Using Air Temperature to Quantitatively Predict the MODIS Fractional Snow Cover Retrieval Errors over the Continental US (CONUS)

Jiarui Dong[1,2], Mike Ek[1], Dorothy Hall[3], Christa Peters-Lidard[4], Brian Cosgrove[5], Jeff Miller[3,6], George Riggs[3,7], and Youlong Xia[1,2]

1 NOAA/NCEP/EMC, College Park, Maryland, 20740
2 I.M. System Group, Rockville, MD20852
3 Cryospheric Sciences Laboratory, NASA/GSFC, Greenbelt, Maryland, 20771
4 Hydrological Sciences Laboratory, NASA/GSFC, Greenbelt, Maryland, 20771
5 NOAA/NWS/OHD, Silver Spring, Maryland
6 Wyle Inc., Houston, Texas, 77058
7 SSAI Inc., Lanham, MD, 20706

Correspondence
Jiarui Dong
NOAA/NCEP/EMC
5830 University Research Ct
College Park, Maryland 20740
Email: Jiarui.Dong@noaa.gov

(Submitted to Drought Special Collection of Journal of Hydrometeorology)
April 5, 2013

Revised on September 12, 2013
Revised on November 21, 2013

Abstract

Understanding and quantifying satellite-based remotely sensed snow cover uncertainty are critical for its successful utilization. The Moderate Resolution Imaging Spectroradiometer (MODIS) snow cover errors have been previously recognized to be associated with factors such as cloud contamination, snowpack grain sizes, vegetation cover, and topography; however, the quantitative relationship between the retrieval errors and these factors remains elusive. Joint analysis of the MODIS fractional snow cover (FSC) from Collection-6 (C6) and in-situ air temperature and snow water equivalent (SWE) measurements provides a unique look at the error structure of the MODIS C6 FSC products. Analysis of the MODIS FSC data set over the period from 2000 to 2005 was undertaken over the Continental US (CONUS) with an extensive observational network. When compared to MODIS Collection-5 (C5) snow cover area (SCA), the MODIS C6 FSC product demonstrates a substantial improvement in detecting the presence of snow cover in Nevada (30% increase in POD-probability of detection), especially in the early and late snow seasons, some improvement over California (10% POD increase), and a relatively small improvement over Colorado (2% POD increase). However, significant spatial and temporal variations in accuracy still exist, and a proxy is required to adequately predict the expected errors in MODIS C6 FSC retrievals. We demonstrate a relationship between the MODIS FSC retrieval errors and temperature over the CONUS domain, captured by a cumulative double exponential distribution function. This relationship is shown to hold for both in-situ and modeled daily mean air temperature. Both of them are useful indices in filtering out the misclassification of MODIS

snowcover pixels and in quantifying the errors in the MODIS C6 product for various hydrological applications.

Keywords: Moderate Resolution Imaging Spectroradiometer (MODIS), fractional snow cover, temperature, errors.

1. Introduction

In the middle to high latitude and alpine regions, the seasonal snowpack can dominate the surface energy and water budgets due to its high albedo, low thermal conductivity, high emissivity, considerable spatial and temporal variability, and ability to store and then later release a winter's cumulative snowfall (Cohen, 1994; Hall, 1998). With this in mind, the snow drought across the U.S. has raised questions about impacts on water supply, ski resorts and agriculture. Knowledge of various snowpack properties is crucial for short-term weather forecasts, climate change prediction, and hydrologic forecasting for producing reliable daily to seasonal forecasts. One potential source of this information is the multi-institution North American Land Data Assimilation System (NLDAS) project (Mitchell et al., 2004). Real-time NLDAS products are used for drought monitoring to support the National Integrated Drought Information System (NIDIS) and as initial conditions for a future NCEP drought forecast system. Additionally, efforts are currently underway to assimilate remotely-sensed estimates of land-surface states such as snowpack information into NLDAS. It is believed that this assimilation will not only produce improved snowpack states that better represent snow evolving conditions, but will directly improve the monitoring of drought.

In the western United States, over half of the water supply is derived from mountain snowmelt (Stewart et al., 2005). In many mid-latitude, high elevation regions, the snowpack delays runoff and thus provides much-needed water in the spring and summer, which can mitigate agricultural droughts through irrigation when water is needed most. However, little is known about the spatial and temporal variations of critical processes like snowmelt and runoff in these mountainous areas. As both the model predictions and passive microwave snow water equivalent (SWE) observations contain large errors due to land surface complexities and temporally frequent snowmelt processes in the western United States (e.g., Tait and Armstrong, 1996; Rodell et al., 2004; Foster et al., 2005; Dong et al., 2005; Tong et al., 2010), the 500 m daily MODIS C5 SCA product has been widely used as an important constraint on snowpack processes in land surface and hydrological models. Assimilation experiments with MODIS SCA (Rodell and Houser, 2004; Andreadis and Lettenmaier, 2006; Molotch and Margulis, 2008; Liu et al, 2013) or synthetic data (Liston et al., 1999; Clark et al., 2006) have demonstrated some improvements in the accuracy of both streamflow and SWE simulations spatially and temporally. Yatheendradas et al. (2012) used MODIS fractional snow cover to perform assimilation experiments over the Distributed Model Intercomparison Project – Phase 2 (DMIP II) western basin domain and achieved large improvements judged against the control run, but degraded the simulated streamflow when compared against the calibrated run due to lack of below-canopy measurements. To attain the optimal estimate of snowpack state, it is essential that the assimilation scheme accounts for the relative uncertainty of both model predictions and observations. For example, direct replacement of the modeled snow states with observations by assuming that the observations are error-

free can often yield degraded model predictions in certain situations (e.g., Liston et al., 1999; Rodell and Houser, 2004). Users need to know when and where the data are most reliable, and account for uncertainty when ingesting satellite information into models (Dong et al., 2007; Dong and Peters-Lidard, 2010).

A snowpack is an integrated response to climate, weather and land surface complexity. Understanding and quantifying MODIS fractional snow cover retrieval errors are critical for successful utilization of the FSC product. A time-series comparison performed by Klein and Barnett (2003) between MODIS C5 SCA retrievals and the in-situ SWE measurements at 15 SNOTEL (for SNOwpack TELemetry) stations in the Upper Rio Grande basin over one entire snow season from 13 October 2000 to 30 March 2001 showed an overall high accuracy (94%). However, an extended comparison of MODIS against SNOTEL sites from 1 October 2000 to 9 June 2002, showed a slightly lower overall classification accuracy of 88% (Klein and Barnett, 2003). As summarized in Parajka and Bloschl (2012), most of the MODIS accuracy assessments reported the overall accuracy to be between 85% and 99% during clear sky conditions. Potential sources of misclassification in MODIS-derived standard snow-cover products have been previously identified as a thin snowpack (Klein and Barnett, 2003; Shreve et al., 2009), clouds (Maurer et al., 2003), patchy snow (Parajka and Bloschl, 2006) and forest cover (Hall et al., 1998; Simic et al., 2004; Roy et al., 2010; Parajka et al., 2012). Hall and Riggs (2007) review these potential sources and conclude that lower accuracy is found in forested areas and complex terrain, and when snow is thin and ephemeral.

