

Statistics, Lasers, and Pillows: Leveraging historical patterns and
observations to predict distributed 1 April SWE

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Abstract

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This dissertation investigates statistical and satellite-based approaches for estimating snow water equivalent (SWE) and its spatial distribution in mountain regions to inform water management. In the western United States, near-real-time SWE estimates can have low domain-wide bias but tend to misrepresent the spatial distribution of SWE, which controls snowmelt runoff magnitude and timing. A retrospective SWE reanalysis product (UCLA Western U.S. SWE Reanalysis) more accurately represents the spatial distribution of SWE, but is not available in real-time. This motivates the question: can we leverage the more accurate historical spatial information contained in SWE reanalysis products to improve near-real-time SWE estimation? We focus on 1 April SWE, a benchmark for peak seasonal accumulation in northern hemisphere mid-latitude basins. Throughout this dissertation, we combine historical SWE patterns with various current-year observations to develop and test methods for estimating near-real-time distributed mountain SWE. We test these methods in the western U.S. to evaluate their potential for use in data-sparse regions globally.

In Chapter 2, we combined real-time in-situ snow station observations with a SWE reanalysis product in the Upper Colorado River Basin using standard anomaly (SA) and quantile-based methods. Within a leave-one-out framework, these statistical approaches produced distributed SWE estimates with higher spatial correlation and lower bias relative

to the reanalysis than did physically-based modeling systems. However, the residual errors revealed elevational and regional gradients not captured by the SA framework, particularly in anomalous years.

In Chapter 3, recognizing that long-term in-situ station networks are not available everywhere, we evaluated ICESat-2 altimetry as an additional, potentially global snow depth data source. We custom processed ICESat-2 elevations and accessed bare earth elevations from the USGS 3D Elevation Program using the SlideRule Earth tool. To calculate snow depth, we subtracted the bare earth elevations from the ICESat-2 measurements. We excluded measurements over steep slopes and aggregated the remaining ICESat-2 snow depth estimates by date across the California Sierra Nevada (the domain). Daily domain-median ICESat-2 snow depth and the running 10-day median of ICESat-2 snow depth showed high correlations and minimal biases relative to the domain-wide reanalysis snow depth. This large-scale aggregation of ICESat-2 snow depths yielded accurate snow quantity estimates that could extend snow observations globally where high-quality snow-off terrain models exist.

In Chapter 4, we extended the SA framework that was used in Chapter 2 by additionally applying an empirical orthogonal function (EOF) analysis to the 1 April SA values to identify dominant modes of spatial and temporal variability in Sierra Nevada SWE. We used data available in near-real-time from the ERA5 reanalysis product and ICESat-2 snow depth estimates to develop linear regressions to the time-varying principle components (PCs) that resulted from the EOF analysis, and combined these with the time-static spatial EOF patterns to estimate distributed SWE within a leave-one-out framework. We compared SWE estimates from the SA method, EOF method, and an operational model that assimilates in-situ observations relative to the SWE reanalysis product. In most years, statistical approaches performed comparably to or better than the operational product. However, in an extreme low snow year the operational product performed best, indicating that additional

observations are needed to constrain estimates in low snow years. In places without in-situ SWE observations, the EOF method could be used with meteorological information from ERA5 to estimate SWE distributions. In places without dense meteorological observations for assimilation in the ERA5 reanalysis, additional observations from ICESat-2 or other satellite products will likely become more important.

Collectively, this dissertation demonstrates that accurate historical SWE distributions can be leveraged to produce computationally efficient, near-real-time estimates of distributed mountain SWE. The ERA5 reanalysis product is available globally, so at minimum the techniques used here require a reliable SWE reanalysis product. The inclusion of additional observations, for example from ICESat-2, could provide added value in low-snow years and in regions with sparse in-situ observations for assimilation in the ERA5 reanalysis.

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Even though my time as a student is finally over, there's so much more to learn. I look forward to continuing the journey.

Chapter 1

INTRODUCTION

Real-time estimates of peak snow water equivalent (SWE) are critical for spring runoff forecasting in snow-dominated basins. However, substantial uncertainty remains due to the high spatial variability of snow distribution and the large interannual variability of peak SWE. This dissertation evaluates techniques and data sources that can improve spatially distributed SWE estimates. We test these approaches in the well-studied western United States and provide recommendations for their application in less-observed mountain regions worldwide.

The methods presented here integrate multiple data sources and statistical frameworks, including in-situ snow pillow observations, satellite-derived snow depth from ICESat-2 elevation measurements, ERA5 global reanalysis meteorological fields, and historical SWE patterns from the UCLA Western U.S. SWE Reanalysis. We apply statistical approaches based on standard anomalies (SAs), quantiles, and empirical orthogonal functions (EOFs) to leverage recurring spatial patterns in snow distribution. These patterns, documented across many mountain regions and over long time periods, provide a foundation for estimating current-year SWE from limited observations.

The following sections outline the structure and contributions of each chapter in this dissertation.

1.1 Outline

We used snow observations and statistical techniques to estimate snow quantity across regions of the western United States. These efforts are presented in Chapters 2–4, which are outlined below. Chapter 5 concludes the dissertation by summarizing the objectives addressed in

Chapters 2–4 and discussing broader implications and directions for future research.

Chapter 2 *Mapping 1 April SWE in the Western US Using Standardized Anomalies and Quantiles From SWE Reanalysis and In Situ Stations*

- **Objective:** Quantify annual patterns in 1 April Western U.S. SWE distribution using standardized anomalies, and evaluate statistical SWE estimation methods based on standard anomalies and quantiles in the Upper Colorado River Basin.
- This work was published in *Water Resources Research* and is reproduced from the following citation.

Besso, H., Mower, R., Pflug, J. M., and Lundquist, J. D. (2026). Mapping 1 April SWE in the Western US using standardized anomalies and quantiles from SWE reanalysis and in situ stations. *Water Resources Research*, 62, e2025WR040902. <https://doi.org/10.1029/2025WR040902>

Chapter 3 *Mountain-Range Snow Depth from ICESat-2: Aggregated Observations in the Sierra Nevada*

- **Objective:** Determine how ICESat-2 elevation measurements can be optimally used to estimate snow depth across the California Sierra Nevada throughout the snow season.
- This chapter is in preparation for submission to the *Proceedings of the National Academy of Sciences of the United States of America*.

Besso, H., Treichler, D., Shean, D., Henderson, S., and Lundquist, J.D. Mountain-Range Snow Depth from ICESat-2: Aggregated Observations in the Sierra Nevada. *Manuscript in preparation*.

Chapter 4 *Evaluating Statistical SWE Methods Informed by Meteorology and Satellite Observations*

- **Objective:** Evaluate the accuracy of SWE estimates produced from two statistical methods in California's Sierra Nevada to inform their application in ungauged mountain regions worldwide.
- This chapter is in preparation for submission to *Water Resources Research*.

Besso, H. and Lundquist, J. D. Evaluating Statistical SWE Methods Informed by Meteorology and Satellite Observations. *Manuscript in preparation*.

Chapter 2

MAPPING 1 APRIL SWE IN THE WESTERN US USING STANDARDIZED ANOMALIES AND QUANTILES FROM SWE REANALYSIS AND IN SITU STATIONS

2.1 Introduction

Snow acts as a natural water tower that stores winter precipitation and delays the timing of runoff until snow melts in the spring and summer [Immerzeel *et al.*, 2020; Li *et al.*, 2017]. The spatial distribution of accumulated snow during the winter controls the onset timing, duration, and quantity of spring snowmelt [Berghuijs *et al.*, 2014; Brauchli *et al.*, 2017b; Clark *et al.*, 2011; Egli *et al.*, 2012; Luce *et al.*, 1998; Lundquist and Dettinger, 2005; Pflug and Lundquist, 2020]. These snowmelt characteristics determine when and how much water is available to the billions of people worldwide who rely on snowmelt as a water resource [Barnett *et al.*, 2005; Dozier *et al.*, 2016]. Snow also influences ecological functions [Keller *et al.*, 2005; Kudo, 1991; Kudo and Ida, 2013; Laforge *et al.*, 2021; Powers *et al.*, 2022; Rose-Person *et al.*, 2024; Severson *et al.*, 2021; Wipf *et al.*, 2009] and the exchange of energy and mass between the land and atmosphere in snowy regions [Liston, 1999]. Accurate maps of the spatial distribution of seasonal snow accumulation are therefore important inputs to hydrological, ecological, and land-surface models.

In the Western US, half of total runoff and two thirds of reservoir inflow originate as snow in the mountains [Li *et al.*, 2017], so snow measurements have long been important to water managers. For over a century, in situ measurements of SWE taken near the timing of peak snow accumulation have been used as indexes for streamflow [Church, 1914; Raleigh *et al.*, 2025; Work, 1953] and more recently as input to hydrologic forecast models [Fleming *et al.*, 2023; Pagano *et al.*, 2009]. There are now over 700 automated snow measurement

stations throughout the Western US that are used for streamflow forecasting [Pagano *et al.*, 2009]. The locations of these stations were chosen based on the usefulness of the site as an index for spring runoff, although logistical considerations for station install and upkeep often keep them from the highest elevations that provide the strongest correlations to streamflow [Fleming *et al.*, 2023; Raleigh *et al.*, 2025]. Snow measured at these stations correlates with streamflow, with an R^2 between 0.63 and 0.93 depending on timing within the snow season and number of stations used in the regression [Raleigh *et al.*, 2025], but these stations under-sample the spatial variability of SWE in the mountains [Herbert *et al.*, 2024; Meromy *et al.*, 2013; Molotch and Bales, 2005; Rice and Bales, 2010]. As such, they do not directly provide information about the total amount or distribution of SWE stored in the basin, leaving uncertainty in snow cover duration and the timing of snowmelt arrival to downstream reservoirs.

Resolving the spatial distribution of SWE in the mountains is a complex problem and has been named the most important unsolved problem in snow hydrology [Dozier *et al.*, 2016]. This challenge is in part due to mountain topography, which causes large variability in precipitation amount and phase, contributing to large uncertainties in precipitation estimates over mountains [Beck *et al.*, 2020] and making snowfall difficult to quantify. After snow has fallen, various processes at multiple scales control SWE redistribution and melt. A suite of methods for estimating the spatial distribution of SWE have been developed since the mid-20th century, including physical and statistical models, new satellite observations, data assimilation frameworks, and airborne and in situ observations. But there is still no one way to accurately measure SWE throughout the mountains [Dozier *et al.*, 2016].

Many satellite sensors are sensitive to snow properties, and some even directly measure SWE in regions that are flat, non-vegetated, or have shallow, low-moisture snowpacks [Lettenmaier *et al.*, 2015]. But satellite observations struggle to resolve snow in the mountains where snowpacks are deep, terrain is complex, and vegetation exists. Meanwhile, models can represent the physical processes driving mountain SWE variability, but suffer from inaccurate precipitation inputs and partitioning schemes [Cho *et al.*, 2022; Lundquist *et al.*,

2019; *Wayand et al.*, 2013], which are the largest contributors to modeled SWE uncertainties [*Cho et al.*, 2022; *Fang and Leung*, 2023; *Raleigh et al.*, 2016]. Current research is therefore focused on combining multiple modeling frameworks and temporally- or spatially-sparse observations for improved SWE output [*of Reclamation*, 2021; *Frei et al.*, 2012; *Lettenmaier et al.*, 2015], often using data assimilation (DA; e.g., [*Aalstad et al.*, 2018; *Alonso-González et al.*, 2022, 2023; *Barrett*, 2003; *Liston and Hiemstra*, 2008] or its subset, machine learning (e.g., [*Bair et al.*, 2018; *Burdett and Craig*, 2025; *Crumley et al.*, 2024; *Steele et al.*, 2024]). These methods can produce improved estimates of SWE with reduced uncertainties compared to both input models and observations. However, DA techniques often have complex methods with steep learning curves and can be computationally expensive [*Largerón et al.*, 2020]. One of the most accurate methods for estimating distributed SWE does so retrospectively in a reanalysis framework [*Bair et al.*, 2016; *Largerón et al.*, 2020; *Mortimer et al.*, 2020; *Yang et al.*, 2023]. Reanalysis products commonly use DA techniques to update ensembles of high-resolution modeled SWE with satellite observations of fractional snow covered area (fSCA) to determine what SWE must have been throughout the season (e.g., [*Alonso-González et al.*, 2021; *Bair et al.*, 2016; *Durand et al.*, 2008; *Fang et al.*, 2022; *Giroto et al.*, 2014; *Margulis et al.*, 2016]). Although reanalysis products don't provide information about the current state of the snowpack, they give some of the most accurate records of historical daily SWE estimates in mountain regions [*Bair et al.*, 2016; *Mortimer et al.*, 2020; *Yang et al.*, 2023].

The processes that shape SWE accumulation and melt are spatially complex, but their cumulative effects at the end of the accumulation season (commonly approximated as 1 April) tend to be consistent year after year [*Gauthier et al.*, 2022; *Pflug et al.*, 2022; *Schirmer and Lehning*, 2011]. Topography and vegetation interact with synoptic storm systems in consistent ways [*Deems et al.*, 2008; *Herbert et al.*, 2024; *McGrath et al.*, 2018; *Pflug and Lundquist*, 2020; *Schirmer and Lehning*, 2011; *Schirmer et al.*, 2011; *Sturm et al.*, 2010]. Specifically, mountains block, deflect, or extract precipitation, creating coherent storm pathways and precipitation patterns [*Alexander et al.*, 2015; *Changnon et al.*, 1993; *Chu et al.*, 2011; *Rutz*

et al., 2014, 2015]. This leads to patterns in annual SWE accumulation that have remained relatively stable for multiple centuries [Gauthier *et al.*, 2022] and forms large regions where 1 April SWE tends to vary in similar ways [Aguado, 1990; Cayan, 1996; Changnon *et al.*, 1991, 1993; Clark *et al.*, 2001; McCabe, 1994; McCabe Jr. and Legates, 1995; Schöner *et al.*, 2019]. For example, the entire California Sierra Nevada tends to have either above- or below-average SWE in any year, a pattern which explains 84% of the spatial variability in 1 April snow course measurements [Aguado, 1990].

Accordingly, annually-repeating SWE patterns have been used in various regions of the world to inform SWE estimates. They have been used to inform precipitation inputs [Pflug *et al.*, 2021, 2022; Vögeli *et al.*, 2016; von Kaenel and Margulis, 2025], downscale coarse-resolution snow models [Gauthier *et al.*, 2022], and infer and model snow depth distributions [Pflug *et al.*, 2022; Pflug and Lundquist, 2020; Sturm *et al.*, 2010]. However, except for Gauthier *et al.* (2022), these studies were done in small-scale basins less than 1,200 km², at scales far smaller than the extents at which SWE patterns change from year to year. Although Gauthier *et al.* (2022) used large-scale repeating SWE patterns across the Western US, they did so to downscale model simulations rather than to calculate SWE directly.

A common way to quantify annually-repeating SWE patterns is to calculate the difference, or anomaly, of the current-year SWE from the long-term mean or median [Cayan, 1996; Clark *et al.*, 2001; Gauthier *et al.*, 2022; Jörg-Hess *et al.*, 2014; McCabe Jr. and Legates, 1995; Moore and McKendry, 1996; Schöner *et al.*, 2019]. In some cases this anomaly is standardized by dividing by the standard deviation (standardized anomaly, also known as the z-score) or is expressed as a quantile, and these tend to be consistent over much larger regions than the SWE values themselves. Standardized anomalies (SAs) have been used to quantify and group 1 April snowpack variability and to relate this variability to atmospheric circulation patterns [Cayan, 1996; Changnon *et al.*, 1991, 1993; Clark *et al.*, 2001; McCabe, 1994; McCabe Jr. and Legates, 1995; Moore and McKendry, 1996]. Quantile mapping is commonly used in atmospheric science as a bias-correction and downscaling method (e.g., [Boé *et al.*, 2007; DeGaetano and Shulman, 1990; Gudmundsson *et al.*, 2012; Rajczak *et al.*,

2016; *Solman and Menéndez*, 2003; *Thiemeßl et al.*, 2011; *Wood et al.*, 2002, 2004], and has been used less-commonly to bias-correct and down-scale snow cover [*Matiu and Hanzer*, 2022] and SWE [*Jörg-Hess et al.*, 2014], and to homogenize snow depth time series [*Resch et al.*, 2023].

Here we present new methods that use annually-repeating SWE patterns to propagate the high accuracy of SWE reanalysis products into real-time SWE estimates. We rely on the assumption that 1 April SWE anomalies are consistent over large spatial regions, which allows us to use the anomaly as measured at an in situ station to represent the anomaly of the surrounding area. We first use a clustering algorithm to find regions of the Western US that historically have spatially consistent 1 April SWE anomalies. Then we test several combinations of statistical methods and in situ stations to map the current-year SWE anomaly onto the historical distribution of reanalysis grid cells [*Fang et al.*, 2022] to calculate the current-year spatially-explicit 1 April SWE within these clusters. We calculate the accuracy of our SWE products relative to the reanalysis in the entire study area and to LiDAR measurements [*Painter et al.*, 2016] in three subdomains of our study area, and compare this accuracy to that of two physically-based modeling systems. We test our methods in the Upper Colorado River Basin (UCRB) with the following questions: (a) Which combination of statistical methods (SA or quantile) and in situ stations result in SWE maps that best reproduce the reanalysis SWE? (b) How do canopy cover, elevation, and extreme versus average snow conditions affect the accuracy of our SWE maps? (c) How does the accuracy of our SWE products compare to that of commonly-used physically-based SWE models?

Others have used historical information from reanalysis products to inform SWE estimates, using techniques such as machine learning [*Bair et al.*, 2018], pattern-based snowfall adjustment [*Pflug et al.*, 2022], and precipitation bias correction [*von Kaenel and Margulis*, 2025], but here we seek a simpler approach. Our methods have the benefits of being computationally and conceptually simple, easily scaleable, real-time, and they directly compute SWE. In this study, the accuracy of the SWE output is predominantly measured relative to the input reanalysis product, although we also compare to LiDAR measurements in small

subbasins. Since biases and errors in the reanalysis product are propagated to the calculated SWE output, we don't expect our results to achieve a higher accuracy relative to lidar measurements than that of the input data. If these methods can output current-year SWE with high fidelity to the reanalysis product, then advancements in reanalysis methods will lead to improvements in the accuracy of SWE output from our methods.

The paper proceeds as follows. In 2.2, we provide background information about the data sets and study area. In Section 2.3, we explain the clustering analysis (2.3.1), introduce SA and quantile mapping as the two statistical distribution methods (2.3.3 and 2.3.3.1), and describe the SWE calculation methods in more detail (2.3.2). In Section 2.4, we provide results for the clustering analysis and SWE calculation methods described in 2.3, as well as an analysis of the SWE errors by elevation, canopy cover, and year. Finally, we end with a discussion in 2.5 and a conclusion in 2.6.

2.2 Data and Study Area

2.2.1 Study Area

We analyzed the spatial clustering of SWE anomalies across the continental western US to identify patterns in those anomalies at the synoptic scale. Then we focused our SWE calculations on the $\sim 295,000$ km² upper Colorado River Basin (UCRB; Figure 2.1a, b) as defined by the US Geological Survey's 2-Digit Hydrologic Unit [*Jones et al.*, 2022] watershed boundary. We chose to focus on the UCRB because (a) there were multiple clusters present in the watershed, indicating that the meteorology there is complex and therefore decisions about which in situ stations to use may impact results, (b) the region is cold enough that 1 April SWE represents accumulation processes with minimal melt, (c) the alpine regions are generally cloud-free during times of snow disappearance and have less dense forest cover than in more maritime mountains, improving the reliability of reanalysis SWE products, and (d) the region is critically important to water resources in the broader Colorado River Basin.

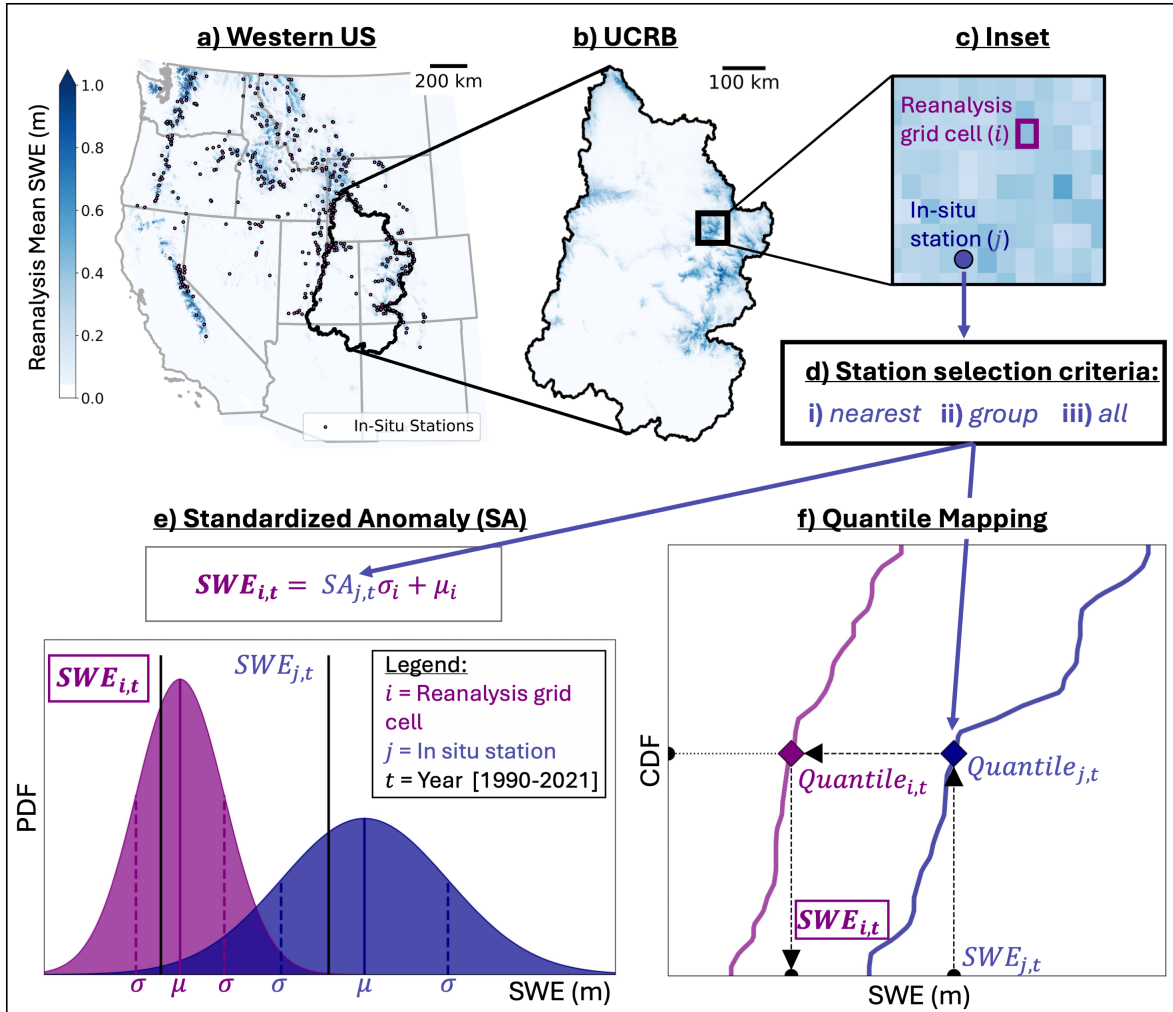


Figure 2.1: *Caption on next page.*

Figure 2.1: Panel (a) shows the average 1 April snow water equivalent (SWE) for 1990–2021 from the reanalysis product and the location of the 445 in situ stations with continuous 1 April SWE records for 1990–2021 in the Western US. Panel (b) provides an inset of the Upper Colorado River Basin where we tested our methods. Panel (c) is a further inset map showing a reanalysis grid cell (purple) and an in situ station location (blue). Panel (d) provides the station selection criteria used to determine which station(s) should inform calculations at each grid cell. Panel (e) gives the equation for calculating SWE at a grid cell using the standardized anomaly (SA) from in situ stations and gives an example of the theoretical normal probability distribution function (PDF) at a grid cell (purple) and station (blue). The PDFs represent the long-term distribution of 1 April SWE at each location. Current-year 1 April SWE is calculated at a grid cell by first measuring SWE at a station, calculating the SA for that SWE value relative to the long-term distribution at that station, and then finding what SWE value that SA value corresponds to on the long-term distribution of the grid cell. Panel (f) gives the empirical cumulative distribution functions (eCDFs) for a grid cell (purple) and station (blue), and demonstrates the quantile mapping process. This process involves taking the 1 April SWE as measured at an in situ station, determining its position on the CDF of that station, mapping that same position to the CDF of the grid cell, and finding which SWE value that position corresponds to. The blue arrows between Panel (d, e, and f) indicate where the in situ station information from the selection criteria gets used in each method.

2.2.2 *In Situ Snow Station Data*

We compiled 1 April SWE measurements from the Natural Resources Conservation Service’s SNOw TELelemetry (SNOTEL) network and the California Department of Water Resource’s snow pillow network. These stations weigh the snowpack and convert weight to the water equivalent, or measurement of water volume at that point. To maximize both number of

stations and length of record, we started our study period in 1990. We only included stations that had continuous 1 April SWE records for the duration of the study period and a mean of 1 April SWE >0.1 m (Figure 2.1a). This resulted in a total of 445 stations distributed across the Western US, and 85 stations in the UCRB.

2.2.3 Airborne Snow Observatory SWE Products

We used SWE products from the Airborne Snow Observatory (ASO) [Painter *et al.*, 2016] to evaluate the accuracy of the reanalysis product and our calculated SWE products. ASO conducts airborne LiDAR surveys of select basins in the Western US that are of high importance to regional water resources. They create a summer snow-off gridded surface from the LiDAR last returns, and then difference this from snow-on surfaces measured in the winter and spring. They coarsen these snow depth products to 50 m, and the resultant grids have an uncertainty of <0.02 m [Painter *et al.*, 2016]. They model snow density using a spatially-distributed snowpack evolution model and in situ data, with errors of 3%–8% [Painter *et al.*, 2016], and then convert snow depth to SWE by combining the gridded snow depth product with the spatially-distributed snow density output. The resultant SWE maps have 50 m resolution and are used as input to hydrologic models to estimate reservoir inflow and timing by water managers in Western states. SWE and snow depth products from ASO are also commonly used as ground truth in snow studies [Bair *et al.*, 2016; Behrangi *et al.*, 2018; Fang *et al.*, 2022; McGrath *et al.*, 2019; Oaida *et al.*, 2019; Pflug *et al.*, 2022; Yang *et al.*, 2023]. We used SWE products from the Gunnison-East River, Gunnison-Taylor River, Crested Butte, and Conejos basins to evaluate the reanalysis data, our calculated SWE products, and modeled SWE. We accessed this data from the National Snow and Ice Data Center (NSIDC), and reprojected and resampled the data to the coordinate reference system and resolution (CRS) of the reanalysis product.

2.2.4 Western US SWE Reanalysis Product

The Western United States UCLA Daily SWE Reanalysis data set (reanalysis; [Fang *et al.*, 2022]) consists of gridded daily SWE estimates from 1985 to 2021 at about 500 m (16 arc-s) spatial resolution (Figure 2.1a) and is hosted by NSIDC. It was created by assimilating Landsat fractional snow-covered area using a Bayesian framework into an ensemble of land surface model prior snow estimates. This product does not provide real-time SWE information, as it can only be produced once all snow has melted for the season. Fang *et al.* (2022) compared peak SWE from the reanalysis product to peak SWE at Western US SNOTEL stations and to ASO SWE derived from airborne LiDAR data. Fang *et al.* (2022) found the correlation (R value) between each Western US station and collocated reanalysis grid cell was 0.77, the mean difference (MD) was -0.15 m, and the root mean squared difference (RMSD) was 0.28m. In the UCRB specifically, the R was 0.70, MD was -0.06, and RMSD was 0.19 m. The range of R values between the LiDAR data and collocated reanalysis data were 0.74–0.91, the range of MDs was -0.15–0.05 m, and the range of RMSDs was 0.07–0.38 m. Fang *et al.* (2022) also found that the accuracy of peak SWE in the reanalysis product compared to in situ data was sensitive to forest cover fractions above 40%, with a consistent RMSD of ~ 0.18 m at 40% cover and below, increasing steadily to ~ 0.38 m at 60% cover. Accuracy was also sensitive to locations and years with fewer than 40 available fSCA measurements.

The comparison to ASO SWE data in Fang *et al.* (2022) only included data from one basin in the UCRB (Aspen/Castle Maroon Basin). Therefore, we performed an additional accuracy assessment within two other Colorado basins for locations and years with both reanalysis and ASO LiDAR data near the timing of peak SWE. This resulted in four comparison years: the Conejos River Basin in 2015 and 2016, and the East River Basin in 2018 and 2019. We found R values between 0.74 and 0.85; MDs between -0.5 and -0.03 m; and RMSEs between 0.10 and 0.59 m (2.2). For use in our study, we compiled 1 April SWE maps for 1990–2021 and only included grid cells in our analysis that had a mean 1 April SWE of >0.1 m.

2.2.5 *SnowModel*

SnowModel is a widely used modeling system which simulates the evolution of spatially distributed snow properties such as SWE [Liston and Elder, 2006]. It incorporates snow redistribution by wind and simulates distributed multilayer snow properties [Liston *et al.*, 2020]. We used a subset of SnowModel data on 1 April within the UCRB that was previously simulated using a parallelized version over CONUS at 100 m spatial resolution for water years 2000–2021 [Mower, 2025; Mower *et al.*, 2024]. The model was forced by the WRF CONUS 404 data set [Rasmussen *et al.*, 2023], and parameters were calibrated for the entire CONUS domain rather than for the UCRB specifically. We coarsened and re-gridded the model output to match that of the reanalysis data and calculated the differences between the reanalysis and SnowModel for each year of overlap in the UCRB domain. SnowModel was included to evaluate how the accuracy of the SWE output from our methods compared to more intensive process-based modeling intended to resolve the physics of snow accumulation and depletion.

2.2.6 *SNODAS*

The National Operational Hydrologic Remote Sensing Center SNOw Data Assimilation System (NOHRSC SNODAS) product is hosted by NSIDC [Barrett, 2003]. It is a modeling and data assimilation system that outputs SWE and associated variables for hydrologic purposes. It ingests and downscales output from Numerical Weather Prediction models, runs a physically based, spatially-distributed energy- and mass-balance snow model, and assimilates satellite, airborne, and ground-based observations of snow cover and SWE [Barrett, 2003]. SNODAS has a spatial resolution of about 1 km (30 arc-s), and is run daily. Analysts decide on a daily basis which observations to include in the data assimilation scheme. There are not many published comparisons to independent observations because SNODAS assimilates many observational data sources. In the independent analyses that have been performed, SNODAS has been found to underestimate SWE accumulation in alpine terrain [Anderson,

2011; *Clow et al.*, 2012; *Hedrick et al.*, 2015] and overestimate SWE in the California Sierra Nevada with annual biases ranging from +13% to +61% [*Bair et al.*, 2016]. An independent analysis in a 750 km² subset of the UCRB found an R^2 of 0.72 and RMSD of 12.6 cm between SNODAS and aerial LiDAR survey snow depth changes in forested areas, though those decreased to an R^2 of 0.16 and RMSE of 55 cm in alpine terrain [*Clow et al.*, 2012]. Clow et al. (2012) found different signals in the SNODAS discrepancies in regions with different physiographic characteristics, such as exposure to wind, shrub and canopy cover, elevation, and the representativeness of nearby SNOTEL stations used in the data assimilation. We collated the 1 April SNODAS output for water years 2005–2021, excluding data from before October 2004, since routine snow data assimilation did not start until then. We reprojected and resampled the data to match the CRS and resolution of the reanalysis data.

