remote sensing

Article

A Practical Approach to Landsat 8 TIRS Stray Light Correction Using Multi-Sensor Measurements

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Abstract: It has been noticed that the Landsat 8 Thermal Infrared Sensor (TIRS) had an issue with stray light since its launch in 2013. This artifact is due to out-of-field radiance that scatters onto the TIRS focal plane. Much effort has been taken to develop an algorithm to remove this artifact. One proposed approach involves using TIRS data itself (referred to as TIRS-on-TIRS) to retrieve the true sensor-reaching radiance. This approach has been proven to be operational and supports the TIRS Collection-1 product. A methodology of calibrating the TIRS sensor with information from the Geostationary Operational Environmental Satellite (GOES) instrument may optimally reduce the stray light effect for special cases where there is a large temperature contrast between the edge of the TIRS image and out-of-field radiance (referred to as GOES-on-TIRS). This paper illustrates a GOES to TIRS conversion (GTTC) algorithm with the North American Regional Reanalysis (NARR) data to support the GOES-on-TIRS method. Results show this GOES_TIRS correction method performs similarly to the TIRS Collection-1 product. Additionally, a simplified methodology is proposed to improve the GOES data processing which can operationalize the GOES-on-TIRS algorithm. Results also show that, using the proposed algorithm with these special cases, the maximum difference between the Collection-1 product and the GOES-on-TIRS correction results in a temperature difference from 0.5% to 0.7%.

Keywords: Landsat 8; TIRS; stray light; GOES; calibration

1. Introduction

The TIRS instrument on the Landsat 8 satellite provides thermal infrared images for the global land and sea surface temperature measurement. TIRS is a push-broom sensor with long linear detector arrays and has two spectral bands centered at 10.9 and 12.0 µm (known as band 10 and band 11) with $-7.5°$ to $+7.5°$ field-of-view (FOV). TIRS thermal band absolute radiometric uncertainty requirement is 2% in the 260 K to 330 K range [1]. Conventional calibration methods have been applied to the TIRS instrument during the checkout period after launch. However, after the first year of on-orbit calibration, a seasonal-varying absolute calibration error was observed that could not be mitigated by standard calibration adjustments. This bias error was approximately 0.29 ($Wm^{-2}sr^{-1}\mu m^{-1}$) in band 10 and 0.51 ($Wm^{-2}sr^{-1}\mu m^{-1}$) in band 11 (i.e., 8% or even higher) [2,3]. It has been determined that the third lens element in the TIRS telescope structure is reflecting off-axis thermal infrared rays into the focal plane. The origin of the stray light artifacts has been well documented in previous studies [4–7]. An example illustrating the origin of the incoming stray light can be seen in Figure 1. Two algorithmic approaches have been proposed to remove stray light artifacts and make the TIRS data more reliable for further scientific usage [5]. One approach involves using the TIRS data itself (referred to as TIRS-on-TIRS) to retrieve the true sensor-reaching radiance.

Another methodology is based on thermal infrared images captured by external geostationary sensors, such as Geostationary Operational Environmental Satellite (GOES-N) in the North America regions (referred to as GOES-on-TIRS). The TIRS-on-TIRS approach has been implemented operationally into the Landsat Product Generation System as of early 2017 and is referred to as the Landsat 8 Collection-1 product. However, there is a reason to believe that certain extreme scenario's, where TIRS pixels are of a different radiance than out-of-field data, may pose a challenge to the TIRS-on-TIRS methodology. By contrast, the GOES-on-TIRS method may be able to estimate the stray light origin more accurately from geostationary wide-field imagery. However, difficulties in the process of using different sensors may involve extra uncertainties in the final correction result. The conversion algorithm of the external sensor's data to TIRS sensor-reaching radiance may be time consuming and costly. It will make investigation and validation of the GOES-on-TIRS method much more laborious. In this paper, we describe a GOES-N to TIRS Conversion (GTTC) methodology with the North American Regional Reanalysis (NARR) data. Additionally, a simplified quick-GTTC (Q-GTTC) algorithm, is proposed to improve the feasibility of the GOES-on-TIRS stray light removal algorithm. Finally, we validate results of the GOES-on-TIRS approach with Collection-1 data.

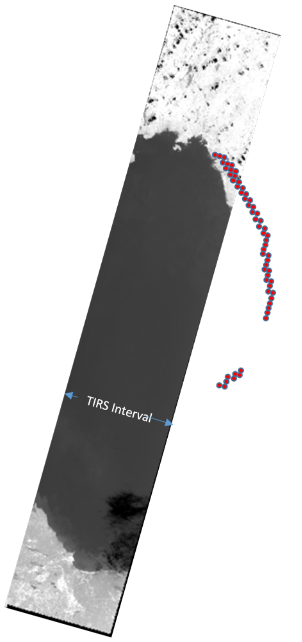


Figure 1. The geometry of stray light in Landsat 8 TIRS. The red dots indicate the various sources of stray light inside and outside the field of view (FOV), for a particular focal plane detector. Some of these locations fall inside the TIRS interval while other are located outside the FOV.

2. Background

Landsat 8 stray light artifacts add non-uniform additional radiance onto the focal plane through the TIRS field-of-view. This error can be 4% to 5% in band 10 and 8% to 9% in band 11 [3]. The origin and geometry of the stray light artifacts has been documented by previous study [5], which described the methodology to remove the stray light (often referred to as ghost effect) artifacts as;

$$L_{bias} = L_{TIRS} - L_{truth} = aL_G + c\,, \tag{1}$$

where the left side of Equation (1) represents the stray light bias on the focal plane in radiance units. It can be derived by differencing the radiance actually measured by the TIRS sensor and a ground truth radiance. On the right side of Equation (1), L_G is the spatially dependent stray light radiance from outside the field-of-view. Once the bias and out-of-field radiances have been determined, a linear regression can then be established to solve for the gain a and offset c terms. These coefficients can be used to estimate stray light bias for future corrections. The bias radiance can be estimated by comparing the TIRS data with other near-coincident thermal data, such as the Moderate Resolution Imaging Spectroradiometer (MODIS) Terra/Aqua instrument. Therefore, the major issue in the stray light removal problem is to obtain the out-of-field radiance. Two different scenarios have been proposed in [5] as described below.