A number of recent studies have focused on improving MODIS fractional snow cover detection. MODSCAG (MODIS Snow Covered Area and Grain size) is a

physically based and geographically consistent model that accounts for the spatial and temporal variation in surface reflectance of snow and other surfaces (Dozier et al., 2008; Painter et al., 2009). Rittger et al (2013) gives a quantitative analysis of the MOD10A1 binary and fractional snow cover errors, along with those of the MODSCAG algorithm. MODSCAG has the ability to detect fraction of snow covered area down to values of 10% to 15%, and is able to detect snow cover at lower elevations near the snowline where snow is not the dominant surface cover. Parajka et al. (2012) used a 2-day temporal filter that led to a significant reduction in the number of days with prohibitive cloud coverage and to an increase in overall snow mapping accuracy. In particular the 2-day temporal filter decreases the number of cloudy days from 61% to 26% and increases the snow mapping accuracy from 91.5% to 94%. Dong and Peters-Lidard (2010) compared the 500 m daily MODIS C5 SCA product to the in-situ SWE measurements from SNOTEL and the U. S. Historical Climatology Network in two distinct climatic regions (California and Nevada versus Colorado) in the western United States from 2000 to 2005. The region encompassing California and Nevada differs significantly from the Colorado area in its proximity to the ocean, topography, warmer climate and wetter snow. Dong and Peters-Lidard (2010) demonstrated for the first time that MODIS C5 SCA retrieval errors can be predicted by simultaneous MODIS-based land surface temperature (LST) or in-situ based daily mean air temperature measurements. This study will use the methodology from Dong and Peters-Lidard (2010) to assess the errors associated with the MODIS C6 FSC product over a CONUS-wide domain. Accordingly, the purpose of this paper is ultimately to make the MODIS C6 FSC product more useful to the hydrologic and drought communities.

2. Observational Data

2.1. Satellite Observations

MODIS is a multispectral instrument with 36 bands featuring nominal spatial resolutions of 250 m (two bands), 500 m (five bands), and 1km (29 bands). MODIS data have been available on Terra since 24 February 2000 and on Aqua since 24 June 2002. In this study, we focus on the Terra-MODIS Level 3 500 m Collection-5 SCA (snow covered area) and Collection-6 FSC data (Hall et al., 2002; Riggs and Hall, 2012). MODIS snow cover data are based on a snow mapping algorithm that employs a Normalized Difference Snow Index (NDSI) (Valovcin, 1976; Crane and Anderson, 1984; Dozier 1989; Hall et al., 1995; Salomonson and Appel, 2004, 2006) and other criteria tests. The binary value in the C5 (MOD10A1) product returns a positive result if the NDSI is 0.4 or above, which corresponds to about 50% snow coverage (Riggs et al., 2006). The MODIS fractional snow cover (FSC) algorithm for C6 is the same as in C5; however, the screens applied to alleviate snow detection errors of commission and omission have been changed (Riggs and Hall, 2012). The surface temperature screen for snow commission errors has been deleted from the algorithm in C6 because it was discovered that the screen has a detrimental impact on mapping snow cover on mountains in the spring and summer, consistent with the results reported in Dong and Peters-Lidard (2010). One of the largest problems affecting MODIS SCA products is false detection of cloud cover; however, the false detection of snow and land under clear sky conditions is

also recognized as another potentially significant issue due to land surface complexity and frequent weather variations (e.g., Hall and Riggs, 2007).

2.2. In-situ Observations

The Natural Resources Conservation Service (NRCS) installs, operates, and maintains an extensive, automated system to collect snowpack and related climatic data in the Western United States called SNOTEL. The system evolved from NRCS's Congressional mandate in the mid-1930's to measure snowpack in the mountains of the West and forecast the water supply. The programs began with manual measurements of snow courses; since 1980, SNOTEL has reliably and efficiently collected the data needed to produce water supply forecasts and to support the resource management activities of the NRCS (Crook, 1977; Natural Resources Conservation Service, 1997). Basic SNOTEL sites feature a pressure sensing snow pillow, storage precipitation gage, and air temperature sensor. A pressure pillow of 3.66-meter size can provide an accurate measurement of snow water equivalent, its response time to new snow is on the scale of minutes and snowfall rates as low as 0.762 mm per hour can be observed (Beaumont, 1965). However, it should be noted that a small rise or decrease in SWE values may not be due to snowfall or snowmelt. Rather, these fluctuations may reflect effects such as drifting, wind scour, sublimation, blowing snow, and foreign material being deposited on the snow pillow, especially in areas of low snow cover (Serreze et al., 1999). The 670 available SNOTEL stations in our study area are predominantly located in high mountainous regions with a mean elevation about 2272 m (dots in Figures 1).

Molotch and Bales (2006) showed that SNOTEL sites poorly represent a region with respect to spatial distribution of snow persistence, introducing a bias. Additionally, SNOTEL sites do not adequately represent high elevation regions and therefore, their use introduces yet another bias by not addressing patchy, high elevation snow cover. Although they are limited in their spatial representativeness, ground-based SWE observations from the SNOTEL network have been widely used to evaluate, initialize and update grid-element SWE estimates within spatially distributed snowmelt models (e.g., Carroll et al., 2001), develop the remotely sensed SWE detection algorithms (Chang et al., 1991), and evaluate the spatial distribution of remotely sensed SWE using statistical models (Klein and Barnett, 2003). Although SNOTEL locations may not represent the full range of physiographic and snowpack conditions found within the watersheds in which they are located, they are placed in areas intended to be representative of water-producing regions of a watershed (US Soil Conservation Service, 1972).

Previous work has suggested that SNOTEL SWE values are inherently biased toward overestimating mean basin-wide SWE (e.g., Daly et al., 2000). In this study, we also use the U. S. Historical Climatology Network (USHCN) Daily Temperature, Precipitation, and Snow Data Set containing daily observations of maximum and minimum temperature, precipitation and snowfall amount, and snow depth (Williams et al., 2006). Most station records are essentially complete for at least 50 years, and the most recent station start date is 1948. Data from 1005 of a total of 1062 observing stations extend through 2000, while 920 station records extend through 2005. The USHCN stations are located in relatively flat regions scattered across the CONUS and feature a mean elevation about 520 m (pluses in Figure 1).

2.3. NLDAS forcing

The NLDAS project has produced over 30-years of retrospective and real-time forcing from 1979 to the present to support its land surface modeling activities (Cosgrove et al., 2003; Xia et al., 2012). NLDAS forcing features a 1/8th degree spatial resolution and an hourly temporal resolution, and is based on spatially and temporally interpolated 3-hourly North American Regional Reanalysis (NARR) model output (Mesinger et al., 2006) along with precipitation and shortwave observations. An elevation adjustment has been applied in the generation of NLDAS air temperature, pressure, longwave radiation, and humidity fields from the 32 km NARR output grid which adjusts for the significant differences in the NARR and NLDAS topography fields. Additionally, NARR shortwave radiation has been bias corrected via use of Geostationary Operational Environmental Satellite (GOES) shortwave data. Luo et al. (2003) used observed forcing data at Oklahoma Mesonet stations and Atmospheric Radiation Measurement/Cloud and Radiation Testbed stations (ARM/CART) over the Southern Great Plains to evaluate NLDAS downward solar radiation, downward long wave radiation, 10-m wind speed, specific humidity, 2 m air temperature, surface pressure, and precipitation. The results indicated good agreement between NLDAS forcing data and observations for all meteorological variables except for hourly precipitation. The hourly NLDAS air temperature data will be used in the study.

3. Collection-6 update to previous results

The overall estimate of MODIS snow retrieval accuracy limits its usefulness in many hydrologic applications including drought monitoring, as it displays significant spatial and temporal variability. Thus, the investigation of spatial and temporal sampling representativeness is important before its successful use. The quality of MODIS-retrieved SCA and FSC relative to the in-situ observations described above is evaluated using a confusion matrix, which appears to provide an excellent summary of two types of thematic error that can occur, namely, omission and commission (Foody, 2002). Similar to Dong and Peters-Lidard (2010), we chose to use the probability of detection (POD) and false alarm ratio (FAR) in the following contexts. The probability of detection, POD=SS/(SS+NS), measures the fraction of observed snow cover cases that were correctly detected by MODIS, and the false alarm ratio, FAR=SN/(SN+NN), measures the fraction of observed snow-free land cases that were incorrectly detected as snow covered cases by MODIS. The SS denotes that snow cover is detected in MODIS and it does occur, the NS denotes that snow cover is not detected in MODIS but it does occur, the SN denotes that snow cover is detected in MODIS but it does not occur, and the NN denotes that snow cover is not detected in MODIS and it does not occur. Table 1 illustrates the confusion matrix for assessing MODIS SCA retrieval accuracy including the aforementioned four categories in this study. A perfect sample occurs when SN and NS are zero.