2.3 Methods

The goal of this work is to demonstrate how current-year SWE anomalies measured at in situ stations can be combined with historical gridded reanalysis data to parsimoniously calculate current-year gridded SWE on 1 April. In 2.3.1 we describe the clustering analysis used to outline regions of similarly varying SAs in the Western US. In 2.3.2 we describe the SWE calculations using parametric (SA method; 2.3.3; Figure 2.1e) and nonparametric (quantile mapping method; 2.3.3.1; Figure 2.1f) long-term statistics, and describe the three different station selection criteria used in this study (Figure 2.1d). We calculate SWE for the gridded domain of the entire UCRB (2.3.2) and illustrate the methods at two in situ stations (2.3.3.2).

2.3.1 Clustering on the Standardized Anomaly

For the clustering analysis only, we coarsened the reanalysis data from 500 m to 4 km resolution to capture large-scale patterns and maintain the geographic cohesion of the clusters. Then we calculated the SA at each grid cell of the reanalysis data and at each in situ station for the Western US domain for 1990–2021. SA was calculated according to

$$SA_{i,t} = \frac{SWE_{i,t} - \sigma_i}{\mu_i}, \quad (2.1)$$

where $SWE_{i,t}$ is the SWE on 1 April at location i in year t , μ_i is the mean of the 1 April SWE for 1990–2021 at i , and σ_i is the standard deviation of the 1 April SWE for 1990–2021 at i . We performed three different clustering analyses, using a different input for each. One used the reanalysis data, another the reanalysis grid cells collocated with in situ stations, and the final one used in situ station data. We created one matrix of the SA values for each data set, where dimensions were location and time. We input each matrix to a k -means++ clustering algorithm [Arthur and Vassilvitskii, 2006], which grouped the location dimension into k clusters based on the SA values of the year dimension, resulting in clusters of stations or grid cells that had similar variations in SWE through time. K -means clustering is a commonly used algorithm due to its simplicity and speed (i.e., [Carvalho et al., 2016; Fovell and Fovell, 1993; Massart and Kaufman, 1983; Santos et al., 2005; Solman and Menéndez, 2003]). Downsides are that it tends to favor similarly sized spherical clusters in the variable space (Text S2 in Supporting Information).

We specified a k -value of 5 based on a silhouette score analysis, which is a measure of the ratio between within-cluster similarity and between-cluster similarity [Rousseeuw, 1987], and previous work that identified climate and snow patterns in the Western US [Aguado, 1990; Cayan, 1996; Changnon et al., 1991; McCabe Jr. and Legates, 1995; Schumacher et al., 2024; Trujillo and Molotch, 2014]. We then compared the clusters resulting from the three inputs at in situ station locations to check the fidelity of the clustering results, since sample size could impact cluster boundaries. We used the clusters formed by the full reanalysis data for the *group* station selection criteria (Figure 2.1d) because we needed each grid cell to be included within a cluster boundary.

2.3.2 SWE Calculations

We calculated 1 April SWE using two methods (SA and quantile) and three station selection criteria (*nearest*, *group*, and *all*) for a total of six SWE products (Figure 2.1). Both methods used the anomaly from the long-term measure of central tendency (either the mean or median) but differed in their assumptions of the data’s distribution (parametric or non-parametric). For each of these methods we used the following station selection criteria: (a) the nearest-neighbor station to each grid cell (*nearest*), (b) the mean or median of stations within the same cluster as each grid cell (*group*), and (c) all stations in the UCRB (*all*; Figure 2.1d). We used a leave-one-out approach, where each year of reanalysis data was independently treated as the current year, excluded from the 1 April SWE historical distribution (Figures 2.1e and 2.1f), and then used to evaluate the accuracy of the current-year estimate. We used the original resolution of the reanalysis product (500 m), in contrast to the coarser resolution used for the clustering analysis. For each current year, we took the SWE measurement at an in situ station and found its position relative to the long-term mean or median at that station, where the long-term distribution excluded data from the current year. Then we found this same position relative to the mean or median of the long-term distribution of a reanalysis grid cell and identified what SWE value that position corresponded to (Figure 2.1e,f). This is discussed more in 2.3.3-2.3.3.2.

We compared each of the six resultant SWE products to the withheld reanalysis data from each year (1990–2021) by calculating the coefficient of determination (R^2 value), root mean squared error (RMSE), and percent bias (Pbias) in each year. We calculated these same metrics for the SnowModel and SNODAS output relative to the reanalysis, and for all products compared to three dates of ASO LiDAR measurements that were collected within 4 days of 1 April in two different years.

We compared the spatial distribution of the errors relative to the reanalysis product in three different years: a low-snow year (2018), high-snow year (2019), and an average snow year (2020). Finally, we calculated the same metrics by grouping all years and separating

by elevation bands and canopy cover percentages. Elevation bands were chosen to group areas with similar snow-cover climatology (e.g., [Hammond *et al.*, 2023; Moore *et al.*, 2015]), with the highest elevation cut-off approximately aligned with treeline ($\sim 3,500$ m; [Lukas and Payton, 2020]) and mid-elevations separated at 2,900 m to split up the highest percentage of the basin by area. Elevation bands are defined as low ($< 2,300$ m), low-mid (2,300–2,900 m), high-mid (2,900–3,500 m), and high ($> 3,500$ m) elevations.

2.3.3 Standardized Anomaly

We make two assumptions when using the SA to calculate SWE. The first is that 1 April SWE values are normally distributed in time. This was found to hold true for the distribution of 1 April SWE values from 1948–1987 in the Gunnison River Basin, which is a subbasin of the UCRB [McCabe, 1994]. Other studies have used a theoretical normal or lognormal distribution to represent the spatial rather than temporal distribution of SWE and snow depth in individual years [Elder *et al.*, 1991; Jonas *et al.*, 2009; Kuchment and Gelfan, 1996; Liston, 2004; Marchand and Killingtonveit, 2005; Pflug and Lundquist, 2020; Sturm *et al.*, 2010], with the best fits occurring near the timing of peak SWE [Alfnes *et al.*, 2004] and with the exclusion of zero values [Elder *et al.*, 1991]. To test this for the temporal distribution of our SWE data, we ran the Shapiro-Wilks test for normality on the 32 years of untransformed and log transformed 1 April SWE data from each Western US in situ station. We found that a normal distribution fit better than a lognormal distribution, with 80% of stations passing the Shapiro-Wilks test, and determined that the 1 April SWE values could be approximated with a normal distribution.

The second assumption is that SA values are spatially consistent between the grid cells and the in situ stations used to calculate SWE at those grid cells (the domain over which we make this assumption depends on the station selection criteria). Essentially, this second assumption means that these locations accumulate SWE from the same synoptic storm systems, thereby ending the season with the same relative variation from their average peak SWE. Under these two assumptions, we can use the current-year SA value from an in situ

station to solve for SWE at a reanalysis grid cell by rearranging Equation 1 as shown in Figure 2.1e).

2.3.3.1 Quantile Mapping

Quantile values are looked-up from the eCDF [Panofsky and Brier, 1965] of the SWE data, which makes no assumptions about the data’s distribution. We calculated an eCDF from 1 April 1990–2021 SWE values at a given location using the median unbiased estimator (as recommended by [Hyndman and Fan, 1996]; Figure 2.1f).

We make two assumptions when using quantile mapping to calculate SWE. The first is that the 1 April quantile is the same for the grid cells and the in situ stations used to calculate SWE at those grid cells (the domain over which we make this assumption depends on the station selection criteria). This is a similar assumption to the second assumption described for the SA technique. However, when we calculate one quantile value from a collection of stations, we take the median quantile instead of the mean. Therefore, unlike the SA technique, quantile mapping does not assume that the data have a particular statistical distribution. The second assumption is that the historical maximum and minimum SWE values provide adequate bounds on future conditions, such that the current year will not exceed the historical maximum or be lower than the historical minimum. Under these assumptions, we can use quantile mapping to calculate SWE by combining the long-term record at an in situ station with the current-year quantile from a reanalysis grid cell. To do so, we look up the current-year SWE on the station’s eCDF to find the current-year quantile. Then we look up that quantile on the grid cell’s eCDF to find the current year SWE at the grid cell as shown in (Figure 2.1f).

2.3.3.2 Example Application at Station Pairs

We first illustrate these methods at two pairs of in situ stations that each have their own long-term record of 1 April SWE. We calculate SWE at one station using the historical SWE record as measured at that station and the current-year information from the other station.

Then we evaluate the calculated SWE at the first station against the measured SWE at that station. Station pairs were chosen such that each pair was in a different cluster, and stations within a pair were within the same cluster and were physically near to each other. Station pairs were composed of (a) the Butte (3,110 m elevation) and Schofield Pass (3,250 m) SNOTEL stations; and (b) the Dry Lake (2,520 m) and Columbine (2,790 m) SNOTEL stations.

2.4 Results

Here we present the clustering map (2.4.1; Figure 2.2), the SWE calculations for the station pairs (2.4.2; Figure 2.3), the six UCRB SWE products and model output as compared to the reanalysis data (2.4.3; Figure 2.4), spatial maps of the errors in select years (2.4.3; Figures 2.5 and 2.6), metrics from calculated SWE products by elevation band and canopy cover percentage (2.4.3; Figure 2.7), and calculated SWE and model products compared to ASO data (2.4.3; 2.1).

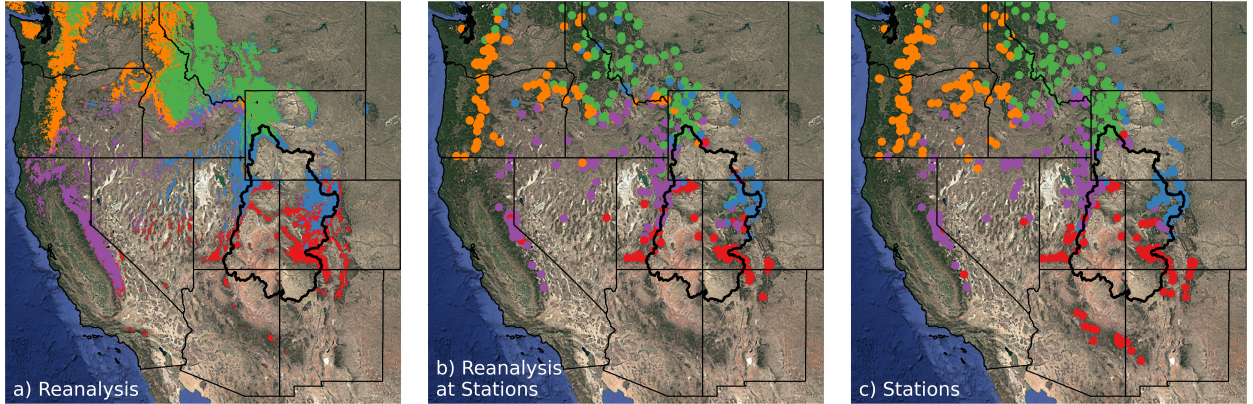


Figure 2.2: Standard anomaly (SA) clusters of 1 April snow water equivalent from 1990–2021 for the (a) reanalysis product, (b) the reanalysis product in only grid cells overlapping in situ stations, and (c) in situ stations. The orange, green, purple, blue, and red colors represent the five different clusters.

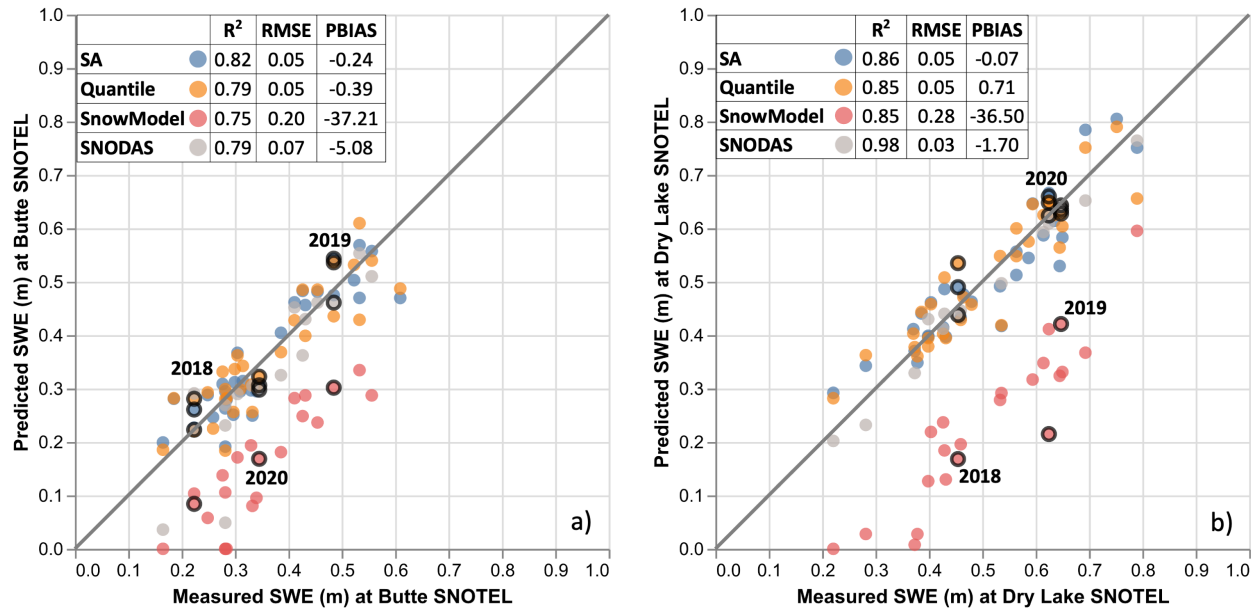


Figure 2.3: Calculated snow water equivalent (SWE) at the two station pairs: (a) Butte station SWE predicted using current-year data from Schofield Pass station, and (b) Dry Lake station SWE predicted using current-year data from Columbine station. Black circles around data points with vertically aligned labels indicate that the data is from one of the highlighted years: 2018, 2019, and 2020. Inset tables give statistics for each product compared to measured SWE at each station.



Figure 2.4: *Caption on next page.*

Figure 2.4: Boxplots of metrics comparing the six calculated snow water equivalent (SWE) products and the SnowModel and SNODAS output to the reanalysis data. The boxplots showing results for the calculated SWE products each contain 32 data points: one for each year of 1990–2021. The SnowModel boxplots contain 22 data points as the model was run for 2000–2021. The SNODAS boxplots contain 17 data points as the model was run for 2005–2021. Subfigure (a) shows the coefficient of determination (R^2 values) for the 32-year period, (b) shows the root mean squared errors, and (c) shows the percent bias. The white lines indicate the median values and the whiskers extend to the furthest point within 1.5x the interquartile range. Criteria refer to the station selection criteria in Figure 2.1: (i) nearest, (ii) group, and (iii) all.

2.4.1 *Clustering on Standardized Anomalies*

The clustering analysis produced three maps (one from the reanalysis, one from the reanalysis grid cells collocated with the stations, and one from the station data) that delineate regions of the Western US with similar variations in SWE accumulation through time (Figure 2). The reanalysis and station data formed similar cluster boundaries for much of the Western US, with one main exception in a region that included northern Utah, southern Idaho, and northeastern Nevada (Figure 2.2a,c). In the reanalysis clusters, this region was grouped with northern Colorado, whereas in the station clusters it was grouped with California (Figure 2.2). The clusters formed from the station data and the collocated reanalysis data had more similar cluster boundaries (Figures 2.2b,c), which indicated that clustering differences in Figures 2.2a,c were driven by interactions between the algorithm and the number and spread of data points in the variable space, rather than caused by underlying differences in SWE patterns represented by the station versus reanalysis data.

The Western US cluster boundaries provided here align well with previous efforts to group standardized 1 April SWE anomalies through a rotated principle component analysis [*Cayan,*

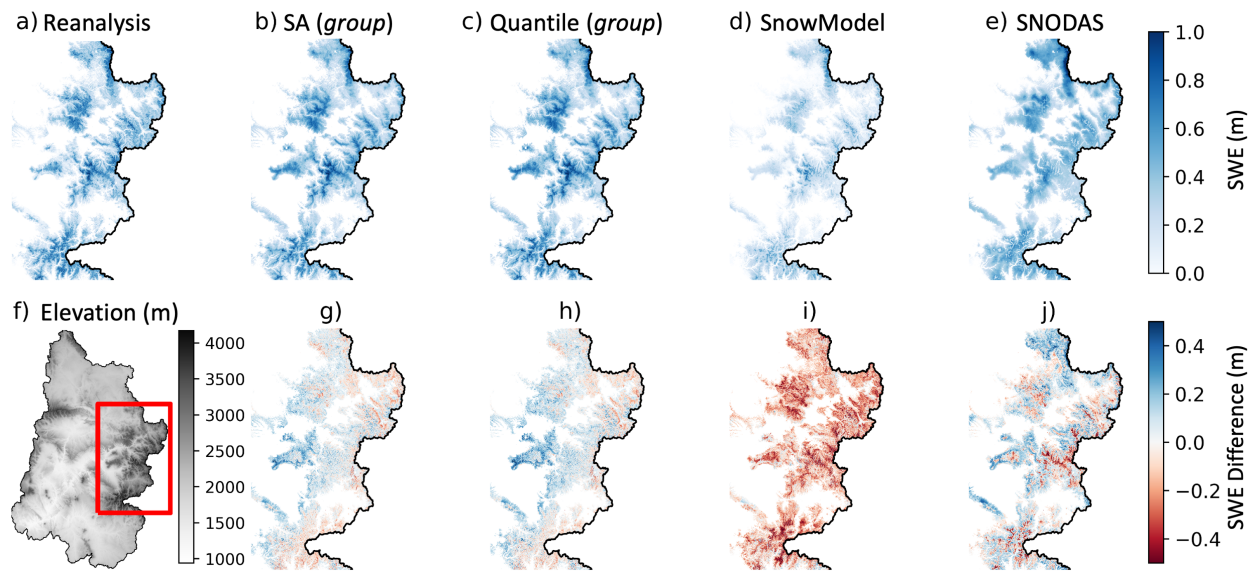


Figure 2.5: The spatial distribution of snow water equivalent (SWE) from the reanalysis, calculation methods, and model outputs (a–e) and the differences between these products and the reanalysis product on 1 April 2020: (a) the reanalysis product within a subset of the UCRB; SWE calculated using the (b) SA group and (c) quantile group methods; (d) SnowModel output; (e) SNODAS output; (f) elevation above mean sea level in the Upper Colorado River Basin with the red box showing the inset location; (g–j) the differences between the reanalysis product and the products shown in b–e.

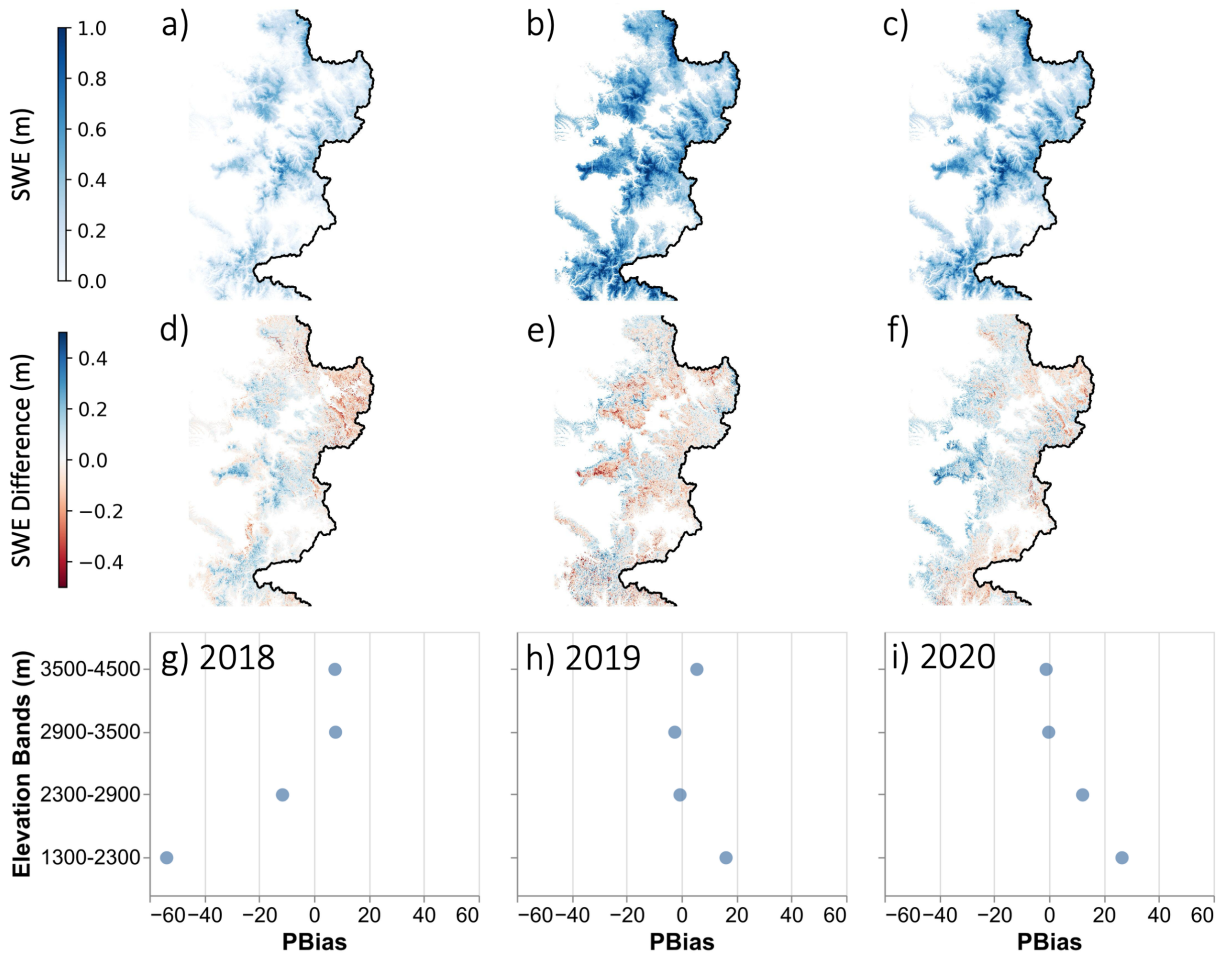


Figure 2.6: The spatial distribution of snow water equivalent calculated using the SA group method on 1 April of (a) 2018, (b) 2019, and (c) 2020. The second row gives the spatial distribution of the errors relative to the reanalysis product, and the third row gives the percent bias within each elevation band. Subfigures in each column correspond to the same year. The region of the Upper Colorado River Basin (UCRB) shown is the same as for the inset map in Figure 2.5f, although the Pbias statistics in the bottom row include the entire UCRB.

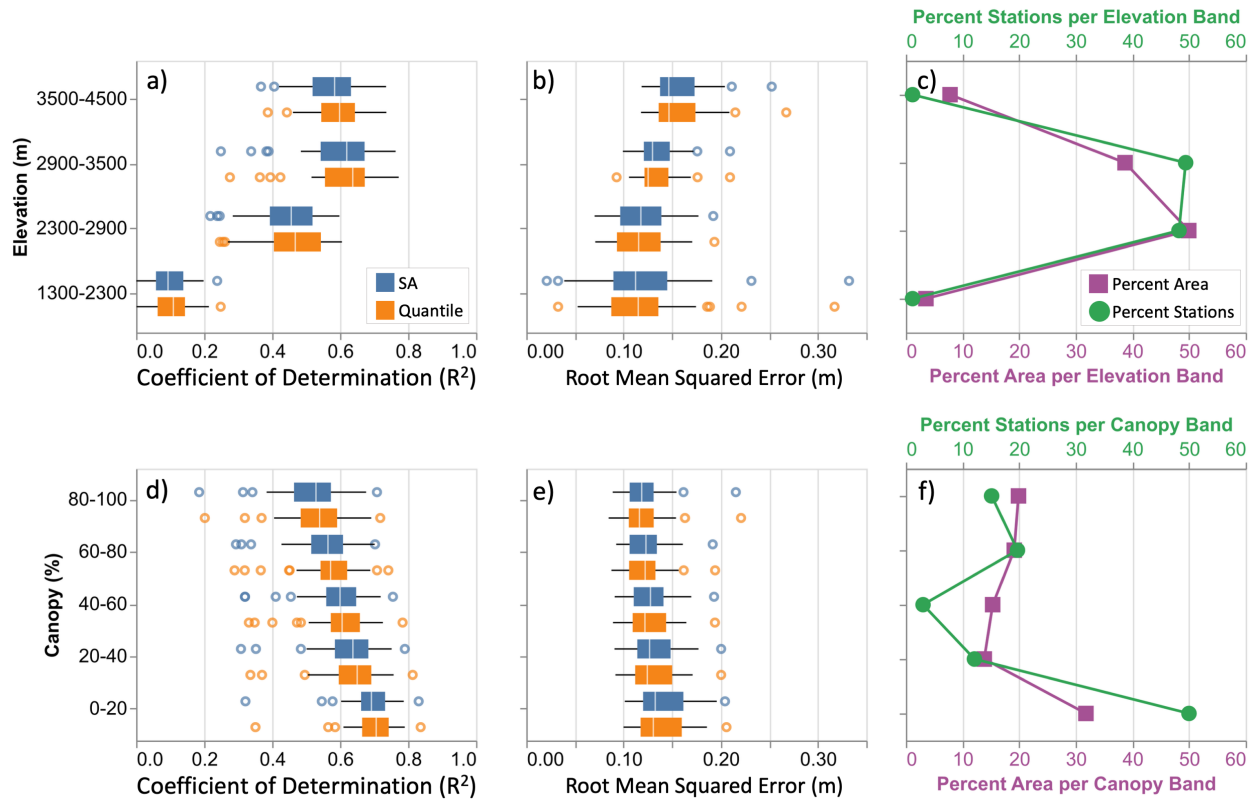


Figure 2.7: Boxplots of error metrics from 1 April snow water equivalent for 1990–2021 as calculated by the SA (blue) and quantile (orange) group methods. These are separated into elevation bands (a–c) and 20% canopy cover bands (d–f). Pbias was not sensitive to elevation or canopy cover, and so is not shown here. The percentage of in situ stations (green) and snow-covered Upper Colorado River Basin area (purple) within each of these bands is shown for (c) elevation and (f) canopy cover.

Table 2.1: Error metrics comparing the five 1 April SWE products used in this study to ASO SWE data acquired within 4 days of 1 April. CB 2016 refers to the Crested Butte data acquisition on 4 April 2016, GE 2018 refers to the Gunnison-East River data acquisition on 31 March 2018, and GT 2018 refers to the Gunnison-Taylor River acquisition on 30 March 2018. The R^2 value refers to the coefficient of determination, Pbias is the percent bias, and RMSE is the root mean squared error in meters.

SWE Product	R^2			Pbias			RMSE (m)		
	CB 2016	GE 2018	GT 2018	CB 2016	GE 2018	GT 2018	CB 2016	GE 2018	GT 2018
Reanalysis	0.40	0.51	0.07	8.97	-8.49	8.27	0.17	0.14	0.15
SA (<i>group</i>)	0.58	0.64	0.35	22.83	17.65	6.04	0.15	0.13	0.10
Quantile (<i>group</i>)	0.59	0.64	0.36	21.88	13.26	0.23	0.15	0.12	0.10
SnowModel	0.33	0.52	0.12	-36.13	-29.41	-31.98	0.21	0.15	0.13
SNODAS	0.02	0.20	0.18	-14.79	-13.13	0.05	0.24	0.18	0.12

1996] and with precipitation patterns we would expect to see from known moisture pathways from the Pacific to the interior [Rutz *et al.*, 2015]. However, years when meteorology deviates from standard patterns will not be well-represented by these clusters. For the rest of the paper, we used the cluster boundaries from the reanalysis data (Figure 2.2a) and will focus on only the UCRB, which contains 3 of the 5 clusters (red, green, and blue).

2.4.2 SWE Calculations at Station Pairs

We calculated SWE at two station pairs (Schofield Pass to predict Butte, and Columbine to predict Dry Lake) to demonstrate the SA and quantile methods before scaling up to the gridded UCRB domain (Figure 2.3). Note that calculations at these stations used historical data from the stations themselves, not the reanalysis product. At both of the predicted stations (Butte and Dry Lake SNOTEL stations), the SA and quantile methods had similar high correlation and low bias. SnowModel had high correlation with measured SWE at both sites but was biased low, while SNODAS had high correlation and low bias with measured

SWE, especially at Dry Lake (Figure 2.3). Differences between the measured SWE and the SnowModel and SNODAS data are likely at least partly due to scale differences between point data and gridded data. SNODAS assimilates data from SNOTEL stations based on daily decisions from analysts [Barrett, 2003], so close fits between the station data and SNODAS grid cell are likely due to assimilation of measured SWE at that site. However we can't confirm whether a specific SNOTEL measurement was assimilated in a given year because the assimilation decision process is not made public. All four methods had similar dispersion. Aside from SnowModel, which was fairly consistently low biased, there was less spread among the different models in 2020 (an average snow year up to 1 April) as opposed to 2018 and 2019 (low and high snow years, respectively) at the Butte site, while at the Dry Lake site both 2019 and 2020 had lower model spread than in 2018.

2.4.3 Gridded SWE Calculations

Following the workflow in Figure 1, we generated 6 different maps of 1 April SWE each year, with summary statistics relative to the reanalysis presented in Figure 2.4. The SA and quantile methods that used the same station selection criteria had similar accuracy (median values and spreads of the three metrics) and outperformed SnowModel (across all metrics) and SNODAS (in all metrics except for Pbias, for which only the SA group method outperformed SNODAS), as compared to the reanalysis (Figure 2.4). The differences between the station selection criteria were generally larger than those between the SA and quantile methods, although the quantile method had more negative Pbias in almost all cases. Among the station selection criteria, the group criterion tended to have less bias and stronger correlation than the other criteria for both the SA and quantile methods (Figure 2.4). Likewise, the all station selection criterion tended to outperform the nearest criterion. Of all method and station selection criteria combinations, the SA group method had the highest median coefficient of determination (0.64), Pbias closest to 0 (0.49%), and lowest RMSE (0.13 m; Figure 2.4). We show the spatial distribution of the SA group products, along with SnowModel and SNODAS, in an average snow year (2020) in Figure 2.5 and

additional example years in Figures 2.14-2.20 in Supporting Information. We also show the spatial distribution of the SA group errors in 3 years to compare performance in a low (2018), high (2019), and average (2020) snow year in Figure 2.6.

