Canopy Adjustment and Improved Cloud Detection for Remotely Sensed Snow Cover Mapping

Karl Rittger1, Mark S. Raleigh2,3, Jeff Dozier4, Alice F. Hill2,3, James A. Lutz5, and Thomas H. Painter6

1Institute for Arctic and Alpine Research, University of Colorado Boulder, Boulder, CO, USA, 2National Snow and Ice Data Center, University of Colorado Boulder, Boulder, CO, USA, 3CIRES, University of Colorado Boulder, Boulder, CO, USA, 4Bren School of Environmental Science & Management, University of California, Santa Barbara, CA, USA, 5Wildland Resources Department, Utah State University, Logan, UT, USA, 6Joint Institute for Regional Earth System Science and Engineering, University of California, Los Angeles, CA, USA

Abstract Maps of snow cover serve as early indicators for hydrologic forecasts and as inputs to hydrologic models that inform water management strategies. Advances in snow cover mapping have led to increasing accuracy, but unsatisfactory treatment of vegetation’s interference when mapping snow has led to maps that have limited utility for water forecasting. Vegetation affects snow mapping because ground surfaces not visible to the satellite produce uncertainty as to whether the ground is snow covered. At nadir, the forest canopy obscures the satellite view below the canopy. At oblique viewing angles, the forest floor is obscured by both the canopy and the projection of tree profiles onto the forest floor. We present a canopy correction method based on Moderate Resolution Imaging Spectroradiometer satellite imagery validated with field observations that mitigates geometric and georegistration issues associated with changing satellite acquisition angles in forested areas. The largest effect from a variable viewing zenith angle on the viewable gap fraction in forested areas occurs in moderately forested areas with 30–40% tree canopy coverage. Cloud cover frequently causes errors in snow identification, with some clouds identified as snow and some snow identified as cloud. A cloud-snow identification method utilizes a time series of fractional vegetation and rock land-surface data to flag snow-cloud identification errors and improve snow-map accuracy reducing bias by 20% over previous methods. Together, these contributions to snow-mapping techniques could advance hydrologic forecasting in forested, snow-dominated basins that comprise an estimated one fifth of Northern Hemisphere snow-covered areas.

Plain Language Summary Mapping snow cover extent informs water resources stored in the winter snowpack, providing important information for planning how and when to utilize available water. Tree canopies shield the forest floor and hinder the determination of snow-covered area in vegetated terrain from above, where satellites view the Earth’s surface. Moreover, satellites that scan the surface (like the Moderate Resolution Imaging Spectroradiometer) are most often not directly overhead, and as the view from the satellite to the surface slants, trees obscure a greater portion of the land surface that a satellite can “see,” especially where trees are tall, adding uncertainty to the satellite-based maps. This effect is greatest in forests where 30–40% of the land area is covered by tree canopy and has little effect in very dense forests where most of the forest floor is obscured already. Here we present a method to accommodate the stretched and hidden forest footprint when a satellite is not directly overhead. A new method for identifying snow-mapping errors caused by clouds is also presented by flagging unusually large changes in the non-snow surfaces over sequential images. These methodological advancements are important because snow-melt water comprises a major portion of the water supply in many regions where humans live.

1. Introduction

Water stored in seasonal snow serves as an important water resource to downstream areas across much of the Northern Hemisphere during seasons when rain-fed supply does not meet the demand (Mankin et al., 2015). Tracking changes to snow-cover patterns is ever more critical for water-resource management in the current era of hydrologic nonstationarity amidst a warming world (Bormann et al., 2018; Milly et al.,...
2008). Historical norms of snow-cover extent (Mudryk et al., 2015), accumulation (Kunkel et al., 2016), and melt patterns (Musselman et al., 2015; Skiles et al., 2015) no longer reliably indicate snowmelt magnitude or timing. In recent decades, snow monitoring has been revolutionized by new satellite capabilities, especially imagery from the National Aeronautics and Space Administration’s Moderate Resolution Imaging Spectroradiometer (MODIS) enabling the MOD10A1 snow products at daily, global coverage (Hall et al., 2002) and the MODIS Snow Covered-Area and Grain Size (MODSCAG) products that provide fractional cover and snow grain size over selected areas (Painter et al., 2009). Snow-cover maps serve as both early indicators for hydrologic forecasts and as inputs to hydrologic models that inform efficient water management strategies. Advances in snow-cover mapping have led to increasing accuracy of forecasts, especially during hydrologically important accumulation and melt periods (Rittger et al., 2013).

Even with improved snow-mapping techniques, clouds and forests present persistent challenges to snow mapping. Cloud cover can create errors in spectral snow-detection algorithms because of the similar reflectance of cloud and snow at wavelengths utilized for snow identification. Clouds are often misclassified as snow leading to an overestimation of snow-covered area on cloudy days, and snow is often misclassified as cloud leading to an underestimation. Discriminating snow from clouds and developing cloud-free products has seen much attention in the literature (Allen et al., 1990; Dozier, 1989; Gafurov & Bárdossy, 2009; Gao et al., 2010; Hall et al., 2010; Parajka & Blöschl, 2008). Forested areas challenge remotely sensed snow-mapping techniques because snow maps only represent the viewable snow-covered area fraction ($f_{SCA}$) of a satellite pixel. Optical sensors only view snow that is visible beneath leafless deciduous stands (such as aspen), in clearings and forest gaps between coniferous trees (i.e., pine, spruce, and fir) and through thin foliage or needles, or snow that has been intercepted by the forest canopy. Often, viewable $f_{SCA}$ maps do not represent the actual snow cover on the land surface in forested regions for two reasons: (1) The forest floor is obscured directly by the canopy or tall understory shrubs, thus shielding snow on the ground from nadir satellite view, and (2) for whiskbroom sensors like MODIS with wide swath widths, the oblique perspective introduced by off-nadir satellite angles decreases the viewable gap fraction (VGF) and stretches the pixel as the viewing zenith angle (VZA) increases (Liu et al., 2004, 2008; Xin et al., 2012) because vertical features like trees become projected, obscuring the sensor view at oblique angles (Figure 1).

Binary snow mapping (Hall et al., 1995) assessments indicate 10% of snow cannot be detected on a single date in the Sierra Nevada under forest with 98% accuracy, but only for pixels covered with 60% snow or more. Treatment of vegetation has been incorporated into this snow-mapping algorithm based on findings in Klein et al. (1998), who used the normalized difference vegetation index to determine where trees were impacting retrievals. Other fractional snow estimates for MODIS that account for forest exist (Metsamaki et al., 2012) but do not explicitly deal with off-nadir viewing. Past studies have attempted vegetation corrections utilizing multiple satellite products with mixed results (Dressler et al., 2006; Durand et al., 2008; Raleigh et al., 2013) and interference from vegetation degrades hydrologic prediction and simulated streamflow in forested, snowy regions (Yatheendradas et al., 2012). With nearly one fifth of the Northern Hemisphere seasonally snow-covered area estimated to intersect with boreal forests (Rutter et al., 2009) and with high proportions of catchments serving anthropogenic use being snow covered (Klein et al., 1998), poor snow maps over forested areas could lead to false interpretation of the extent of seasonal snow resources. More reliable water forecasts in snow-fed, forested basins require improved remotely sensed snow maps that better account for clouds and vegetation.

To address snow-mapping inaccuracies in forested regions caused by reductions in viewable gaps imposed by off-nadir VZA (Figure 1), we present a method to adjust viewable $f_{SCA}$ from MODIS to account for vegetation’s effect on viewing geometry. The VZA is the view angle to the sensor from the ground, measured from zenith. Because of Earth curvature, the maximum VZA for MODIS, 65°, is larger than the maximum nadir view angle, 55°, from the satellite. The VGF-VZA relationship necessitates including the area within the stretched pixels that changes daily as VZA and viewing azimuth angle vary. Our method improves correction for vegetation because (1) it does not require explicit, higher-resolution data about the canopy itself and (2) it utilizes products derived from a single satellite (in this case MODIS), making it wholly self-consistent across data sets. The fractional areas of vegetation, soil, and snow calculated via the canopy-correction process presented here can also be utilized to detect misidentification of clouds as snow. This new technique for improved cloud detection utilizes a MODIS time series that flags abrupt changes to surface reflectance that indicate the presence of clouds.
2. Background

2.1. Evolution of Satellite-Derived Snow-Cover Products and Their Use in Hydrologic Models

Snow-cover mapping techniques have evolved to improve temporal and spatial resolutions using a variety of sensors. Initial binary snow-mapping techniques classifying a pixel as “snow” or “no snow” (Dozier, 1989; Hall et al., 1995) gave way to more sophisticated techniques allowing the determination of pixel-scale fractional snow-covered area (fSCA; Salomonson & Appel, 2004, 2006) based on the Normalized Difference Snow Index (NDSI), which leverages the difference of snow's reflectance in the visible and shortwave-infrared (SWIR) wavelengths. Snow mapping further improved with the development of physically based spectral mixture analysis algorithms that utilize seven bands of data (Painter et al., 2009; Sirguey et al., 2009). These algorithms provide more accurate estimates of viewable fSCA than those based on NDSI, especially during hydrologically important periods (Rittger et al., 2013) of most interest to water managers.

The use of satellite snow maps to aid hydrologic prediction of snowmelt runoff has been explored since the 1970s (Rango et al., 1977; Rango & Martinec, 1979). Applications of snow-cover maps include their use for validating modeled snow cover and snow-depletion curves (Shamir & Georgakakos, 2006; Wrzesien et al., 2015) and reconstructing peak snow water equivalent (SWE) distribution when combined with spatially distributed snow-melt models (Bair et al., 2016; Bair et al., 2018; Durand et al., 2008; Rittger et al., 2016).

