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Permalink

<https://escholarship.org/uc/item/2fh673k4>

Journal

Journal of Atmospheric and Oceanic Technology, 43(1)

ISSN

0739-0572

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[et al.](#)

Publication Date

2026

DOI

10.1175/jtech-d-25-0023.1

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Peer reviewed

Surface Quantitative Precipitation Estimates (SQUIRE) of Snow Water Equivalent from the Surface Atmospheric Integrated Field Laboratory

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(Manuscript received 19 March 2025, in final form 27 August 2025, accepted 24 November 2025)

ABSTRACT: The upper Colorado River basin is the primary source of water for 40 million people. With declining snowpack in the basin, forecasting hydrological budgets in the Southwest United States is more important than ever. However, due in part, to a lack of reliable observations of precipitation in complex terrain, hydrological models struggle to assess and forecast snowpack snow water equivalent (SWE) in the upper Colorado River basin (UCRB). Therefore, the need for more reliable SWE forecasts in the UCRB motivated the U.S. Department of Energy Atmospheric Radiation Measurement Facility's Surface Atmospheric Integrated Field Laboratory (SAIL) that occurred from June 2021 to June 2023. During SAIL, the X-band precipitation radar from Colorado State University conducted volume scans sampling the precipitation properties over the UCRB. The ARM facility developed a gridded Surface Quantitative Precipitation Estimates (SQUIRE) product from the radar observations. To do this, various daily SWE estimates from radar using the radar reflectivity factor Z_e and specific differential phase K_{dp} were compared against ground-based precipitation gauges. SWE in precipitation calculated from Wolfe and Snider's $S-Z_e$ estimator was in best agreement with the rain gauges for the days when $SWE < 12$ mm. For days with $SWE > 12$ mm, the WSR-88D Intermountain West relationship had the best agreement with the precipitation gauges. Airborne snow depth observations show that SQUIRE captures regions of orographic enhancement in the mountains to the west and northwest of the SAIL study area, indicating that the scientific community should focus on understanding and ultimately simulating orographic atmospheric precipitation processes to improve UCRB snowpack SWE assessment and forecasting.

SIGNIFICANCE STATEMENT: This paper looks at snowfall estimates from data collected during a field experiment in the upper Colorado River basin, a critical source of water for 40 million people in the United States. Here, our typical radars do not detect precipitation in this crucial region, so we detail the methods we used to estimate snowfall rates from these new data that will help scientists better predict the amount of water that will be available for people living in the Southwest United States.

KEYWORDS: Snow; Hydrology; Radars/Radar observations

1. Introduction

The Colorado River is the main source of water for 40 million people in the Southwest United States (James et al. 2014). The upper Colorado River basin (UCRB) provides 90% of the water flow into the Colorado River (Lukas and Payton 2020). Since the 1980s, the snowpack in the UCRB has been declining (McCabe and Wolock 2009; Mote et al. 2018), and this trend is expected to persist due to rising global temperatures (McCabe and Wolock 2007; Lute et al. 2015; Marshall et al. 2019; Siirila-Woodburn et al. 2021). Trends in

temperature and precipitation have been found to equally influence snowpack accumulations (Clow 2010; Kalra et al. 2017; Wi et al. 2012). Therefore, accurately estimating the hydrological budget of the UCRB, including snow water equivalent (SWE) precipitation, is crucial to prepare the Southwest United States for increasing droughts, but this could become even harder in the future as our measurement systems become less sensitive to precipitation in the UCRB (Livneh and Badger 2020; Cowherd et al. 2024).

There are fundamental questions about the dominant sources of hydrological uncertainty in the UCRB. Observations of the atmosphere are so sparse that hydrological models may be better informed by atmospheric process model simulations than actual atmospheric observational products (Lundquist et al. 2019). But, essential understanding of UCRB system dynamics remains lacking, leading to major unresolved scientific uncertainties in how much water there is (the “missing water” problem) and where it is going (Woodhouse et al. 2016; McCabe et al. 2017; Milly and Dunne 2020; Hogan and Lundquist 2024). These works showed that UCRB hydrological modeling depends on precipitation and many other processes. Here, we

 Denotes content that is immediately available upon publication as open access.

 Supplemental information related to this paper is available at the Journals Online website: <https://doi.org/10.1175/JTECH-D-25-0023.s1>.

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DOI: 10.1175/JTECH-D-25-0023.1

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focus on precipitation because it is central to the study of UCRB hydrology (Hoerling et al. 2024), one of the dominant sources of uncertainty in hydrological modeling (Raleigh et al. 2015) and the result of many qualitatively known but poorly modeled atmospheric processes (Hoerling et al. 2024). But, precipitation science in complex terrain is fundamentally challenged by the complexities of actually measuring precipitation in complex terrain.

Estimating the amount of snowfall on the UCRB remains a challenge due to the difficulties in installing instruments in complex terrain. Although snow gauges can directly measure SWE, a dense network is required to produce spatial maps of snowfall. Furthermore, wind-induced undercatch can impact snow gauge measurements (Colli et al. 2020; Kochendorfer et al. 2020). Satellite and radar systems can provide continuous spatial coverage. However, operational radar systems like the Next Generation Weather Radar (NEXRAD) network are not well suited to achieve this coverage because precipitation estimates are significantly impacted by beam blockage, resulting in under- and nondetection of precipitation in complex terrain (Young et al. 1999; Maddox et al. 2002). Satellite precipitation estimates such as the Global Precipitation Measurement (GPM) mission are not expected to be affected by beam blockage and, therefore, can scan areas obstructed in the NEXRAD network (Houze et al. 2015). However, SWE estimates from satellite-derived products, such as the Integrated Multi-satellite Retrievals for GPM (IMERG), are also reported to have significant biases in complex terrain (Ramsauer et al. 2018; Barros et al. 2020). Additionally, the Multi-Radar Multi-Sensor (MRMS) system product not only assimilates NEXRAD observations with ground-based observational networks and forecast models to estimate SWE over a Cartesian grid (Zhang et al. 2016) but also suffers from biases due to beam blockage in complex terrain (Bytheway et al. 2019). Furthermore, forested mountain areas are underrepresented in such networks, exacerbating biases in SWE estimates from MRMS and IMERG (Sevruk 1997; Frei and Schär 1998; Rasmussen et al. 2012; Henn et al. 2015).

Absent a technological breakthrough, the undermeasurement of precipitation across mountainous systems like the UCRB will persist (Bales et al. 2006). Scientific advances that use limited data to advance atmospheric process modeling present a promising path toward actually reducing the UCRB hydrological budget uncertainty (Lundquist et al. 2019). While atmospheric models are currently outperforming gridded satellite and radar products in predicting total annual rain and snowfall over complex terrain (Lundquist et al. 2019), further reductions in uncertainties in SWE estimates from atmospheric models require multidisciplinary efforts using both models and a comprehensive set of measurements from various sources, including radars, gauges, and satellites covering undersampled regions in complex terrain (Lundquist et al. 2019).

These requirements motivated the Surface Atmospheric Integrated Field Laboratory (SAIL) experiment conducted from 1 September 2021 to 15 June 2023 in the UCRB (Feldman et al. 2023). The U.S. Department of Energy (DOE) Atmospheric Radiation Measurement (ARM) Facility deployed the ARM Mobile Facility 2 (AMF2), a comprehensive suite of aerosol, meteorological, and precipitation instruments in the UCRB over two winters from 2021 to 2023 in Gothic,

Colorado (Mather and Voyles 2013; Feldman et al. 2023). These data were collected to advance the understanding of how the atmosphere and surface interact to produce the measured snowpack patterns that emerge in complex terrain at the end of winter. The advancements in understanding of those processes that control snowpack patterns are ultimately how a campaign like SAIL, or other campaigns in complex terrain, can drive process model advancement over the UCRB.

Before this can happen, however, a thorough understanding of the measurements themselves must be achieved. The precipitation measurements from the AMF2 included a Pluvio weighing bucket rain gauge and a laser disdrometer. In addition, Gothic weather (<https://www.gothicwx.org/>) has been measuring daily SWE in Gothic, Colorado, about 50 m from the AMF2. Finally, Colorado State University (CSU) deployed a dual-polarization X-band radar approximately 6 km southeast of Gothic, Colorado, providing volume scans of precipitation properties over Gothic at 250-m spatial resolution and 5-min temporal resolution (Fig. 1).

The spatial and temporal resolutions of the X-band radar are far more comprehensive than point measurements and, therefore, contain the most information on those precipitation processes that impact how spatial patterns of snowpack emerge. However, SWE estimates from the suite of measurements collected at SAIL are a nontrivial process. For one, precipitation measurements only provide point measurements of SWE. In addition, scanning radars do not measure SWE, but rather, SWE is calculated from empirical relationships between snowfall rate S and equivalent radar reflectivity factor Z_e , differential reflectivity Z_{dr} , and specific differential phase K_{dp} (i.e., Marshall and Gunn 1952; Sekhon and Srivastava 1970; Puhakka 1975; Boucher and Wieler 1985; Fujiyoshi et al. 1990; Matrosov et al. 2009; Wolfe and Snider 2012; Bukovčić et al. 2018, 2020; Capozzi et al. 2020). Furthermore, the suitability of a given empirical relationship depends on factors such as the snow effective density, particle habit, particle size distribution, and radar wavelength. Before SAIL deployed data, it was expected that estimates of the liquid water content of precipitation at SAIL would be highly uncertain, potentially by $\pm 30\%$ (Matrosov et al. 2009).

