Water Resources Research

RESEARCH ARTICLE

10.1029/2018WR023108

Key Points:

- ASO suggests that satellite and radar products capture the spatial distribution of monthly snowfall, but significantly underestimate
- By moving from 100 m to 2 km spatial scales the perceived snow accumulation bias error increases by an order of magnitude based on ASO data
- ASO acquisitions in cold months can bring a new and effective approach to spatial evaluation of precipitation products

Correspondence to:

A. Behrangi,
behrangi@email.arizona.edu

Citation:

Behrangi, A., Bormann, K. J., & Painter, T. H. (2018). Using the Airborne Snow Observatory to assess remotely sensed snowfall products in the California Sierra Nevada. *Water Resources Research*, 54, 7331–7346. <https://doi.org/10.1029/2018WR023108>

Received 10 APR 2018

Accepted 3 SEP 2018

Accepted article online 10 SEP 2018

Published online 4 OCT 2018

Using the Airborne Snow Observatory to Assess Remotely Sensed Snowfall Products in the California Sierra Nevada

Ali Behrangi^{1,2} , Kat J. Bormann² , and Thomas H. Painter²

¹Department of Hydrology and Atmospheric Sciences, University of Arizona, Tucson, AZ, USA, ²Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA, USA

Abstract The Airborne Snow Observatory (ASO) performed two acquisitions over two mountainous basins in California on 29 January and 3 March 2017, encompassing two atmospheric river events that brought heavy snowfall to the area. These surveys produced high-resolution (50 m) maps of snow depth and snow water equivalent (SWE) that were used to estimate monthly areal snowfall accumulation. Comparison of ASO snow accumulation with point measurements showed that the ASO estimates ranged from −10 to +16% relative bias across three sites, which is likely inflated by the disagreement in areal representation of the quantities from the actual errors in these products. The aggregated SWE accumulations from ASO are then used to evaluate a suite of in situ based and remote sensing precipitation products. During the study period, Parameter-Elevation Regressions on Independent Slopes Model (PRISM) and Mountain Mapper estimates had relative bias <10% compared with ASO-based estimates of snow accumulation, but satellite and radar products largely underestimate snowfall accumulation compared to ASO (up to 50%). Despite their underestimation, satellite and radar products show correlation coefficients >0.8 with ASO snow accumulation over the selected grids at the monthly scale. Finally, we leveraged the fine-scale sampling of the spatially complete ASO products to show that by moving from 100 m to 2 km spatial scales, the perceived bias errors SWE at point locations increased by an order of magnitude, displaying a nonlinear relationship. The study demonstrates that ASO acquisitions in cold months can bring a new and effective approach to spatial evaluation of precipitation products.

1. Introduction

Accurate precipitation estimate is key for hydrologic studies. Considerable progress has been made over the past two decades to increase the accuracy and spatiotemporal resolution of large-scale precipitation estimates (Ashouri et al., 2015; Hsu et al., 1997; Huffman et al., 2007; Xie et al., 2017). Precipitation has traditionally been measured by direct sampling through in situ gauge networks. While these gauges come in a variety of types and specifications, they all provide point measurements with limited spatial representation. Hydrologic studies are generally performed at the basin or broader scales, so these point measurements are often used to produce areal estimates through spatial averaging, interpolation, or extrapolation (Henn et al., 2018; Kurtzman et al., 2009). A dense network of gauges can largely reduce averaging errors, but ground stations are sparse or nonexistent in many regions, especially at higher elevations (Lundquist et al., 2015). Remote sensing of precipitation can help fill these data void, but quantitative precipitation estimates (QPE) that are obtained from radar or satellites must be rigorously evaluated with in situ networks, which are notoriously challenging to conduct in complex terrain (Behrangi et al., 2016, 2017; Maggioni et al., 2017).

Over mountainous regions, accurate estimation of precipitation is important for various applications including water resources management and flood control, but the uncertainty in converting point measurements to areal precipitation is amplified in complex terrain for several reasons including (1) very high spatial variability in precipitation patterns with a large contrast between windward and leeward sides (e.g., Daly et al., 2002) that are often related to orographic effects, (2) data sparseness where gauge networks often have lower density with an uneven distribution toward lower and less exposed locations with virtually no measurements at high elevation (Molotch & Bales, 2006), and (3) gauge undercatch, especially for snowfall where large underestimations have been quantified that can exceed 50% of total amount (Behrangi et al., 2017; Larson & Peck, 1974; Rasmussen et al., 2012).

Snowfall measurement is particularly susceptible to undercatch issues as snow particles have a much larger drag force than raindrops, enabling wind and turbulence to blow the snow away from the mouth of a precipitation gauge (Rasmussen et al., 2012). In addition, the gauge orifice can also become plugged with accumulating snow, a problem commonly referred to as “capping.” While progress has been made to correct gauge undercatch (e.g., Fuchs et al., 2001; Goodison, 1978; Kochendorfer et al., 2017; Legates & Willmott, 1990; Yang et al., 1998, 1999), it still remains a considerable source of uncertainty for in situ precipitation measurements and their derived products in cold and windy regions.

Spaceborne remote sensing and ground-based radars have significantly expanded the spatial coverage of precipitation measurements and are not subject to some of the uncertainties that are incurred in complex terrain with traditional gauge networks. However, these precipitation products are subject to their own set of large uncertainties in cold mountainous terrain due to: (1) poor sensitivity of sensors to light rain and snowfall (e.g., Behrangi, Andreadis, et al., 2014; Smalley et al., 2014), (2) insufficient understanding of precipitation microphysics (Bartsotas et al., 2018), (3) difficulties in retrieving precipitation rate enhanced by orographic effect (Shige et al., 2013), (4) unknown surface emissivities over frozen land (Ferraro et al., 2013), (5) problems in distinguishing light rain and snow from cloud (Berg et al., 2006; Lebsock & L'Ecuyer, 2011), (6) dependence of retrievals on prior knowledge about precipitation phase (Liu, 2008), and (7) spatial resolution of the precipitation retrievals where typical resolutions of ~4–25 km are coarse in complex terrain. Finally, the ground radar products can be subject to mountain blockage and are also uncertain due to imperfect empirical relationships between radar reflectivity and precipitation rate.

While there have been several studies focused on evaluation of precipitation products in the mountains, the general consensus from the literature is that larger underestimations are incurred with increasing altitude for complex terrain in both warm and cold climates (Henn et al., 2018; Hong et al., 2007, 2004; Wen et al., 2016). Global precipitation products have also been shown to disagree the most during winter in both event magnitude and the number of precipitation events (Behrangi, Andreadis, et al., 2014; Tian & Peters-Lidard, 2010; Maggioni et al., 2017), and at high elevation (Henn et al., 2018). As such, it is no surprise that precipitation estimations in cold mountain environments have been identified as one of the outstanding challenges for precipitation products, and studies have called for more research at these locations (Behrangi et al., 2016; Prat & Barros, 2010; Sharifi et al., 2016; Shige et al., 2013). Given the challenges and importance of accurate estimation of precipitation rate over cold mountainous basins (using both traditional in situ gauges and remote sensing products), it is imperative to identify alternative ways to assess the performance of existing products while appropriately considering the spatial disconnect between areal and point measurements (Grünwald & Lehning, 2015), dealing with the limited independent data for evaluation (Lundquist et al., 2015), and embracing technological advances.

One of the major limitations of the previous evaluation studies is that they often have relied on spatially incomplete point measurements, which are particularly prone to undercatch, and thus are an imperfect source of validation data for remote sensing products. With the advent of spatially complete high-resolution snow water equivalent (SWE) products from the Airborne Snow Observatory (ASO; Painter et al., 2016), an unprecedented alternative is available to quantify snow accumulation in cold mountain environments across the western United States. Notably, the ASO products do not suffer from undercatch and capping constraints and provide spatially complete measurements (rather than interpolations) in high resolution.

As such these measurements are invaluable to evaluate satellite snowfall products in complex terrain, particularly at very high elevations where in situ data are largely absent. Fortunately, during the unexpectedly large snow season of 2017, the ASO acquisitions in California started earlier than usual with the first survey conducted on 29 January and the second on 3 March. With air temperatures below the melting point during this time, the chance of rain on snow or snow-melting during the study period was limited. As such, ASO was well placed to monitor the extraordinary snowfall accumulation that occurred during February 2017 from a series of atmospheric river (AR) events (Wen et al., 2018).

