ASSIMILATING LIDAR AND IN-SITU COMMUNITY SNOW MEASUREMENTS TO IMPROVE SNOWPACK ESTIMATES ACROSS THE WESTERN UNITED STATES

David F. Hill[1]*, Zachary Butler[1], Katreen Wikstrom Jones[2], and Gabriel Wolken[2,3]

[1] *Oregon State University, Corvallis, OR, USA*
[2] *Alaska Department of Geological & Geophysical Surveys, Fairbanks, AK, USA*
[3] *University of Alaska Fairbanks, Fairbanks, AK, USA*

ABSTRACT: Seasonal snowpack supplies a large fraction of water resources across the Western United States, making accurate estimates of snow distribution and melt timing critical for water resource management. However, substantial uncertainty persists due to sparse observations and model limitations, particularly in complex terrain. This study integrates high-resolution airborne light detection and ranging (lidar) data with in-situ observations from SNOTEL, Snow Courses, and the Community Snow Observations project (CSO) to improve snowpack estimation across three critical basins: Lake Tahoe, California; the Central Cascades, Oregon; and Summit County, Colorado. Using SnowModel simulations for water years 2022–2024, we evaluate the impact of different data assimilation strategies. This includes spatially distributed data (lidar-derived snow depth) only, point-based observations (SNOTELs, Snow Courses, and CSO) only, and combined approaches, on model performance in representing snowpack distribution. We further assess how lidar acquisition frequency and the spatial resolution of the input lidar influence model skill to identify minimum data requirements for reliable snowpack estimation. Results indicate that assimilating a snow depth raster at 50 meters yields the most accurate representation of snowpack across all study regions. However, comparable performance is achieved using only point-based observations, a resampled lower resolution snow depth raster, and when combining all available datasets. These findings suggest that point-based and lower-resolution spatially distributed assimilation offers a cost-effective alternative in data-limited settings while still providing meaningful improvements in model performance. Overall, assimilating available snow observations substantially enhances snowpack representation, particularly in complex high-elevation terrain. This research provides practical guidance for optimizing snow data assimilation strategies and improving estimates of snowpack characteristics, with direct implications for water supply forecasting and resource management across the Western United States.

KEYWORDS: snowpack modeling, lidar, data assimilation, community science

1. INTRODUCTION

Predicting the amount of water in snow and the spatial coverage of snow is vital for water resource management. This is especially important in the western United States (US), where an estimated 53% of runoff originates as snowpack and where millions of people depend on water that originates as snow (Barnett et al., 2005; Li et al., 2017). Quantifying the amount of water in the snow through the snow water equivalent (SWE) allows for water managers to understand the amount of water they might expect from the snowpack. The SWE varies substantially across a landscape due to elevation, wind redistribution, aspect, and vegetation. Large uncertainties exist in SWE, yet it is critical for water management decisions. Advances in snow detection instruments (i.e. aircraft or satellites), expanding in-situ observation networks, and snowpack modeling have improved snowpack and SWE prediction.

Snowpack information primarily comes from three main sources that include in-situ observation, remotely sensed observations, and snow models. In-situ observations are point-based measurements by instruments or people. The Natural Resource Conservation Service (NRCS) maintains the snow telemetry (SNOTEL) network, which has been measuring SWE since the 1970s. The NRCS and western US states water resource departments also main a network of snow courses, a manual SWE measurement that has existed since the 1910s. Community-based observation networks such as the Community Snow Observations (CSO) have emerged in the last decade to capture greater variability of snowpack from a manual snow depth measurement (Arendt, 2018). CSO users are primarily backcountry recreationists who access more topographically and remote areas than where SNOTELs and snow courses are located. Recent work has established that CSO measurements can help model and predict snowpack conditions

* Corresponding author address:
David Hill, Oregon State University,
Corvallis, Oregon, 97331;
tel: +1 541-737-4939;
email: dfh@oregonstate.edu

https://doi.org/10.15788/1790098737

much more accurately, due to the increased number of observations in remote areas that previously had no in-situ snowpack information (Aragon et al., 2025; Crumley et al., 2021).

