Evaluation of Remotely Sensed Snow Water Equivalent and Snow Cover Extent over the Contiguous United States^①

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ABSTRACT

Global snow water equivalent (SWE) products derived at least in part from satellite remote sensing are widely used in weather, climate, and hydrometeorological studies. Here we evaluate three such products using our recently developed daily 4-km SWE dataset available from October 1981 to September 2017 over the conterminous United States. This SWE dataset is based on gridded precipitation and temperature data and thousands of in situ measurements of SWE and snow depth. It has a 0.98 correlation and 30% relative mean absolute deviation with Airborne Snow Observatory data and effectively bridges the gap between small-scale lidar surveys and large-scale remotely sensed data. We find that SWE products using remote sensing data have large differences (e.g., the mean absolute difference from our SWE data ranges from 45.8% to 59.3% of the mean SWE in our data), especially in forested areas (where this percentage increases up to 73.5%). Furthermore, they consistently underestimate average maximum SWE values and produce worse SWE (including spurious jumps) during snowmelt. Three additional higher-resolution satellite snow cover extent (SCE) products are used to compare the SCE values derived from these SWE products. There is an overall close agreement between these satellite SCE products and SCE generated from our SWE data, providing confidence in our consistent SWE, snow depth, and SCE products based on gridded climate and station data. This agreement is also stronger than that between satellite SCE and those derived from the three satellite SWE products, further confirming the deficiencies of the SWE products that utilize remote sensing data.

1. Introduction

Snow is one of the most important wintertime land surface characteristics due to its impacts on land–atmosphere interactions. Snow insulates the soil from the atmosphere and also increases surface albedo, which reduces net solar radiation at the surface. Furthermore, snowmelt is critical for water resources, as it can account for more than 75% of runoff in places like the western United States (Bales et al. 2006; Mankin et al. 2015). Yet, our understanding of how much snow is on the ground is challenged by uncertainties

of satellite measurements of snow as well as difficulties in scaling up point measurements of snow. As a consequence, there are substantial errors of snow states in operational weather forecasting models, reanalyses, and land data assimilation systems. For example, previous research (Dawson et al. 2016; Broxton et al. 2016a) found that these products tend to underestimate snow depth and snow water equivalent (SWE), which can lead to systematic discrepancies between seasonal forecasts initialized in early versus late winter (Broxton et al. 2017).

At continental scales, SWE can either be determined through snow models based on reanalysis meteorology, upscaling or reconstruction from point snow observations, satellite retrievals, or a combination thereof. These methods should be supported with relatively dense networks of stations and can result in high-quality SWE

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estimates where the station density is high enough, while uncertainty is higher where station measurements are too sparse. Even relatively dense in situ observation networks may be unable to represent snowpack quantities by themselves in mountainous environments (e.g., Molotch and Bales 2005; Guan et al. 2013). Furthermore, reconstruction methods (Bair et al. 2016; Schneider and Molotch 2016) are currently unable to provide information on continental scales (due to the reliance on ground-based SWE observations in the Rocky Mountains). These data gaps can be alleviated with the use of coarse-scale satellite remote sensing SWE data products. At the same time, though, most satellite-based estimates of snow amount, while relatively accurate in flat, open areas (e.g., Mote et al. 2003; Pulliainen 2006; Takala et al. 2011), can exhibit substantial uncertainties in some of these same areas where it is difficult to use point observations to determine snow amount, that is, forested regions (Chang et al. 1997; Foster et al. 1997), mountainous terrain (Dozier 1989; Maurer et al. 2003; Dozier and Painter 2004; Foster et al. 2005; Tedesco and Narvekar 2010; Li et al. 2012; Mizukami and Perica 2012), or when the snowpack is too deep (Markus et al. 2006; Mätzler 1994) or wet (Frei et al. 2012).

One of the factors limiting the improvement of SWE estimates that utilize remotely sensed data in these areas is the lack of high-quality, spatially and temporally extensive snow observations. New technologies, such as airborne lidar as used in the Airborne Snow Observatory (ASO; Painter et al. 2016), can provide ground-truth snow data needed to improve these remotely sensed products in mountain forests. However, the spatial coverage of lidar data is limited and the collection of such data is laborious and costly, which results in low temporal resolution. For example, even the relatively large (for lidar acquisitions) areas flown by ASO ($\sim 1000 \text{ km}^2$) are only a little bigger than a single pixel of a satellite-derived remotely sensed SWE product (at least $\sim 700 \text{ km}^2$), and the fact that the area is irregular means that no single pixel is covered by ASO data. Also, even given the relatively high temporal frequency of ASO (approximately every 2 weeks), it can still miss some large snowpack changes that occur at temporal scales of <1 week, especially in warmer environments. An intermediate-scale SWE product is needed to step between the lidar data and the satellite-derived remotely sensed SWE products.

To bridge this data gap between low-frequency, local-scale lidar data (with derived products having grid sizes from meters to tens of meters) and coarser global-scale SWE products (with grid sizes of 25 km or greater, including the remotely sensed SWE data used in this study), we have recently developed the University of Arizona (UA) daily 4-km SWE dataset over the contiguous

United States (CONUS; Broxton et al. 2016b) from 1982 to present. This dataset is based on SWE, snow depth, and meteorological observations from thousands of climate stations across the CONUS. It has undergone extensive testing for consistency and robustness (Broxton et al. 2016a,b; see section 2) and has been used to evaluate a variety of operational weather and seasonal forecast models, reanalyses, and Land Data Assimilation Systems (Broxton et al. 2016a, 2017; Dawson et al. 2016). In addition, as will be discussed later in section 3, it performs well against independent airborne lidar data and moderate-resolution satellite snow cover data.

