Persistence-based temporal filtering for MODIS snow products

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ABSTRACT

Single-day snow covered area (SCA) products are incomplete and often inadequate representations of ground conditions due to short term variation in cloud cover, snow cover, and sensor geometry. To mitigate these effects, we developed a by-pixel filtering algorithm to produce relatively cloud-free SCA products from 16 days of MODIS imagery. The algorithm uses previous days' data to estimate the current SCA value of each pixel and uses a simple persistence test to reduce the effects of spurious SCA/cloud classifications in the input products. To be positively identified as SCA, a pixel must be snow-covered in the two most recent, cloud-free scenes of the 16-day period. We applied this Time-Domain-Filtering (TDF) methodology to two single-day MODIS fractional snow cover products (MOD10A1 and MODSCAG) over the MODIS period of record (2000-present) and compared the outputs to the unfiltered products, to filtered maps generated using the cloud-gap-filled algorithm (CGF, Hall *et al.* 2010), and to historical snow assessment reports from the U.S. Army Corps of Engineers Cold Regions Research and Engineering Laboratory (CRREL). The CRREL reports were manually generated and quality-controlled by an analyst and are treated as ground truth. We find that, when applied to MODSCAG, the TDF algorithm successfully fills in gap pixels and limits the effects of snow/cloud confusion and produces a filtered product that is more consistent and accurate than the MODSCAG CGF product and comparable to the MOD10A1 CGF product.

KEYWORDS: MODIS, snow covered area, cloud-free, gap-fill

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BACKGROUND

CRREL Snow Assessments

Since the winter of 2004, the Cold Regions Research and Engineering Laboratory (CRREL) of the U.S. Army Engineer Research and Development Center (ERDC) has produced biweekly assessments of snow covered area (SCA) and snow-water equivalent (SWE) for the major watersheds of Afghanistan using both multispectral (AVHRR and MODIS) and passive microwave (SSM/I and AMSR-E) imagery (Daly *et al.*, 2012). Accurate delineation of SCA in this region is important for military transportation and operations planning as well as for constraining estimates of SWE for water management and hydrological/climate modeling. The latter is particularly important in areas like Afghanistan where real-time precipitation and snowpack data are scarce. Imagery from the Terra Moderate Resolution Imaging Spectroradiometer (MODIS) was first used in a CRREL snow assessment in 2008 and each biweekly SCA map was generated using the most acceptable scene, based on low cloud cover and proximity to the assessment day. These maps (CH) were generated from reflectance products using unsupervised classification techniques described by Daly *et al.*, (2012) and validated qualitatively by an analyst. Due to variations in cloud cover, these single day maps provided temporally inconsistent and incomplete snapshots of SCA. Additionally, manually classifying and validating each scene is both time-consuming and subjective.

MODIS Snow Products

The MODIS/Terra Snow Cover Daily L3 Global 500m Grid (MOD10A1, Hall *et al.*, 2006) is a global, gridded fractional snow covered area (FSCA) product produced daily by the National Snow and Ice Data Center (NSIDC). SCA is estimated using the normalized difference snow index (NDSI), which leverages the contrasting reflectance of snow in the visible and shortwave infrared regions of the spectrum (Hall *et al.*, 2002). FSCA is estimated using an empirical relationship between FSCA and NDSI (Salomonson & Appel, 2004).

The MODIS Snow Covered Area and Grain Size (MODSCAG) product includes gridded FSCA produced daily by the Jet Propulsion Laboratory (JPL). MODSCAG uses spectral mixture analysis of the eight MODIS surface reflectance bands (MOD09GA; LPDAAC, 2001) to estimate FSCA (Painter *et al.*, 2009).