Other snowpack information comes from remote sensing such as aircraft. Aircraft use light detection and ranging (lidar) to map snowpack properties at very high resolutions to the meter scale (Deems et al., 2013). Despite the high spatial resolution of snowpack information lidar can provide, it can be very expensive and limited to small areas with only a couple flights per snow season.

The third source for snowpack information is grouped into snow models. Snow models synthesize meteorological forcing with landscape characteristics to continuously estimate snowpack properties and evolution (Liston & Elder, 2006a). Despite a wealth of snow models available, they each have strengths and weaknesses, carrying uncertainty with snowpack processes.

One way uncertainty in snowpack modeling has advanced in recent years is data assimilation. Data assimilation combines the strengths of models and observations to correct a model's estimate (i.e. SWE) to adjust the model's state variables closer to the observations. Data assimilation methods vary in complexity across the snow science community. This study aims to determine whether assimilation of scattered community observations or assimilation of gridded lidar observations offers a distinct advantage over the other, and whether combining the two provides further improvement beyond either alone. In doing so, this study addresses the strengths and limitations of assimilating high-spatial-resolution but infrequent lidar data against lower-spatial-resolution but frequent point data. This is a valuable question because lidar data are expensive to acquire, while point-based data are comparatively inexpensive. If point-based snow data can compete with, or provide acceptable improvements over, lidar snow data, it could offer meaningful value in places where sufficient lidar coverage is unavailable.

2. STUDY AREAS

This study focused on the Blue River basin in Colorado with a modeling domain area of 2,200 km^2 and Truckee basin in California and Nevada with a modeling domain area of 7,016 km^2 (Fig. 1). We chose these two domains to model because they have lidar, SNOTEL, snow courses, and CSO observations. These data sources were needed to test our data assimilation strategies. Additionally, studying two domains of different snow characteristics allows us to test our model in different environmental and snow settings.