In this study, we build on this excellent opportunity to compare the spatial distribution and magnitude of snow accumulation from ASO SWE retrievals to six satellite-based precipitation products, ground-based radar, and three in situ snow pillows. The comparison is conducted over Tuolumne and Cherry/Eleanor basins in the Sierra Nevada of California (Figure 1a). Finally, we use the high-resolution ASO data and in situ

Figure 1. Study area: (a) Tuolumne upstream of Hetch Hetchy reservoir and the adjacent Cherry/Eleanor basins and their elevation map and (b) snow water equivalent (SWE) accumulation during a 34-day period calculated by subtracting ASO 50-m acquisitions on 29 January and 3 March 2017. The locations of three in situ snow pillows (Dana Meadows [DAN] at 2,990-m, Tuolumne Meadows [TUM] at 2,620-m, and Horse Meadow [HRS] at 2,560-m elevations) within the basin are also shown. The three stations are used for evaluation of high-resolution ASO snow accumulation and assessment of biases caused by spatial aggregation. Figure 1c shows time series plots of snow pillows data, adding insights onto the temporal evolution of snow accumulation and melt during the study period. It shows over the 34-day period, the overall SWE losses observed at DAN, TUM, and HRS measurement are 3.56, 2.59, and 3.25 cm, respectively.

measurements to assess the bias-scaling relationship (i.e., point versus areal estimates). This is the first study that has leveraged the ASO snow measurements for evaluation of precipitation products.

2. Data Set

Table 1 provides a summary of the data sets used in this study. The description of the data sets is provided below:

2.1. ASO Validation Data

The National Aeronautics and Space Administration (NASA) ASO is a coupled scanning lidar (Riegl Q1560) and spectrometer system (CASI 1500) that was developed to monitor spatial and temporal distributions of SWE in mountainous terrain for water resource management (Painter et al., 2016). Since 2013, ASO has been undertaking weekly to monthly surveys of key basins throughout California and Colorado typically starting from peak SWE (March–April) to full snowmelt (June–August). In 2017, ASO commenced flying on 29 January during winter, earlier than previous years, and as such captured snow accumulation. The standard products from ASO include basin-scale maps of instantaneous snow depth and SWE at 3- and 50-m resolution, respectively (Painter et al., 2016, see also <https://aso.jpl.nasa.gov>).

In this section we briefly describe the ASO system and retrieval algorithms, whereas Painter et al. (2016) provide the detailed description of these data collection and processing methods. ASO uses the dual-laser scanning lidar to map the snow-free surface elevation mountain basins as baseline, and then again routinely

Table 1
List of the Data Sets Used in This Study

Product name	Name used in this work	Spatial coverage	Spatiotemporal resolution	Gauge bias adjustment
IMERG V4/V5b (late run)	IMERG V4/V5	60°S–60°N	0.1° × 0.1°—½ hr	Partial
IMERG V4/V5b (final run)	IMERG-g V4/V5	60°S–60°N	0.1° × 0.1°—½ hr	Yes
IMERG HQ V4/V5b	IMERG-MW	90°S–90°N	0.1° × 0.1°—½ hr	No
GSMaP-MVK V6	GSMaP-MVK	60°S–60°N	0.1° × 0.1°—1 hr	No
PERSIANN	PERSIANN	60°S–60°N	0.25° × 0.25°—3 hr	No
PERSIANN-CCS	CCS	60°S–60°N	0.04° × 0.04°—1/2 hr	No
MRMS radar-only	Radar	CONUS	1 km × 1 km—2 min	No
MRMS radar-gauge	Radar-g	CONUS	1 km × 1 km—1 hr	Yes
MRMS gauge-only	Gauge	CONUS	1 km × 1 km—1 hr	Yes
Mountain Mapper	Mountain Mapper	Western United States	1 km × 1 km—1 hr	Yes
PRISM	PRISM	CONUS	4 km × 4 km daily	Yes
ASO	ASO	Part of CA and NV	3 m overpass dependent	No
Snow pillow	Snow pillow	Point	Point	No

Note. The description of the data sets is provided in section 2.

during winter and spring when snow is present. The two elevation surfaces are geolocated onto the same spatial grid, allowing snow depth to be retrieved through subtraction of the baseline surface elevation from the snow-on surface elevation. The collocated spectrometer data are fused into the data stream to spatially constrain the surface subtraction to snow covered areas only, and custom algorithms are used to enhance snow retrieval in the forest using lidar return intensity. Finally, a spatially constant bias adjustment is used to vertically snap the two surface elevations prior to the subtraction. The bias adjustment is evaluated from 3-m elevation surfaces over flat, exposed, and known snow-free grids in the basin and is typically <0.08 m (Painter et al., 2016). This bias adjustment reduces vertical biases that may exist between the snow-free and snow-on surveys as incurred through compounding vertical accuracy errors incurred from the flight trajectory (typically a maximum of ~3 cm per survey for a maximum of ~6 cm vertical displacement). Thus, this potential source of geolocation biases is removed from the resulting snow depth product.

The surface subtraction for snow depth is conducted at 3 m spatial resolution and then aggregated to 50-m resolution using the 3-m grid mean. The conversion from instantaneous snow depth to SWE is then conducted at the 50-m resolution using snow densities obtained from a physically based snow model (iSnobal, Marks et al., 1999) that are further nudged with available ground measurements. Grid-wise uncertainty metrics for ASO products are currently under development. Estimated basin-mean uncertainty has therefore been calculated based on best available knowledge following standard propagation of error techniques (Taylor, 1997). Refer to section 3.1 for details. In this study, snow accumulations based on the ASO data are regarded as the validation reference for comparison, due to their accuracy, high spatial resolution, and excellent agreement with available in situ data (see section 3).

2.2. In Situ Snowfall Data

In the Tuolumne Basin, the in situ snow monitoring network is largely operated by the California Department of Water Resources. In 2017, there were three automatic snow pillows located within the qualifying grid cells (see section 3.2) that provide daily SWE data for the study area (Figure 1). Of these three stations, Dana Meadows (DAN) is situated at the highest elevation of 2,990 m, while Tuolumne Meadows (TUM) is at the lowest elevation of 2,620 m and both lie in a known rain shadow zone. Conversely, the Horse Meadow (HRS) snow pillow is situated in the northern part of the basin and is prone to higher precipitation accumulation. Measurements from the snow pillows at these automation stations show that mean SWE accumulation between 29 January 2017 and 3 March 2017 was 53.2 cm, with SWE accumulations at individual stations of 35.9 cm at DAN, 40.2 cm at TUM, and 83.4 cm at HRS. While these in situ measurements provide a useful indication of point-scale snow accumulation, the entire snow-covered area cannot be represented by measurements at only three locations. In this study, we use the in situ data to assess SWE loss during the 34-day study period (section 3.3) as well as undertake a point-to-spatial scale analysis. We do not use the in situ data for

ground validation of the spatial products due to the large disparity in the spatial scale between point measurements and the spatial measurements from the remote sensing data. For evaluation of satellite products, we use the spatially complete measurements from ASO.

2.3. Other Precipitation Products

2.3.1. Satellite Products

Six multisatellite precipitation products were selected for evaluation with ASO estimates: (1) the Integrated Multi-satellite Retrievals for Global Precipitation Measurement (IMERG V5b; Huffman et al., 2018) Late run; (2) Global Satellite Mapping of Precipitation (GSMaP-MVK V6; Ushio et al., 2009); (3) Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN; Hsu et al., 1997; Sorooshian et al., 2000); (4) PERSIANN-Cloud Classification System (CCS; Hong et al., 2004); (5) IMERG final run (V5b), which is IMERG late run with bias-adjustment at monthly scale using the Global Precipitation Climatology Centre (GPCC) product (Schneider et al., 2014), and (6) IMERG high quality (HQ) V5b estimate that consists of only microwave (MW) retrievals from multiple sensors (hereafter referred to as IMERG-MW; see Huffman et al., 2018). Note that IMERG uses precipitation estimates from both MW and infrared (IR) sensors and the IR precipitation rate is based on the PERSIANN-CCS (hereafter CCS) method. Therefore, including both IMERG-HQ and CCS can provide additional insights on the error sources in IMERG late and final runs. IMERG late run (hereafter IMERG for brevity) uses a climatology of in situ (not italic) data to perform bias adjustment, as such the product is released later than the near real-time products, but earlier than IMERG-final run (hereafter IMERG-g for brevity) that becomes available few months after the observation time to include GPCC data.

GSMaP is similar to IMERG as it also uses a combination of MW and IR data. In contrast, PERSIANN and CCS are IR-based retrieval methods, so precipitation rate is determined as a function of IR data through established relationship between IR and MW (or ground radar) precipitation rate (Hong et al., 2004; Hsu et al., 1997). IMERG and its different products are available on a 0.1° grid every 30 min, and GSMaP is available at 0.1° every hour. PERSIANN and CCS are available at 0.25° every 3 hr and at 0.04° every 30 min, respectively. It should be noted that the CPC MORPHing technique (CMORPH; Joyce et al., 2004; Joyce & Xie, 2011) was also considered for analysis. However, CMORPH currently uses pre-GPM MW retrievals that barely capture precipitation over snow and frozen lands (Behrangi, Andreadis, et al., 2014). Furthermore, over frozen surfaces, where MW precipitation estimates from individual sensors can be missed, CMORPH assigns zero to the missed MW precipitation unless precipitation is inferred from IR images. If no precipitation is inferred from IR images, CMORPH assigns missing data to the snow and ice grids (R. Joyce 2013, personal communication). Therefore, the results of CMORPH analysis were considered unsuitable for this analysis.