Figure 1. The view angle to the satellite (a) affects viewable gap fraction (VGF, gray) and percent tree canopy (PTC, green) as demonstrated between an acquisition at nadir (b) and far-off nadir (c). The size of the imaged area at nadir (black dashed square) is stretched for off-nadir acquisitions (red dashed rectangle), up to twice the original pixel dimension in the along-track and 4.8 times in the cross-track direction when the Moderate Resolution Imaging Spectroradiometer viewing zenith angle (VZA) increases to 65° at the edge of the swath. Where vegetation is tall, the off-nadir effect is more extreme.
Using snow maps as inputs to hydrologic models has yielded mixed results. Direct insertion approaches have shown improvements in estimating SWE (Rodell & Houser, 2004) and have reduced error and improved performance in estimating SWE during melt (Andreadis & Lettenmaier, 2006) or modeled streamflow (Clark et al., 2006; Liu et al., 2013). Assimilation of MODIS fSCA into the U.S. National Weather Service SNOW-17 model resulted in a degradation in simulated streamflow due to the lack of MODIS fSCA canopy adjustment (Yatheendradas et al., 2012). The diversity of results achieved by integrating MODIS snow maps into existing models, in part, highlights the inadequate treatment of MODIS fSCA products in river basins with varied vegetation patterns and densities.

### 2.2. Previous Approaches to Address Outstanding Challenges

#### 2.2.1. Viewable and Forest Floor fSCA

Assumptions are often made that the snow cover under the canopy is the same as in the gaps, yielding the canopy adjusted snow cover to be

\[
\text{f}_{\text{SCA}} = \frac{\text{f}_{\text{SCA \ viewable}}}{\text{VGF}}.
\]

However, the assumption that viewable snow cover mimics hidden snow is problematic because vegetation affects snow processes in myriad ways. Vegetation intercepts falling snow that reduces accumulation and increases sublimation (Essery et al., 2003; Pomeroy et al., 1993; Winkler et al., 2005), changes the energy balance in relation to radiation sources for melt (Niu & Yang, 2004), and modifies turbulent fluxes at the snow surface that affect sublimation (Varhola et al., 2010). These dynamics vary at small scales over time and space (Clark et al., 2011) and are often climate specific (Lundquist et al., 2013). Furthermore, the effect of tree cover on snow inherently depends on the nature of the canopy profile—in forests with frequent fire regimes (i.e., ponderosa pine or mixed-conifer), foliage may be arranged well above the snow surface, and in forests with infrequent fire regimes (i.e., spruce/fir forests), foliage may extend down to or even below the level of settled snow (Fites-Kaufman et al., 2006). All of these factors make snow cover obscured by a forest canopy difficult to predict using rule-based algorithms or physically based models (Clark et al., 2011). Because snow accumulation and ablation patterns in forested areas often differ from open regions, the snow cover from openings seen by optical remote sensors may not accurately represent the surfaces obscured by vegetation. In this paper we assume equation (1) holds, and we adjust undercanopy snow surfaces from a temporally and spatially variable VGF, but we acknowledge this is an important area for further research.

#### 2.2.2. VZA’s Effects on VGF

The relationship between VZA and VGF introduces georegistration inaccuracies, daily changes to the area within stretched pixels acquired off-nadir, and diminishing VGF with increasing VZA. The first issue is that georegistration error of nadir MODIS pixels is on the order of 50 to 150 m and can increase nonlinearly with increasing VZA (Wolfe et al., 2002). This leads to a degradation of the georegistration in conversion to the sinusoidal projection used for data distribution and further degradation by transformation to the user’s selected projection. Without correcting for the georegistration error, modeled pixels may not match the actual location of the MODIS pixels. We largely side-step georegistration errors in the vegetation correction because, in estimating VGF, we utilize a vegetation fraction calculated from the same algorithm, as opposed to integrating a separate satellite data set. Second, the instantaneous field of view of MODIS is about 500 m at nadir, but as the MODIS VZA increases to 65° at the edge of the swath, pixels grow by nearly a factor of 10, 4 times in the along-track direction and 4.8 times in the cross-track (Dozier et al., 2008). Consequently, our estimates of canopy properties need to include the area within the stretched pixels that change daily.

The final and more complex obstacle relates to accommodating the decreasing VGF with increasing VZA (Liu et al., 2004; Figure 1). Previous geometric approaches to address VGF-VZA relationships include geometric optical (GO) models that parameterize tree crowns as cones (Li & Strahler, 1985, 1986) or ellipses (Li & Strahler, 1992). GO models capture the basic shape of the relationship between VGF and VZA, but hemispherical photos show they underestimate the VGF because the models do not account for “within-canopy gaps,” solar radiation that reaches the ground surface despite being filtered and scattered through thin foliage (Liu et al., 2004). Efforts to capture the VGF by using a hybrid GO radiative transfer model
that accounts for within-canopy gaps have shown improvements over the simpler GO model. However, in addition to readily available data like terrain slope and aspect, VZA, and satellite viewing azimuth angle, GO and GO radiative transfer models require detailed knowledge of the tree canopy (e.g., vertical and horizontal crown radius, tree density, and foliage area volume density). Ground-based data and lidar have been used to estimate relevant forest properties (Varhola & Coops, 2013); but lidar is not typically available for larger regions, remote locations, and the global scale that MODIS covers.

A more direct way of approximating the VGF used to adjust snow cover for modeling SWE combines the fine resolution (30 m) of the National Land Cover Dataset (NLCD; Homer et al., 2015) to estimate $f_{\text{VEG}}$ with the temporal variation of moderate-resolution imagery to estimate viewable $f_{\text{SCA}}$. The assumption is that $VGF = 1 - f_{\text{VEG}}$ so that equation (1) becomes

$$f_{\text{SCA}} = \min\left(1, \frac{f_{\text{SCA \: viewable}}}{1 - f_{\text{VEG}}}, 1.0\right).$$  \hspace{1cm} (2)

An alternate approach to account for pixel elongation and to reduce the effect of VGF, when interpolating daily fractional snow cover, is to assign less weight to observations at larger VZA and to rely more heavily on the observations from nadir (Dozier et al., 2008; Dozier & Frew, 2009). Still, the off-nadir views have some weight, so snow cover is likely to be underestimated when off-nadir views are cloud-free and nadir views are cloudy. For example, previous research using viewable MODSCAG $f_{\text{SCA}}$ data and a static VGF derived from NLCD showed improved accuracy over viewable $f_{\text{SCA}}$ but underestimated it compared to ground observations (Raleigh et al., 2013). We refer to this as the “static method” in following sections.

### 3. Methods

#### 3.1. MODSCAG

The MODSCAG algorithm (Painter et al., 2009) uses linear spectral mixture analysis to determine subpixel coverage by snow, vegetation, and soil. MODSCAG models each pixel as the linear combination of three physical endmembers: (1) snow (2) vegetation, and (3) soil in two endmember mixtures to match apparent surface reflectance data from MOD09GA (Collection 5 in this paper). A shade fraction is calculated as the additive complement to 1 to the pixel’s sum of physical endmember fractions to account for changes in at-surface irradiance expressed in the apparent surface reflectance of MOD09GA. Both snow and vegetation or soil endmembers are scaled by the shade fraction conserving the retrieved ratio such that the sum of physical endmember fractions equals 1.0. The output includes $f_{\text{VEG}}$ and $f_{\text{SOIL}}$ (fractional soil) maps in addition to those of $f_{\text{SCA}}$ and grain size. An example of this output is shown in Figures 2b–2d as compared to the MODIS false color image (Figure 2a). We refer to “viewable MODSCAG $f_{\text{SCA}}$” simply as “MODSCAG $f_{\text{SCA}}$” hereafter.

#### 3.2. VZA-Dependent Canopy Adjustment

We developed an observation-based approach that utilizes the relationship of MODSCAG $f_{\text{SCA}}$ and MODSCAG $f_{\text{VEG}}$ to estimate VGF. Using MODSCAG $f_{\text{VEG}}$, VGF is then estimated as $VGF = 1 - f_{\text{VEG}}$, and canopy-adjusted $f_{\text{SCA}}$ is calculated by equation (1).

This approach improves over previous uses of equation (1) because of the internal consistency we attain by deriving $f_{\text{VEG}}$ and viewable $f_{\text{SCA}}$ from a single sensor. By using simultaneous observations from MODSCAG to estimate $f_{\text{VEG}}$ and viewable $f_{\text{SCA}}$, we also impose a physical constraint (total fraction of surfaces = 1), whereas this is not guaranteed if combining $f_{\text{VEG}}$ and viewable $f_{\text{SCA}}$ products derived across multiple sensors (e.g., adjusting MODIS $f_{\text{SCA}}$ with Landsat NLCD $f_{\text{VEG}}$ via the static method).