The errors for the SA and quantile group methods in an example average year (2020) had very similar spatial distributions and error magnitudes (Figures 2.5g,h). The SnowModel output had larger error magnitudes and was biased low (Figures 2.4 and 2.5i), and SNODAS was also biased low but to a lesser extent than SnowModel (Figures 2.4 and 2.5j). The SA and quantile methods had a positive bias at lower elevations and were less biased at higher elevations (Figures 2.5g,h; Figures 2.6f,i). In the example low snow year (2018), the spatial distribution of the errors from the SA group method were elevationally dependent, with underestimates at lower elevations and slight overestimates at higher elevations (Figures 2.6d,g). In the example high snow year (2019), the spatial distribution of the errors was less dependent on elevation, with overestimates at the lowest elevations and less bias at all other elevations (Figures 2.6e,h). In other years, the elevational signal of the errors was flipped from that of 2018 (Figures 2.14 and 2.16 in Supporting Information) or depended on north-south gradients within the watershed (Figure 2.15 in Supporting Information), with the inflection point corresponding well with the boundary between groups (blue and red clusters in Figure 2.2a).

We calculated the R^2 , RMSE, and Pbias for elevation and canopy cover bins across all years for the SA and quantile group products. The median R^2 value and RMSE both increased with elevation, although at the highest elevations there was a slight decrease in R^2 (Figures 2.4a,b). The median Pbias value was not sensitive to elevation (not shown). However, the spread was much greater for the lowest elevation band, likely due to the smaller percent area in this band and therefore small denominator in the Pbias calculations. The median R^2 value and the median and spread of RMSE values decreased with percent canopy cover, although the RMSE was less sensitive to canopy cover than was the R^2 (Figures 2.4d,e). The Pbias values were not sensitive to canopy cover and are not shown. Finally, the mid-high elevations (2,900–3,500 m) were slightly over-represented in the number of in

situ stations per area, while the highest elevations ($>3,500$) were slightly under-represented (Figure 2.4c). There were more stations per area at percent canopy cover below 20%, while higher percent canopy covers tended to be under-represented (Figure 2.7f).

Finally, we compared SA and quantile group products, the reanalysis data, and the SnowModel and SNODAS products for 1 April to ASO SWE data on dates within 4 days of 1 April in two subbasins ($<800 \text{ km}^2$) of the UCRB. The SA and quantile group products had lower RMSEs and were more strongly correlated with the ASO SWE than were the other products, although SNODAS had the lowest Pbias of all products (Table 2.1). The SA and quantile group products had slight positive biases, while SnowModel and SNODAS had negative biases of varying magnitude (Table 2.1, Figures 2.21–2.23 in Supporting Information).

2.5 Discussion

Our results demonstrate that current-year point measurements of 1 April SWE anomalies can be combined with patterns of SWE accumulation from a reanalysis product to estimate current-year SWE with similar or higher accuracy compared to common modeling systems. This held true relative to the reanalysis data and to ASO SWE data. Due to the complete spatial coverage and length of record, the reanalysis statistics are more robust overall, but the ASO SWE data are more robust with respect to absolute ground truth. Therefore, we primarily define accuracy as reproducing the reanalysis data, while the ASO SWE data provide reality checks for this comparison. The following addresses our three main research questions regarding (a) the selection of the most accurate statistical method and station combination; (b) how canopy cover, elevation, and extreme versus average snow conditions affect accuracy; and (c) how our methods' accuracy compare to that of common physically-based models. We also discuss considerations for future work related to changing climactic conditions.

2.5.1 Comparison Between Statistical Methods

All combinations of statistical methods and station selection criteria had similar performance, and what differences there were appeared to be driven more by the station selection criteria than by the statistical distribution assumptions. The station selection criteria that aggregated anomaly measurements from multiple stations (group and all) consistently performed better than the criterium that used the single nearest station (nearest). This suggests that the aggregation process reduced random errors from individual stations, and perhaps removed any incidental local changes to the terrain or canopy that could cause small-scale pattern changes, such as fire, clearcuts, or landslides. Therefore, multiple stations should be used for these methods when possible.

The *group* criterion performed only slightly better than the *all* criterion, indicating that the clustering was less impactful in the UCRB than we expected. However, in certain years the direction of elevation-dependent error gradients was different along cluster boundaries (Figure 2.15 in Supporting Information), so the clusters may have varying importance depending on the meteorology in a given year. The silhouette score for the Western US clustering analysis was low (see 2.3.1 and Text S2 in Supporting Information for more details), which can indicate that clusters are not well-separated or have varying densities. We hypothesize that the clusters containing the Sierra Nevada (purple cluster) and Cascade Range (orange cluster) are better defined than those in the interior (red and blue clusters). Previous studies have found evidence separating the Sierra Nevada, Cascade Range, and interior ranges from each other, but are less conclusive about separations within the interior [Cayan, 1996; Changnon *et al.*, 1991; Trujillo and Molotch, 2014]. Cayan (1996) also calculated the SAs of 1 April SWE at in situ stations and found long correlation length scales of the SAs in the Cascade Mountains and Sierra Nevada, with a break in the correlation around the California/Oregon border consistent with the boundary between our purple and orange clusters (Figure 2.2). Trujillo and Molotch (2014) found that the accumulation and melt characteristics at Western US snow stations could be categorized as maritime, intermountain, or

continental, which clearly defined the coastal mountains as different from the interior but did not strongly differentiate regions within the Rocky Mountains. Meanwhile, Changnon et al. (1991) calculated the variability of 1 April SWE at in situ stations in the northern Rocky Mountains and found 11 distinct regions. Given these findings, cluster boundaries within the UCRB might be less clearly defined than those between major mountain ranges. We anticipate that sorting snow stations by cluster will become more important in SWE calculations that include the entire Western US and therefore multiple major mountain ranges.

The SA method consistently performed slightly better (stronger correlation and lower bias) than the quantile method relative to the reanalysis, although the opposite was true compared to the ASO SWE data. We had expected quantile mapping to perform better than the SA method because there were fewer assumptions about the distribution, but our results suggest that the temporal distribution of 1 April SWE can be reasonably approximated by a normal distribution. For the calculations that used the *group* criteria, it is possible that the performance of the quantile method would have improved had we run the clustering algorithm on the quantile instead of SA values. It is also possible that our sample size of 32 years was too small to build an empirical distribution that fit better than the theoretical normal distribution.

Additionally, our quantile method was limited by the bounds of the historical data used to build the eCDF. In years when conditions exceed the historical data at a grid cell in either direction (sometimes called new extremes), the quantile method will under- or over-estimate these new extremes by pulling them toward the center of the distribution. The SA method deals with new extremes slightly better by allowing them to exceed the historical bounds, but still may pull them closer to the center than they should be. Given our short historical record and leave-one-out approach, extreme years were not included in the record used to predict them. As the length of historical records and range of observations increase, the quantile and SA methods will both become more robust. Finally, the limitations of dealing with new extremes in quantile mapping is a well-known problem [Byun and Hamlet, 2024]. Methods exist to deal with these extreme values (e.g., [Boé et al., 2007; Bürger et al., 2013;

Byun and Hamlet, 2024; Chen et al., 2013; Themeßl et al., 2012], and future work could incorporate such methods into our workflow.

2.5.2 Canopy Cover, Elevation, and Year-to-Year Accuracy

The majority of metrics reported here were calculated relative to the reanalysis product, which has some known errors. The reanalysis is biased slightly low compared to ASO data and in situ observations, and its accuracy is sensitive to canopy cover density and the availability of cloud-free fSCA observations during the ablation period [*Fang et al., 2022*]. Systematic errors in the reanalysis product were propagated to our calculated SWE products, so even though the accuracy of our calculated SWE relative to the reanalysis product was only slightly sensitive to percent canopy cover, there could be additional canopy-dependent errors that were not revealed by this comparison. We expect that our methods will yield higher-accuracy SWE maps relative to observations in regions with low canopy cover densities that are well-suited for optical fSCA observations.

The errors in the example low-snow year (2018) had a more pronounced elevational dependence than in the example high-snow year (2019) and average year (2020; Figure 2.66. In 2018, the SA group method exaggerated the existing elevational SWE gradient by underestimating low elevation snow and overestimating high elevation snow. Precipitation is the main driver in SWE variability in the Colorado River basin, with temperature increasing in importance at lower elevations [*Zeng et al., 2018*]. Therefore, years in which precipitation and temperature (and the elevational gradients of these conditions) differ from average will be more difficult for our methods to resolve the spatial distribution of SWE. Indeed, 2018 was generally warmer and drier than normal all season, and this year had higher magnitude percent biases at all elevation bands than did 2019 and 2020. The statistical methods used here will best capture the average pattern scaled by annual perturbations. These methods can still be used to predict SWE in years with abnormal meteorology, but will do so with less confidence.

Our methods assumed that within each cluster, perturbations in winter precipitation

affected SWE anomalies at all snow-covered locations with the same magnitude and sign (either positive or negative). This assumption holds for regions that experience synoptic storm systems as either all snow or all rain. However, if a storm deposits rain over part of the snow-covered domain and snow over another part, then the response of the resultant snow pattern will be bifurcated: some areas will lose SWE, and some will gain SWE. This rain-snow division is driven by elevation according to the temperature lapse rate and violates our assumptions about snow accumulation patterns. Likewise, when midwinter melting occurs at lower elevations but not at higher elevations, lower regions will lose SWE while higher regions will have no change in SWE. Conversely, abnormally cold storms can deposit more snow than normal at lower elevations. The impact of elevation on both midwinter rain and melt is likely more pronounced in warmer regions such as the Pacific Northwest, where temperatures in snow-covered regions often fluctuate between below and above freezing.

In a warming climate, rainfall over typically snow-covered areas becomes more common ([*Knowles et al.*, 2006]), and SWE patterns will change even in historically cold regions like the UCRB [*Cowherd et al.*, 2024]. Therefore, these deviations from historically normal conditions will become more common. Changes to SWE patterns can also occur due to changes to synoptic weather patterns [*Cayan et al.*, 1998; *Changnon et al.*, 1991, 1993; *McCabe Jr. and Legates*, 1995; *Moore and McKendry*, 1996]. To capture these changes to the historical normal conditions, reanalysis products should be generated on a regular, continuing basis, and should cover long periods of record to enable more accurate predictions of extreme events. In future years with more rain on snow, elevation could become a more important factor than geographic region in driving cluster boundaries, and these cluster boundaries would therefore become more important for identifying patterns.

Finally, as average conditions change, melt may become more common during and before peak SWE timing. We assumed negligible melt before 1 April, but this assumption will likely be violated more frequently in future years. Melt patterns are spatially consistent, although they are distinct from accumulation patterns [*Pflug et al.*, 2022]. Future studies could incorporate both accumulation and melt patterns by weighting them as a function

of the amount of daily melt and accumulation at each grid cell and station up to 1 April, according to Pflug et al. (2022), using the daily SWE evolution available from both the reanalysis and in situ station data.

2.5.3 Comparison With Physically-Based Models

We did not expect the SnowModel or SNODAS output to exactly match the reanalysis product, as the data were produced using different methods. However, SnowModel and SNODAS provided a useful benchmark for concluding that our calculated SWE products (a) reproduced the reanalysis product more closely than did these independent model output, and (b) performed similarly or better relative to ASO SWE data. SNODAS performed better than SnowModel relative to the reanalysis and ASO SWE data, which is expected behavior since SnowModel was not calibrated to the UCRB, and SNODAS benefits from the assimilation of in situ and remotely sensed observations. The consistent negative bias of the SnowModel output relative to the reanalysis product and ASO SWE data was likely caused by biased precipitation input, as the input WRF precipitation over the UCRB is biased low on the order of 20% Rudisill et al. [2023]. The low R^2 of the SNODAS and SnowModel data compared to both the reanalysis product (Figure 2.4a) and the ASO SWE data (Table 2.2 in Supporting Information) suggests that certain processes may be represented poorly, especially in alpine terrain [Clow et al., 2012].

These issues with the SnowModel and SNODAS output highlight some advantages of our statistical methods over physical models: our methods don't require bias-correction of precipitation input, nor site-specific parameter tuning or computationally expensive resolution of physical processes. Our methods also have the benefit of being easily applied to new reanalysis products, which could have higher resolution and cover additional regions of the globe. Finally, our open-source methods are simple for new users to adopt relative to physically-based models and data assimilation schemes (<https://github.com/bessoh2/correlated-domains>).

2.6 Conclusions

The distribution of snow across the landscape is controlled by complex processes. The cumulative effects of these processes repeat from year to year, resulting in annually-repeating patterns in SWE distribution at the end of the accumulation season. Here we quantified these patterns by calculating annual SWE anomalies, and tested several statistical methods that used these anomalies to calculate the 1 April SWE distribution in the UCRB. We used a SWE reanalysis product to provide the long-term record of distributed 1 April SWE and in situ snow stations to provide current-year SWE measurements. We found that SWE anomalies were consistent over large regions of the Western US, and that using the current-year standardized anomaly from a snow station to offset the long-term record at reanalysis grid cells could accurately replicate current-year SWE maps. The most accurate method calculated SWE using the average standardized anomaly (often called the z-score) from stations that were placed in the same cluster by a k-means clustering algorithm. This method reproduced current-year SWE with a coefficient of determination (R^2) of 0.64, percent bias of 0.49%, and a median root mean squared error of 0.13 m. We found that separating by cluster was less important in the UCRB than expected, but that using anomaly data averaged from multiple stations was more accurate than using data from a single station. For studies spanning the whole Western US, the clusters will likely become more important for separating large-scale anomaly patterns. We also found elevation-dependent errors, indicating that future work may need to account for factors such as spatially varying rain versus snow and midwinter melt patterns, and limitations in the bounds of the historical data. These methods best represent average meteorological conditions, so years with extreme or distinct meteorology may have larger errors.

These methods effectively mapped sparse real-time measurements of near-peak SWE to the surrounding area, based on historical knowledge of SWE accumulation patterns within the domain. They provide an elegant solution to the complexity of estimating mountain SWE and could be used in conjunction with hydrologic models to better estimate the timing

of snowmelt runoff, and to inform ecological function and the radiation balance in snowy domains. The method framework introduced here is best used for estimating SWE near the end of the accumulation season (around 1 April) to optimize the repeatability of seasonal SWE accumulation patterns, which differ from melt patterns. Our method is also quite flexible in terms of the input data and could be used anywhere that has an accurate long-term record of SWE distribution and sparse real-time measurements. Though the UCLA Western US SWE Reanalysis product [Fang *et al.*, 2022] worked well for this domain, any accurate and distributed record could be used. For example, other SWE reanalysis products exist, some with higher resolution and covering different geographic regions and extents than the product used here, such as the Andes Mountains, High Mountain Asia, Lebanese Mountains, and the European Alps (e.g., [Alonso-González *et al.*, 2021; Bair *et al.*, 2016; Cortés *et al.*, 2016; Fiddes *et al.*, 2019; Margulis *et al.*, 2016; Molotch, 2009; Rittger *et al.*, 2016]). As more accurate SWE reanalysis products are released for more regions of the globe, they can be incorporated into the framework presented here. Other data sets, or ensembles of data sets, with consistent long-term records could also be used. Such data sets should be continually updated to account for changing SWE patterns with a warming climate.

Acknowledgments

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Data availability

The Western US UCLA SWE Reanalysis data [Fang *et al.*, 2022] were accessed through the National Snow and Ice Data Center (NSIDC; https://nsidc.org/data/wus_ucla_sr/versions/1) via API. The SNOw Data Assimilation System data were also accessed through NSIDC (<https://doi.org/10.7265/N5TB14TC>) via API. In situ station data (Natural Resources Conservation Service, 2025; State of California Department of Water Resources, 2025) was accessed through the Natural Resources and Conservation Service (NRCS; <https://www.nrcs.usda.gov>) and the California Department of Water Resources (DWR; <https://cdec.water.ca.gov/snow.html>). The SnowModel output (Mower, 2025) used in this paper is available in a Zenodo dataset archive with doi: <https://doi.org/10.5281/zenodo.15261609>. All code used to prepare, process, and analyze these datasets is available in a public GitHub repository: <https://github.com/bessoh2/correlated-domains>.

2.7 Supporting Information

This document contains additional details about certain sections of the main text. The ideas and information presented here are not necessary for the understanding of the main text but are provided for those who wish to learn more about this study. Text 2.7.1, Table 2.1, and Figure 2.8 detail the comparison we made between the Western U.S. UCLA SWE Reanalysis data and airborne lidar surveys and correspond to Section 2.2 of the main text. Text 2.7.2 and Figures 2.10 – 2.13 give more details about the clustering analysis and correspond to 2.3.1 and 2.4.1 of the main text. Figures 2.14 - 2.20 are referenced only in the main text. They expand the number of years plotted to show the spatial distribution of errors in the calculated SWE maps and correspond to 2.4.3 of the main text. Figures 2.21 – 2.23 are referenced only in the main text and show the spatial distribution of errors between the SWE products in the main text and airborne lidar data on three dates near 1 April.

2.7.1 Text S1: Comparison of SWE reanalysis to airborne lidar surveys

To further evaluate the accuracy of the Western US UCLA SWE Reanalysis data *Fang et al.* [2022], we compared it to airborne lidar data from the Airborne Snow Observatory, Inc. [Painter et al., 2016] in several Colorado basins. We used the 50 m resolution SWE product (ASO SWE) accessed through the National Space and Ice Data Center (NSIDC). The ASO team calculates snow depth by differencing snow-on and snow-off digital elevation models (DEMS) derived from aerial laser altimetry. They then use modeled density to convert snow depth to SWE. The 50 m resolution product has a reported depth uncertainty of < 2 cm and density uncertainty of about $13\text{--}30 \text{ kg m}^3$ [Painter et al., 2016].

We compared SWE reanalysis to ASO SWE in 3 subbasins within the UCRB: Conejos River Basin, East River Basin, and Aspen/Castle Maroon. Metrics from Aspen/Castle Maroon are from [Fang et al., 2022], and we calculated the corresponding metrics for the other two basins. We used ASO data that were collected near 1 April in years for which SWE Reanalysis exists (2015 and 2016 in the Conejos basin and 2018 and 2019 in the East River basin), and resampled ASO SWE to the same resolution and grid as the SWE Reanalysis product (~ 500 m). We downloaded SWE Reanalysis data from the corresponding date of the ASO flights and calculated the R value, mean difference (MD), and root mean squared error (RMSE) of the SWE Reanalysis compared to the ASO SWE values.

The SWE Reanalysis product compared to ASO performed best in the Conejos River Basin, and performed the worst in the East River Basin in 2019 (Table 2.2). The SWE Reanalysis product relies on timely optical satellite imagery from Landsat to identify grid cell melt-out dates, which informs the back-calculations of daily SWE [Fang et al., 2022]. So differences in accuracy between locations and years is likely tied to differences in the availability of cloud-free Landsat images during the ablation season.

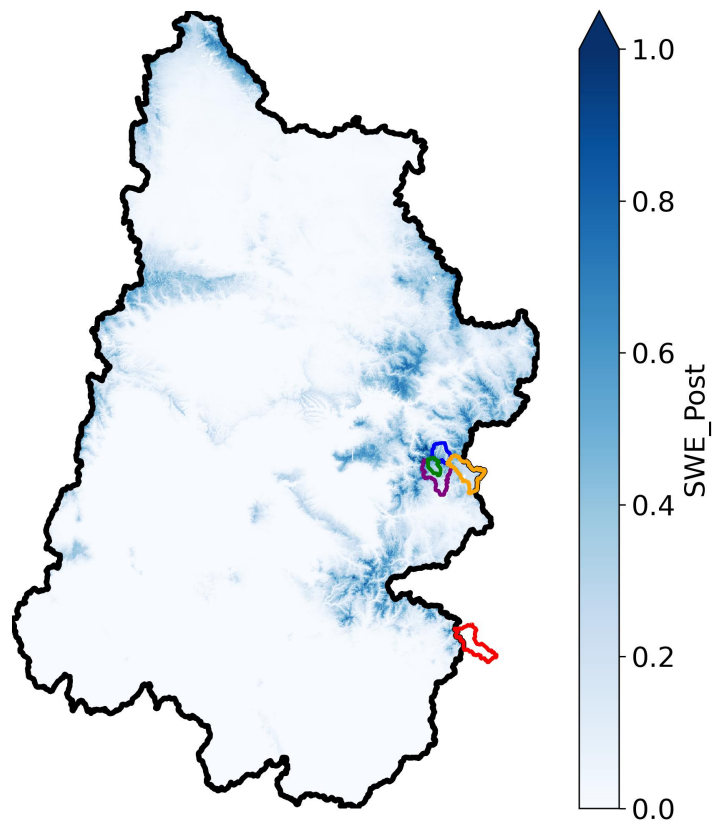


Figure 2.8: The UCRB domain with reanalysis SWE represented by the color bar and the basins where we conducted the ASO comparisons: Blue = Castle-Maroon, purple = East River, red = Conejos, orange = Taylor River, and green = Crested Butte.

Table 2.2: Error metrics comparing the SWE Reanalysis product to ASO SWE from the same day. The R value refers to the correlation coefficient, MD is the median difference in meters, and RMSE is the root mean squared error in meters. The date refers to the date the ASO data were collected, and the reanalysis product from that same day was used in the calculations.

Basin	Date	R	MD (m)	RMSE (m)
Conejos River Basin	4/6/2015	0.83	-0.03	0.10
Conejos River Basin	4/3/2016	0.85	-0.028	0.11
East River Basin	3/31/2018	0.74	-0.20	0.24
East River Basin	4/7/2019	0.8	-0.50	0.59

2.7.2 Text S2: Details about the clustering analysis

K-means clustering is a commonly-used unsupervised machine learning algorithm that aims to group data such that Euclidean distances in a feature space are minimized within a cluster (e.g. [Carvalho et al., 2016; Fovell and Fovell, 1993; Massart and Kaufman, 1983; Santos et al., 2005; Solman and Menéndez, 2003]). The algorithm requires that the user specifies the number of clusters (the k-value), so we used the silhouette score to guide our choice of k-value (Figures 2.9-2.12). The silhouette score is a ratio metric of the similarity within clusters versus between clusters [Rousseeuw, 1987; Shahapure and Nicholas, 2020]:

$$S_i = \frac{b_i - a_i}{\max\{a_i, b_i\}}, \quad (2.2)$$

where s_i is the silhouette score for an individual clustered object, b_i is the minimum average dissimilarity of i to all objects of another cluster, and a_i is the average dissimilarity of i to all other objects within the same cluster. The range of possible values is -1 to 1, where negative values indicate the object is probably in the wrong cluster, and values near 1 indicate that the object is in the correct cluster. Cluster numbers should be chosen to

maximize the average silhouette score for all clusters (indicated by the dashed red line in Figs. 2.10 and 2.12). We used the average silhouette scores and silhouette plots to help determine the k-value of 5. For the in-situ data, $k=5$ provided a local maxima for the average silhouette score (Fig. 2.11), and for the SWE reanalysis data, $k=5$ provided a break in the slope of the average silhouette scores such that the average score decreased less from $k=4$ to $k=5$ than for any other single-step change in k for $k < 7$ (Fig. 2.9). The overall low silhouette scores for all k -values tested in the reanalysis and in-situ data indicates weak cluster structure, and many data points likely lie somewhere in between multiple clusters. We chose $k = 5$ because of the relatively high silhouette score combined with our intuition about snow patterns in the Western U.S. (see 2.3.1 of main text for more details).

The k-means method attempts to find roughly spherical clusters in the variable space, and sparse data have cluster centroids that can get stuck at local minima. To counteract the issue of centroids at local minima, we used the `kmeans++` algorithm for initializing the centroid location [Arthur and Vassilvitskii, 2006] and specified 10 initialization iterations. We used the Lloyd (1982) k-means clustering algorithm as implemented in the scikit learn python package, which seeks to minimize the Euclidean distances between objects and the centroid of the cluster to which they are assigned. Centroid locations are iteratively updated to minimize these distances. K-means is best for clusters that are normally distributed (similar variance) and isotropic (see Roth and Amor for more details: https://scikit-learn.org/stable/auto_examples/cluster/plot_kmeans_assumptions.html#sphx-glr-auto-examples-cluster-plot-kmeans-assumptions-py).

We first calculated clusters using the raw SWE data, but these only highlighted elevational gradients (Fig. 2.13), so we focus in the main text on the clusters calculated from the standardized anomaly data.

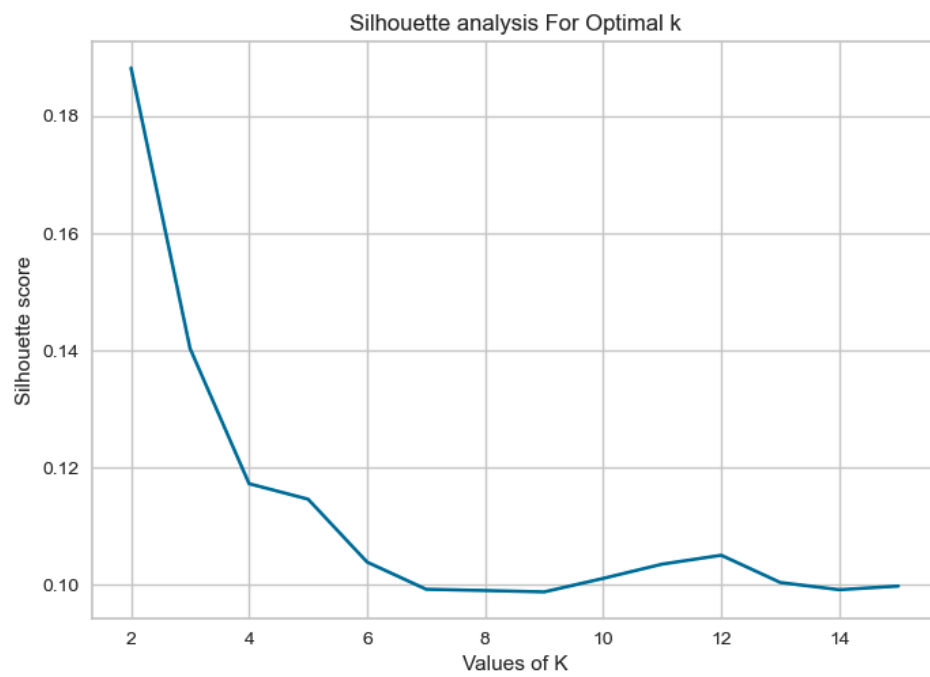


Figure 2.9: Average silhouette scores for clusters with k-values of 2 through 15 for the SWE reanalysis standard anomaly data.

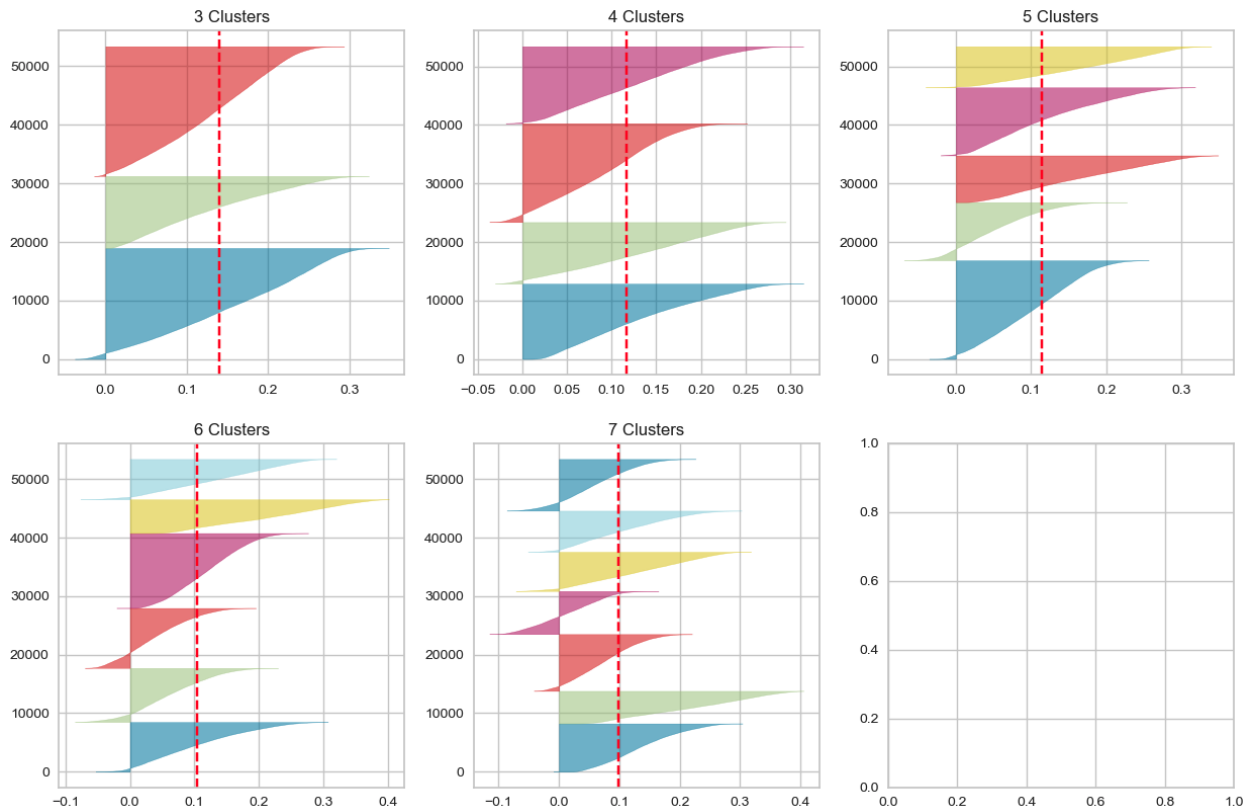


Figure 2.10: Silhouette figures for k-values of 3 through 7 SWE reanalysis standardized anomaly data. The selection of the optimal k-value aims to maximize the average silhouette score (dashed red line) and to have more symmetrical cluster bars.

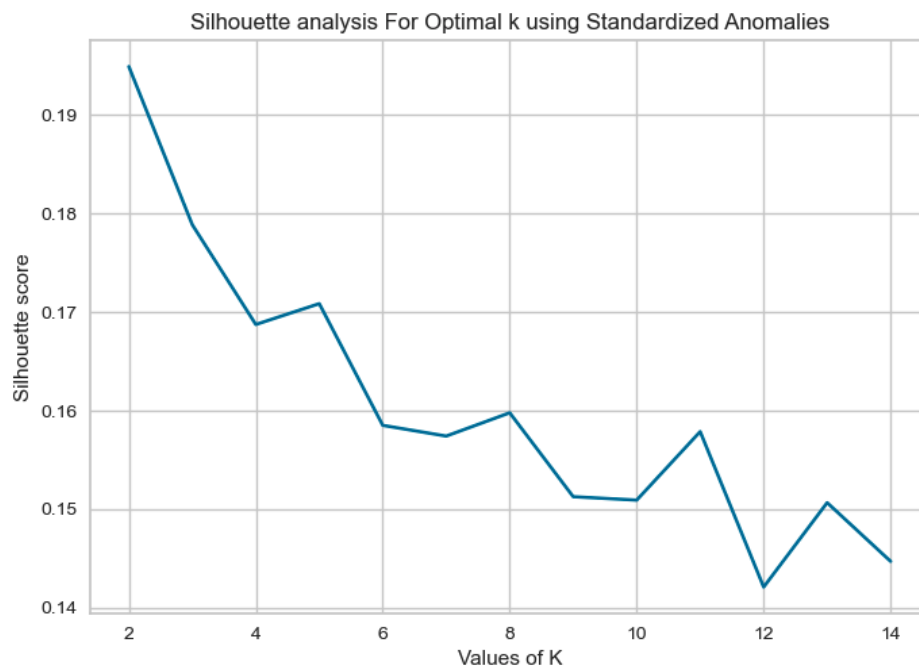


Figure 2.11: Average silhouette scores of clusters for k-values of 2 through 14 for in-situ station standardized anomaly data.