2.3.2. Ground Radar and Gauge Products

Various ground radar and gauge products were considered in this analysis including the Multi-Radar/Multi-Sensor (MRMS) precipitation products, Mountain Mapper, and Parameter-Elevation Regressions on Independent Slopes Model (PRISM). MRMS products use a QPE system that integrates information from ~180 radars, precipitation gauges, and numerical weather prediction data (Zhang et al., 2016). Currently, MRMS mainly produces four types of observations-based QPE products: (1) radar-based QPE, (2) gauge-based QPE, (3) local gauge bias-corrected radar QPE, and (4) gauge-and-precipitation-climatology-merged QPE. These products are described in Zhang et al. (2016) and here are referred to as Radar, Gauge, Radar-gauge (Radar-g), and Mountain Mapper, respectively.

Multiradar integration can reduce deficiencies in the single-radar framework and help better capture physical processes in the atmosphere than using single radar data alone. However, radars also carry uncertainties in estimating a true rate of precipitation due to imperfect empirical relationships between radar reflectivity and precipitation rate, discrepancies between radar measurements aloft and near the ground, and mountain blockage. Radar QPE provides a high-resolution (~ 1 km) and rapid update (2 min), and the gauge-only QPE product (hereafter referred to Gauge) that is archived in MRMS system is an hourly product interpolated from about 7,000 rain gauges from the Hydrometeorological Automated Data System (HADS; <https://hads.ncep.noaa.gov/index.shtml>). These gauge data are quality controlled through an automated scheme that compares each gauge report with collocated hourly radar QPE values. Generally, gauge bias correction shows improvements over the radar-only QPE (Zhang et al., 2016).

In addition to the typical MRMS products, a special data set of monthly precipitation climatology is used in MRMS to produce a gauge-and-climatology-merged QPE named “Mountain Mapper” (Schaake et al., 2004). The Mountain Mapper algorithms improve upon QPEs in the western United States by using an inverse distance weighting approach to estimate precipitation rate at ungauged locations from values at gauged locations. The algorithms also take into account the climatology of precipitation at the gauged and ungauged locations using PRISM (Daly et al., 1994, 2002) precipitation climatologies to assist the spatial analysis of gauge precipitation amounts obtained from HADS. PRISM data interpolate higher quality meteorological station observations to a 4-km grid using a human expert and statistical knowledge-based system that uses a digital elevation model and is available over the continental United States (CONUS; <http://www.prism.oregonstate.edu>). In the western United States the PRISM data are often used as a source of spatially distributed precipitation data in complex terrain for snow studies (Currier et al., 2017; Raleigh & Lundquist, 2012). Considering large disagreement with other gridded precipitation data sets (Henn et al., 2018), these data are expected to have substantial uncertainty in high-elevation rain shadow areas. In this study, PRISM daily precipitation data are used for comparison, while the PRISM near-surface air temperature products are used to refine the analysis extent to areas below freezing referred to in this paper as qualifying cells (described in section 3.2).

3. Method

3.1. ASO Data Preparation

To estimate SWE accumulation from the standard ASO products, the difference between the 50-m SWE products from two survey dates must be extracted. The resulting SWE accumulation estimate is therefore a measure of the net precipitation accumulation after precipitation deposition, sublimation, redistribution due to wind, and melt losses between the two survey dates. To maximize the snowfall accumulation signal and minimize the losses, we selected an analysis period that encompassed a significant precipitation event with a large accumulation signal during a period when SWE losses were expected to be negligible.

The ASO 50-m SWE data that were collected for the Tuolumne and the adjacent Cherry/Eleanor basins (hereby known as TE) for two dates (29 January and 3 March 2017) were differenced to retrieve the SWE accumulation during the 34-day period. Previous work suggests that at peak conditions snow density uncertainty forms a larger contribution to overall uncertainty in the ASO SWE products than snow depth uncertainty (Raleigh & Small, 2017). For our purposes here, we adopt the mean of the published preliminary uncertainty ranges for ASO snow depth and snow density products (at the 50-m scale) of 1.5 cm and 21.5 kg/m³, respectively (Painter et al., 2016). Then, in conjunction with the basin-averaged snowpack characteristics for each date of 2.41-m depth and 363 kg/m³ for 29 January and 3.20-m depth and 413 kg/m³ for March 3 (K. J. Bormann, personal communication, August 1, 2018), we used standard error propagation techniques to estimate the overall uncertainty of the SWE products for each date. The resulting estimated uncertainty in ASO SWE products for the 29 January acquisition was 5.2 and 6.9 cm for the 3 March acquisition. The uncertainty for the March products was slightly higher due to increased basin-averaged depth and density values. The two individual SWE product uncertainties were then pooled, using the mean uncertainty value for each date and the number of snow-covered pixels (samples) in each scene, to estimate a standard uncertainty of 6.04 cm for the SWE accumulation product.

To compare the ASO-derived SWE accumulation with coarser satellite products, the 50-m data were resampled to 0.1° grid using bilinear interpolation. This will also reduce uncertainties pertaining to SWE redistribution due to wind. Only PERSIANN has a coarser spatial resolution than 0.1°; other products studied here have either identical or higher resolution. The steps taken to maximize the snowfall signal and minimize the influence of confounding factors such as sublimation and melt losses are described below.

3.2. Minimization of Confounding Factors

During the 34-day study period between 29 January and 3 March 2017, the mean daily air temperature at the Tuolumne Meadows snow pillow (at 2,620-m elevation; TUM in Figure 1) was −3.9 °C. Approximately 54% of the TE area is at elevations higher than the relatively low-lying Tuolumne Meadows station. Therefore, at higher elevations the influence of liquid precipitation is not expected to have a significant impact on the ASO SWE accumulation estimates (Figure 1b). However, to further reduce potential uncertainties from

Figure 2. Daily near-surface air temperature and precipitation time series: (a) Daily $T_{\min}$, T_{mean} , and $T_{\max}$ averaged over the entire basins. (b) Daily $T_{\min}$, T_{mean} , and $T_{\max}$ averaged over the selected grids marked by “plus” sign in Figure 3. (c) Daily mean precipitation averaged over the entire TE basin at qualifying grids. Both temperature and precipitation data in this plot are obtained from Parameter-Elevation Regressions on Independent Slopes Model (PRISM).

potential rainfall, melting and sublimation impacts that are exacerbated in warmer temperatures, the 0.1° grid cells across the TE basin were filtered using PRISM air temperature data.

A detailed analysis was conducted using daily PRISM air temperature data, (minimum [$T_{\min}$], mean [T_{mean}], and maximum [$T_{\max}$]), over the entire TE area to identify qualifying grids for analysis, defined as grids at which air temperatures remain below snow-melting temperature threshold of 1°C (as can be inferred from Liu, 2008, and Behrangi et al., 2018) for the entire study period. Figure 2 shows time series of daily $T_{\min}$, T_{mean} , and $T_{\max}$ averaged over the entire TE area (Figure 2a) and the qualifying grids (Figure 2b). These qualified grids are also marked in Figure 3 (by “plus” sign of which there are $8 \times 0.1^\circ$ grids, equating to an evaluation area of $\sim 900\text{ km}^2$) and used to spatially constrain the detailed comparison between ASO and other precipitation products.

February 2017 saw two strong AR events occur in the western United States, resulting in considerable snowfall deposition in the study area. ARs are narrow streams of large water vapor transport concentrated in the lower atmosphere (Ralph et al., 2004). By investigating the water years 2004–2010, Guan et al. (2010) showed that on average 6–7 ARs per winter can bring about 40% of the annual snow accumulation in California’s Sierra Nevada. The exceptional magnitude of the snowfall that was experienced in February 2017 is highlighted by the ASO data, where more than one third of the total annual snowfall for the TE basins during the 2017–2018 water year was deposited during these two February AR events. The 2–13 February storm over the region was initiated as upper-level high pressure weakened near southeast Alaska by low pressure to the south.

Consequently, a strong subtropical jet stream passed through the Pacific and penetrated into the United States. This together with a two-phase significant moisture plume (with precipitable water values up to 1.3–1.4” reported by sounding analysis) and cold front brought intense precipitation over northern and central CA. The 15–22 February displayed persistent low pressure aloft over Alaska, persistent high pressure aloft over the tropical NE Pacific, and a few shortwave troughs and associated frontal systems moving into CA and the Pacific NW according to California-Nevada river forecast system. As moisture plume and cold front intersected the region, heavy precipitation was brought to NW California and stretched to southern part of the state at lighter intensity. Figure 2c shows these AR events in the daily mean precipitation fields from PRISM as averaged over the qualifying grids in the TE basin.