2.1. TIRS Collection-1 Product

A calibration method which utilizes the TIRS data itself as the source of ghost radiance to correct the stray light was proposed in 2015 [5]. In this TIRS-on-TIRS method, the stray light radiance location that falls within the TIRS interval is sampled directly. For those stray light origin locations (referred to as ghost locations) that fall outside of the TIRS interval, the closest TIRS pixels at the edge of the interval, will be utilized to represent the actual ghost radiance values. The performance of this algorithm has been validated and documented by [6]. In most cases, this approach reduced the radiometric stray light error to 0.5%. In early 2017, this technique was integrated into the Landsat Product Generation System because of its simplicity. The TIRS data, with this operational stray light removal algorithm, is known formally as the TIRS Collection-1 product. Although the TIRS-on-TIRS method has shown a high potential to reduce stray light artifacts, there are some special cases in which the TIRS-on-TIRS method may not optimally mitigate stray light. These are cases where there is a large temperature contrast between the edge of the TIRS image and of out-of-field radiance, which is further discussed in Section 4.3.

2.2. Stray Light Correction with External Sensors

An alternative stray light removal algorithm, which relies on near-coincident thermal infrared data from an external satellite sensor, was proposed in 2015 by Montanaro et al. [5]. This methodology has been implemented based on the Geostationary Operational Environmental Satellite (GOES) System where initial calibration results have been documented in the literature [8]. GOES-N instruments can provide full disk (i.e., outside the FOV of TIRS) infrared imagery. Therefore, this GOES-on-TIRS calibration technique has the ability to reveal any true negative circumstances outside the TIRS field-of-view. However, the orbit status and spectral response of the external sensor may be significantly different from the TIRS instruments. Thus, much effort to cross-calibrate data from such data sources to TIRS top-of-atmosphere radiance is required, which may introduce additional uncertainties to the stray light correction result and reduce the feasibility of the process.

3. Methodology

This section describes the GOES-on-TIRS stray light reduction algorithm. The first part of this section focuses on the conversion of GOES-N data to TIRS sensor-reaching radiance (GTTC algorithm) where we estimate the out-of-field radiance. Differences in sensor response, viewing angle, and slant path between GOES and TIRS instruments needs to be taken into account. Different from the previously published algorithm [5,9], the GTTC algorithm uses NARR data to support atmospheric understanding and characterization. Although preliminary results have shown the GOES-on-TIRS method, based on GTTC algorithm, has similar performance to the TIRS-on-TIRS method, the GOES-on-TIRS method is intricate and computational. For each TIRS scene, the GOES-on-TIRS methodology needs extra operating step so as to prepare the GOES data for algorithm input.

We end this part with analysis of a proposed approach which simplifies many of the sensor/data adjustments, what we will call the “Quick-GOES to TIRS Conversion” (Q-GTTC) algorithm, which can lead to faster processing of data. The remainder of this section describes GOES-on-TIRS stray light correction based on the GTTC and Q-GTTC algorithms.

3.1. Conversion of GOES-N Data to TIRS Sensor-Reaching Radiance

The flowchart of the proposed GOES to TIRS conversion (GTTC) algorithm is shown in Figure 2. First, we get the input GOES-N data, which is accessible from NOAA Comprehensive Large Array-Data Stewardship System (CLASS) [10]. After the calculation of effective viewing angle, MOTRAN simulations and the Relative Sensor Response (RSR) adjustment can be conducted to estimate the gain and offset coefficients for the conversion. The last step is applying the estimated coefficients to GOES-N data.

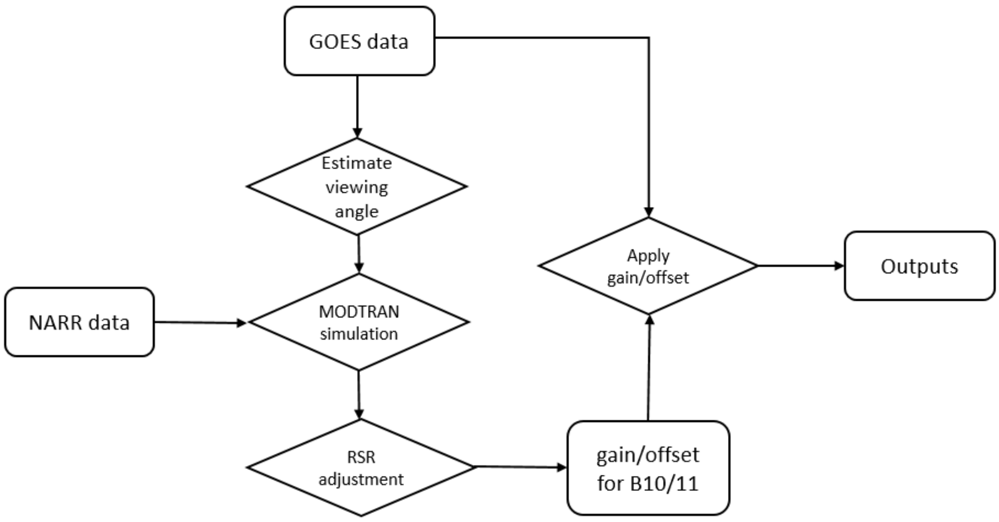


Figure 2. The standard flowchart for the GTTC algorithm.

3.1.1. Simulation Setup

The moderate resolution atmospheric transmission (MODTRAN) code was used to relate GOES-N data to TIRS sensor-reaching radiance from 10 to 13 µm. For a given location or Landsat scene, the surface temperature input was varied from 270 K to 330 K in increments of 10 K. Three different surface emissivity materials (i.e., water, soil, and grass) were used in the simulations. Information such as humidity, geo-potential height and temperature, has been obtained from the North American Regional Reanalysis (NARR) data [11] and used as input for MODTRAN. The sensor viewing angle (SVA) is set to zero degrees (nadir) in the first run to simulate the TIRS at-sensor radiance. In the second run, since the GOES-N instrument is a geosynchronous satellite, the effective viewing angle of the instrument is factored in to simulated GOES sensor-reached radiance. This viewing angle parameter is estimated by an ellipsoidal technique [12].

3.1.2. Relative Spectral Response (RSR) Adjustment

The GOES-N instruments (i.e., GOES-13 and GOES-15) only have a single thermal infrared band (i.e., band 4), which is similar to band 10 from TIRS (but not band 11). In order to utilize the GOES data as a references for the origin of the stray light source, a relative spectral response (RSR) adjustment is necessary. That is, GOES-N radiance is adjusted to look like TIRS radiance. These spectral responses can be seen in Figure 3.