We explore the relationship of viewable MODSCAG $f_{\text{SCA}}$ and $f_{\text{VEG}}$ with VZA to test how VGF affects retrievals. To evaluate the relationship of $f_{\text{SCA}}$ with VZA, an independent estimate of VGF at nadir is needed. “Percent tree canopy” (PTC) from the NLCD (Homer et al., 2015) shows the best agreement to nadir $f_{\text{VEG}}$ from MODSCAG as compared to other available products and was selected as the independent estimate of VGF.
We utilize viewable MODSCAG fSCA maps for 2001–2012 for the Sierra Nevada together with VZA from the MODIS atmospherically corrected reflectance product, MOD09GA (Collection 5), to examine VZA’s effect on fSCA. This range of years includes relatively wet years such as 2006 and 2011 and relatively dry years such as 2007 and 2012. The data are analyzed in increments of 10% tree canopy cover using NLCD’s PTC data. We match each pixel’s fSCA and fVEG with its VZA for the 12-year period and calculate the mean fSCA in VZA increments of 5°. However, fVEG from MODSCAG includes both tree cover and other shorter vegetation (e.g., low shrubs and herbaceous plants) that would not obscure the viewing angle. To distinguish visible shrubs and herbs from tall shrubs and tree cover, we use tree height data from the LANDFIRE 30-m data set (Rollins, 2009) to filter fVEG to MODIS pixels that have mean canopy heights greater than 2.5 m.

### 3.3. Complementary Cloud Detection

This analysis of MODSCAG creates a new procedure for detecting clouds utilizing fVEG and fSOIL that flags snow-cloud confusion errors. Discriminating clouds and snow has been a topic of research since the inception of optical remote sensing (see section 1). In a binary classification of pixels, clouds are brighter in the SWIR; so these wavelengths can be used to differentiate clouds from snow (Dozier, 1989). If viewable fSCA is above a fractional pixel threshold, typically 0.9, the retrieved grain size can also be used to distinguish snow from clouds (Dozier et al., 2008). For pixels that have snow-cover fractions less than this threshold, cloud discrimination remains a consistent problem, especially for ice clouds (Allen et al., 1990).

Here we present an additional cloud-detection approach that can be used together with existing algorithms to improve snow-cloud discrimination. This new approach uses the daily sequence of fVEG and fSOIL to detect clouds that would otherwise remain undetected. To filter clouds that are not previously eliminated in forested regions (vegetation height > 2.5 m) through the SWIR or grain-size methods described above, we calculate the 70th percentile value of fVEG for each pixel over the period of interpolation and remove days with less than 5% of the 70th percentile fVEG value. These fVEG thresholds were determined based on analysis that showed they reject the most errors; refining these thresholds is an area for further research. Understanding a pixel’s most likely vegetation fraction gives us insight into cloud detection described in section 4. After the cloud detection step, we apply the adjustment as in equation (2).

### 3.4. Canopy-Adjusted, STC MODSCAG fSCA

We then apply an interpolation with smoothing splines in the time dimension that weighs nadir observations more than off-nadir observations as in Dozier et al. (2008) to the canopy-adjusted fSCA. In the final step, we apply three-dimensional smoothing with a [3 3 3] box convolution kernel, thereby creating a canopy adjusted spatially and temporally complete (STC)-MODSCAG fSCA that we hereafter refer to as “STC-MODSCAG fSCA.” The spatial smoothing essentially enables fractional pixel values for the accumulation...
and melt season in forested areas. Nearby snow-covered alpine and meadow pixels included in the box convolution where $f_{SOIL}$ is retrieved instead of $f_{VEG}$ also contribute in this way.

### 3.5. Field Observations for Canopy-Adjusted Snow Map Validation

Grids of temperature measurements at 5-cm depth below the soil surface in four plots (Figure 3) at a subgrid MODIS scale provide ground truth data to compare with STC-MODSCAG $f_{SCA}$. Field data are available for comparison for an average year (2010), a wet year (2011), and a dry year (2012).

The four Sierra Nevada sites—Tuolumne Meadows (TUM), Dana Meadows (DAN), Onion Creek (OCR), and Yosemite Forest (Figure 3)—represent a progression of forest density with PTCs of 0.19, 0.31, 0.66, and 0.81, respectively. These mean forest density values were computed using a slightly different set of 30-m pixels than in Raleigh et al. (2013), nonetheless yielding similar forest densities (differences of $+0.04$, $+0.01$, $-0.01$, and $-0.02$). The sensor networks in 2010 and 2011 are described in detail by Raleigh et al. (2013). The 2012 network, which replicates the 2011 network except at the Yosemite Forest (Lutz et al., 2012), is analyzed here for the first time. All hourly ground temperature data and derived daily $f_{SCA}$ time series are included with this paper (see Supporting Information S1).

The temperature sensors detect snow, after the snowpack is established, by taking advantage of the insulating effect of the snow blanket from ambient temperatures. When snow is present, the near-surface ground temperature remains nearly constant, usually near 0 °C, with little diurnal variability (Lundquist & Lott, 2008; Tyler et al., 2008). This approach has been successfully used in several studies for mapping snow duration and snow cover in forests and mountains (Dickerson-Lange et al., 2015; Ford et al., 2013; Schmid et al., 2012; Selkowitz et al., 2014).

Accuracy of snow presence detection with the sensors is challenged in the early season when tracking of diurnal temperature variation can be confused by ephemeral snowfall events (i.e., episodic snow cover that persists for 1–3 days and then melts away). Prior studies have shown agreement to within ±1 day in both snow duration and the timing of snow disappearance derived from ground-temperature sensors versus time-lapse cameras when the pixel location of temperature sensors is known in the camera view. Likewise, $f_{SCA}$ depletion derived from temperature sensors has achieved high-temporal correlation ($R^2 = 0.98$) with $f_{SCA}$ derived from time-lapse imagery and agreed to within 4% of $f_{SCA}$ from 15-m maps from Advanced Spaceborne Thermal Emission and Reflection Radiometer (Raleigh et al., 2013). Point-scale comparisons between temperature sensors and automatic snow sensors are more difficult to interpret due to (1) differences in measurement support (i.e., 1.7-cm iButton vs. 100- to 300-cm sensing area for acoustic snow depth sensors or snow pillows) and (2) ambiguities in automated observations of snow disappearance (e.g., acoustic rangers may measure grass height rather than snow depth once snow cover becomes thin). However, temperature sensors installed near automatic snow measurements show reasonable correspondence in observing snow disappearance, typically within 2 or 3 days (Lundquist & Lott, 2008; Merio et al., 2018). When snow depth declines to less than ~30 cm, the insulating effect of the snowpack diminishes (Taras et al., 2002), and damped diurnal variations emerge in the temperature of the snow-soil interface.

Our methodology for identifying snow presence from ground temperature accounts for the reduced
insulation in thinning snow by permitting diurnal variations of 1 °C (daily range), as Raleigh et al. (2013) advise. We apply the same technique to the temperature data to derive daily snow presence at each temperature sensor and then estimate daily fractional snow cover based on the number of sensors reporting snow presence in a network.

### 3.6 Evaluation Metrics

#### 3.6.1 Binary Metrics

To quantitatively assess errors between observed \( f_{SCA} \) (i.e., inferred from temperature sensor networks) and STC-MODSCAG \( f_{SCA} \), we use a set of binary metrics that rely on the common classification of four possible outcomes in identifying a MODIS pixel as containing snow or not: true positive (TP), true negative (TN), false positive (FP), and false negative (FN). These outcomes are used to calculate the binary statistics Precision, Recall, and \( F \) score in equations (3)–(5) typically used to assess snow cover accuracy (Masson et al., 2018; Painter et al., 2009; Raleigh et al., 2013; Rittger et al., 2013). These three statistics do not rely on TNs, when both STC-MODSCAG \( f_{SCA} \) and ground-observed \( f_{SCA} \) are zero to avoid inflating statistical performance.

\[
\text{Precision} = \frac{TP}{TP + FP} \quad (3)
\]

\[
\text{Recall} = \frac{TP}{TP + FN} \quad (4)
\]

\[
F = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = \frac{2TP}{2TP + FP + FN} \quad (5)
\]

Publicly available viewable MODSCAG \( f_{SCA} \) products mask out values less than 0.15 to eliminate FPs; hence, previous MODSCAG-based work does not include these low \( f_{SCA} \) values (Painter et al., 2009; Raleigh et al., 2013; Rittger et al., 2013). In a recent study, Masson et al. (2018) assessed products from another spectral mixture algorithm for snow cover, MODiMLAb, that retain values for \( f_{SCA} \) less than 0.15 by using an NDSI threshold greater than 0.2 to mask out FPs instead of using the <0.15 \( f_{SCA} \) threshold. In our analysis, we calculate the full range of values, 0 to 1, in a similar manner to Masson et al. (2018) shown in Table 1.

By including values of 0.01 to 0.14 in the analysis, we are essentially making it harder to score well in Precision because differentiating snow in that range from spectrally bright soils can be difficult resulting in more FPs. Simultaneously, Recall would be easier to score well because there should be fewer FN as the \( f_{SCA} \) is not set to zero. These differences balance each other in \( F \) scores, but we considered evaluating the full range as more justified.

#### 3.6.2 Fractional Metrics

To quantitatively assess the fractional errors between observed temperature sensor \( f_{SCA} \) and STC-MODSCAG \( f_{SCA} \), we calculate mean and median difference and root mean squared error (RMSE) shown in equation (6) where \( N \) is the number of observations.

\[
RMSE = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (f_{SCA}^{\text{MODIS}} - f_{SCA}^{\text{Observed}})^2} \quad (6)
\]

Like Rittger et al. (2013), we compare only observations where either MODIS \( f_{SCA} \) or ground-observed \( f_{SCA} \) are greater than zero (i.e., excluding TNs like with the binary analysis); but here we include values between 0.01 and 0.14 (Masson et al., 2018). Excluding these TNs results in fewer observations to compare in the fractional analysis than the binary analysis as indicated in lower fractional counts than binary counts in Table 1.