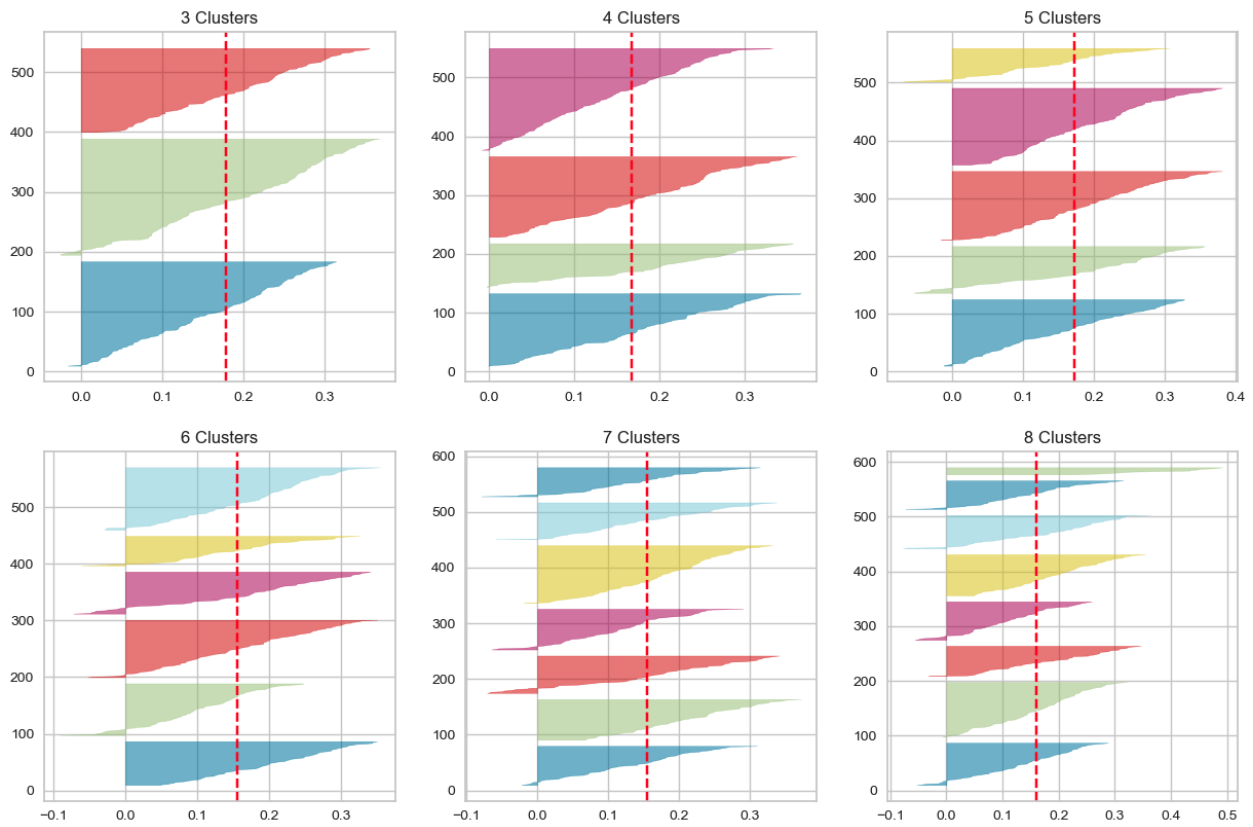


Figure 2.12: Silhouette figures for k-values of 3 through 8 in-situ station standardized anomaly data.

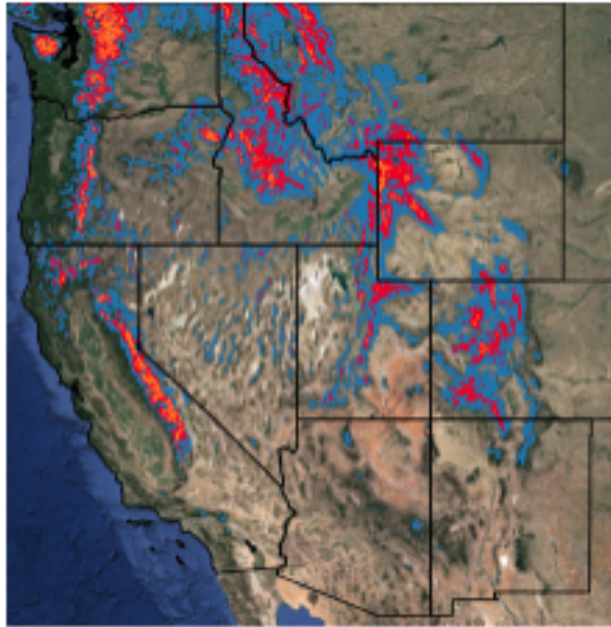


Figure 2.13: Cluster results from inputting SWE reanalysis data without calculating SA first. Elevation is the main differentiator between clusters.

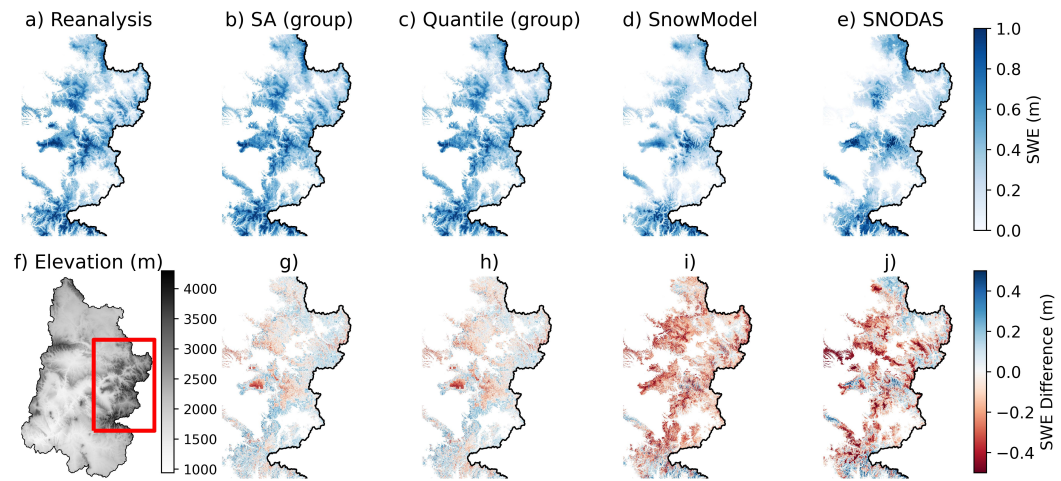


Figure 2.14: Same as Figure 5 in the paper but for water year 2005. This was an above-average snow season, and the SA and quantile group SWE maps tended to overestimate lower elevation and underestimate higher elevations.

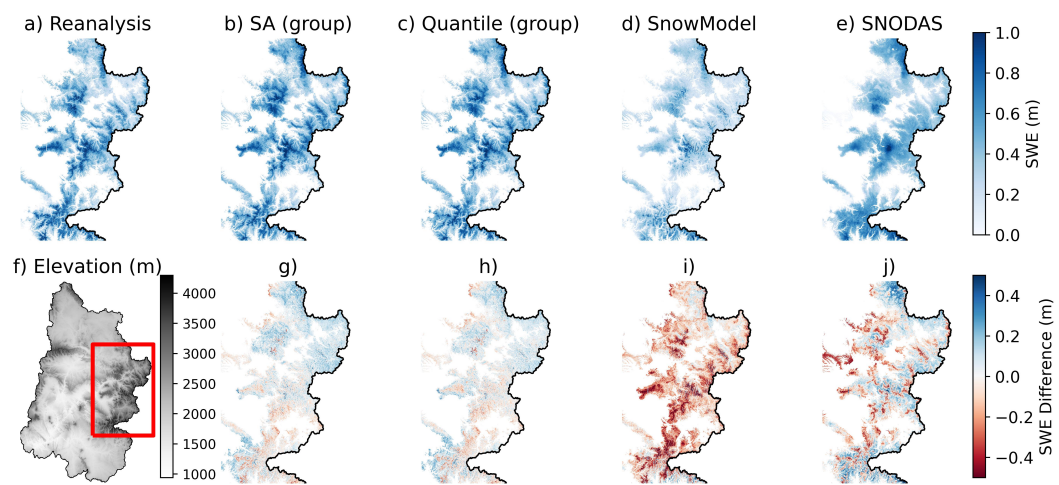


Figure 2.15: Same as Figure 5 in the paper but for water year 2008. This was an above-average snow season. The SA and quantile group SWE maps tended to overestimate low elevations and underestimate high elevations in the south of the inset and vice versa in the north of the inset. The inflection point for the different elevational gradients in these errors approximately corresponds to the boundary between the red and blue clusters in Figure 2 of the main text.

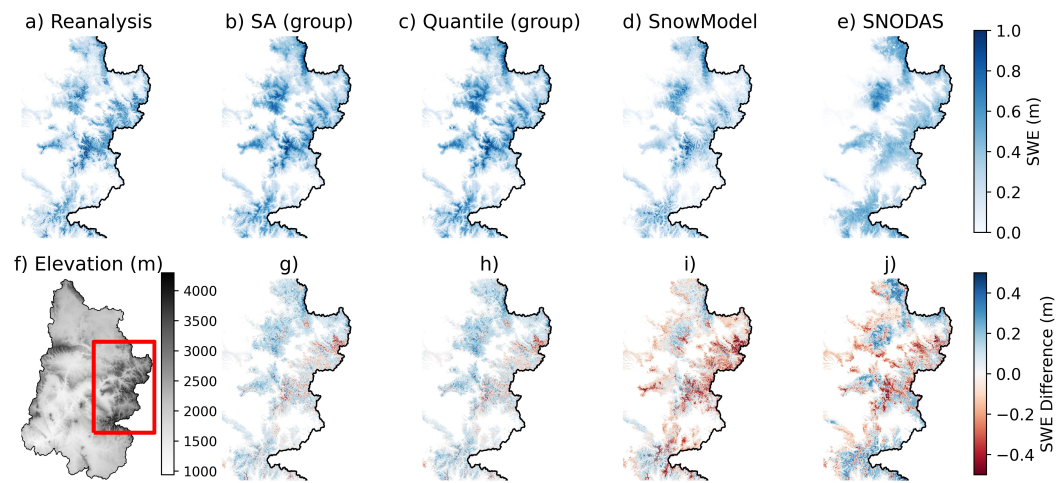


Figure 2.16: Same as Figure 5 in the paper but for water year 2009. This was a slightly above-average snow season. SA and quantile group SWE maps tended to overestimate most elevations but underestimate certain high elevation regions.

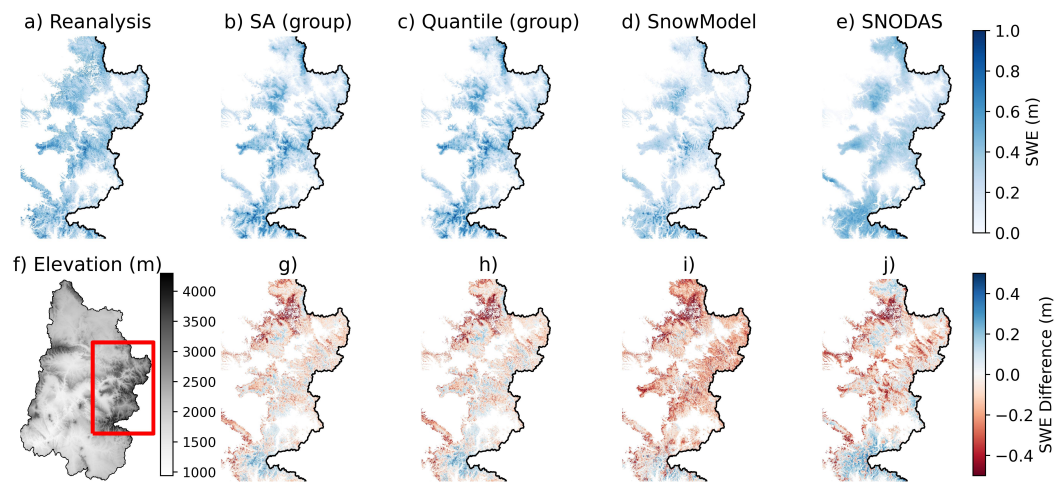


Figure 2.17: Same as Figure 5 in the paper but for water year 2010. This was a nearly average snow season (it was slightly below-average for most of the snow year). SA and quantile group SWE maps tended to underestimate all but the highest elevations, with more extreme underestimation in the north and more extreme overestimation in the south of the inset.

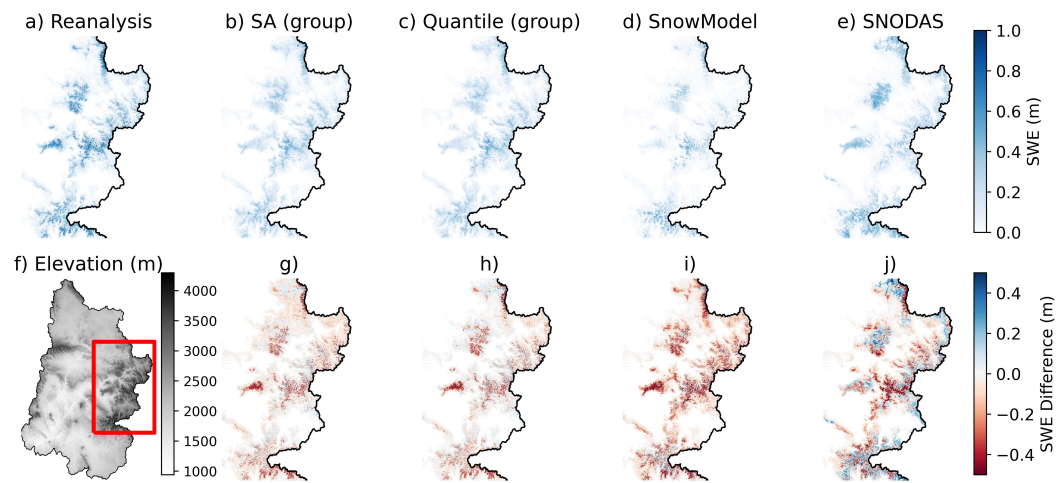


Figure 2.18: Same as Figure 5 in the paper but for water year 2012. This was a below-average snow season. The SA and quantile group SWE maps tended to underestimate high elevations especially.

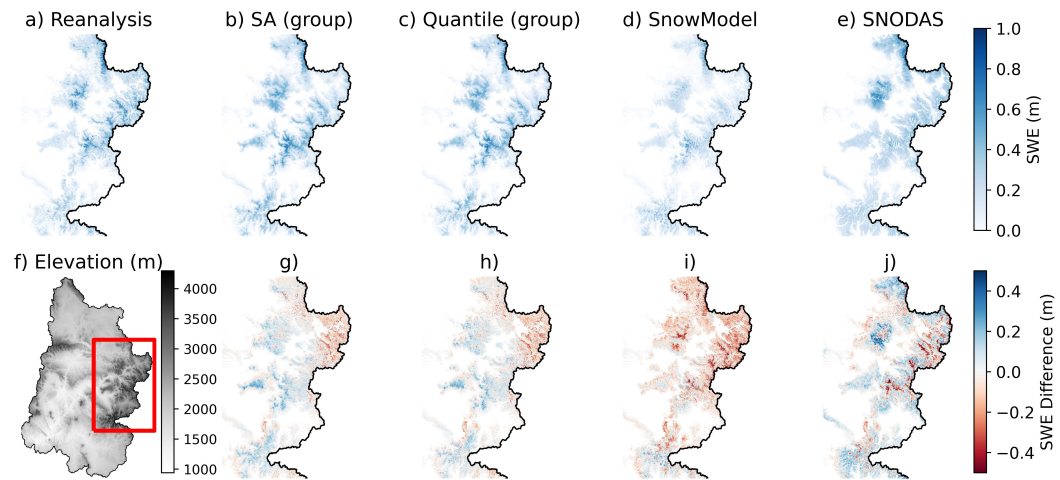


Figure 2.19: Same as Figure 5 in the paper but for water year 2018. This was a below-average snow season. The SA and quantile group SWE maps tended to overestimate SWE at high elevations and underestimate SWE at lower elevations in the south part of the inset and underestimated high elevation SWE in the north of the inset.

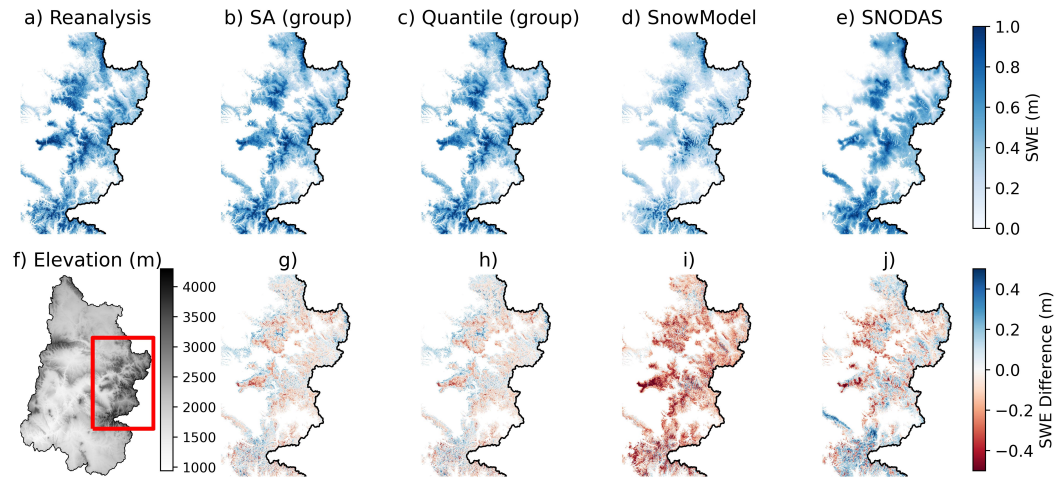


Figure 2.20: Same as Figure 5 in the paper but for water year 2019. This was an above-average snow season. The SA and quantile group SWE maps tended to overestimate certain low elevation SWE and underestimate higher elevation SWE, although the elevational pattern was less clear than in other years.

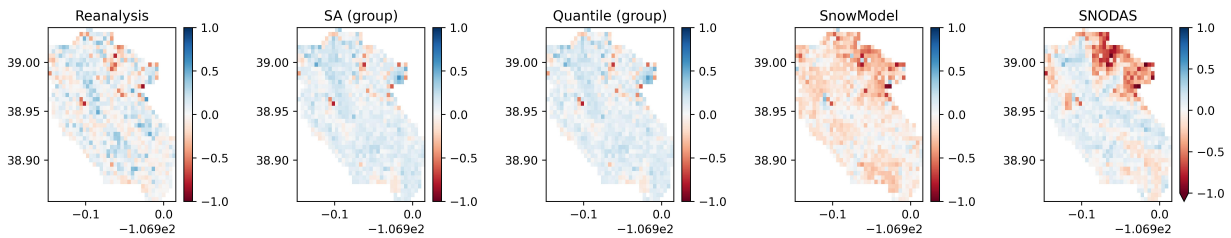


Figure 2.21: Spatial distribution of the errors for each SWE product used in the main text compared to the ASO lidar flight in the Crested Butte basin on 4 April 2016. The color bar shows the SWE difference in meters.

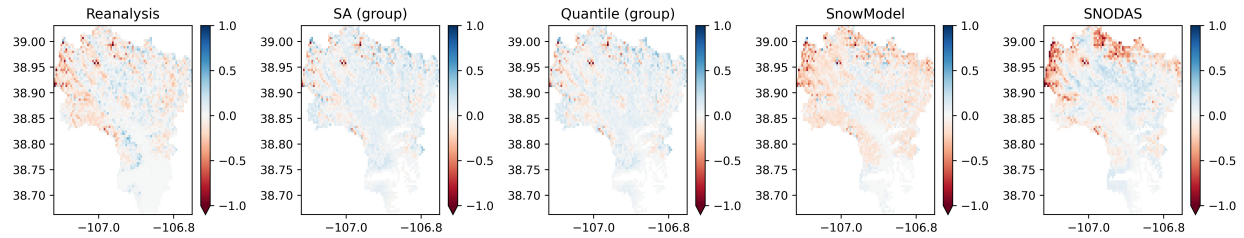


Figure 2.22: Spatial distribution of the errors for each SWE product used in the main text compared to the ASO lidar flight in the East River basin on 31 March 2018. The color bar shows the SWE difference in meters.

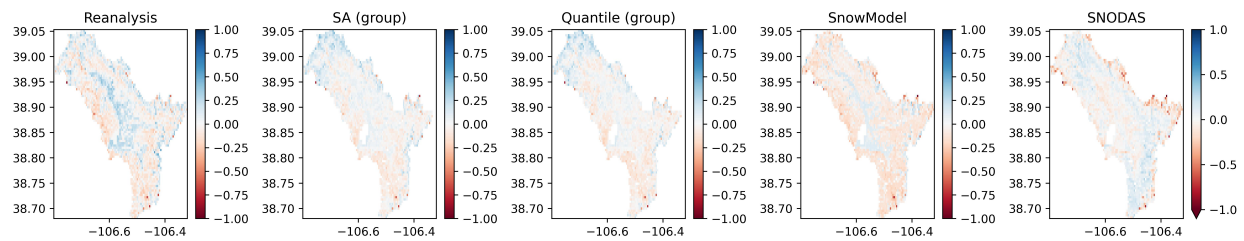


Figure 2.23: Spatial distribution of the errors for each SWE product used in the main text compared to the ASO lidar flight in the Gunnison-Taylor River basin on 30 March 2018. The color bar shows the SWE difference in meters.

Chapter 3

MOUNTAIN-RANGE SNOW DEPTH FROM ICESAT-2: AGGREGATED OBSERVATIONS IN THE SIERRA NEVADA

3.1 Introduction

Despite its importance, large uncertainties remain in estimates of both the magnitude and spatial distribution of snow water equivalent (SWE), particularly in mountainous and forested terrain *Lettenmaier et al.* [2015]; *Dozier et al.* [2016]; *Yang et al.* [2023]; *Fang et al.* [2023]; *Mudryk et al.* [2025]; *Mortimer et al.* [2020]. Recent satellite missions, such as the ICESat-2 laser altimeter, provide new opportunities to observe snow in these environments. However, more work is needed to determine optimal processing approaches and how best to translate these observations into improved estimates of snow storage and streamflow.

ICESat-2 is one of the most promising satellite missions for measuring snow quantity in mountains. It was launched in October 2018 to observe polar ice sheets, operating in a near-polar orbit and measuring surface elevation along six ground tracks (Figs. 3.1 and 3.2) using a photon-counting lidar system. The satellite has a 91-day repeat interval at high latitudes, with more variable revisit times at lower latitudes. ICESat-2 measurements can be used to estimate snow depth, and since changes in snow depth rather than density explain most of the variations in SWE *Sturm et al.* [2010], snow depth observations can be combined with modeled snow density to calculate SWE (e.g. *Painter et al.* [2016]). The most common approach for estimating snow depth from ICESat-2 is to difference snow-on satellite measurements and snow-off digital terrain models (DTMs) derived from airborne lidar. Using this method, snow depth can be retrieved with centimeter-scale accuracy over relatively flat terrain *Fair et al.* [2025b, a]; *Feng et al.* [2025]; *Lu et al.* [2022]. However, the uncertainty increases for terrain with greater slope and surface roughness *Feng et al.* [2025];

Zhang et al. [2021]; *Feng et al.* [2023]; *Hu et al.* [2021]; *Fair et al.* [2025b], such that *Zikan et al.* (2026) established a threshold of <20 degree surface slope where ICESat-2 snow depths are most accurate.

In non-flat regions even below this 20 degree threshold, aggregating ICESat-2 acquisitions to estimate basin-scale median snow depth provides more robust results than analyzing individual measurements *Besso et al.* [2024]. This spatial aggregation technique has only been tested within small headwater basins *Besso et al.* [2024] or along individual ICESat-2 acquisitions *Zikan et al.* [2026], limited in scope by the extent of the DTM used to provide snow-off elevations. If more extensive DTM coverage were available, aggregating ICESat-2 acquisitions at larger scales would increase the temporal resolution and spatial sample size, with the caveat that snow depths throughout the domain would need to be correlated for statistics to remain representative. For example, ICESat-2 acquisitions within the same footprint may occur only once per snow season, but acquisitions across a mountain range can occur with frequency on the order of days or weeks. It may also be possible to aggregate ICESat-2 acquisitions collected within a few days of each other to increase the spatial sample size. Larger domains can also encompass a wider range of snow-covered terrain, which would enable users to more selectively filter out ICESat-2 measurements over steep surface slopes.

Recent advances in available high-resolution snow-off DTMs in the Western U.S. now enable streamlined ICESat-2 analyses at larger spatial scales. The U.S. Geological Survey 3D Elevation Program (3DEP) provides seamless 1- and 10-m resolution DTMs across the Western U.S. derived from airborne lidar acquisitions that meet the standards of a vertical root mean squared error ≤ 10 cm (19.6 cm vertical accuracy at the 95-percent confidence level; as specified in *Arundel et al.* [2015] and updated at <https://www.usgs.gov/ngp-standards-and-specifications/lidar-base-specification-online>). Additionally, the SlideRule Earth service has enabled scalable, cloud-based access to ICESat-2 data and efficient sampling of gridded snow-off products, including the 3DEP DTMs *Shean et al.* [2023].

To evaluate ICESat-2-derived snow depth at these scales requires a product that covers the same large spatial extent. The Western U.S. UCLA SWE Reanalysis (WUS-SR) *Fang*

et al. [2022] provides a reliable spatially-continuous estimate of snow conditions for water years 1985–2021 (defined as October 1 of the previous year to September 30 of the current year). WUS-SR reconstructs SWE, snow depth, and fractional snow-covered area (fSCA) across the Western U.S. at 500 m resolution. Compared to estimates from snow-on airborne lidar, WUS-SR exhibits the least basin total SWE volume bias (1.6%) of all full-coverage snow products in the Western U.S., with strong fidelity in elevation-dependent snow distributions *Lundquist et al.* [2026]. Specifically in a headwater basin of the Sierra Nevada, WUS-SR snow depth showed strong agreement with airborne lidar, with correlations of 0.82 to 0.92, median differences (MDs) from -0.20 to 0.09 m, and root mean squared error (RMSE) of 0.14 to 0.56 m *Fang et al.* [2022].

The recent updates to the availability of seamless 3DEP DTMs and ease of processing through SlideRule present an opportunity to test the capabilities of ICESat-2 snow depth aggregation at large scales. The Sierra Nevada is well-suited for this evaluation. Snow accumulation anomalies are spatially coherent across the range *Aguado* [1990]; *Besso et al.* [2026], indicating that aggregated statistics should capture regionally-consistent signals. Also, about 65% of the snow-covered Sierra Nevada has terrain slope <20 degrees, which leaves a sufficiently-sized study region when masking out areas above that threshold. Here we define the snow-covered Sierra Nevada (the domain) as having an average fSCA from the WUS-SR product of less than 0.5 on 1 April for the 1985–2021 period (Fig. 3.1). Compared to other major Western U.S. ranges such as the Cascade Mountains, the Sierra Nevada experiences relatively frequent clear-sky conditions and sparser canopy cover, which should improve lidar retrieval quality by minimizing attenuation from clouds and vegetation.

Here we use this domain as a test case for global applications. Specifically, we use the SlideRule Earth service to prepare customized ICESat-2 returns (referred to as ATL06-SR) and sample co-located snow-off DTM elevation and slope values from the 3DEP archive. We calculate snow depth as the difference between the ATL06-SR elevations and snow-off 3DEP bare earth data, and then calculate the spatial median of the snow depth values on each acquisition date. We compare these daily median values to daily median WUS-SR

snow depth 1) collocated with ATL06-SR data, and 2) aggregated over the entire domain. We also calculate and compare the running 10-day median values for both data sets, to test whether temporal aggregation is a viable way to increase the spatial sample size of ATL06-SR. We only include ATL06-SR measurements over terrain with <20 degree surface slope, and exclude acquisition dates on which the ATL06-SR sample size is ≤ 100 . We show that using these criteria, aggregate measurements from ICESat-2 can provide consistently accurate snow depth information that matches annually varying snow depths in the WUS-SR product.

3.2 Results

The SlideRule Earth service returned 2,083,348 ATL06-SR measurements between October 2018 and September 2021 over the Sierra Nevada (Fig. 3.1). Of those, 1,446,262 measurements met our slope and sample size criteria, with data spanning 260 acquisition dates. This resulted in a median return interval of 3 days within the domain. When only considering months during the approximate snow season (December–June), there were 871,306 ATL06-SR measurements on 145 acquisition dates with a median return interval of 2.5 days.

Relative to collocated WUS-SR grid cells on the same date (which were bilinearly sampled at each ATL06-SR data point), ATL06-SR daily median snow depth values had a bias (MD) of -0.01 m, R^2 of 0.92, and an RMSE of 0.18 m (Fig. 3.3). Relative to the median WUS-SR throughout the domain, the ATL06-SR daily median snow depth values captured the temporal evolution of snow depth in the mountain range and had a bias of -0.01 m, an R^2 of 0.77, and an RMSE of 0.32 m (Fig. 3.3). Certain ATL06-SR acquisitions deviated substantially from the domain-wide median; to illustrate this, three dates are highlighted in Figures 3.3 and 3.4 as i) underestimating, ii) overestimating, and iii) unbiased relative to the domain-wide median value depending on the location of the ATL06-SR acquisition. By further aggregating the ATL06-SR data via a 10-day running median, the spatial coverage increases and the RMSE decreases (Figs. 3.3 and 3.4). Compared to median domain-wide snow depth, the ATL06-SR running median had a bias of -0.01 m, an R^2 0.90, and an RMSE

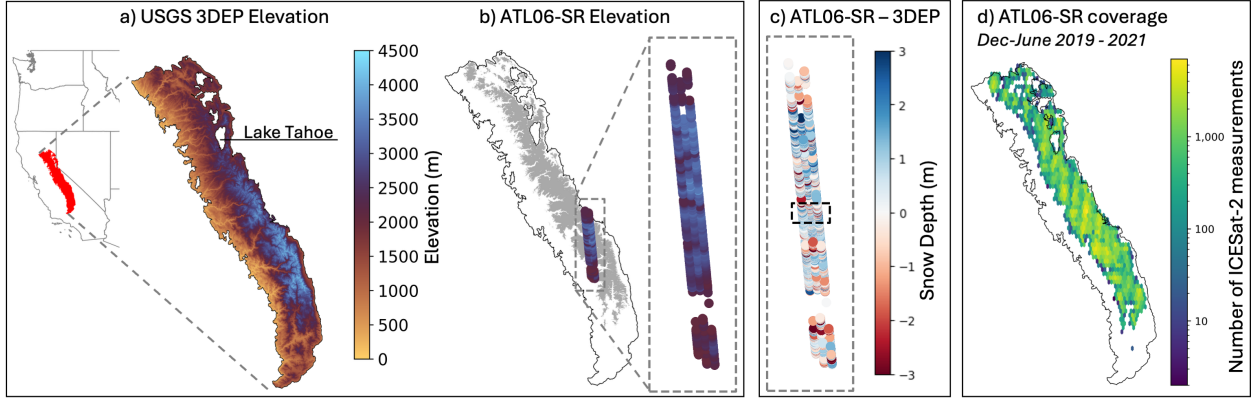


Figure 3.1: The study area domain of the snow-covered Sierra Nevada, with an example ATL06-SR acquisition and ATL06-SR measurement frequency over the domain. a) The California Sierra Nevada as defined by the global mountain database *Snethlage et al.* [2022] spans an elevation range of about 70 to 4400 m. The elevation map shown is sourced from the seamless 10 m 3DEP product. b) Within the Sierra Nevada, the snow-covered domain (grey shading) was defined as having an average 1 April fSCA value of 0.5 for 1985 - 2021. ICESat-2 elevation data for this domain were accessed through SlideRule Earth and are referred to as ATL06-SR data. The acquisition shown is from 7 April 2021, and data for terrain with surface slope ≥ 20 degrees were removed. c) Bare earth data from USGS 3DEP were differenced from the ATL06-SR data to estimate snow depth. The dashed black box shows the extent of Figure 3.2a,c. d) Number of ATL06-SR elevation measurements for terrain with < 20 degrees slope during December–June (the approximate snow season) of 2019–2021 within $\sim 17 \text{ km}^2$ hexagon bins.