For the qualifying grids, the second storm was entirely below melting temperature (even the $T_{\max}$), but $T_{\max}$ for the first storm reached about 2°C on 9 and 10 February. At 2°C precipitation may fall as rain. However, further analysis using hourly geostationary IR data suggests that the timing of $T_{\max}$ for these two days likely corresponded to nonprecipitation scenes, so we conclude that this diurnal excursion of $T_{\max}$ above melting level did not likely occur during a precipitation event and the products are measuring snowfall during this time. Furthermore, based on daily in situ rainfall and mean air temperature data from the California Data Exchange Center (<https://cdec.water.ca.gov>), the presence of liquid precipitation during the analysis period above 2620 m is unlikely.

It should be noted that over high mountains ($\sim 4,000\text{-m}$ peaks), it is expected that the transition of snowfall to rainfall will occur at warmer temperatures than normal because (1) at higher elevation (lower pressure) the air is less dense and thus snowflakes can land faster, suppressing the change of snowflakes to melt (Dai, 2008), and (2) at lower relative humidity, the vapor pressure difference between the surface of the snow particle and the ambient air becomes larger, increasing the evaporative cooling effect on the falling droplets and thus helps to slow melting as snow falls (Behrangi et al., 2018). Therefore, even if precipitation did occur in the qualifying grids when the $T_{\max}$ was at 2°C , the likelihood of the precipitation phase containing rainfall or significant mixed precipitation in this context is again quite low. Based on this analysis, we remain confident that the impact of liquid precipitation was minimal during the study period.

Figure 3. Spatial distribution of snowfall accumulation from Airborne Snow Observatory (ASO) and several other gridded products over the Tuolumne and adjacent Cherry/Eleanor basins for the period of 29 January to 3 March 2017. In the ASO maps (Figure 3a) grids with no data are shown in gray color.

3.3. Consideration for Snowmelt and Sublimation Losses

Both the derived ASO SWE accumulation data and the in situ accumulation data report the net change in SWE during the analysis period, and as such the estimates incorporate the overall effect of snowfall deposition and snowpack losses (including sublimation and snowmelt runoff). At higher elevations during a cold period in winter, the contribution of snowpack losses relative to the snowpack depth are expected to be minor. However, before comparing ASO SWE accumulation and in situ measurements with other precipitation products, which report snowfall deposition rather than a net change, the ASO SWE and in situ data must be adjusted for these processes.

By determining the cumulative water content loss from daily SWE measurements at the in situ measurement sites over the 34-day period, the overall SWE losses observed at DAN, TUM, and HRS measurement sites during the analysis period are 3.56, 2.59, and 3.25 cm, respectively (Figure 1c). These estimates include sublimation, snowmelt, infiltration processes, and blowing snow. As our analysis is limited to areas that remain frozen during the study period, the infiltration and snowmelt contributions are negligible. Mass redistribution due to blowing snow is also considered negligible at about 10 km spatial resolution. However, SWE losses are

expected to reflect sublimation losses. In support, the modeled winter sublimation rates from the adjacent Merced basin were used to estimate 3.9 cm of sublimation for the 34-day period of analysis (Dettinger et al., 2004).

These sublimation estimates are higher than those obtained from the latest European Center for Medium-Range Weather Forecasting (ECMWF) global atmospheric reanalysis (ERA-interim) of ~ 1.73 cm for the same study period and location, perhaps due to the sensitivity of sublimation calculations to roughness length and wind speed (Beljaars & Viterbo, 1994) and the challenges of simulating these parameters in complex terrain. Despite the relatively large pixel size of 80 km, the sublimation estimates from ERA-interim falls in the range of winter sublimation climatology (1.0–2.2 cm/month) estimated at a point location in Lake Tahoe (Fassnacht, 2004) along with February observations at high elevations in the Kings Basin of 2.0 cm (Goulden et al., 2012).

When considering point estimations, we also recognize that the spatial distribution of sublimation is likely variable due to variability in exposure (vegetation, elevation, and wind speeds). In addition, the value of sublimation required for this study must translate beyond the point scale to the satellite scale. It is difficult to attribute observed SWE losses at in situ sites to individual processes, especially sublimation, and it is not required for the purposes of this study. In order to take into account potential sublimation losses, we add 2.5 cm (a value around the mean of the observations) to the ASO SWE accumulation estimates and provide statistics for both with and without this ASO adjustment for losses.

By the adjustment of the ASO data for estimated SWE losses, which has relatively small magnitude compared to the large snowfall accumulation during the period 29 January to 3 March 2017, we therefore consider the remote sensing precipitation products to be directly comparable to the adjusted ASO snow accumulation measurements with limited impact of potential confounding factors.

4. Results

4.1. Spatial Distribution

Maps of snow accumulation based on ASO (Figure 3a) and several popular gridded products (Figures 3b–3k) over the TE basins between 29 January and 3 March 2017 show a large spread among the popular precipitation products in capturing snow accumulation. Mountain Mapper (Figure 3b), PRISM (Figure 3c), Gauge (Figure 3d), Radar-g (Figure 3e), and IMERG-g (Figure 3g) products directly use ground stations in their estimate or bias adjustment, while other products (i.e., CCS, PERSIANN, and GSMaP-MVK) do not directly include gauge information.

Among the products that directly use gauge data, PRISM and Mountain Mapper agree better with ASO, capturing elevation-dependent spatial features and the dynamic range of accumulation, while gauge and Radar-g show marked underestimation (about 50% of the qualifying grids) and lack of spatial features. IMERG-g shows much lower estimate than all other products that use gauge data, although improvement of IMERG-g compared to IMERG (Figure 3h) is clearly noticeable. As described in section 2.3.2, PRISM and Mountain mapper use digital elevation model and statistical knowledge-based system to improve their interpolation scheme. This is not the case in the Gauge product and thus the Radar-g that uses the Gauge product for bias adjustment.

While the reason for the underestimation of IMERG-g compared to the other gauge-adjusted products is not the focus of this study, it is important to recognize that IMERG-g uses the GPCC product (Schneider et al., 2014) with a resolution of 1° and GPCC does not originally account for gauge undercatch correction. IMERG applies a factor to mitigate the undercatch issue, but this correction cannot exceed a certain limit, so if the original estimate is too low the final adjustment also remain low (G. J. Huffman, personal communication, 2017). Furthermore, GPCC uses less in situ data and a different interpolation method than the other gauge-based products studied here.

Other products without gauge bias adjustment show significantly lower snow accumulation than PRISM, Mountain Mapper, and the ASO evaluation data. Among these products IMERG-MW (Figure 3i) shows the lowest estimate, followed by PERSIANN (Figure 3j). GSMaP-MVK (Figure 3k) also shows underestimation over the studied basins but also shows large overestimations over the lower elevations in the west of the domain. Further analysis (not shown here) suggests that GSMaP has a significantly higher precipitation rate than other

Table 2

A Summary of the Statistical Comparison Between Snow Accumulations From Various Precipitation Products and ASO Over the Qualified Grids in the Two Study Basins

Product	SWE Acc. (cm)	CORR	RMSE (cm)	BIAS _f	Bias _f [*]
ASO	48.9	—	—	—	—
ASO + Sublimation	51.4	—	—	—	—
Mountain Mapper	44.0	0.88*	0.76	0.90	0.86
PRISM	51.3	0.87*	0.68	1.05	1.00
Gauge	27.4	0.87*	2.53	0.56	0.53
Radar-g	25.9	0.86*	2.69	0.53	0.50
Radar	15.6	0.81*	3.89	0.32	0.30
IMERG-g V4/V5	18.1/18.1	0.88*/0.88*	3.55/3.59	0.37/0.37	0.35/0.35
IMERG V4/V5	8.8/21.0	0.83*/0.85*	4.63/3.26	0.18/0.43	0.17/0.41
CCS	21.0	0.81*	3.22	0.43	0.41
PERSIANN	9.8	0.84*	4.50	0.20	0.19
GSMaP	13.2	0.88*	4.09	0.27	0.26
IMERG-MW V4/V5	2.0/4.9	0.79*/0.81*	5.38/5.08	0.04/0.10	0.04/0.09

*Statistical significance of the correlation at the 90% level.

precipitation products over the coastal region of the west coast. The observed underestimation of PERSIANN compared to CCS (Figure 3i) is also consistent with a previous study (Behrangi et al., 2016), in which a decade of land-falling ARs that impact the North American west coast were compared to PRISM. As can be seen from Figures 3h, 3i, and 3l, much of the large underestimations from the IMERG product is rooted in the low estimates from MW, a long-standing challenge over cold regions (e.g., Behrangi, Andreadis, et al., 2014). This is partly because of large reliance of MW precipitation retrieval method on scattering signals and high-frequency channels over land, especially in the presence of ice and snow on the surface. As a result, large fraction of snowfall is missed over land (Behrangi, Tian, et al., 2014). Furthermore, the current precipitation retrieval methods, especially those that are based MW data, underperform in capturing the orographic enhancement of precipitation rates over mountainous regions (Shige et al., 2013, 2017). The observed underestimation of satellite precipitation products is also consistent with previous studies over the mountainous western U.S. region (e.g., Wen et al., 2016, 2018).