![Table 1](https://example.com/table1.png)

**Note.** TUM = Tuolumne Meadows; DAN = Dana Meadows; OCR = Onion Creek; FDP = Yosemite Dynamics Forest Plot; RMSE = root mean squared error; DJF = December, January, and February; MAM = March, April, and May; JJA = June, July, and August; SON = September, October, and November.
However, those TN were not used in the Precision, Recall, or F score equations. Unlike Raleigh et al. (2013), we do not set MODIS fSCA values between 0.01 and 0.14 to zero.

4. Results

4.1. Relationship Between Viewable MODSCAG fSCA and VZA

The advantage of using the fVEG approach with MODSCAG instead of the static adjustment is that we can apply a per-pixel adjustment with a concurrent daily estimate of fVEG to account for VGF using equation (1).

Figure 4 shows the viewable MODSCAG fSCA (also interpolated and smoothed), STC-MODSCAG fSCA, and fVEG for 1 March and 1 July 2012 in the Tuolumne and Merced River basins. On 1 March, nearly half the basin’s snow cover needs to be adjusted. In contrast, on 1 July, after much of the snow has melted in the subalpine forests, the alpine snow cover does not require an adjustment. Also, visible on 1 July is an increase in fVEG relative to 1 March most likely from the spring greening of the understory in forested areas. An apparent increase in fVEG due to VZA is a less plausible explanation because VZA was 10° smaller for 1 July than 1 March.

While Figure 4 shows an example of our snow and vegetation maps, Figures 5a and 5b demonstrate the relationship of viewable fSCA and fVEG with VZA for the entire region covered in Figure 2. Land-surface changes (e.g., fSCA and fVEG) due to PTC are shown for the spectrum of VZAs in Figure 5c. The analysis used data across the Sierra Nevada (Figure 2) from 2001 to 2012.
Changes to viewable MODSCAG $f_{SCA}$ and $f_{VEG}$ caused by VZA are smallest for dense forest canopies ($\geq 75$ PTC), with only an 8% change in land-cover fraction ($f_{SCA}$ or $f_{VEG}$) resulting from 65° VZA as compared to nadir (Figures 5a and 5b). This is expected in dense forest canopies where most of the forest floor is obscured regardless of the satellite’s position overhead, so there is little possible change in land-cover fractions with increasing VZA (Figures 1 and 5c). The greatest effect of VZA on land-surface fraction occurs between 30% and 40% PTC (Figure 5c). At these moderate forest densities, there is a linear response to $f_{SCA}$ and $f_{VEG}$ from VZA (Figures 5a and 5b). In contrast, in sparse canopies, the relationship between land-cover fraction and VZA is nonlinear. For PTC of 5%, there is little change (<0.02) to $f_{SCA}$ and $f_{VEG}$ land-cover fraction at VZAs less than 40° but a 0.2 change for VZAs between 40° and 65°.

For $f_{SCA}$ (Figure 5a), the $y$ intercepts are smaller than the VGF calculated with NLCD; and for $f_{VEG}$ (Figure 5b), the $y$ intercepts are larger. The overestimate of $f_{VEG}$ may be the result of MODSCAG’s three-endmember approach, where the first endmember is snow, the second is vegetation, and the third is shade, and a no-soil endmember is used if the residual from spectral mixing is small enough. Occasional snow intercepted by the tree canopy may also explain the $f_{SCA}$ underestimate.

In a parallel analysis for MOD10A1 $f_{SCA}$, the effect of VZA was twice as large as for viewable MODSCAG $f_{SCA}$ (Figure S1) possibly because the NDSI method is not as sensitive to detecting snow in forests because of the limited use of spectral information. This analysis sheds light on the snow-research community’s current priorities (e.g., National Aeronautics and Space Administration’s SnowEx) to identify limitations of satellite observations and algorithms in snowy vegetated areas.

### 4.2. MODSCAG Endmembers for Cloud Detection

The improved cloud detection method is demonstrated by an example showing a daily sequence of adjusted $f_{SCA}$ and viewable $f_{SCA}$, $f_{VEG}$, and $f_{SOIL}$ (Figure 6). In Figure 6a, the area shaded in gray identifies that the images from 13 through 18 May 2011 are correctly classified as cloudy by either quality flags in MOD09GA or grain size filtering. Figure 6b shows the sequence of images centered on the pixel in Figure 6a, with noticeable clouds on 19 and 23 May, dates that were not flagged as cloudy in MOD09GA or grain size filtering. Figure 6c shows the reflectance of the pixel for each day, with clearly elevated near-infrared (0.86 $\mu$m) and SWIR ($\geq 1.24$ $\mu$m) reflectance on 19 and 23 May. Those cloudy days, which were not correctly filtered by quality flags or grain size, instead produce incorrect fractional land-cover maps (Figure 6a).

While viewable $f_{SCA}$ appears reasonable on 19 and 23 May given viewable $f_{SCA}$ in the adjacent days (Figure 6a), it is unlikely the solution is achieved for the right reasons. Instead of previously retrieved $f_{VEG}$, we see higher values for $f_{SOIL}$ on 19 and 23 May as compared to the correctly identified days. Given the higher SWIR reflectance from the presence of clouds, the MODSCAG algorithm is compelled to...
address a physically unrealistic subspace of the spectral vector space (for assumption of re
fl
ectance only from


the land surface) and in turn mistakenly results in producing fSOIL. Previous algorithms (Dozier et al., 2008) do not address these un-mixing errors. To catch these errors, an additional flagging technique is implemented that identifies anomalous fVEG data points (refer to section 3.3) over the period of interpolation.

On 19 and 23 May, adjusted fSCA is the same as viewable fSCA because apparent fVEG = 0. Sensor viewing zenith angle is shown on the top axis for clear acquisitions and those incorrectly identified as clear (b) MODIS false-color image using MODIS band centered on 1.64, 0.86, and 0.47 μm to enhance snow (cyan) and clouds (white) for dates and centered on the pixel shown in (a). (c) Seven-band reflectance from MOD09GA for each date of observations in (a). Note the elevated reflectance in the near-infrared (0.86 μm) and shortwave infrared (≥1.24 μm) for 19 and 23 May.

address a physically unrealistic subspace of the spectral vector space (for assumption of reflectance only from the land surface) and in turn mistakenly results in producing fSOIL. Previous algorithms (Dozier et al., 2008) do not address these un-mixing errors. To catch these errors, an additional flagging technique is implemented that identifies anomalous fVEG data points (refer to section 3.3) over the period of interpolation.

On 19 and 23 May, adjusted fSCA using equation (1) turns out to be the same as viewable fSCA because fVEG is erroneously assigned to zero due to cloud cover. Figure 6 shows the VZA on the top axis. These acquisitions are closer to nadir than some of their neighbors and, if not identified with this new technique, are weighted heavily in interpolating across time, resulting in a false decrease in canopy-adjusted fSCA. The data need to be discarded because the spectral mixture analysis is again forced to explore a nonphysical vector subspace with respect to land surface reflectance. This new algorithm presented here flags days like 19 and 23 May and excludes them from the temporal interpolation.

4.3. Comparison of Adjusted fSCA With Ground Observations

4.3.1. Seasonal Comparison

We compare the observed fSCA from the temperature sensors in four sites to the STC-MODSCAG fSCA in water years 2010, 2011, and 2012, starting on 1 December until melt out (Figure 7). Given the geolocation
accuracies described in section 2.2.2. We use the mean fSCA of all MODIS pixels that contain at least one temperature sensor as shown in Figure 3.

As described above, the accuracy of temperature sensor data requires a sustained snowpack. For 2010 and 2011, the snowpack was established by 1 December, whereas in 2012, the snowpack was not established until late January. Viewable MODSCAG fSCA retrievals have best accuracy above a threshold of 0.15 (Rittger et al., 2013), and by the time fSCA drops to this threshold (gray band in Figures 7 and 8), the largest SWE volume has already melted. We show this threshold so that readers can see how well STC-MODSCAG fSCA performs in periods where inputs from MODSCAG fSCA are uncertain and previously unused. In 2010, the observed fSCA is approximately 1.0 for the entire season until melt onset for all sites. STC-MODSCAG fSCA slightly underestimates snow cover for TUM and DAN, the least forested sites. Raleigh et al. (2013) describe rock outcrops at TUM that remain snow free during the season, which can explain this difference since the temperature sensors were placed in the soils of meadows and forests, not over the outcrops. Similar to TUM, DAN also has rock outcrops. At the OCR site, because of the relatively dense forest cover and absence of rock outcrops, this apparent underestimate does not occur. For OCR in 2010, STC-MODSCAG fSCA matches the observed fSCA until the onset of melt in May, when it overestimates fSCA until a late-season storm fully covers the pixels again prior to a second onset of melt. Melt out begins mid-May for OCR, early-May for TUM, and early-June for DAN and is discussed in more detail in section 4.3.2.

In 2011, we have a fourth study site, the Yosemite Dynamics Forest Plot (FDP) with the densest forest cover. For TUM, DAN, and OCR, observed fSCA is again approximately 1.0 for the entire season until melt with similar small underestimates from STC-MODSCAG fSCA relative to observed fSCA for TUM and DAN but not OCR. For FDP, observed fSCA shows three melt events in mid-winter during early December, mid-January, and early February not seen in the STC-MODSCAG fSCA. In this dense canopy, STC-MODSCAG fSCA underestimates in late March and shows complete melt out well before the observed snow cover disappears. STC-MODSCAG fSCA does capture the late season storm in May but not the magnitude of the storm indicating a possible need for reducing or removing smoothing (Bair et al., 2019). In 2011 for OCR, STC-MODSCAG fSCA has similar performance as in 2010, but the observed fSCA does not have an early melt signal like 2010, so the satellite observations better match the ground data.