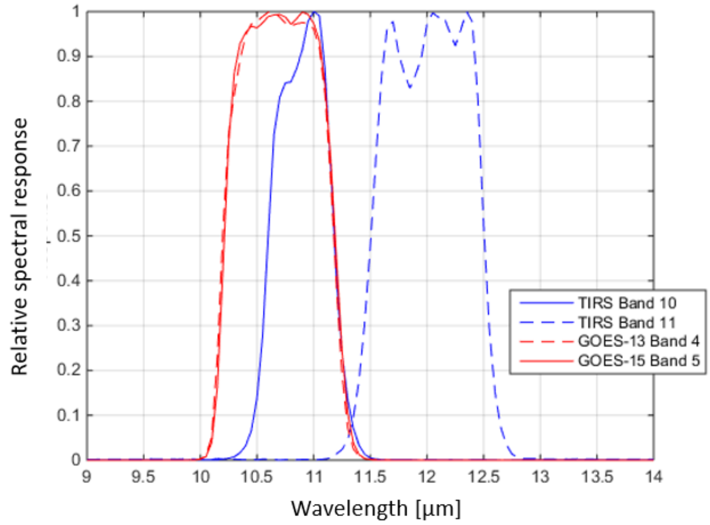


Figure 3. Relative spectral response for GOES-N versus Landsat 8 TIRS. The blue solid and dash lines are TIRS bands 10 and 11. The red solid and dash lines represent the band 4 of GOES-13 and GOES-15 separately. Notice the RSR of GOES-13 and 15 are relatively close.

In Section 3.1.1, MODTRAN simulation results utilized spectral at-sensor radiances for seven different surface temperatures and three materials. Thus, for a specific TIRS scene, 42 simulations were generated (21 for TIRS and 21 for GOES). These spectral radiances were integrated with different RSR functions to generate band-effective radiances for each of the TIRS and GOES bands. This was then followed by a 21-point linear regression, as shown in Figure 4, in which the gain and offset coefficients were computed. These coefficients are used to convert the effective radiance of GOES-N band 4 to effective radiances for TIRS bands 10 and 11.

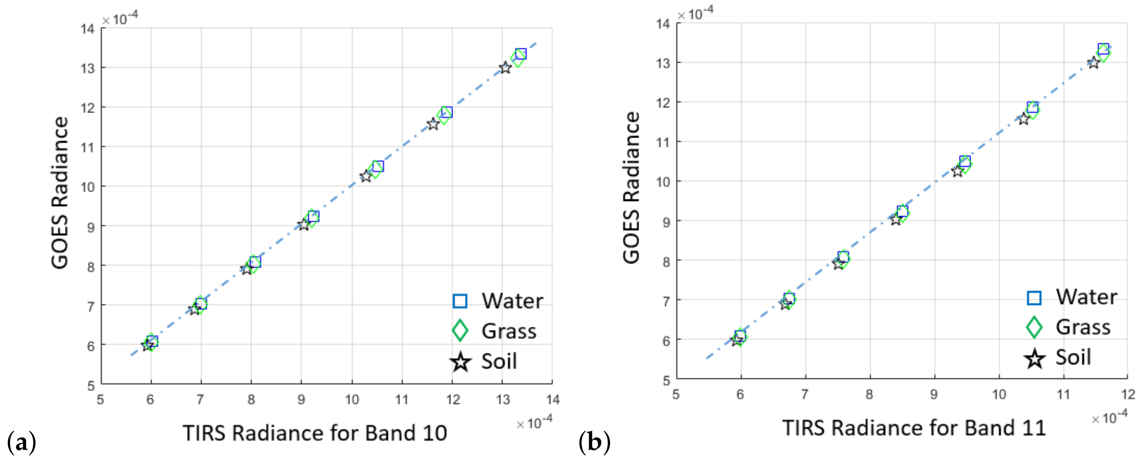


Figure 4. Linear regression relating TIRS radiance to GOES band 4 radiance for (**a**) TIRS band 10 and (**b**) band 11. In both cases the MODTRAN simulation was based on three different materials (water, grass, and soil) with a temperature range from 270 to 330 K. A total of 21 top-of-atmosphere (TOA) spectral radiances were simulated for each sensor (i.e., both TIRS and GOES).

3.2. Quick-GOES to TIRS Conversion (Q-GTTC) Algorithm

For each given TIRS scene, all the steps in Sections 3.1.1 and 3.1.2 need to be run to estimate the unique slope and intercept coefficients to compensate GOES-N data. This procedure involves multiple tools and databases. As shown in Figure 2, the most time consuming part is the MODTRAN simulation, which can take 2 to 3 h. Other steps, such as viewing angle calculating, need manual manipulation for each TIRS scene. To make the GOES-on-TIRS algorithm more operational, as in the TIRS-on-TIRS approach, a simplified Q-GTTC algorithm is proposed.

Instead of calculating the coefficients for each case or scenario, "general" conversion coefficients for all the GOES-N scenes could be derived from a relatively small geographic dataset. For example, our representative dataset contains 20 to 30 TIRS scenes, which span different temperature ranges and locations specifically in North America. We then ran the GOES-N to TIRS cross-calibration to estimate the different gain/bias coefficients for each case. This was followed by estimating a mean slope and intercept, as seen in Figure 5. This mean slope and intercept is then used as "general" coefficients to calibrate/correct new cases. As shown in Figure 6, the most time consuming steps in GTTC algorithm have been removed. For the conversion of new cases, the general gain/offset coefficients can be applied to the GOES-N data directly. With this alternative simplified methodology, the processing time for a single TIRS scene is reduced to less than 30 min.

We then examined the uncertainty of using Q-GTTC algorithm for the GOES-N data conversion, for both TIRS bands 10 and 11. Figure 5 illustrates the lookup-tables (LUTs) for GOES-N radiance to TIRS radiance for seven test cases. The red dashed line is the mean mapping value for the given cases. Figure 7 shows the uncertainty involved using Q-GTTC algorithm where we examine error and radiance ranges. We first plot the error between the mean LUT mapping and each of the seven cases, as can be seen by the various colored lines. The typical GOES-N radiance range is from 6 to 11 ($Wm^{-2}sr^{-1}\mu m^{-1}$) (corresponding to cold snow to hot land pixels), as illustrated by the heavy vertical red dashed lines. Thus, using Q-GTTC algorithm will introduce error on the order of ± 0.15 (band 10) to ± 0.2 (band 11) ($Wm^{-2}sr^{-1}\mu m^{-1}$) in the GOES-N conversion process. In some very extreme temperature cases, the error can be up to ± 0.4 ($Wm^{-2}sr^{-1}\mu m^{-1}$). In Section 4, we discuss the impact of this uncertainty on the overall stray light removal algorithm.