Both of these products are released in the MODIS sinusoidal projection and gridded to the MODIS tile system at nominally 500 m (463.3 m) pixel resolution. Examples and analysis presented in this study are limited to tile H23V05 (30 to 40°N, 57.7 to 78.3°E), which encompasses the majority of Afghanistan (Figure 1A). While a

relatively small area of interest, this region includes a wide variety of SCA environments ranging from high elevation glaciated mountains to perennial lowland desert. Additionally, there is relatively little vegetation in this region, so any differences in SCA detections caused by canopy will be minimized in the unfiltered products allowing for better isolation of the filtering algorithms' effects.

The CRREL snow assessments were delivered as binary snow maps. When comparing the products to CH, each product was assumed to be binary with the FSCA>20% set as SCA. We find this assumption appropriate for this application because (1) individual pixel's FSCA retrievals from the two different detection methodologies can vary widely, particularly at low FSCA, and (2) noise in MODIS band 5 tends to produce artifacts in MODSCAG's FSCA estimates that can be easily ignored when considering the binary case. The FSCA threshold value was adopted based on documentation for the MOD10A1 product (Riggs *et al.*, 2006), which suggests that values below 20% are often errors of commission caused by snow/cloud confusion and cloud shadows. We find such errors to be more common in MODSCAG and take the 20% FSCA threshold to be a reasonable starting point.

Cloud Masking

Clouds constitute the most common 'data gap' in optical imagery, though determination of which pixels are cloud-covered, or for which pixels FSCA is calculated and which are masked, differs significantly by product. The MODIS cloud mask (MOD35) uses a host of algorithms and 19 of MODIS's 36 bands to determine whether or not MODIS is viewing clear skies (Ackerman *et al.*, 2010). The MOD35 confidence level is an ancillary input to many of the MODIS level 2 land, ocean, and atmosphere science algorithms including the MOD10- snow cover products. The MOD10A1 Version 4 employed a more liberal cloud mask to mitigate overly aggressive masking and algorithm confusing between clouds and snow in some regions; however, Version 5 does not use the liberal mask in an effort to provide a more globally consistent product but may over-classify cloud cover as a result (Riggs *et al.*, 2003; Hall *et al.*, 2006; Riggs & Hall, 2007). In an effort to avoid overly aggressive cloud cover classification, MODSCAG uses a cloud mask based on surface reflectance from the MOD09GA, modified by grain size estimates of snow and cloud. Clouds with relatively large particle size are mapped as snow, and, similarly, snow with too-fine particle sizes are mapped as clouds (Painter *et al.*, 2009). This results in lower cloud cover estimates when compared with the MOD10A1 and potentially more accurate characterization of FSCA (Rittger *et al.*, 2013) but also more false positives in SCA detections. In each case, we assume that all calculated values of FSCA (0 – 100%) are valid inputs and that all other values, whether cloud, water, no decision, or the variety of other negative flags present in

the products, are treated as ‘cloud’ and will be attempted to be filled by the algorithm. For simplicity, further discussion of ‘cloudy’ pixels will pertain to any pixel that does not have an FSCA/SCA (whether binary or 0 – 100%) value. False positives due to snow/cloud confusion are the largest source of error in the input imagery in terms of FSCA/SCA, which, when coupled with significant differences in cloud covered area extent in the two input products, provides a compelling test environment for the algorithm.

Cloud Mitigation and Removal

Gap-filling methods use the values of temporally or spatially adjacent pixels to interpolate the values of pixels in data gaps which may be caused by clouds, sensor or illumination geometry, or sensor malfunction. Spatial gap-filling such as kriging use data from surrounding non-gap pixels to estimate the values of missing data (Rossi *et al.*, 2004). Temporal filtering leverages non-gap values of a pixel from nearby scenes within a time series to estimate the value in the gap, often using curve-fitting on non-gap data from both before and after the gap (Jönsson & Eklundh, 2004). Spatio-temporal gap-filling methods use a combination, usually in alternating steps, of spatial and temporal techniques to incrementally remove data gaps.