In this study, we use this product to provide one of the most comprehensive and quantitative measures of the performance of satellite-based products available across the entire CONUS. We evaluate a suite of global SWE products that are based, in whole or in part, on remote sensing data, including AMSR-E (Chang and Rango 2000), GlobSnow SWE (Takala et al. 2011), and the Canadian Sea Ice and Snow Evolution Network (CanSISE; Mudryk et al. 2015) SWE products. Products that utilize remotely sensed data are grouped together as remotely sensed products in this study for simplicity. However, it is important to note that these products may additionally include point observations, reanalyses, models, and microwave modeling. As a further evaluation and leveraging the better quality of higher-resolution satellite detection of snow cover extent (SCE), SCE [and associated snow-covered area (SCA)] derived from these SWE products are compared using three higher-resolution satellite SCE products: the Interactive Multisensor Snow and Ice Mapping System (IMS; Helfrich et al. 2012) SCE product, SCE from the Moderate Resolution Imaging Spectroradiometer (MODIS) on board the *Terra* satellite (MOD10C1), and SCE from Rutgers University (RU; Robinson et al. 2014). Particular emphasis is placed on how the remotely sensed SWE and SCE data perform in forested versus nonforested regions. While both the SWE and SCE data are affected by forest cover, the remotely sensed SWE data are expected to be more adversely affected by forests because SCE is generally 100% when SWE is greater than a critical value (and hence is mostly impacted at low SWE values). The uncertainty information gained about each product in this study in forested versus nonforested regions will help determine optimal combinations of snow datasets for the development of a merged global SWE product in the future.

2. Data description

Our UA SWE data (Broxton et al. 2016b) are available from October 1981 to present on a $\sim 4 \text{ km} \times 4 \text{ km}$ grid. The UA dataset combines snow depth observations

from thousands of sites from the National Weather Service Cooperative Observer Program (COOP) network and SWE observations from hundreds of sites from the Natural Resource Conservation Service Snowpack Telemetry (SNOTEL) networks and a network maintained by the California Department of Water Resources with a background SWE field generated using an empirical temperature-index snow model. This model is forced with Parameter-Elevation Regressions on Independent Slopes Model (PRISM; [Daly et al. 1994](#)) precipitation and temperature data, and model parameters are derived from in situ observations. While PRISM data have uncertainties in complex terrain ([Henn et al. 2018](#); [Rice et al. 2011](#)), it is the best gridded climate dataset available at this time, particularly over the western CONUS. Station SWE data are incorporated by interpolating differences in SWE, normalized by cumulative snowfall minus cumulative snow ablation, between the station observations and the model estimates. For stations that only report snow depth (COOP sites), SWE is derived from measured snow depth and snow density estimates from a recently developed snow density parameterization ([Dawson et al. 2016](#)).

The UA product has been tested extensively and shown to perform well in two significant respects. First, when predicting SWE data between points, our method of interpolation of normalized SWE produces much smaller differences than other interpolation methods using SWE itself ([Broxton et al. 2016b](#)). Second, the method is robust, as interpolation differences are similar regardless of whether a small or large number of stations are used for the interpolation ([Broxton et al. 2016b](#)). This is also true of the gridded SWE estimates produced from the interpolation, which are similar regardless of the number of stations used ([Broxton et al. 2016a](#)).

For this study, two improvements have been made over the original UA dataset used in [Broxton et al. \(2016a,b\)](#). First, we have replaced the simple snow density treatment ([Broxton et al. 2016a](#)) by the [Dawson et al. \(2016\)](#) snow density parameterization. The hydroclimate classes used for this snow density parameterization are determined using the gridded snow classification data of [Sturm et al. \(1995\)](#), interpolated (using nearest neighbor resampling) to the 2.5-min grid used by the UA SWE data. This parameterization is used to both compute snow depth from the gridded SWE data and convert COOP snow depth data into SWE estimates. In addition, we now include snow sensors from the California Department of Water Resources in addition to the SNOTEL and COOP data. In our algorithms, these stations are treated the same as SNOTEL stations (which also record daily SWE values).

In addition to these two improvements, we have also fixed a few issues with the original dataset. First, we

corrected a small geolocation error that caused the normalized SWE field to be incorrectly mapped onto the model grid. We also improved the computation of cumulative snow ablation by the temperature-index snow model. Before, this was based on accumulated degree days (above freezing) since the snow began to melt. This gave rise to some unrealistic discontinuities between areas where snow melted completely in between snowfall events and areas where snow persists between snowfall events. In the revised model, ablation is computed separately for each day. Although parameters were chosen such that the new model still follows an observed relationship between temperature and snow ablation used for the original model ([Broxton et al. 2016b](#)), the new model gives more consistent results for areas that have more ephemeral snow packs.

To further demonstrate the quality of the UA data, they are compared to the completely independent ASO measurements over the Toulumne basin in California (latest available as of publication time; contact information in acknowledgments). ASO is a coupled scanning lidar system and imaging spectroradiometer that measures snow depth and snow albedo ([Painter et al. 2016](#)). The lidar data are used to generate snow depth (by differencing the ground elevations from snow-off and snow-on scenes) and SWE (by using snow density estimates from an energy balance snow model that assimilates the lidar snow depth data). The ASO SWE dataset that is used here has a grid size of $50\text{ m} \times 50\text{ m}$ and uses a bias-corrected snow density model to estimate SWE. Total spatial extent is on the order of hundreds of kilometers for each flight. [Section 3a](#) provides an evaluation of the UA SWE dataset with ASO data.

