Increasing the Accuracy of MODIS Snow Product MOD10_L2/MYD10_L2 using Quantitative Restoration for MODIS Band 6 on Aqua

Report

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1 Introduction

Currently, the MODIS instrument on the Aqua satellite has a number of broken detectors, resulting in unreliable data for 1.6 micron band (Band 6) measurements. Specifically, only five of every twenty rows produce accurate data and many of the malfunctioning detectors are adjacent, so there are large spatial gaps in the data which make spatial interpolation inappropriate. Figure 1 shows a portion of an Aqua image where the malfunctioning detectors are represented by dark stripes. The damaged bands create uncertainty in the reliability of the results of prediction algorithms that rely on Band 6 data from MODIS on Aqua [1], such as the NASA snow mask. The calculation of the NASA snow mask relies prominently on the Band 6 measurement in determining the likelihood of snow cover on the ground at the location of each pixel in the image [2]. The current NASA-utilized solution to this problem is to use 2.1 micron (Band 7) measurements from MODIS on Aqua with an appropriately-adjusted algorithm [3].

Figure 1: A portion of the MODIS/Aqua-Band 6 image showing striping due to broken detectors. Because many of the stripes are consecutive, naive interpolation is not appropriate for estimating the missing data.

In response to the Band 6 problem, our group has developed an algorithm to recreate the missing Band 6 data from reliable data in Bands 3, 4, 5, and 7, using quantitative restoration techniques [4], and improving the results of the Snow Product is one of the potential uses of this restoration algorithm. Our algorithm uses values in a neighborhood of the pixel to be estimated, and propose a value based on training data from the uncorrupted pixels. Since we use the spatial variations in other channels, we avoid the blurring inherent spatial interpolation, which have implicit smoothness priors. A brief description of the algorithm is given in the next section.
2 Restoration Algorithm

The outline of the algorithm is presented in the diagram shown in Figure 2. The first step when working with the data is destriping the radiances. In theory the calibrated radiances should not have stripes. Nevertheless, some artifacts remain which can be removed using histogram specification [7]. As observed in Rakwatin et al. [8], destriping can significantly improve regression.

After destriping, the image is then broken into disjoint non-overlapping large tiles consisting of $I$ scanlines and $J$ columns within a scanline, as shown in Figure 3. Reconstruction within each tile is accomplished with single multi-linear function which varies from tile to tile. It is also possible to use sliding overlapping tiles centered at the band 6 pixel to be restored, providing for a per-pixel varying reconstruction function. While a sliding window approach will potentially improve accuracy it does so an enormous cost compared to non-overlapping tiles. Similarly, the choice of tile size is data-set dependent. Training data is used to find a balance between accuracy and speed, empirically, when setting the tile size.

Once the data is broken into fixed spatial tiles, sliding overlapping spatial windows of data within a tile are extracted as shown in Figure 3. The windows are of size $m \times n$ pixels with $m$ and $n$ odd. In Figure 4 the pixels in stack of undamaged bands (Aqua 3,4,5,7) are considered independent (input) variables. The middle pixel the damaged band, Aqua band 6, is shown in Figure 3 as the dependent variable. For those spatial windows where the dependent variable corresponds to a pixel from a working band 6 detector, we have both independent variable values, and the dependent variable value. These pairs are fed into linear least squares regression as indicated in Figure 2. The result of the regression is a multi-linear map for each tile whose input is a stack of values in bands Aqua 3,4,5 and 7 within a window, and which computes a restored value at the center pixel in band 6. Again referring to Figure 2, the mapping for each tile is used to estimate the missing pixel value in Band 6, and with the pixel values from the working detectors in band 6, left intact.

![Diagram](image)

Figure 2: Block-diagram showing the steps of the reconstruction algorithm. Radiance values from working detectors in each band are destriped using histogram matching as a pre-processing step. The entire image is broken into non-overlapping tiles with the tile size chosen empirically. Within each tile, for each pixel value corresponding to a working band 6 detector, a surrounding geometric window of surrounding is defined. Values from pixels within geometric window measured in bands 3,4,5 and 7 are treated as independent variables, with the single band 6 value as a dependent variable to set up a multi-linear regression. The coefficients determined by the regression are then applied to the window of values measured in bands 3,4,5 and 7 to estimate the missing values in band 6.
While we have already described the extensive damage to Band 6 on Aqua, the corresponding band 6 of the MODIS instrument on Terra has no such problem. This makes it possible to evaluate our restoration algorithm by simulating Aqua’s Band 6 damage on Terra’s Band 6 and compare the restored values with the snow mask values. The original Terra data shown in Figure 5 appears nearly identical to that of our restoration Figure 6.

