Snow Problem! Improving SWE Estimates Using Bayesian Analysis

Bayesian Analysis and Computation, Winter 2025

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water in the west:

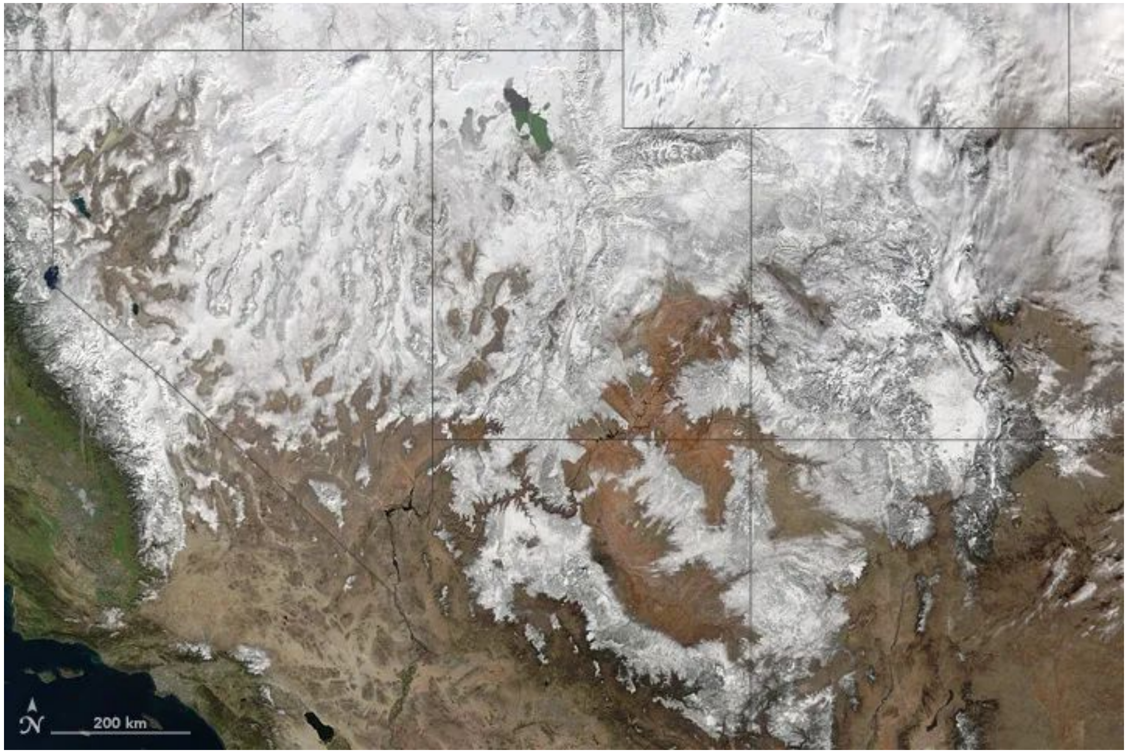


Figure 1: View of snow cover from NASA Modis in January 2017

1. As much as 75% of water supplies in some western states are derived from snowmelt [1]
2. The colorado river supplies water to ~30 million people! [2]

water resource managers want to know **how much water is in the snowpack** for operational decisions.

Figure 2: The Glen Canyon Dam was constructed to harness the power of the Colorado River in order to provide resilience to the water and power needs of millions of people in the west. [3]

characterizing snow cover & SWE

need for **snow characterization** of snow water equivalent **(SWE)** on large scales (i.e. remote sensing)