Several cloud removal strategies have been developed specifically for MODIS snow products using a variety of spatial and temporal filtering techniques. The temporal and spatial variability in snow cover makes spatial filters somewhat unreliable; however, Gafurov and Bárdossy (2009) used one in conjunction with elevation as part of a multi-step spatio-temporal algorithm, assigning snow cover to gap pixels that were both higher elevation and adjacent to snow-covered pixels. Temporal filters are powerful because cloud cover is more variable than snow cover. MODIS provides the unique advantage of collecting both a morning and afternoon pass each day from NASA Terra and Aqua satellites, respectively. This time difference alone can remove significant clouds from an aggregated daily product (Parajka & Blöschl, 2008); however, we limited imagery used in this study to Terra both to illustrate the filtering algorithm’s applicability to other data sets that do not have twice-daily acquisitions and because Aqua MODSCAG was not available for analysis. Multi-day filtering solutions use time windows of different sizes to either fill gap data with recently available data (Hall *et al.*, 2010) or interpolate gap data using curve-fitting. Spatio-temporal interpolation and smoothing techniques, like that developed by Dozier and others (2008), provide powerful cloud-removal but are computationally expensive and can retain and exacerbate spurious SCA detections from the input imagery.

Our goal was to create an efficient gap-filling solution that required only daily FSCA/SCA as an input and that could be applied to methodologically different input sources while producing consistent, commensurate results. This approach provides flexibility in terms of data availability and portability with regards to location, data source, and overall processing scheme. Both the need for and application of our process are shown in Figure 2, which compares data from MODSCAG and MOD10A1 that was filtered using our time-domain-filtering (TDF) algorithm and the cloud-gap-filled (CGF) algorithm (Hall *et al.*, 2010). Fundamentally, the CGF algorithm outputs the most recent cloud-free value (SCA or no SCA) for each pixel. In the absence of temporal or spatial curve-fitting solutions that can extrapolate SCA extent into areas with no cloud-free data, using the last clear view as a proxy for unknown data works well as long as the input data is reliably accurate. For the MOD10A1, which is relatively conservative in its SCA detections (and aggressive in its cloud masking), this works well; however, applying the CGF algorithm to MODSCAG resulted in highly variable, high magnitude SCA extent due to errors of commission in the daily SCA input. The TDF filtering algorithm aims to reconcile the differences in the input imagery and produce more or less equivalent and accurate estimates of SCA.

METHODS

Temporal Filtering

Between November 1 and June 1 for each year of the period of record (2000-2014), the chance of cloud cover or invalid data in any pixel in H23V05 in either MOD10A1 or MODSCAG was 12.7%; however, some pixels were cloudy up to 48.7% of the time (Figure 3A). We note that the spatial distribution of mean cloud presence is similar to that of mean snow presence (Figure 1B), suggesting strong orographic effects, particularly in the Hindu Kush. Despite clouds being common, we find mean cloud persistence, or the average time between cloud-free scenes, to be less than a day (Figure 3B) at Terra MODIS' temporal scale (1 day). This cloud cover transience gives us the opportunity to fill in gaps in the current day's imagery with contemporary data. Because we use multiple days' imagery as inputs and assume that cloud cover is more variable than snow cover, we choose to limit our outputs to SCA that is persistent on a multi-day scale. Each output pixel's value is based on up to 16 daily images (Figure 4, panels 0-15), though only the two most recent cloud-free images influence the value of the outputs. This approach limits errors of commission, false positives, in snow cover that arise from cloud and cloud shadow misclassification in both the MOD10A1 and MODSCAG detection algorithms; this phenomenon is readily visible on the edges of the

cloud in the northwest of Figure 4A. If SCA is present in both of the two most recent cloud-free images, the output pixel's value (Figure 4C) is set to the FSCA value of the most recent image. If either pixel's value in the cloud-free pair is snow-free, the output pixel is assumed to be snow-free. This requirement sometimes filters transient SCA from the output product in addition to spurious SCA but creates a conservative and robust delineation of SCA extent. In the rare occurrence that a pixel does not have two cloud-free readings in the 16 input scenes, the output is cloud. In cases where there is only one cloud-free value during the 16 day period, we retain that pixel's value in the output, ignoring the persistence requirement. We define a decision age (Figure 4B) equal to the number of days elapsed between 'today' (day 0 in Figure 4A,0) and the oldest image that contributes to the output.