We then use the UA data to evaluate the AMSR-E, GlobSnow SWE, and CanSISE products. These products include satellite-derived SWE data, but two of them also include data from other sources, and so can be considered merged products. The AMSR-E SWE dataset ([Tedesco et al. 2004](#)) is derived from brightness temperatures obtained from the AMSR-E instrument on board the *Aqua* satellite ([Parkinson 2003](#)). GlobSnow SWE, funded by the European Space Agency (ESA) and led by the Finnish Meteorological Institute, combines point observations with remotely sensed data to create a gridded SWE dataset ([Takala et al. 2011](#)). AMSR-E and GlobSnow data are available on a $25\text{ km} \times 25\text{ km}$ Equal-Area Scalable Earth (EASE-2.0) grid. The CanSISE dataset is composed of five products: GlobSnow (described above), Modern-Era Retrospective Analysis for Research and Applications data (MERRA; [Rienecker et al. 2011](#)), ECMWF interim reanalysis (ERA-Interim; [Dee et al. 2011](#)), Crocus (a snow model; [Vionnet et al. 2012](#)) forced with

TABLE 1. Metadata for native products before processing. Grid sizes are approximate based on the nominal resolution of each product. Availability is in water years.

Product	Quantity	Availability	Grid size	Projection
UA	SWE/SCE	1982–present	4 km × 4 km	Regular lat–lon
AMSR-E	SWE	2003–11	25 km × 25 km	Polar stereographic
GlobSnow	SWE	1980–2012	25 km × 25 km	Regular lat–lon
CanSISE	SWE	1982–2009	1° × 1°	Polar stereographic
IMS	SCE	2007–present	4 km × 4 km	Polar stereographic
RU	SCE	2000–12	25 km × 25 km	Polar stereographic
MODIS	SCE	2001–12	0.05° × 0.05°	Polar stereographic

ERA-Interim meteorological data (Brun et al. 2013), and SWE from the Global Land Data Assimilation System, version 2 (GLDAS-2; Rodell et al. 2004). The final CanSISE product (which we are evaluating) is an equally weighted mean of the five datasets (though GlobSnow is not included in mountainous grid cells) and has a grid size of 1° × 1°. Since UA SWE covers the entire time period of all products, comparisons are performed for overlapping periods between each respective product (data availability provided in Table 1) except where noted. Further details about the AMSR-E and GlobSnow products are provided in the online supplemental material.

As a further evaluation, we compare SCE derived from the above SWE products with the higher-resolution IMS, MODIS (MOD10C1), and RU SCE products. IMS is created by analysts who compare data from more than 20 different sources (a list of current sources is available at <https://nsidc.org/data/g02156>) to create a daily map of SCE. Here, we use 4 km × 4 km gridded IMS data from 2004 to present. IMS is used as a best guess of SCE since it is used in operational forecasting centers around the world for data assimilation. The MODIS MOD10C1 product determines SCE within a grid cell if the snow cover fraction (Salomonson and Appel 2004) is greater than 0% on a 0.05° × 0.05° Climate Modeling Grid. This threshold is chosen as remotely sensed SCE products tend to underestimate SCE in forests (Liu et al. 2008; Raleigh et al. 2013). Additionally, MODIS grid cells that are less than 20% clear [data available as “Clear Index” within the MOD10C1 dataset; similar threshold as Hall et al. (2010)] are masked. SCE from RU is a combination of three remotely sensed products available from 1999 to 2012 on a 25 km × 25 km grid. Input products include 4 km × 4 km IMS data (described above), cloud-gap-filled MODIS SCE data, and data from the Special Sensor Microwave Imager (SSM/I) and Special Sensor Microwave Imager Sounder (SSMIS) instruments. In this study, we use RU-merged SCE, which provides SCE where at least one of the three products indicates SCE. Further details about these products, including their underestimation

of SCE in forested areas, are available in the supplemental material.

The derivation of SCE from each SWE product is based on a threshold value. For GlobSnow, we use a threshold of 0.001 mm, as recommended in its final report (link provided in the acknowledgments). For other SWE products, sensitivity tests are performed to determine the most appropriate threshold for conversion between SWE and SCE (see section 3b).

We use the open-source Geospatial Data Abstraction Library (GDAL)’s `gdalwarp` command-line tool to perform spatial reprojection to facilitate comparison between all of the products. First, data from each product are interpolated to a latitude–longitude grid using nearest-neighbor interpolation, with the resulting grid having the same nominal grid size of the original data. Then, for each comparison, pairs of data products are interpolated to the resolution of the coarser product (e.g., for the comparison between the UA and AMSR-E SWE data, both products are interpolated to the nominal grid size of the AMSR-E data). In the case of SWE data, this “coarsening” is done by using “average” interpolation, and in the case of SCE data, this coarsening is done using nearest-neighbor interpolation (fractional snow cover is not created for consistency between products as IMS does not provide fractional snow cover while MODIS and UA SWE can). In all comparisons, if one product indicates missing data, associated grid cells are masked from both products for a fair comparison. Information about the spatial characteristics and temporal availability for all products is provided in Table 1.