However, these SWE estimates are essential for constraining hydrological models, as current gridded estimates suffer from large biases in complex terrain (Ramsauer et al. 2018; Barros et al. 2020). These needs and challenges motivated the U.S. DOE ARM Facility to develop the Surface Quantitative Gridded Precipitation Estimate (SQUIRE) product from the suite of SAIL radar and SWE observations. SQUIRE incorporates a methodology for estimating SWE throughout SAIL by evaluating the suitability of various SWE estimators using the SWE measurements from ground-based sites. This product builds upon past efforts to use gap-filling radar observations with narrow beamwidth radars to obtain more accurate SWE estimates in complex terrain, such as in the mountains of California (Cifelli et al. 2018; Willie et al. 2017), as well as current operational techniques used in the Swiss Alps (Germann et al. 2006).

In this paper, we will discuss how the SQUIRE product was developed for the SAIL campaign. Section 2 will discuss the

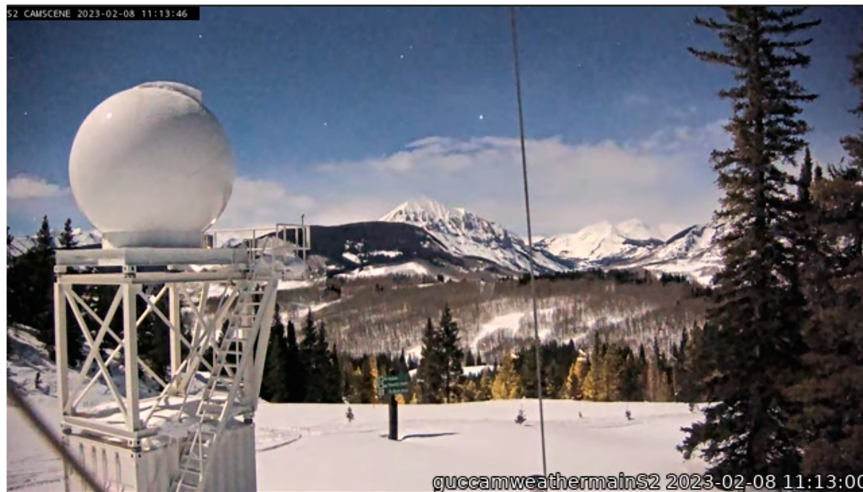


FIG. 1. CSU X-band precipitation radar overlooking the East River watershed in the UCRB. Image taken from the ARM "camweathermainmovie" datastream (Stuefer and Wong 2022).

methodology for estimating SWE from the suite of SAIL observations. Section 3 evaluates the different radar-based SWE estimators using ground-based measurements and provides a summary of the seasonal SWE statistics over Gothic for the two SAIL winters. Finally, section 4 presents the main conclusions of this study and discusses how SQUIRE observations can support larger efforts to advance UCRB hydrology science.

2. Data and methods

a. CSU X band and calibration

The CSU X-band precipitation radar (XPrecipRadar) was installed at a supplemental site about 6 km east-southeast of

the AMF1 (Figs. 1 and 2). The XPrecipRadar performed plan position indicator (PPI) scans at 1°, 2°, 4°, 6°, 8°, 10°, 12°, and 45° every 5 min to provide a full volume scan of radar moments over the area shown in Fig. 2. XPrecipRadar's beamwidth is 0.3° with a gate spacing of 60 m. The pulse repetition frequency was set such that XPrecipRadar had a maximum unambiguous range of 40.2 km and a Nyquist velocity of 15.9 m s⁻¹. The lowest heights above the ground that were observable in the complex terrain were generally less than 1.5 km in the East River basin (Fig. 2). For this study, we consider all XPrecipRadar data taken between 1 December and 31 March for both the 2021–22 and 2022–23 seasons. This, in combination with only using radar gates identified as snow

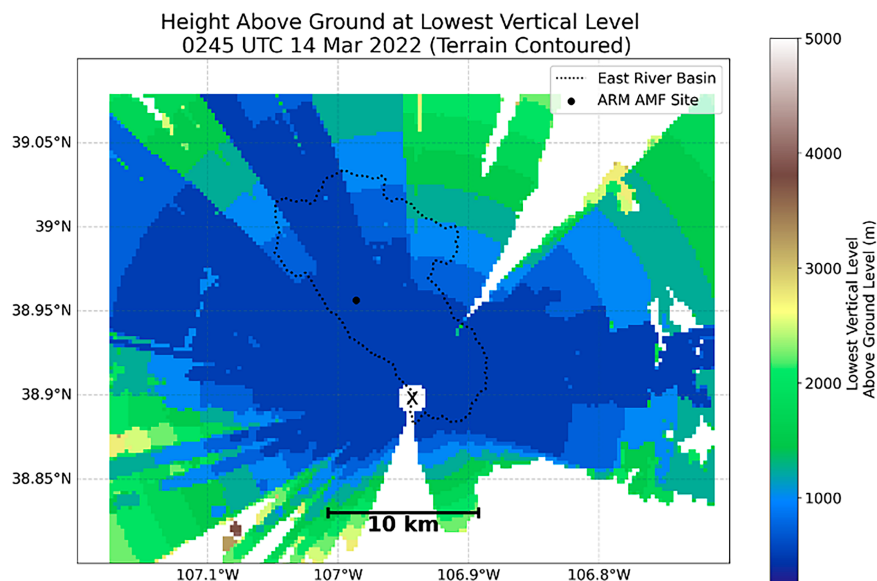


FIG. 2. The lowest height above ground level scanned by the CSU X-band precipitation radar. The "X" denotes the location of the CSU X-band radar.

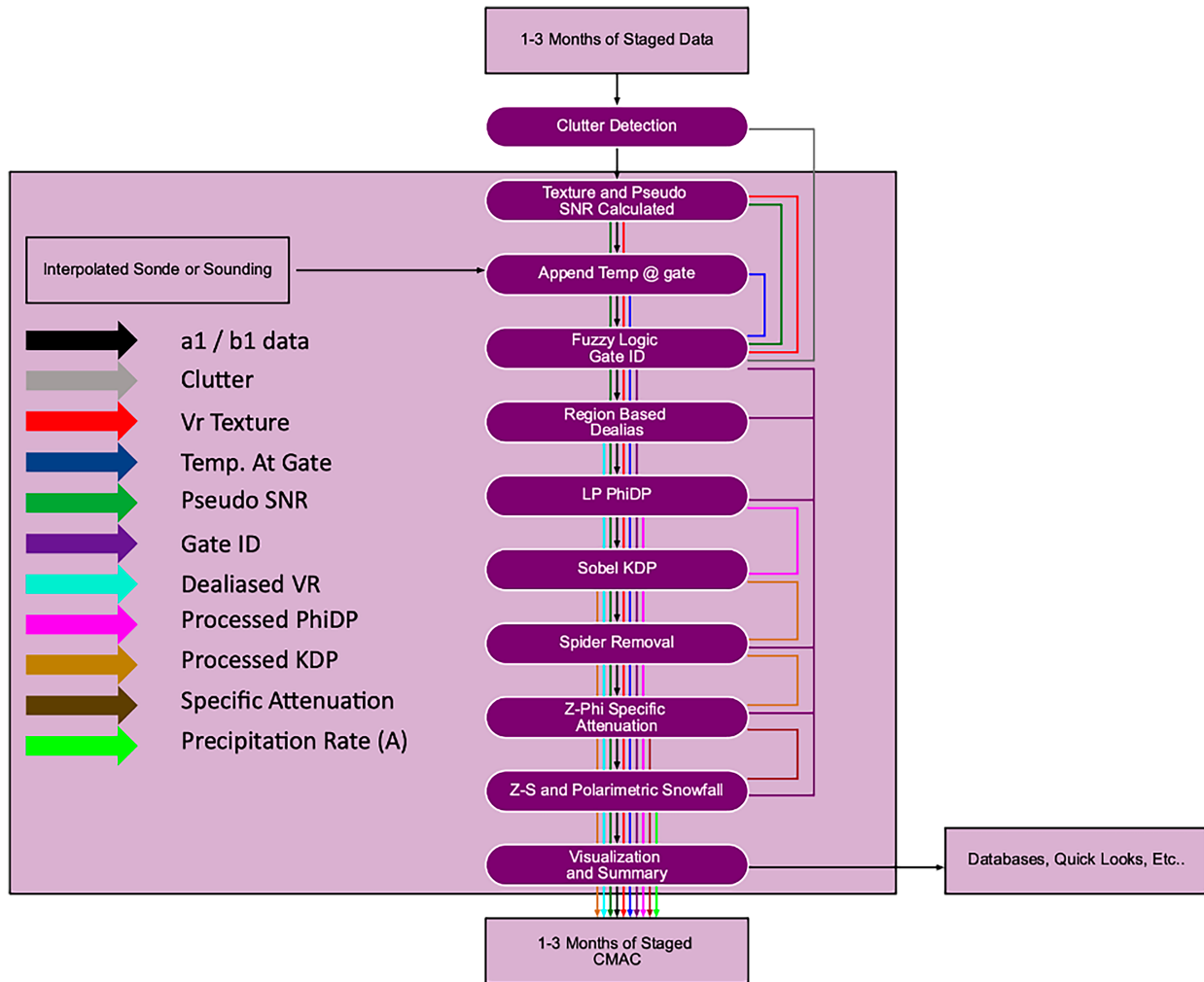


FIG. 3. Workflow for CMAC.

using the methodology in [section 2b](#), ensures that we are not including scans with rainfall at the 1° elevation scan.