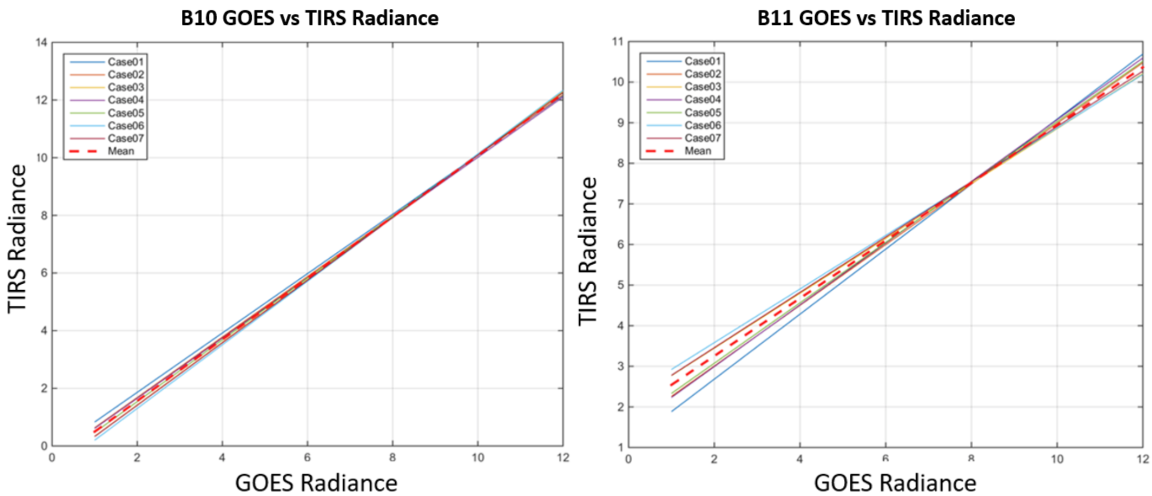


Figure 5. Lookup-tables for the mapping of GOES-N radiance to TIRS radiance for seven test cases. The figure on the left is for TIRS band 10, while the right is for TIRS band 11.

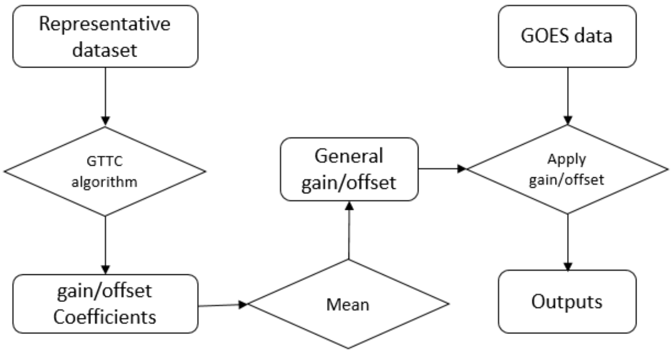


Figure 6. The Quick-GTTC algorithm work-flow. Once the GOES data is prepared, band math can be implemented directly.

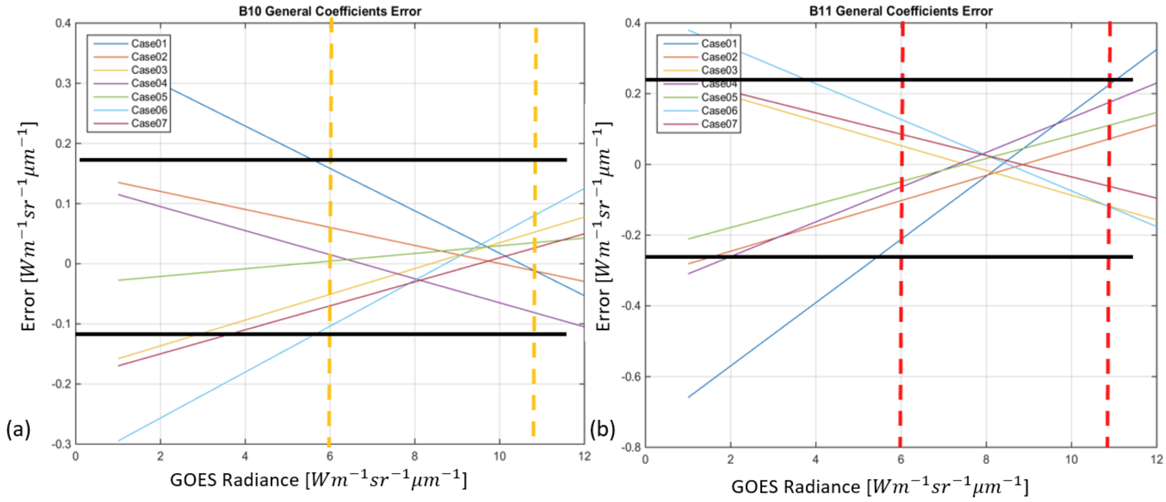


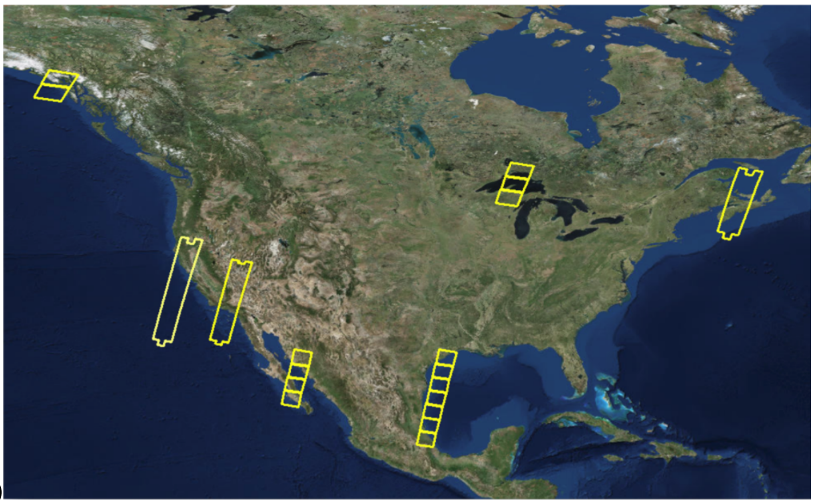
Figure 7. The uncertainty involved when using Q-GTTC algorithm. (**a**) is for TIRS band 10. (**b**) is for TIRS band 11.

