Toward the Estimation of Global Snow-Derived Water Resources



Outline

Introduction and Motivation

- Importance of mountain snow
- Challenges of characterizing mountain snow

Toward the estimation of global mountain Snow Water Equivalent (SWE)

- Remote sensing data assimilation as an enabling tool
- ➤ Utilizing the existing historical remotely-sensed optical record to estimate mountain SWE

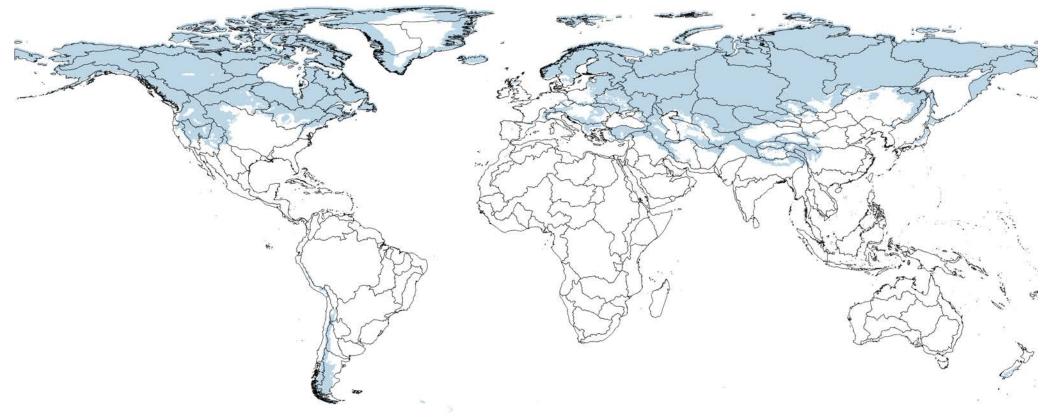
Future Work

- Creating global-scale harmonized datasets
- Improving modeling frameworks
- New satellite measurement methods

Importance of Mountain Snow

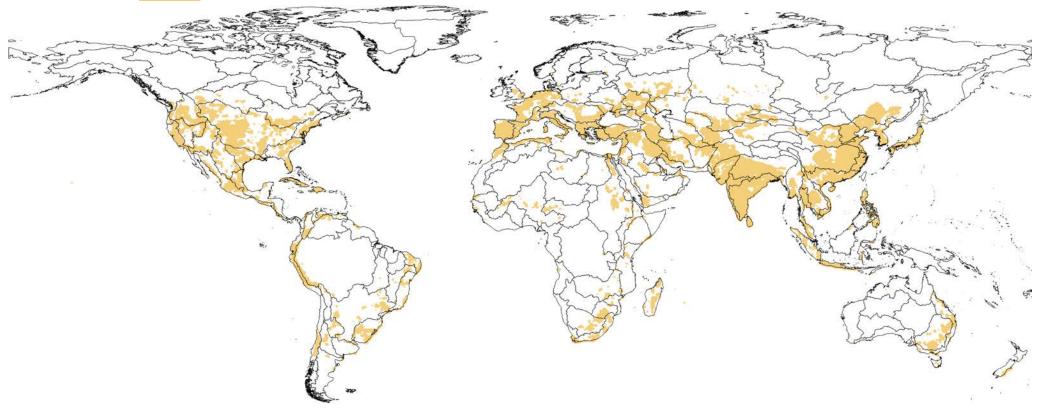
Where is snow most important for humans?

Global regions with significant amount (>20%) of estimated annual runoff generated from snowmelt



Where is snow most important for humans?

Global regions with significant amount of annual freshwater runoff used for irrigation, industrial, and domestic use



Where is snow most important for humans?