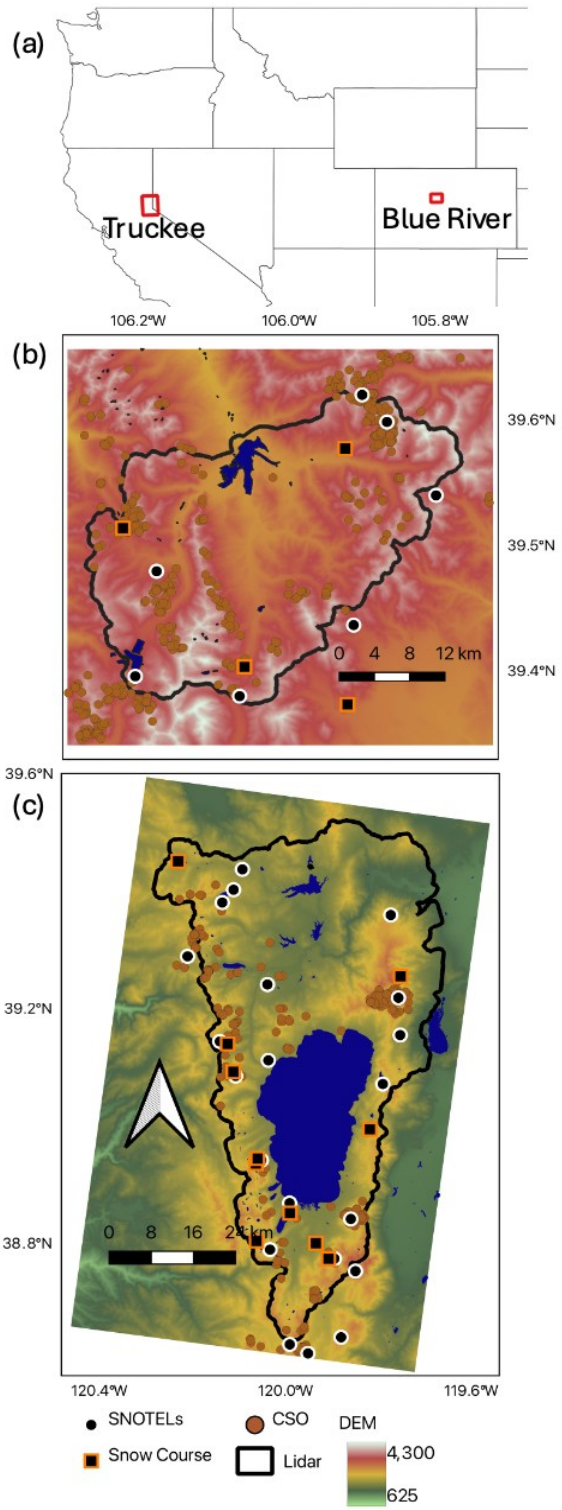


Figure 1: Study area map. (a) Western United States, with the red boxes showing the two domains, (b) the Blue River domain and (c) the Truckee domain. The background digital elevation model (DEM) is at 30 m for (b) and 50 m for (c). The Community Snow Observation (CSO) are from water years 2022–2024. The lidar footprint is overlain on the maps, along with the location of all SNOTEL stations and snow course sites.

3. METHODS AND DATA

This study utilizes SnowModel, a spatially distributed energy-balanced snowpack modeling system designed for application in landscapes, climates, and conditions where snow occurs (Liston & Elder, 2006a). SnowModel has a variety of applications and consists of five submodels. This includes MicroMet (Liston & Elder, 2006b), SnowPack, EnBal, SnowTran-3D (Liston et al., 2007), and SnowAssim (Liston & Hiemstra, 2008). MicroMet is used for the meteorological forcing. EnBal calculates surface energy exchanges. SnowPack simulates snowpack properties (i.e. snow depth and SWE). SnowTran-3D accounts for snow redistribution by wind. SnowAssim assimilates snow observations and interpolates them to correct for differences between the observed and modeled snow values to constrain modeled outputs. The focus of this research is on the SnowAssim submodel to test what snowpack data produces the best model output. We test what type of snow observations (point, gridded, or all data) allow for the optimal model performance.

There are many other snowpack models that can be used to simulate snow processes, including iSnobal (Marks et al., 1999) and SNOWPACK (Bartelt & Lehning, 2002), each with its own strengths and limitations in representing snow processes. Identifying a 'best' snow model is not the aim of this study. Rather, we adopt SnowModel as a representative physically based snow model and use it as a consistent model for evaluating how different assimilation data strategies (point, gridded, or all data assimilated) affect model performance relative to one another.

3.1 Forcing and Assimilation Data

The SnowModel framework requires elevation, land-cover, and meteorologic data as input forcing files. Elevation data was achieved from NASA via Google earth engine, and we use a 30 m (Blue River) and 50 m (Truckee) digital elevation model (DEM) (Farr et al., 2007). Land cover data was accessed from the United States Geologic Survey (USGS) National Landcover Cover Database (NLCD) to create the landcover inputs (USGS, 2025).

For the meteorological forcing data, we use the Climate Forecast System Version 2 (CFSv2), which are available at a spatial resolution of 0.2 arcdegree, and a 6-hour temporal resolution (Saha et al., 2011). We note other similar work uses ERA5-Land hourly reanalysis product (Aragon et al., 2025), CONUS404 (Mower et al., 2024), and National Land Data Assimilation System-2 (Barnhart et al., 2024). For Blue River there are 42 CFSv2 pixels and in Truckee there are 72 CFSv2 pixels. In SnowModel, MicroMet downscales the CFSv2 data to the DEM resolution.

The point snow data comes from SNOTEL, snow courses, and CSO. SNOTEL data was accessed from the NRCS, and snow course data was accessed from the California Cooperative Snow Surveys (California Department of Water Resources, 2026) and the NRCS snow survey program (USDA NRCS, 2026). The Blue River domain has seven SNOTELs and four snow courses (Fig. 1 and Table 1). The Truckee River domain has 21 SNOTELs and 11 snow courses (Fig. 1 and Table 1).

The gridded snow data comes from available lidar via ASO, and we accessed this Hs data at 50 m (Airborne Snow Observatories, 2025; Painter et al., 2016). For the Blue River domain, we resampled the gridded Hs data to match the SnowModel grid at 30 m. For the Truckee domain, we kept the gridded Hs data at 50 m. The Blue River domain has two ASO lidar flights per WY, while the Truckee domain has three or four ASO lidar flights per WY (Table 1).