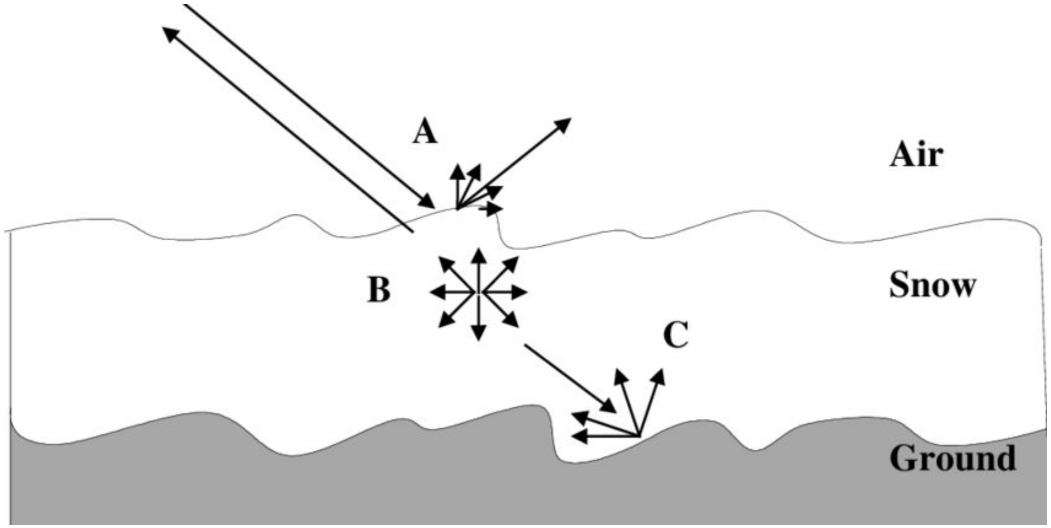


Figure 2: The scattering mechanisms of snow-covered terrain (Koskinen 2001)

} scattering is a complex problem!

digging snow pits is time-intensive:

~30 minutes digging per location

New Data: SnowEx Campaign

“ a multi-year field experiment, which includes extensive surface-based observations to evaluate how to best combine different remote sensing technologies to accurately observe snow throughout the season in various landscapes.” [5]