Calibrated values of Z_e are crucial for accurately estimating SWE using radar-based estimators. For example, a 0.5-dB error in Z_e can result in a 9.4% error in SWE, and a 2.0-dB error can produce a 36.7% error in calculated SWE. Therefore, we performed an absolute calibration of Z_e using a target simulator. This calibration demonstrated that the XPrecipRadar Z_e exhibited a low bias of 2 dB. This low bias was subsequently verified by comparing Z_e from the 0.5° tilt over Gothic to simulated Z_e measurements generated from the ARM disdrometer observations using T-matrix scattering theory ([Mishchenko et al. 1996](#)). Therefore, we applied a 2-dB offset to Z_e to provide calibrated Z_e for estimating SWE.

b. Corrected Moments in Antenna Coordinates

To utilize the XPrecipRadar moments for estimating SWE, the XPrecipRadar data must be first corrected for artifacts due to beam blockage, clutter, multitrip echoes, and attenuation. In addition, the phase data must be dealiased and

denoised before deriving K_{dp} . To do this, we have implemented a workflow called Corrected Moments in Antenna Coordinates (CMAC), shown in [Fig. 3](#). CMAC is based around the Python ARM Radar Toolkit (Py-ART), using Py-ART for data ingest, visualization, and processing ([Helmus and Collis 2016](#)). CMAC first determines what gates are hydrometeors for processing by applying a series of algorithms to classify gates into seven categories: rain, snow, no hydrometeors, multitrip, melting layer, clutter, and beam blockage. To start this classification, the clutter and beam blockage maps must be determined. To calculate the clutter maps for flagging gates as clutter, CMAC uses statistics from Z_e in a month of clear air data to flag persistent returns as clutter ([Lakshmanan et al. 2012](#)). Beam blockage flags, numbers from 0 to 1 indicating the percent of the radar beam blocked by terrain, are then created using the technique of [Bech et al. \(2003\)](#), implemented in `ωradlib` that uses a digital elevation map of the UCRB ([Heistermann et al. 2013](#)). These two flags are then used to classify gates as clutter and beam blocked.

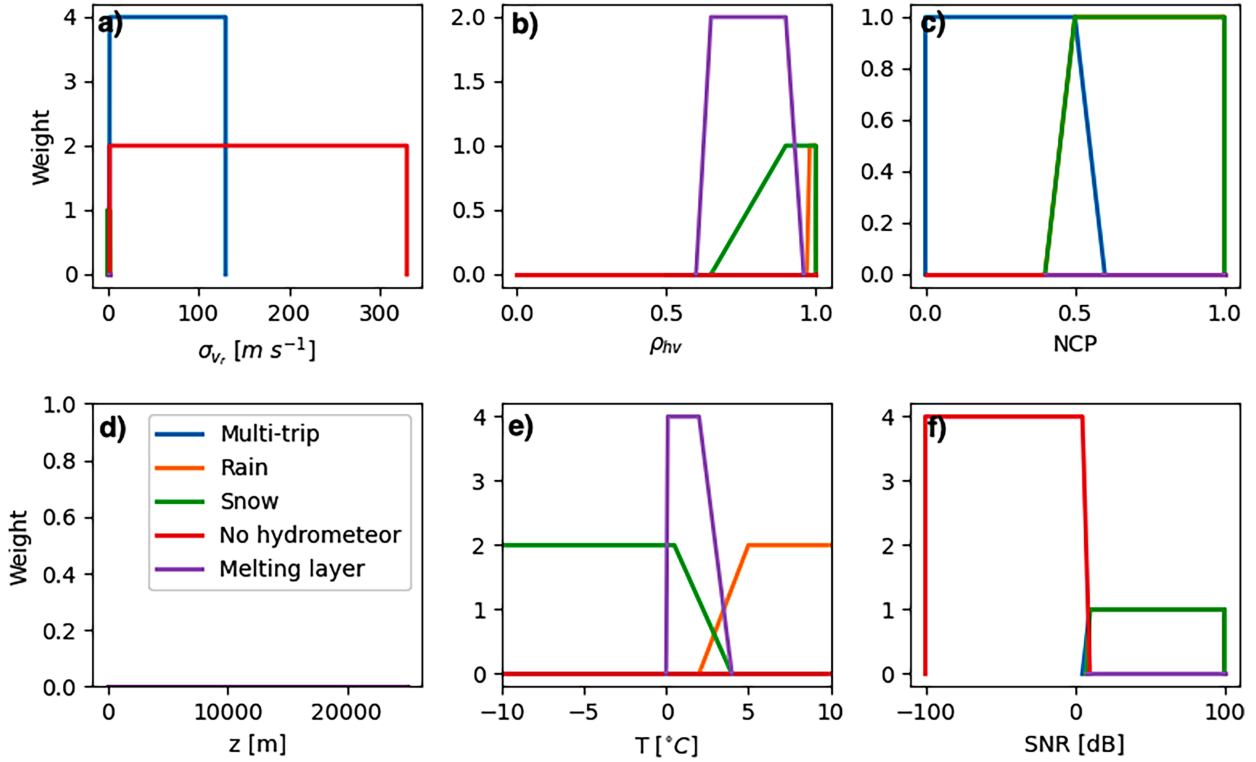


FIG. 4. Trapezoidal membership functions used by fuzzy logic gate identification in CMAC to classify each gate before processing.

Second, after classifying and removing clutter and beam-blocked gates, CMAC distinguishes the remaining gates that represent hydrometeors from nonhydrometeors using a fuzzy logic classifier that determines the probability that the gate is a given category given as a score. Fuzzy logic classifiers were first used by Vivekanandan et al. (1999) to classify radar hydrometeor type from S-band radar. Fuzzy logic classifiers are typically used to distinguish between different types of hydrometeors after processing, such as those developed by Dolan and Rutledge (2009), Al-Sakka et al. (2013), and Wen et al. (2015). However, CMAC classifies gates as hydrometeors or nonhydrometeors before any other processing is done, following Neely et al. (2018), Dufton and Collier (2015), Gourley et al. (2007), Cho et al. (2006), and Schuur et al. (2003). This ensures that only hydrometeors are included in processing the radar moments in the later steps. For the fuzzy logic classifier, σ_{v_r} , the texture of the radial velocity v_r over a 3×3 gate window, is calculated to distinguish hydrometeors from noise and multitrip echoes (Jackson et al. 2018). To preserve aliased velocities in regions with hydrometeors, v_r is projected onto a unit circle that has a smooth transition between the Nyquist velocity V_{nyq} and $-V_{nyq}$ before σ_{v_r} is calculated. In addition, temperature T from the nearest rawinsonde launch in time is projected onto each radar gate. Finally, the signal-to-noise ratio (SNR) is estimated using the Py-ART SNR estimation algorithm (Helmus and Collis 2016). The algorithm calculates the radial average of $Z_e - 20 \log r$ at 25-km range as the noise floor then dividing $Z_e - 20 \log r$ by the noise floor at each gate. The $20 \log r$ term, where r is the range in kilometers,

accounts for the expected decrease in backscattered power with the square of the range.

Fuzzy logic identification algorithms require membership functions of radar moments for given classes that represent the typical distribution of radar moments for a given category. CMAC uses trapezoidal membership functions, shown in Fig. 4. These membership functions were determined by trial and error by testing membership functions from the literature (Gourley et al. 2007; Dolan and Rutledge 2009; Al-Sakka et al. 2013). For the σ_{v_r} membership function, Fig. 4a is consistent with Jackson et al. (2018)'s threshold for distinguishing clear air and precipitation. Rain drops from T-matrix simulations have $\rho_{hv} > 0.95$ at X band and ρ_{hv} from 0.6 to 0.95 (Al-Sakka et al. 2013) for snow. Gourley et al. (2007)'s membership functions have $\rho_{hv} < 0.95$ as being representative of nonhydrometeors. More specifically, second trip echoes typically have ρ_{hv} ranging from 0.6 to 0.95 (Fig. 4b) (Zhang et al. 2021). Multitrip echoes typically have normalized coherent power (NCP) less than 0.5, since the signal would be less coherent than that from rain or snow (Fig. 4c). The T membership functions are from Islam et al.'s (2013) fuzzy logic-based algorithm identifying the melting layer and where rain and snow are present. Finally, the SNR membership function has a transition region from 2 to 8 dB to distinguish between nonhydrometeors and hydrometeors (Fig. 4d), matching Zhang et al.'s (2021) SNR threshold of 5 dB for hydrometeors. While CMAC's fuzzy logic scheme supports membership functions based on height above the radar, height was not factored as an input variable due to the variable nature of the melting-

TABLE 1. Hard constraints used to force given category's score to be zero.

Category	Condition
Melting layer	$T > 10^{\circ}\text{C}$
Melting layer	$T < -2^{\circ}\text{C}$
Melting layer	$\sigma_{vr} > 3$
Rain	$T < -5^{\circ}\text{C}$
Multitrip	$z > 10\text{ km}$

layer heights observed by the XPrecipRadar during the SAIL. Finally, after the fuzzy logic classification is made, hard constraints are placed on gates to further modify this classification to enforce zero scores for the given category so that unrealistic classifications are not made (Table 1). The category with the highest score is then determined to be the classification for the gate.

After the gate is classified, the remainder of the CMAC workflow operates on the rain and snow gates. The Φ_{dp} is then unwrapped and processed to remove noise using a finite response filter, from which then $K_{dp} = (1/2)[d(\Phi_{dp})/dr]$ is calculated. The v_r is dealiased using the region-based dealiasing algorithm from Py-ART (Helmus and Collis 2016). The Z_e and Z_{dr} are corrected for attenuation using the Z-PHI method (Gu et al. 2011). Figure 5 shows CMAC applied to XPrecipRadar PPI scans from snowfall case sampled during SAIL on 14 March 2022. The bottom third of the scan is blocked, with all of the hydrometeor returns identified as snow (Fig. 5a), with $\sigma_{vr} < 2$ in these regions (Fig. 5c). CMAC is ensuring that no blocked gates or noise present in Fig. 5b are present in Fig. 5d.

c. Radar-based SWE estimators

Estimating SWE from the CMAC-corrected radar moments is a nontrivial task. In many past studies using scanning radars, snowfall rate S has been estimated by using an empirical relationship in the form of $S = aZ^b$ (Marshall and Gunn 1952; Sekhon and Srivastava 1970; Braham 1990; Fujiyoshi et al. 1990; Matrosov 1992; Matrosov et al. 2009; Wolfe and Snider 2012). The a and b coefficients vary significantly due to the different densities (Matrosov 1992), degrees of riming (Matrosov et al. 2009), and particle size distributions (PSDs) of snowflakes that are encountered in various conditions (Table 2). In recent years, Capozzi et al. (2020) and Bukovčić et al. (2018, 2020) have developed estimators using the specific differential phase K_{dp} , in the form of $S = aZ_e^b K_{dp}^c$. This form accounts for variability in snowflake number concentrations since K_{dp} is directly proportional to the number of snowflakes present. The B18-KDP and B18-Z-KDP estimators, adapted to X band by Capozzi et al. (2020), are listed in Table 2 alongside Capozzi et al.'s (2020) estimators.