Masking

Spurious classification of clouds, water bodies, and land features (salt flats) as SCA, as determined by visual inspection of the daily MODIS surface reflectance product (MOD09GA), is common in both MODSCAG and MOD10A1. To mitigate the effects of these misclassifications, pixels with FSCA values less than 20% were ignored (Riggs *et al.*, 2006; Hall *et al.*, 2010). Additionally, a 5-year historical water mask was created using visible and near infrared bands of the MOD09GA from November to April, 2008-2013. Rivers were extrapolated from the USGS HydroSHEDS flow accumulation data set (Lehner *et al.*, 2008), resampled to 500 m resolution. These pixels were assumed to be snow-free in all outputs (and cloud-free when assessing data age and cloud persistence). A mean historical snow mask was created using the MOD10A2 product, the 8-day maximum SCA extent of the daily MOD10A1, over the period of record. Those regions where snow did not appear in more than 5% of winter, cloud-free, unfiltered scenes were assumed to be snow-free in all outputs. Because the maximum extent map overestimates daily SCA, this final exclusion has little effect on the final product, though it can produce overly conservative estimates during anomalously large snow events. It was employed to further limit the effects of water bodies and other persistent land features that were commonly misclassified as snow in this region but may not be as positively impactful in other locales.

Validation

When comparing total SCA between products we use the mean difference, median difference, and root mean squared error (*RMSE*). These summary statistics are limited to the winter season (Nov 1 to June 1) for the period of

record to avoid anomalously low errors associated with the persistent summer snowfields and glaciers in the region. The CH maps also fall within this period. *RMSE* is defined as:

$$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^N (SCA_{A,t} - SCA_{B,t})^2} \quad (1)$$

N is the total number of days in the compared time series (SCA_A and SCA_B), while t is the ordinal day. For comparisons between MODSCAG and MOD10A1 products, $N=2644$ and $t=1$ corresponds to 17 February 2000; for those comparisons involving the CRREL reports, $N=110$ and $t=1$ corresponds to 25 November 2006.

While total snow covered area is perhaps the most commonly derived parameter from SCA maps, we also compared the different products to CH spatially. To assess this, we track three possible outcomes for each pixel in those products compared to CH: true positives (TP), false positives (FP), and false negatives (FN). Using these, we calculate the following performance statistics:

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F = 2 \frac{Precision \times Recall}{Precision + Recall} = \frac{2TP}{2TP+FP+FN} \quad (4)$$

Precision is the chance that a pixel identified as snow has snow, while *Recall* is the probability of identifying a snow-covered pixel. *F* score is a combined statistic that describes the overall accuracy of the classification but ignores true negatives, effectively considering only those pixels that were snow-covered in one of the products being compared. This omission is important for assessing a phenomenon as spatially and temporally variable as SCA because it prevents snow-free areas from inflating the perceived accuracy (Rittger *et al.*, 2013). For example, a scene with 5% snow cover that was classified as totally snow-free would be 95% accurate but have *Precision*, *Recall*, and *F* score of 0%. The same scene with half of the snow correctly classified would be 97.5% accurate but have an *F* score of 67%. This provides a sensitive accuracy assessment that is not biased by either the extent of the assessment area or seasonal changes in SCA.

RESULTS

Daily TDF and CGF SCA maps were produced using imagery from February 17, 2000 to December 31, 2014. Figure 4 shows example inputs and outputs for MODSCAG TDF from 5 March 2003. Panel A shows the unfiltered MODSCAG on that day, which includes several areas of low-FSCA that are probably erroneous, as determined by

inspection of the surface reflectance data and the MOD10A1. The 16 input images used by TDF are shown in the upper right panel, and the filtered image appears in panel C, notably with the low-FSCA pixels in the northwest removed and the cloudy pixels removed .