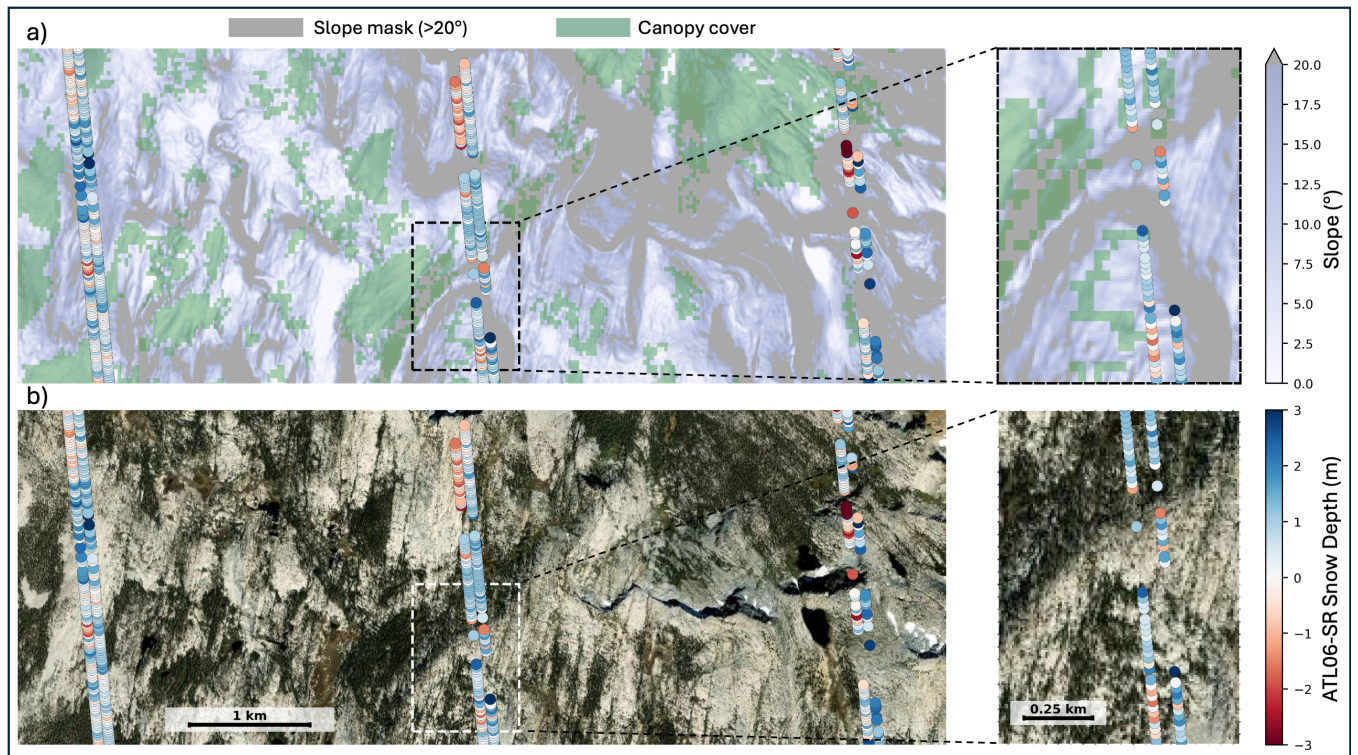


Figure 3.2: Insets of the ATL06-SR acquisition from 7 April 2021. a) The extent corresponds to the dashed black box in Fig 3.1c. Surface slope was derived from the seamless 10 m 3DEP DEM, with slopes <20 degrees shown in the purple colorbar and slopes ≥ 20 degrees in grey. ATL06-SR data for terrain ≥ 20 degrees have been removed. Canopy cover is depicted in green and is from the North American Land Change Monitoring System (NALCMS). The inset shows details of a single beam pair. b) The same spatial extent and ATL06-SR snow depth data as in a), with satellite imagery from Esri World Imagery.

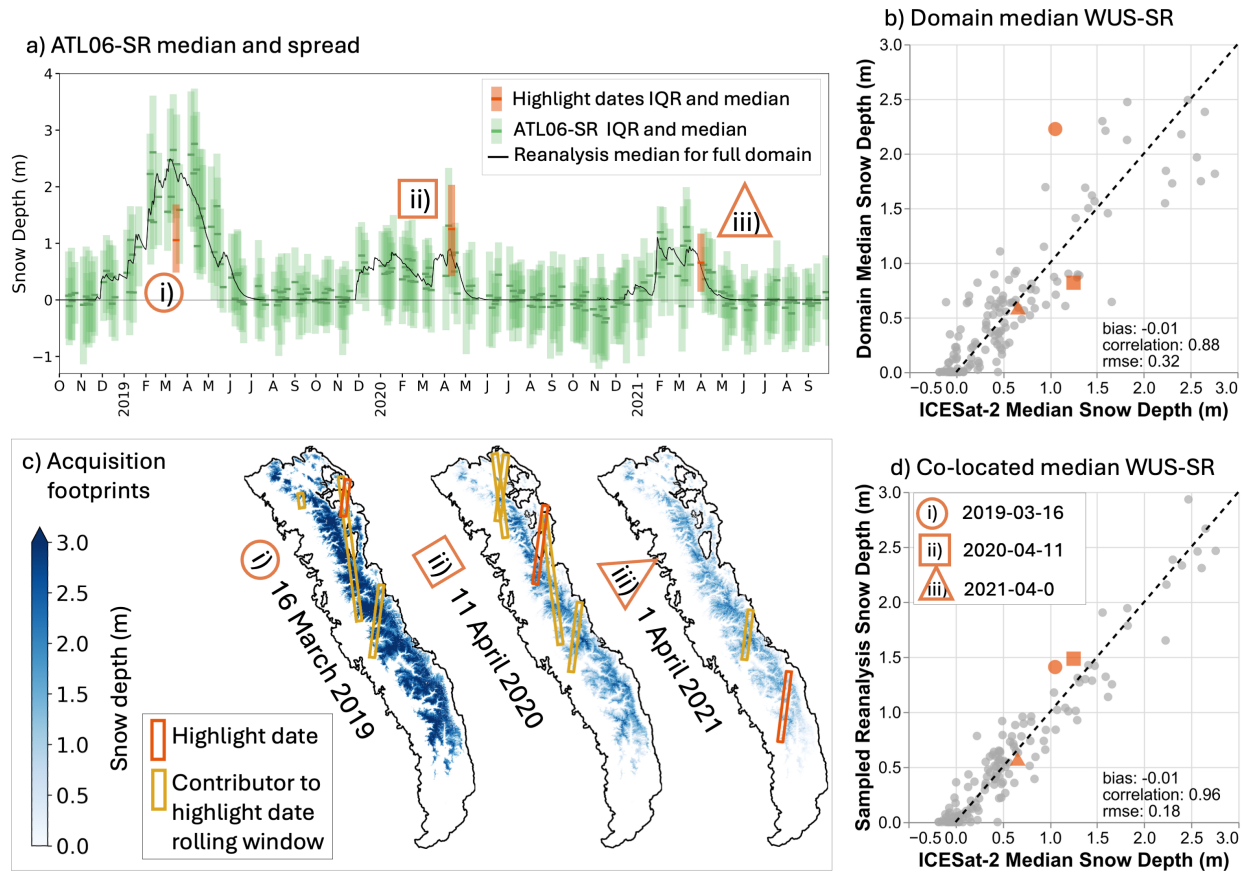


Figure 3.3: *Caption on next page.*

of 0.19 m (Fig. 3.4).

3.3 Discussion

This study demonstrates a simple approach to effectively use ICESat-2 data to measure snow depth at large scales: select the most suitable measurements, calculate the daily median of those measurements, and then increase the spatial sample size by calculating the 10-day running median snow depth for the entire domain. This technique can capture the temporal evolution of snow depth with a median return interval of 2.5 days, and provide large-scale estimates with strong fidelity to WUS-SR reference snow data. A low-latency

Figure 3.3: Timeseries of ATL06-SR snow depth over the study period, with the spatial location of highlighted acquisitions and comparisons to WUS-SR snow depth. a) Each boxplot contains the ATL06-SR snow depth estimates from one acquisition date, with the median in dark green and the interquartile range (IQR) in light green. The domain spatial median of WUS-SR is shown as the black line. Orange boxplots highlight example acquisition dates in which the ATL06-SR median was i) less than, ii) greater than, and iii) similar to the domain median WUS-SR value. b) The median snow depth data from a) for each December–June acquisition date. The dashed black line indicates the 1:1 relationship. The spread from the 1:1 line is partly due to the spatial offset between the domain-wide WUS-SR median and the median within the more local ATL06-SR footprint. c) The spatial footprint of each highlighted ATL06-SR acquisition date (orange boxes) with the spatially-explicit WUS-SR snow depth from the same date in blue. The golden boxes show the spatial footprint for acquisitions that contribute to the rolling medians for those highlight dates, shown in Fig. 3.4. d) The median ATL06-SR snow depth from each December–June acquisition date (same as in b) but compared to snow depth values co-located with the ATL06-SR data on that acquisition date, rather than the domain-wide median. Here, the only spatial offset is that of the resolution differences between the data sets.

(4-7 days) ICESat-2 product is projected to become available in late 2026 (ICESat-2 Project Science Office personal comms); if this is achieved, our results can provide a pathway for improving operational snow estimates and streamflow forecasts in global snow-dominated regions starting with the 2026–2027 snow season. Locations that will benefit the most from this data are areas with accurate preexisting snow-off DTMs and few-to-no in-situ snow measurement stations. Since access to ICESat-2 data is free, there is a lower threshold for use by local water resources agencies compared to installing a new in-situ observation network. Areas that do have in-situ stations could still benefit from the additional spatial

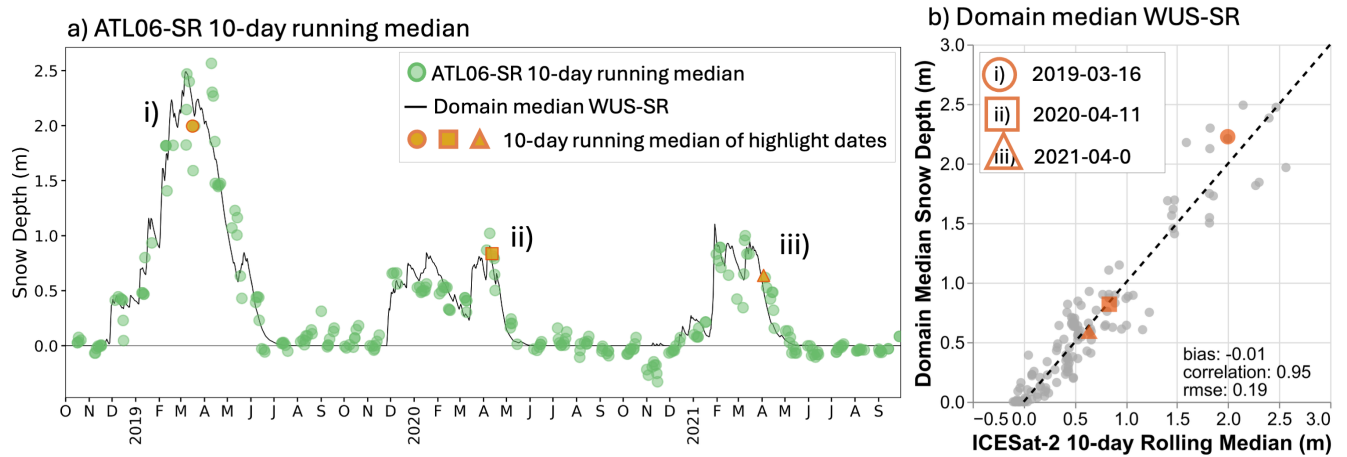


Figure 3.4: Comparison of the 10-day running medians from ATL06-SR and domain-wide WUS-SR snow depth. a) The domain median WUS-SR snow depth is shown in the black line (same as in Fig. 3.3a). Green dots show the date-centered running median of ATL06-SR median snow depth values, using a window of 10 days. The highlight dates are shown using the same symbols as in Fig. 3.3, but here they also contain ATL06-SR data from the acquisitions within their 10-day window, shown in gold in Fig. 3.3c. b) The December–June ATL06-SR 10-day running medians from a) are compared to the domain median WUS-SR snow depth with highlight dates shown in orange. Note that compared to Fig. 3.3b, the running median values contain data from multiple acquisitions dates (and therefore contain a larger spatial sample size) and have a tighter distribution around the 1:1 line (dashed black line).

coverage provided by ICESat-2 acquisitions, particularly at high elevations where in-situ stations are most sparse. This could be particularly helpful for late-season snow in low-snow years such as 2015 or 2026 after most low- and mid-elevation in-situ stations have melted out.

3.3.1 Impacts of acquisition location on representativeness

The low spread, minimal bias, and strong correlation between daily median ATL06-SR values and co-located daily median WUS-SR shows that ATL06-SR accurately captures aggregated daily median snow depth for locations within the satellite’s footprint (Fig. 3.3). There is sizeable spread for ATL06-SR snow depth values within an acquisition date (shown by the interquartile range in Fig. 3.3), which results from a combination of factors, including true spatial variability of snow depth measured on each acquisition date, and uncertainties associated with lidar instrument precision, geolocation uncertainty, and atmospheric path delay for both the ICESat-2 altimetry and the airborne lidar used to generate the snow-off DTM. In some cases, this combination of uncertainties leads to negative differences between the ATL06-SR measurements and DTM elevations (Fig. 3.3). ICESat-2 measurement errors have been shown to become more negative with increases in slope *Deschamps-Berger et al.* [2023], due in part to the increased spread of photon returns over sloped surfaces *Smith et al.* [2019]. However, when aggregated to the median value per acquisition date, this negative signal becomes negligible.

For the spatially-sparse ATL06-SR data to be useful in places outside the satellite footprint, some spatial extrapolation is needed. When we compared the 1) median values for each acquisition date with the domain median WUS-SR for those same dates and 2) the rolling 10-day medians, the bias (-0.01 m) remained constant. All metrics for the 10-day running median remained similar to those for the collocated comparison, suggesting that the spatial sample was large enough to represent the statistics of the domain just as well as the statistics within individual footprints. However, the spread and correlation degraded when using a single acquisition to represent the domain median.

This concept is illustrated by the three acquisition dates highlighted in Figures 3.3 and 3.4 in orange. Though all three acquisitions had minimal bias relative to co-located WUS-SR data, they did not all represent the domain median with similar accuracy, likely based on the location of each acquisition (Fig. 3.3). The 16 March 2019 acquisition underestimated domain median snow depth; it was located on the eastern side of the Sierra Nevada north of Lake Tahoe, where snow was shallower than along the crest of the range (Fig. 3.3c-i). The 11 April 2020 acquisition overestimated domain median snow depth; it was located along the crest of the Sierra Nevada, where snow was deep, and also east of the crest near Lake Tahoe, where snow was shallower (Fig. 3.3c-ii). The 1 April, 2021 acquisition was unbiased relative to the domain median snow depth; it was located in the southern Sierra Nevada, where snow depth was variable (Fig. 3.3c-iii). By calculating the 10-day running median, we included data from additional acquisition dates (yellow rectangles in Fig. 3.3c) and therefore additional locations within the domain in the median calculations for each date. Doing so increased the spatial coverage at the cost of temporal smoothing, and decreased the bias for all three highlighted acquisition dates relative to the domain median (Fig. 3.4).

3.3.2 Recommendations for future use

While the 10-day running median appeared to provide adequate temporal resolution and spatial coverage to accurately represent median snow depth in the Sierra Nevada, other techniques might be necessary in domains that receive fewer acquisitions, where snow depth is more temporally variable, or for purposes that require spatially-explicit maps of snow depth. For example, the running median calculations could be adjusted to more heavily weight data from more recent acquisitions, or the number of days included in the window could be adjusted up (as in the case of a domain with fewer available acquisition dates) or down (to lessen smoothing in more temporally variable snowpacks). For spatially explicit maps of snow depth or SWE, median ATL06-SR values could be combined with other techniques and products, such as updating distributed snow models in a data assimilation framework (e.g. *Mazzolini et al.* [2025]) or with spatially explicit snow accumulation patterns (e.g. *Besso*

et al. [2026]; *Pflug and Lundquist* [2020]; *Small et al.* [2026]).

At midlatitudes, ICESat-2 is systematically off-pointed (with a pointing accuracy of 4.4 ± 6 m *Luthcke et al.* [2021]) to target data collection in specific locations, such as to increase the spatial density of measurements over forests for carbon budget studies (*Markus et al.* [2017], <https://icesat-2.gsfc.nasa.gov/science/specs>). In mountain ranges with especially steep terrain, high alpine meadows and valley floors may provide the best chance for low-slope ICESat-2 snow depth measurements. Future work could identify orbitally-aligned locations with representative snow depth and low-slope terrain in mountain ranges of interest, where ICESat-2 could be off-pointed to target acquisitions during the snow-on period.

Further, certain mountain ranges are likely better suited for ICESat-2 snow depth measurements than others. The best-suited mountain ranges will have a large proportion of snow-covered terrain with shallow surface slopes. For reference, 65% of our Sierra Nevada study domain had terrain slope <20 degrees. Also, regions with sparser canopy cover and less frequent cloud cover will have less attenuation of the lidar signal, and therefore higher accuracy surface lidar measurements. Finally, high-accuracy lidar is a prerequisite for the snow depth calculations used here, since snow-off ICESat-2 measurements are so sparse and current global elevation products such as the Copernicus 30-m product have prohibitively large errors for snow depth calculations *Deschamps-Berger et al.* [2023]; *Fair et al.* [2025b]. For this study, we used a DTM with 10 m horizontal accuracy and 10 cm vertical RMSE derived from airborne lidar; we also tested the 1 m resolution version of this DTM, but the higher resolution did not improve the results and increased computation times. Therefore, it appears that accuracy of the source point cloud is more important than using the highest horizontal resolution available. We did not co-register the ICESat-2 acquisitions and the snow-off DTM; future work could include a co-registration step to test resultant improvements in snow depth accuracy.

The dependence on high-accuracy airborne lidar data is one of the biggest constraints on the use of ICESat-2 for global snow depth estimates. Previous studies have calculated snow

depth without the use of an external DTM by differencing snow-off and snow-on ICESat-2 acquisitions where the acquisitions cross each other *Hu et al.* [2021], but these cross-overs have been too sparse to use the aggregation techniques presented here. The longer ICESat-2 is in orbit, the greater the spatial density of snow-off coverage and therefore of cross-over locations. Future lidar satellite missions such as the NASA Earth Dynamics Geodetic Explorer (EDGE) could also expand this coverage, increasing the potential for snow depth to be calculated exclusively from satellite lidar measurements. Another technique has been developed to calculate snow depth directly from ICESat-2 (without the use of snow-off elevation measurements) using the distribution of multiple-scattered photons in the snowpack *Lu et al.* [2022]. This technique has been demonstrated in tundra and boreal forest snow environments *Lu et al.* [2026], but more work is needed to evaluate it in denser, wetter snowpacks. Future work should choose between this direct estimation method and the differential altimetry used here based on the characteristics of the study region and the availability of accurate DTMs.

3.3.3 Additional Considerations

For the purposes of this study we treated WUS-SR as truth, since it is the best available product for evaluations of historical Western U.S. snow distributions *Lundquist et al.* [2026]. However, the product has known limitations that factor into the differences we found between the ATL06-SR snow depths and the WUS-SR product. Although the accuracy of WUS-SR was not found to decrease at elevation bands below tree line in the Sierra Nevada ?, accuracy was found to decrease throughout the Western U.S. with increases in canopy density and with decreases in available Landsat imagery *Fang et al.* [2022]. Additionally, glaciers and permanent snow fields have to be manually masked by the user, since accurate estimates of snow accumulation in this reconstruction technique rely on the disappearance of snow in each pixel. We did not mask out glaciers or permanent snow fields in this study because they cover such a small percentage of the snow-covered area in the Sierra Nevada, but for regions with more glaciers such as the Cascade Mountains or High Mountain Asia, this would

become more important.

3.4 Methods

3.4.1 ICESat-2 Data

The Advanced Topographic Laser Altimeter (ATLAS) instrument on-board ICESat-2 has a photon-counting lidar system that operates at a wavelength of 532 nm. The time-of-flight from satellite to Earth’s surface and back again is measured for individual photons, which is then converted to a range measurement. With precise position and pointing knowledge, and additional corrections, a geolocated 3D point is determined for each photon, with height above the WGS84 ellipsoid. The laser source is split into 6 beams, separated into 3 beam pairs spaced 3.3 km apart, with 90 m separation between the two beams (Fig. 3.2). Each beam pair consists of a weak and strong beam; the strong beam produces about 4 times as many photons as the weak beam. The ICESat-2 project team distributes several higher-level data products from these low-level geolocated photons (ATL03). The higher-level products aggregate these photons into along-track elevation estimates. The ATL06 algorithm uses iterative windowing and outlier removal to calculate the surface elevation within overlapping 40 m segments, resulting in point elevations spaced every 20 m *Smith et al.* [2019]. This product was designed for land-ice applications and does not distinguish ground from canopy returns. ATL08, developed for land and vegetation analysis, uses 100 m segments and classifies photons to extract terrain elevation and canopy height *Neuenschwander and Pitts* [2019]. These products have various benefits and drawbacks, and we have found that the best option for snow depth calculations combines customized ATL06 processing of ATL03 photons classified as ground returns by the ATL08 algorithm, which can be achieved with the SlideRule Earth service *Besso et al.* [2024]; *Shean et al.* [2023].

Sliderule Earth *Swinski et al.* [2022] is an on-demand custom-processing service for Earth science data stored in the cloud, including ICESat-2. SlideRule Earth accesses ATL03 granules, and uses the user-supplied parameters to process the photon data using the ATL06

algorithm. SlideRule Earth also reprojects and samples the seamless 1- and 10-m DTM products from the USGS 3DEP archive, using the same coordinate reference system of ICESat-2 elevation values (EPSG:7912). We processed ICESat-2 data for the snow-covered Sierra Nevada domain for water years 2019–2021, which corresponded to the timing of overlapping data availability of ICESat-2 and the UCLA Western U.S. Reanalysis product.

3.4.2 Evaluation Data

The Western U.S. UCLA SWE Reanalysis (WUS-SR) data set *Fang et al.* [2022] uses snow disappearance observations from Landsat to retroactively update model ensembles of snow depth and SWE. As such, it cannot provide current snow data, but provides a record of snow distribution for the period 1985–2021. Further details of the reconstruction technique can be found in *Margulis et al.* [2019].

3.4.3 Snow-off Digital Elevation Model

The USGS 3D Elevation Program produces a collated and homogenized 1 m resolution DTM product for almost the entire United States. A 10 m resolution product derived from the 1 m product is also available. The lidar data used to create these products have a minimum point density of >2 pts/m² *Arundel et al.* [2015] and accuracy as outlined in Section 4.1. The Sierra Nevada domain had full coverage of both the 1 m and 10 m resolution 3DEP products (Fig. 3.5), and we used the 10 m product for computational efficiency since it did not result in a degradation of snow depth accuracy relative to use of the 1 m product in tests we ran using ATL06-SR data.

3.4.4 Data Availability

All data are publicly available for download from the National Snow and Ice Data Center (NSIDC), The National Map (TNM), and through the SlideRule Earth service. Code for accessing this data are publicly available in the github repository for this work: [https](https://github.com/SlideRuleEarth/SlideRuleEarth) :

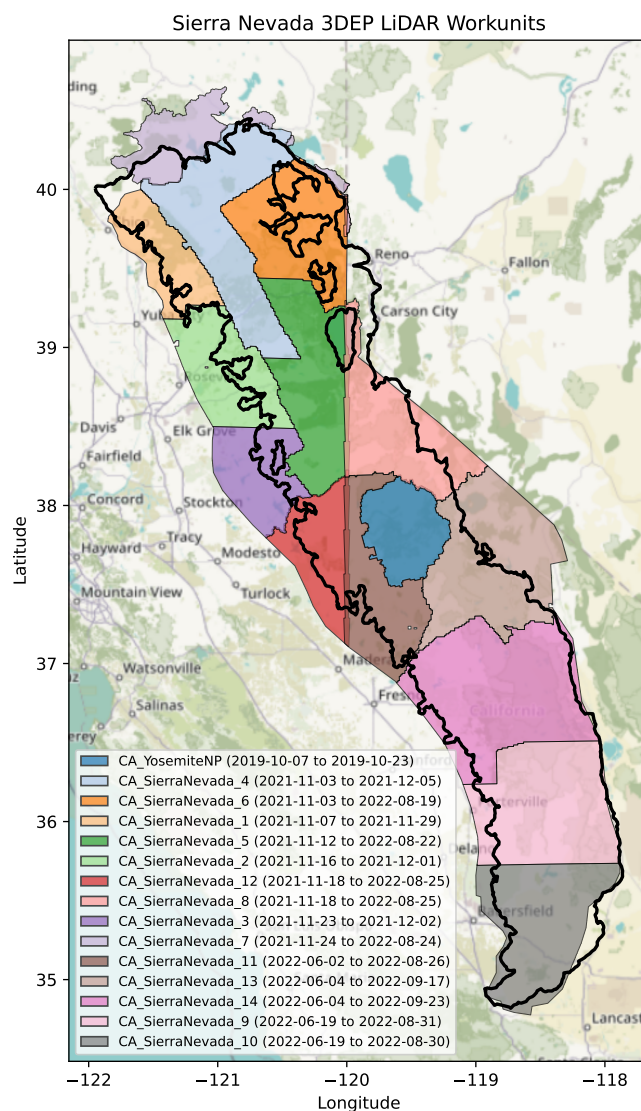


Figure 3.5: The name and location of source lidar acquisitions over the study domain used to create the seamless 1- and 10-m digital terrain models (DTMs) from the USGS 3DEP archive.

//github.com/bessoh2/analog_snowmapping.

Acknowledgments

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Chapter 4

EVALUATING STATISTICAL SWE METHODS INFORMED BY METEOROLOGY AND SATELLITE OBSERVATIONS

4.1 Introduction

Measuring snow quantity and distribution in mountain regions is a central challenge in hydrologic remote sensing [Lettenmaier *et al.*, 2015]. This challenge is particularly important in regions where a large share of precipitation falls in winter while water demand peaks in summer. Approximately one-sixth of the global population depends on snowmelt [Barnett *et al.*, 2005], and interannual variations in snowpack can determine whether a year brings drought or adequate water supply.

Accurate estimates of snow water equivalent (SWE) are therefore critical for runoff forecasting, particularly in the late melt season Brauchli *et al.* [2017a]. In addition to total volume, the spatial distribution of SWE strongly influences the magnitude, timing, and duration of meltwater runoff [Clark *et al.*, 2011; Luce *et al.*, 1998]. Yet large uncertainties remain. Global SWE products have a spread of a factor of five [Fang *et al.*, 2023] and even among products with the highest accuracy in the well-studied Western U.S., systematic elevation-dependent biases persist [Lundquist *et al.*, 2026].

Coherent spatial patterns in SWE accumulation can be used to improve SWE estimates [Pflug *et al.*, 2021, 2022; Pflug and Lundquist, 2020; von Kaenel and Margulis, 2025; Gauthier *et al.*, 2022; Sturm *et al.*, 2010; Besso *et al.*, 2026]. For example, accurate historical SWE reanalysis products such as the UCLA Western U.S. SWE Reanalysis (WUS-SR; Fang *et al.* [2022]) can provide spatially-distributed historical context to guide mapping of current-year in-situ observations to larger regions using the standard anomaly (SA) of measured SWE [Besso *et al.*, 2026]. While this method performs well under typical conditions, it is less

accurate when elevational gradients or storm-track patterns deviate from historical norms. In regions without ground observations—or during anomalous years—additional sources of current-year information and pattern adjustments are needed.

Such adjustments could come in the form of additional coherent spatial modes in inter-annual SWE variability, which can be identified using empirical orthogonal function (EOF) analysis [Aguado, 1990; Cayan, 1996; McCabe and Dettinger, 2002; Gauthier *et al.*, 2022]. Dominant modes of variability have been used to characterize SWE variability and to down-scale historical coarse-resolution snow products without the use of in-situ data [Gauthier *et al.*, 2022]. Using such methods, detailed spatial information is supplied by historical pattern data, while coarse or sparse near-real-time observations are needed to identify the current-year SWE pattern. Globally, many mountain ranges lack sufficient in-situ measurements to supply this near-real-time information. However, coarse resolution climate reanalyses such as ERA5 Hersbach *et al.* [2020] may provide sufficient large-scale information about variables such as snowfall and precipitation to inform current-year pattern adjustment. Additionally, recent studies show that the relatively new satellite altimeter on board NASA’s ICESat-2 satellite can supply accurate snow depth estimates of mountain-range median snow depth (Besso *et al.*, in prep) that may also provide sufficient current-year context for pattern analysis.

This study asks: how can near-real-time global data sources (specifically ERA5 and ICESat-2) and pattern-based methods that use a historical SWE reanalysis product (Fang *et al.* [2022]) be combined to estimate both total SWE and its spatial distribution within a mountain range? We address this question by evaluating two SWE estimation techniques in water years (1 October–30 September) 1985–2021. The first technique uses SA values to identify historical SWE patterns Besso *et al.* [2026], and the second uses an EOF analysis to identify SWE patterns. We use and evaluate these techniques in the well-studied California Sierra Nevada, and compare their accuracy to that of an operational model that assimilates in-situ observations. The goal is to guide future applications of these techniques in data-sparse regions where operational estimates can’t assimilate in-situ observations.

The paper proceeds as follows: in Section 4.2 we provide background on the data sets (Sections 4.2.1 - 4.2.4), statistical techniques (Sections 4.2.5 and 4.2.6), and study site (Section 4.2.7). In Section 4.3 we describe the methods, including data preprocessing (Sections 4.3.1, 4.3.2, 4.3.3.1, 4.3.3.2) and SWE estimation using the SA (Section 4.3.3) and EOF (Sections 4.3.4 and 4.4.2) techniques. In Section 4.4 we present the dominant modes of SWE variability from the EOF analysis (Section 4.4.1), the accuracy of the SWE estimates from both techniques (Section 4.4.3), and a comparison of SWE estimates in three example years (Section 4.4.3.1). We end with a discussion (Section 4.5) and conclusions for future work (Section 4.6).