Therefore, to determine which of these relationships provides the best estimate of S , estimates of daily SWE from radar-estimated S must be compared against the independently measured bulk SWE observations. Comparing daily SWE estimates from XPrecipRadar observations and the Pluvio² and Gothic weather measurements requires that the radar column directly above Gothic, Colorado, be extracted. This is done using the ARM Extracted Radar Columns and In Situ Sensors (RadCLss) Value-Added Product. RadCLss contains the 3×3 window gate average of each radar moment, with the center of the window directly over Gothic, Colorado. We apply the estimators in Table 2 to the RadCLss Z_e and K_{dp} in

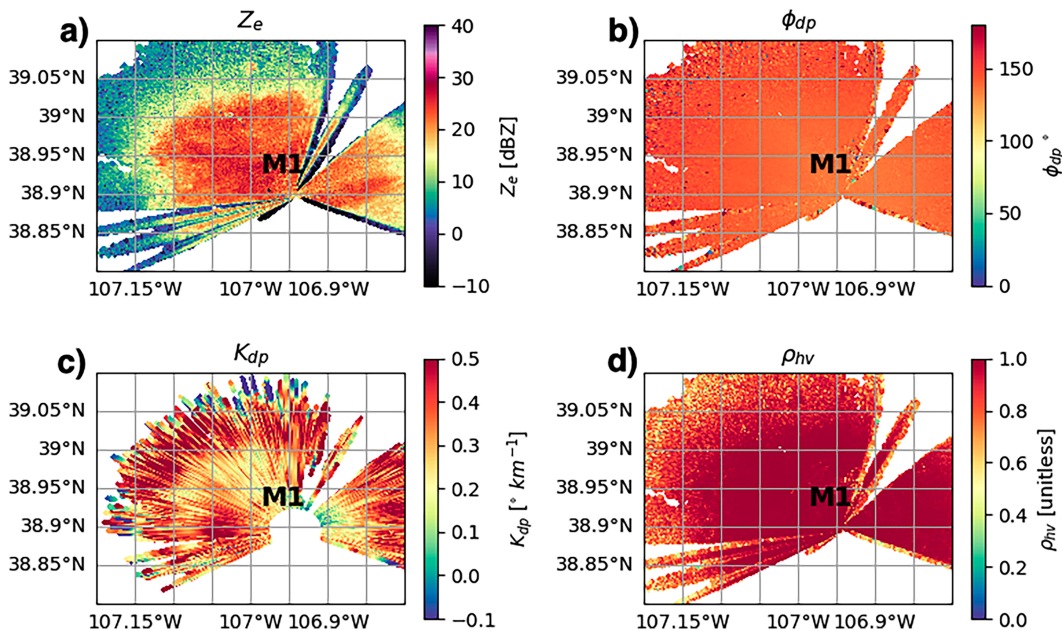


FIG. 5. Example PPI scan at 6° elevation for a snowfall case on 14 Mar 2022, processed by CMAC. (a) Reflectivity Z_e , (b) differential phase Φ_{DP} , (c) specific differential phase K_{DP} , and (d) copolar correlation coefficient ρ_{hv} , for the gates containing hydrometeors.

TABLE 2. List of radar-based S estimators used in this study.

Name	Formula	Abbreviation	Citation
WSR-88D IW	$Z_e = 40S^2$	WSR-88D IW	
WSR-88D High Plains	$Z_e = 110S^2$	WSR-88D HP	
Wolfe and Snider	$Z_e = 130S^2$	WS2012	Wolfe and Snider (2012)
Fujiyoshi et al. (1990)	$Z_e = 130S^2$	F90	Fujiyoshi et al. (1990)
Boucher and Wieler (1985)	$Z_e = 229S^{1.65}$	BW85	Boucher and Wieler (1985)
Puhakka (1975)	$Z_e = 1050S^2$	P75	Puhakka (1975)
Sekhon and Srivastava (1970)	$Z_e = 1780S^{2.21}$	SS70	Sekhon and Srivastava (1970)
Matrosov et al. (2009)-1	$Z_e = 67S^{1.28}$	M2009-1	Matrosov et al. (2009)
Matrosov et al. (2009)-2	$Z_e = 110S^2$	M2009-2	Matrosov et al. (2009)
Matrosov et al. (2009)-3	$Z_e = 114S^{1.39}$	M2009-3	Matrosov et al. (2009)
Matrosov et al. (2009)-4	$Z_e = 136S^{1.3}$	M2009-4	Matrosov et al. (2009)
Matrosov et al. (2009)-5	$Z_e = 36S^{1.56}$	M2009-5	Matrosov et al. (2009)
Matrosov et al. (2009)-6	$Z_e = 48S^{1.45}$	M2009-6	Matrosov et al. (2009)
Buković et al. (2018)	$S = 15.16K_{dp}^{1.08}$	B18-KDP	Capozzi et al. (2020)
Buković et al. (2018)	$S = 0.71Z_e^{0.33}K_{dp}^{0.61}$	B18-Z-KDP	Capozzi et al. (2020)
Capozzi et al. (2020)	$S = 13.08K_{dp}^{1.04}$	C20-KDP	Capozzi et al. (2020)
Capozzi et al. (2020)	$S = 0.48Z_e^{0.37}K_{dp}^{0.44}$	C20-Z-KDP	Capozzi et al. (2020)

the lowest gate above Gothic, Colorado, that is not beam blocked. A potential source of error in this comparison is due to the impact of various hydrometeor processes that impact how much snow scanned in the lowest gate above Gothic, Colorado, reaches the surface, including aggregation, advection, breakup, and sublimation. However, quantifying such errors was not possible with the data presented here. The 17 estimates provide an a priori range of plausible S for hydrological budget estimates in the UCRB.

d. Bulk SWE measurements

The wide variety of estimators in Table 2 demonstrates the need to compare these estimates against ground-based measurements of SWE taken during SAIL. At the AMF2 site, an OTT Pluvio² sensor measured rainfall accumulations every 5 min. The AMF2 site was located about 50 m away from the Gothic weather site where a snow accumulation was measured on a snow board with a snow pole and SWE measured by a scale. In addition, the choice of estimator in Table 2 to use depends, in part, on the snowflake density. Therefore, to quantify the snowflake density for each day, the snow accumulation measured on the snow board was divided by the SWE measured by the scale to calculate the snow-to-liquid ratio (SLR). The collocated bulk SWE measurements therefore provided an opportunity to intercompare these techniques to assess the uncertainty due to the different snow sampling techniques used. To perform this comparison, the daily SWE from the OTT Pluvio² (SWE_{Pluvio^2}) and Gothic weather ($SWE_{GothicWx}$) was calculated for each day from December 2021 to March 2022 and from December 2022 to March 2023. Figure 6 shows that SWE_{Pluvio^2} and $SWE_{GothicWx}$ are in good agreement. The $SWE_{GothicWx}$ is 9% higher than SWE_{Pluvio^2} when $SWE_{Pluvio^2} > 1$ mm. Therefore, the agreement between $SWE_{GothicWx}$ and SWE_{Pluvio^2} demonstrates that there is high confidence in the bulk measurements of SWE to use as a standard for evaluating different radar-based SWE estimates. For days with $SWE_{Pluvio^2} < 1$ mm, $SWE_{GothicWx}$ overestimated

SWE_{Pluvio^2} by up to an order of magnitude for these cases. The Pluvio² recorded all SWE rates below 0.5 mm h^{-1} as 0 mm h^{-1} , leading to potential underrecording of light snow events, which can explain this discrepancy between the Pluvio² and Gothic weather measurements.

3. Results

a. Case study—10–11 December 2021

Having 17 estimators in Table 2 complicates the decision behind which estimator to use. Therefore, to select a range of potential candidates that would provide the best estimate

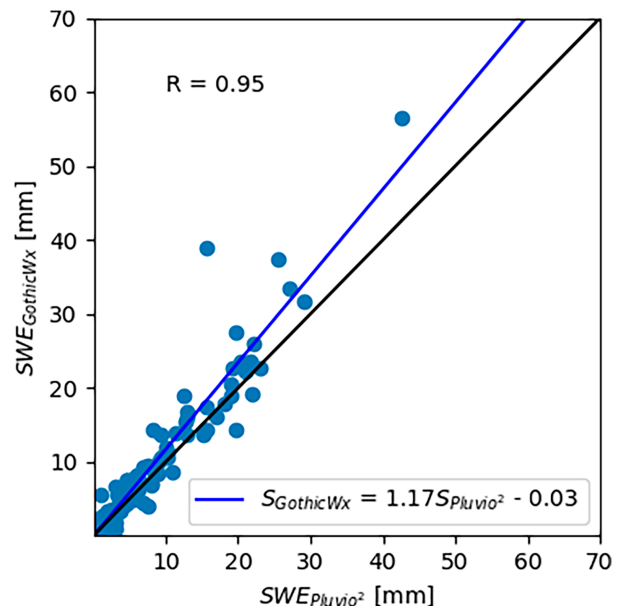


FIG. 6. Scatterplot of daily SWE from the Gothic weather scale measurements ($SWE_{GothicWx}$) as a function of daily SWE from the OTT Pluvio² (SWE_{Pluvio^2}).