Dong and Peters-Lidard (2010) used the binary part of the MOD10A1 product (1=snow covered or 0=snow-free) in their study. To match this use, the MODIS C6 FSC (varying from 0.0=snow-free to 1.0=full snow coverage) and in-situ measured SWE are transformed into a binary snow cover product (FSC=0 and SWE=0 for snow-free land or

FSC>0 and SWE>0 for snow cover). While this is not a proper evaluation of the fractional snow cover and snow water equivalent, it serves as means of achieving the important match with the MODIS C5 binary estimates. We consider only clear-sky days at the study sites, and MODIS snow-cover results are compared to data from SNOTEL and the USHCN. Comparison of MODIS C5 binary and C6 FSC monthly climatologies is made for three states: California, Nevada and Colorado, for each month over 2000-2005 (Figure 2).

The POD of snow cover using MODIS improves in C6 relative to C5 for all cases with the exception of the month of June in the California study area. The improvement in snow-cover detection is especially substantial in Nevada in the months of March, April, May and June. Improvement using C6 is less dramatic in the Colorado study area. The overall POD increase is about 2% (from 82% to 84%) for Colorado, 10% (from 76% to 86%) for California, and 30% (from 54% to 84%) for Nevada. The difference in snow cover between Nevada and Colorado is likely due to the deletion of the temperature screen in the C6 product and due to possible warmer temperatures over the mountains in Nevada than in Colorado. The surface temperature screen for snow commission errors was removed from the algorithm in C6 because it was discovered that the screen has a detrimental impact on mapping snow cover on mountains in the spring and summer when temperatures are close to freezing point. The mean air temperature over snow cover surfaces in Colorado (-4°C) is much lower than the freezing point, but is close to the freezing point in California (-0.24^{o}C) and Nevada (-1.24^{o}C) during the snow season. Therefore, removing the surface temperature screen did not have a large impact in Colorado, but did lead to a substantial impact in Nevada and, to some extent, in

California. The FAR of the C6 fractional snow cover product is equal to or lower than that of the C5 product in all months (with the exception of May and June in the Nevada study area), but again, mixed results are shown in the Colorado study area.

Building on this analysis, the study was expanded to include all SNOTEL and USHCN stations in the CONUS. The POD and FAR results over the CONUS are shown in Figure 3. The lower POD in autumn and spring could stem from the challenges of comparing 500 m satellite pixel data to point measurements at geographically-fixed stations due to the occurrence of patchy snow packs. Uncertainty in the geolocation of MODIS pixels within the data processing system may be a factor to consider in comparisons to ground station data. For the CONUS, the C6 MODIS FSC product demonstrates a strong ability to detect the presence of snow cover (over 90% from December to March), and the FAR is less than 1.5% over all four seasons. While not shown here, large spatial variability exists in the POD of C6 MODIS FSC retrievals compared with coincident ground truth station data.

The length of the evaluation period for SCA retrievals must be long enough to provide an unbiased estimate of the true product accuracy. This is supported by Klein and Barnett (2003) which confirmed that analysis periods of different lengths produce significant differences in accuracy estimates. In our study, we address this concern by investigating the MODIS SCA retrieval errors in each month during the multi-year period from 2000 to 2005. There are significant temporal variations in accuracy from less than 60% in October to 94% in January and February. Generally, MODIS shows a strong ability to detect snow presence during the snow season with POD above 80% from November to April and snow-free land with FAR below 1.5% all year round (Figure 3).

However, in months from May to October, MODIS correctly detects the presence of snow cover less than 60% of the time under cloud-free conditions, which may result from a combination of patchy snow and land surface complexity.

Such significant spatial and temporal variations in MODIS SCA retrieval accuracy suggest that adequately predicting the MODIS SCA retrieval errors can be important for hydrological applications including drought monitoring. In the following section, we re-visit and extend the temperature-based proxy approach of Dong and Peters-Lidard (2010) to the C6 data for CONUS.

4. Factors affecting MODIS snow cover detection

Uncertainty in MODIS C6-retrieved FSC relative to in-situ observations is investigated using the above-defined POD statistics and their relationships to snowpack mass and air temperature. POD statistics are calculated for MODIS 500 m by 500 m cloud-free pixels having coincident in-situ observations over the snow season (October to June) during the period from 2000 to 2005. As shown in Figure 4, the POD for MODIS to detect snow cover shows a steady increase with increasing snow amount, with a FAR of about 3%. The POD increases from about 50% in shallow snowpacks with SWE values less than 1 cm, to about 85% in deep snowpacks with SWE values above 5 cm (black bars in Figure 4). As the SWE approaches zero, it would be expected that there would be a more patchy distribution within a 500 m by 500 m MODIS pixel, as discussed by Klein and Barnett (2003). When the fractional snow product is characterized by the most issues, i.e., more patchy distribution during the snowmelt season, the assimilation of

snow cover information is at its most important (Clark et al, 2006). However, the MODIS FSC product provides only a minor benefit via assimilation during the snowmelt season due to the lower POD statistics and a relatively low 50% accuracy value. In addition, the POD statistics are insensitive to increasing snow water amounts over 5 cm. As SWE is only partially effective in demonstrating the uncertainty in the MODIS FSC product, we need to seek an alternative index to better predict the uncertainty and to make the MODIS FSC product more useful to the hydrologic and drought communities.

We further investigate the relationship between POD and SWE for three different daily mean air temperature groups calculated using in-situ data: (i) temperatures less than -5°C, (ii) temperatures between -5°C and 0°C, and (iii) temperatures above 0°C. Each of these groups is illustrated as different color bars in Figure 4. As this figure shows, the strong positive relationship between POD and SWE is also a function of daily mean air temperature. For daily mean air temperatures below -5 ^{o}C, the MODIS SCA retrievals are reliable at all values of SWE (i.e., POD greater than 80% for all SWE values and greater than 95% for SWE amounts over 3 cm, indicated as green bars), and therefore the FSC retrieval accuracy is insensitive to the snowpack depth in the colder climate with less snowmelt. However, for warmer temperatures, the POD changes significantly from about 30% for SWE values less than 1 cm, to above 85% for SWE values greater than 50 cm, thus confirming the strong relationship between snowpack thickness and the MODIS FSC retrieval error.

At any given SWE, the POD consistently decreases with increasing temperature, and there is a large difference in the POD between the depth-groups with average temperatures above 0°C (red bars) and below 0°C (blue and green bars).When the

snowpack is thin, the POD difference is large among the three temperature groups, with a POD of just 30% for temperatures above 0°C and over 80% for temperatures below -5°C. When the snowpack is deeper, the POD appears to be less a function of temperature, supporting the intuitive concept that colder, deeper packs are less patchy and easier to detect. In particular, when the SWE value is larger than 100 mm, the POD shows little difference between the > 0°C and < -5°C temperature groups (red *versus* green bars). Across all three temperature groups, the FAR increases from 0.6% for temperatures above 0°C to about 14% for temperature below -5°C due to more mixed snow and land contamination. This statistic measures the fraction of observed snow-free land cases that were incorrectly detected as snow covered cases. There are more opportunities for the observed snow-free land pixels to be covered with patches of snow in cold temperatures below -5°C than in warm temperatures above 0°C.