Statistical comparison between the precipitation products and ASO is performed only for qualifying grids that have minimal chance of rain or snowmelt. These grids are marked by plus signs “+” in Figure 3 (also see section 3). This selection was made to enhance the robustness of the comparison by avoiding rainfall and melting as much as possible. Table 2 shows a summary of the basin-wide snowfall accumulation estimates along with statistical comparison between snow accumulations from various precipitation products and ASO. The statistical metrics include the correlation coefficient, root-mean-square error, and BIAS_f (defined as fraction of ASO snow accumulation that is captured by the different precipitation products with perfection represented by 1). The correlation coefficient values superior to 0.8 suggest that while the precipitation products have a large spread in estimating snow accumulation, they can better produce snow accumulation patterns similar to ASO.

BIAS_f^{*} is slightly different from BIAS_f, as prior to its calculation estimated sublimation (i.e., 2.5 cm; see section 3.3) was added to the ASO estimate. It should be noted that the ASO estimate of snow accumulation during the study period over the entire selected grids was about 48.9 cm. By including the snow losses, the ASO estimate of snow accumulation increases to about 51.4 cm. The PRISM estimate (BIAS_f = 1.05 and BIAS_f^{*} = 1.00) followed by Mountain Mapper (BIAS_f = 0.90 and BIAS_f^{*} = 0.86) are most consistent with those from ASO. Other products produce about half or less snow accumulation compared to ASO. Among the satellite products with no gauge adjustment, CCS performs the best (Table 2). The better performance of PRISM and Mountain Mapper compared to ASO is expressed in their root-mean-square error values (0.68 and 0.79 cm, respectively) that are the smallest among all the examined products.

It should be noted that in Figure 3, the 50-m resolution ASO estimates were first averaged onto 0.1° grids and then plotted for comparison with other products. Throughout this averaging, detailed spatial information offered by ASO is lost, and thus, Figure 3 underutilizes the value of high spatial resolution data provided

Figure 4. A representation of spatial information that might be lost due to the spatial averaging of Airborne Snow Observatory snow water equivalent (SWE) accumulation from 50 m to 10 km. Figures 4a–4d show ASO estimate at 50-m, 1-km, 4-km, and 10-km resolution, respectively. Figures 4e–4g show maps of SWE differences by subtracting the 50 m SWE accumulation map from the SWE accumulation maps at 1-, 4-, and 10-km resolution.

by ASO. Figure 4 represents spatial information that might be lost due to the spatial averaging of ASO SWE accumulation from 50 to 10 km. Figures 4a–4d show ASO estimate at 50-m, 1-km, 4-km, and 10-km resolution, respectively. Figures 4e–4g show maps of SWE differences by subtracting the 50-m SWE accumulation map from the SWE accumulation maps at 1-, 4-, and 10-km resolution. Figure 4 clearly shows that by moving from 50-m to 10-km resolution, SWE estimation errors increase significantly. For example, at 10-km resolution the SWE differences, due to spatial averaging, can exceed 50 cm at several grids compared to the 50-m resolution SWE map. Therefore, utilizing ASO estimates at its highest resolution is recommended.

4.2. Time Series

The time series of daily mean precipitation rate as averaged over the selected grids (displayed in Figure 3) shows the two AR events along with the temporal variability in snowfall rate (Figure 5). The ASO data are not included in Figure 5 as it does not have daily sampling. Given that the monthly precipitation patterns and amounts of PRISM and Mountain Mapper are similar to ASO (see Figure 3 and Table 2) and both products use higher quality meteorological station observations and a statistical knowledge-based interpolation system using a digital elevation model, one may expect that the daily time series from the two products are more suitable to serve as comparison reference.

Figure 5 shows that PRISM and Mountain Mapper are relatively consistent in temporal distribution of precipitation, although PRISM tends to show higher precipitation rates than Mountain Mapper on most days, especially during the extreme precipitation events. Radar-g and Gauge products show fairly similar daily mean precipitation rates to each other, but they both underestimate compared to PRISM and Mountain Mapper.

While the other products show skill in detecting precipitation during the intense precipitation events, they generally face greater difficulties in capturing the intensity and temporal distribution of daily precipitation. For example, for the first AR event, PRISM and Mountain Mapper show two extreme events with peaks around 8 and 11 February, the former is more intense. However, all of the other products except Gauge and Radar-g suggest that precipitation on 11 February was larger than that on 8 February. Further analysis using the three

Figure 5. Time series of daily mean precipitation rate, averaged over the selected grids displayed in Figure 3.

in situ observations (section 2.2) suggests that on 8 February, the higher elevations and the northern side of the basin received larger accumulation while on 11 February TUM (at lower altitudes in the rain shadow) captured larger accumulation. The observed elevation dependency of precipitation suggests that a more skillful precipitation product should be able to capture this feature, which is not the strength of the current remote sensing products (e.g., Hirpa et al., 2009; Maggioni et al., 2017; Shige et al., 2017). During the second AR event, the temporal pattern of precipitation was more consistent among the products, but GSMap shows a large isolated peak on 18 February that exceeds all other products and is not reflected in the in situ data. These analyses suggest that besides quantifying the total snow accumulation, the satellite products may have large uncertainties in determining the temporal distribution of precipitation.

It should be noted that the MW estimates used in IMERG V5 are based on the version V5 of Goddard Profiling (GPROF) algorithm (Kummerow et al., 2016), which uses an updated GPROF 2017 a priori database and has several new features that have improved the MW estimates compared to its previous version (V4). Figure 6 clearly shows that IMERG V5 outperforms IMERG V4 as compared to the daily Mountain Mapper snowfall averaged over the qualifying grids confirming that the new version is improved in complex terrain.

4.3. Spatial Representation

One of the unique advantages of using the ASO-derived SWE accumulation to evaluate snowfall from remote sensing products is that the ASO data provide spatially complete measurements that are derived from sampling the broad spatial distribution of SWE accumulation within each 50-m grid cell. Each SWE accumulation estimate at 50 m is derived from an aggregation of over 275 pixels in the 3-m high-resolution snow depth maps. The snow depth in each of these 3-m snow depth pixels is derived from at least 4–5 individual lidar measurements, which when upscale d provides at least 1,200 spatially distributed measurements of snow depth for each 50-m pixel.

It is clear that the degree of sampling in the ASO-derived products provide an areal measurement of snowfall accumulation, which is distinctly different from the point-scale measurements that are obtained at in situ sites. However, often these point measurements are the only data available for evaluation. Here we leverage the fine-scale sampling of the spatially complete ASO products to examine the relationships between in situ point and areal measurements across a range of spatial scales.

From the in situ measurements (section 2.2), the accumulated SWE at the lowest elevation site TUM was 40.2 cm, 35.9 cm was observed at DAN, and 83.4 cm was measured at the highest accumulation site (HRS). Figure 7 shows increasing differences between ASO snow accumulation and the in situ measurements (calculated by subtracting ASO estimates from the in situ measurements) with increasing spatial scales (i.e., 100, 200, 500, 1,000, 2,000, and 2,200 m). While at 100 m the differences between point and areal measurements range from -0.08 to $+0.07$ m (or -80 to $+70$ mm) over the three sites, at 2,200 m the differences are much larger, ranging from -0.24 to -0.14 m (or -240 to -140 mm).

Figure 6. Similar to Figure 4 but for comparing IMERG V4 to IMERG V5.

The spatial coarsening was performed by averaging the ASO estimates (from the original resolution of 50 m) within an expanding buffer around each in situ station. The reason for using 100 m as the lowest buffer size around the stations is that the precision of the coordinates of the stations is only two decimal places, making it difficult to select the exact corresponding 50 m ASO grid. The expanding spatial scale limit of 2,200 m was realized for this study when the aggregation buffer reached the watershed boundary and thus the spatial limit of the ASO data.

The range of differences shown in Figure 7 between ASO and the point measurements at the 100 m scale represents a -10 to $+16\%$ relative bias range across the three sites. This confirms that the SWE accumulation estimates as derived from the standard ASO data has relatively consistent

Figure 7. The spatial representation of in situ snow accumulation measurements at point locations when compared to spatially aggregated snow accumulation data from Airborne Snow Observatory (ASO).

accuracy across both rain shadow and high accumulation sites. As the spatial scale of the ASO aggregation increases, the coarsened ASO data continues to report larger perceived negative biases when compared to the in situ measurements, reaching a maximum negative difference ($\sim 54\%$ for DAN, 35% for TUM, and 29% for HRS) at the maximum aggregation tested of 2.2 km. Henn et al. (2018) likewise found such differences, which are ascribed to the deliberate situating of snow pillows at sites with greater accumulation in order to have greater temporal duration of snow information each year.