Because the quality of remote sensing SWE products is at least partially affected by the presence of forests (but additional nonremote sensing data may help offset these effects in merged products), results from our product intercomparison are stratified by grid cells dominantly covered, or not covered, by forests (Fig. S1 in the supplemental material). The global 0.5-km land cover dataset of Broxton et al. (2014), which uses the International Geosphere–Biosphere Programme (IGBP; Townshend 1992) land cover classification, is interpolated to match the grid size of the respective

products. If the dominant (defined as the mode) land-cover type is needle leaf forest, broadleaf forest, mixed forest, or woody savannah, the grid cell is categorized as a “forested” grid cell. If the land-cover type is anything else (except water), the grid cell is categorized as a “nonforested” grid cell.

3. Results

a. Comparison between ASO and UA data

To assess the capability of the UA SWE dataset to agree with lidar SWE data, the UA SWE dataset is first compared to the completely independent ASO dataset for the upper Tuolumne basin, a basin with complex terrain in California’s Sierra Nevada (Painter et al. 2016). This comparison is performed for all dates for which there are ASO data between water years (WYs) 2013 and 2016 for a total of 32 days. Figure 1 (top) shows that for these dates, the relative mean absolute deviation (MAD) normalized by the mean ASO SWE between UA SWE and ASO SWE is 30%, while the correlation coefficient is 0.98. Note that the ASO data (and hence the comparisons) are for days spanning the period from approximately peak SWE until melt out, and it is estimated that ASO SWE uncertainty can be as high as 20% for this period (Painter et al. 2016). Based on this comparison, relative MAD above 30% will be considered significant for products compared hereafter.

Because ASO SWE data are generated by converting the lidar snow depth data to SWE using a snow density model, we also compared snow depth from the UA dataset directly to the lidar snow depth data (Fig. 1, middle). The MAD relative to mean ASO snow depth is slightly lower (26%), and the correlation coefficient is 0.99. The slightly better agreement between the ASO and UA data for snow depth (compared to SWE) is possibly related to added uncertainty of incorporating model snow density estimates into the ASO data to generate SWE estimates. Indeed, the effective snow density (SWE/snow depth) for the UA data tends to be a little higher than for the ASO data, particularly when the effective snow density for ASO data is low (when it is high, they tend to be comparable; Fig. 1, bottom).

In addition, we compared the ASO and UA SWE under different elevations and forest cover conditions. Figure S2 shows that the SWE differences increase with elevations, but they decrease with the increase of forest cover (which is explained by the fact that forest cover decreases with the increase of elevation in this basin; figure not shown). The higher SWE differences at higher elevations (Fig. S2a), however, still represent lower values relative to the mean ASO SWE (Fig. S2c).

FIG. 1. Comparison of area-averaged (top) UA SWE, (middle) UA snow depth (SD), and (bottom) snow density (RHO; calculated as SWE/SD) data to ASO data from WYs 2014 to 2016 in the upper Tuolumne basin. MAD is provided as a percentage of the mean ASO quantity.

Furthermore, the normalized SWE differences (by the mean ASO SWE for each bin) do not vary much with forest cover (Fig. S2d), providing additional confidence in using the UA SWE dataset to evaluate satellite products at forested regions.

b. Satellite SWE evaluations

After all compared products are interpolated to a common grid and missing data are masked appropriately (GlobSnow mountain mask is applied to all SWE products to ensure a consistent comparison between all products; Fig. S3), comparisons are performed between the UA SWE data and the AMSR-E, GlobSnow, and CanSISE datasets. Figure 2 shows that AMSR-E SWE has high relative MAD in forested grid cells (73.5% of mean UA SWE). It is known that AMSR-E SWE is poor in forested areas (Foster et al. 2005), and its algorithm attempts to increase SWE values in these areas by considering forest fraction (Chang and Rango 2000). However, the algorithm is still unable to produce reasonable SWE values in forested grid cells. While other SWE product comparisons in Fig. 2 produce a smooth day-to-day transition, the AMSR-E comparison appears noisy. This is due to a relatively large amount of missing

FIG. 2. (left) Comparison of daily mean SWE for all grid cells over the CONUS between UA and (top) AMSR-E, (middle) GlobSnow, and (bottom) CanSISE for all overlapping WYs (2003–09). The mountain mask of GlobSnow is applied to all datasets. Data are stratified by comparing locations (center) dominantly covered by forests and (right) dominantly not covered by forests. Dot color indicates time: 1 Nov is black and 31 May is light gray. The MAD (mm) is provided. The MAD as a percentage of the mean UA SWE is also provided in parentheses along with the MAD IQR. Note changes in the x and y axes.

grid cells daily. Figure 2 also shows that the underestimate of SWE by AMSR-E becomes worse during the snowmelt season.

The GlobSnow SWE product combines a first guess field (obtained by kriging climate station snow depth) with remotely sensed data from the Scanning Multichannel Microwave Radiometer, SSMI, and SSMIS instruments. It uses a microwave inversion model (with a vegetation component) to determine effective grain size so errors should be independent of land cover type. This explains why it performs better than AMSR-E over forested areas (Fig. 2). Despite a more elegant approach to retrieval, GlobSnow still inherits deficiencies from the coarse-resolution microwave data. The MAD is 45.8% of the mean UA SWE when all grid cells are included, but only 36.0% when nonforested grid cells are considered (Fig. 2). Forested grid cells perform the worst with a MAD of 8.7 mm (62.8% of mean UA SWE) and a MAD interquartile range (IQR) of 2.2 mm (47.2%–78.5% of mean UA SWE).