Mean cloud cover in filtered images was 1,675 pixels (360 km²) for MODSCAG and 26,791 pixels (5,751 km²) for MOD10A1 or 0.03% and 0.5% of the tile, respectively. We chose to retain some cloud-covered pixels rather than extend the filtering window both out of concerns for the age of the data in the final product as well as the processing time; however, dynamically updating the filtering window on a per pixel basis to create a completely cloud-free product does not add significant processing time after creating the first product in a series because each day's product can be created from the previous day's filtered SCA, the corresponding age rasters, and the new unfiltered input. For all images and pixels in the period of record, mean decision age was 1.5 and 2.4 days for MODSCAG and MOD10A1, respectively. The daily mean decision age was highly variable but generally greatest in January and February (Figure 2D). With the exception of brief periods with missing imagery, when we assumed all pixel's values to be cloud, daily mean decision age for MODSCAG was less than a week. Mean decision ages for those pixels determined to be SCA were expectedly higher than the mean, about a day longer for both inputs, and relatively uniform, spatially (Figure 3C).

When evaluating different estimates of total SCA, we started by comparing products from different inputs that had been subject to the same filtering process. MODSCAG and MOD10A1 are derived from the same sensor data, though they use different techniques to estimate SCA. It is then reasonable to expect that the filtered products would observe a similar SCA signal. While comparison of the filtered products to CH allows us to assess the accuracy of the filtered products, this comparison is limited to 110 scenes. Inter-comparison of total SCA between products allows us to extend the accuracy assessment by proxy; if we then identify which filtered product is most similar to CH, we can draw conclusions about how that product compares to the others over a much larger number of scenes. While the unfiltered products are not ultimately of interest in this study, it is notable how different they are (RMSE = $102.2 \times 10^3 \text{ km}^2$) from each other. The majority of that difference (mean difference of $92.6 \times 10^3 \text{ km}^2$ more SCA in MODSCAG) is due to many fewer clouds in MODSCAG than in MOD10A1 (mean difference = $121.3 \times 10^3 \text{ km}^2$). Filling in the clouds using CGF alleviates some of these differences, reducing RMSE to $72.3 \times 10^3 \text{ km}^2$; TDF further improves the agreement (RMSE = $41.2 \times 10^3 \text{ km}^2$). Because TDF requires SCA persistence and neither CGF nor TDF has a mechanism to add SCA outside of gap pixels, it follows that increased agreements

in total SCA estimates can be largely attributed to reducing SCA detections in MODSCAG. The TDF persistence test also removes SCA from MOD10A1, which, due to its more aggressive cloud mask, results in anomalously low total SCA estimates during cloudy periods and likely underestimates of SCA in general. Under the assumption that the MOD10A1 CGF (for which CGF was developed and validated by Hall *et al.*, 2010) is accurate, we compared the MODSCAG TDF to the MOD10A1 CGF, and found that they are in better agreement than the TDF products are to each other ($RMSE = 17.9 \times 10^3 \text{ km}^2$). While this study focused on binary SCA because of the limitations of CH and the wide use and applicability of binary SCA products, we did consider the fractional case in the inter-product comparisons of total SCA. In most cases, errors were reduced when using FSCA as algorithm inputs; this is particularly notable in the TDF comparison. In general FSCA comparisons, MOD10A1 tends to detect fewer SCA pixels with an average higher FSCA than MODSCAG. Coincidental balancing of these tradeoffs results in lower errors when comparing total SCA, but this is not supported by the spatial statistics. Statistics for select comparisons of total SCA, including those above, appear in Table 1.