Figure 3: Diagram of the spatial arrangement of pixels used for prediction.

Figure 4: View multi-spectral/spatial neighborhoods considered for prediction.

Figure 5: Original MODIS Band6 Terra Image with Surface Structure. Within the image small several rivers and tributaries are visible.

Figure 6: MODIS Band 6 Terra Restored Surface image. After simulated damage the restoration algorithm we have presented is applied. The restored image recovers the river and surface edge features without distortion.
Figure 7: This shows the distribution of errors for a restoration of a band 6 from Terra with simulated damage using 5x5 windows. Note that the errors are well concentrated about 0.

Table in Figure 8 shows a selection of 14 randomly chosen granules with the root mean square error for the restoration. Given the large number of detectors lost these RMSE are quite low across granules. Even within a granule the spread of errors is quite narrow. Figure 7 shows the histogram of errors using 5x5 windows within the tiles. Most of the errors are tightly concentrated around zero.

3 Analysis of the effect on snow products

By using our restoration algorithm to restore the artificially corrupted Terra band 6, we obtained snow mask datasets, which through the rest of this report will be called RES6. The RES6 datasets serve as an effective proxy for other damaged NASA products when evaluating the effectiveness of our restoration algorithm. The RES6 data was compared to snow mask data generated by using band 7 from the same Terra granules as input to NASA’s adjusted algorithm (which we indicate as B7). The performance of both of these algorithms was measured against the actual NASA snow mask for these Terra granules (which we indicate as GT for ground truth), which is computed using true Terra band 6 as input into NASAs snow mask algorithm.
Snow, fog, and low clouds in western Europe

The set of 4 figures above shows a NASAs original snow mask product or GT (top left), an RGB image (top right) for Terra Granules with an undamaged Band 6. The granule was processed to simulate Aqua band 6 damage and the snow mask was computed, using NASA’s band 7 proxy algorithm, B7 and our restoration of band 6 followed by NASA’s band 6 algorithm, denoted RES6. The NASA snow mask algorithm using B7 tends to overestimate the amount of snow in order to avoid missing snow pixels. This can be seen in error images are shown above for both the B7 (bottom left) and RES6 (bottom right) results (where white pixels indicate agreement with ground truth and black pixels indicate a discrepancy). The RES6 based snow mask clearly is in much closer agreement with the GT snow mask.
Images for the rest of the tested granule are provided in the appendix. All of the RGB images (top right) were taken from the MODIS Rapid Response System website [5]. NASA’s operations snow mask algorithms were obtained from Dorothy Hall of NASA. All of the NASA snow mask images (top left) have white pixels representing the presence of snow. The bottom 2 images in each case represent the errors (discrepancies from the GT) for B7 (left) and RES6 (right). These images support the that the restoration algorithm yields more reliable results in two critical areas: areas with high vegetation index and the border between snow-covered regions and snow-free regions.

We evaluated RES6 and B7 by comparing the results of both algorithms to the GT algorithm through the use of number of statistical measures. One metric used in performance evaluation was accuracy (ACC), which is the degree of closeness of measurements of a quantity to its actual (true) value. All datasets were interpreted as binary snow masks, so:

$$ACC = \frac{TP + TN}{P + N},$$

where $TP$ (true positive or hit) is the number of the snow pixels that were identified as snow pixels, $TN$ (true negative or correct rejection) is the number of pixels not covered by snow that were not identified as snow pixels, $P$ is the number of pixels covered by snow in the GT, $N$ is the number of pixels not covered by snow in the GT.

ACC metric was used because it is widely regarded and captures in a single number the performance of the estimator both with respect to false positives and false negatives. As seen in Figure 9, the RES6 data outperformed the B7 data in terms of accuracy for all thirteen tested granules. In one case the improvement in accuracy was over 20.

Another standard way of evaluating the performance of the binary classifier is a graphical plot of the sensitivity, or true positives, vs. (1 - specificity), or false positives. $TPR$ true positive rate measures the proportion of actual positives which are correctly identified as such and is defined as $TPR = \frac{TP}{P}$ and $FPR$ false positive rate (or fall-out) is defined as $FPR = \frac{FP}{N}$. The scatter plot (cf. Figure 10), compares the rates of false positives (FP) and true positives (TP) for RES6 and B7 across all tested granules. The restoration algorithm’s mitigation of the relatively high rate of false positives associated with the use of the band 7 algorithm demonstrates that its snow predictions for individual pixels have a higher degree of reliability.