The $1^\circ \times 1^\circ$ CanSISE product has consistently less SWE than UA SWE (Fig. 2, bottom row). With

few forested grid cells available after applying the GlobSnow mountain mask, the comparison for forested grid cells is not useful. However, CanSISE still uses GlobSnow (for nonmountainous grid cells) to estimate SWE. The impact of GlobSnow, which incorporates remotely sensed data, is not as prevalent since CanSISE is an equally weighted mean of five products (the other four do not rely on remote sensing). The remaining products that comprise CanSISE are known to have too little SWE (Broxton et al. 2016a), which is reflected in Fig. 2.

To determine how products compare spatially, maximum SWE from 1 November to 1 March averaged for WYs 2003–09 is compared (Fig. 3). The chosen end date is 1 March because AMSR-E has difficulty retrieving SWE during snowmelt. The ratio of maximum SWE in each of the products to UA maximum SWE (averaged to the grid size of each product) exhibits a similar pattern for AMSR-E and GlobSnow, but CanSISE is markedly different. The expected large underestimation of SWE in mountainous grid cells in the western half of CONUS is apparent for AMSR-E data (green grid cells

FIG. 3. (a) Mean maximum UA SWE (mm) and mean ratio of (b) AMSR-E, (c) GlobSnow, and (d) CanSISE maximum SWE to UA maximum SWE (mm) for all overlapping WYs (2003–09). UA maximum SWE is averaged to match the grid size of each product in (b)–(d). White areas indicate grid cells with less than 10 days of continuous UA SWE.

in Fig. 3b). Forested grid cells located in the northeastern United States and west of the Great Lakes indicate ratios of around 0.5. Even though GlobSnow performs additional processing of brightness temperatures, the western United States (nonmountainous grid cells) are similar to the AMSR-E product. The CanSISE ratios are generally less than one. A few grid cells, mainly in ephemeral areas, have ratios above 1, and these are also areas with little UA SWE.

The interannual correlation r over grid cells where at least one product indicates nonzero SWE averaged for all overlapping water years between UA SWE and the three remotely sensed SWE products is shown in Fig. 4. CanSISE has the highest correlation with the smallest standard deviation, especially from December through March, which may indicate improvements related to non-remote-sensing data sources used in CanSISE. After March, GlobSnow has the lowest correlation, which is likely related to ephemeral areas along the edges of the snowpack (i.e., green grid cells in Fig. 3c) and difficulty in the (nonmasked) western United States.

The correlation between UA and AMSR-E SWE is around 0.4–0.5 throughout the winter until April. The reason for the spikes in the average correlation is possibly related to spurious jumps in AMSR-E SWE data. Figure S4

shows the maximum daily SWE change for WY 2006 from 1 December to 1 March. Large jumps in the UA SWE data are confined to high elevations where one would expect larger increments due to large snowfall amounts. In contrast, grid cells with large jumps are mainly confined to the middle of the CONUS for AMSR-E, which can be caused by the deficiency of the AMSR-E SWE retrieval during melt–refreeze cycles.

Data are also compared using all available WYs for each respective product and with masks applied to the respective product comparison (i.e., GlobSnow mountain mask is only applied to GlobSnow; Fig. S5). There are more years of data used in Fig. S5 than in Fig. 2, which explains the small differences in the GlobSnow SWE results between these two figures. Furthermore, there are more grid cells used in the AMSR-E and CanSISE SWE evaluations when the GlobSnow mask is not applied. These two factors lead to less AMSR-E SWE in both forested and nonforested grid cells and less CanSISE SWE during the second half of winter. The overall conclusions from Fig. S5, however, remain the same as those from Fig. 2.

c. Snow cover evaluations

To further understand the results in section 3b, we compare the SCE values derived from the UA, AMSR-E,

FIG. 4. Correlation between UA SWE and GlobSnow, AMSR-E, and CanSISE SWE averaged for all overlapping WYs (2003–09). The GlobSnow mountain mask is applied to all products. Correlation is the average of temporal correlations over all grid cells where at least one product has SWE. For each product, the dark line shows the average correlation, and the shaded area indicates plus or minus one standard deviation.

and CanSISE data to the IMS data. The threshold (for separating snow-covered versus non-snow-covered grid cells) for UA SWE is determined using sensitivity tests whereby this threshold is set at 1, 3, and 5 mm. Figure 5a shows the cross tabulation between the UA SCE based on these thresholds versus IMS. In general, a lower threshold (e.g., 1 mm) increases the false positives (i.e., where the UA data have snow but the IMS data do not),

and decreases the false negatives (i.e., where the UA data have no snow but the IMS data do). Furthermore, Fig. 5a shows that results are not very sensitive to the threshold value. Therefore, a 3-mm threshold (red lines) is chosen as a balance for the UA data. For AMSR-E, there are conflicting recommendations in the literature about an appropriate threshold. Liang et al. (2008) used an SWE threshold of 1 mm, and Tong and Velicogna (2010) suggested a threshold of 6–8 mm when creating 8-day SCE maps. Here, we perform a similar sensitivity test with the AMSR-E SWE data as with the UA SWE data, except that the thresholds tested are 1, 3, and 6 mm to test the lower end of Tong and Velicogna (2010) (Fig. 5b). Again, a threshold of 3 mm (red lines) is chosen as a balance between 1 mm (black lines) and 6 mm (blue lines). A 3-mm threshold is also used to estimate CanSISE SCE.