Comparing the unfiltered, CGF, and TDF results to CH tell a similar story. As we assumed above, MOD10A1 CGF is a very accurate measure of total SCA ($RMSE = 26.3 \times 10^3 \text{ km}^2$) as compared to CH. Again, we see poorer performance of TDF when applied to the MOD10A1, resulting in lower accuracy ($28.5 \times 10^3 \text{ km}^2$) than the MOD10A1 CGF, and a reversal in sign of the mean difference ($-7.4 \times 10^3 \text{ km}^2$) due to removal of SCA by the persistence check, as previously suggested; however, we see dramatic improvements in MODSCAG TDF over MODSCAG CGF and, ultimately, a similar RMSE ($29.5 \times 10^3 \text{ km}^2$) to the MOD10A1 CGF. Summary statistics appear in Table 1. For all methods except MOD10A1 TDF, error tends to manifest in overestimation of SCA relative to CH (Figure 5). Among the tested data sets, MOD10A1 CGF and MODSCAG TDF minimize this error and exhibit the least variance.

Analysis of the spatial accuracy of the filtered products supports the previous findings. The most accurate, with an *F score* of 0.906, was the MOD10A1 CGF, while MODSCAG TDF ($F = 0.894$) was an improvement over MODSCAG CGF ($F = 0.877$), and MOD10A1 TDF ($F = 0.884$) was less accurate than its counterpart. The tendency of MODSCAG to overestimate SCA is evidenced in the high *Recall*, which is driven by false negatives, of both filtered products; it is then no surprise that the improvement in *Precision* between MODSCAG TDF and CGF was over 5%. Again, MOD10A1 TDF shows persistent underestimation as evidenced by a 7% drop in recall as compared to MOD10A1 CGF. Spatial accuracy statistics appear in Table 2.

DISCUSSION

Our results show that, when applied to unfiltered MODSCAG imagery, the persistence-based time-domain-filtering (TDF) produces a more consistent and accurate gap-filled SCA map than the cloud-gap-filled (CGF) methodology. CGF, which retains the value of the last cloud-free pixel as the output, causes false positive misclassifications of SCA, commonly found adjacent to clouds in MODSCAG, to appear in the filtered product. TDF prevents many of these misclassifications by requiring consecutive (considering only cloud-free detections) snow-covered readings to produce a snow pixel in the filtered output. While MODSCAG TDF and MOD10A1 CGF minimized error in total SCA estimates when compared to CH, they also performed best spatially. As both MODSCAG and MOD10A1 detections methodologies differ from that used to generate CH, some differences are expected. Figure 6 maps the spatial accuracy statistics across the comparison region for the filtered MODSCAG products and MOD10A1 CGF as color composites where the Red, Green, and Blue channels are mean *Recall*, mean *F score*, and mean *Precision*, respectively. Each color channel's output is scaled to the dynamic range of its variable, so the color combinations are indicative of the relative contribution of each variable rather than their absolute magnitudes; this highlights spatial trends in the accuracy statistics and, when considered in combination with their scene-wide summary statistics found in Table 2, paints a more complete picture of how each algorithm performs. MODSCAG CGF displays large regions of relatively low *Precision* and high *Recall*, consistent with common false positives. These red regions are largely absent in the MODSCAG TDF and MOD10A1 CGF panels, replaced by more nuanced regional inaccuracies. These two panels show very similar spatially distributed error, largely confined to low-elevation regions where snow is less common. These regions show a more mottled appearance than in the top panel because they are not dominated by a particular error type and are mapped over smaller dynamic ranges due to their higher overall accuracy. The MODSCAG TDF map as a whole, when compared to the MOD10A1 CGF, has a slightly bluer hue. This suggests that TDF's logic is systematically removing some true positive snow pixels, resulting in relatively lower *Recall* scene-wide, a problem which was immediately noticeable in the MOD10A1 TDF; however, the improvements in both spatial accuracy and total SCA estimation far outweigh this bias.