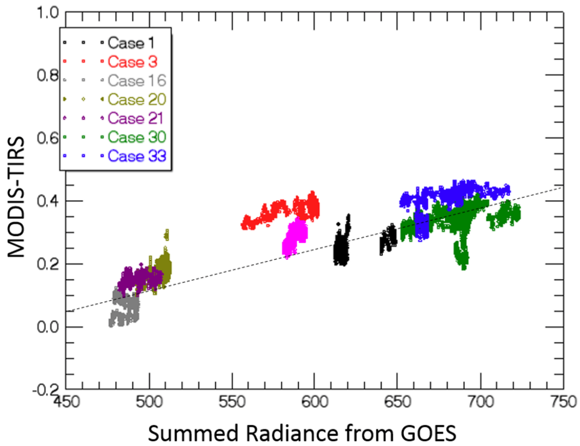
3.3. Estimation of Stray Light Bias

As previously mentioned, the left side of Equation (1) represents the stray light bias. Ground truth for TIRS radiance is necessary to estimate what the bias radiance might be. MODIS is an Earth Observation instrument which has spatial and temporal overlap with Landsat. MODIS detectors are sensitive from 0.405 to 14.385 µm broken up in 36 separate spectral bands while the spatial resolution is 1000 m in the LWIR region. A Sea Surface Temperature (SST) Product derived from MODIS data provides high quality global sea-surface temperatures, which has a reported bias less than 0.5 K [13]. In some cases the MODIS overpass time can be a couple hours later than TIRS. However, the water temperature of a rather deep ocean typically does not change rapidly over such an interval, assuming it stays cloud free. Therefore, the SST product is considered sufficient for stray light calibration. Using a broadband compensation methodology [14,15] to convert the MODIS SST product to TIRS TOA radiance, the (converted) SST product could be used as a benchmark (i.e., cross comparison) for the stray light calibration algorithm.

3.4. Build the Regression to Remove the Stray Light

Once the stray light bias and stray light source or ghost radiances are estimated, a training dataset is built for the ordinary linear regression so as to determine the slope and intercept coefficients for Equation (1). Considering the GOES data is only available for North America, all the scenes for training and validation were selected from this region. The data sets used for algorithm training spanned the range of temperatures from 270 K to 330 K. Figure 8a shows the locations and scenes that were used for the regression training.

(a)




(b)

Figure 8. (**a**) shows the locations of various scenes used for training the algorithm. To span a large temperature range, scenes from different regions, ranging from Alaska to Mexico Gulf, were included. (**b**) shows a typical relationship between the out-of-field radiance and the stray light bias for one detector element. The x-axis is the integrated radiance from the GOES-N while the y-axis indicates the stray light bias derived from MODIS minus TIRS data. The dashed line is the best fit linear regression.

For each detector in the TIRS focal plane, the total stray light radiance was calculated from cloud-free water frames of a TIRS image. The integrated radiance values are sampled from GOES-N images and stored in the ghost energy vector L_G in Equation (1). The stray light bias L_{bias} corresponding to these locations, is calculated via subtracting MODIS ground truth (propagated to equivalent TOA radiance) from the TIRS radiance data. Linear regression is implemented to estimate the gain and offsets coefficients a and c. Figure 8b shows the plot of the out-of-field radiance versus stray light bias. This procedure is repeated for every detector on the focal plan array. Once the linear regression is fully constructed, the gain and offset coefficients are obtained so as to be used for correcting new TIRS scenes.

4. Results and Discussion

In this section, we show the stray light correction results with the GOES-on-TIRS methodology. We first compare the stray light correction approach based on the GOES-on-TIRS and Q-GTTC algorithms so as to investigate the uncertainties related to this new approach. Secondly, the corrected data is validated with the TIRS Collection-1 product so as to show the GOES-on-TIRS approach has the same performance as the current Collection-1 product. Following this, several extreme cases, in which there is a significant temperature contrast between the out-of-field pixels and the TIRS edge-image pixels, will be corrected via the Q-GTTC method. These results will be compared with the TIRS Collection-1 product in order to examine the impact of extreme out-of-field ghost artifacts.

4.1. The Uncertainties from Q-GTTC Algorithm

To investigate the impact of using the Q-GTTC algorithm, the seven TIRS scenes in Figure 5 were corrected by the standard GTTC algorithm as discussed in Sections 3.1.1 and 3.1.2, and the Q-GTTC algorithm outlined in Section 3.2, respectively. The two cases which had the largest uncertainties are plotted in Figure 9. According to the analysis, applying the Q-GTTC algorithm in Section 3.2 can introduce a 0.4 to 0.5 ($Wm^{-2}sr^{-1}\mu m^{-1}$) error in the GOES-N data. Using GOES-N data for the GOES-on-TIRS stray light correction will only change the results by no more than 0.1 K, in water regions.