3.2 Model Calibration

We performed model calibration by systematically adjusting the precipitation correction factor, maximum snow density, snow density adjustment, conifer leaf area index, and canopy gap fraction within SnowModel. We calibrated SnowModel at all SNOTEL stations located in each domain for WYs 2016–2019. The SnowModel calibration compares the modeled SWE time series with the observed SWE at each SNOTEL station. Performance metrics included coefficient of determination (r^2), mean bias (MB), root mean square error (RMSE), Nash-Sutcliffe Efficiency (NSE), and Kling-Gupta efficiency (KGE). We compute each metric between the modeled and observed SWE time series for each calibration run. To identify the optimal parameter set, we employed a rank aggregation approach. Parameter sets were ranked independently according to the performance metric, and individual ranks were summed to produce a composite score, thereby giving equal weight to each performance metric. Parameter sets were subsequently ranked by their composite score, and the parameter set with the top score was selected as the top model parameter combination. This approach favors parameter sets that consistently perform well across multiple evaluation metrics rather than excelling in only a single metric.

3.3 Data Assimilation Strategies

We utilize different data assimilation strategies per point and gridded assimilation in SnowAssim.

For the SNOTEL point data in Blue River, we use a leave-one-out (LOO) method. Blue River has seven SNOTEL stations and the LOO allowed for seven separate SnowModel runs. LOO allows us to assimilate six SNOTELs and leave the last SNOTEL out for the evaluation. For the SNOTEL point data in Truckee, we use a k-folding method. Truckee has 21 SNOTEL stations, and we create five k-folds to have four groups of four SNOTELs and one group of five SNOTELs for five separate SnowModel runs. We decided on k-fold groups by grouping the SNOTELs into five directional quadrants in the domain. We then ranked each SNOTEL per quadrant group by the average climatology SWE value (1991–2020) for each SNOTEL. We assigned a k-fold group by a different quadrant and the average SWE value. This allowed each k-fold group to have a SNOTEL from a different quadrant of the domain and so that all k-fold groups would have a diverse set of snow characteristics. For the other point data assimilation, we assimilate all available snow course and CSO data. We chose to assimilate all available snow course and CSO data because these data points are inconsistently measured. We do not evaluate snow course and CSO data because of the inconsistency when measurements are recorded.

For the gridded lidar data in each domain, we utilize an n-1 approach. This means we assimilate all available lidar surveys except for the last. By reserving the final lidar survey from the assimilation, we can evaluate it. For all data assimilation in each domain (point and gridded), we experiment with several strategies to test the best way to assimilate both point and gridded snow data. Based on evaluation metrics, we find it optimal to assimilate the combined data in the order of n-1 (gridded data) then LOO or k-fold (point data). This means we first assimilate gridded data, then after the gridded assimilation, we then start assimilating point data. We continue to use the LOO (Blue River) or k-fold (Truckee) approach and use all available snow course and CSO snow data.

4. RESULTS

The SNOTEL SWE validation shows that the three data assimilation strategies improve upon the baseline SnowModel in both domains for WY 2022 (Fig 2; Colorado results show only for brevity). In WY 2022, the average of the four SNOTELs in the lidar footprint shows that the point data assimilation has the best evaluation metrics, however, this ranking is not consistent across the other WYs. For WYs 2023 and 2024, the gridded data assimilation has the best evaluation metrics with the lowest RMSE and highest KGE. All three data assimilation strategies improve on the baseline, but the standard deviation ranges for RMSE and KGE overlap substantially across strategies, so no single approach is a clearly superior performer once spread across all SNOTELs and all WYs is considered. Notably, combining point and gridded data does not outperform gridded or point assimilation alone on any metric.