Figure 7. fSCA from the temperature sensor networks (solid lines) and the mean spatially and temporally complete-Moderate Resolution Imaging Spectroradiometer (MODIS) Snow Covered-Area and Grain Size fSCA of surrounding MODIS pixels (dashed lines) after the snowpack is established on 1 December, thereby providing more reliable temperature sensor data. The grayed area indicates the 0.15 threshold for reliable viewable MODIS Snow Covered-Area and Grain Size fSCA retrievals prior to interpolation. The abbreviations TUM, DAN, OCR, and FDP refer to the sites Tuolumne Meadows, Dana Meadows, Onion Creek, and Yosemite Forest.
In 2012, the snowpack was not well established until late January. Variability between early December and late January is difficult to interpret because the errors could be either from the temperature sensor or the STC-MODSCAG fSCA. After the snowpack is well established, performance is similar to the two previous years. Notably, two melt-season storms are captured by both the temperature sensors and MODIS, which are explored more in the following section.

4.3.2. Melt Out

The most hydrologically important part of the season to water managers is when the snow melts and disappears. Many forecasts rely on snowmelt depletion curves that describe the relationship between snow-covered area and SWE. The subplots in Figure 8 show the mean fSCA values defined in the previous section during the period from full snow cover to no snow (melt out).

TUM has the least PTC coverage. In 2010, the mean of the STC-MODSCAG fSCA drops to zero on 7 June, matching the threshold (0.15) melt out date. Actual full melt out occurs approximately 10 days later. In 2011, MODSCAG fSCA performs better than in 2010, with the individual STC-MODSCAG fSCA pixel values enveloping (not shown) the true day of melt out with the mean corresponding well to the actual melt-out date. In 2012, the threshold melt-out date is the same, but snow cover again persists for a week with values below 0.15.

At DAN, the STC-MODSCAG fSCA from individual pixels envelopes the true observed fSCA melt-out date all 3 years. The STC-MODSCAG fSCA are slightly elevated just prior to melt most likely from the influence of shrubs and grass in forests on the fVEG signal boosting STC-MODSCAG fSCA but possibly also from data gaps that are interpolated.

At OCR, observed fSCA reaches the threshold value of 0.15 on 13 June 2010, 29 June 2011, and 9 May 2012. The STC-MODSCAG fSCA reaches zero just a few days afterward in all 3 years.

At the FDP (data in 2011 only), the observed fSCA reaches 0.15 on 26 May, 2 weeks after the initial melt out from STC-MODSCAG fSCA. A storm on 19 May 2011 brought a notable fSCA spike that was captured well by canopy-adjusted STC-MODSCAG fSCA in timing but not in magnitude. A similar result occurred at TUM, OCR, and DAN with late season snowfalls on 25 May and 5 June 2012. MODIS registers this event to some level but underestimates the total magnitude for all sites in the 25 May storm and overestimates for DAN in the 5 June event. Examination of the raw data shows that STC-MODSCAG fSCA registers a value of 1.0 for...

Figure 8. Same as Figure 7 showing STC-MODSCAG fSCA but zoomed in to the melt season each year. The x axes on the subplots vary in date and scale to provide the best view, because the length of melt season is different for each year and each site.

In 2012, the snowpack was not well established until late January. Variability between early December and late January is difficult to interpret because the errors could be either from the temperature sensor or the STC-MODSCAG fSCA. After the snowpack is well established, performance is similar to the two previous years. Notably, two melt-season storms are captured by both the temperature sensors and MODIS, which are explored more in the following section.

4.3.2. Melt Out

The most hydrologically important part of the season to water managers is when the snow melts and disappears. Many forecasts rely on snowmelt depletion curves that describe the relationship between snow-covered area and SWE. The subplots in Figure 8 show the mean fSCA values defined in the previous section during the period from full snow cover to no snow (melt out).

TUM has the least PTC coverage. In 2010, the mean of the STC-MODSCAG fSCA drops to zero on 7 June, matching the threshold (0.15) melt out date. Actual full melt out occurs approximately 10 days later. In 2011, MODSCAG fSCA performs better than in 2010, with the individual STC-MODSCAG fSCA pixel values enveloping (not shown) the true day of melt out with the mean corresponding well to the actual melt-out date. In 2012, the threshold melt-out date is the same, but snow cover again persists for a week with values below 0.15.

At DAN, the STC-MODSCAG fSCA from individual pixels envelopes the true observed fSCA melt-out date all 3 years. The STC-MODSCAG fSCA are slightly elevated just prior to melt most likely from the influence of shrubs and grass in forests on the fVEG signal boosting STC-MODSCAG fSCA but possibly also from data gaps that are interpolated.

At OCR, observed fSCA reaches the threshold value of 0.15 on 13 June 2010, 29 June 2011, and 9 May 2012. The STC-MODSCAG fSCA reaches zero just a few days afterward in all 3 years.

At the FDP (data in 2011 only), the observed fSCA reaches 0.15 on 26 May, 2 weeks after the initial melt out from STC-MODSCAG fSCA. A storm on 19 May 2011 brought a notable fSCA spike that was captured well by canopy-adjusted STC-MODSCAG fSCA in timing but not in magnitude. A similar result occurred at TUM, OCR, and DAN with late season snowfalls on 25 May and 5 June 2012. MODIS registers this event to some level but underestimates the total magnitude for all sites in the 25 May storm and overestimates for DAN in the 5 June event. Examination of the raw data shows that STC-MODSCAG fSCA registers a value of 1.0 for...
DAN and TUM in relation to the 25 May 2012 storm; however, the surrounding observations (in time) of zero have an unfavorable effect on the interpolated SCA. Given the short duration of these events, there is likely some noise in the ground data as well. In summary, accounting for the sensitivity limitation of 0.15, STC-MODSCAG SCA can estimate the day of melt (±3 days) except for the most vegetated plot, FDP, where it melts out 2 weeks early.

4.3.3. Binary Statistics
In Table 1, we summarize the binary statistics for all dates as well as seasonally segmenting statistics for the winter (December, January, and February; DJF), spring (March, April, and May; MAM), summer (June, July, and August; JJA), and fall (September, October, and November; SON).

Over the available years and sites, Precision, Recall, and F score range from 0.87 to 0.95, 0.86 to 0.97, and 0.86 to 0.96, respectively. Precision is highest for DAN followed by TUM, OCR, and FDP. Recall is highest for OCR, closely followed by DAN and TUM, then FDP. F score, which balances Precision and Recall, is highest for DAN followed by TUM, OCR, and FDP. F score is highest for DAN followed by TUM, OCR, and FDP, indicating the two sites with the highest levels of PTC (OCR and FDP) were the hardest to map correctly.

Seasonally, Precision is high in the winter and spring (DJF and MAM) with minimum values of 0.97. Precision is also high in the summer, with the lowest value of 0.87 at DAN. It decreases in the fall (SON) for all sites to values as low as 0.48 and 0.31 for the two most forested sites. Recall is also highest in the winter and the spring with a minimum value of 0.84, but in contrast to Precision, Recall is lower in the summer (JJA) and higher in the fall except at DAN. The minimum Recall value is for TUM in the summer. F score that balances Precision and Recall is highest in the snowy period (DJF and MAM) and tends to decrease in the summer.

F score has its two lowest values (0.65 and 0.47) in the most forested sites (OCR and FDP) in the fall because of the very low Precision values. The only other F score below ~0.8 was TUM in the winter with a value of 0.74 when Recall was 0.59. F scores deteriorate over the melt out in summer relative to the winter, perhaps reflecting the challenge of mapping the heterogeneous mixed pixels and constantly changing land surfaces over this period with lower SCA and few snow-covered pixels. DAN’s (PTC = 0.31) slightly better performance over TUM (PTC = 0.19) could be related to the size and number of rock outcrops discussed in section 4.3.1.

4.3.4. Fractional Statistics
RMSE is lowest for the least forested site (TUM) and highest for the most forested site (FDP) and ranges from 0.17 to 0.36. Seasonally, RMSE is lowest in the spring followed by summer, winter, and fall for all sites except at FDP, which also has the highest errors in the fall, but in contrast to the other three sites has relatively high errors in the spring as well.

The mean and median differences are calculated as the STC-MODSCAG SCA minus the ground-observed SCA. Mean differences for all dates range from −0.05 to 0.05, and median differences range from −0.07 to 0. Seasonally, these two statistics show that STC-MODSCAG SCA overestimates in the fall; while the winter, spring, and summer are mixed with more underestimates than overestimates. The early melt out for FDP seen in Figure 8 accounts for large negative mean and median differences of −0.34 and −0.36 in the spring.

Mean and median differences for some sites differ in sign, indicating occasional larger overestimates but regular small underestimates; for example, the small underestimates at TUM and DAN attributed to rock outcrops unsampled in the ground data. Large overestimates as seen in January 2012 (Figure 7) could be from still undetected clouds or, alternatively, errors in the early season ground data before an established snowpack.

At OCR, overestimates and underestimates balance errors resulting in very small mean and median differences except in the fall where the not-yet-established snowpack in 2012 drives up the differences. Similarly, TUM and DAN have small mean and median differences throughout the season except in the fall.