Besides IMS, MODIS and RU SCE products are also widely used in weather and climate studies. To further gain the confidence of the UA SWE (which does not use any SCE information in its development) and its derived SCE product, scatterplots between UA versus IMS, RU, and MODIS products are shown in Fig. 6. Overall, the mean UA SCA over CONUS for all categories is slightly higher than the products, especially in forested grid cells. This is an encouraging result as remotely sensed SCA is generally underestimated in forested grid cells (Liu et al. 2008; Raleigh et al. 2013), and UA SWE

FIG. 5. Yearly cross tabulations presented as percentages of the total from 1 Dec through 31 May for overlapping WYs for (a) UA-derived SCE and (b) AMSR-E-derived SCE in comparison with IMS SCE product. Black, red, and blue lines indicate a threshold of 1, 3, and 5 mm applied to the UA SWE product, respectively. Colors are the same for AMSR-E except blue indicates a 6-mm threshold. False positive means that UA (AMSR-E) had snow cover but IMS did not. False negative means that UA (AMSR-E) did not have snow cover but IMS did.

FIG. 6. As in Fig. 2, but for (top) IMS, (middle) MODIS, and (bottom) RU compared to UA-derived SCA ($\times 10^6$ km²). Note changes in the x and y axes.

performs well in forested grid cells when compared to ASO (Fig. S2). Note that missing data due to cloud cover reduce the number of grid cells available for the MODIS comparison. The 25 km $\times$ 25 km RU product agrees well with the UA data for nonforested grid cells (particularly during the snow accumulation period) but has less SCA than the UA in forested grid cells. Since IMS and MODIS are included in the RU product, it cannot be considered truly independent of the other two, despite its inclusion of microwave data and coarser resolution. The average maximum SCA and snow-covered duration compare well between UA and IMS, and the agreements are even better than those between MODIS and IMS (Table 2). The difference in the day of maximum SCA between UA and IMS is similar to those between RU and IMS (Table 2).

Daily cross tabulations provide additional insight into the temporal agreement between IMS and UA SCE (Fig. 7). The percentages of true positives (where both datasets indicate snow) are similar to the true positive percentages in Fig. 5a from late December through mid-March, after which the agreement declines. However, this decline occurs when relatively few grid cells indicate SCE, and so the absolute number of true positives is not

much affected by this decline. After March, most of the snow-covered grid cells reside in the mountainous western United States. False negatives (where UA SCE does not indicate snow but IMS does) stay relatively low, which indicates that the main cause of the decline in true positives is the increase of false positives (where UA SCE indicates snow but IMS does not). Most of these occur when fewer than 20% of the grid cells that are covered by snow at any point in the winter indicate SCE. Similar comparisons between UA and MODIS (not shown) show a similar decline in true positives, but the decline in true positives and increase of false positives do not occur until mid-April. The results in Figs. 6 and 7 indicate the overall close agreement (in the spatial pattern each day and in the seasonal variation of daily data) between the SCE data derived from the UA SWE product (which uses no SCE information from any sources in its development) and the IMS and MODIS data.

The agreement between UA and IMS SCA (Fig. 6) is also better than those between data derived from AMSR-E, GlobSnow, and CanSISE SWE products and the IMS data (Fig. 8). The GlobSnow mountain mask is applied to all products as in Fig. 6 using all overlapping WYs (2007–09). The AMSR-E-derived SCA compares

TABLE 2. Average maximum SWE (mm) and SCA, WY day of maximum, and snow-covered duration for SWE (the number of continuous days of SWE averaged over the CONUS above 1.5 mm) and SCA (the number of continuous days of SCA above $1.5 \times 10^6 \text{ km}^2$). The AMSR-E, GlobSnow, and CanSISE columns utilize the GlobSnow mask. Results include only overlapping years (2003–09 for SWE and 2007–09 for SCA). Values in parentheses for SWE and SCA are the UA SWE and IMS SCA values, respectively, after interpolation to the specific product's grid. Dashes for MODIS, RU, and IMS indicate that no SWE values are available.

	UA	AMSR-E	GlobSnow	CanSISE	MODIS	RU	IMS
SWE							
Max	27.6	14.4 (21.9)	13.4 (18.3)	6.4 (12.3)	—	—	—
Day of max	148	133 (142)	140 (147)	114 (140)	—	—	—
Duration	219	98 (83)	109 (141)	130 (151)	—	—	—
SCA							
Max ($\times 10^6$)	4.4 (4.4)	2.9 (3.0)	2.8 (3.7)	3.7 (3.5)	2.0 (2.3)	4.4 (4.4)	4.4
Day of max	105 (118)	119 (93)	106 (96)	118 (106)	113 (114)	110 (105)	118
Duration	111 (109)	141 (141)	142 (139)	139 (140)	170 (146)	112 (115)	109

much better with IMS (Fig. 8, top row; Table 2). The MAD is 22.3% of mean IMS SCA when all grid cells are considered, decreasing to 19.2% for nonforested grid cells. The MAD increases to 40.9% when only forested grid cells are considered, but the performance in forested grid cells is still much better for SCA here than for SWE (Fig. 2). On the other hand, the relatively larger SCA underestimation for forested grid cells than nonforested grid cells (Fig. 8) is similar to the SWE comparison (Fig. 2). The average maximum extent and snow-covered duration compare well to IMS, but the day of maximum extent is 26 days late (Table 2).