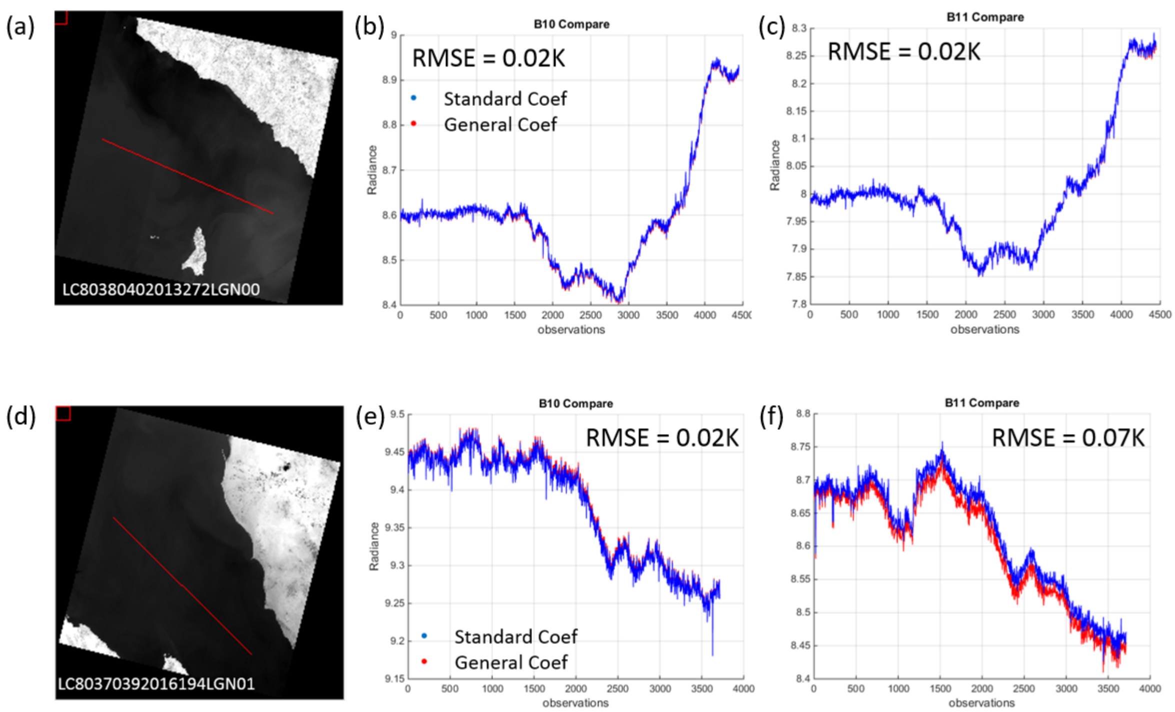


Figure 9. Comparison of the standard GOES-on-TIRS results with Q-GTTC results. (**a**,**d**) are the TIRS example scenes. The radiance profiles along the red line are plotted in (**b**,**e**) for band 10 and (**c**,**f**) for band 11. The blue curve is from standard GOES-on-TIRS stay light removal algorithm. The red curve shows results from the GOES-on-TIRS correction with Q-GTTC algorithm. The differences between the two curves (cloud free water pixels) are less than 0.01 ($Wm^{-2}sr^{-1}\mu m^{-1}$), which is less than 0.07 K.

4.2. Validate the Q-GTTC-Based GOES-on-TIRS Correction with Collection-1 Data

Since the GOES-N to TIRS conversion has been significantly simplified, as discussed in Section 3.2, the remaining concern, in using external sensors to eliminate stray light artifacts, is the introduction of additional uncertainties or errors to the final correction result. Previous studies have shown that stray light artifacts, in TIRS Collection-1 imagery, have been reduced to approximately 0.5% [6]. Therefore, the TIRS Collection-1 data could be considered as a benchmark to validate the external sensor-based stray light removal algorithm.

The seven TIRS scenes in Figure 5 were corrected via the Q-GTTC-based GOES-on-TIRS method, the correction results were compared to the TIRS Collection-1 data, pixel-by-pixel. The two cases which had the most disagreement are shown in Figure 10. According to the experiment, the maximum difference between the GTTC and Q-GTTC results is around 0.5 ($Wm^{-2}sr^{-1}\mu m^{-1}$) in land-type regions. The disagreement will be much lower in cloud free water regions. When comparing to the TIRS Collection-1 data, the uncertainties from the new proposed GOES-on-TIRS method is well below the 2% requirement [1]. In cloud-free water regions, the disagreement between the Q-GTTC-based GOES-on-TIRS approach and Collection-1 data is around 0.2% to 0.3%. Therefore, this faster operational methodology shows excellent potential to mitigate stray light artifacts from TIRS imagery.

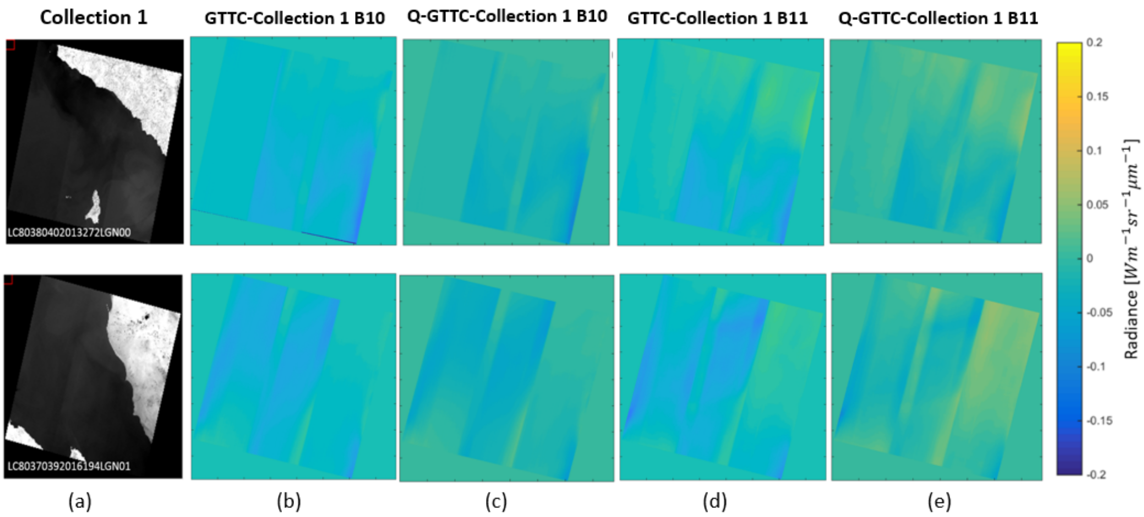


Figure 10. Comparison of the Q-GTTC-based GOES-on-TIRS algorithm with TIRS Collection-1 data. Column (**a**) shows the original two TIRS scenes. (**b**) Shows the differences between the GTTC-based GOES-on-TIRS approach and Collection-1 data in band 10 while (**c**) shows the difference maps based on Q-GTTC algorithm. The difference maps for band 11 are shown in (**d**,**e**).

4.3. Extreme Landscape and Cloud Case Studies

Considering the Q-GTTC-based GOES-on-TIRS methodology has the same performance as the TIRS Collection-1 data, the analysis in this section focuses on the stray light removal from some, what we call, extreme cases. We define extreme cases as those in which there is a very large temperature contrast (i.e., difference) between the out-of-field pixels and the TIRS edge-image pixels.

