of atmospheric temperature, moisture, and ozone from MODIS infrared radiances", Proc. SPIE 4895, Applications with Weather Satellites. https://doi.org/10.1117/12.466686

Shrestha, A., Wu, A., & Xiong, X. (2018). Evaluating calibration consistency of Terra and Aqua MODIS LWIR PV bands using Dome C, Proc. SPIE”, 10644, 106440N

Soehn, B.-I., Ham, S.-H., & Yang, P. (2005). Possibility of the visible-channel calibration using deep convective clouds overshooting the TTL. *Journal of Applied Meteorology and Climatology*, 48, 2271–2283.

Xiong, X., Wu, A., Wenny, B. N., Madhavan, S., Wang, Z., Li, Y., et al. (2015). Terra and Aqua MODIS thermal emissive bands on-orbit calibration and performance. *IEEE Transactions on Geoscience and Remote Sensing*, 53(10), 5709–5721.