CONCLUSION

Clouds, sensor and solar geometry, and sensor malfunction introduce gaps into multispectral remotely sensed data. In many cases, these data gaps are temporally variable, and a time series of imagery can be used to estimate the values of gap pixels. We developed an algorithm to remove clouds and limit false positives due to cloud confusion from daily snow covered area products. The value of cloudy pixels was assumed to be snow-covered if the two most recent cloud-free days were snow-covered. Because cloud cover is generally more variable than SCA on a daily time scale, this simple persistence test limits false positives in SCA caused by cloud/snow confusion that are common in daily products. While we use up to 16 days of imagery to estimate SCA for any given day, we find that most gaps are filled in just a few days despite the persistence test. We found that, when compared to manually derived historical SCA estimates (CH), the Time-Domain-Filtered (TDF) MODSCAG and Cloud-Gap-Filled (CGF) MOD10A1 produced the most consistent and accurate estimates of SCA. MODSCAG CGF and MOD10A1 TDF tended to overestimate and underestimate SCA, respectively, and exhibited more classification inaccuracies spatially. While the most similar to the CH, MODSCAG TDF and MOD10A1 CGF were also the most similar to each other of those tested. This reconciliation of SCA signals is important because the inputs products, while using different SCA detection methodologies, are derived from the same sensor data and should arrive at similar estimations of SCA in a filtered product. This method for removing spurious SCA detections from MODSCAG, while interpolating the values of cloud-covered pixels, results in a product that is more comparable, spatially, to existing filtered SCA data sets and allows the user to potentially leverage MODSCAG's fractional snow cover capabilities without the burden of the extra snow/cloud-confused SCA misclassifications.

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Information System (EOSDIS) Reverb (<http://reverb.echo.nasa.gov/reverb/>). MODSCAG data product is courtesy of the NASA Jet Propulsion Laboratory (JPL), Pasadena, California.

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FIGURE CAPTIONS

Figure 1. (A) Map of geopolitical boundaries, watersheds (red), and elevation for Afghanistan. Black hashed line denotes extent of MODIS tile H23V05. (B) SCA presence or the chance of an area being snow covered between November and June (2000-2014), derived from daily MODSCAG and MOD10A1 (n=6068). Areas with no SCA detections during the period of record (POR) appear grey.

Figure 2. Filtered SCA Time Series for Select Years. This figure shows two of the cloudier years in the period of record to highlight both the need and application of the TDF algorithm. When applied to MODSCAG, the cloud-gap-filled (CGF) logic results in a noisy, high magnitude SCA signal (light red) that is not consistent with either the other products nor the CRREL historic (CH) maps. Similarly, MOD10A1 TDF (blue) tends to underestimate total

SCA relative to the other products, including major failures during very cloudy periods (March 2003) due to its aggressive cloud mask. The black and grey lines show the area covered by clouds for 16 days straight, prior to and including that day, on any given day for MODSCAG and MOD10A1, respectively. MOD10A1 CGF (light blue) and MODSCAG TDF (red) were found to perform best both when compared to the other filtered data sets as a data reconciliation exercise and when compared to the CH data set. X-axis spans 1 October, 2002, to 30 September 2004 with ticks on the first of each year.

Figure 3. Cloud Presence and Persistence. The first panel (**A**) shows the chance of cloud cover in the tile (in either unfiltered product) between November and June in each year of the POR. Despite significant cloud cover, particularly in the higher elevations, the average number of days between the current day and a cloud-free scene (**B**) is short. Panel **C** shows the mean decision age, or the age of the oldest data that appears in the filtered SCA map for all snow-covered pixels, most often the age of the older image in the cloud-free pair. Mean decision age across the entire tile, calculated on each day of the POR, is plotted in panel D for MODSCAG (red) and MOD10A1 (blue) TDF. These differ considerably because of the different cloud layers in the unfiltered products.