One extreme cases are shown in Figure 11. This TIRS imagery was acquired near Baja California in the summer of 2017. The white regions in the imagery represent hot materials, such as heated land; The dark parts indicate cold deep ocean water. These pixels are approximate 20 kelvin colder than the hot land pixels. When applying the TIRS-on-TIRS correction method for this scene, the ghost radiance will be acquired from the blue region (outlined in the image), which are predominantly deep ocean water pixels. If the stray light removal algorithm is based on the GOES-on-TIRS method, the ghost radiance will be sampled from the red circle, as illustrated in Figure 11, where the land pixels are much hotter than the water. Therefore, on the right side of the example TIRS scene, the total ghost radiance (L_G in Equation (1)) from the GOES-on-TIRS method will be larger than that from TIRS-on-TIRS method. This, in-turn, using the GOES-on-TIRS method will extract more bias radiance from the raw TIRS data and make the result colder than TIRS Collection-1 data. This can be seen in the plots of Figure 11 where we see perfect correction on the left side with some differences on the right, for both bands 10 and 11. The maximum disagreement in temperature can be up to 0.68 kelvin in band 10 and 0.35 kelvin in band 11.

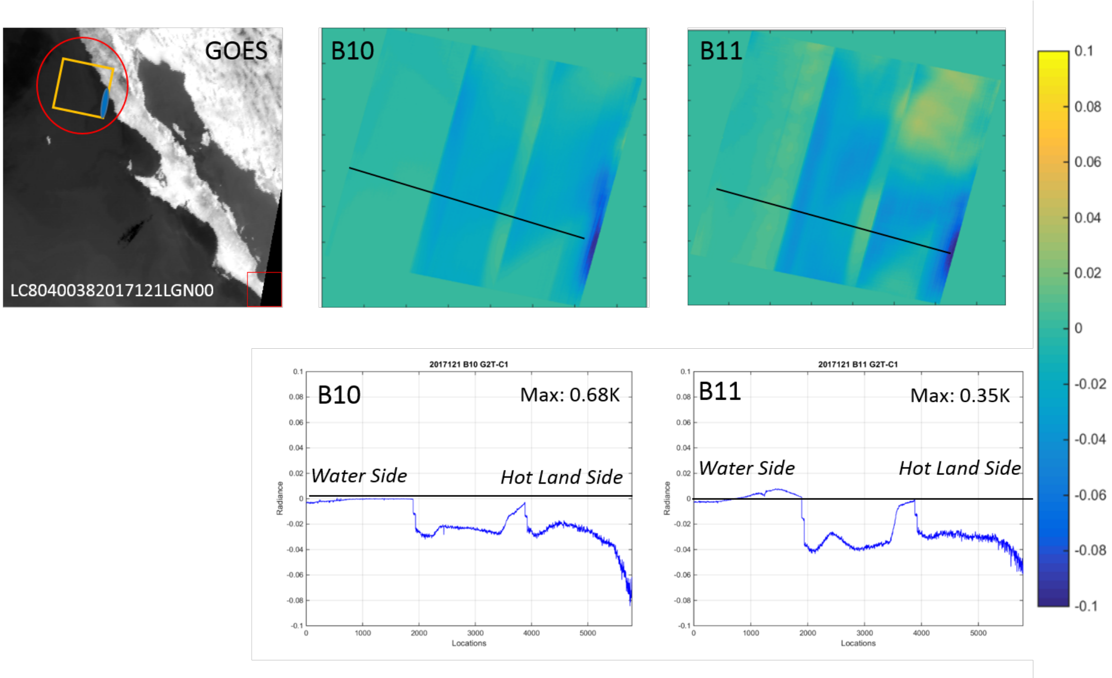


Figure 11. An extreme case involving TIRS stray light correction. This case has hot land on the right side. The small yellow box in the GOES image indicates the location of the actual TIRS scene. The red circle shows where the ghost radiance will come from. The color maps on the right are the differences maps between the results from the GOES-on-TIRS method and Collection-1 data (i.e., the TIRS-on-TIRS method). The differences in radiance space (from the drawn black line) are plotted as well for both bands 10 and 11.

Another extreme case which captured cold clouds in the out-of-field region, is shown in Figure 12. This is a TIRS case from the Gulf of Mexico in the summer of 2015. In this case, the white and gray pixels indicate the warm sea water and hot Florida peninsula during the summer. The temperature difference between these two types of materials is only 3 to 4 degrees. A large cold cloud region is present on the left side of the TIRS scene (the large dark region). These cloud pixels are 50 kelvin colder than the sea water pixels inside the TIRS field-of-view, which is considered on extreme high contrast case. In such circumstances, the total ghost radiance L_G, based on GOES-on-TIRS, will be smaller than using the TIRS-on-TIRS method. This will make the GOES-on-TIRS stray light correction results hotter than the Collection-1 data on the left side. The maximum differences can be up to 0.75 kelvin in band 10 and 0.67 kelvin in band 11.

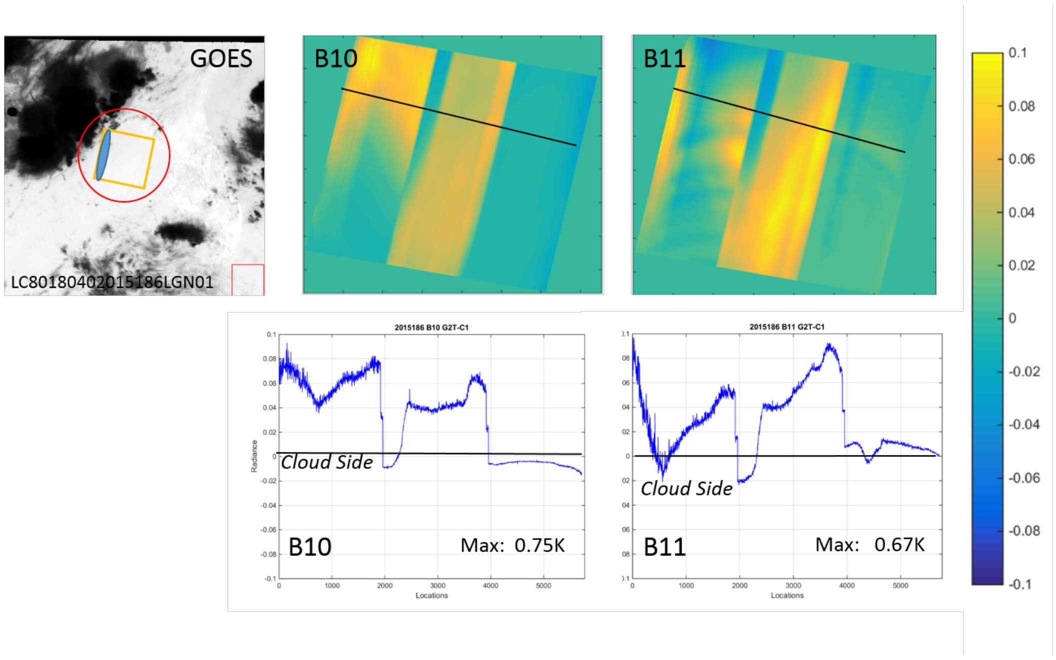


Figure 12. Another extreme case involving TIRS stray light correction. This case has cold cloud on the left side. The color maps on the right are the differences maps between the results from the GOES-on-TIRS method and Collection-1 data (i.e., the TIRS_TIRS method). The differences in radiance space (from the drawn black line) are plotted as well for both bands 10 and 11.