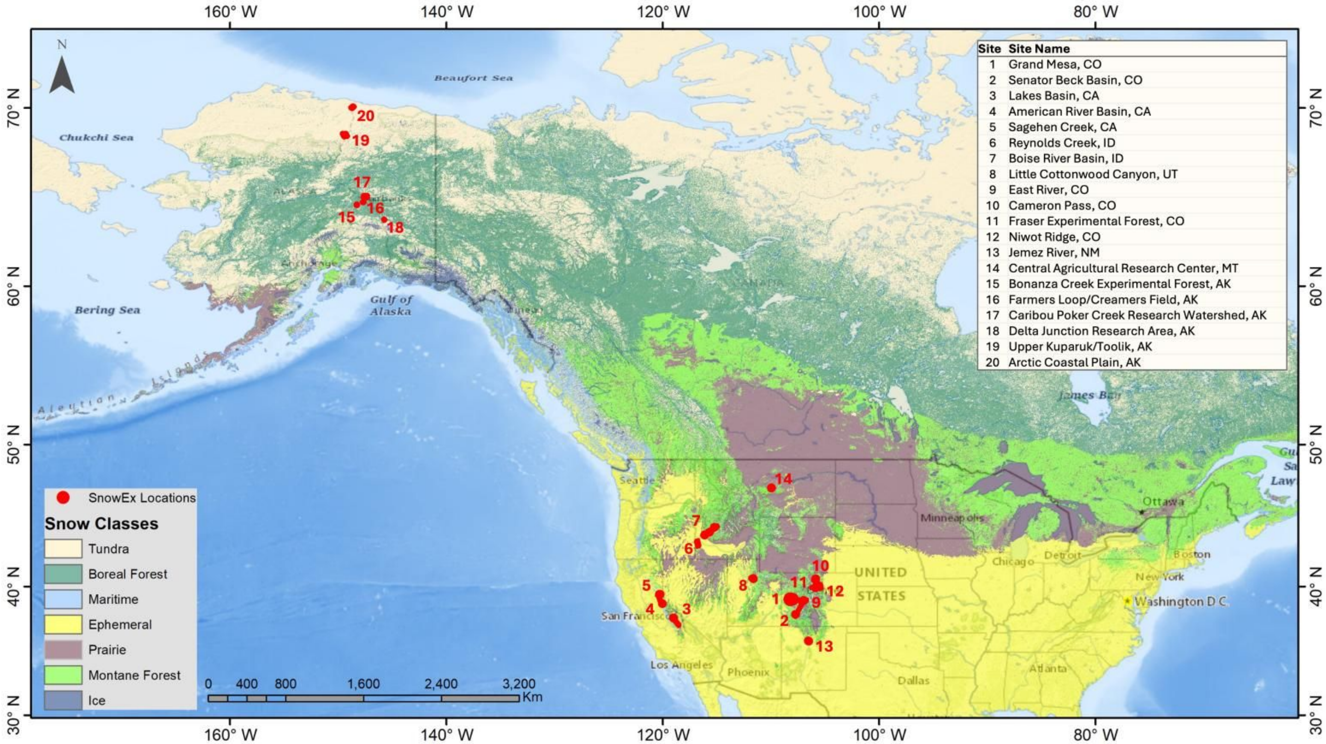


Figure 3: SnowEx Campaign Locations [5]

data flow:

Airborne Obs

Snowpit Obs

2D Field SWE Estimates

+

topography & weather forcings

iSnobal Energy Balance Model [4]

Meltwater Runoff Estimate

data flow:

Airborne Obs

Snowpit Obs

How can we improve this estimate using Bayesian analysis?

2D Field SWE Estimates

\+

topography & weather forcings

iSnobal Energy Balance Model [4]

Meltwater Runoff Estimate

Hypothesis:

If the SnowEx campaign datasets have enough concurrent ground observations to compute residuals for airborne observations, then a bayesian framework and co-kriging will be able to reduce 2D SWE field uncertainty as compared to individual sensor uncertainty in estimating SWE.

Methods & Hypothesis

Bayesian Framework: Combine airborne microwave estimates and LiDAR SWE estimates using sparse in-situ ground observations to compute residuals between modeled (airborne data) and observed (ground).

ϐ[LiDAR] + ϱ[SWESARR] = [SWE-Observed] + Ɛ (1)

Computational Approach: use MCMC to handle the complexity of geospatial data by sampling efficiently.

Co-Kriging: Next, we will use co-kriging to interpolate our 2D field, and use **elevation, vegetation, slope,** as our secondary variables known to affect SWE [11].