Figure 4. Example algorithm inputs, temporal diagnostic, and output from March 5, 2003. MODSCAG from this date (**A**, **0**) shows significant cloud cover (red). Our algorithm uses up to 15 previous days' data (numbered panels, increasing backwards in time) to estimate current SCA (**C**). The decision age (**B**) for this day, or the time since a pixel recorded two cloud-free readings, illustrates the effective age of each of the output pixels and constrains the temporal resolution and accuracy of the product.

Figure 5. Comparison of Filtered SCA Products and CRREL Historic (CH) Maps. This scatterplot details individual comparisons between the filtered maps and CH. The two data sets that performed best, MODSCAG TDF and MOD10A1 CGF, appear in bright red and blue, respectively. Summary statistics for these comparisons appear in Table 1.

Figure 6. Spatial Distribution of Accuracy Statistics. These three panels show the spatial distribution of the accuracy statistics as color composite images where R,G,B = mean *Recall*, mean *F score*, mean *Precision* for both filtered MODSCAG products and MOD10A1 CGF. Each band is normalized to its own dynamic range to maximize contrast and, therefore, represents the relative distribution of the error signal, as opposed to its absolute magnitude,

which is summarized in Table 2. This means that areas dominated whose error is dominated by false positives appear in red and those dominated by false negatives appear in blue. Brightness differences depend on the relative contributions of the three variables and are dominated by *Recall* and *Precision* (there are no green areas as it is impossible to have a high *F score* with low *Precision* and *Recall*). The large bright red regions in the upper panel denote areas of high *Recall*, low *F score*, and low *Precision* in the MODSCAG CGF. This corresponds to areas that were often classified as snow (this incidentally results in high *Recall*) but were often false positives. The duller reds in the interior of the upper panel highlight areas that were more accurate overall (uniformly greater *F score* and *Precision*) but still showed more false positives (greater *Recall* than *F score* or *Precision*).

Table 1.

Summary statistics of estimates of total SCA for winters over the period of record

Comparison	Statistic	Area (1000 km ²)	
		Binary	Fractional
MODSCAG MOD10A1 Unfiltered	RMSE ¹	102.2	61.3
	Mean difference ²	92.6	52.6
	Median difference	85.8	47.1
MODSCAG MOD10A1 Unfiltered (Cloud)	RMSE	138.6	
	Mean difference	-121.3	
	Median difference	-115.8	
MODSCAG MOD10A1 CGF	RMSE	72.3	28.5
	Mean difference	60.7	6.5
	Median difference	53.9	3.2
MODSCAG MOD10A1 TDF	RMSE	41.2	22.0
	Mean difference	35.4	0.4
	Median difference	31.1	-1.4
MODSCAG TDF MOD10A1 CGF	RMSE	17.9	25.2
	Mean difference	10.8	-17.7
	Median difference	9.6	-14.6
	Mean SCA extent	254.2	
	MODIS Tile	1236.4	
Comparison	Statistic	Area (1000 km ²)	
		MODSCAG	MOD10A1
Unfiltered CH	RMSE	37.4	74.7
	Mean difference	13.7	-53.9
	Median difference	17.3	-42.2
CGF CH	RMSE	45.6	26.3
	Mean difference	39.2	11.2
	Median difference	34.1	10.9
TDF CH	RMSE	29.5	28.5
	Mean difference	19.5	-7.4
	Median difference	17.6	-5.5
	Mean SCA extent	200.9	
	CH Mask ³	661.1	

¹ RMSE is defined in Eq. (1).

² Difference is total SCA (or cloud) in the first product listed in the comparison minus the second.

³ Area of interest monitored by CH varied over time. Comparisons with CH are limited to the area intersected by the 110 maps.

Table 2.

By-pixel comparison of filtered products to CRREL historic maps

	<i>Precision</i>	<i>Recall</i>	<i>F score</i>
MOD10A1 CGF	.879	.935	.906
MODSCAG CGF	.797	.975	.877
MOD10A1 TDF	.903	.865	.884
MODSCAG TDF	.849	.943	.894

Figure 1

Figure 2

Figure 3

Figure 4

Figure 5

Figure 6