While the exact physical interpretation of the observed bias-scaling relationship may not be straightforward, the relationships at each of the three locations show some similarities in shape. Nonetheless, the experiment shown in Figure 7 suggests that the use of point measurements to assess areal estimates (e.g., satellite products) may lead to significant errors simply due to sampling constraints. For example, based on Figure 7, the bias

at 2.2 km is an order of magnitude larger than the ASO biases inferred at 100 m even when the same data are simply coarsened. Therefore, the use of alternative evaluation data that provide areal estimates (such as good-quality radar or ASO) are crucial in the robust evaluation of remote sensing products.

5. Concluding Remarks

Accurate estimation of snowfall and its spatial distribution is difficult for in situ and remote sensing products. Challenges in estimating precipitation over frozen surfaces from satellite, lack of robust signal and retrieval methods from radars, and the dependence on spatially incomplete in situ point measurements have hindered reliable areal evaluation of global- and regional-scale snowfall products. With enhanced limitations in complex terrain the same dependencies on in situ measurements are particularly problematic for snowfall estimation in cold mountain environments. As such, the uncertainty of global and regional precipitation products in mountainous terrain is notoriously high and difficult to assess. The present study showcases the excellent opportunity for addressing this long-standing challenge for precipitation remote sensing efforts through application of spatially complete SWE accumulation estimates from the NASA ASO.

The results from this study show that most satellite products and radar face large underestimation of snowfall accumulation compared to the ASO estimates (e.g., about half or more). Despite their underestimation, satellite and radar products can show correlations ≥ 0.8 with ASO snow accumulation at the selected grids, suggesting that satellite and radar products have skill in capturing the spatial distribution of snowfall at coarse spatial scales but not magnitude. Gauge correction for IMERG was effective in reducing the underestimation but not sufficient.

During the study period of 29 January to 3 March 2017 and for cold, high-elevation grids (qualifying grids), mean snow accumulation from PRISM (51.3 cm) and mountain mapper (44.0 cm) show the best match with ASO snow accumulation (48.9 cm before and 51.4 cm after accounting for estimated SWE losses). Comparison of daily snowfall time series from PRISM with other precipitation products shows that the satellite and radar products generally capture the temporal pattern fairly well, but large differences exist in the magnitude of accumulations.

Besides providing unprecedented measurements for the spatial distribution and magnitude of precipitation accumulation, the high spatial resolution of the ASO data enabled an assessment of the relationships between point and areal estimates by plotting snowfall bias as inferred from in situ point measurements across a range of aggregation scales. The results showed that as the ASO data are aggregated from 100 to 2,200 m, the differences between the areal measurements and the in situ measurements increased by an order of magnitude in a nonlinear relationship, where at 2,200 m a relative bias of up to 54% could be deduced. Such a mismatch in spatial scales can cause large perceived biases when using point data to evaluate areal quantities, and has the potential to misguide evaluations of coarse-scale gridded products.

This study is performed using two ASO acquisitions encompassing two AR events that brought large snowfall to the area. Therefore, the intent of this study is not to generalize the outcomes obtained from the comparative analysis between ASO, radar, and satellite products. This work demonstrates the effectiveness and unique value of ASO SWE retrievals for the evaluation of global and regional precipitation products and highlights the need for additional acquisitions in cold months that bracket snow storm events. The typical ASO surveys that often start in April and continue throughout spring and into summer could be started earlier in the season during winter to capture valuable insight into precipitation deposition in the mountains. This extension of ASO utility to capture storm events is critical for the evaluation of broad-scale precipitation products that could be performed independently or in coordination with the precipitation ground validation programs, such as those conducted under the GPM Ground Validation efforts (Skofronick-Jackson et al., 2017). Preliminary efforts at such validation of precipitation products were likewise performed in the OLYMPEX project with ASO over the Olympic Peninsula, Washington (Cao et al., 2018).

In this study, we provide a demonstration of how measurements of SWE accumulation can be used to assess broad-scale precipitation estimates in complex terrain. While the study leverages ASO data for this purpose, this type of evaluation could use similar observations from an alternative data stream. With the recent National Academies of Sciences, Engineering, and Medicine's, 2018 Earth Science Decadal Survey (DS) Thriving on Our Changing Planet: A Decadal Strategy for Earth Observation from Space, we are poised for a potential global Snow Depth/SWE effort based on the legacy of the NASA ASO (NASEM DS 2018). Such measurements, as expressed in the DS, would provide similar validation opportunities in regions, beyond California and Colorado, where ASO does not yet reach, thus allowing the expansion of evaluation efforts of broad-scale precipitation products across a wider spread of snow-prone mountain environments.

Acknowledgments

The research described in this paper was carried out at the University of Arizona and the Jet Propulsion Laboratory, California Institute of Technology, under a contract with the National Aeronautics and Space Administration. ASO, PRISM, and MRMS products were obtained from <https://aso.jpl.nasa.gov/>, <http://www.prism.oregonstate.edu/>, and <http://mrms.ncep.noaa.gov/data/>, respectively. The station data used here are collected from NOAA's National Centers for Environmental Information: <https://www.ncei.noaa.gov/> and the California Department of Water Resources: <https://cdec.water.ca.gov/>. TRMM 3B42 and IMERG products were collected from <https://mirador.gsfc.nasa.gov/> and <http://ftp://jsimpson.pps.eosdis.nasa.gov>. PERSIANN and PERSIANN-CCS were downloaded from <ftp://persiann.eng.uci.edu/CHRSdata/PERSIANN/> and <ftp://persiann.eng.uci.edu/CHRSdata/PERSIANN-CCS/>. GSMaP product was collected from The Japan Aerospace Exploration Agency: <http://ftp://rainmap@hokusaieorc.jaxa.jp>. The study is partially supported by the NASA Energy and Water Cycle Study (NNH13ZDA001N-NEWS) and the NASA Terrestrial Hydrology Programs. Government sponsorship is acknowledged. Funding for these particular ASO flights came from the NASA Western Water Applications Office.