Initial Results: SnowEx 2020 Data

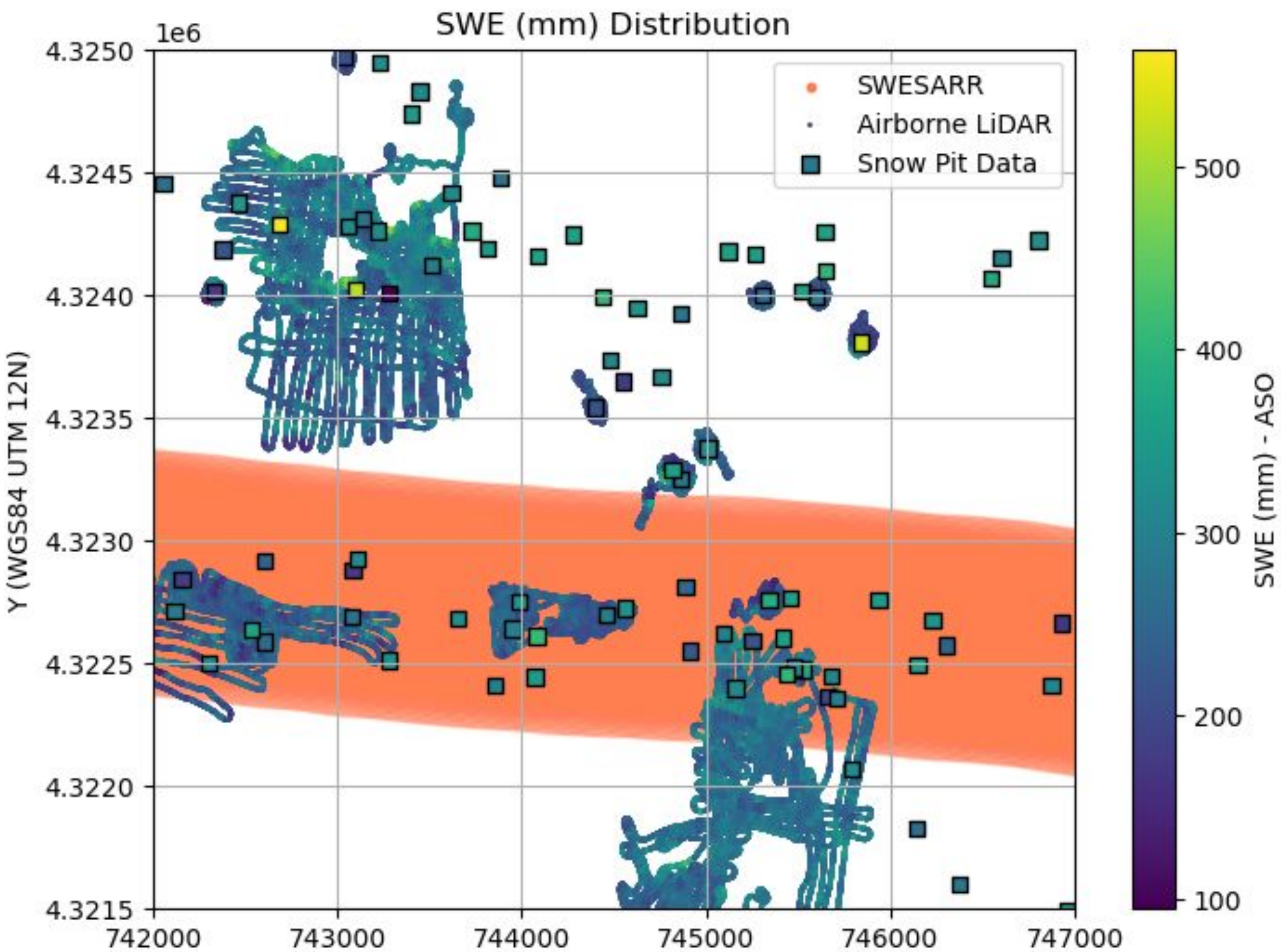
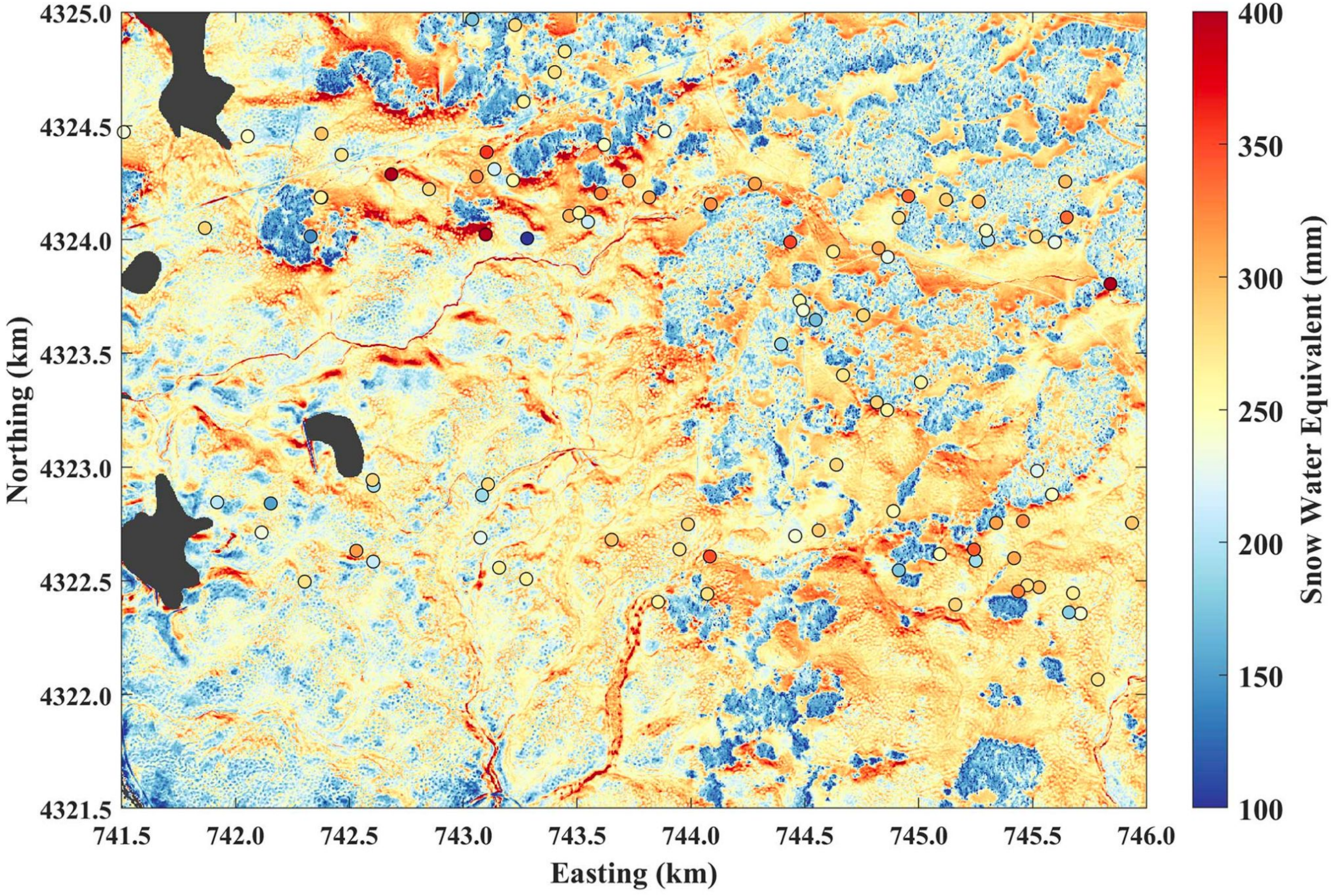