Based on these findings, temperature can be used as a proxy to predict MODIS FSC retrieval errors across regions and at times that feature large spatial and temporal variability. This approach is conceptually grounded in the fact that land surface factors contribute to MODIS FSC retrieval errors. These factors include patchy snow in regions of high topographic roughness, tree crown exposure in forested regions, dirty snow in regions with significant dust, and complex terrain, and each of these factors has a strong relationship to temperature. This temperature-based approach is further aided by the fact that temperature data are easy to obtain and of relatively high accuracy, making them convenient to use as a dynamic index to quantify the uncertainty in MODIS SCA retrievals.

5. Error quantification and mitigation

In this study we select temperature data from two independent sources. One is the in-situ daily mean air temperature, and the other is daily mean air temperature from NLDAS. Both data sets can capture the cumulative diurnal temperature variation. The error in MODIS FSC retrieval is simply defined as: *err* = 100-POD. We further investigate the retrieval error relative to temperature by matching the defined errors to their mean temperatures in each temperature group for snow cover and snow-free land retrievals.

We calculate the MODIS FSC retrieval error over the CONUS for cloud-free pixels at times when all data including MODIS FSC, in-situ SWE and daily mean air temperature are available. The results of this temperature versus MODIS FSC retrieval error investigation for the 2000-2005 period are shown in Figure 5. For the MODIS FSC retrievals, error levels trend larger as the daily mean temperature increases, with the largest rate of increase occurring at temperatures above 0°C (Figure 5). It is perhaps not surprising that the potential error sources in the MODIS FSC product are related to differential snow melting processes in the early and late snow seasons. The error is estimated at nearly 80% for daily mean temperatures above 12°C and less than 20% for temperatures below 2°C. The retrieval errors are relatively insensitive to temperatures below -2°C, and are generally below 10% in magnitude.

There is a clear nonlinear relationship between the MODIS retrieval error and daily mean temperature (Figure 5). We use the cumulative double exponential distribution function given in Equation (1) to represent this nonlinear relationship between retrieval

error (*err*) and daily mean air temperature (T, ^oC) for MODIS snow cover retrievals over the CONUS. Using a slightly different methodology from Dong and Peters-Lidard (2010) with a fixed *Coeff* at a value of 90, three parameters (*Coeff*, T_f and b) are allowed to change.

$$err = 100 - POD = 2.718 + \frac{Coeff}{1 + e^{-(T - T_f)/b}} \quad , \tag{1}$$

Where e is the base of the natural logarithm, T_f (^{o}C) is the reference temperature as a location parameter, b is a scale parameter, and *Coeff* is a derived constant. We obtained the parameters for the CONUS study area based on a least squares fitting approach, using values of *Coeff* from 0 to 200 at a 1 increment, for reference temperature T_f from 0 to 20 at a 0.1 increment, and scale parameter b from 0 to 10 at a 0.1 increment. These optimal parameters (*Coeff*, T_f and b) are listed in Table 2. The parameters derived from using the C5 MODIS SCA product over Colorado (CO) and California/Nevada (CA/NV) from Dong and Peters-Lidard (2010) are also included in the table for the purpose of comparison. There are negligible statistical errors in the fitting by using the double exponential distribution function. The fitting bias is 0.6% when using in-situ temperature and -0.05% when using NLDAS temperature, and their RMS errors are 3% and 0.5% respectively.

Inserting these numbers into Equation 1 reveals that both the MODIS C5 SCA and C6 FSC products have very similar error ranges (minimum error of 2.7% to maximum error of 92.7% for C5 and 91.7% for C6) when the in-situ 2m air temperature data is used. When the air temperature equals the reference temperature (T=T_f), the errors reach their

mid-point values (*err*=2.718+*Coeff*/2). We have processed the hourly NLDAS 2m air temperature data into daily mean temperature values for consistency with the in-situ daily mean air temperature measurements. When daily mean air temperature is used from both in-situ and NLDAS data sources, the derived reference temperature (T_f) is the same (7.8^{o}C) for both temperature data sources and the scale factors (*b*) vary little (3.7 for in-situ temperature and 4.2 for NLDAS temperature). However, the *Coeff* shows a large increase from 89 when using in-situ temperature to 98 when using NLDAS temperature. This results from the regrouping of MODIS pixels by the NLDAS temperature data. In this case, some previous pixels with missed detection of snow have been reassigned from the low in-situ temperature group to the high NLDAS temperature group. In practical applications, either the in-situ daily mean temperature or the modeled 2-meter daily mean air temperature could be used. Using calibrated parameters from different temperature data sources and a user-defined error tolerance level, this approach can be applied to any given time and cloud free pixel to guide the decision of whether or not to use the MODIS snow cover product for a given application.

As discussed above, MODIS C5 SCA and C6 FSC estimates derived when the temperature is relatively high are characterized by large detection errors. Thus, eliminating these pixels using a temperature threshold will help to avoid assimilating unreliable data into land surface and hydrological applications. As illustrated in Figure 6, if the pixels with temperatures above 10°C are eliminated, the POD will increase about 2% when using NLDAS 2m air temperature data and about 1.5% when using in-situ 2m air temperature. The use of modeled 2m temperatures to define a temperature threshold leads to a slightly better increase in POD than does using in-situ temperature, and a

comparison using both temperature data sources shows similar results in the number of pixels retained (98% when using in-situ air temperature and 97% when using NLDAS temperature at a 10°C defined temperature threshold). If the temperature threshold is set at 0°C, the POD increases approximately 10% when using either temperature data source. However, this also leads to the elimination of over 30% of MODIS pixels (not shown here). Thus, there is a need to coordinate the POD increase and the pixels eliminated so that more reliable MODIS data can be used in the data assimilation practices. With this in mind, a temperature threshold of 6°C—leading to a 4% increase in POD and approximately 90% of MODIS pixels retained—is recommended.

6. Summary and Discussion

This study has investigated remotely-sensed MODIS snow cover estimation uncertainty for the new Collection 6 (C6) products. In this study, we find significant improvements in C6 POD and FAR relative to C5 for California, Nevada and to a lesser extent Colorado. We have also extended the previous error analysis of Dong and Peters-Lidard (2010) by analyzing all USHCN and SNOTEL data for CONUS. This analysis demonstrates that MODIS C6 shows a strong ability to detect snow presence during the snow season with POD above 80% from November to April and snow-free land with FAR below 1.5% all year round.

For cloud-free pixels, the MODIS C6 FSC retrieval errors can be quantitatively predicted using temperature data and a calibrated set of parameters over the CONUS. Generally, both in-situ and model-based NLDAS daily mean air temperature data are

good proxies for predicting MODIS FSC retrieval errors. It is shown that MODIS FSC errors may be reliably predicted from temperature using a cumulative double exponential distribution function with parameters that are a function of temperature over the CONUS.

The in-situ daily mean air temperature data represent cumulative diurnal temperature variations. These measurements are limited in their spatial representativeness and by their spatial and temporal availability in mountainous regions. Model-based 2-m air temperature data are of relatively high accuracy (Luo et al., 2003), and so could replace the in-situ air temperature in successfully classifying the error-prone pixels in the MODIS FSC product for land surface hydrological data assimilation applications. The quantitative nonlinear relationship of MODIS snow cover retrieval error versus temperature will enable end users to merge MODIS snow cover information into various hydrological applications in a more informed and beneficial fashion.

The high spatial resolution Landsat snow cover product provided an alternate capability to validate the model for estimating the MODIS fractional snow cover (FSC) (Painter et al., 2009), and evaluating the FSC product (Rittger et al., 2013). Landsat ETM+ is available at a 30 m spatial resolution, and the Landsat systems, in particular, are a source of data for hydrological and glaciological research at the drainage basin scale. Using Landsat images to validate MODIS retrieval does assume that errors in the MODIS retrieval derive mostly from spatial effects. The less frequent (16-day interval) Landsat snow cover mapping provides less assimilation benefit in the spring when melt frequently occurs. Saturation in some of the Landsat ETM+ bands makes the sensor an imperfect source of validation data, and even at a 30 m resolution, many ETM+ pixels are mixed. Therefore, a future, more complete approach may combine the in-situ field measurements

and fine resolution Landsat imagery in the validation and verification of model simulations and remote sensing estimates to characterize the MODIS fractional snow cover over moderate resolution scales.