5. Discussion
5.1. Improvements in Snow Mapping Accuracy
Previous validation efforts that use gap-filled time series from MODIS and evaluate the remote sensing observations under various canopy densities are scarce. The commonly used MOD10C1 product has been
gap filled and evaluated by assimilation into a land-surface model but not compared to ground observations of fSCA (Hall et al., 2010). Alternative gap-filling approaches also exist (Parajka et al., 2010). These studies did not adjust fVEG dynamically with VZA, whereas this study accounted for these effects (Figure 1). Previous studies also did not use a physically based snow mapping model like MODSCAG with the advantage of concurrent fVEG and fSOIL estimates that can be used for better cloud filtering. We evaluated the adjusted fSCA using the same metrics as previous studies but for the full range of fSCA values from 0 to 1. Based on our melt-out comparisons shown in section 4.3.2 and the statistical comparison, STC-MODSCAG fSCA is valid below 0.15.

A recent assessment of existing methodologies for snow cover fraction from Masson et al. (2018) included MOD10A1 C5 and MOD10A1 C6, both based on top-of-atmosphere reflectance, and NDSIATOPCOR, MODImLAB, and LMMpure, (another spectral mixture method) in the Alps, the Pyrenees, and Morocco. The average Precision, Recall, and F score over all the sites for STC-MODSCAG fSCA (0.905, 0.931, and 0.917) in the Sierra Nevada compare very well to the average (0.489, 0.645, and 0.466) and best (0.705, 0.950, and 0.670) of all models from Masson et al. (2018). The RMSE for STC-MODSCAG fSCA averaged over all sites (0.240) was similar to the RMSESNOW (0.228) for the best model in Masson et al. (2018). However, Masson et al. (2018) only evaluate on clear days with other remote sensing data, while we evaluate STC-MODSCAG fSCA also under tougher cloud conditions that can be used for better cloud filtering. To best understand improvements gained by the methods presented in this paper, we can directly compare to previous work on adjusting MODSCAG snow cover for vegetation using NLCD (Raleigh et al., 2013). In Table 1, “All” is most comparable to tables 2 and 3 in Raleigh et al. (2013). Finally, previous comparisons of STC-MODSCAG fSCA to airborne-derived snow cover shows similar accuracy even in extreme drought years such as 2015 (Bair et al., 2016).

With regard to Precision, values reported in Table 1 are 0.08, 0.01, 0.12, and 0.09 lower than values reported by Raleigh et al. (2013). This can be explained by Raleigh et al. (2013) setting all MODIS values of 0.15 to zero, decreasing the number of FPs and increasing the Precision (equation (3)). In contrast, values of Recall in Table 1 were 0.11, 0.00, 0.13, and 0.24 larger than in Raleigh et al. (2013) for precisely the same reason: We include the values below 0.15 for STC-MODSCAG fSCA boosting the number of TPs while simultaneously decreasing FNs resulting in a higher Recall (equation (4)). The F score that balances Precision and Recall is equal to or greater (0.02, 0.00, 0.01, and 0.11) in this study than in Raleigh et al. (2013), showing the clear improvement even while considering the full range of possible snow fractions from 0 to 1.

RMSE in this study is 0.08, 0.03, 0.01, and 0.19 less than in the previous study at TUM, DAN, OCR, and FDP, respectively, showing the most significant improvements at the least and most forested sites. Most notably, the mean bias has been reduced to 0.02, 0.03, 0.05, and −0.05 from previous values of −0.22, −0.09, −0.09, and −0.37 at TUM, DAN, OCR, and FDP, respectively, for a 20% overall reduction in bias. In addition to the binary statistics, these fractional statistics also show the clear improvement using the new techniques presented in this paper.

Although not obvious from these statistics, there is improved ability to estimate fSCA at OCR when fSCA is less than the PTC of 66%. Scatterplots (Figure 9) presented over the same time frames as in Raleigh et al. (2013) show the method presented in this paper can provide more accurate results everywhere but show a considerable improvement at moderately forested sites like OCR. In contrast, the static method did not perform well when fSCA was less than the complement of the fVEG (i.e., to the left of the black lines in Figure 9). This issue is only visible in FDP with the largest PTC of our sites. At FDP, canopy cover is both taller (maximum 67 m) and more variable than at the other sites. Lower values of fSCA shown here are generally in later months and near melt out; the improved cloud detection appears to help considerably. For example, in Raleigh et al. (2013) in 2010 and 2011, OCR melted out 2 weeks too early; but our method captures the threshold melt out to within 3 days and actual melt out to within 5 days.

In summary, STC-MODSCAG performs favorably compared to the previous ground-based study with a higher F score and a lower bias and RMSE on average over most of the season, likely from the improved vegetation adjustment and more accurate melt-out dates due to improved cloud detection. The assessment provides errors segmented by season and forest density that can be used for data assimilation in future studies and applications utilizing the STC-MODSCAG product.
5.2. Limitations of the Approach and Future Improvements

Several outstanding areas of research not addressed in our approach may produce snow-mapping errors. As discussed in section 2.2.1, we assume that viewable fSCA in open areas can be applied to undercanopy forest floors. This increases snow-mapping error where and when the assumption is not true. Previous studies have shown that snow-cover differences between open areas and forests vary regionally (Lundquist et al., 2013). Developing a more informed approach to estimating fSCA on the forest floor remains an outstanding challenge that either requires additional remote-sensing observations, for example, lidar that can delineate the vertical profile of canopy cover (Kostadinov et al., 2019; Painter et al., 2016), or more reliance on an integrative framework that incorporates models with existing remotely sensed data to discriminate differences between open and subcanopy fSCA.

Snow intercepted by the forest canopy can also increase snow-map errors since viewable snow in the canopy is not differentiated from viewable snow on the ground. The issue is made more complicated by the differential time that snow remains in the canopy in warmer or cooler temperatures. We expect that the STC-MODSCAG fSCA will not be extremely sensitive to this issue. If there is snow in the canopy, there is likely to be snow on the ground, but we acknowledge viewable fSCA will be enhanced and fVEG will be reduced during periods with snow in the canopy. Discriminating snow in the canopy from snow on the ground is a possible avenue for future development and could be useful for evaluating model representations of snow-forest interactions.

Figure 9. Comparison of spatially and temporally complete-Moderate Resolution Imaging Spectroradiometer Snow Covered-Area and Grain Size fSCA to ground fSCA across all sites and all years segmented by month. The bold black bar represents the percent tree canopy at each site. The 1:1 line shown for reference. As in figure 7 of Raleigh et al. (2013).
Validation of our product is provided via four Sierra Nevada sites over 3 years, including only 1 year in the most heavily forested site. This limits our ability to extrapolate the accuracy of the product in heavily treed environments and over regions other than the Sierra Nevada that experience different patterns in snow processes and forest effects on snow cover. The temperature sensor network data we use provide ideal temporal information and sufficient spatial sampling for validation but lack the spatially intensive snow-cover mapping data afforded by other remote-sensing data sources such as lidar or very high-resolution optical products which are only available for cloud-free days. Possible future validation approaches include comparing the STC-MODSCAG \( \text{f}_{\text{SCA}} \) to \( \text{f}_{\text{SCA}} \) derived from lidar data sets in areas with varying forest cover or from time-lapse camera networks (e.g., SnowEx).

Finally, there is a sustained need for improved cloud masks. The approach presented here detects cloudy conditions not found in the original MOD09GA cloud mask, but geostationary or commercial satellites with sufficient spatial resolution and repeat cycles hold promise in helping to further develop and evaluate more advanced cloud masking algorithms.

6. Conclusions

We test an adjustment for MODIS snow-cover maps to account for VZA dependencies in forest cover and to better detect clouds. For STC-MODSCAG \( \text{f}_{\text{SCA}} \), estimates of snow-covered area are consistent with ground observations except for the densest canopy (i.e., forest cover exceeding 80%). The method of observing snow cover on the ground using temperature sensors is of great utility for evaluating optical satellite data and interpolation algorithms. However, more ground data are necessary to better understand the threshold at which optical data become unreliable for various tree species and densities. Rock outcrops should be quantitatively assessed during the nonsnow-covered period, for example, using high spatial-resolution imagery to improve the accuracy of the ground observations. Large-scale efforts such as SnowEx in 2017 that focused on identifying the forest density threshold for reliable snow remote sensing provide well-timed complimentary initiatives and field data upon which to further validate our canopy-adjustment approach. MODSCAG is a physically based model producing vegetation and soil endmembers that allows us to constrain cloud identification in ways not possible with conventional index-based algorithms like NDSI. Together, these contributions to snow-mapping techniques have the potential to advance natural resource management for quantifying the effects of forest disturbance on canopy structure due to insect- and pathogen-related infestations (Baker et al., 2017) and fire (Micheletty et al., 2014) as well as for hydrologic forecasting in the snowy forested basins that comprise one fifth of Northern Hemisphere snow-covered areas.