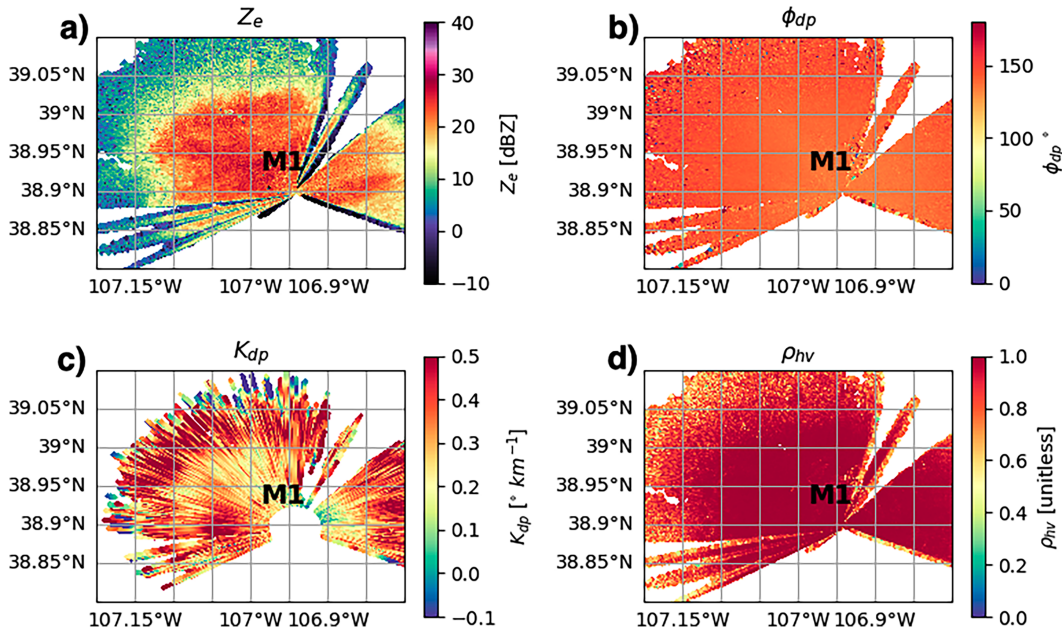


FIG. 7. The (a) Z_e , (b) Φ_{dp} , (c) K_{dp} , and (d) ρ_{hv} from the 6° PPI scan of the XPrecipRadar at 0314:01 UTC 10 Dec 2021.

of S for SAIL, we first examined a case study of snowfall that occurred over on 10 and 11 December 2021. This case was chosen because the daily S from the Pluvio² and Gothic weather measurements was within 20% for both days, ensuring that there was high confidence in the ground-based measurements of S . Figure 7 shows Z_e , Φ_{dp} , K_{dp} , and ρ_{hv} from the 6° PPI scan at 0314:01 UTC 10 December 2021. During this time, the Pluvio² was showing the highest accumulations (Fig. 8). The Z_e echoes of 25–30 dBZ are present over Gothic, Colorado, indicating moderate to heavy snowfall (Fig. 7a). There are relatively large signals for snowflakes in Φ_{dp} and K_{dp} with K_{dp} generally from 0.3° to 0.6° km⁻¹ over Gothic, Colorado, for the case study period (Figs. 8b,c). The ρ_{hv} values of near 1 are indicative of hydrometeors (Fig. 7d).

We examine the performance of the S estimators by comparing the total case SWE as a function of time for the

8 estimators that were closest to the Pluvio² and Gothic weather measurements in Fig. 8. The B18-Z-KDP, C20-Z-KDP, and M2009-1 estimators are performing the best for this case, being within 30% the Pluvio² and Gothic weather measurements (Fig. 8). Dry snow was present as indicated by the SLR of 11.6 at the Gothic weather site on this day. Therefore, since C20-Z-KDP was developed for dry snow, the agreement between the estimates from the C20-Z-KDP estimator and the bulk SWE measurements seen here is not surprising.

b. Comparison of daily S measurements

The previous analysis showed that M2009-1, B18-Z-KDP, and C20-Z-KDP estimated were in best agreement with the Pluvio² and Gothic weather SWE for a given case study when there was high confidence in the SWE measured by ground sensors. The SLR measured at the Gothic weather site

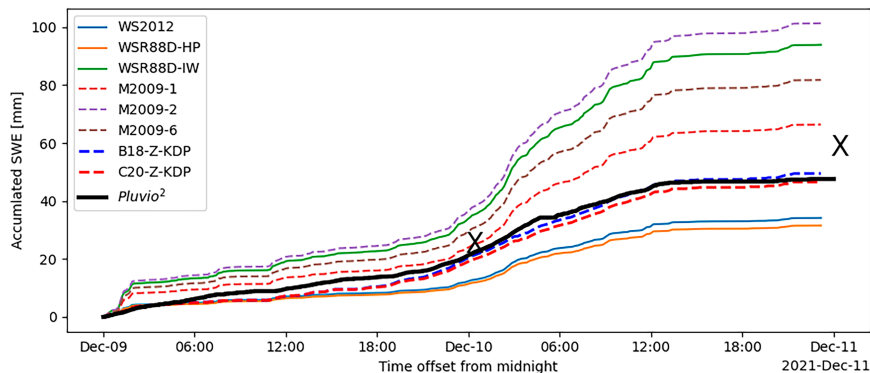


FIG. 8. Cumulative SWE from the different radar-based S estimates and the OTT Pluvio² from the lowest nonblocked gate over Gothic. The X denotes a Gothic weather measurement of cumulative SWE. Only the top eight performing estimators are shown for clarity.

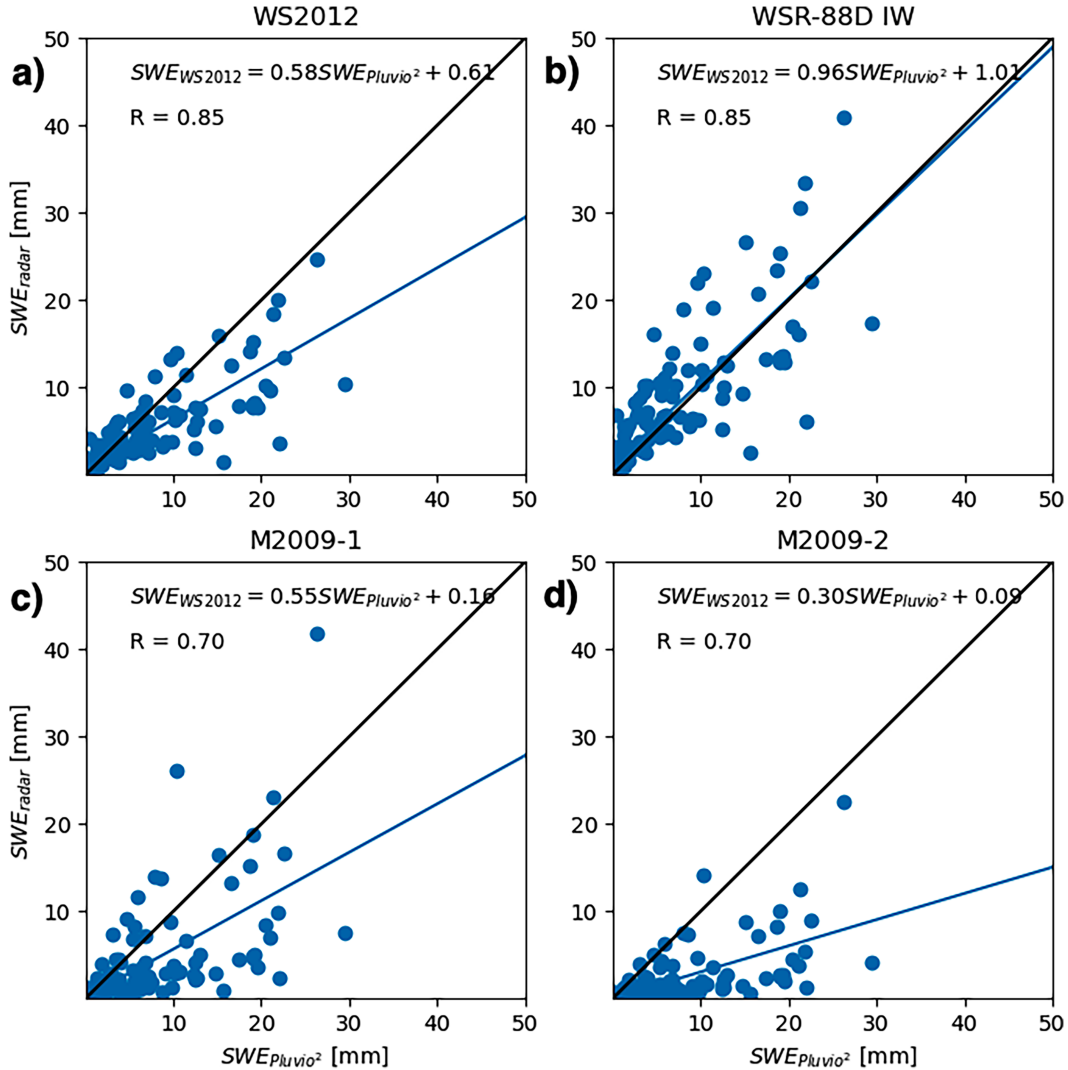


FIG. 9. Daily radar-estimated SWE (SWE_{radar}) over Gothic from (a) WS2012, (b) WSR-88D IW, (c) M2009-1, and (d) M2009-2 as a function of SWE_{Pluvio^2} . The blue line shows the best fit between SWE_{radar} and SWE_{Pluvio^2} .

throughout SAIL varied from 8.0 to 19.7, demonstrating a wide variety of snowflake densities throughout SAIL. Therefore, since there is a wide range of estimates that can be used for SWE that depend on snowflake density (Table 2 and Fig. 8), we need to test the applicability of the various estimators to all of the snowfall days during SAIL. To do this, we calculated daily SWE from the RadCLss product (SWE_{radar}) using the different estimators and compared these calculated SWE_{radar} against both the Pluvio² and Gothic weather daily SWE measurements.