References

- Ashouri, H., Hsu, K.-L., Sorooshian, S., Braithwaite, D. K., Knapp, K. R., Cecil, L. D., et al. (2015). PERSIANN-CDR: Daily precipitation climate data record from multisatellite observations for hydrological and climate studies. *Bulletin of the American Meteorological Society*, 96(1), 69–83. <https://doi.org/10.1175/BAMS-D-13-00068.1>
- Bartsotas, N. S., Anagnostou, E. N., Nikolopoulos, E. I., & Kallos, G. (2018). Investigating satellite precipitation uncertainty over complex terrain. *Journal of Geophysical Research: Atmospheres*, 123, 5346–5359. <https://doi.org/10.1029/2017JD027559>
- Behrangi, A., Andreadis, K., Fisher, J. B., Turk, F. J., Granger, S., Painter, T., et al. (2014). Satellite-based precipitation estimation and its application for streamflow prediction over mountainous western U.S. basins. *Journal of Applied Meteorology and Climatology*, 53(12), 2823–2842. <https://doi.org/10.1175/JAMC-D-14-0056.1>
- Behrangi, A., Gardner, A. S., Reager, J. T., & Fisher, J. B. (2017). Using GRACE to constrain precipitation amount over cold mountainous basins. *Geophysical Research Letters*, 44, 219–227. <https://doi.org/10.1002/2016GL071832>
- Behrangi, A., Guan, B., Neiman, P. J., Schreier, M., & Lambriksen, B. (2016). On the quantification of atmospheric rivers precipitation from space: composite assessments and case studies over the eastern North Pacific Ocean and the western United States. *Journal of Hydrometeorology*, 17(1), 369–382. <https://doi.org/10.1175/JHM-D-15-0061.1>
- Behrangi, A., Tian, Y., Lambriksen, B. H., & Stephens, G. L. (2014). What does CloudSat reveal about global land precipitation detection by other spaceborne sensors? *Water Resources Research*, 50, 4893–4905. <https://doi.org/10.1002/2013WR014566>
- Behrangi, A., Yin, X., Rajagopal, S., Stampoulis, D., & Ye, H. (2018). On distinguishing snowfall from rainfall using near-surface atmospheric information: Comparative analysis, uncertainties, and hydrologic importance. *Quarterly Journal of the Royal Meteorological Society*. <https://doi.org/10.1002/qj.3240>
- Beljaars, A. C. M., & Viterbo, P. (1994). The sensitivity of winter evaporation to the formulation of aerodynamic resistance in the ECMWF model. *Boundary-Layer Meteorology*, 71(1–2), 135–149. <https://doi.org/10.1007/BF00709223>
- Berg, W., L'Ecuyer, T., & Kummerow, C. (2006). Rainfall Climate Regimes: The Relationship of Regional TRMM Rainfall Biases to the Environment. *Journal of Applied Meteorology and Climatology*, 45(3), 434–454. <https://doi.org/10.1175/jam2331.1>
- Cao, Q., Painter, T. H., Currier, W. R., Lundquist, J. D., & Lettenmaier, D. P. (2018). Estimation of precipitation over the OLYMPEX domain during winter 2015/16. *Journal of Hydrometeorology*, 19(1), 143–160. <https://doi.org/10.1175/JHM-D-17-0076.1>
- Currier, W. R., Thorson, T., & Lundquist, J. D. (2017). Independent Evaluation of Frozen Precipitation from WRF and PRISM in the Olympic Mountains. *Journal of Hydrometeorology*, 18(10), 2681–2703. <https://doi.org/10.1175/jhm-d-17-0026.1>
- Dai, A. (2008). Temperature and pressure dependence of the rain-snow phase transition over land and ocean. *Geophysical Research Letters*, 35, L12802. <https://doi.org/10.1029/2008GL033295>
- Daly, C., Gibson, W. P., Taylor, G. H., Johnson, G. L., & Pasteris, P. (2002). A knowledge-based approach to the statistical mapping of climate. *Climate Research*, 22(2), 99–113. <https://doi.org/10.3354/cr022099>
- Daly, C., Neilson, R. P., & Phillips, D. L. (1994). A Statistical-Topographic Model for Mapping Climatological Precipitation over Mountainous Terrain. *Journal of Applied Meteorology*, 33(2), 140–158. [https://doi.org/10.1175/1520-0450\(1994\)033<0140](https://doi.org/10.1175/1520-0450(1994)033<0140)
- Dettinger, M. D., Cayan, D. R., Meyer, M. K., & Jeton, A. E. (2004). Simulated hydrologic responses to climate variations and change in the Merced, Carson, and American River Basins, Sierra Nevada, California, 1900–2009. *Climatic Change*, 62(1–3), 283–317. <https://doi.org/10.1023/B:CLIM.0000013683.13346.4f>
- Fassnacht, S. R. (2004). Estimating Alter-shielded gauge snowfall undercatch, snowpack sublimation, and blowing snow transport at six sites in the coterminous USA. *Hydrological Processes*, 18(18), 3481–3492. <https://doi.org/10.1002/hyp.5806>
- Ferraro, R. R., Peters-Lidard, C. D., Hernandez, C., Turk, F. J., Aires, F., Prigent, C., et al. (2013). An Evaluation of Microwave Land Surface Emissivities Over the Continental United States to Benefit GPM-Era Precipitation Algorithms. *IEEE Transactions on Geoscience and Remote Sensing*, 51(1), 378–398. <https://doi.org/10.1109/tgrs.2012.2199121>

- Fuchs, T., Rapp, J., Rubel, F., & Rudolf, B. (2001). Correction of synoptic precipitation observations due to systematic measuring errors with special regard to precipitation phases. *Physics and Chemistry of the Earth, Part B: Hydrology, Oceans and Atmosphere*, 26, 689–693.
- Goodison, B. E. (1978). Accuracy of Canadian snow gauge measurements. *Journal of Applied Meteorology*, 17(10), 1542–1548. [https://doi.org/10.1175/1520-0450\(1978\)017<1542:AOCSGM>2.0.CO;2](https://doi.org/10.1175/1520-0450(1978)017<1542:AOCSGM>2.0.CO;2)
- Goulden, M. L., Anderson, R. G., Bales, R. C., Kelly, A. E., Meadows, M., & Winston, G. C. (2012). Evapotranspiration along an elevation gradient in California's Sierra Nevada. *Journal of Geophysical Research*, 117, G03028. <https://doi.org/10.1029/2012JG002027>
- Grünwald, T., & Lehning, M. (2015). Are flat-field snow depth measurements representative? A comparison of selected index sites with areal snow depth measurements at the small catchment scale. *Hydrological Processes*, 29(7), 1717–1728. <https://doi.org/10.1002/hyp.10295>
- Guan, B., Molotch, N. P., Waliser, D. E., Fetzer, E. J., & Neiman, P. J. (2010). Extreme snowfall events linked to atmospheric rivers and surface air temperature via satellite measurements. *Geophysical Research Letters*, 37, L20401. <https://doi.org/10.1029/2010GL044696>
- Henn, B., Newman, A. J., Livneh, B., Daly, C., & Lundquist, J. D. (2018). An assessment of differences in gridded precipitation datasets in complex terrain. *Journal of Hydrology*, 556, 1205–1219. <https://doi.org/10.1016/j.jhydrol.2017.03.008>
- Hirpa, F. A., Gebremichael, M., & Hopson, T. (2009). Evaluation of high-resolution satellite precipitation products over very complex terrain in Ethiopia. *Journal of Applied Meteorology and Climatology*, 49(5), 1044–1051. <https://doi.org/10.1175/2009JAMC2298.1>
- Hong, Y., Gochis, D., Cheng, J.-t., Hsu, K.-l., & Sorooshian, S. (2007). Evaluation of PERSIANN-CCS rainfall measurement using the NAME event rain gauge network. *Journal of Hydrometeorology*, 8(3), 469–482. <https://doi.org/10.1175/jhm574.1>
- Hong, Y., Hsu, K. L., Sorooshian, S., & Gao, X. G. (2004). Precipitation estimation from remotely sensed imagery using an artificial neural network cloud classification system. *Journal of Applied Meteorology*, 43(12), 1834–1853. <https://doi.org/10.1175/JAM2173.1>
- Hsu, K. L., Gao, X. G., Sorooshian, S., & Gupta, H. V. (1997). Precipitation estimation from remotely sensed information using artificial neural networks. *Journal of Applied Meteorology*, 36(9), 1176–1190. [https://doi.org/10.1175/1520-0450\(1997\)036<1176:PEFRSI>2.0.CO;2](https://doi.org/10.1175/1520-0450(1997)036<1176:PEFRSI>2.0.CO;2)
- Huffman, G. J., Adler, R. F., Bolvin, D. T., Gu, G. J., Nelkin, E. J., Bowman, K. P., et al. (2007). The TRMM multisatellite precipitation analysis (TMPA): Quasi-global, multiyear, combined-sensor precipitation estimates at fine scales. *Journal of Hydrometeorology*, 8(1), 38–55.
- Huffman, G. J., Bolvin, D. T., Braithwaite, D., Hsu, K., Joyce, R., Kidd, C., et al. (2018). Integrated Multi-satellite Retrievals for GPM (IMERG) Technical Documentation (V5.2). https://docserver.gesdisc.eosdis.nasa.gov/public/project/GPM/IMERG_ATBD_V5.pdf
- Joyce, R. J., Janowiak, J. E., Arkin, P. A., & Xie, P. (2004). CMORPH: A Method that Produces Global Precipitation Estimates from Passive Microwave and Infrared Data at High Spatial and Temporal Resolution. *Journal of Hydrometeorology*, 5(3), 487–503.
- Joyce, R. J., & Xie, P. (2011). Kalman Filter–Based CMORPH. *Journal of Hydrometeorology*, 12(6), 1547–1563. <https://doi.org/10.1175/jhm-d-11-022.1>
- Kochendorfer, J., Rasmussen, R., Wolff, M., Baker, B., Hall, M. E., Meyers, T., et al. (2017). The quantification and correction of wind-induced precipitation measurement errors. *Hydrology and Earth System Sciences: Katlenburg-Lindau*, 21(4), 1973–1989. <https://doi.org/10.5194/hess-21-1973-2017>
- Kummerow, C. D., Randel, D., & Petkovic, V. (2016). Results from GPM GPROF V4 and Improvements Planned for V5, 8th IPWG and 5th IWSSM Joint Workshop Bologna, 3–7 October, 2016. Retrieved from http://www.isac.cnr.it/~ipwg/meetings/bologna-2016/Bologna2016_Posters/P1-20_Kummerow.pdf
- Kurtzman, D., Navon, S., & Morin, E. (2009). Improving interpolation of daily precipitation for hydrologic modelling: Spatial patterns of preferred interpolators. *Hydrological Processes*, 23(23), 3281–3291. <https://doi.org/10.1002/hyp.7442>
- Larson, L. W., & Peck, E. L. (1974). Accuracy of precipitation measurements for hydrologic modeling. *Water Resources Research*, 10(4), 857–863. <https://doi.org/10.1029/WR010i004p00857>
- Legates, D., & Willmott, C. J. (1990). Mean Seasonal and Spatial Variability in Gauge-Corrected, Global Precipitation. *International Journal of Climatology*, 10, 111–127.
- Lebsock, M. D., & L'Ecuyer, T. S. (2011). The retrieval of warm rain from CloudSat. *Journal of Geophysical Research*, 116, D20209. <https://doi.org/10.1029/2011JD016076>
- Liu, G. (2008). Deriving snow cloud characteristics from CloudSat observations. *Journal of Geophysical Research*, 113, D00A09. <https://doi.org/10.1029/2007JD009766>
- Lundquist, J. D., Hughes, M., Henn, B., Gutmann, E. D., Livneh, B., Dozier, J., et al. (2015). High-elevation precipitation patterns: Using snow measurements to assess daily gridded datasets across the Sierra Nevada, California. *Journal of Hydrometeorology*, 16(4), 1773–1792. <https://doi.org/10.1175/JHM-D-15-0019.1>
- Maggioni, V., Nikolopoulos, E. I., Anagnostou, E. N., & Borga, M. (2017). Modeling satellite precipitation errors over mountainous terrain: The influence of gauge density, seasonality, and temporal resolution. *IEEE Transactions on Geoscience and Remote Sensing*, 55(7), 4130–4140. <https://doi.org/10.1109/TGRS.2017.2688998>
- Marks, D., Domingo, J., Susong, D., Link, T., & Garen, D. (1999). A spatially distributed energy balance snowmelt model for application in mountain basins. *Hydrological Processes*, 13(12–13), 1935–1959. [https://doi.org/10.1002/\(SICI\)1099-1085\(199909\)13:12<1935::AID-HYP868>3.0.CO;2-C](https://doi.org/10.1002/(SICI)1099-1085(199909)13:12<1935::AID-HYP868>3.0.CO;2-C)
- Molotch, N. P., & Bales, R. C. (2006). SNOTEL representativeness in the Rio Grande headwaters on the basis of physiographics and remotely sensed snow cover persistence. *Hydrological Processes*, 20(4), 723–739. <https://doi.org/10.1002/hyp.6128>
- National Academies of Sciences, Engineering, and Medicine (2018). *Thriving on our changing planet: A decadal strategy for Earth observation from space*. Washington, DC: The National Academies Press. <https://doi.org/10.17226/24938>
- 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>
- Prat, O. P., & Barros, A. P. (2010). Ground observations to characterize the spatial gradients and vertical structure of orographic precipitation—Experiments in the inner region of the Great Smoky Mountains. *Journal of Hydrology*, 391(1–2), 141–156. <https://doi.org/10.1016/j.jhydrol.2010.07.013>
- Raleigh, M. S., & Lundquist, J. D. (2012). Comparing and combining SWE estimates from the SNOW-17 model using PRISM and SWE reconstruction. *Water Resources Research*, 48, W01506. <https://doi.org/10.1029/2011WR010542>
- Raleigh, M. S., & Small, E. E. (2017). Snowpack density modeling is the primary source of uncertainty when mapping basin-wide SWE with lidar. *Geophysical Research Letters*, 44, 3700–3709. <https://doi.org/10.1002/2016GL071999>
- Ralph, F. M., Neiman, P. J., & Wick, G. A. (2004). Satellite and CALJET Aircraft Observations of Atmospheric Rivers over the Eastern North Pacific Ocean during the Winter of 1997/98. *Monthly Weather Review*, 132(7), 1721–1745. [https://doi.org/10.1175/1520-0493\(2004\)132<1721:SACAOO>2.0.CO;2](https://doi.org/10.1175/1520-0493(2004)132<1721:SACAOO>2.0.CO;2)