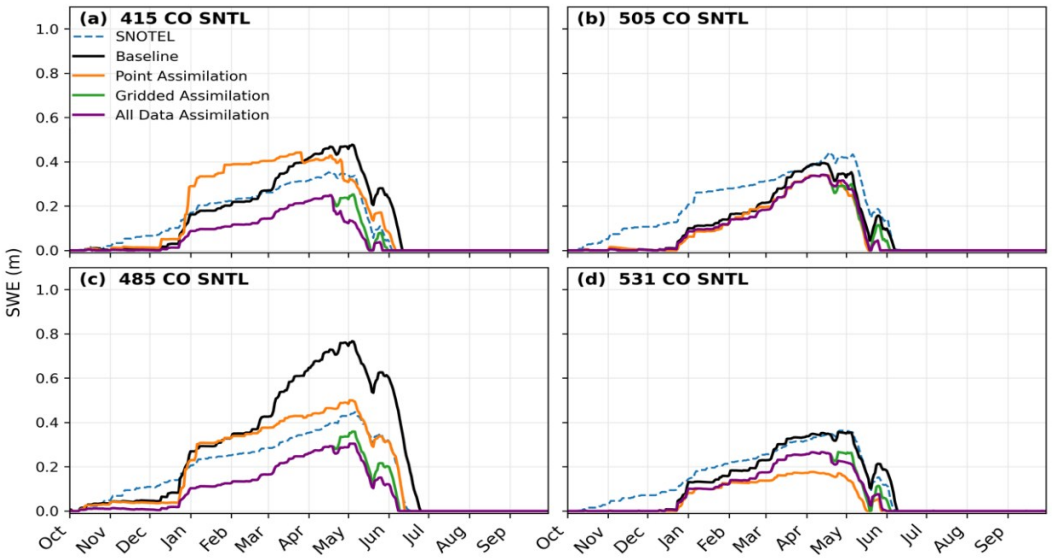


Figure 2: Simulated and observed snow water equivalent (SWE) time series at Blue River for the four SNOTELs in the lidar footprint (a–d) for WY 2022. Each colored line is the SnowModel simulation for daily SWE (m). The baseline simulation (black), point data assimilation (orange), gridded assimilation (green), all data combined point and gridded assimilation (purple), and SNOTEL observations (blue dashed)

(a) Blue River average of 4 SNOTELs, WYs 2022–2024

	Baseline	Point Assim	Gridded Assim	All Data Assim
RMSE (m)	0.12 ± 0.08	0.10 ± 0.05	0.10 ± 0.02	0.11 ± 0.02
MB (m)	0.03 ± 0.11	-0.02 ± 0.09	-0.08 ± 0.02	-0.09 ± 0.02
KGE	0.39 ± 0.44	0.50 ± 0.23	0.58 ± 0.11	0.52 ± 0.12

(b) Truckee average of 16 SNOTELs, WYs 2022–2024

	Baseline	Point Assim	Gridded Assim	All Data Assim
RMSE (m)	0.20 ± 0.14	0.16 ± 0.11	0.16 ± 0.12	0.17 ± 0.13
MB (m)	-0.15 ± 0.13	-0.01 ± 0.15	-0.09 ± 0.12	-0.12 ± 0.11
KGE	0.46 ± 0.30	0.58 ± 0.33	0.62 ± 0.25	0.56 ± 0.25

Figure 3: (a) Blue River and (b) Truckee SnowModel average validation at SNOTEL sites within the lidar footprint for WYs 2022–2024. Blue River has four SNOTELs and Truckee has 16 SNOTELs in the lidar footprint. Each column is a SnowModel run configuration (baseline, point assimilation, gridded assimilation, or all data assimilation), and each row is a statistic (RMSE, MB, or KGE). The statistics report the mean and standard deviation across the SNOTELs and the three water years.