4.2 Background

The data sets and techniques used here are described in detail below. In brief, SNODAS is used as the benchmark for operational SWE product accuracy (Section 4.2.1). We will evaluate whether the SWE products produced here can exceed this accuracy. The WUS-SR product is used to provide historical SWE information. It is the most accurate historical SWE product currently available in the Western U.S. but is not available in real-time. The methodological framework used to create this reanalysis does not use in-situ data, so could be applied globally (Section 4.2.2). The ERA5 reanalysis product and ICESat-2 snow depth are used to provide current-year context for historical pattern adjustment. The ERA5 reanalysis is one of the best available atmospheric reanalyses and is available with 5-day latency, although the spatial resolution is too coarse to correctly resolve mountain processes such as orographic lifting (Section 4.2.3). ICESat-2 can be used to calculate snow depth in global regions where high-quality digital terrain models (DTMs) exist and has been shown to accurately measure median snow depth within the Sierra Nevada (Besso et al., in prep; Section 4.2.4). The statistical techniques (SA and EOF) used with these products are described in Sections 4.2.5 and 4.2.6.

4.2.1 SNODAS

The Snow Data Assimilation System (SNODAS) is an operational snow modeling and data assimilation system run by the National Oceanic and Atmospheric Administration (NOAA) National Operational Hydrologic Remote Sensing Center (NOHRSC) for the continental U.S. [Barrett, 2003]. It is forced with meteorological data from the Rapid Refresh (RAP) national weather prediction model. It assimilates airborne, satellite, and in-situ observations of snow cover and SWE, with daily decision-making by analysts about which specific observations to include. It outputs daily SWE and associated variables at a spatial resolution of 1 km for the period from 2003 to present, although routine data assimilation did not start until 2004.

Several studies have compared the SNODAS SWE product to independent airborne lidar observations not assimilated by the model. One study found that SNODAS has basin-total SWE volume bias of 7.8% across basins in the Rocky Mountains, Sierra Nevada, and Olympic Mountains, and in the Sierra Nevada it overestimated March and April SWE at lower elevations while underestimating SWE at higher elevations [Lundquist *et al.*, 2026]. Another found that SNODAS explained only 40% of the variance in airborne lidar-derived SWE for the Tuolumne River basin above Hetch Hetchy (referred to here as the Tuolumne River Basin) - a headwater basin of the Sierra Nevada - for airborne lidar acquisitions between 2013-2017, and that the basin average SWE percent bias ranged from 13.6 to 68% [Yang *et al.*, 2023]. SNODAS is one of the most accurate SWE products available in near-real-time [Lundquist *et al.*, 2026; Yang *et al.*, 2023] and is regularly used for water resources operations. However, it is only available in the United States, and its reliance on assimilated in-situ observations and airborne lidar mean that it could not readily be expanded to mountain ranges that lack these measurements.

4.2.2 UCLA Western U.S. SWE Reanalysis

The UCLA Western U.S. SWE Reanalysis (WUS-SR; [Fang *et al.*, 2022]) contains gridded daily SWE, snow depth, and fractional snow-covered area (fSCA) at a spatial resolution of

about 500 m (16 arc-s) for the period from 1984 to 2021. The SWE and snow depth estimates are the result of a retrospective data assimilation framework in which an ensemble of forward-run models are forced with MERRA2 meteorology and then fit to the timeseries of fSCA Landsat observations using a Bayesian particle batch smoother (see more details in [Margulis *et al.*, 2016, 2019]). Compared to SWE derived from airborne lidar, Fang *et al.* (2022) report peak SWE correlation coefficients for scenes throughout the Western U.S. of between 0.75 and 0.91, with mean differences <0.15 m and root mean squared differences <0.38 m. The accuracy of the SWE and snow depth products diminishes with forest cover fractions above 40% and with fewer available cloud-free fSCA observations [Fang *et al.*, 2022]. The WUS-SR framework does not rely on in-situ observations and so can be applied to mountains globally where quality fSCA data exist and has already been used in the Andes Cortés and Margulis [2017] and High Mountain Asia [Liu *et al.*, 2021]. WUS-SR is not available in real-time so cannot be used for operational forecasts, but has been recommended for use in retrospective evaluations and analyses [Lundquist *et al.*, 2026].

In studies that compared multiple Western U.S. SWE data sets (including WUS-SR and SNODAS) to independent airborne lidar observations, WUS-SR had the most accurate spatial distribution near the timing of peak SWE (March – April), with the highest R^2 (0.87) and lowest RMSE (0.11 m) of all products compared by Yang *et al.* (2023) in the Tuolumne River Basin. It had a similar average percent bias (8.3%) to SNODAS (9.3%) [Yang *et al.*, 2023]. WUS-SR had the least bias (1.6%) in basin-total SWE volume of any Western U.S. data set compared in Lundquist *et al.* (2026) and had the closest match to SWE elevation distributions from airborne lidar [Lundquist *et al.*, 2026]. In the Tuolumne River Basin, SNODAS consistently estimated higher basin SWE volume than WUS-SR [Lundquist *et al.*, 2026; Fang *et al.*, 2023] by about 12% across the 17 years of overlap between the products [Fang *et al.*, 2023]. SNODAS exhibited comparable ratios in SWE distribution between windward and leeward slopes to WUS-SR, and similar interannual variability of peak SWE, with Pearson’s correlation coefficient of 0.92 (R^2 of 0.85) Fang *et al.* [2023]. In summary, previous studies showed that WUS-SR more accurately captures the spatial distribution of

SWE and has similar or lower bias than SNODAS relative to airborne lidar-derived SWE. Accordingly, we use WUS-SR here as the reference product against which other products, including SNODAS, are compared.

4.2.3 ERA5 Meteorology

The European Centre of Medium-range Weather Forecasts (ECMWF) Reanalysis v.5 (ERA5) [Hersbach *et al.*, 2020] is a global reanalysis produced by ECMWF through the Copernicus Climate Change Service. Using the ECMWF Integrated Forecasting System, ERA5 assimilates a wide range of in situ and satellite observations to generate hourly estimates of atmospheric, land surface, and oceanic variables from 1940 to present at 31 km horizontal resolution with a five day latency [Hersbach *et al.*, 2020]. The performance and known limitations of ERA5 near-surface temperature, precipitation, and snowfall fields are summarized below.

ERA5 snowfall reproduces broad spatial patterns and interannual variability consistent with other reanalysis products, although magnitudes differ substantially among datasets [Boisvert *et al.*, 2020]. Long-term spatial distributions, mean annual snowfall (1980–2023), and temporal trends are consistent with observations, although performance decreases at daily timescales [Wang *et al.*, 2025]. Snowfall accuracy is spatially heterogeneous, with reduced skill in mountainous terrain, in regions with sparse assimilated observations, and during intense snowfall events [Wang *et al.*, 2025].

ERA5 precipitation performs best in extratropical regions (approximately 30–60° latitude) and generally captures the spatial structure of precipitation events, though it exhibits a wet bias in certain regions and tends to underestimate extremes [Lavers *et al.*, 2022]. ERA5 temperature fields show strong skill in reproducing daily and extreme apparent temperature values but may exhibit regional cold bias. Correlation with station observations is lower in the western United States than in the east, likely due to complex terrain and sparser observational networks. These limitations may be amplified in even more remote mountain ranges with limited assimilated data.

For studies focused on spatial patterns and interannual variability, accurately representing relative differences and spatial structure is more important than eliminating absolute biases. Although the observing system has evolved over time—affecting the statistical stationarity of data assimilation products—ERA5 remains among the most widely used global reanalysis products and provides physically consistent estimates of historical meteorology *Hersbach et al.* [2020].

4.2.4 ICESat-2 Altimetry

NASA launched ICESat-2 in October 2018 to measure polar ice-sheet elevation change, with a secondary objective of characterizing vegetation structure in non-polar regions. The Advanced Topographic Laser Altimeter System (ATLAS) instrument on-board ICESat-2 has a photon-counting lidar system separated into 6 beams. Each laser pulse has an effective footprint of approximately 11 m [*Magruder et al.*, 2020] and a 0.7 m nominal along-track pulse spacing on the ground. ATLAS has beam-specific horizontal mean geolocation errors of between 0.5 and 2.4 m [*Luthcke et al.*, 2021; *Neumann et al.*, 2019] and operates at a wavelength of 532 nm, which is strongly reflected by snow and ice [*Warren*, 1982]. The satellite has a 91-day repeat cycle at the poles, while revisit intervals at midlatitudes vary due to off-pointing campaigns that increase spatial sampling for vegetation studies.

The fundamental ICESat-2 data product (ATL03) consists of geolocated photon returns for each beam. Higher-level products aggregate these photons into along-track elevation estimates. The ATL06 algorithm uses iterative windowing and outlier removal to calculate the surface elevation within overlapping 40 m segments, resulting in point elevations spaced every 20 m [*Smith et al.*, 2019]. This product was designed for land-ice applications and does not distinguish ground from canopy returns. ATL08, developed for land and vegetation analysis, uses 100 m segments and classifies photons to extract terrain elevation and canopy height [*Neuenschwander and Pitts*, 2019].

ICESat-2 measurement accuracy depends on instrument precision, geolocation uncertainty, atmospheric path delay, and surface characteristics such as slope and roughness

[*Neuenschwander and Pitts*, 2019]. Sloped terrain introduces vertical errors through (1) horizontal geolocation offsets projected onto the slope and (2) pulse spreading over inclined surfaces, which broadens the return and can negatively bias elevations or lead to false detections of canopy cover [*Deems et al.*, 2013; *Smith et al.*, 2019].

Although no standard ICESat-2 product is optimized for snow retrievals in midlatitude mountains, several studies have derived snow depth from ICESat-2 data using elevation differencing between snow-on measurements and snow-off reference surfaces [*Fair et al.*, 2025b]. Reported absolute biases relative to airborne lidar snow depth measurements range from 0.05 to 1 m, with uncertainties of 0.09 – 1.48 m that increase with terrain slope, roughness, and canopy cover [*Fair et al.*, 2025b]. In some cases, derived ICESat-2 snow depths are negative, an artifact of combined measurement and processing uncertainties *Besso et al.* [2024].

Performance in complex terrain can be improved using the SlideRule Earth service, which enables user-defined, on-the-fly processing of ATL03 data rather than relying on fixed higher-level products [*Swinski et al.*, 2022; *Shean et al.*, 2023; *Besso et al.*, 2024]. Adjustable parameters include photon confidence thresholds, segment length, and ground–canopy classification, allowing configurations that combine short segments with vegetation filtering for mountainous environments. SlideRule-processed data will be referred to as ATL06-SR for the rest of this paper. SlideRule also supports sampling of snow-off elevations from the USGS 3D-Elevation Program (3DEP) 1- and 10-m elevation data sets, which cover much of the continental U.S. This facilitates ATL06-SR snow depth calculations at scales larger than that of individual airborne lidar acquisitions, such as for an entire mountain range (*Besso et al.*, in prep).

Even with customized processing, ATL06-SR elevation estimates have uncertainty, with a residual standard deviation of 1.25 m relative to snow-off airborne lidar in the Tuolumne River Basin, and negative values [*Besso et al.*, 2024]. However, median snow depth aggregated for each ATL06-SR acquisition date had minimal bias relative to collocated (0.04 m) and basin-wide (-0.14 m; 1600 km²) airborne lidar snow depth [*Besso et al.*, 2024].

ATL06-SR snow depth estimates can be aggregated at even larger scales in areas where

snow depth is spatially correlated (Besso et al., in prep). This can also increase usable data quantity, allowing for stricter filtering of input photons based on qualities such as terrain characteristics and photon confidence. Across the Sierra Nevada, ATL06-SR median snow depth had minimal bias (-0.01 m), strong correlation (R^2 of 0.92), and low RMSE (0.18 m) compared to co-located WUS-SR (Besso et al., in prep). When a 10-day running median of ATL06-SR snow depth was calculated to increase the spatial representativeness of the ATL06-SR data, these values represented domain-wide median snow depth with similar fidelity (bias of -0.01 m, R^2 of 0.90, and RMSE of 0.19 m; Besso et al., in prep). While large-area aggregation improves median estimates, it reduces spatial information, motivating additional methods for using non-spatially-explicit current-year data with spatially-explicit historical patterns to reconstruct the spatial distribution of snow depth. A low-latency (4-7 day) geo-corrected ICESat-2 product is planned for release in late 2026 (ICESat-2 Project Science Office personal comm), which could make ICESat-2 data useful in an operational context.

4.2.5 SWE calculation technique using standard anomalies

Accumulation patterns tend to repeat from year to year because prevailing storm tracks interact with topography and vegetation in consistent ways [Sturm et al., 2010; Vögeli et al., 2016; Deems et al., 2008; Schirmer and Lehning, 2011; Pflug and Lundquist, 2020]. These patterns are the most interannually consistent at the timing of maximum accumulation [Schirmer and Lehning, 2011]. Melt patterns also repeat annually but differ from accumulation patterns because they are driven by different physical processes [Pflug and Lundquist, 2020]. In northern midlatitudes where accumulation and melt seasons are well separated, 1 April can be treated as the transition between these periods, assuming minimal midwinter melt or rain-on-snow prior to that date.

Under this assumption, standard anomalies (SAs) of 1 April SWE can represent annual accumulation patterns. Historical distributions of 1 April SWE are approximately normal [McCabe, 1994; Besso et al., 2026], allowing anomalies to be expressed relative to the clima-

tological mean and standard deviation. SAs of peak SWE exhibit greater spatial coherence than SWE magnitudes themselves [Cayan, 1996; Changnon *et al.*, 1993; Clark *et al.*, 2001; McCabe, 1994; Besso *et al.*, 2026], such that standard anomalies derived from in-situ measurements near peak SWE (approximated as 1 April) can be used to estimate SWE at nearby locations with historical records [Besso *et al.*, 2026]:

$$SWE_{i,t} = SA_t \times \sigma_i + \mu_i, \quad (4.1)$$

where $SWE_{i,t}$ is the 1 April SWE at grid cell i in year t , SA_t is the standard anomaly for year t derived from an in-situ station, σ_i is the climatological standard deviation at grid cell i , and μ_i is the climatological mean at grid cell i .

When applied to the Upper Colorado River Basin and compared to WUS-SR, this method produced SWE maps that more accurately captured the spatial distribution of SWE, while SNODAS represented basin-wide totals slightly better [Besso *et al.* [2026]. The SA method performed best in years with average meteorological conditions. However, in years with atypical conditions, spatial errors showed coherent elevational and latitudinal structure, likely due to deviations from average precipitation gradients, temperature, and storm track positions [Besso *et al.*, 2026]. In addition, the approach as implemented by Besso *et al.* (2026) requires long-term in-situ observations, limiting its applicability in data-sparse regions.

4.2.6 Empirical orthogonal functions and principal component regression

The variations in 1 April SWE as represented by the SA also exhibit coherent spatial patterns [Gauthier *et al.*, 2022; Cayan, 1996; Aguado, 1990; Changnon *et al.*, 1993]. These patterns can be identified using empirical orthogonal functions (EOFs), which decompose a space-time field into orthogonal modes that represent dominant structures of variability [Hannachi *et al.*, 2007]. EOFs are typically computed using singular value decomposition (SVD), which identifies orthogonal linear combinations that successively maximize explained variance. The decomposition yields spatial patterns (EOFs) and associated temporal coefficients, referred

to here as principal components (PCs). The original space-time field can be reconstructed as the sum of EOF patterns weighted by their PCs, and an approximate reconstruction can be obtained using only the leading modes that explain most of the variance.

EOF analysis reduces complex spatial variability to a small number of dominant modes, facilitating interpretation of the large-scale processes that drive SWE variability. Previous studies have applied EOF analysis to SWE anomalies across the Western U.S. [*Gauthier et al.*, 2022; *Cayan*, 1996; *Changnon et al.*, 1993; *McCabe and Dettinger*, 2002] and within the Sierra Nevada specifically [*Aguado*, 1990]. In the Sierra Nevada, the leading mode of 1 April SWE variability reflects region-wide coherence, with positive or negative anomalies occurring across most of the range simultaneously [*Aguado*, 1990]. The second mode is strongly related to elevation and becomes prominent during years with anomalously warm or cold winter storms, while the third mode reflects north–south variability [*Aguado*, 1990]. Because EOF solutions depend on the spatial domain and sampling period, the dominant modes for the Sierra Nevada differ from those derived for the Western U.S. [*Hannachi et al.*, 2007; *Aguado*, 1990; *Gauthier et al.*, 2022; *Cayan*, 1996; *McCabe and Dettinger*, 2002].

EOF frameworks can also be used for statistical downscaling by relating PC time series’ to coarse-resolution meteorological predictors or snow model output (e.g. [*Gauthier et al.*, 2022]). The physical interpretation of each EOF mode can guide predictor selection in the principal component regression (e.g. [*Lundquist and Cayan*, 2007; *Gauthier et al.*, 2022]). Because PCs are mutually orthogonal (uncorrelated over the training period), separate regressions can be developed for each mode without multi-collinearity between predictands. Assuming the EOF spatial patterns of SAs are stationary, SWE for a target year can be reconstructed by (1) estimating the leading PC values from the predictor relationships and (2) summing the corresponding EOF patterns weighted by the predicted PCs, followed by transformation back to SWE units (see Fig. 4.4 for details).

4.2.7 Sierra Nevada, California, USA

California’s Sierra Nevada spans approximately 35–40°N and is oriented northwest–southeast, roughly parallel to the Pacific Coast (Fig. 4.1). The range intercepts midlatitude storm systems that typically approach from the west, with a large fraction of annual snow accumulation delivered by a small number of high-intensity storms, many associated with atmospheric rivers [Dettinger *et al.*, 2004, 2011; Rutz *et al.*, 2014; Guan *et al.*, 2010]. Maritime influences produce relatively mild winter conditions, and storm freezing levels often vary across elevational and latitudinal gradients, resulting in spatially heterogeneous precipitation phase and frequent rain-on-snow and midwinter melt events [Lundquist *et al.*, 2008; Bales *et al.*, 2006]. Outside of storm periods, the region experiences predominantly clear-sky conditions. Topographically, the Sierra Nevada generally has gently sloping terrain on the windward (western) side and steep, high-relief slopes on the leeward (eastern) side. The northern portion of the Sierra Nevada typically receives more precipitation than does the southern portion, but snow accumulation tends to be greater at the higher elevations in the southern portion [Bales *et al.*, 2006]. In addition, southern portions of the range experience greater solar loading and higher temperatures due to lower latitude and the prevalence of south-facing terrain [Bales *et al.*, 2006]. For this study, the domain is defined as the snow-covered Sierra Nevada, where snow-covered areas are identified as WUS-SR pixels with a mean 1 April snow depth of >0.1 m for the period 1985 to 2021.

4.3 Methods

We combine the techniques and data products described above to estimate 1 April SWE in the snow-covered Sierra Nevada (the domain). The WUS-SR gridded dataset provides the historical SWE record used to compute climatological statistics for the standard anomaly (SA) method, and then an EOF analysis is run on these WUS-SR SA values to determine modes of variability in the SA values. ERA5 meteorological variables and ATL06-SR snow depth observations are assumed to be available in near-real-time for the target year and

are used to estimate SA values and to predict principal component weights. We evaluate the accuracy of these approaches relative to WUS-SR using a leave-one-out cross-validation framework, in which each water year (1985–2021) is treated as the target year, excluded from the historical record used to compute climatological statistics, and then used for independent evaluation. We compare annual metrics and spatial errors across all products to the WUS-SR data in the target year, and assess the spatial distribution of errors in an example low (2015), average (2009), and high (2019) snow year. We categorize snow years based on whether the domain average SWE was within, above, or below one standard deviation of the climatological WUS-SR SWE. We also compare SNODAS to WUS-SR in each target year to determine whether the approaches tested here can outperform an operational product, with the caveat that any errors in WUS-SR can be propagated into the SWE estimates and will not then show up in the error statistics. We recommend the most promising approaches for use in less-studied mountain regions (Fig. 4.1).

4.3.1 *SNODAS Data Access*

We accessed 1 April gridded SWE output for water years 2005 – 2021 from the National Snow and Ice Data Center (NSIDC). We aligned grid cells with those of WUS-SR using cubic resampling (Fig. 4.1b).

4.3.2 *Western U.S. UCLA SWE Reanalysis Data Access*

We accessed daily gridded SWE and snow depth for water years in the period 1985 to 2021. We defined the domain as grid cells within the Global Mountain Biodiversity Assessment’s Sierra Nevada region [Sneath et al., 2022] that had WUS-SR 1 April average SWE $> 0.1\text{m}$ (e.g. [Besso et al., 2026]). This data are treated as observations for the purposes of the study. Uncertainties discussed in Section 4.2.2 will propagate to the SWE calculations described below.

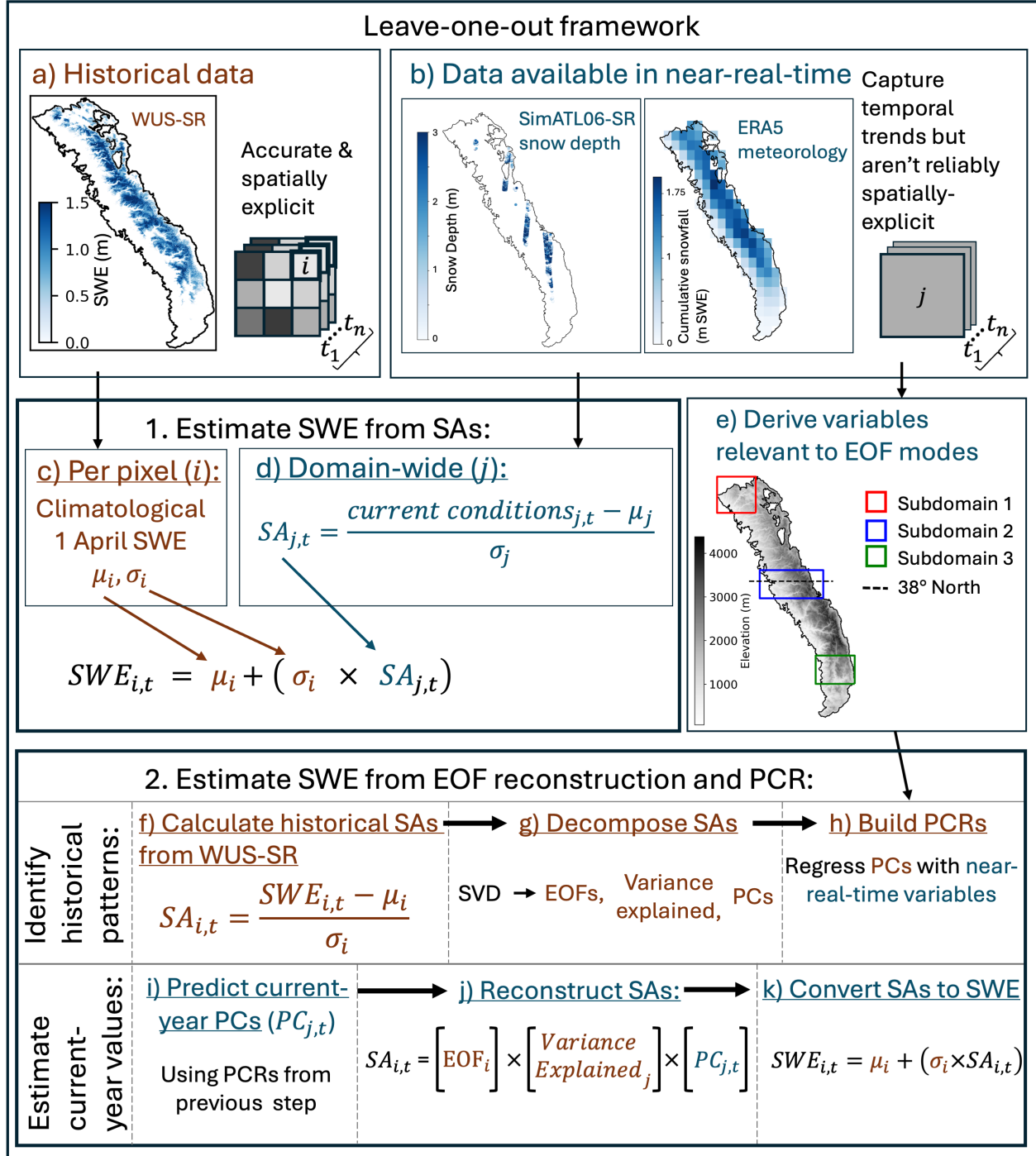
Figure 4.1: *Caption on next page.*

Figure 4.1: This study estimates 1 April SWE using two statistical frameworks applied in the Sierra Nevada, California. Both frameworks rely on historical spatial patterns of a) SWE from the UCLA Western U.S. SWE Reanalysis dataset (WUS-SR). Individual 500 m resolution WUS-SR grid cells are referred to here as i and the temporal component (1 April of each year for the period 1985 to 2021) is referred to as t . b) Current-year updates to the historical patterns are provided by data available in near-real-time: simulated ATL06-SR (SimATL06-SR) data and ERA5 meteorology. For the first statistical framework, c) the climatological mean (μ) and standard deviation (σ) of SWE from WUS-SR is calculated at each grid cell (excluding the target year from these calculations). Then the d) target-year domain-wide standard anomaly (SA) is calculated from SimATL06-SR and ERA5 cumulative snowfall relative to each data set’s climatological μ and σ and is applied as an adjustment on the climatological WUS-SR data at each grid cell to calculate target year distributed SWE. For the second statistical framework, f) SA values for each grid cell and year (excluding the target year) are calculated from WUS-SR SWE and then g) decomposed using a single value decomposition (SVD) into empirical orthogonal functions (EOFs), variance explained by each EOF, and principle components (PCs; these vary in time). h) Regressions are then built between PC values (referred to as PC regressions, or PCR) and e) data available in near-real-time, which are aggregated within subdomains to isolate different spatial patterns. Then these regressions are used to i) predict target-year PC values, which are combined with j) the spatial EOFs and variance explained to reconstruct the SA values for the target year. Finally, k) SWE in the target year is calculated from the reconstructed SA values using the μ and σ from WUS-SR SWE at each grid cell.

4.3.3 SWE calculations using the standard anomaly

Using the leave-one-out framework, we calculated the climatological mean and standard deviation of 1 April SWE at each WUS-SR grid cell. Then we calculated the SA value

for the domain in each target year using 1) ERA5 cumulative water year snowfall and 2) simulated ATL06-SR snow depth estimates, described below. Finally, we calculated the SWE value at each grid cell according to Equation 1 and then evaluated against the WUS-SR SWE map for the target year (Fig. 4.1).

4.3.3.1 ERA5 cumulative water-year snowfall

We accessed the ERA5 daily sum of snowfall and hourly total precipitation for the domain from the Climate Data Store for water years in the period 1985 to 2021 (Fig. 4.1). We calculated the domain cumulative water-year snowfall as the sum of the 1 October - 1 April spatially averaged daily snowfall. We then calculated the climatological mean and standard deviation of the cumulative water-year snowfall for the study period and then calculated the SA value for the target year as described in Section 4.2.3.

4.3.3.2 ATL06-SR median snow depth and simulations

We followed the methodology of Besso et al. (in prep) by accessing ATL06-SR data through the SlideRule Earth service for water years in the period 2019 to 2021. We processed the data using a 40 m segment length, 20 m point spacing, and high confidence photons only. We also used SlideRule Earth to sample collocated 3DEP 10 m elevations and to calculate terrain slope at each point. We calculated snow depth as the difference between ATL06-SR and 3DEP elevations, excluding points where surface slope exceeded 20° and removing acquisition dates with fewer than 100 valid observations.

Because the spatial representativeness of ATL06-SR median snow depth varies by acquisition date (Besso et al., in prep) and SWE patterns differ between the northern and southern Sierra Nevada (Sections 4.2.4 and 4.2.6), we increased spatial coverage by combining multiple acquisitions near 1 April. The timing and locations of acquisitions were similar across the three years (Fig. 4.2). We selected a ± 2 week window around 1 April to capture acquisitions from different parts of the domain. Within this window, we calculated the median snow depth for each acquisition date and then aggregated these values to represent 1 April

conditions. Note that most acquisitions occurred in the 2 weeks after 1 April, such that in 2020 and 2021 the effective window was approximately 1-15 April.

To extend the analysis period, we generated synthetic ATL06-SR observations for 1985 – 2021. First, we bilinearly sampled the WUS-SR data at each ATL06-SR data point, and calculated the differences between the ATL06-SR and WUS-SR snow depth at each data point. We calculated the mean and standard deviation of the residuals for acquisitions between 1 March and 31 May during the period 2019 to 2021 (Fig. 4.3). Then we selected ATL06-SR acquisitions within the 1 April window that provided the most complete spatial coverage of the domain. The location of these acquisitions served as the spatial template for our simulated data. We assigned each of these an acquisition date based on the observed temporal distribution of acquisitions within the 1 April window in 2021 (Fig. 4.2). For each year in the period 1985 - 2021, we bilinearly sampled the WUS-SR snow depth at these locations and dates. Then we randomly sampled residuals to add to each sampled WUS-SR value, such that the residuals added to the simulated data followed the same distribution as that of the real ATL06-SR data (Fig. 4.3). Finally, we removed simulated observations where ERA5 hourly precipitation was nonzero at the corresponding time and location to approximate cloud-related data gaps in the ATL06-SR observations.

We calculated 1 April SAs from observed ATL06-SR data (2019 – 2021) and simulated ATL06-SR (referred to hereafter as SimATL06-SR; 1985-2021) as the median snow depth within the ± 2 -week window relative to the climatological mean and standard deviation of windowed medians derived from WUS-SR (for the real ATL06-SR SAs) and the simulated data (for SimATL06-SR SAs) for the same dates and locations. The SA values calculated from the real ATL06-SR data were used to calculate SWE using the SA technique for the available years of data (2019-2021) but were not used in the EOF analysis.

4.3.4 *SWE calculations using EOFs and PC regression*

We calculated the standard anomaly (SA) of SWE at each 1 April WUS-SR grid cell for each year of the study period, and then decomposed this spatial and temporal SA dataset using

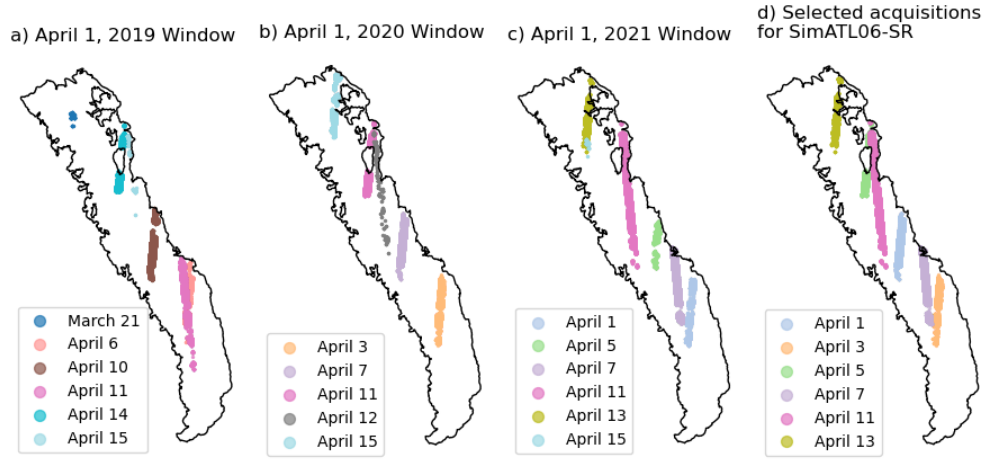


Figure 4.2: ATL06-SR acquisitions for the 2 weeks before and after 1 April in 2019 – 2021, and b) the location and simulated dates of the acquisitions selected for creating simulated ATL06-SR data.