- Rasmussen, R., Baker, B., Kochendorfer, J., Meyers, T., Landolt, S., Fischer, A. P., et al. (2012). How well are we measuring snow: The NOAA/FAA/NCAR winter precipitation test bed. *Bulletin of the American Meteorological Society*, 93(6), 811–829. <https://doi.org/10.1175/BAMS-D-11-00052.1>
- Schaake, J., Henkel, A., & Cong, S. (2004). Application of PRISM climatologies for hydrologic modeling and forecasting in the western U.S. 18th Conf. on Hydrology, Seattle, WA, Amer. Meteor. Soc., 5.3. Retrieved from https://ams.confex.com/ams/84Annual/techprogram/paper_72159.htm
- Schneider, U., Becker, A., Finger, P., Meyer-Christoffer, A., Ziese, M., & Rudolf, B. (2014). GPCC's new land surface precipitation climatology based on quality-controlled in situ data and its role in quantifying the global water cycle. *Theoretical and Applied Climatology*, 115(1-2), 15–40. <https://doi.org/10.1007/s00704-013-0860-x>
- Sharifi, E., Steinacker, R., & Saghaian, B. (2016). Assessment of GPM-IMERG and other precipitation products against gauge data under different topographic and climatic conditions in Iran: Preliminary results. *Remote Sensing*, 8(2), 135. <https://doi.org/10.3390/rs8020135>
- Shige, S., Nakano, Y., & Yamamoto, M. K. (2017). Role of orography, diurnal cycle, and intraseasonal oscillation in summer monsoon rainfall over the Western Ghats and Myanmar Coast. *Journal of Climate*, 30(23), 9365–9381. <https://doi.org/10.1175/JCLI-D-16-0858.1>
- Shige, U., Kida, S., Ashiwake, H., Kubota, T., & Aonashi, K. (2013). Improvement of TMI rain retrievals in mountainous areas. *Journal of Applied Meteorology and Climatology*, 52(1), 242–254. <https://doi.org/10.1175/JAMC-D-12-074.1>
- Skofronick-Jackson, G., Petersen, W. A., Berg, W., Kidd, C., Stocker, E. F., Kirschbaum, D. B., et al. (2017). The Global Precipitation Measurement (GPM) Mission for Science and Society. *Bulletin of the American Meteorological Society*, 98(8), 1679–1695. <https://doi.org/10.1175/bams-d-15-00306.1>
- Smalley, M., L'Ecuyer, T., Lebsock, M., & Haynes, J. (2014). A comparison of precipitation occurrence from the NCEP stage IV QPE product and the CloudSat cloud profiling radar. *Journal of Hydrometeorology*, 15(1), 444–458. <https://doi.org/10.1175/JHM-D-13-048.1>
- Sorooshian, S., Hsu, K. L., Gao, X., Gupta, H. V., Imam, B., & Braithwaite, D. (2000). Evaluation of PERSIANN system satellite-based estimates of tropical rainfall. *Bulletin of the American Meteorological Society*, 81(9), 2035–2046.
- Taylor, J. (1997). An introduction to error analysis: The study of uncertainties in physical measurements (2nd ed., 327 pp.). Suva, CA: University Science Books.
- Tian, Y., & Peters-Lidard, C. D. (2010). A global map of uncertainties in satellite-based precipitation measurements. *Geophysical Research Letters*, 37, L24407. <https://doi.org/10.1029/2010GL046008>
- Ushio, T., Sasashige, K., Kubota, T., Shige, S., Okamoto, K., Aonashi, K., et al. (2009). A Kalman Filter Approach to the Global Satellite Mapping of Precipitation (GSMaP) from Combined Passive Microwave and Infrared Radiometric Data. *Journal of the Meteorological Society of Japan*, 87A, 137–151. <https://doi.org/10.2151/jmsj.87A.137>
- Wen, Y., Behrangi, A., Chen, H., & Lambriksen, B. (2018). How well were the early 2017 California atmospheric river precipitation events captured by satellite products and ground-based radars? *Quarterly Journal of the Royal Meteorological Society*, 0. <https://doi.org/10.1002/qj.3253>
- Wen, Y., Behrangi, A., Lambriksen, B., & Kirstetter, P.-E. (2016). Evaluation and uncertainty estimation of the latest radar and satellite snowfall products using SNOTEL measurements over mountainous regions in western United States. *Remote Sensing*, 8(11), 904. <https://doi.org/10.3390/rs8110904>
- Xie, P., Joyce, R., Wu, S., Yoo, S.-H., Yarosh, Y., Sun, F., et al. (2017). Reprocessed, Bias-corrected CMORPH global high-resolution precipitation estimates from 1998. *Journal of Hydrometeorology*, 18(6), 1617–1641. <https://doi.org/10.1175/JHM-D-16-0168.1>
- Yang, D., Goodison, B. E., & Ishida, S. (1998). Adjustment of daily precipitation data at 10 climate stations in Alaska: Application of World Meteorological Organization intercomparison results. *Water Resources Research*, 34(2), 241–256. <https://doi.org/10.1029/97WR02681>
- Yang, D., Ishida, S., Goodison, B. E., & Gunther, T. (1999). Bias correction of precipitation data for Greenland. *Journal of Geophysical Research*, 105(D6), 6171–6182.
- Zhang, J., Howard, K., Langston, C., Kaney, B., Qi, Y., Tang, L., et al. (2016). Multi-Radar Multi-Sensor (MRMS) Quantitative Precipitation Estimation: Initial Operating Capabilities. *Bulletin of the American Meteorological Society*, 97(4), 621–638. <https://doi.org/10.1175/bams-d-14-00174.1>