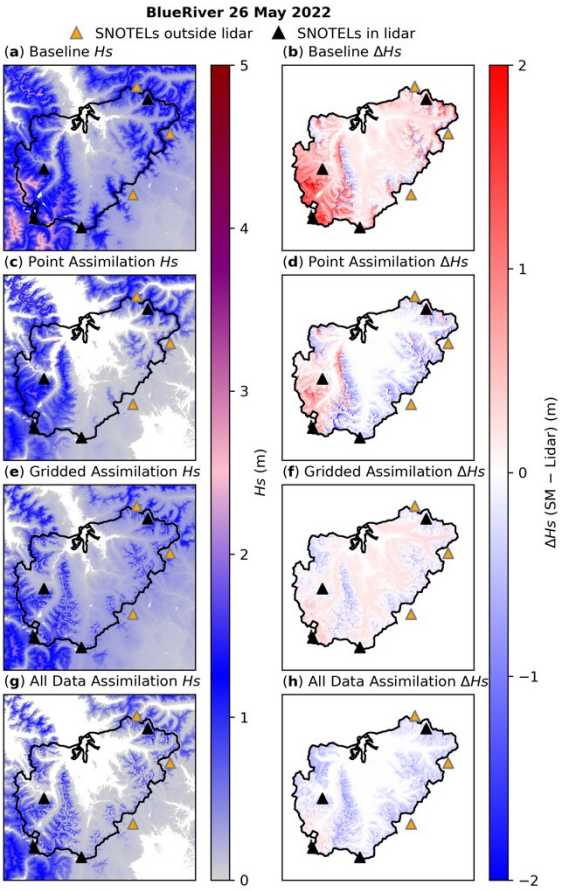


Figure 4: Simulated and difference from the observed (ASO 50 m lidar) Hs on 26 May 2022, in the Blue River domain. Subplots a–d are the SnowModel outputs of Hs per model run. Subplots e–h is the difference between a–d and the observed lidar Hs (not shown). Positive values (red colors) indicate SnowModel overpredicts Hs and negative values (blue colors) indicate SnowModel underpredicts Hs. In each subplot, the SNOTELs inside the lidar footprint used in evaluation (Fig. 4) are in black triangles and SNOTELs outside the lidar footprint are in orange.

Tabular results summarized in Figure 3 demonstrate that all the assimilation strategies improve the snowpack model estimates, but that assimilation of the gridded lidar data has a slight edge, when SNOTEL SWE is used for validation.

The gridded lidar Hs validation shows that the three data assimilation strategies improve upon the baseline SnowModel (Fig. 4; Colorado results shown only for brevity). In Blue River, averaged across all three lidar validation dates, the baseline RMSE is 0.62 ± 0.07 m, compared with 0.49 ± 0.10 m for point assimilation, 0.34 ± 0.14 m for gridded assimilation, and 0.33 ± 0.09 m for all data assimilation. The gridded and all data assimilation show the lowest RMSE, though their ranges overlap almost completely and are not clearly distinguishable from one another, and are similar to the point assimilation as well. The MB shows a substantial change in all three data assimilation strategies compared to the baseline. The baseline MB is 0.20 ± 0.12 m, and all three data assimilation strategies flip to negative. Despite all data assimilation having among the lowest RMSE, it has the worst MB among assimilation strategies at -0.15 ± 0.10 m, compared to point assimilation (-0.04 ± 0.13 m) and gridded assimilation (-0.07 ± 0.20 m). The r^2 shows another picture of the lidar results and is the cleanest signal in this. The baseline and point assimilation are similar with 0.24 ± 0.10 and 0.23 ± 0.10 respectively, while the gridded and all data assimilation are nearly three times higher at 0.68 ± 0.12 and 0.67 ± 0.13 respectively.

5. DISCUSSION

The validation of SNOTEL SWE and lidar Hs highlight that each data assimilation strategy has distinct strengths and weaknesses. No single strategy is best across each domain, WY, and validation type. Gridded assimilation provides the highest KGE in SNOTEL validation and the highest r^2 in the lidar validation, yet it performs worst among the assimilation strategies and the baseline in the Truckee basin volume analysis. A water resource manager relying on gridded assimilation for total water storage could therefore be misled even though the same configuration is the strongest performer for mapping the spatial pattern of Hs. Averaged across the three WYs, the standard deviation ranges for RMSE, KGE, and volume bias overlap substantially across the baseline and all three assimilation strategies in both domains. This overlap means that, statistically, no strategy is decisively superior given the sample size of this study. The apparent ranking of strategies also shifts from WY to WY and from validation to validation. Therefore, a ranking built from a single WY or a single SNOTEL should not be generalized. Running SnowModel for additional WYs would narrow these ranges and provide a more confident picture of relative performance.

All data assimilation strategy rarely produces the single best RMSE, MB, KGE, or r^2 of the three strategies, but it consistently carries the lowest standard deviation. At the highest elevation bin in both domains, all data assimilation nearly matches gridded assimilation's RMSE while carrying roughly half the standard deviation. It also has the lowest MB standard deviation in the lidar Hs validation. This stability follows directly from how the strategy is constructed. All data assimilation continues to apply daily point corrections after the lidar survey(s), so SnowAssim keeps

correcting after flights, which it does not with gridded assimilation alone. For an application where the cost of a large error (gridded assimilation) matters more than the cost of a small average error (all data assimilation), such as operational water supply forecasting, this consistency with the all data assimilation strategy may be more valuable.