We first assess the performance of the Z_e -based estimators since these estimators do not require a quantity that is sensitive to noise such as K_{dp} . Since K_{dp} is only determined by the measured phase (Bringi and Chandrasekar 2001), this noise can even be present in high SNR conditions. In addition, K_{dp} has no standard processing technique, with many such techniques that can be applied (i.e., Ryzhkov et al. 2005; Cifelli et al.

2011; Vulpiani et al. 2012; Giangrande et al. 2013). So, if possible, it is preferable to use estimators using only Z_e since fewer assumptions and processing steps are required for these estimates. Therefore, we first show the comparison of four best-performing S estimators using only Z_e in Fig. 9. The SWE_{radar} estimated using the WSR-88D Intermountain West (IW) estimator is in the best agreement with the SWE from Pluvio² observations SWE_{Pluvio^2} ($R = 0.85$, Fig. 9b). The SWE_{radar} calculated using the WS2012 estimator has similar scatter ($R = 0.85$, Fig. 9a) but underestimates the SWE from the Pluvio² with a lower best fit line slope of 0.58. Given that the WSR-88D IW estimator was developed for snowfall in the Intermountain West, its performance here in the UCRB is not surprising. The SWE_{radar} M2009-1/2 estimators underestimate SWE_{Pluvio^2} as shown by the slopes of the best fit lines being less than 0.6 (Figs. 9c,d). These estimates are also less correlated with SWE_{Pluvio^2} ($R = 0.70$, Figs. 9c,d) than the

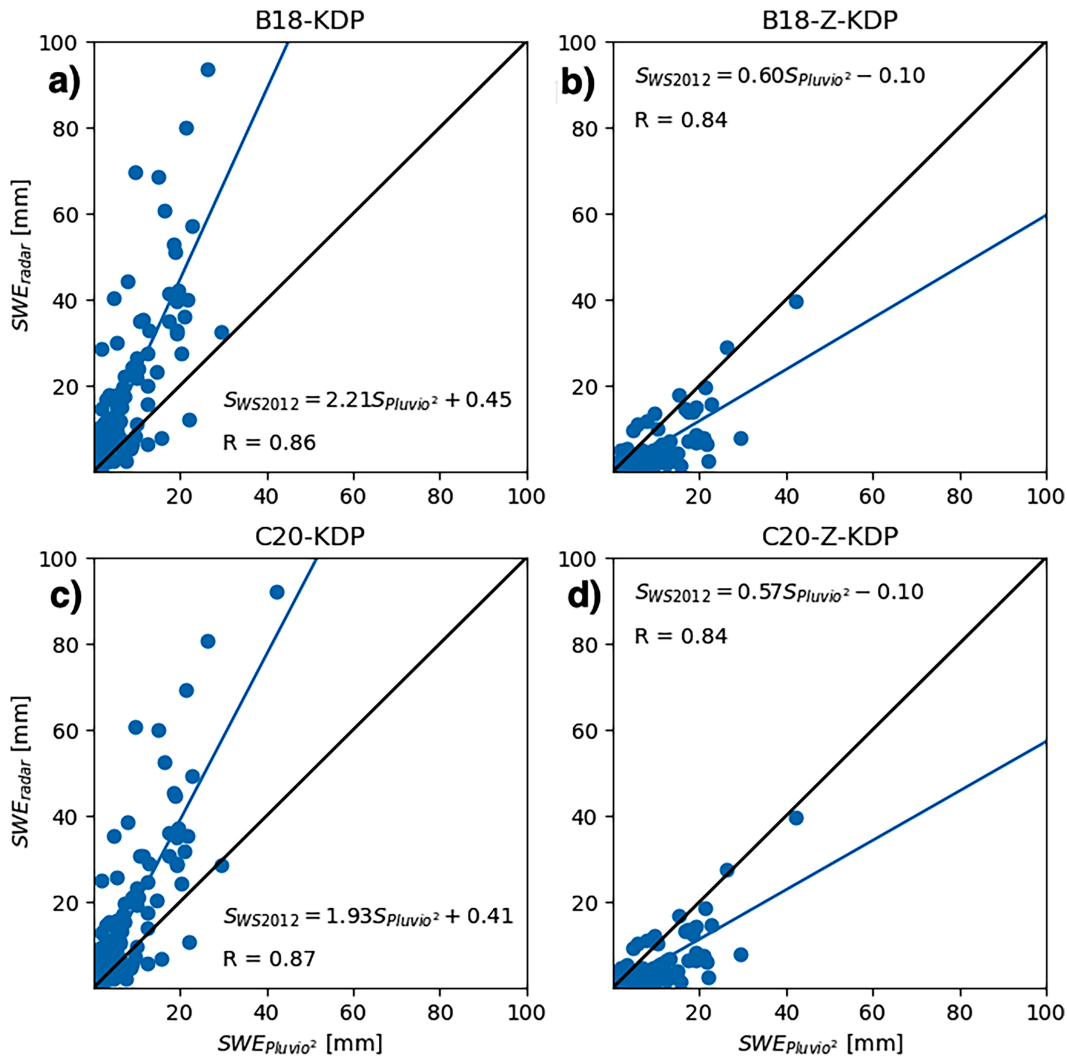


FIG. 10. As in Fig. 9, but using SWE_{radar} from (a) B18-KDP, (b) B18-Z-KDP, (c) C20-KDP, and (d) C20-Z-KDP. Refer to Table 2.

WSR-88D IW-estimated SWE_{radar} . Therefore, when only assessing the estimators that only use Z_e to estimate S , WSR-88D IW-estimated SWE_{radar} is in best agreement with SWE_{Pluvio^2} .

Next, we repeat the analysis in Fig. 9, except only using estimators that use both Z_e and K_{dp} (Fig. 10). Both B18-KDP- and C20-KDP-estimated SWE_{radar} greatly overestimate SWE_{Pluvio^2} with slopes of the best fit line being greater than 1.9 (Figs. 9a,c). While these slopes are closer to unity for the B18-Z-KDP- and C20-Z-KDP-estimated SWE_{radar} (Figs. 9a,c), they are still only around 0.6. Therefore, the B18-Z-KDP- and C20-Z-KDP-estimated SWE_{radar} underestimate SWE_{Pluvio^2} . This analysis shows that the WSR-88D IW-estimated SWE_{radar} is in the best agreement with SWE_{Pluvio^2} . While B18-Z-KDP and C20-Z-KDP showed better performance than Z_e -based SWE estimators for their snowfall cases in their respective studies, that improved performance is not seen here. This is likely due to the fact that snowfall during SAIL did not always have K_{dp} that was above the noise floor. In fact, $K_{\text{dp}} > 0.2^\circ \text{ km}^{-1}$ (a typical

noise floor for X band) only 27% of the time when $Z_e > 10 \text{ dBZ}$. Therefore, the particle size distributions and shapes of the snowfall occurring during SAIL are likely more poorly suited for the B18-Z-KDP and C20-Z-KDP estimators than for the snowfall in the studies in which these estimators were developed. Overall, the top three estimators ranked according to correlation coefficient and best fit line slopes in Figs. 9 and 10 were WS2012, WSR-88D IW, and C20-Z-KDP.

Snow particle habits and PSDs, as well as the sensitivity of the OTT Pluvio² measurements, vary for different daily SWE. Therefore, we also examine the performance of the top three ranking estimators WS2012, WSR-88D IW, and C20-Z-KDP by plotting the mean ratio as a function of SWE_{Pluvio^2} in millimeters (Fig. 11). For the all estimators, $SWE_{\text{estimator}}/SWE_{\text{Pluvio}^2}$ is either greater than 2 or less than 0.7 when $SWE_{\text{Pluvio}^2} < 2$. Since the OTT Pluvio² does not record time periods when $S < 0.5 \text{ mm h}^{-1}$, this can result in a high uncertainty in measured SWE_{Pluvio^2} when $SWE_{\text{Pluvio}^2} < 1 \text{ mm}$, consistent with the

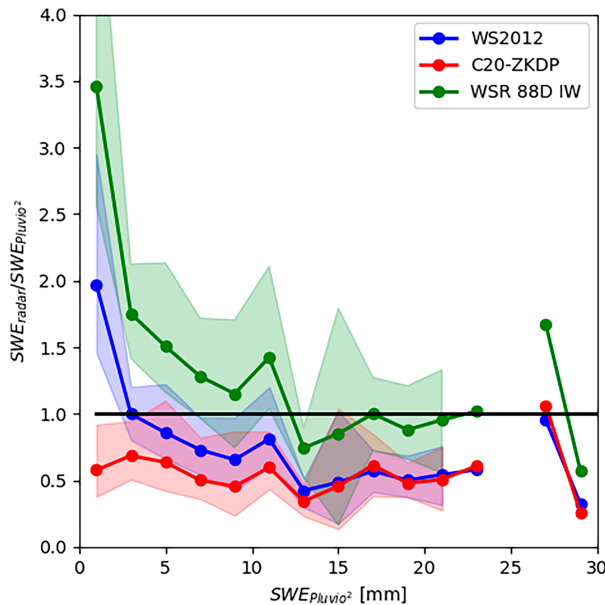


FIG. 11. Mean ratio of different estimates of SWE_{radar} to SWE_{Pluvio^2} as a function of SWE_{Pluvio^2} (mm). Shading denotes the 95% confidence interval of the mean.