GlobSnow-derived SCA is much less than IMS for the first half of winter but only a slight underestimation exists for the second half of winter for both forested and nonforested grid cells (Fig. 8, middle row). The MAD for forested grid cells is 39.2% of the mean IMS SCA with an IQR of 36.9%–41.6%. The reason for poor performance of early winter GlobSnow SCA is primarily an unrealistically low SCE over the northeastern United States compared to both IMS and UA, and problems with the southern (ephemeral) edge of the snowpack. Figure 3c provides an example that GlobSnow has difficulty providing SWE (and associated SCE) in the northeastern United States and along the southern edge of the snowpack. Underestimations may also stem from the dry-snow mask that GlobSnow requires before estimating SWE. GlobSnow compares well with IMS for the maximum extent date and snow-covered duration, but its maximum SCA differs most from IMS compared with the differences between other products and IMS (Table 2).

The CanSISE-derived SCA dataset performs the best compared to IMS (Fig. 8, bottom row). Similar to all products, forested SCA relative MAD is worse than nonforested. Since the threshold was determined via sensitivity tests with the higher-resolution IMS product, we have tested other thresholds with the lower-resolution CanSISE product and found that higher thresholds

show slightly better agreement between UA and CanSISE (not shown). CanSISE agrees with IMS in the maximum SCA and the snow-covered duration, but the maximum occurs 12 days later in CanSISE (Table 2).

A comparison without applying the GlobSnow mountain mask to all products is available in Fig. S6. While the overall SCA values are larger due to an increase in sampled areas, results are similar. Differences for GlobSnow are due to a different sample of years.

4. Further discussion

The good comparison between the UA SWE data and lidar-based (ASO) SWE data and higher-resolution

FIG. 7. Daily tabulations between IMS and UA snow cover extent (threshold of 3 mm) with shaded error bars of one standard deviation of each category, respectively. Daily values are normalized by the daily total number of grid cells where at least one product indicates snow cover. The data covers WYs 2007–15 from 1 Dec to 31 May. False negative indicates that UA did not have snow cover but IMS did, and false positive indicates that UA had snow cover but IMS did not. Overlaid is the daily total number of pixels where at least one product indicated snow cover (normalized by the maximum number of grid cells). Missing data are masked across both products.

FIG. 8. As in Fig. 6, but for (top) AMSR-E, (middle) GlobSnow, and (bottom) CanSISE derived SCA ($\times 10^6 \text{ km}^2$) compared to IMS SC. Only overlapping WYs are shown (2007–09) and the GlobSnow mountain mask is applied to all products. Snow cover thresholds are 0.001 mm for GlobSnow and 3 mm for CanSISE and AMSR-E. Note changes in the x and y axes.

satellite SCE data demonstrates that it is an effective product to bridge the scale gap between local-scale (e.g., lidar; $<100\text{-m}$ grid spacing) and coarse (e.g., satellite remotely sensed data; $>25\text{-km}$ grid spacing) SWE data. These and prior evaluations demonstrate that the UA product has passed four rigorous tests: consistency and robustness tests (as mentioned in section 2; Broxton et al. 2016a,b) as well as comparison with independent airborne lidar (ASO) data and the easier-to-measure satellite-derived SCE data (discussed in section 3). In addition, it provides daily SWE and snow depth data for more than 35 years, so it can be used to provide a more comprehensive and quantitative measure of the performance of SWE products over a longer period and over a larger area than was possible in the past.

In this study, we used these data to evaluate the AMSR-E, GlobSnow, and CanSISE SWE products over regional to continental scales. This evaluation is preferable to that with in situ data because of the widely recognized challenge of matching point and gridded SWE data (Molotch and Bales 2005). Furthermore, the UA dataset offers advantages over other gridded SWE datasets such as the Snow Data Assimilation System (SNODAS; Barrett 2003) because of the much longer

data record (as SNODAS began in 2003). Furthermore, although some studies showed that SNODAS can successfully simulate snow depth changes depicted in airborne lidar surveys (e.g., Hedrick et al. 2015), other studies found that SNODAS estimates of SWE and snow density can be uncertain, particularly in mountainous environments (Clow et al. 2012; Boniface et al. 2015; Dawson et al. 2017).

On average, AMSR-E, GlobSnow, and CanSISE underestimate maximum SWE in areas of high SWE (though they also overestimate maximum SWE in some areas with low SWE; Fig. 3). These products all have a slightly early date of maximum SWE, and GlobSnow and CanSISE's snow season duration is shorter by more than 20 days when compared to UA SWE (Table 2). CanSISE, while depicting less SWE than the UA product in most places (e.g., Table 2), consistently compares better to UA SWE than the other two products in terms of the interannual variability of SWE for a given day, particularly during the middle of the winter (Fig. 4). GlobSnow and AMSR-E SWE are comparable to UA SWE for nonforested grid cells as the lower ends of the MAD IQR are less than 30% of mean UA SWE data (Fig. 2). This is comparable to the MAD of 30%

between the UA SWE data and ASO data. All three products perform better in nonforested grid cells than in forested grid cells (Fig. 2). Since GlobSnow uses a microwave inversion model (with vegetation canopy), this suggests that improvements can be made to the microwave vegetation model in forested regions. All three products (but especially AMSR-E) are closer to the UA SWE data earlier in the snow season, with larger differences developing later in the snow season (Fig. 2). One factor (besides snowmelt) that could influence especially the AMSR-E product is that snow density in AMSR-E's retrieval algorithm is treated as temporally constant (Byun and Choi 2014), whereas it can vary by a factor of 2 or more through the course of the snow period (Dawson et al. 2017). This would cause an incorrect conversion between snow depth and SWE in the AMSR-E product for at least part of the cold season.