Defining which data assimilation strategy is preferable therefore depends on the question being asked and on how well the existing point network samples the domain's elevation distribution. Gridded assimilation is the strongest choice for predicting the spatial pattern of Hs, reflected in its high r^2 (Table 5) and predicts snowpack the best at higher elevations (Table 6). Point assimilation shows weaknesses with predicting Hs at higher elevations, where each domain stores most of the snowpack (Table 6). Neither domain's SNOTEL network fully spans its highest elevation bin. Blue River has no SNOTELs above 3,536 m, leaving the entire 3,600–4,400 m bin without a station, and Truckee's SNOTELs top out at 2,683 m even though the highest elevation bin extends to 3,300 m. Despite CSO covering areas of the highest elevation zone in each domain, the measurements are too few and far between, which prevent point assimilation from predicting Hs accurately at higher elevations. Gridded and all data assimilation are not constrained by point observation placement, so they correct this high-elevation deficit.

Taken all together across the two domains, three WYs, and all validation metrics; it is difficult to name a single 'best' data assimilation strategy from this work. Every strategy provides a meaningful improvement on the baseline, and the differences between strategies are often smaller than the spread introduced by inter-annual variability across only three WYs. A meaningful result from this work is how closely the point only assimilation competes with the gridded and all data assimilation strategies, given the enormous cost asymmetry between the underlying data sources. A single lidar acquisition flight costs on the order of $75-100K, while SNOTEL and snow course data are collected at comparatively minimal marginal cost and CSO data are effectively free. This directly answers the motivating question of this study, whereby community-based and low-cost point networks can provide much of the benefit of an expensive lidar program, and in places where dense lidar coverage is not available or affordable. The point only data assimilation strategy represents a low-cost way to meaningfully constrain modeled snowpack. This conclusion should be read alongside three limitations of the present study. First, the three WYs and two domains evaluated here limit how far these strategy rankings can be generalized until tested against a longer record and a broader range of snow climates. Second, CSO observations are opportunistic rather than systematically distributed, and their value in each basin depends on the size and consistency of the local backcountry recreation community, a condition that will not hold everywhere. Third, our comparisons among assimilation strategies rely on a single climatological Hs to SWE density conversion (Hill et al., 2019), and the uncertainty this introduces, particularly for the basin snow volume estimates, is not quantified and suggested as future work.

ACKNOWLEDGEMENTS

We acknowledge funding support from the USBR SNOFO program.

REFERENCES

Airborne Snow Observatories. (2025, September 1). Retrieved September 1, 2025, from https://www.airbornesnowobservatories.com/

Aragon, C. M., Hill, D. F., Wolken, G., Wikstrom Jones, K., & Crumley, R. (2025). Assimilation of Community Science Data to Improve Mountain Snow Distribution Estimates. *Water Resources Research*, *61*(11), e2025WR040019. https://doi.org/10.1029/2025WR040019

Arendt, D. F. H., G. J. Wolken, K. W. Jones, R. Crumley, A. (2018, December 3). Crowdsourcing Snow Depth Data with Citizen Scientists. Retrieved June 10, 2026, from https://eos.org/science-updates/crowdsourcing-snow-depth-data-with-citizen-scientists

Barnett, T. P., Adam, J. C., & Lettenmaier, D. P. (2005). Potential impacts of a warming climate on water availability in snow-dominated regions. *Nature*, *438*(7066), 303–309.

Barnhart, T. B., Putman, A. L., Heldmyer, A. J., Rey, D. M., Hammond, J. C., Driscoll, J. M., & Sexstone, G. A. (2024). Evaluating Distributed Snow Model Resolution and Meteorology Parameterizations Against Streamflow Observations: Finer Is Not Always Better. *Water Resources Research*, *60*(7), e2023WR035982. https://doi.org/10.1029/2023WR035982

Bartelt, P., & Lehning, M. (2002). A physical SNOWPACK model for the Swiss avalanche warning: Part I: numerical model. *Cold Regions Science and Technology*, *35*(3), 123–145. https://doi.org/https://doi.org/10.1016/S0165-232X(02)00074-5

California Department of Water Resources: California Data Exchange Center Current Snow Depth, available at: (last access: 3 August 2026), 2026.

