Problem Set #6: Project Presentation Video

Anna M. Valentine

Winter 2025

Due: 03/02/2025

video presentation link: https://youtu.be/xEKsHOSOLPo

Transcript:

***slides are noted by bolded headers**

Snow Problem: Improving SWE Estimates Using Bayesian Analysis (slide 1)

Water in the West (2)

In the western United States, 75% of water supplies come from snowmelt [1]. The Colorado River alone provides water to 30 million people [2] . Water resource managers must accurately estimate how much water is stored in the winter snowpack to make informed decisions.

Glen Canyon Dam (3)

Before diving into quantifying snowpack, it's crucial to understand its significance. One good example is Glen Canyon Dam (Figure 2)[3]. This dam not only generates hydropower but also regulates water allocation for agriculture and public use. Effective snowmelt predictions guide dam operations, helping to mitigate risks in the event of drought or flood.

Characterizing Snowpack (4)

To assess a snowpack, we rely on the snow water equivalent, otherwise known as SWE (pronounced sweee), a measure of snow depth and density that determines how much water is stored on the ground. Remote sensing offers a basin-scale solution, by utilizing electromagnetic scattering to infer snow depth and density, but the physical processes involved are not yet fully understood, introducing significant uncertainty into these estimates.

Digging Snow Pits (5)

The alternative, digging a snow pit, provides highly accurate data but is limited in scale, as only about 10 locations per day per person can be sampled.

SnowEx (6)

The SnowEx campaign is a multi-year field experiment across the nation, as seen in Figure 3, designed to evaluate remote sensing techniques by combining diverse airborne and surface-based observations [5]. Advances in LiDAR, microwave radar, and spectrometers have improved large-scale SWE estimation, but uncertainty remains—especially in complex alpine terrain, where much of the snowpack in the US resides!

This study aims to improve SWE estimation by both combining airborne data sources through Bayesian inference from the SnowEx dataset, and incorporating terrain influences with known connection to SWE [11].

Data Flow 1 (7)

1. Airborne SWE observations are calibrated against snow pit measurements to generate a sparse 2D SWE field.
2. This SWE field, combined with topography and weather forcings, feeds into the iSnowball energy balance model, a proven tool for basin-scale water resource forecasting from a 2023 study by Meyer et. al. [4].
3. From here, we derive meltwater runoff estimates, the output water resource managers are most interested in.

Data Flow 2 (8)

improving this 2D SWE field is the main focus on this proposed research. The novelty of this study lies in leveraging SnowEx's extensive concurrent airborne and ground data for better hydrological modeling.

Hypothesis (9)
My hypothesis is as follows:
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 (10)

I propose developing a simple Bayesian geostatistical framework for fusing LiDAR and SWESARR estimates, using ground observations to compute residuals as seen in equation 1.

Computationally, I'll use Markov Chain Monte Carlo (MCMC), implemented in PyMC, to efficiently sample the poster distribution, as geospatial data is very computationally complex. Finally, using co-kriging from the Python toolkit pyGeoStatistics package, we integrate elevation, vegetation, and slope as secondary variables to generate a continuous 2D SWE field, addressing high-alpine terrain challenges where remote sensing struggles.

Initial Results (11)

I started with SnowEx 2020 data, mapping SWE distributions and coverage for initial analysis and dataset feasibility. The likelihood function can be constructed by using the observed SWE from snowpits as shown in Fig. 4 as squares, and computing residuals from our observed airborne data SWE estimations, shown as points and as our orange microwave radar footprint, formal SWE estimates are in preparation, or can be computed through the open-source snow microwave radiative transfer model. By restricting residual computations to locations with concurrent airborne and in-situ measurements (~100 ground observation sites), interpolation errors can be minimized.

Meehan et. al. 2024 (12)

Our expected outcome: a continuous 2D SWE field similar to this plot generated in Meehan et. al. 2024 [14]. which utilized machine learning and ground penetrating radar measurements in conjunction with LiDAR data. However, this studies' choice of ground penetrating radar limits its applicability to the future of satellite missions.

Intellectual Merit (13)

Prior work (Meehan et al.), as shown in the previous slide, demonstrated integrated SWE estimates using GPR and LiDAR reduces SWE uncertainty. However, our study extends this by using airborne-only datasets, making it applicable for future satellite missions to enable global SWE monitoring.

Secondarily, Unlike decision-tree-based machine learning which has been used in a variety of previous studies [8][9][11], the choice to use bayesian co-kriging is motivated by reducing the risk of overfitting and co-kriging works well with sparse, geospatial datasets that are spatially correlated, like SWE.

Expected Outcome (14)

I anticipate that 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 (15)

1. New SWE observation techniques justify research into generating state-of-the-art input parameters for meltwater runoff models.
2. Results will inform 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 (16)

Thank you. See references on next slide, this presentation is published to my GitHub.

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.