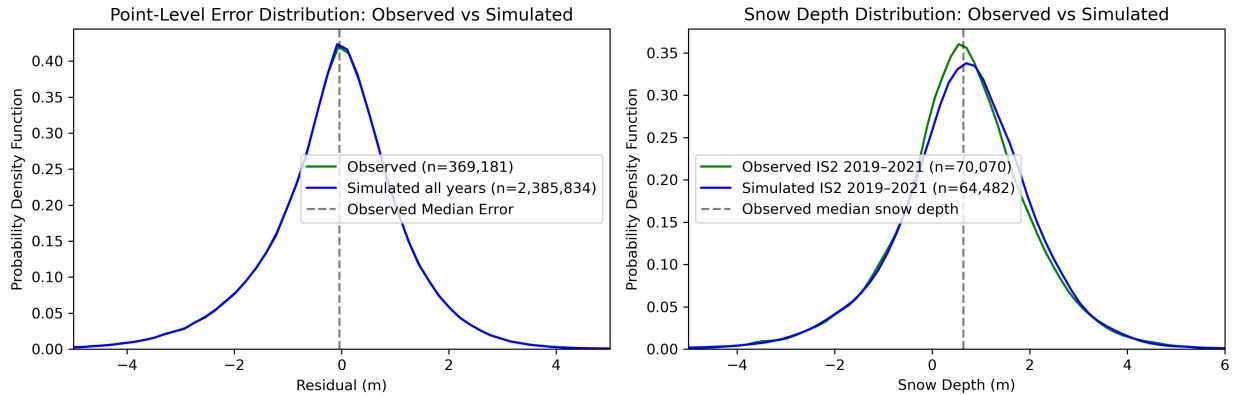


Figure 4.3: The left subplot shows the distribution of the residuals between the linearly sampled WUS-SR and ATL06-SR snow depth values for 1 March – 31 May of 2019 – 2021 (green) and the sampled residuals that were used for simulated data in 2019. The right plot shows the distribution of snow depth values from the ATL06-SR for the acquisitions chosen for the simulation (green) and the simulated data (blue) for those locations and dates.

a singular value decomposition (SVD). Previous studies have primarily run decompositions on SWE anomalies rather than standardized anomalies; we chose to standardize the SWE anomalies using the standard deviation so that regions with large SWE variability did not dominate the solution, and to better highlight coherent spatial patterns across elevations and latitudes. The SVD produced EOF spatial patterns, the variance from the input data explained by each EOF, and associated PC time series'. We retained the EOF modes that explained the most variance and ignored the subsequent modes, assuming that these explained noise in the input data. This SVD was run outside the leave-one-out framework, and was used to select how many EOF modes to retain, how to interpret those modes, and for building the PC regressions. Later SVDs were run within the leave-one-out framework as described below.

We then developed principal component regressions (PCRs) to relate the PC time series' to three predictor sets: (1) ERA5 meteorological variables, (2) SimATL06-SR snow depth variables, and (3) a combined set of ERA5 and SimATL06-SR variables. Keeping predictor sources separate allowed us to quantify the incremental value of SimATL06-SR relative to ERA5 alone. Candidate predictors for the entire domain and for selected subdomains (4.1) for each mode were selected based on the physical interpretation of the EOF patterns and prior studies (Section 4.2.6), and are described in Section 4.4.2.

To develop linear regressions for the first principal component (PC1), we regressed the true PC values against all combinations of one to three predictor variables within each predictor set. Model performance was evaluated using leave-one-out cross-validation, in which a single observation was withheld, the regression was fit to the remaining observations, and the withheld PC value was predicted. This process was repeated for all observations, and the coefficient of determination (R^2) was calculated between the predicted and true PC values. For each predictor set, the regression with the highest cross-validated R^2 was selected. For subsequent PCs, we followed a similar procedure but first removed the influence of all preceding PCs from each predictor variable. Specifically, each predictor was regressed against the preceding PCs, and the resulting residuals were used as predictors for the current PC.

This ensured that only the component of each predictor that was orthogonal to the preceding PCs contributed to the regression. During development of the PC regressions (PCRs), the true values of the preceding PCs were used to calculate these residuals. However, when applying the PCRs within the EOF SWE calculation technique, the predicted values of the preceding PCs were used instead.

Once the PCRs were established for each predictor set, we used the selected regression relationships to estimate PC values from the predictors in each target year. Then we re-calculated the WUS-SR SAs for each target year, excluding the target year from the calculations for the mean and standard deviation. We ran a new SVD on each SA dataset such that no information from the target year was included in the analysis. Then we estimated the gridded SA values for the target year as the sum of the retained EOF spatial patterns weighted by the variance explained by each pattern and by the predicted PCs (Figs. 4.1 and 4.4). Finally, we converted SA values to SWE by multiplying by the WUS-SR grid-cell climatological standard deviation and adding the grid-cell climatological mean. Since we did not retain all of the modes of variability, we did not expect to reproduce the input data exactly. To establish the highest accuracy that could be achieved using this method, we also calculated SWE using the true PC values from the retained modes and refer to this as the EOF Best Case.

4.4 Results

4.4.1 EOF spatial patterns

The first three EOFs derived from the SVD of all years of 1 April SWE SAs showed spatial patterns that broadly aligned with those reported by Aguado (1990). (Fig. 4.5). The first mode had the same sign across the entire domain, indicating region-wide coherence in SWE variability, and explained 24% of the variance in the SA data (Fig. 4.6). The second mode had opposite signs at low versus high elevations and explained 7.5% of the variance. The third mode had opposite signs between the northern and southern Sierra Nevada, with a

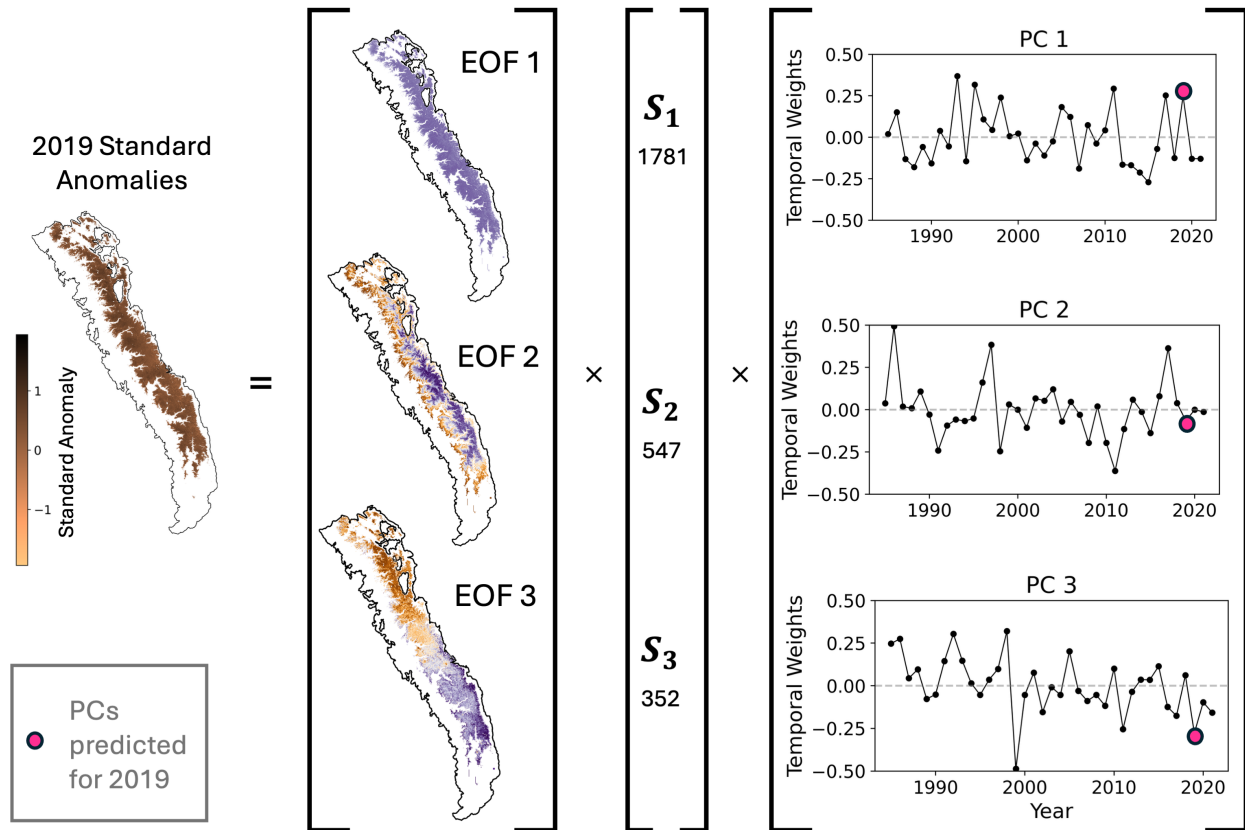


Figure 4.4: The WUS-SR SA values in the target year (in this case, the example is 2019) are calculated by summing the products of each spatial EOF pattern (EOF 1-3) with the variance explained by that pattern (S_1 -3) and the temporal PC weights estimated from the PC regression in the target year (pink dots depict the estimated PC weights 1-3 for 2019). After the SA values are reconstructed, they can be transformed back to SWE using the WUS-SR mean and standard deviations (as shown in Fig 4.1).

transition near 38 degrees N, and explained 5% of the variance. The percent of variance explained by subsequent modes tapered considerably after the first three, so we retained the first three modes of variability and assumed the rest explained noise in the data. Together, these three modes explained 36% of the variance in 1 April SA values (Fig. 4.6). Further spatial modes are shown in Fig 4.7 and were not used in the subsequent analysis.

4.4.2 *PC Regression*

4.4.2.1 *ERA5 meteorological variable selection*

We selected ERA5 meteorological variables for the PCR based on our interpretation of the EOF modes described above: we used ERA5 daily cumulative precipitation, daily cumulative snowfall, and daily mean 2m temperature. For daily cumulative precipitation and snowfall, we calculated cumulative values from 1 October to 1 April, and for daily mean 2m temperature we calculated the average temperature for that same period on days when there was nonzero precipitation in the daily cumulative precipitation data. Then we calculated the domain spatial average for each of these variables. Based on the EOF spatial patterns described above, we hypothesized that different areas of the domain could be better correlated with certain EOF patterns. We created three subdomains (as shown in 4.1 and 4.5) that we hypothesized would capture differences between the northern and southern Sierra Nevada without a strong elevational gradient (subdomains 1 and 3) and that would contain strong elevational gradients without a strong north-south signal (subdomain 2). The resulting subdomains corresponded to: (1) northern low elevations, (2) central high and low elevations, and (3) southern low elevations. Within these subdomains, we calculated the spatial average of cumulative precipitation and snowfall, and average temperature on days with precipitation. We also calculated the difference and the ratio between the variables in subdomains 1 and 3 in an attempt to capture differences between the northern and southern Sierra Nevada. The ERA5 variables selected for each regression and the associated correlation coefficients (R^2 values) are shown in Table 4.1.

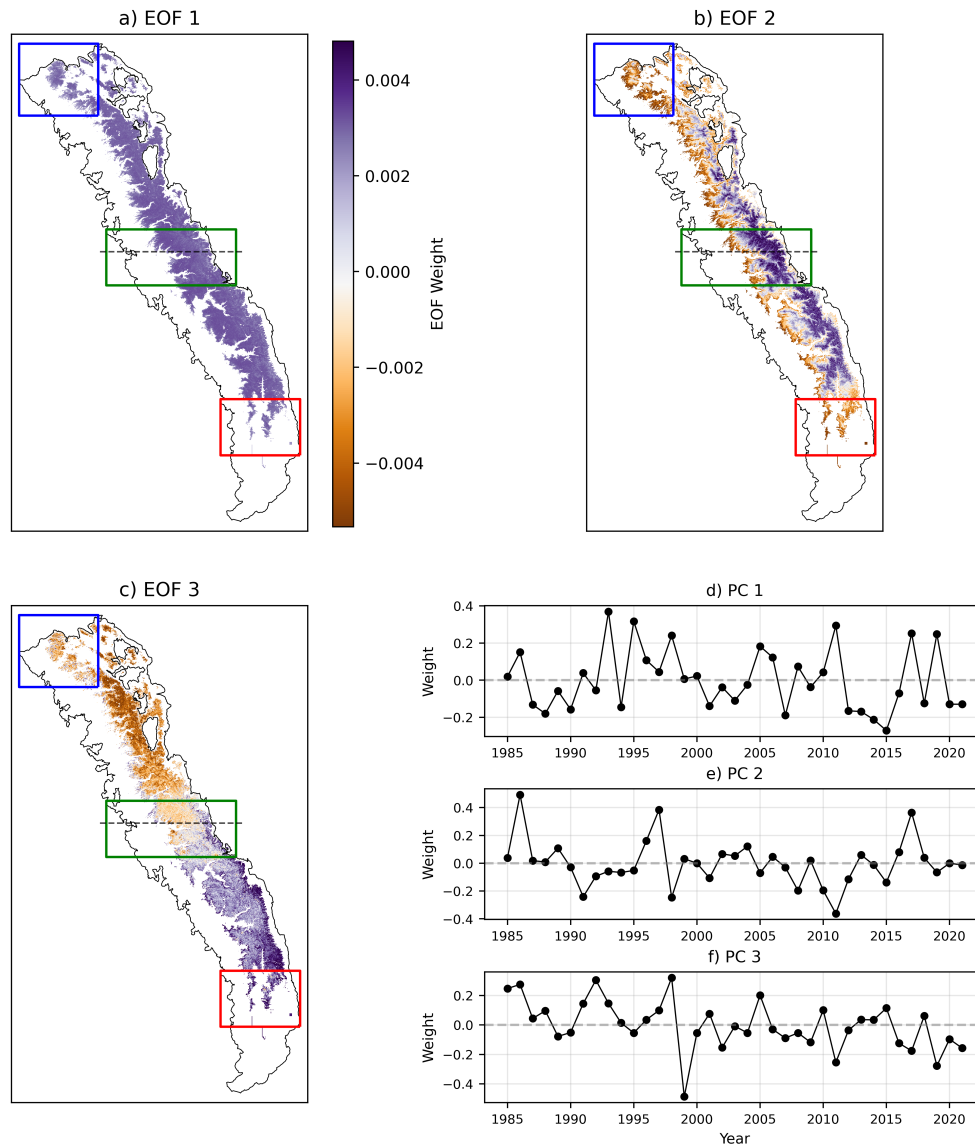


Figure 4.5: The first three modes of variability in SWE standard anomalies in the Sierra Nevada. A) EOF 1 has weights of the same sign throughout the region, b) EOF 2 has weights of different sign at different elevations, and c) EOF 3 has weights of different sign by latitude. The blue, green, and red boxes and the dashed line at 38 degrees latitude correspond to the subdomains and north/south regions shown in 4.1 and used in the PC regressions (see Section 4.4.2). The PC timeseries' associated with the first three EOFs (PCs 1-3) are shown in d-f.

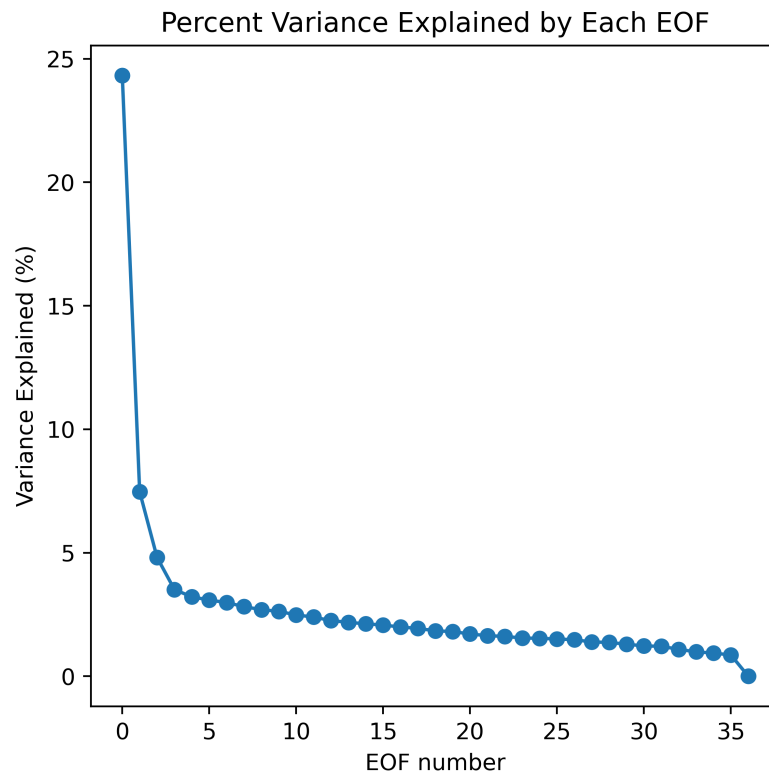


Figure 4.6: The percent variance explained by all the modes of variability from the SVD of standard anomalies of SWE in the Sierra Nevada. The percent variance explained tapers off after the first three modes.

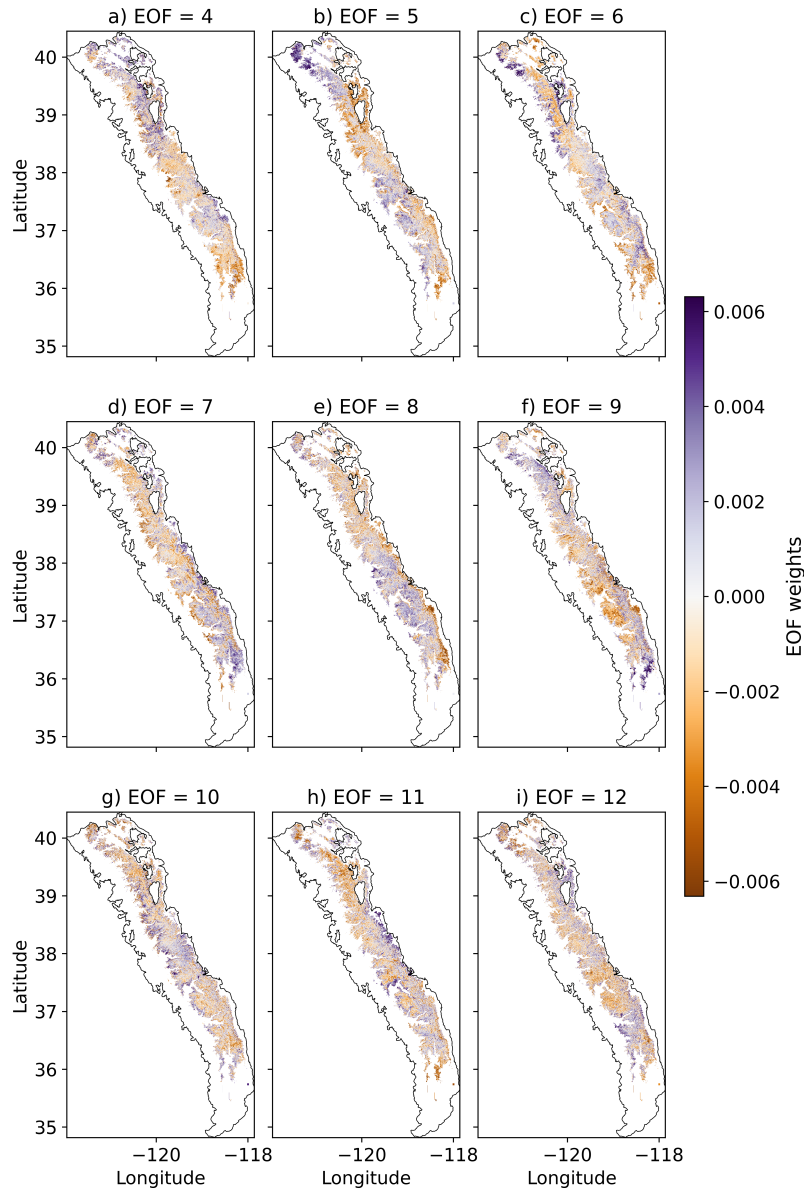


Figure 4.7: Modes beyond the first three were not used in the analysis and are included here for context. The subfigures (a-i) show EOF modes 4 - 12. The spatial patterns in these modes are more difficult to interpret and were assumed to contain mostly noise or error structures built in to WUS-SR. Future work could investigate these modes further.

4.4.2.2 *Simulated ATL06-SR snow depth variable selection*

We calculated several variables to describe snow depth using the SimATL06-SR snow depth data within the +/- 2-week window around 1 April. We calculated median snow depth within the domain, within 500 m elevation bands spanning 1750 m - 2250 m (referred to as the 2000 m band), 2250 m - 2750 m (2500 m band), 2750 m - 3250 m (3000 m band), and 3250 m - 3750 m. (3500 m band), and within 250 m elevation bands consisting of 10 bands spanning 1500 m to 4000 m. We then used the median snow depth within the 250 m bands to fit a linear regression between snow depth and elevation, and calculated the gradient and y-intercept of this relationship. The gradient was an indication of how strongly snow depth varied with elevation, and the y-intercept served as an approximation of the elevation of snowline. To target the spatial pattern in EOF 3, we identified the latitude line at 38° North where the sign of EOF3 weights changed. We used this line of latitude to distinguish between the northern and southern Sierra Nevada. We found the median SimATL06-SR snow depth north of this line and south of this line, and calculated the difference and ratio between these medians. We did not use subdomains 1 and 3 for this purpose because those domains were too small to receive enough ATL06-SR data. The SimATL06-SR variables selected for each regression and the associated correlation coefficients (R^2 values) are shown in Table 4.1.

4.4.2.3 *Regression Results*

All three predictor sets had the strongest correlations to weights from PC1 (R^2 of 0.93 - 0.95). For PC2, the correlations were lower, especially for the ERA5 predictor set (R^2 of 0.52 - 0.77). For PC3, the correlations were the lowest for the SimATL06-SR and combined predictor sets (R^2 of 0.61 and 0.68, respectively), although the ERA5 predictor set had a higher correlation for PC3 than for PC2 (R^2 of 0.66 and 0.52, respectively). In each case the combined predictor set had the highest correlation.

Table 4.1: Variables that resulted in regressions with the strongest correlation for PCs 1, 2, and 3 are listed for each PC and predictor set. The square of Pearson’s correlation coefficient (R^2) is listed in parenthesis to show the correlation after adding each subsequent variable, and is listed for the full regression in the final column.

PC	Source	Selected Variables	R^2 value
1	ERA-5	Cumulative domain snowfall (0.92); cumulative precipitation in subdomain 3 (0.93)	0.93
1	SimATL06-SR	Median SimATL06-SR snow depth in 3500 m band (0.87); intercept of the gradient of SimATL06-SR snow depth by elevation (0.93); median SimATL06-SR snow depth in 2000 m band (0.94)	0.94
1	ERA-5 + SimATL06-SR	Cumulative domain snowfall (0.92); median SimATL06-SR snow depth in 3000 m band (0.95); cumulative precipitation in subdomain 1 (0.95)	0.95
2	ERA-5	Cumulative domain precipitation (0.37); cumulative domain snowfall (0.39), average temperature on days with precipitation (0.52)	0.52
2	SimATL06-SR	Median SimATL06-SR snow depth in 2000 m band (0.26); median SimATL06-SR snow depth in 3000 m band (0.58); ratio between median SimATL06-SR snow depth in the north and south regions (0.73)	0.73
2	ERA-5 + SimATL06-SR	Median SimATL06-SR snow depth in 3500 m band (0.42); median SimATL06-SR snow depth in 2000 m band (0.64), cumulative domain precipitation (0.77)	0.77
3	ERA-5	Cumulative precipitation in subdomain 3 (0.31); cumulative domain snowfall (0.55); cumulative snowfall in subdomain 3 (0.66)	0.66
3	SimATL06-SR	Median SimATL06-SR snow depth in 3500 m band (0.16); domain median SimATL06-SR snow depth (0.43); difference between median SimATL06-SR snow depth in the north and south regions (0.61)	0.61
3	ERA-5 + SimATL06-SR	Cumulative precipitation in subdomain 3 (0.31); median SimATL06-SR snow depth in 2000 m band (0.40); median SimATL06-SR snow depth in 3500 m band (0.68)	0.68

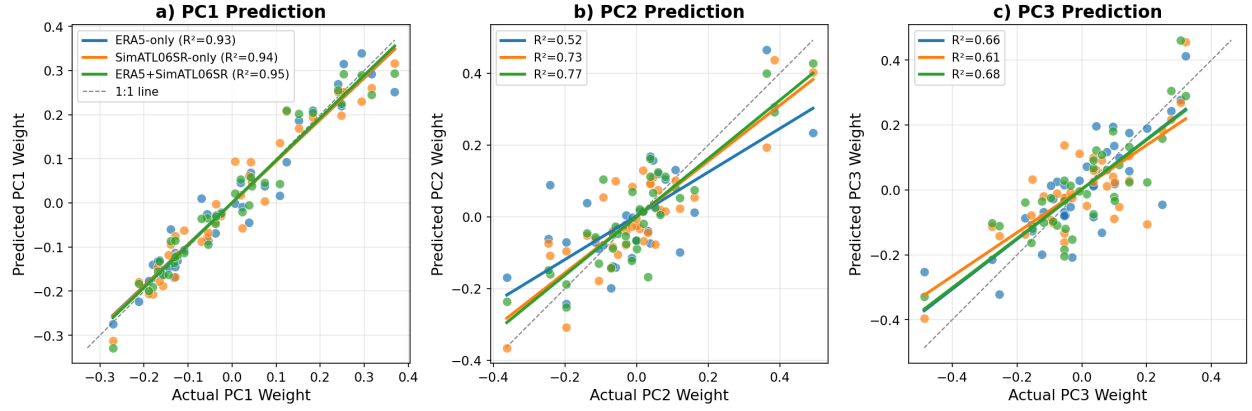


Figure 4.8: Regression results for each predictor set for a) PC1, b) PC2, and c) PC3. Each predictor set is represented by a different color in the scatter plots and the regression lines, with the 1:1 line shown as a dashed grey line. Each dot represents one year of the study period (1985 - 2021). For all regressions, the combined predictor set (ERA5+SimATL06-SR) resulted in the highest R^2 value.

4.4.3 SWE calculations

The spatial distribution of reconstructed 1 April SWE error for an average year (2009), a low-snow year (2015), and a high-snow year (2019) is shown in Figure 4.9. The mean SWE volume binned by elevation and latitude is shown in Figure 4.10. Domain-wide SWE metrics (R^2 , RMSE, and Pbias) for all years (1985 to 2021) are shown in Figure 4.11, with example years highlighted. Differences in SWE error between estimates that include ATL06-SR (SA SimATL06-SR, EOF SimATL06-SR, and EOF ERA5+SimATL06-SR) and those that do not (SA ERA5, EOF ERA5) are shown in Figure 4.12.

The distribution of metrics for the EOF Best Case reconstruction showed the least Pbias and highest correlation with WUS-SR (Figs. 4.9-4.11). This product used the true PC values from the SVD analysis, so could not be calculated in near-real-time and served as the upper ceiling for the accuracy we could expect the EOF methods to achieve. The following comparisons focus on the other products.

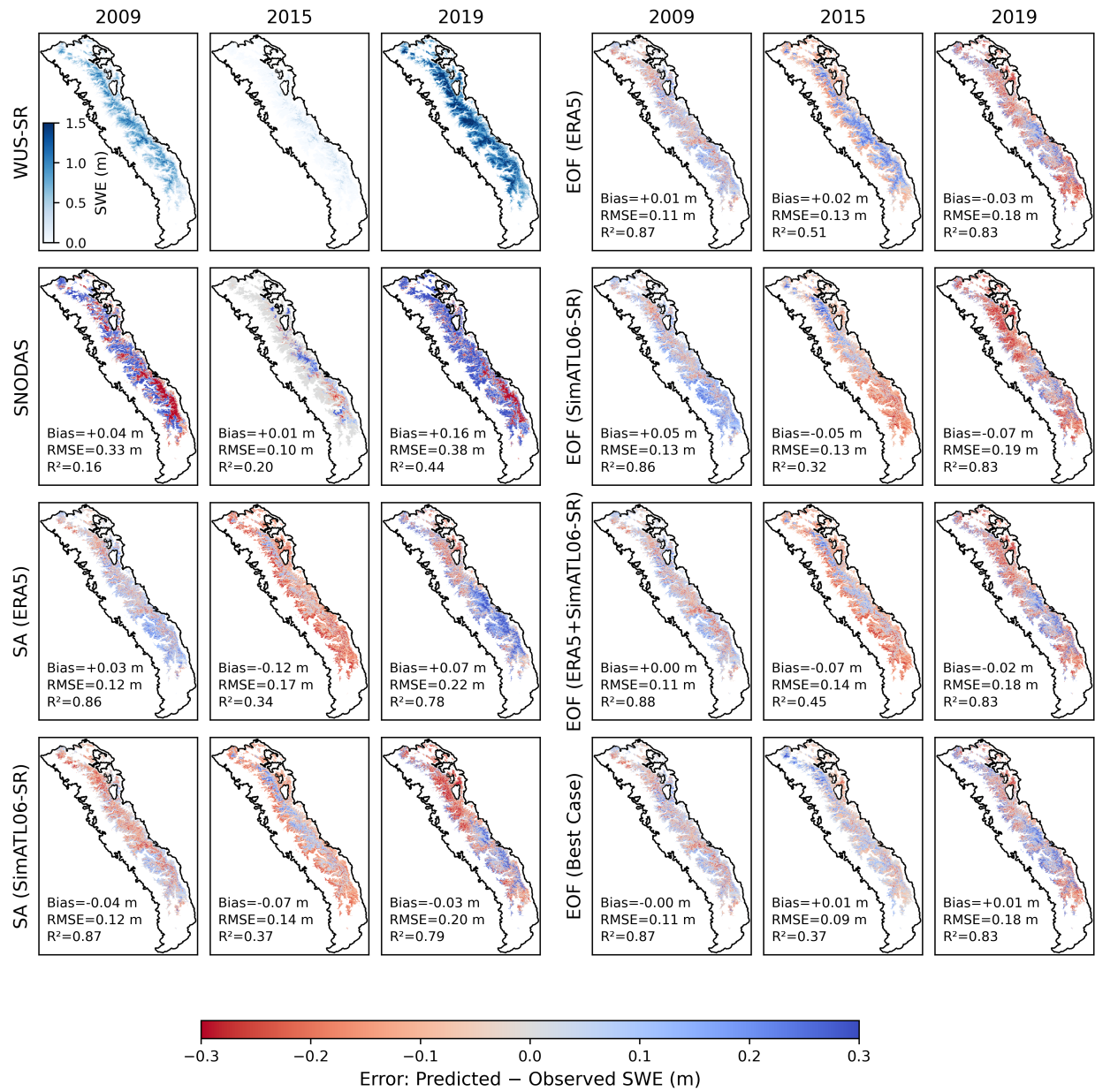


Figure 4.9: *Caption on next page.*

Figure 4.9: The spatial distributions of SWE errors by method and input data in three example years: 2009 (an average year), 2015 (a low-snow year), and 2019 (a high-snow year). The top left row shows the 1 April SWE in each year from the WUS-SR product. Each year is shown in two different columns to allow all method iterations to be displayed on one page. The bias, RMSE, and R^2 are displayed in the bottom left of each subplot. Note that SNODAS had the lowest R^2 values but tied the EOF Best Case for the least bias in 2015, while the EOF (ERA5+SimATL06-SR) generally had the lowest bias and highest R^2 , except for in 2015.