MODSCAG performs the most consistently through the accumulation, mid-winter and melt stages as assessed by comparing 172 images spanning a range of snow classes and vegetation types including the Colorado Rocky Mountains, the Upper Rio Grande, California's Seerra-Nevada, and the Nepal Himalaya (Rittger et al, 2013). Snow class and forest factors are considered as the key inputs of the MODSCAG (future GOESRSCAG) spectral library and have been shown to impact snow cover estimation accuracy (Painter et al., 2009). The snow class indicates the snow crystal size by climate and season, which shows differences in the spectral reflectance of snow. We note that the defined recall and F score in Rittger et al (2013) still show some temperature effects in the early snow season (October and November) and in the late snow season (June and July). It should be also noted that MOD10A1 is a global, automated algorithm that is not tuned to any particular area. To properly understand and be able to predict the relationship between the MODIS SCA retrieval error and temperature for different land surface characteristics, future work will investigate the relationships between the parameters of the error model and known sources of FSC error, such as elevation, topographic roughness, land cover, and forest fraction. As in the investigation of Dong and Peters-Lidard (2010), each of these land surface factors result in modifications to the relationship between MODIS FSC retrieval errors and temperature. These modifications could be represented by slightly adjusting the parameters (*Coeff*, T_f and/or b) in Equation 1.

Acknowledgements. We would like to thank Kingtse Mo from NOAA/NCEP/CPC for her contributions. This work was directly funded by NOAA Climate Program Office (CPO) Modeling, Analysis, Prediction, Projection (MAPP) program. The NASA EOS Project supported the participation of D. Hall, J. Miller and G. Riggs.

References

Andreadis, K. M., and D. P. Lettenmaier, 2006: Assimilating remotely sensed snow observations into a macroscale hydrology model. *Adv. Water Resour.*, **29**(6), 872-886.

Beaumont, R. T., 1965: Mt. Hood pressure pillow snow gage. *Journal of Applied Meteorology*, **4**, 626-631.

Clark, M. P., A. G. Slater, A. P. Barrett, L. E. Hay, G. J. McCabe, B. Rajagopalan and G. H. Leavesley, 2006: Assimilation of snow covered area information into hydrologic and land-surface models. *Adv. Water Resour.*, **29**(8), 1209-1221.

Cohen, J., 1994: Snow cover and climate. *Weather*, **49**, 150-155.

Cosgrove, B. A., D. Lohmann, K. E. Mitchell, P. R. Houser, E. F. Wood, J. Schaake, A. Robock, C. Marshall, J. Sheffield, L. Luo, Q. Duan, R. T. Pinker, J. D. Tarpley, R. W. Higgins, and J. Meng, 2003: Real-time and retrospective forcing in the North American Land Data Assimilation System (NLDAS) project, *J. Geophys. Res.*, **108**(D22), 8842, doi:10.1029/2002JD003118.

Crane, R. G., and Anderson, M. R., 1984: Satellite discrimination of snow/cloud surfaces. *International Journal of Remote Sensing*, **5**(1), 213–223.

Crook, A. G., 1977: SNOTEL: Monitoring climatic factors to predict water supplies. *Journal of Soil and Water Conservation*, **32**, 294-295.

Dong, J., J. P. Walker, and P. R. Houser, 2005: Factors affecting remotely sensed snow water equivalent uncertainty. *Remote Sens. Environ.*, **97**(1), 68-82.

Dong, J., J. P. Walker, P. R. Houser, and C. Sun, 2007: Scanning multichannel microwave radiometer snow water equivalent assimilation. *J. Geophys. Res*., **112**, D07108, doi:10.1029/2006JD007209.

Dong, J. and C. Peters-Lidard, 2010: On the relationship between temperature and MODIS snow cover retrieval errors in the western US. *IEEE the Journal of Selected Topics in Earth Observations and Remote Sensing*, **3**(1), 132-140, doi:10.1109/JSTARS.2009.2039698.

Dozier, J, 1989: Spectral signature of alpine snow cover from the Landsat Thematic Mapper. *Remote Sens. Environ.*, **28**, 9-22.

Dozier, J., T. H. Painter, K. Rittger, and J. E. Frew, 2008: Time-space continuity of daily maps of fractional snow cover and albedo from MODIS. *Advances in Water Resources*, **31**, 1515-1526, doi: 10.1016/j.advwatres.2008.08.011.

Foody, G. M., 2002: Status of land cover classification accuracy assessment. *Remote Sens. Environ.*, **80**, 185-201.

Foster, J. L., C. Sun, J. P. Walker, R. E. J. Kelly, A. T. C. Chang, J Dong, and H. Powell, 2005: Quantifying the uncertainty in passive microwave snow water equivalent observations. *Remote Sens. Environ.*, **94**(2), 187-203.

Hall, D. K., Riggs, G. A., and Salomonson, V. V., 1995: Development of methods for mapping global snow cover using Moderate Resolution Imaging Spectroradiometer (MODIS) data. *Remote Sensing Environment*, **54**, 127–140.

Hall, D. K., J. L. Foster, D. L. Verbyla, A. G. Klein and C. S. Benson, 1998: Assessment of snow-cover mapping accuracy in a variety of vegetation-cover densities in central Alaska. *Remote Sens. Environ.*, **66**(2), 129-137.

Hall, D. K., 1998: Remote sensing of snow and ice using imaging radar. *Manual of Remote Sensing*, *3rd edition* (pp. 677-703). American Society for Photogrammetry and Remote Sensing, Falls Church, VA.

Hall, D. K., G. A. Riggs, V. V. Salomonson, N.E. DiGirolamo, and K.J. Bayr, 2002: MODIS snow-cover products. *Remote Sens. Environ.*, **83**(1-2), 181-194.

Hall, D. K. and G. A. Riggs, 2007: Accuracy assessment of the MODIS snow products. *Hydrol. Processes*, **21**(12), 1534-1547.

Klein, A. G. and A. C. Barnett, 2003: Validation of daily MODIS snow cover maps of the upper Rio Grande river basin for the 2000-2001 snow year. *Remote Sens. Environ.*, **86**, 162-176.

Liston, G. E., R. A. Pielke Sr., and E. M. Greene, 1999: Improving first-order snow-related deficiencies in a regional climate model. *J. Geophys. Res*., **104**, 19,559-19,567.

Liu, Y., C. D. Peters-Lidard, S. Kumar, J. L. Foster, M. Shaw, Y. Tian, G. M. Fall, 2013: Assimilating satellite-based snow depth and snow cover products for improving snow predictions in Alaska, *Advances in Water Resources*, **54**, 208-227.

Luo, L., A. Robock, K. E. Mitchell, P. R. Houser, E. F. Wood, J. C. Schaake, D. Lohmann, B. A. Cosgrove, F. Wen, J. Sheffield, Q. Duan, R. W. Higgins, R. T. Pinker, and J. D. Tarpley, 2003: Validation of the North American Land Data Assimilation System (NLDAS) retrospective forcing over the southern Great Plains. *J. Geophys. Res*., **108**(D22), 8843, doi:10.1029/2002JD003246.

Maurer, E.P., J.D. Rhoads, R.O. Dubayah, and D.P. Lettenmaier, 2003: Evaluation of snow-covered area data product for the 2000-2001 snow year. *Remote Sens. Environ*., **86**, 162-176.