Data

Data for all study sites can be found in the supporting information as Excel (.xlsx) files. The files include temperature sensor data and derived \( \text{f}_{\text{SCA}} \) as well as corresponding STC-MODSCAG \( \text{f}_{\text{SCA}} \). Viewable MODSCAG \( \text{f}_{\text{SCA}} \) was obtained from JPL (https://snow.jpl.nasa.gov/portal/data/). STC-MODSCAG data sets used in this study can be found on the CWEST snow server at CU Boulder (ftp://snowserver.colorado.edu/pub/fromRittger/201901_STC-MODSCAG_WRR_data). If the paper is accepted, these data will be submitted to an appropriate repository such as the NSIDC DAAC or a FAIR-aligned repository.
Bormann, K. J., Brown, R. D., Derksen, C., & Painter, T. H. (2018). Estimating snow-cover trends from space. Nature Climate Change, 8(11), 924–928. https://doi.org/10.1038/s41558-018-0318-3

Clark, M. P., Hendriks, J., Slater, A. G., Kavetski, D., Anderson, B., Cullen, N. J., et al. (2011). Representing spatial variability of snow water equivalent in hydrologic and land-surface models: A review. Water Resources Research, 47, W07539. https://doi.org/10.1029/2011wr010745

Clark, M. P., Slater, A. G., Barrett, A. P., Hay, L. E., McCabe, G. J., Rajagopalan, B., & Leavesley, G. H. (2006). Assimilation of snow covered area information into hydrologic and land-surface models. Advances in Water Resources, 29(8), 1209–1221. https://doi.org/10.1016/j.advwatres.2005.10.001

Dickerson-Lange, S. E., Lutz, J. A., Martin, K. A., Raleigh, M. S., Gersonde, R., & Lundquist, J. D. (2015). Evaluating observational methods to quantify snow duration under diverse forest canopies. Water Resources Research, 51, 1203–1224. https://doi.org/10.1002/2014wr015744

Dozier, J. (1989). Spectral signature of alpine snow cover from the Landsat Thematic Mapper. Remote Sensing of Environment, 28, 9–22. https://doi.org/10.1016/0034-4257(89)90101-6

Dozier, J., & Frew, J. (2009). Computational provenance in hydrologic science: A snow mapping example. Philosophical Transactions of the Royal Society A, 367(1890), 1021–1033. https://doi.org/10.1098/rsta.2008.0187

Dozier, J., Painter, T. H., Rittger, K., & Frew, J. E. (2008). Time-space continuity of daily maps of fractional snow cover and albedo from MODIS. Advances in Water Resources, 31(11), 1515–1526. https://doi.org/10.1016/j.advwatres.2008.08.011

Durand, M., Molotch, N. P., & Margulis, S. A. (2008). Merging complementary remote sensing datasets in the context of snow water equivalent reconstruction. Remote Sensing of Environment, 112(3), 1212–1225. https://doi.org/10.1016/j.rse.2007.08.010

Essery, R., Pomeroy, J., Parvainen, J., & Storck, P. (2003). Sublimation of snow from coniferous forests in a climate model. Journal of Climate, 16(11), 1855–1864. https://doi.org/10.1175/1520-0442(2003)016<1855:SOSFCF>2.0.CO;2

Fites-Kaufman, J., Bradley, A. F., & Merrill, A. G. (2006). Fire and plant interactions. In N. G. Sugihara, J. W. van Wagtenendonk, K. E. Shaffer, J. Fites-Kaufman, & A. E. Thode (Eds.), Fire in California's ecosystems, (pp. 94–117). Berkeley, CA: University of California Press. https://doi.org/10.1525/california/9780520246058.003.0006

Ford, K. R., Ettinger, A. K., Lundquist, J. D., Raleigh, M. S., & Lambers, J. H. R. (2013). Spatial heterogeneity in ecologically important climate variables at coarse and fine scales in a high-snow mountain landscape. Plos One, 8(6), e65098. https://doi.org/10.1371/journal.pone.0065008

Gafarov, A., & Bárdossy, A. (2009). Cloud removal methodology from MODIS snow cover product. Hydrocl. Earth Syst. Sci., 13(7), 1361–1373. https://doi.org/10.5194/hess-13-1361-2009

Hall, D. K., Riggs, G. A., Foster, J. L., & Kumar, S. V. (2010). Development and evaluation of a cloud-gap-filled MODIS daily snow-cover product. Remote Sensing of Environment, 114(3), 496–503. https://doi.org/10.1016/j.rse.2009.10.007

Hall, D. K., Riggs, G. A., & Salomonson, V. V. (1995). Development of methods for mapping global snow cover using Moderate Resolution Imaging Spectroradiometer data. Remote Sensing of Environment, 54(2), 127–140. https://doi.org/10.1016/0034-4257(95)00137-p

Hall, D. K., Riggs, G. A., Salomonson, V. V., DiGirolamo, N. E., & Bayr, K. J. (2002). MODIS snow-cover products. Remote Sensing of Environment, 81(1-2), 181–194. https://doi.org/10.1016/S0034-4257(02)00095-0

Homer, C., Dewitz, J., Yang, L., Jin, S., Danielson, P., Xian, G., et al. (2015). Completion of the 2011 National Land Cover Database for the Conterminous United States—Representing a decade of land cover change information. Photogrammetric Engineering & Remote Sensing, 81, 345–354.

Klein, A. G., Hall, D. K., & Riggs, G. A. (1998). Improving snow cover mapping in forests through the use of a canopy reflectance model. Hydrological Processes, 12(10), 1723–1744. https://doi.org/10.1002/(SICI)1097-0686(19980809)12:10<1723::AID-HYP13>3.3.CO;2-U

Kostadinov, T. S., Schumer, R., Hausner, M., Bormann, K. J., Gaffney, R., McGwire, K., et al. (2019). Watershed-scale mapping of fractional snow cover under conifer forest canopy using lidar. Remote Sensing of Environment, 222, 34–49. https://doi.org/10.1016/j.rse.2018.11.037

Kunkel, K. E., Robinson, D. A., Champion, S., Yin, X., Estillow, T., & Frankson, R. M. (2016). Trends and extremes in Northern Hemisphere snow cover characteristics. Current Climate Change Reports, 2(2), 65–73. https://doi.org/10.1007/s40641-016-0036-8

Li, X., & Strahler, A. H. (1985). Geometric-optical modeling of a conifer forest canopy. IEEE Transactions on Geoscience and Remote Sensing, GE-23(5), 705–721. https://doi.org/10.1109/16.298398

Li, X., & Strahler, A. H. (1986). Geometric-optical bidirectional reflectance modeling of a conifer forest canopy. IEEE Transactions on Geoscience and Remote Sensing, GE-24(6), 906–919. https://doi.org/10.1109/16.289706

Li, X., & Strahler, A. H. (1992). Geometric-optical bidirectional reflectance modeling of the discrete crown vegetation canopy—Effect of crown shape and mutual shadowing. IEEE Transactions on Geoscience and Remote Sensing, 30(2), 276–292. https://doi.org/10.1109/36.134078

Li, X., Strahler, A. H., & Woodcock, C. E. (1995). A hybrid geometric optical-radiative transfer approach for modeling albedo and directional reflectance of discontinuous canopies. IEEE Transactions on Geoscience and Remote Sensing, 33(2), 466–480. https://doi.org/10.1109/36.377947

Liu, J. C., Mello, R. A., Woodcock, C. E., Davis, R. E., & Ochs, E. S. (2004). The effect of viewing geometry and topography on viewable gap fractions through forest canopies. Hydrological Processes, 18(18), 3595–3607. https://doi.org/10.1002/hyp.5802

Liu, J. C., Woodcock, C. E., Mello, R. A., Davis, R. E., McKenzie, C., & Painter, T. H. (2008). Modeling the view angle dependence of gap fractions in forest canopies: Implications for mapping fractional snow cover using optical remote sensing. Journal of Hydrometeorology, 9(5), 1005–1019. https://doi.org/10.1175/2008jhms66.1

Liu, Y., Peters-Lidard, C. D., Kumar, S., Foster, J. L., Shaw, M., Tian, Y., & Fall, G. M. (2013). Assimilating satellite-based snow depth and snow cover products for improving snow predictions in Alaska. Advances in Water Resources, 54, 208–227. https://doi.org/10.1016/j.advwatres.2013.02.005

Lundquist, J. D., Dickerson-Lange, S. E., Lutz, J. A., & Cristea, N. C. (2013). Lower forest density enhances snow retention in regions with warmer winters: A global framework developed from plot-scale observations and modeling. Water Resources Research, 49, 6356–6370. https://doi.org/10.1002/wrcr.20594
Lundquist, J. D., & Lott, F. (2008). Using inexpensive temperature sensors to monitor the duration and heterogeneity of snow-covered areas. *Water Resources Research, 44*, W09116. https://doi.org/10.1029/2008WR007035

Lutz, J. A., Larson, A. J., Swanson, M. E., & Freund, J. A. (2012). Ecological importance of large-diameter trees in a temperate mixed-conifer forest. *Plos One, 7*(5), e36131. https://doi.org/10.1371/journal.pone.0036131

Mankin, J. S., Viviroli, D., Singh, D., Hoekstra, A. Y., & Diffenbaugh, N. S. (2015). The potential for snow to supply human water demand in the present and future. *Environmental Research Letters, 10*(11), 114016. https://doi.org/10.1088/1748-9326/10/11/114016

Masson, T., Dumont, M., Mura, M., Sigury, G., Gascoin, S., Dedieu, J.-P., & Chausseau, J. (2018). An assessment of existing methodologies to retrieve snow cover fraction from MODIS data. *Remote Sensing, 10*(4), 619. https://doi.org/10.3390/rs10040619

McGuire, M., Wood, A. W., Hanlet, A. F., & Lettenmaier, D. P. (2006). Use of satellite data for streamflow and reservoir storage forecasts in the snake river basin. *Journal of Water Resources Planning and Management-ASCE, 132*(2), 97–110. https://doi.org/10.1061/(ASCE)0733-9496(2006)132:2(97)