4.4.3.1 *Spatial errors in example years*

Aside from SNODAS, most products had generally similar patterns to the spatial distribution of the errors in each example year, particularly among methods. In the average year (2009), all products overestimated SWE at southern low and mid elevations and some products underestimated certain higher elevations (SNODAS, SA SimATL06-SR, EOF ERA5+SimATL06-SR, and EOF Best Case) (Fig. 4.10). SNODAS had the most extreme bias of all products in this year. In the low-snow year (2015), most products tended to underestimate SWE, especially at low and mid elevations. This underestimation was the most extreme for SA ERA5, SA SimATL06-SR, and EOF ERA5+SimATL06-SR. Higher elevations tended to be overestimated, particularly for EOF ERA5. SNODAS was the exception; it had the least bias of all products in this year. In the high-snow year (2019), most products underestimated SWE in the north and at mid elevations in the south, and overestimated SWE at low and high elevations in the south. SNODAS had the largest magnitude biases of all products in this year, with overestimation at low and mid elevations at all latitudes, and underestimation at only the highest elevations (Fig. 4.10). Most of the area in the snow-covered Sierra Nevada occurs at northern and central low and mid elevations (Fig. 4.10).

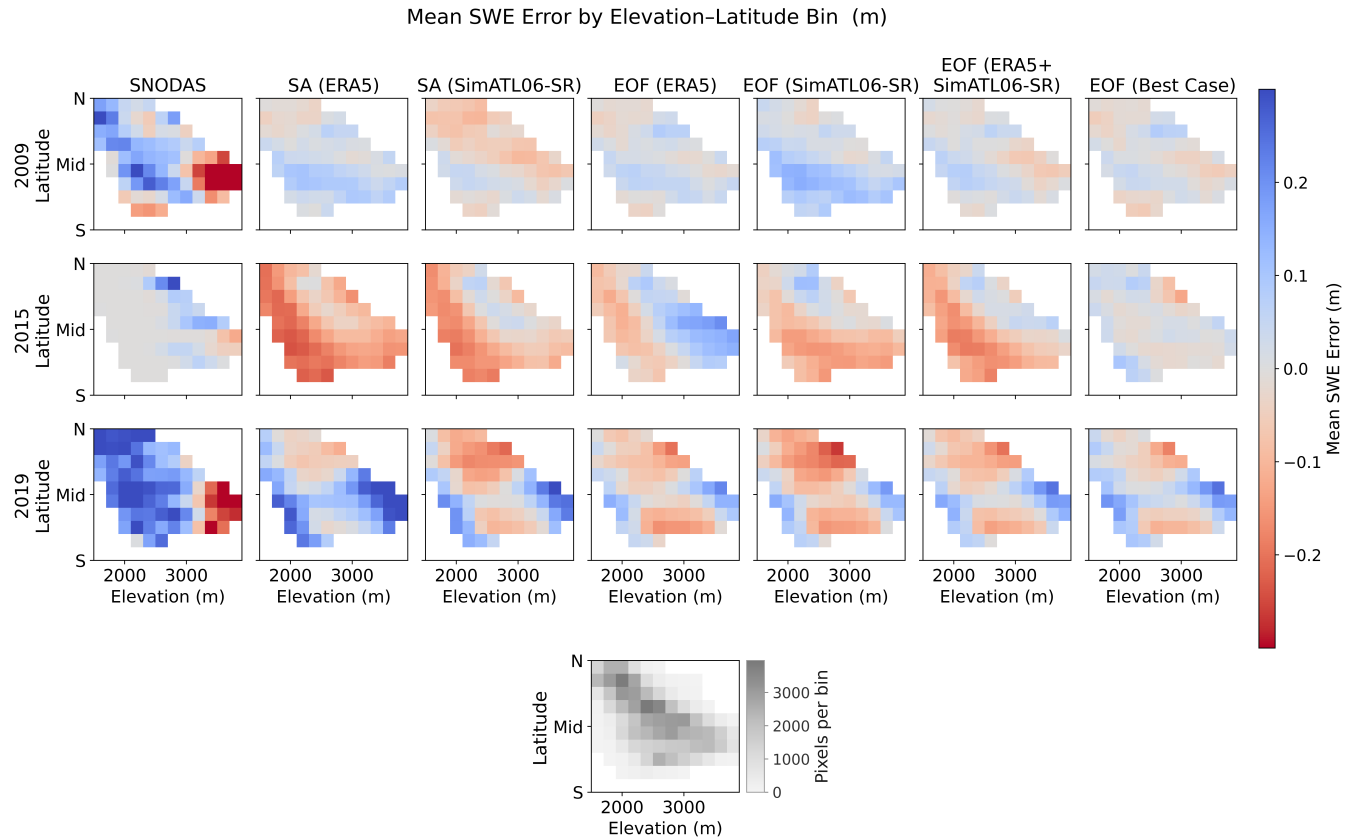


Figure 4.10: Mean SWE errors in meters within elevation and latitude bins. Each row presents results for one of the three example years (2009, 2015, and 2019) and columns show results for each method and data input combination. The number of pixels within each bin is shown under the main graph in greyscale. Note that SNODAS had the least error in 2015 but overestimated lower elevations and underestimated the highest elevations in the other years, while the EOF ERA5+SimATL06-SR method generally resulted in less bias than other methods but tended to underestimate SWE (especially at low and mid elevations) in 2015.

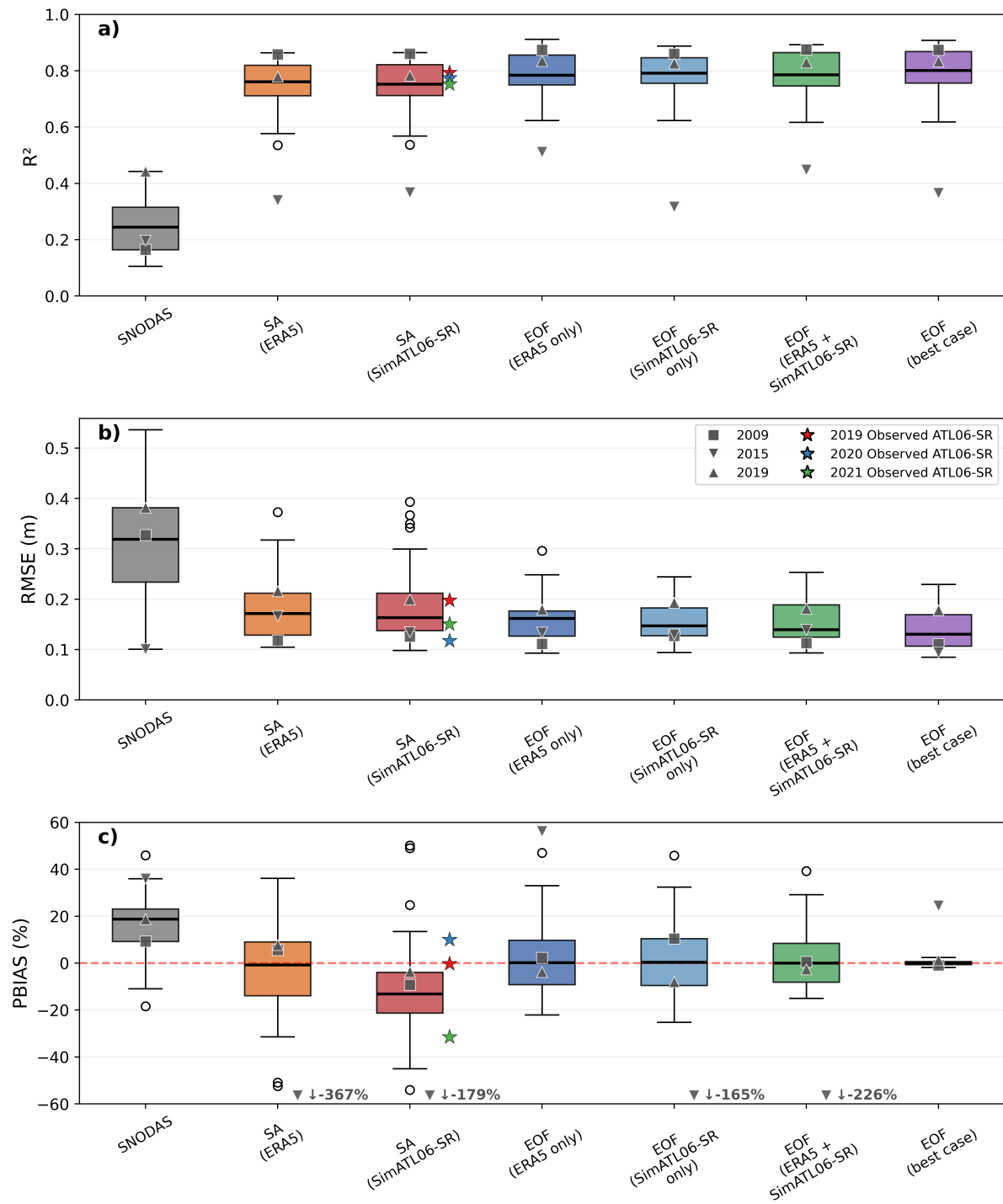


Figure 4.11: *Caption on next page.*

Figure 4.11: Distributions of annual metrics for all SWE estimates: a) the square of the Pearson’s correlation coefficient, b) the root mean squared error (RMSE), and c) the percent bias (Pbias). The SNODAS distribution contains 17 years of data, while all other distributions contain 37 years of data. The example years are shown in grey as a square (2009), downward triangle (2015), and upward triangle (2019). For years in which observed ATL06-SR data exists (2019 - 2021), results from the SA technique using these observations are shown as stars and are colored by year. Note that SNODAS has the lowest R^2 values and highest RMSE values, while most other estimates have more similar metrics to each other. In general, the EOF methods tend to outperform the SA methods.

4.4.3.2 Metrics in all years

Compared to WUS-SR SWE across all years, SNODAS had the lowest correlation (R^2), whereas the EOF-based products had similar correlations that were consistently slightly higher than those of the SA estimates (Fig. 4.11). Note that all SWE products except for SNODAS were trained on SWE patterns in WUS-SR. For all products except SNODAS, 2015 was a low outlier in correlation, 2009 ranked near the highest values, and 2019 fell closer to the median of the distribution. SNODAS also had the largest median RMSE and the widest interquartile range. RMSE values among the other products were similar, though the interquartile spread was slightly smaller for the EOF products than for the SA products. For most products, RMSE in 2009 was near the lower end of the distribution, while RMSE in 2019 was near the upper end. The RMSE in 2015 was near the bottom of the distribution for all products except SA ERA5.

SNODAS tended to have positive Pbias values (SWE overestimation) and had the largest magnitude median value (Fig. 4.11). SA SimATL06-SR tended to have negative Pbias values (SWE underestimation) and had an interquartile range whose lower bound exceeded the magnitude of the upper bound of the SNODAS Pbias. The remaining products were

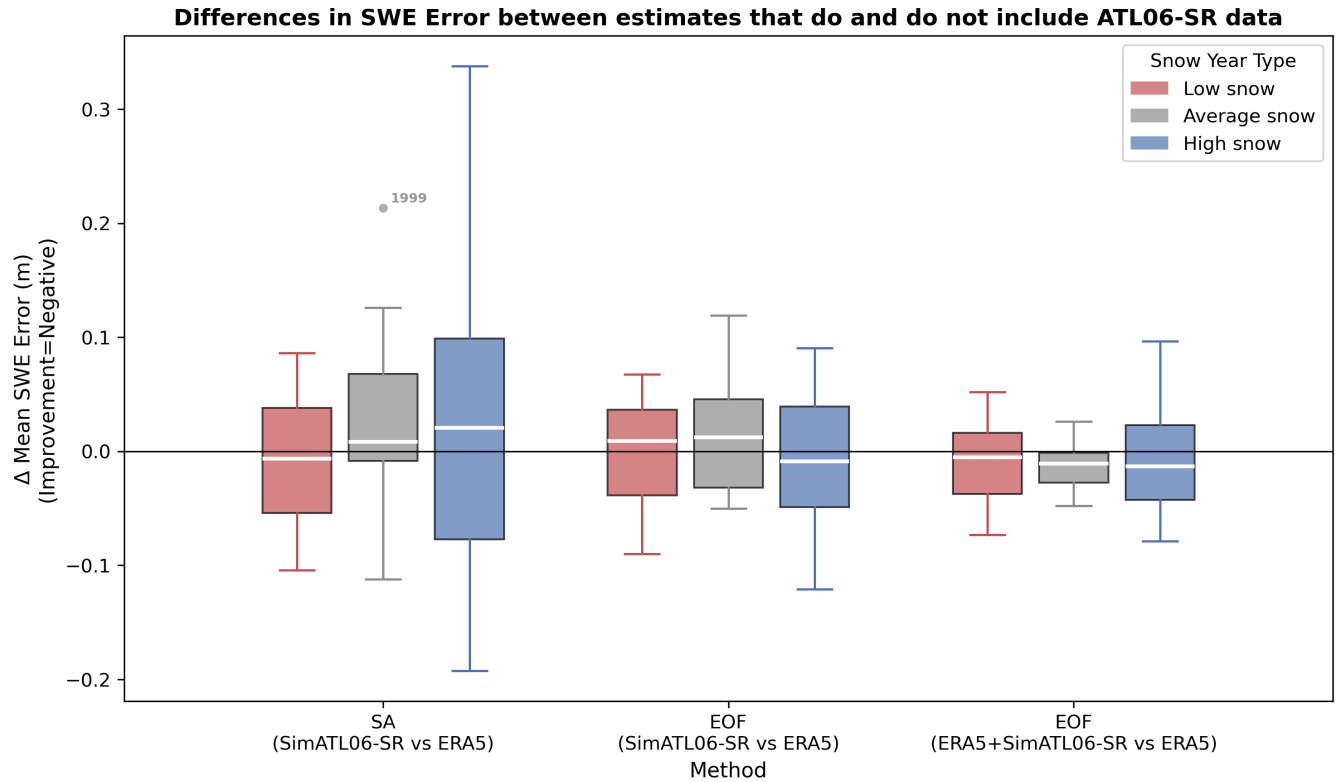


Figure 4.12: Negative values on the y-axis indicate a reduction in error while positive values indicate an increase in error. The boxplot color indicates the snow year type, where low snow years (red) have spatially-averaged 1 April SWE that was more than one standard deviation below the historical average from WUS-SR, average snow years (grey) are within one standard deviation, and high snow years (blue) are above one standard deviation. The difference in mean SWE error between methods that used input data from SimATL06-SR versus ERA5 are shown. For example, the mean SWE absolute error in each year for the SA ERA5 was subtracted from the mean SWE absolute error in each year for the SA SimATL06-SR. Outlier years are labeled. Note that there is no consistent trend indicating that the inclusion of SimATL06-SR data reduced SWE estimation error relative to using ERA5 data alone, although the combined EOF approach (ERA5+SimATL06-SR) had lower median absolute SWE error than the ERA5-only EOF across all snow year types.

centered closer to zero Pbias, with the narrowest Pbias distribution observed for EOF ERA5+SimATL06-SR (aside from the EOF Best Case). In 2015, Pbias was an outlier for most products except SNODAS, although the direction of bias varied by product.

4.4.3.3 Errors for estimates that used ERA5 versus ATL06-SR

We also compared differences in the SWE error across all years between methods that used ERA5 versus SimATL06-SR. There was large interannual variability and no clear trend. However, there was the least difference in SWE errors (smallest distribution and medians near zero) between the EOF methods that used ERA5+SimATL06-SR and just ERA5, and there was the most difference between SA methods (Fig. 4.12).

4.5 Discussion

4.5.1 Method Performance

Both the EOF and SA methods outperformed SNODAS relative to WUS-SR, in part because they were trained on WUS-SR historical spatial distributions. In typical years, most statistical methods produced reasonable estimates of SWE spatial distribution. However, in the extreme low snow year (2015), SNODAS had the lowest magnitude Pbias (although the correlation remained substantially lower than for any other method). This suggests that in years that deviate strongly from climatological patterns, observations (in this case, via data assimilation) are especially important. The high snow year (2019) did not show up as an outlier for any of the metrics, while the low snow year was an outlier for most methods in terms of R^2 and Pbias. This suggests that low snow years are more difficult for these methods to predict. Incorporating additional information such as observations of fractional snow covered area (fSCA) might improve accuracy in low-snow years. In most years, however, pattern-based approaches performed as well as or better than SNODAS. This could be especially important for regions that lack the density of observations used for assimilation in SNODAS. In anomalous years, targeted additional observations could potentially be used

to help improve the statistical estimates.

The SA method exhibited systematic elevational and latitudinal biases in some years, indicating sensitivity to temperature gradients and storm-track variability that are not captured by an assumption of spatially uniform standard anomalies. Across nearly all metrics, the EOF method outperformed the SA method. This outcome was expected because the EOF framework represented multiple spatial modes of SWE variability rather than assuming spatially uniform standard anomalies. Conceptually, the SA method resembled an EOF method that retained only the leading mode, since the EOF analysis was performed on SA values and the first mode exhibited strong domain-wide coherence. In addition, the SA approach tends to dampen extremes by pulling anomalous years toward the climatological mean, reducing performance in years outside the historical range [Besso *et al.*, 2026]. The EOF Best Case provided an upper bound on achievable skill given the three retained modes; remaining errors reflect variability associated with additional modes not included in the analysis. These additional modes (for example those shown in Fig. 4.7) could be associated with noise in the snow depth signal or error structures within the WUS-SR product itself. Future work could evaluate whether incorporating additional modes reduces this residual error.

Regression-based EOF SWE estimates approached, but did not match, the performance of the EOF Best Case benchmark. However, for some methods and years, coherent spatial errors remained. For example, most EOF estimates had elevationally-dependent errors in 2015 while the EOF Best Case did not, suggesting that the elevation-dependent variability associated with PC2 was not fully captured by the PC2 regressions (Fig. 5). Additionally, while EOF modes are often interpreted in terms of large-scale meteorology, such interpretations are inherently limited. Because EOFs impose linearity and orthogonality, they may result in predictable patterns that are a result of the underlying math, not the physical behavior of climate dynamics (Hannachi, 2007). As a result, associations between the first three PCs and the variables we used related to temperature, precipitation, or snow depth likely simplify more complex interactions. Future work could use nonlinear forms of machine learning to capture more complex interannual variations that were not accounted for here,

such as by varying the orographic precipitation gradient *Lundquist et al.* [2010].

Regressions using the predictor sets from ERA5 and SimATL06-SR performed similarly overall, although SimATL06-SR-based predictions had higher magnitude Pbias in 2015. There was no consistent trend as to whether including SimATL06-SR variables improved estimates relative to those that used ERA5. This lack of a trend likely reflects a tradeoff between the high quality of ERA5 patterns in the western United States and limits in the accuracy of ATL06-SR snow depth estimates. However, the PC regressions that used variables from both predictor sets had the highest correlations to the true PC values, and resultant SWE estimates had improved median RMSE values and reduced Pbias spread compared to estimates that used the uncombined sets 4.11. In some years ERA5-only estimates performed better, while in others SimATL06-SR-based estimates did; the combined approach appeared to moderate these year-specific differences (Figure 4.10).

4.5.2 Considerations for using WUS-SR

Because the statistical methods depended on WUS-SR to define historical SWE distributions, any biases in WUS-SR propagated into the SWE estimates. However, given the documented agreement between WUS-SR and airborne lidar observations (Section 4.2.2), these results indicate that both the SA and EOF methods are competitive with the other products compared by previous studies (e.g. [*Lundquist et al.*, 2026; *Yang et al.*, 2023]), although we did not directly compare our results to airborne lidar in this study. There are some known limitations to the WUS-SR data that may have impacted our SWE estimates. Although the accuracy of WUS-SR was not found to decrease at elevation bands below tree line in the Sierra Nevada *Lundquist et al.* [2026], accuracy was found to decrease throughout the Western U.S. with increases in canopy density and with decreases in available Landsat imagery *Fang et al.* [2022]. Additionally, glaciers and permanent snow fields have to be manually masked by the user, since accurate estimates of snow accumulation in this reconstruction technique rely on the disappearance of snow in each pixel. We did not mask out glaciers or permanent snow fields in this study because they cover such a small percentage of the

snow-covered area in the Sierra Nevada, but for regions with more glaciers this would become more important. Finally, our approach assumes that SWE spatial patterns are stationary over the study period. However, these patterns can change as climate conditions evolve and have been shown to be shifting already in parts of the western United States *Cowherd et al.* [2024]. To account for such changes, reanalysis products such as WUS-SR should be continually updated so that evolving SWE patterns are reflected in the historical record used to estimate current-year SWE. As climate conditions continue to change, future applications of this approach may also need to exclude older years that no longer represent current snow conditions.

4.5.3 Comparison to previous EOF-based SWE analyses

Our findings are consistent with prior EOF-based SWE analyses that identified dominant modes of variability in the Sierra Nevada (e.g., [Aguado, 1990]). Unlike previous downscaling studies conducted across the broader western United States (e.g., *Gauthier et al.* [2022]), this study focused specifically on the Sierra Nevada. Because EOF solutions depend on the spatial domain, this regional focus yields distinct dominant modes and associated predictor relationships. The leading modes in our analysis explained less of the total variance than reported by Aguado (1990), in part because we standardized the SWE anomalies before running the EOF analysis (although this is fairly minimal - the first three modes explain 38% of the variance if the anomalies are not standardized), but likely primarily because of the spatial complexity of the spatially-continuous WUS-SR data compared to the sparse snow course measurements used by Aguado (1990). By standardizing the WUS-SR anomaly data, we reduced the influence of regions with especially large variability and spread the variability more evenly across modes.

4.5.4 Transferability

The methods presented here are transferable to mountain regions lacking dense in-situ observations. SWE reanalysis products are available for regions such as the Andes, High Mountain

Asia, the Lebanese Mountains, and the European Alps (e.g., [Alonso-González *et al.*, 2021; Bair *et al.*, 2016; Cortés *et al.*, 2016; Fiddes *et al.*, 2019; Margulis *et al.*, 2016; Molotch, 2009; Rittger *et al.*, 2016]), providing the historical records needed to compute climatological statistics and perform EOF analyses. Because ERA5 meteorological variables are globally available, they could be used for current-year SA calculations and regression-based estimation of PC values using the EOF method. In data-sparse regions such as the Andes Mountains—where ERA5 assimilates fewer observations and therefore has greater uncertainty—the inclusion of ATL06-SR snow depth estimates may provide larger incremental improvements than those observed in the Sierra Nevada, as they offer direct observations of snow conditions that are less common in the Andes. Even in the Sierra Nevada, where ERA5 performs well, the inclusion of ATL06-SR data in addition to ERA5 improved the SWE estimates in many cases. Where high-resolution snow-off digital terrain models (DTMs) are available, we therefore recommend the combined EOF ERA5+ATL06-SR framework. However, limited availability of suitable terrain models remains a constraint outside the continental United States and Europe, so in regions without available DTMs we recommend the EOF ERA5 approach. Future missions such as the NASA Earth Dynamics Geodetic Explorer (EDGE) may expand global laser altimetry data coverage, enabling the broader use of this data. However, in regions such as High Mountain Asia, cloudy conditions, extreme slopes, and flowing glacier ice and firn may preclude the use of ICESat-2 data. Finally, in regions with a well-defined melt season, observations of fractions snow covered area may provide additional constraints on SWE estimates, particularly in low-snow years; future work should evaluate whether the inclusion of this data could provide improvements to the SWE estimates presented here.

4.6 Conclusion

In this study, we calculated 1 April SWE in the Sierra Nevada using two different pattern-based methods: standard anomalies (SA) and empirical orthogonal function (EOF) analysis. We used the UCLA Western U.S. SWE Reanalysis (WUS-SR) product to establish historical SWE spatial patterns, and the globally-available ERA5 reanalysis meteorology and ICESat-

2 snow depth estimates to inform these methods in a leave-one-out framework. This study demonstrates that pattern-based SWE estimation methods can produce spatially-realistic 1 April SWE distributions with skill comparable to, or exceeding, an operational product (SNODAS), while requiring substantially fewer inputs. The EOF-based framework consistently outperformed the SA approach, though both methods had higher correlations and lower RMSE than SNODAS relative to WUS-SR. The method that provided the most consistently accurate SWE maps used the EOF framework in conjunction with both ERA5 meteorology and ICESat-2 snow depth estimates.

Because ERA5 is globally available and SWE reanalysis products exist for many global mountain ranges, the EOF approach using ERA5 meteorological predictors alone represents the most broadly transferable technique. ICESat-2 snow depth estimates can provide additional value, and may be more important in regions where ERA5 performance is limited by sparse meteorological observations. Where accurate snow-off DTMs exist, ICESat-2 could support both SA- and EOF-based SWE estimates. A low-latency (4-7 days) ICESat-2 product is projected to become available in late 2026 (ICESat-2 Project Science Office personal comms), which would enable operational seasonal SWE estimation. Additionally, future altimetry missions such as the planned Earth Dynamics Geodetic Explorer (EDGE) may extend and improve global altimetry coverage, expanding the availability of this data within and beyond the lifespan of ICESat-2.

The statistical techniques tested here have the potential to supply near-real-time 1 April SWE maps in global mountain ranges that have high-quality SWE reanalysis products. These data could be used as input to hydrologic models used by water managers, and could be especially important in regions lacking dense in-situ observations. The SWE reanalysis data used here could also be used to train a variety of statistical approaches for combining current year data with historical patterns. This work establishes a template for a wide range of such techniques beyond the SA and EOF methods used here, and future work should explore these methods for improved SWE estimation.

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Chapter 5

CONCLUSIONS

5.1 Summary

In this dissertation, we evaluated statistical and satellite-based approaches for estimating snow water equivalent (SWE) and its spatial distribution in the mountains of the western United States. Although the analyses focused on well-observed basins, the broader goal was to develop methods that can be applied in data-sparse mountain regions worldwide. Below, we summarize the key findings and their implications.

In Chapter 2 we combined real-time in-situ snow station data with a high-resolution historical SWE reanalysis to estimate spatially distributed SWE in the Upper Colorado River Basin. We evaluated statistical approaches in a leave-one-out framework that used either the standard anomaly (SA) or quantile at in-situ stations to adjust historical SWE distributions at each reanalysis grid cell for current-year SWE predictions. These products were compared to two physically based modeling systems: SnowModel and SNODAS. Relative to the reanalysis dataset, the statistical methods showed higher spatial correlation and lower bias than the physically based models. We recommend the SA-based approach in regions where in-situ stations are available and where historical records indicate spatial coherence in SA values. This framework is broadly transferable to regions with a reliable SWE reanalysis and sparse station networks.

In Chapter 3 we evaluated how ICESat-2 surface elevation measurements can be used to estimate median snow depth across the Sierra Nevada. Using the SlideRule Earth service, we processed low-level ICESat-2 data to produce a customized elevation product (ATL06-

SR) that excluded observations for surface slopes >20 degrees. Snow depth was calculated relative to high-resolution terrain models, and we aggregated measurements over the entire snow-covered Sierra Nevada to capitalize on the strong agreement between daily ATL06-SR median snow depth and reanalysis-derived snow depth while reducing point-scale variability. Daily ATL06-SR median snow depth showed high correlation and minimal bias relative to collocated and domain-wide values from the UCLA Western U.S. SWE Reanalysis. Seasonal snow depth evolution during water years 2019–2021 closely matched the reanalysis time series, although variable spatial sampling influenced accuracy on some dates. To increase the spatial sample size, we further aggregated ATL06-SR snow depth values within a 10-day moving window, which led to improved representativeness of the domain median snow depth. ICESat-2 provides global coverage, but snow depth estimation depends on high-quality snow-off terrain models, which are not yet available worldwide. Where such terrain models exist, ICESat-2 processed through SlideRule can provide valuable mountain-range-scale snow estimates for direct analysis or for assimilation into modeling frameworks.

In Chapter 4 we integrated the statistical framework from Chapter 2 with ICESat-2-derived snow depth measurements from Chapter 3 to evaluate multiple SWE estimation techniques in the Sierra Nevada. Using the UCLA Western U.S. SWE Reanalysis as the historical reference, we calculated climatological statistics for the SA method and performed empirical orthogonal function (EOF) analysis on 1 April SWE standardized anomalies to identify leading modes of variability. We then estimated 1 April SWE using two approaches: 1) the SA method with current-year inputs from (a) ERA5 cumulative snowfall and (b) ATL06-SR snow depth; and 2) EOF-based reconstruction using principal component (PC) regressions built from (a) ERA5 temperature, precipitation, and snowfall, (b) simulated ATL06-SR snow depth, and (c) predictors from both data sets. Across most years, all statistical techniques produced SWE estimates with skill comparable to or exceeding SNODAS, with the exception of extreme low snow years. For regions without in-situ SWE networks, where products such as SNODAS don't exist, we recommend using the combined EOF

ERA5+ATL06-SR framework when terrain models and satellite data are available. The incremental value of ATL06-SR is likely greatest in regions where ERA5 assimilates fewer in-situ observations and in years when SWE patterns depart from climatology; however, for regions without terrain models we recommend the EOF ERA5 framework.

Overall Implications Collectively, this dissertation demonstrates that statistical pattern-based methods can produce spatially realistic SWE estimates with relatively modest data requirements. The applicability of each chapter depends on the following data availability:

- *Chapter 2* requires a high-quality SWE reanalysis and sparse in-situ stations.
- *Chapter 3* requires high-resolution snow-off terrain models.
- *Chapter 4* requires, at minimum, a reliable reanalysis product (and ERA5 meteorology, which is available globally), with terrain models needed for the inclusion of satellite snow depth observations.

These methods are particularly relevant for mountain regions with limited in-situ networks but available reanalysis products, such as the Andes, High Mountain Asia, and the Lebanese Mountains. As reanalysis datasets continue to improve, the utility of statistical SWE estimation methods will expand.

Future satellite missions such as Earth Dynamics Geodetic Explorer (EDGE) may extend global altimetry coverage within and beyond the lifespan of ICESat-2. Testing simulated EDGE data within these frameworks is a promising next step. Additional research should evaluate dominant SWE variability modes in ungauged regions to refine predictor selection and improve transferability. Future work could test whether the inclusion of fractional snow covered area within the EOF SWE estimation framework could improve SWE estimates in low snow years, and could evaluate the use of additional pattern-based techniques for estimating SWE. Hydrologic modeling studies could further quantify the benefits of incorporating these SWE estimates into operational water management systems.

Finally, expanded installation of in-situ snow stations, improved global terrain models, and updates to SWE reanalysis products would substantially enhance the effectiveness of statistical SWE estimation worldwide.

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