trends seen in Fig. 11. For $1 \text{ mm} < SWE_{\text{Pluvio}^2} < 12 \text{ mm}$, the WS2012 relationship-estimated SWE_{radar} is in best agreement with SWE_{Pluvio^2} . For $SWE_{\text{Pluvio}^2} > 12 \text{ mm}$, the WSR-88D IW-based estimates are in best agreement with SWE_{Pluvio^2} . Therefore, for estimating SWE throughout the SAIL campaign, we recommend using WS2012 when daily SWE $< 12 \text{ mm}$ and WSR-88D IW when SWE $> 12 \text{ mm}$. One reason for this change in recommended estimator could be due to increased snowflake effective densities on the days with $SWE_{\text{Pluvio}^2} > 12 \text{ mm}$. The SLRs measured at the Gothic weather site were 12.7 ± 3.2 on the days with $SWE_{\text{Pluvio}^2} < 12 \text{ mm}$ and 11.6 ± 2.7 on days with $SWE_{\text{Pluvio}^2} > 12 \text{ mm}$. This is consistent with wetter, denser snowflakes on the days with $SWE_{\text{Pluvio}^2} > 12 \text{ mm}$. This change in recommended estimator at daily SWE = 12 mm can also be due to the higher S present during these days that Pluvio² is more sensitive to. However, similar trends were noted between SWE_{radar} and SWE_{GothicWx} (not shown). Therefore, this change in recommended estimator is most likely due to changing snowflake densities as daily SWE increases.

c. Summary of seasonal statistics

Seasonal estimates of SWE for use in estimating hydrological budgets in the UCRB requires that SWE_{radar} be available on a Cartesian grid. Therefore, in response to this need, ARM has developed a value-added product called SQUIRE. The SQUIRE product includes estimates of S from the WSR-88D IW, WS2012, and M2009-1/2 estimators to provide modelers a range of feasible estimates of S at each 5-min radar observation time period. In addition, the inclusion of multiple estimators in this product permits modelers interested in estimating SWE and S to incorporate the recommended estimators for given daily SWE in their analysis. As a first step, these

SWE_{radar} estimates at the lowest gate are first interpolated to a $20 \text{ km} \times 20 \text{ km} \times 5 \text{ km}$ three-dimensional Cartesian grid at a 250-m resolution using a nearest-neighbor interpolation approach. Then, for each horizontal grid point, SWE_{radar} from the lowest height level that is not beam blocked is then projected onto a two-dimensional horizontal grid. This resulting horizontal grid also spans $20 \text{ km} \times 20 \text{ km}$ with a 250-m resolution. SQUIRE is available on ARM Data Discovery.

A summary of the average statistics of SWE_{radar} for both December–March seasons during SAIL is shown in Fig. 12. In addition, the estimated April snow depth from the Airborne Snow Observatories, Inc. (ASO) (Painter et al. 2016) is shown alongside the mean SWE_{radar} to demonstrate whether SQUIRE is able to capture snowfall patterns in the UCRB. There are persistent regions of $SWE_{\text{radar}} > 5 \text{ mm day}^{-1}$ in the northwest region of the East River watershed as well as in the mountains to the west of the East River watershed. These persistent features are collocated with the mountaintops around the East River watershed, suggesting that orographic precipitation enhancement is occurring in these regions.

The persistent regions of total $SWE_{\text{radar}} > 300 \text{ mm}$ are collocated with elevated snow depths in the western mountains (WMs) adjacent to the East River watershed. For example, to the west of the East River watershed, SQUIRE is showing $SWE_{\text{radar}} > 8 \text{ mm day}^{-1}$ collocated with snow depths greater than 5 m. These collocated SWE_{radar} and snow depths are also present in the western portion of the East River watershed (Figs. 12a–d). This shows that SQUIRE is capturing orographic snowfall patterns that are occurring in the western portion of the East River watershed and in the mountains to the west of the watershed. In the eastern portion of the East River watershed, there are snow depths up to 5 m where SQUIRE is showing less than 5 mm of seasonal-mean SWE_{radar} (Figs. 12a–d). The linear nature of the regions with reduced SWE_{radar} indicates that, even after CMAC and SQUIRE’s corrections to remove beam blockage, beam blockage is still likely causing SQUIRE to underestimate the amount of SWE in the eastern portion of the East River watershed. Therefore, SQUIRE’s SWE_{radar} estimates are least impacted by beam blockage on the lee side of the mountains to the west of the East River watershed and in the northwestern portion of the East River watershed.

d. Overview of cases for SAIL’s scientific objectives

Science objective 1 (SO1) in SAIL was to “characterize the spatial distribution of orographic and convective precipitation processes on diurnal to seasonal time scales and how those processes interact with large-scale circulation” (Feldman et al. 2023). SQUIRE helps achieve this scientific objective by providing gridded SWE estimates over a wide range of synoptic-scale conditions for two Colorado winter seasons. In particular, one key point of interest is to examine how orographic enhancement of precipitation is impacted by meteorological factors. Therefore, to provide an overview of cases present in SQUIRE that would be of interest to scientists studying orographic precipitation processes in the UCRB, we estimate the amount of orographic enhancement per day for each case in SAIL. Figure 13

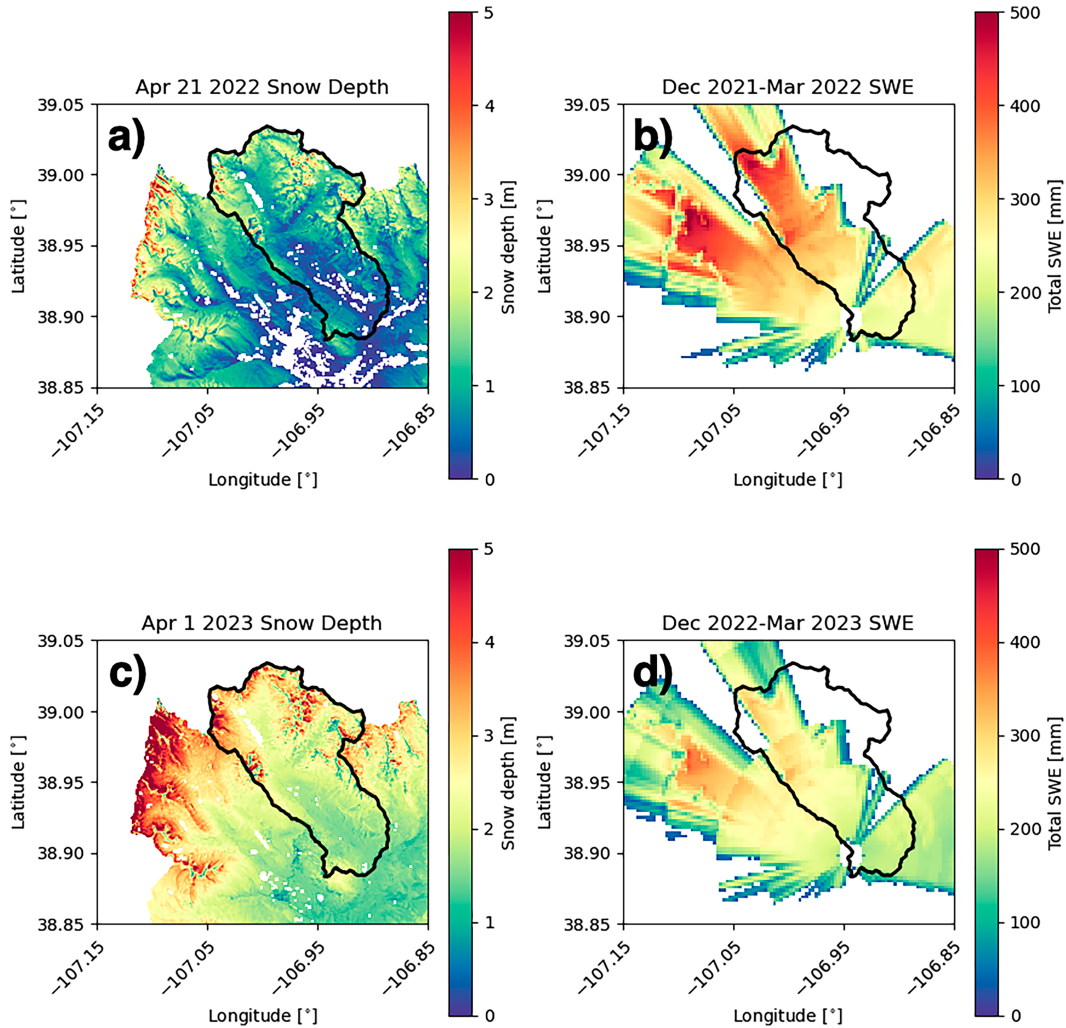


FIG. 12. April snow depth from ASO for April (a) 2022 and (c) 2023. The average SWE_{radar} estimated using the WSR-88D IW estimator (b) from 1 Dec 2021 to 30 Mar 2022 and (d) from 1 Dec 2022 to 30 Mar 2023. The dashed contour represents the boundaries of the East River watershed.

shows time series of SWE_{radar} from SQUIRE over Gothic, Colorado, and a grid point in the western mountain range at 38.96°N, 107.09°W. The difference between SWE_{radar} in the western mountain range and Gothic, Colorado, is provided to demonstrate the mountain–valley SWE gradients that result from orographic precipitation enhancement.

