Problem Set #5: Project Outline and Video Pitch

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Winter 2025

Due: 02/14/2025

Problem Set #5: Produce a script and an up to ten minutes video (based on the script) to pitch your project.

For this, I thought it would be helpful to see my planning document, where I outline each of these things. Then below is my script, and finally a GitHub link to my presentation and to a YouTube link of my presentation. Hope you enjoy!

Overview:
- Project Outline & Planning
- Presentation Script
- YouTube & GitHub Link
- References

Project Outline & Planning

Project Outline: (not the script, but helped me make my slides and my general planning)

a. **Problem Definition:** The western United States heavily relies on snowpack as a natural water reservoir. The combination of seasonal precipitation patterns, arid climate, population growth, and climate change impacts makes accurate runoff predictions essential for water resource management, which impact public drinking water, hydropower, agriculture, and flood risk mitigation. To better forecast water resource management, quantifying the snow water equivalent captured in the snowpack during winter months is essential to snowmelt runoff modeling. As new technologies emerge to observe SWE (snow water equivalent), we must wage their uncertainties and spatial coverage to best understand what data needs to be collected for robust water resource management.

b. **Question:** What role do priors play in the Bayesian framework that uses SWE observations from different instruments (ground based, airborne, space borne) in the posterior runoff models? Can we understand what kind of data density / uncertainty is acceptable for runoff predictions.

c. **State-of-the-art:** This is state-of-the-art because we have previously not had concurrent data series with multiple ground observations, airborne, and spaceborne data. Satellite and airborne missions are becoming increasingly more popular, although trade-offs of uncertainty of snow density and how this may affect forecasting are unknown.

   I really like this paper about how iSnobal is ideal for actual water forecasting. After m attending the SnowEx Community meeting in conference this summer, I realized how much water resource managers need scientists to focus on end -users!

   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.

d. **Nexus that enables project:** The nexus of this project is that we now have basin-scale energy balance snowpack runoff models, and multiple methods to measure SWE at different scales. Additionally, the SnowEx 2023 dataset allows us to have concurrent measurements!

e. **Hypothesis:** Airborne and satellite data, while offering broad coverage, have higher uncertainty in posteriors than required for water management. Combining them with sparse ground observations can significantly improve posterior certainty.

   I am aware that this hypothesis might be obvious, but many folks want to jump right into the satellite SWE observations as if they are true, when in reality, they lack fundamental understanding of microwave scattering. I need to find some literature to review to make this statement but here are a few good places to start:

R. Bonnell et. al.. (2024). *L-Band InSAR Snow Water Equivalent Retrieval Uncertainty in Montane Forests*. *Geophysical Research Letters*. https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2024GL111708

Durand et. al.. (2024). *Retrieval of Snow Water Equivalent from Dual-Frequency Radar Time Series*. *The Cryosphere*. https://tc.copernicus.org/articles/18/139/2024/

Dong, Jiarui & Walker, Jeffrey & Houser, P.. (2005). Factors affecting remotely sensed snow water equivalent uncertainty. Remote Sensing of Environment. 97. 68-82. 10.1016/j.rse.2005.04.010.

f. **Methods:**
   i. **Method Description:** I will use Bayesian analysis with my prior as the SWE observations, likelihood as the iSnobal runoff model and posterior of runoff. I will use MCMC approach because geospatial data is very computationally expensive.
   ii. **Why?** Bayesian methods allow me to understand the uncertainty of these different observational tools. From class, Bayesian seems to be a great tool for understanding uncertainties' role in operations management.
   iii. **What is my data?** SnowEx 2023 data has ground based, airborne, and satellite data during a concurrent series near Fairbanks, AK. This is very new data, just published by NSIDC.

g. **Expected Results:** I expect to be able to communicate uncertainty in runoff models for my different observational methods (ground based, airborne, satellite). The proposed work will need to be highly relevant to operational water resource forecasting.

h. **Intellectual Merit:** This project will advance hydrological modeling and uncertainty quantification by integrating Bayesian inference into snowmelt-runoff modeling using diverse SWE observations (ground-based, airborne, and spaceborne). The research is particularly novel because it leverages the SnowEx 2023 dataset, which provides a unique opportunity to analyze concurrent SWE data from multiple observational platforms.

i. **Broader Impacts:** The Western U.S. faces an increasing need for more accurate and resilient water resource forecasting due to climate change, prolonged droughts, and population growth. This project has broad societal and environmental implications, particularly for water managers, policymakers, and satellite mission designers.