Figure 4: SWE distribution generated from SnowEx 2020 data

Meehan et. al. 2024 (Machine Learning using GPR) [14]



Intellectual Merit:

- Meehan et. al. 2024 demonstrated sensor integration improved SWE estimates, using GPR and LiDAR data [14]. **This research will build by using airborne-only datasets.**
- decision tree regression (ML) [8][9][11] has been previously used to interpolate SWE, by using co-kriging we aim to **decrease the risk of over-fitting.**

Expected Outcome:

By combining airborne observations through a Bayesian framework and co-kriging will reduce the overall uncertainty in the 2D SWE field to below 15%, improving on studies that relied on machine learning approaches and ground-based methods.

Conclusions:

1. **New SWE observation techniques** justify research into generating state-of-the-art input parameters for meltwater runoff models.
2. Shows **proof-of-concept** for combining airborne sensors for future satellite missions.
3. Informing water resource forecasting is an important goal in the face of **exacerbated floods, droughts, and imminent water resource uncertainties** [6].

thank you

find slides:
https://github.com/annavalentine/BayesianStats

References:

[1] United States Geological Survey (USGS). *"Snowmelt Runoff and the Water Cycle." Water Science School*, U.S. Department of the Interior, https://www.usgs.gov/special-topics/water-science-school/science/snowmelt-runoff-and-water-cycle. Accessed 16 Feb. 2025.

[2] U.S. Bureau of Reclamation. *Colorado River Basin Water Supply and Demand Study: Executive Summary.* U.S. Department of the Interior, Dec. 2012, https://www.usbr.gov/watersmart/bsp/docs/finalreport/ColoradoRiver/CRBS_Executive_Summary_FINAL.pdf. Accessed 16 Feb. 2025.