For the December 2021–March 2022 season, the gradients in SWE_{radar} suggest that orographic enhancement was most present during the month of December and then again from 15 February to 30 March. However, from 1 January to 15 February, orographic enhancement is likely weaker (Fig. 13a), with SWE_{radar} gradients less than 5 mm. This is supported by the emergence of higher cumulative SWE in the mountains west of Gothic during the seventh week of 2022 (see supplemental material). Meanwhile, for the December 2022–March 2023 season, orographic enhancement of precipitation is more persistent than for the 2022 season, supported by the emergence of elevated cumulative SWE in the mountains west of Gothic earlier in the season,

during the 52nd week of 2022 (see supplemental material). Since orographic precipitation enhancement is a mesoscale mechanism, this suggests that synoptic-scale phenomena produced more of the snowfall over the UCRB for the December 2021–March 2022 season, while mesoscale processes produced more of the snowfall for the 2023 season. Future work for achieving SAIL’s SO1 should use SQUIRE data from these cases with varying orographic enhancement that provides cases for comparison that scientists can use to study orographic processes in the UCRB.

4. Conclusions

The upper Colorado River basin (UCRB) is one of the most vital freshwater sources for communities in the southwestern United States. However, mountain snowpack in the UCRB has been declining since the 1980s (McCabe and Wolock 2009; Mote et al. 2018). Hydrological models are highly uncertain in

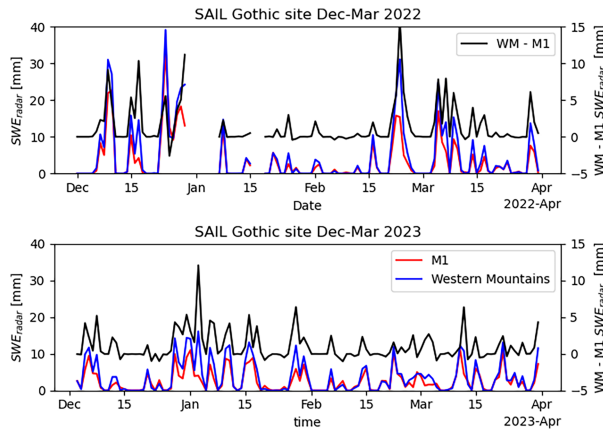


FIG. 13. The daily SWE_{radar} calculated using the WSR-88D IW estimator over Gothic and the WM range (38.96°N , 107.09°W) for (a) December–March 2022 and (b) December–March 2023.

their prediction of the amount of snow water equivalent (SWE) that is available in the UCRB snowpack (He et al. 2012; Micheletty et al. 2022). One of the underlying reasons for this is due to the difficulty of comprehensively measuring precipitation in complex terrain. For example, much of the Next Generation Weather Radar (NEXRAD) coverage in the UCRB is blocked by terrain, including the East River watershed. Having accurate SWE predictions is vital for warning Southwest U.S. communities about potential water shortages in a changing climate. This therefore motivated the U.S. Department of Energy Atmospheric Radiation Measurement (ARM) Facility’s Surface Atmospheric Integrated Field Laboratory (SAIL) (Feldman et al. 2023). During SAIL, the CSU X-band Precipitation Radar (XPrecipRadar) was installed at the southern end of the East River watershed where it conducted volume scans to obtain the distribution of hydrometeors over the UCRB. Using CSU XPrecipRadar data and ground-based rain gauges at the ARM Mobile Facility, we developed the Surface Quantitative Precipitation Estimates (SQUIRE) product. As a part of developing SQUIRE, we noted the following conclusions and recommendations for estimating SWE using the XPrecipRadar data:

- 1) The daily SWE from the OTT Pluvio² and Gothic weather site measurements were generally within 10% for the duration of SAIL. This showed high confidence in the ground-based measurements of SWE and generally higher than was expected before the campaign (Matrosov et al. 2009).
- 2) Comparing various radar-based methods to estimate SWE showed that radar-estimated SWE calculated using Wolfe and Snider (2012)’s estimator from the lowest non-blocked gate over Gothic was in best agreement with OTT Pluvio² and Gothic weather measurements for the days when $SWE < 12$ mm. For the days when $SWE > 12$ mm, the radar-estimated SWE calculated using the WSR-88D Intermountain West estimator had the best agreement with the OTT Pluvio² and Gothic weather measurements. This shift in estimator performance was likely due to the lower SLRs encountered on the days with $SWE > 12$ mm, suggestive of wetter denser snowflakes for these cases.

- 3) None of the radar-based SWE estimates from estimators that use both radar reflectivity factor Z_e and specific differential phase K_{dp} was within 40% of the OTT Pluvio² and Gothic weather measurements. This is likely due to the fact that snowfall during SAIL, for 74% of the SAIL study period, did not have K_{dp} above the noise floor. This suggests that the microphysical properties of snowfall in the UCRB are poorly tailored to using estimators based on K_{dp} .
- 4) The radar-based SWE estimates from WSR-88D Intermountain West and Wolfe and Snider (2012) were interpolated to a final gridded product that is SQUIRE. Elevated regions of SWE collocated with mountains from this gridded product were collocated with elevated snow depths in the lee side of the mountains to the west of the East River watershed and the northwestern portion of the East River watershed. Beam blockage is significantly impacting the radar-based SWE estimates over eastern portion of the East River watershed. Hence, we strongly recommend using SQUIRE in the mountains to the west of the East River watershed and the western portion of the East River watershed that are not impacted by beam blockage.
- 5) A preview of the SQUIRE product for interested scientists suggests that orographic snow enhancement was more persistent for the December 2022–March 2023 season than for the December 2021–March 2022 season. These contrasts in orographic enhancement provide numerous case studies for studying SAIL’s scientific objective to study how orographic processes impact snowpack over the UCRB.

The SQUIRE product is available on ARM Data Discovery for the scientific community to use as the “gucxprecipradarsquire” datastream. The results presented here also demonstrate that further work is needed to improve radar-based SWE estimates in complex terrain. For example, due to the differences in snowfall microphysical properties between the SAIL data in the UCRB and snow in the Apennine Mountains (Capozzi et al. 2020), this shows that further refinement of radar-based SWE estimators is needed. While the goal for this study was to provide a range of feasible SWE estimates for use as inputs for hydrological modeling, future developments in developing radar-based SWE estimates should examine the potential for the use of a blend of radar-based SWE estimates. This notion is supported by the change in the recommended method for snowfall estimation from CSU X-band radar measurements at snowfall rates of 12 mm day^{-1} . This type of approach is not atypical in radar applications: for example, blended techniques have been used for estimating rainfall rates over the tropics (Cifelli et al. 2011; Thompson et al. 2018; Jackson et al. 2021). To develop such blended products, more realistic representations of snowflake scattering properties are required. Obtaining these scattering properties requires long-term measurements of snowflake habit and particle size distributions at the ground, such as those from the recently developed Video In Situ Snowflake Sensor (Maahn et al. 2024). In addition, since dual polarization moments were not useful for estimating snowfall

rates during SAIL, future work should also explore the utility of time dependent, adaptive relationships between snowfall rate and reflectivity, similar to work done by Alfieri et al. (2010) for rainfall rates.

Finally, the similarity in snowfall and snowpack spatial patterns between SQUIRE and ASO data is remarkable and worth discussing. The precipitation patterns that emerge in SQUIRE seasonal totals are not evident in subdaily or daily data, but they do emerge after several storms as seen in Fig. S1 in the online supplemental material. There is much information to be gained from understanding this emergence. It indicates that the specifics of individual storm direction and other synoptically varying variables matter less than those surface–atmosphere interaction processes that occur regardless of storm direction.

Finally, the precipitation/snowpack pattern similarities also suggest that surface snow redistribution processes produce a modest effect, at most, on end-of-season snowpack. Instead, atmospheric precipitation processes are responsible for the snowpack patterns that hydrological models need most as inputs. To reduce hydrologic modeling uncertainty, the scientific community should continue to focus on precipitation processes to understand the physical processes responsible for the emergence of spatial pattern and, as we showed here, should look at those processes that occur in the majority of storms.

Acknowledgments. The submitted manuscript has been created by UChicago Argonne, LLC, Operator of Argonne National Laboratory (“Argonne”). Argonne, a U.S. Department of Energy Office of Science laboratory, is operated under Contract DE-AC02-06CH11357. The U.S. Government retains for itself, and others acting on its behalf, a paid-up nonexclusive, irrevocable worldwide license in said article to reproduce, prepare derivative works, distribute copies to the public, and perform publicly and display publicly, by or on behalf of the government. The Department of Energy will provide public access to these results of federally sponsored research in accordance with the DOE Public Access Plan (<http://energy.gov/downloads/doe-public-access-plan>). Argonne National Laboratory’s work was supported by the U.S. Department of Energy, Office of Science, Office of Biological and Environmental Research (BER), under Contract DE-AC02-06CH11357. Argonne’s work was funded by BER’s Atmospheric Radiation Measurement Facility. Berkeley Lab’s work was supported by the U.S. Department of Energy, Office of Science, Office of Biological and Environmental Research and the Atmospheric System Research under U.S. Department of Energy Contract DE-AC02-05CH11231.

Data availability statement. The CMAC-corrected XPrecip-Radar data are available at ARM Data Discovery (<https://adc.arm.gov//discovery>) in the gucxprecipradarcmapppiS2.c1 datastream on ARM Data Discovery. The SQUIRE product is available in the gucxprecipradarsquireS2.c1 datastream on ARM Data Discovery. RadCLss is available as the gucxpreipradarradclssS2.c1 datastream on ARM Data Discovery. Cookbooks showing the development of SQUIRE and RadCLss

are available at <https://arm-development.github.io/sail-xprecip-radar/overview.html>. The GitHub repository for CMAC is available at <https://github.com/EVS-ATMOS/cmac2.0>.

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