Presentation Script:

Snow Problem: Improving SWE Estimates Using Bayesian Analysis of Priors

In the western United States, as much as 75% of water supplies come from snowmelt. The Colorado River alone provides water to around 30 million people. Water resource managers need to know how much water is in this winter snowpack.

Before jumping into quantifying the snowpack, it's important to know why this quantification matters. One good example is the Glen Canyon Dam, shown here in Figure 2. The dam was constructed not only to harness the Colorado River's for hydropower, but it also helps allocate water for agriculture and public use by determining when to release or retain water. Accurate snowmelt predictions are critical for informed water resource operations, managers must know how much water will runoff into rivers in the springtime to make these release or retain decisions. This becomes increasingly important as we face increasing droughts and floods.

Characterizing snow cover and snow water equivalent, also known as (SWE), is key to this challenge. SWE refers not only to the presence of snow but also to its depth and density—essentially, how much water is stored on the ground's surface. To estimate SWE at the basin scale, we rely on remote sensing via satellites or airborne campaigns.

However, this approach is complex. Remote sensing uses electromagnetic scattering to infer snow depth and density, but the physical processes involved are not yet fully understood, introducing significant uncertainty into these estimates. The alternative is digging snow pits, which provide highly accurate, geolocated measurements but are time-intensive, limiting data collection to only about 10 locations per day.

Currently, SWE observations come from three primary methods: ground-based snow pits, airborne sensors, and satellite instruments. As accuracy increases, spatial coverage and speed decrease. My research focuses on combining these new technologies with the old and reliable to improve forecasting using Bayesian inference.

I'll use the iSnobal snowmelt energy balance model for this analysis. A 2023 study by Meyer et al. found that iSnobal is well-suited for operational water forecasting due to its ability to model mass and energy balance across large spatial domains, like the one shown here in Colorado.

Our SWE data from snow pit, airborne, and satellite sources– will be combined with topography and weather parameters as inputs to the iSnobal model. The model will then generate runoff estimates, which water forecasters can use to make operational decisions.

Key Question:

How do priors shape SWE-based runoff models, and what data density and uncertainty thresholds ensure reliable predictions for water forecasting?

To answer this question, I'll apply a Bayesian framework. Our SWE observations serve as our priors, the iSnobal model provides the likelihood, and the runoff predictions form the posterior. Because of the computational demands of geospatial data, I'll use a Markov Chain Monte Carlo (MCMC) approach. The dataset will come from SnowEx 2023, which provides concurrent SWE observations from ground, airborne, and satellite instruments near Fairbanks, Alaska—recently published by the NSIDC.

I hypothesize that airborne and satellite data, despite their broad spatial coverage, will exhibit higher uncertainty in the posterior estimates than what is acceptable for water management. However, combining these datasets with even sparse ground observations may significantly improve posterior certainty. This certainty is crucial for water managers making operational decisions.

This project advances hydrological modeling by applying Bayesian inference to SWE datasets that, for the first time, combine ground-based, airborne, and satellite measurements simultaneously. Traditionally, models use only one observational method, so this work represents a novel step forward.

Informing observational standards for water resource forecasting is essential as we face increasingly severe floods, droughts, and water resource uncertainties.

The key takeaways from this research are:

1. New SWE observation techniques justify research into how their complexities affect runoff models.
2. Water resource management depends on accurate runoff models to guide operational and policy decisions.
3. Informed water management ensures water security for hydropower, agriculture, and public use.

Thank you! The next slide provides references, and my slides as well as the transcript can be found on the GitHub link below.

Links:

YouTube Link to Video:
https://youtu.be/OP-J4CK5XRY

GitHub HW Folder Link Here:
https://github.com/annavalentine/BayesianStats/tree/main/project_pitch

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REFERENCES:

I consulted with Klaus Keller regarding the initial ideas of this project and how to incorporate a Bayesian framework. Many thanks to Klaus.

[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 2023 Data*. 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