Crumley, R. L., Hill, D. F., Wikstrom Jones, K., Wolken, G. J., Arendt, A. A., Aragon, C. M., et al. (2021). Assimilation of citizen science data in snowpack modeling using a new snow data set: Community Snow Observations. *Hydrology and Earth System Sciences*, *25*(9), 4651–4680. https://doi.org/10.5194/hess-25-4651-2021

Deems, J. S., Painter, T. H., & Finnegan, D. C. (2013). Lidar measurement of snow depth: a review. *Journal of Glaciology*, *59*(215), 467–479. https://doi.org/10.3189/2013JoG12J154

Farr, T. G., Rosen, P. A., Caro, E., Crippen, R., Duren, R., Hensley, S., et al. (2007). The Shuttle Radar Topography Mission. *Reviews of Geophysics*, *45*(2). https://doi.org/10.1029/2005RG000183

Hill, D. F., Burakowski, E. A., Crumley, R. L., Keon, J., Hu, J. M., Arendt, A. A., et al. (2019). Converting snow depth to snow water equivalent using climatological variables. *The Cryosphere*, *13*(7), 1767–1784. https://doi.org/10.5194/tc-13-1767-2019

Li, D., Wrzesien, M. L., Durand, M., Adam, J., & Lettenmaier, D. P. (2017). How much runoff originates as snow in the western United States, and how will that change in the future? *Geophysical Research Letters*, *44*(12), 6163–6172. https://doi.org/10.1002/2017GL073551

Liston, G. E., & Elder, K. (2006a). A Distributed Snow-Evolution Modeling System (SnowModel). https://doi.org/10.1175/JHM548.1

Liston, G. E., & Elder, K. (2006b). A Meteorological Distribution System for High-Resolution Terrestrial Modeling (MicroMet). *Journal of Hydrometeorology*, *7*(2), 217–234. https://doi.org/10.1175/JHM486.1

Liston, G. E., & Hiemstra, C. A. (2008). A Simple Data Assimilation System for Complex Snow Distributions (SnowAssim). *Journal of Hydrometeorology*, *9*(5), 989–1004. https://doi.org/10.1175/2008JHM871.1

Liston, G. E., Haehnel, R. B., Sturm, M., Hiemstra, C. A., Berezovskaya, S., & Tabler, R. D. (2007). Simulating complex snow distributions in windy environments using SnowTran-3D. *Journal of Glaciology*, *53*(181), 241–256. https://doi.org/10.3189/172756507782202865

Marks, D., Domingo, J., Susong, D., Link, T., & Garen, D. (1999). A spatially distributed energy balance snowmelt model for application in mountain basins. *Hydrological Processes*, *13*(12–13), 1935–1959. https://doi.org/10.1002/(SICI)1099-1085(199909)13:12/13%3C1935::AID-HYP868%3E3.0.CO;2-C

Mower, R., Gutmann, E. D., Liston, G. E., Lundquist, J., & Rasmussen, S. (2024). Parallel SnowModel (v1.0): a parallel implementation of a distributed snow-evolution modeling system (SnowModel). *Geoscientific Model Development*, *17*(10), 4135–4154. https://doi.org/10.5194/gmd-17-4135-2024

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

Saha, S., Moorthi, S., Wu, X., Wang, J., Nadiga, S., Tripp, P., et al. (2011). NCEP Climate Forecast System Version 2 (CFSv2) 6-hourly Products. Boulder, CO: NSF National Center for Atmospheric Research. https://doi.org/10.5065/D61C1TXF

U.S. Department of Agriculture, Natural Resources Conservation Service (USDA NRCS): Snow Survey and Water Supply Forecasting Program (SNOTEL), available at: https://www.nrcs.usda.gov/programs-initiatives/sswsf-snow-survey-and-water-supply-forecasting-program (last access: 3 August 2026), 2026.

USGS. (2025). Annual National Land Cover Database (NLCD) Collection 1 Products (ver. 1.1, June 2025) [Pdf,png]. U.S. Geological Survey. https://doi.org/10.5066/P94UXNTS