Merio, L.-J., Marttila, H., Ala-aho, P., Hanninen, P., Okkonen, J., Sutinen, R., & Klove, B. (2018). Snow profile temperature measurements in spatiotemporal analysis of snowmelt in a subarctic forest-mire hillslope. *Cold Regions Science and Technology, 151*, 119–132. https://doi.org/10.1016/j.coldregions.2018.03.013

Niu, G. Y., & Yang, Z. L. (2004). Effects of vegetation canopy processes on snow surface energy and mass balances. *Journal of Geophysical Research, 109*(D23111). https://doi.org/10.1029/2004JD004884

Painter, T. H., Berisford, D. F., Boardman, J. W., Bormann, K. J., Deems, J. S., Gehrke, F., et al. (2016). The Airborne Snow Observatory: Fusion of scanning lidar, imaging spectrometer, and physically-based modeling for mapping snow water equivalent and snow albedo. *Remote Sensing of Environment, 184*, 139–152. https://doi.org/10.1016/j.rse.2016.06.018

Painter, T. H., Rittger, K., McKenzie, C., Slaughter, P., Davis, R. E., & Dozier, J. (2009). Retrieval of subpixel snow covered area, grain size, and albedo from MODIS. *Remote Sensing of Environment, 113*(4), 868–879. https://doi.org/10.1016/j.rse.2009.01.001

Parajka, J., & Blöschl, G. (2008). Spatiotemporal combination of MODIS images—Potential for snow cover mapping. *Water Resources Research, 44*, W03406. https://doi.org/10.1029/2007WR006204

Parajka, J., Pepe, M., Rampini, A., Rossi, S., & Blöschl, G. (2010). A regional snow-line method for estimating snow cover from MODIS during cloud hydrogen. *Journal of Hydrology, 381*(3-4), 203–212. https://doi.org/10.1016/j.jhydrol.2009.11.042

Pomeroy, J. W., Gray, D. M., & Landine, P. G. (1993). The Prairie blowing snow model. *Parajka, J., Pepe, M., Rampini, A., Rossi, S., & Blöschl, G. (2010). A regional snow-line method for estimating snow cover from MODIS during cloud hydrogen. *Journal of Hydrology, 381*(3-4), 203–212. https://doi.org/10.1016/j.jhydrol.2009.11.042

Pomeroy, J. W., Gray, D. M., & Landine, P. G. (1993). The Prairie blowing snow model—Characteristics, validation, operation. *Journal of Hydrology, 144*, 165–192. https://doi.org/10.1016/0022-1694(93)90171-5

Pomeroy, J. W., Gray, D. M., & Landine, P. G. (1993). The Prairie blowing snow model—Characteristics, validation, operation. *Journal of Hydrology, 144*, 165–192. https://doi.org/10.1016/0022-1694(93)90171-5

Rittger, J. (2009). Assessment of snow-melt runoff model using Landsat data. *Nordic Hydrology, 10*(4), 225–238. https://doi.org/10.2166/nh.2009.0006

Rango, A., & Martinec, J. (1979). Application of a snowmelt-runoff model using Landsat data. *Nordic Hydrology, 10*(4), 225–238. https://doi.org/10.2166/nh.2009.0006

Rango, A., Salomonson, V. V., & Foster, J. L. (1977). Seasonal streamflow estimation in Himalayan region employing meteorological satellite snow cover observations. *Water Resources Research, 13*(1), 109–112. https://doi.org/10.1029/WR013i001p0109

Rittger, K., Bair, E. H., Kahl, A., & Dozier, J. (2016). Spatial estimates of snow water equivalent for reconstruction. *Advances in Water Resources, 94*, 345–363. https://doi.org/10.1016/j.advwatres.2016.05.015

Rittger, K., Painter, T. H., & Dozier, J. (2013). Assessment of methods for mapping snow cover from MODIS. *Advances in Water Resources, 51*, 367–380. https://doi.org/10.1016/j.advwatres.2012.03.002

Rodell, M., & Houser, P. R. (2004). Updating a land surface model with MODIS-derived snow cover. *Journal of Hydrometeorology, 5*(6), 1064–1075. https://doi.org/10.1175/1525-7541(2004)005<1064:ULSMWMS>2.0.CO;2

Rollins, M. G. (2009). LANDFIRE: A nationally consistent vegetation, wildland fire, and fuel assessment. *International Journal of Wildland Fire, 18*(3), 235–249. https://doi.org/10.1071/WF08088

Rutter, N., Essery, R., Pomeroy, J., Altimir, N., Andreadis, K., Baker, I., et al. (2009). Evaluation of forest snow processes models (SnowMIP2). *Journal of Geophysical Research, 114*, D06111. https://doi.org/10.1029/2008JD011063

Salomonson, V. V., & Appel, I. (2004). Estimating fractional snow cover from MODIS using the Normalized Difference Snow Index. *Remote Sensing of Environment, 89*(3), 351–360. https://doi.org/10.1016/j.rse.2003.10.018

Salomonson, V. V., & Appel, I. (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. https://doi.org/10.1109/TGERS.2006.876029

Schmid, M. O., Gubler, S., Fiddes, J., & Gruber, S. (2012). Inferring snowpack ripening and melt-out from distributed measurements of near-surface ground temperatures. *The Cryosphere, 6*(5), 1127–1139. https://doi.org/10.5194/tc-6-1127-2012

Selkowitz, D. J., Forster, R. R., & Caldwell, M. K. (2014). Prevalence of pure versus mixed snow covered pixels across spatial resolutions in alpine environments. *Remote Sensing, 6*(12), 12478–12508. https://doi.org/10.3390/rs61212478

Silver, J. R., & Georgakakos, K. P. (2006). Distributed snow accumulation and ablation modeling in the American River basin. *Advances in Water Resources, 29*(4), 558–570. https://doi.org/10.1016/j.advwatres.2005.06.010

Sirdaee, M., Mathieu, R., & Arnaud, Y. (2019). Subpixel monitoring of the seasonal snow cover with MODIS at 250 m spatial resolution in the Southern Alps of New Zealand: Methodology and accuracy assessment. *Remote Sensing of Environment, 113*(1), 160–181. https://doi.org/10.1016/j.rse.2018.09.008

Skiles, S. M., Painter, T. H., Belnap, J., Holland, L., Reynolds, R. L., Goldstein, H. L., & Lin, J. (2015). Regional variability in dust-on-snow processes and impacts in the Upper Colorado River Basin. *Hydrological Processes, 29*(26), 5397–5413. https://doi.org/10.1002/hyp.10569
Taras, B., Sturm, M., & Liston, G. E. (2002). Snow-ground interface temperatures in the Kuparuk river basin, arctic Alaska: Measurements and model. *Journal of Hydrometeorology, 3*(4), 377–394. https://doi.org/10.1175/1525-7541(2002)003<0377:Sgitit>2.0.Co;2

Tyler, S. W., Burak, S. A., McNamara, J. P., Lamontagne, A., Selker, J. S., & Dozier, J. (2008). Spatially distributed temperatures at the base of two mountain snowpacks measured with fiber-optic sensors. *Journal of Glaciology, 54*(187), 673–679. https://doi.org/10.3189/002214308786570827

Varholá, A., & Coops, N. C. (2013). Estimation of watershed-level distributed forest structure metrics relevant to hydrologic modeling using LiDAR and Landsat. *Journal of Hydrology, 487*, 70–86. https://doi.org/10.1016/j.jhydrol.2013.02.032

Varholá, A., Coops, N. C., Weiler, M., & Moore, R. D. (2010). Forest canopy effects on snow accumulation and ablation: An integrative review of empirical results. *Journal of Hydrology, 392*(3-4), 219–233. https://doi.org/10.1016/j.jhydrol.2010.08.009

Winkler, R. D., Spittlehouse, D. L., & Golding, D. L. (2005). Measured differences in snow accumulation and melt among clearcut, juvenile, and mature forests in southern British Columbia. *Hydrological Processes, 19*(1), 51–62. https://doi.org/10.1002/hyp.5757

Wolfe, R. E., Nishihami, M., Fleig, A. J., Kuyper, J. A., Roy, D. P., Storey, J. C., & Pati, F. S. (2002). Achieving sub-pixel geolocation accuracy in support of MODIS land science. *Remote Sensing of Environment, 83*(1-2), 31–49. https://doi.org/10.1016/S0034-4257(02)00085-8

Wrzesien, M. L., Pavelsky, T. M., Kapnick, S. B., Durand, M. T., & Painter, T. H. (2015). Evaluation of snow cover fraction for regional climate simulations in the Sierra Nevada. *International Journal of Climatology, 35*(9), 2472–2484. https://doi.org/10.1002/joc.4136

Xin, Q., Woodcock, C. E., Liu, J., Tan, B., Melloh, R. A., & Davis, R. E. (2012). View angle effects on MODIS snow mapping in forests. *Remote Sensing of Environment, 118*, 50–59. https://doi.org/10.1016/j.rse.2011.10.029

Yatheendradas, S., Peters-Lidard, C. D., Koren, V., Cosgrove, B. A., de Goncalves, L. G. G., Smith, M., et al. (2012). Distributed assimilation of satellite-based snow extent for improving simulated streamflow in mountainous, dense forests: An example over the DMIP2 western basins. *Water Resources Research, 48*, W09557. https://doi.org/10.1029/2011WR011347