For comparison, there is an overall close agreement (in the spatial pattern each day and in the seasonal variation of daily data) between the SCE data derived from the UA SWE product (which uses no SCE information from any sources in its development) and the IMS, MODIS, and RU products (Fig. 6). This is encouraging because it is easier to detect SCE from satellite remote sensing than it is to measure SWE (Frei et al. 2012). The largest difference between SCE derived from the UA SWE product and the satellite SCE data occurs during snowmelt and along snow edges where SCE is ephemeral and SWE values are low. The SCA differences over forested versus nonforested grid cells between UA and IMS or MODIS (Fig. 6) are much smaller than the SWE differences between AMSR-E or GlobSnow and UA (Fig. 2), suggesting that SCE is less affected by forests than SWE. Note that while the IMS, MODIS (as compared here), and RU products are binary (snow versus no snow) and their effective threshold SWE values are unknown, binary or fractional SCE can be derived from UA SWE in a similar manner as Tong and Velicogna (2010).

The SCA agreement between UA and IMS (Fig. 6) is better than those between the three products (AMSR-E, GlobSnow, and CanSISE) and IMS (Fig. 8). Of these products, agreement is better over nonforested grid cells, and it is best between CanSISE and IMS (Fig. 8). In contrast, the SCA agreement between UA and IMS (or MODIS) is quite similar over nonforested versus forested grid cells (Fig. 6), suggesting that the UA dataset is useful over both nonforested and forested regions. This is further demonstrated by the good performance of the UA SWE data with the increase of forest cover in comparison with the ASO data (Fig. S2).

Some of the discrepancies between the AMSR-E, GlobSnow, and CanSISE SWE products and the

intermediate-resolution data (UA SWE and IMS SCE) may be related to their coarse grid size. To explore this issue, we compare the UA SWE product at its original resolution and at coarser resolutions, averaged over six CONUS regions (Figs. S7, S8). Negligible differences exist between the original UA SWE data ($\sim 4 \text{ km} \times 4 \text{ km}$ grid cell size) and the averaged data at a coarser $25 \text{ km} \times 25 \text{ km}$ grid cell (resolution of AMSR-E and GlobSnow), suggesting that grid size is not a major issue. The UA SWE data coarsened to $1^\circ \times 1^\circ$ grid cell (resolution of CanSISE) exhibit a small decrease, but this may be because the large grid cells incorporate areas outside of the latitude–longitude boundaries used in Fig. S7 (gridcell latitude–longitude centers within each region are selected). Furthermore, the difference between the $\sim 4 \text{ km} \times 4 \text{ km}$ and the $1^\circ \times 1^\circ$ UA SWE data are small compared to the difference between the UA SWE data and the AMSR-E, GlobSnow, and CanSISE SWE data on their respective grids.

5. Conclusions and outlook

This study indicates that while our intermediate grid-size product (UA SWE) is capable of providing reasonable SWE (when compared to infrequent small-scale lidar surveys) and SCE data remotely sensed over the CONUS, where there is a dense network of ground observations, remotely sensed SWE products remain deficient in many areas. Our findings are in general agreement with previous research, which suggests that no single remotely sensed product is capable of reliable SWE estimates (e.g., Wang and Tedesco 2007; Gao et al. 2010; Foster et al. 2011). Instead, a combination of products that utilize remotely sensed data ($>25\text{-km}$ grid spacing) and intermediate products ($0.1\text{--}25\text{-km}$ grid spacing, including ground-based observations) is needed, especially in areas where satellite remote sensing of SWE has the most trouble, for example, mountainous and forested regions. These areas are where station-based products can provide the most improvement. UA SWE's unique strength is the use of snowfall to constrain the interpolation and the consistent assimilation of all available in situ SWE and snow depth data. This constraint provides reasonable SWE estimates in mountainous terrain as well as flat regions, allowing UA SWE to bridge the gap between small-scale lidar and SWE datasets that at least partly utilize remotely sensed data.

Because of the deficiencies identified in this work and in prior studies, the remote sensing retrieval of SWE needs to be improved; for example, using insights gained from this study and/or using alternative approaches, such as the application of artificial neural networks

(Tedesco et al. 2004; Tedesco and Narvekar 2010; Tong et al. 2010). Alternative approaches for estimating SWE based on remote sensing data [e.g., using satellite SCE data along with inverse SWE modeling to estimate SWE based on snow disappearance as in Bair et al. (2016); Schneider and Molotch (2016)] could be further explored. Furthermore, continued field measurements, such as the ongoing SnowEx campaign (<https://snow.nasa.gov/campaigns/snowex>), are necessary to determine an optimal set of remotely sensed data for snow quantity retrieval. While it is infeasible to collect continuous daily airborne and ground-based SWE measurements, these field campaign measurements (such as the ASO data) must also be used to provide further evaluation of SWE products.

Based on this work, we plan to create a global version of the UA SWE dataset by combining global temperature and precipitation datasets with limited in situ SWE and/or snow depth measurements and by improving global remote sensing SWE retrieval based on the UA product over the CONUS. This will involve designing a weighting scheme for different SWE data according to their various strengths. A method to combine sources of information is to use an ensemble Kalman filter (Andreadis and Lettenmaier 2006; Liu et al. 2013; Kumar et al. 2014, 2015) to combine all products to provide an optimal global SWE estimate by using error statistics created by the results presented in this study.

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