5. Conclusions

Stray light impacts and artifacts were addressed in previous publications along with the operational implementation of the TIRS-on-TIRS correction methodology. The concern of using external sensor data is that it may include additional errors into the stray light correction results. Furthermore, the complexity involved in the conversion of external sensor data to TIRS sensor-reaching radiance data may lead to implementation issues and difficulties impacting the algorithm's ability to become fully operational.

According to the results in Section 4, the GOES-on-TIRS methodology has good tolerance to the variation in GOES-N data. That is, a certain degree of change in the GOES-N data will not lead to considerable errors in the stray light correction results. We also addressed the issue of processing GOES-N data in a more efficient manor. In Section 3.2 a simplified processing scheme was proposed and was shown to have the same performance as the TIRS Collection-1 data. This Q-GTTC algorithm allowed for an approximate 2 to 3 h speed up in processing which introduced negligible error. In this way, the GOES-on-TIRS approach can become reasonably operational. It allows for the introduction of many more test cases for additional study. In the future, the GTTC and Q-GTTC algorithms can be extended to data acquired by Meteosat or Himawari instruments for stray light reduction outside North America. The Modern-Era Retrospective analysis for Research and Applications (MERRA) reanalysis dataset can be used as NARR data to support atmospheric descriptions.

For common TIRS cases, the differences between the TIRS-on-TIRS and GOES-on-TIRS methodologies was approximately 0.2% to 0.3%, which is small enough to indicated that the GOES-on-TIRS method performs similarly to the TIRS-on-TIRS approach. In some extreme cases, where there exist an extreme temperature contrast between inside and outside the field of view, the disagreement between the GOES-on-TIRS and TIRS-on-TIRS methods can be 0.5% to 0.7%.

Finally, the level of disagreement is strongly correlated to the temperature contrast between the out-of-field pixels and the TIRS edge-image pixels. However, the differences between the two methods is so close that current benchmarks, such as the MODIS SST product, might not have low enough uncertainty to determine which method is optimal.

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References

1. NASA. *Landsat Data Continuity Mission Thermal Infrared Sensor Requirements Document-Revision F2*; GSFC 427-15-02; NASA Goddard Space Flight Center: Greenbelt, MD, USA, 2013.
2. Montanaro, M.; Lunsford, A.; Tesfaye, Z.; Wenny, B.; Reuter, D. Radiometric Calibration Methodology of the Landsat 8 Thermal Infrared Sensor. *Remote Sens.* **2014**, *6*, 8803–8821, doi:10.3390/rs6098803.
3. Montanaro, M.; Julia, B.; Lunsford, A.; Rohrbach, S.; Markham, B. Performance of the Thermal Infrared Sensor on-board Landsat 8 over the first year on-orbit. In Proceedings of the SPIE Earth Observing Systems XIX, San Diego, CA, USA, 2 October 2014; Volume 10402.
4. Montanaro, M.; Gerace, A.; Lunsford, A.; Reuter, D. Stray Light Artifacts in Imagery from the Landsat 8 Thermal Infrared Sensor. *Remote Sens.* **2014**, *6*, 10435–10456.
5. Montanaro, M.; Gerace, A.; Rohrbach, S. Toward an operational stray light correction for the Landsat 8 thermal infrared sensor. *Appl. Opt.* **2015**, *54*, 3963–3978, doi:10.1364/AO.54.003963.
6. Montanaro, M.; Gerace, A. Derivation and validation of the stray light correction algorithm for thethermal infrared sensor onboard landsat 8. *Remote Sens. Environ.* **2017**, *191*, 246–257.
7. Barsi, J.; Schott, J.; Hook, S.; Raqueno, N.; Markham, B.; Radocinski, R. Landsat-8 thermal infrared sensor TIRS vicarious radiometric calibration. *Remote Sens.* **2014**, *6*, 11607–11626.
8. Wang, Y.; Ientilucci, E.; Raqueno, N.; Schott, J. Landsat 8 TIRS calibration with external sensors. *Proc. SPIE* **2017**, *9218*, doi:10.1117/12.2272766.
9. Gerace, A.; Montanaro, M.; Connal, R. Leveraging intercalibration techniques to support stray-light removal from Landsat 8 Thermal Infrared Sensor data. *J. Appl. Remote Sens.* **2017**, *12*, 1–13, doi:10.1117/1.JRS.12.012007.
10. NOAA Office of Satellite, and Product Operations, Geostationary Operational Environmental Satellites (GOES). 2017. Available online: https://www.class.ncdc.noaa.gov/saa/products/welcome (accessed on 21 March 2017).
11. Research Data Archive at the National Center for Atmospheric Research, Computational and Information Systems Laboratory, National Centers for Environmental Prediction/National Weather Service/NOAA/U.S. Department of Commerce (2005): NCEP North American Regional Reanalysis (NARR). 2017. Available online: http://rda.ucar.edu/datasets/ds608.0/ (accessed on 21 March 2017).
12. Soler, T.; Eisemann, D.W. Determination of Look Angles to Geostationary Communication Satellites. *J. Surv. Eng.* **1994**, *120*, 115–127.
13. Kilpatrick, K.A.; Podesta, G.; Walsh, S.; Williams, E.; Halliwell, V.; Szczodrak, M.; Brown, O.B.; Minnett, P.J.; Evans, R. A decade of sea surface temperature from MODIS. *Remote Sens. Environ.* **2015**, *165*, 27–41.
14. Cook, M.J.; Schott, J.R. Initial validation of atmospheric compensation for a Landsat land surface temperature product. *Proc. SPIE* **2013**, *8743*, doi:10.1117/12.2015320.
15. Cook, M.; Schott, J.; Mandel, J.; Raqueno, N. Development of an operational calibration methodology for the Landsat thermal data archive and initial testing of the atmospheric compensation component of a Land Surface Temperature (LST) product from the archive. *Remote Sens.* **2014**, *6*, 11244–11266, doi:10.3390/rs61111244.