Mesinger, F., G. DiMego, E. Kalnay, K. Mitchell, P. C. Shafran, W. Ebisuzaki, D. Jovic, J. Woollen, E. Rogers, E. H. Berbery, M. B. Ek, Y. Fan, R. Grumbine, W. Higgins, H. Li, Y. Lin, G. Manikin, D. Parrish, and W. Shi, 2006: North American Regional Reanalysis. *Bull. Amer. Meteor. Soc.*, 87, 343–360. doi: http://dx.doi.org/10.1175/BAMS-87-3-343

Mitchell, K. E., D. Lohmann, P. R. Houser, E. F. Wood, J. C. Schaake, A. Robock, B. A. Cosgrove, J. Sheffield, Q. Duan, L. Luo, R. W. Higgins, R. T. Pinker, J. D. Tarpley, D. P. Lettenmaier, C. H. Marshall, J. K. Entin, M. Pan, W. Shi, V. Koren, J. Meng, B. H. Ramsay, and A. A. Bailey, 2004: The multi-institution North American Land Data Assimilation System (NLDAS): Utilizing multiple GCIP products and partners in a continental distributedhydrological modeling system. *J. Geophys. Res.*, *109*, D07S90, doi:10.1029/2003JD003823.

Molotch, N. P. and R. C. Bales, 2006: SNOTEL representativeness in the Rio Grande headwaters on the basis of physiographics and remotely sensed snow cover persistence. *Hydrol. Processes*, *20*(4), 723-739.

Molotch, N. P., and S. A. Margulis, 2008: Estimating the distribution of snow water equivalent using remotely sensed snow cover data and a spatially distributed snowmelt model: a multi-resolution, multi-sensor comparison, *Adv. Water Resour.*, *31*(11), 1503–1514.

Natural Resources Conservation Service, 1997: SNOTEL Data Collection System. Available at http:/www.nrcs.usda.gov/factpub/sntlfct1.html.

Painter, T. H., K. Rittger, C. Mckenzie, P. Slaughter, R. E. Davis, and J. Dozier, 2009: Retrieval of subpixel snow covered area, grain size, and albedo from MODIS, *Remote Sens. Environ.*, **113**, 868-879, doi:10.1016/j.rse.2009.01.001.

Parajka, J. and G. Bloschl, 2006: Validation of MODIS snow cover images over Austria. *Hydrol. Earth Syst. Sci*., **10**, 679-689.

Parajka, J. and G. Blöschl, 2012: MODIS-based Snow Cover Products, Validation, and Hydrologic Applications. In: Eds (Ni-Bin Chang) Multiscale Hydrologic Remote Sensing: Perspectives and Applications, Chapter 9, CRC Press, 550 pp..

Parajka, J., L. Holko, Z. Kostka, G. Blöschl, 2012: MODIS snow cover mapping accuracy in small mountain catchment - comparison between open and forest sites. *Hydrol. Earth Syst. Sci*., **16**, 2365-2377.

Riggs, G. A., D. K. Hall, and V. V. Salomonson, 2006: MODIS Snow Products User Guide for Collection 4 Data Products, http://modis-snow-ice.gsfc.nasa.gov/sugkc2.html.

Riggs, G. A. and D. K. Hall, 2012: Improved snow mapping accuracy with revised MODIS snow algorithm. *Proceedings of the 69th Annual Eastern Snow Conference,* 5-7 June 2012, YMCA Frost Valley, Claryville, NY. In press.

Rittger, K., T. H. Painter, and J. Dozier, 2013: Assessment of methods for mapping snow cover from MODIS. *Adv. Water Resour*., **51**, 367-380.

Rodell, M., and P. R. Houser, 2004: Updating a Land Surface Model with MODIS-Derived Snow Cover. *J. Hydrometeorol.*, **5,** 1064-1075.

Rodell, M., P. R. Houser, U. Jambor, et al., 2004: The Global Land Data Assimilation System. *Bull. Amer. Meteor. Soc.*, **85**(3), 381-394.

Roy, A., A. Royer, and R. Turcotte, 2010: Improvement of springtime streamflow simulations in a boreal environment by incorporating snow-covered area derived from remote sensing data. *J. Hydrol.*, *390*, 35-44.

Salomonson, V. V. and I. Appel, 2004: Estimating fractional snow cover from MODIS using the normalized difference snow index, *Remote Sens. Environ.*, **89**, 351-360.

Salomonson, V. V. and I. Appel, 2006: Development of the Aqua MODIS NDSI fractional snow cover algorithm and validation results, *IEEE Transactions on Geoscience and Remote Sensing*, **44**(7), 1747-1756, doi: 10.1109/TGRS.2006.876029.

Serreze, M. C., M. P. Clark, R. L. Armstrong, D. A. McGinnis, and R. S. Paulwarty, 1999: Characteristics of the western United States snowpack from telemetry (SNOTEL) data. *Water Resources Research*, **35**(7), 2145-2160.

Shreve, C. M., G. S. Okin, and T. H. Painter, 2009: Indices for estimating fractional snow cover in the western Tibetan Plateau. *J. Glaciol.*, **55**(192), 737-745.

Simic, A., R. Fernandes, R. Brown, P. Romanov and W. Park, 2004: Validation of vegetation, MODIS, and GOES+SSM/I snow cover products over Canada based on surface snow depth observations. *Hydrol. Processes*, **18**, 1089-1104.

Stewart, I. T., D. R. Cayan, and M. D. Dettinger, 2005: Changes towards earlier streamflow timing across Western North America. *J. Climate*, **18**, 1136-1155.

Tait, A., and R. Armstrong, 1996: Evaluation of SMMR satellite-derived snow depth using ground-based measurements. *Int. J. Remote Sens.*, **17**, 657-665.

Tong, J., S. J. Déry, P. L. Jackson, and C. Derksen, 2010: Testing snow water equivalent retrieval algorithms for passive microwave remote sensing in an alpine watershed of western Canada. *Can. J. Remote Sens.*, **36**, S74-S86.

US Soil Conservation Service, 1972: Snow survey and water supply forecasting. In *SCS National Engineering Handbook*, US Department of Agriculture, Washington DC, section 22.

Valovcin, F. R., 1976: Snow/cloud discrimination, AFGL-TR-76-0174, ADA 032385.

Williams, C. N., R. S. Vose, D. R. Easterling, and M. J. Menne, 2006: United States Historical Climatology Network Daily Temperature, Precipitation, and Snow Data. *ORNL/CDIAC-118, NDP-070*. Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, Oak Ridge, Tennessee.

Xia, Y., K. Mitchell, M. Ek, J. Sheffield, B. Cosgrove, E. Wood, L. Luo, C. Alonge, H. Wei, J. Meng, B. Livneh, D. Lettenmaier, V. Koren, Q. Duan, K. Mo, Y. Fan, and D. Mocko, 2012: Continental-scale water and energy flux analysis and validation for the North American Land Data Assimilation System project phase 2 (NLDAS-2): 1. Intercomparison and application of model products. *J. Geophys. Res.,* **117***,* D03109*,* doi:10.1029/2011JD016048.

Yatheendradas, S., C. D. Peters-Lidard, V. Koren, B. A. Cosgrove, L. G. G. De Goncalves, P. Restrepo, M. Smith, J. Geiger, Z. Cui, J. Borak, S. V. Kumar, D. L. Toll, G. Riggs, and N. Mizukami, 2012: Distributed assimilation of satellite-based snow extent for improving simulated streamflow in mountainous, dense forests: An example over the DMIP2 western basins. *Water Resour. Res.*, doi:10.1029/2011WR011347.

Figure Captions:

Figure 1. Spatial distribution of in-situ SWE and meteorological stations including 670 SNOTEL (dots) and 1062 USHCN (plus) stations over CONUS. The background colors show the mean elevation at 4 km resolution derived from the United States Geological Survey (USGS) 1 arc-second National Elevation Dataset (NED).