![Figure 9: Accuracy for snow product calculated with the restoration algorithm (RES6) and the current NASA’s Aqua algorithm based on band 7 (B7) across all tested granules.](image9)

![Figure 10: Comparison of the false positives rates (FPR) and true positives rates (TPR) for RES6 and B7 snow masks across all tested granules.](image10)
Figure 11 shows the NDVI vs. NDSI histogram of error pixels for snow product produced from restored band 6 (RES6). Note the errors due to restoration are highly concentrated near the boundary between snow and no snow shown by the line and polygon in figure 13 (see [6] for polygon definition). This might be expected as this is exactly the part of the NDVI vs. NDSI scatter where the presence or absence of snow is most uncertain. Figure 12 shows the NDVI vs. NDSI histogram of error pixels for snow product produced from NASA’s algorithm for Aqua that relies on band 7 (B7). Unlike the highly concentrated errors due to restoration in the snow-no-snow boundary, the errors appear over a much wider area. This suggests that the B7 algorithm is producing errors in regions of the NDVI vs. NDSI domain where the presence or absence of snow is unambiguous.

Figure 11: Histogram of the number of errors relative to NDVI and NDSI for RES6.  
Figure 12: Histogram of the number of errors relative to NDVI and NDSI for B7.

Figure 13: Original Diagram used in the NASA snow mask algorithm.
4 Conclusion

The metrics mentioned above are only a few of the possible measures of the relative performance of these snow prediction algorithms, but they demonstrate that the use of the original NASA algorithm with the restored Band 6 data (RES6) generates a more reliable snow mask (closer to the one computed with the true Band 6 data (GT)) than the modified algorithm with Band 7 data (B7). In particular, the restored Band 6 data is much more reliable under certain conditions where the Band 7 algorithm tends to run into problems, including the very important border areas between snowy regions and snow-free regions, and areas where tree cover makes determinations of snow on the ground difficult.

References


Snow was again over-identified by the Band 7 algorithm in the eastern portion of this granule, while the restored Band 6 algorithm performed somewhat better.

2004/360 - 12/25 at 17:35 UTC **Snow in the Great Plains**

Snow was again over-identified by the Band 7 algorithm in the eastern portion of this granule, while the restored Band 6 algorithm performed somewhat better.
Snow across the midwestern United States

Here the Band 7 algorithm can be clearly seen to be less reliable than the restored Band 6 algorithm along the southern border of the large snowy region. This is a recurring pattern. Unsurprisingly, correctly determining the border is of considerable interest for many applications, and the restored Band 6 consistently performs much better in this area.
2004/354 - 12/19 at 11:30 UTC Snow in Scotland

This granule, centered on the United Kingdom and Ireland, shows widely distributed false identifications of snow by the Band 7 algorithm. The use of the restored Band 6 largely avoided this problem.
Another indication that the restored Band 6 algorithm reduces error at the border of a snowy region and a snow-free region.

Spring snow in New England and eastern Canada
Yet another indication that the restored Band 6 algorithm is more reliable along the border between snow-covered and snow-free regions.
Once again, the Band 7 algorithm over-identified snow, and the restored Band 6 algorithm performed much better.
The algorithms performed more similarly for this granule, where the snow-determined area was largely delimited by cloud cover, but the restored Band 6 algorithm still resulted in less error than the Band 7 algorithm.
Snow across the northeastern United States

This is another case where the restored Band 6 algorithm increased reliability along the border between a snow-covered region and a snow-free region.
2009/321 - 11/17 at 18:00 UTC **Snow in the Rocky Mountains**

In this granule, the snow was more distributed in a mountainous area. Nevertheless, the restored Band 6 algorithm proved more reliable along the borders than the Band 7 algorithm.
Low clouds along the Himalayas

Another mountainous area where the restored Band 6 algorithm outperformed the Band 7 algorithms in borderline cases.
This granule from coastal western North America reveals a general tendency toward overestimation of snow on the part of the Band 7 algorithm. The restored Band 6 is considerably better in this regard.
This granule shows a more sparsely-distributed area of inland snow. Here too, the restored Band 6 algorithm is more reliable at the border between snow and non-snow regions.