[3] U.S. Bureau of Reclamation. *Glen Canyon Dam – Colorado River Storage Project.* U.S. Department of the Interior, https://www.usbr.gov/uc/rm/crsp/gc/. Accessed 16 Feb. 2025.

[4]Meyer, J., et al. *"iSnobal: A Snowpack Energy Balance Model for Hydrological Applications." Geoscientific Model Development*, vol. 16, 2023, pp. 233–256, https://gmd.copernicus.org/articles/16/233/2023/. Accessed 16 Feb. 2025.

[5] National Snow and Ice Data Center (NSIDC). *SnowEx*. National Aeronautics and Space Administration, 2023. Accessed 16 Feb. 2025.

[6]Milly, P.C.D., Betancourt, J., Falkenmark, M., Hirsch, R.M., Kundzewicz, Z.W., Lettenmaier, D.P., & Stouffer, R.J. (2008). *Stationarity is Dead: Whither Water Management?* Science, 319(5863), 573–574. https://doi.org/10.1126/science.1151915

[1]

[7] B. Balk and K. Elder, "Combining binary decision tree and geostatistical methods to estimate snow distribution in a mountain watershed," *Water Resources Research*, vol. 36, no. 1, pp. 13–26, 2000, doi: 10.1029/1999WR900251.

[2]

[8] J. Erxleben, K. Elder, and R. Davis, "Comparison of spatial interpolation methods for estimating snow distribution in the Colorado Rocky Mountains," *Hydrological Processes*, vol. 16, no. 18, pp. 3627–3649, 2002, doi: 10.1002/hyp.1239.

[3]

[9] N. P. Molotch, M. T. Colee, R. C. Bales, and J. Dozier, "Estimating the spatial distribution of snow water equivalent in an alpine basin using binary regression tree models: the impact of digital elevation data and independent variable selection," *Hydrological Processes*, vol. 19, no. 7, pp. 1459–1479, 2005, doi: 10.1002/hyp.5586.

[4]

[10] A. Ferraz, S. Saatchi, K. J. Bormann, and T. H. Painter, "Fusion of NASA Airborne Snow Observatory (ASO) Lidar Time Series over Mountain Forest Landscapes," *Remote Sensing*, vol. 10, no. 2, Art. no. 2, Feb. 2018, doi: 10.3390/rs10020164.

[5]

[11] J. I. López-Moreno and D. Nogués-Bravo, "Interpolating local snow depth data: an evaluation of methods," *Hydrological Processes*, vol. 20, no. 10, pp. 2217–2232, 2006, doi: 10.1002/hyp.6199.

[6]

[12] J. Meyer, J. Horel, P. Kormos, A. Hedrick, E. Trujillo, and S. M. Skiles, "Operational water forecast ability of the HRRR-iSnobal combination: an evaluation to adapt into production environments," *Geoscientific Model Development*, vol. 16, no. 1, pp. 233–250, Jan. 2023, doi: 10.5194/gmd-16-233-2023.

[7]

[13] S. R. Fassnacht, K. A. Dressler, and R. C. Bales, "Snow water equivalent interpolation for the Colorado River Basin from snow telemetry (SNOTEL) data," *Water Resources Research*, vol. 39, no. 8, 2003, doi: 10.1029/2002WR001512.

[8]

[14] T. G. Meehan *et al.*, "Spatially distributed snow depth, bulk density, and snow water equivalent from ground-based and airborne sensor integration at Grand Mesa, Colorado, USA," *The Cryosphere*, vol. 18, no. 7, pp. 3253–3276, Jul. 2024, doi: 10.5194/tc-18-3253-2024.

[9]

[15] T. H. Painter *et al.*, "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*, vol. 184, pp. 139–152, Oct. 2016, doi: 10.1016/j.rse.2016.06.018.