Figure 2. Comparison of POD (upper row) and FAR (lower row) for MODIS Collection-5 (C5 shown as black bars) binary (from Dong & Peters-Lidard, 2010) and Collection-6 (C6 shown as gray bars) FSC results, 2000 - 2005. The three selected states are California, Nevada, and Colorado from left to right columns. MODIS snow-cover results are compared to data from SNOTEL and the U.S. Historical Climatology Network (USHCN) daily temperature, precipitation and snow data.

Figure 3. Probability of detection (POD-black bars) and false alarm ratio (FAR-gray bars) for MODIS C6 fractional snow cover in each month over the SNOTEL and the U.S. Historical Climatology Network (USHCN) stations shown in Figure 1 from February 2000 to December 2005.

Figure 4. POD for MODIS snow cover relative to in-situ SWE (black bars) for snow season (October to June) from February 2000 to December 2005 and for three given daily mean air temperature groups: above 0°C (red bars), between -5°C and 0°C (blue bars), and below -5°C (green bars). Left end shows the FAR with three air temperature groups.

Figure 5. MODIS SCA retrieval error relative to in-situ daily mean air temperature for all in-situ sites over CONUS (plusses). The cumulative double exponential distribution

function is used to construct the nonlinear relationship between the errors and temperature (solid line).

Figure 6. Percent changes in POD of MODIS snow cover (thin solid line for using in-situ air temperature and thick solid line for using NLDAS air temperature) and percent changes in pixels of MODIS snow cover retrievals (thin dash line for using in-situ air temperature and thick dash line for using NLDAS air temperature) eliminated for daily mean air temperature greater than given temperature thresholds.

Table 1. Illustration of a confusion matrix for MODIS snow covered area retrievals relative to the field measurements.

		Field measurement	
		Snow	Non snow
MODIS	Snow	SS	SN
	Non Snow	NS	NN

Table 2. Statistical parameters for reference temperature (T_f) and scale factor (b) in Equation (1) for fractional snow cover retrievals in California and Nevada (CA/NV), Colorado (CO) and over Continental US (CONUS) domain.

Study region	MODIS snow	Temperature data	T_f (^{o}C)	b	*Coeff*
CA/NV	C5	In-situ	4.5	5.0	90
CO	C5	In-situ	6.5	3.5	90
CONUS	C6	In-situ	7.8	3.7	89
CONUS	C6	NLDAS	7.8	4.2	98

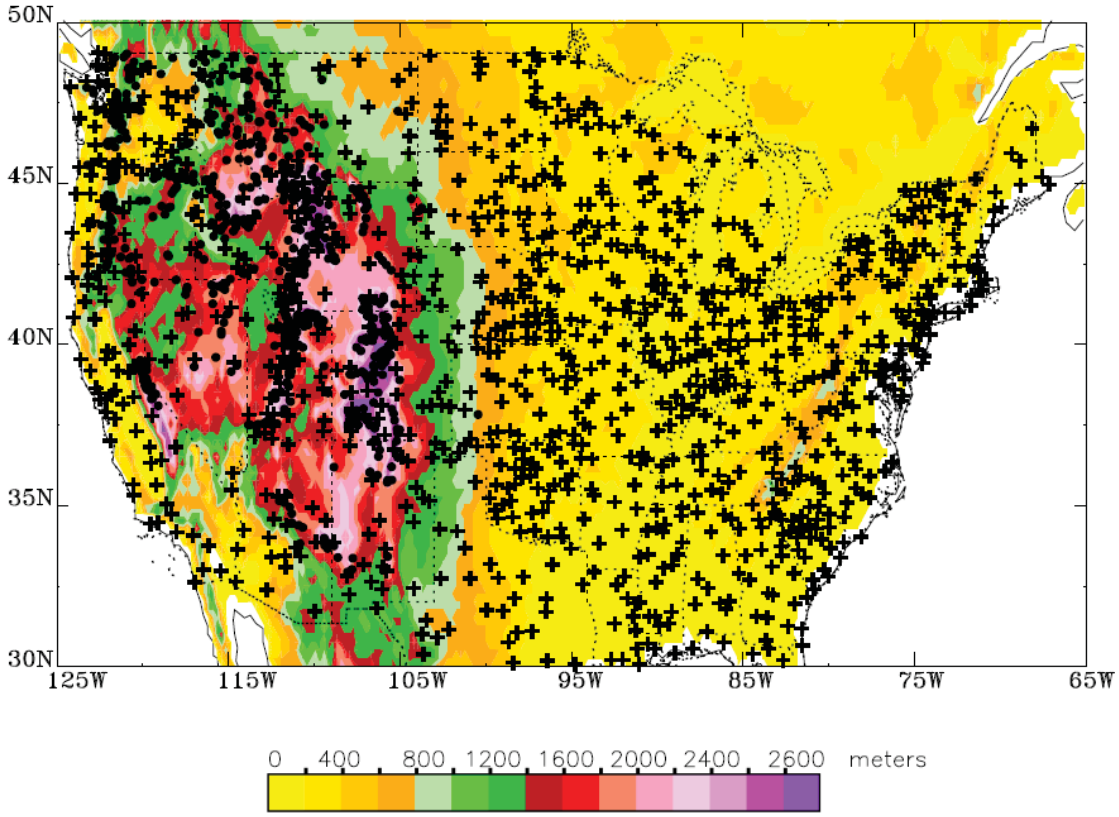

Figure 1. Spatial distribution of in-situ SWE and meteorological stations including 670 from SNOTEL (dots) and 1005 of 1062 from USHCN (plus) over CONUS. The background colors show the mean elevation at 4 km resolution derived from the United States Geological Survey (USGS) 1 arc-second National Elevation Dataset (NED).

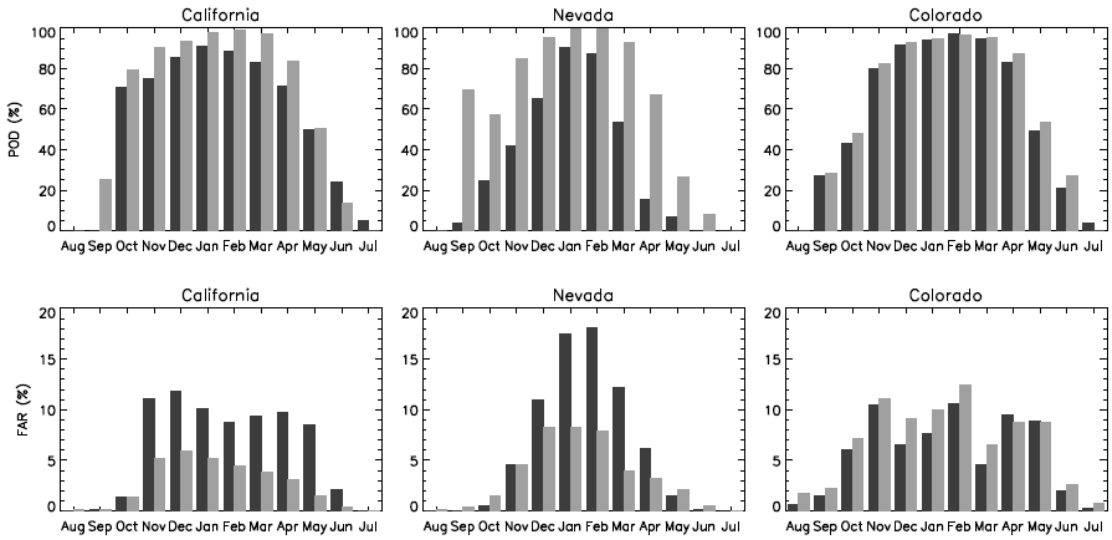

Figure 2. Comparison of POD (upper row) and FAR (lower row) for MODIS Collection-5 (C5 shown as black bars) binary (from Dong & Peters-Lidard, 2010) and Collection-6 (C6 shown as gray bars) FSC results, 2000 - 2005. The three selected states are California, Nevada, and Colorado from left to right columns. MODIS snow-cover results are compared to data from SNOTEL and the U.S. Historical Climatology Network (USHCN) daily temperature, precipitation and snow data.

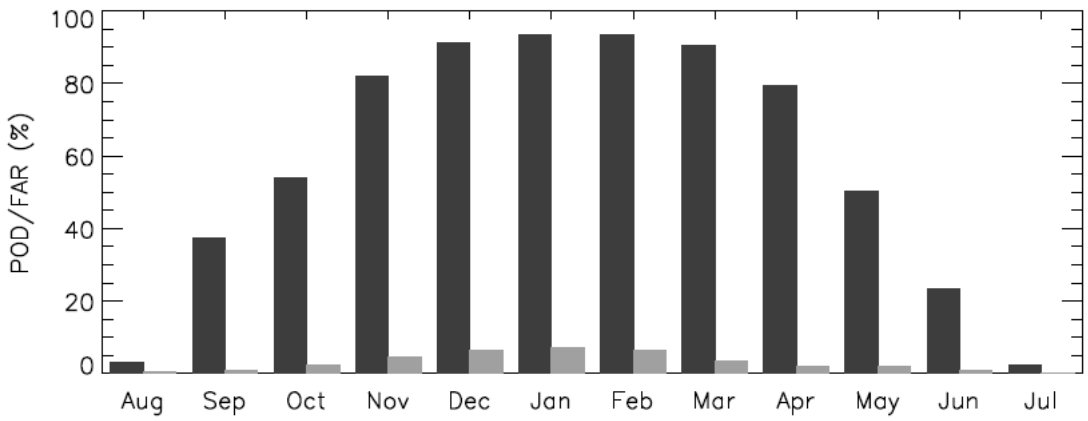

Figure 3. Probability of detection (POD-black bars) and false alarm ratio (FAR-gray bars) for MODIS C6 fractional snow cover in each month over the SNOTEL and the U.S. Historical Climatology Network (USHCN) stations shown in Figure 1 from February 2000 to December 2005.

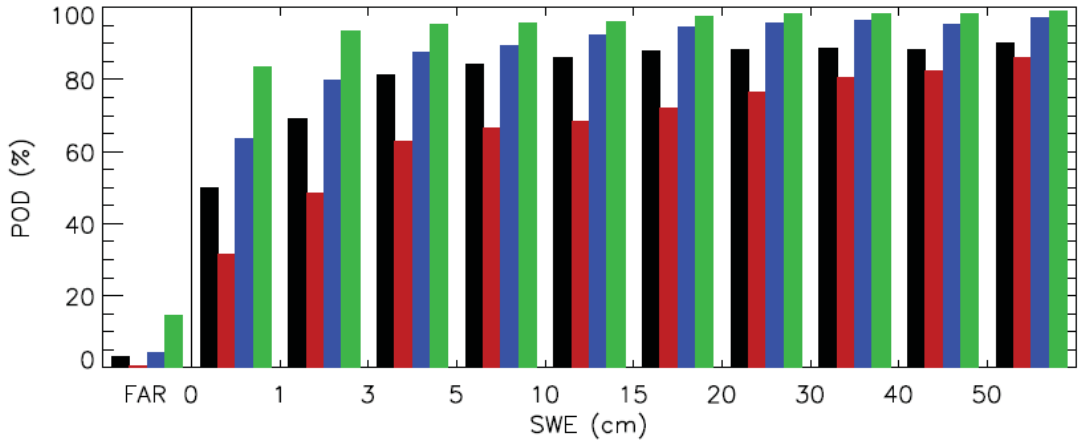

Figure 4. POD for MODIS snow cover relative to in-situ SWE (black bars) for snow season (October to June) from February 2000 to December 2005 and for three given daily mean air temperature groups: above 0°C (red bars), between -5°C and 0°C (blue bars), and below -5°C (green bars). Left end shows the FAR with three air temperature groups.

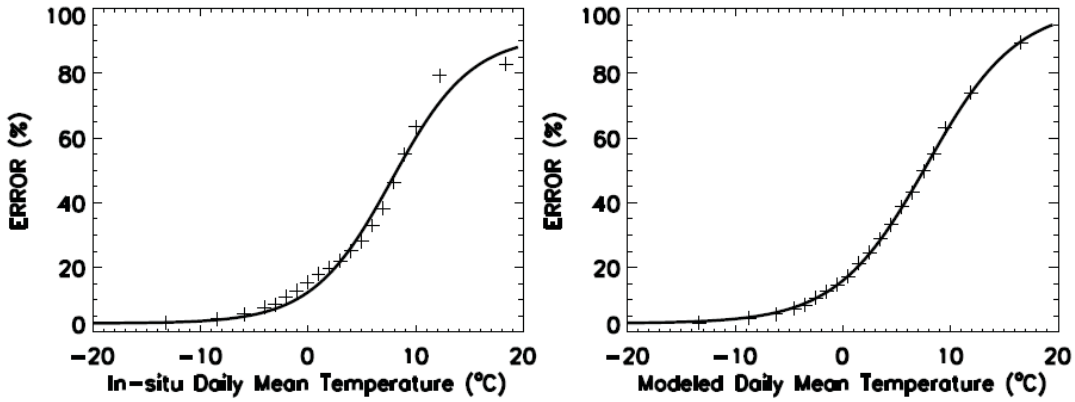

Figure 5. MODIS FSC retrieval error relative to in-situ (left) and NLDAS (right) daily mean air temperature for all in-situ sites over CONUS (pluses). The cumulative double exponential distribution function is used to construct the nonlinear relationship between the errors and temperature (solid lines).

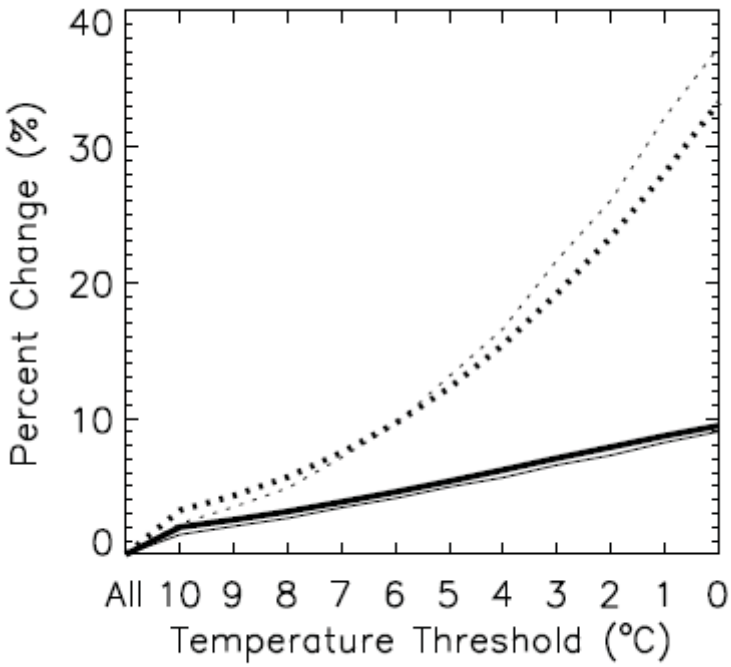

Figure 6. Percent changes in POD of MODIS snow cover (thin solid line for using in-situ air temperature and thick solid line for using NLDAS air temperature) and percent changes in pixels of MODIS snow cover retrievals (thin dash line for using in-situ air temperature and thick dash line for using NLDAS air temperature) eliminated for daily mean air temperature greater than given temperature thresholds.