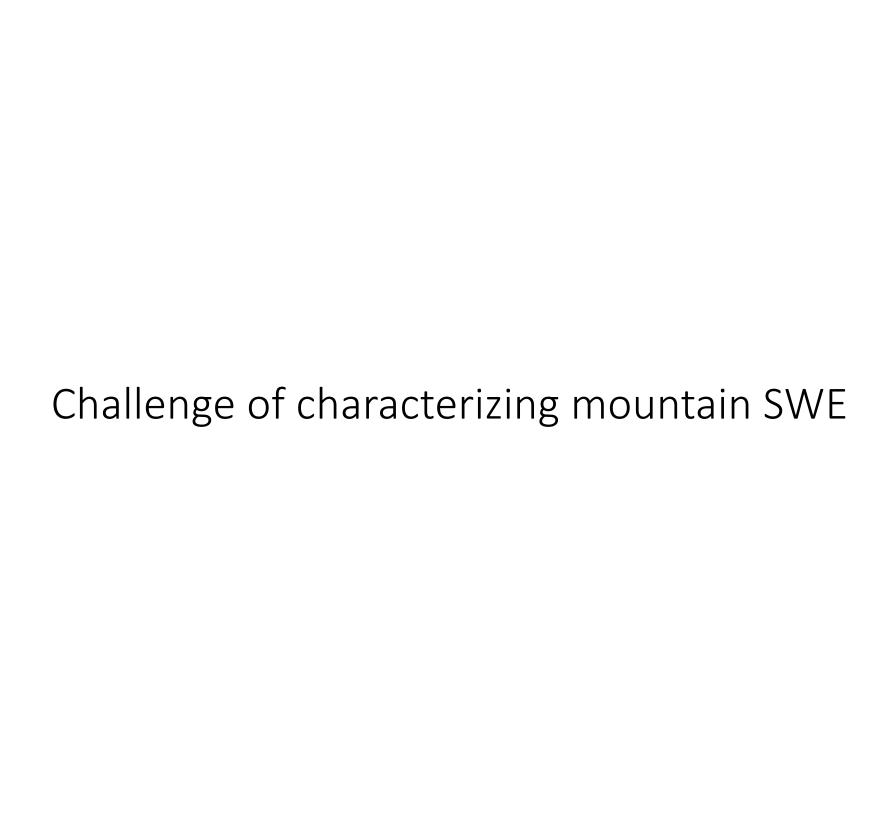
Global nexus regions where snow-derived runoff contributes significantly to downstream human water use



Nexus areas are the midlatitude mountain "water towers" of the globe, including those over the Western U.S., Andes, High Mountain Asia, and the Alps

These snow-derived water supply headwaters are inherently trans-boundary in nature





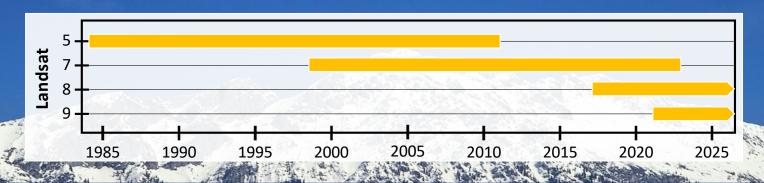
"Estimating the spatial distribution of snow water equivalent (SWE) in mountainous terrain is currently the most important unsolved problem in snow hydrology. ... Good characterization of the snow is necessary to make informed choices about water resources and adaptation to climate change and variability." (Dozier et al., 2016)

"Among all areas of hydrologic remote sensing, ... SWE ... is the one that is most in need of new strategic thinking from the hydrologic community." (Lettenmaier et al., 2015)

Measuring mountain SWE

Snow remote sensing in the <u>optical (visible/near infrared spectrum)</u> among the most successful demonstrations of land surface remote sensing (late 1970s – present)

→ only provides retrieval of fractional snow covered area (fSCA, not SWE)

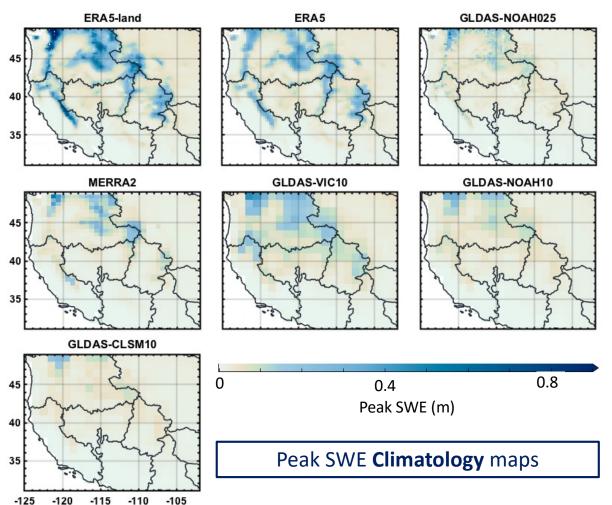


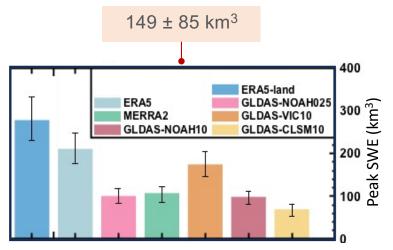
There has never been a dedicated SWE satellite mission

- → Opportunistic SWE retrieval algorithms from Passive or Active Microwave missions
- → Confounding factors: snowpack stratigraphy, grain size, and liquid water content, forest, sub-grid heterogeneity

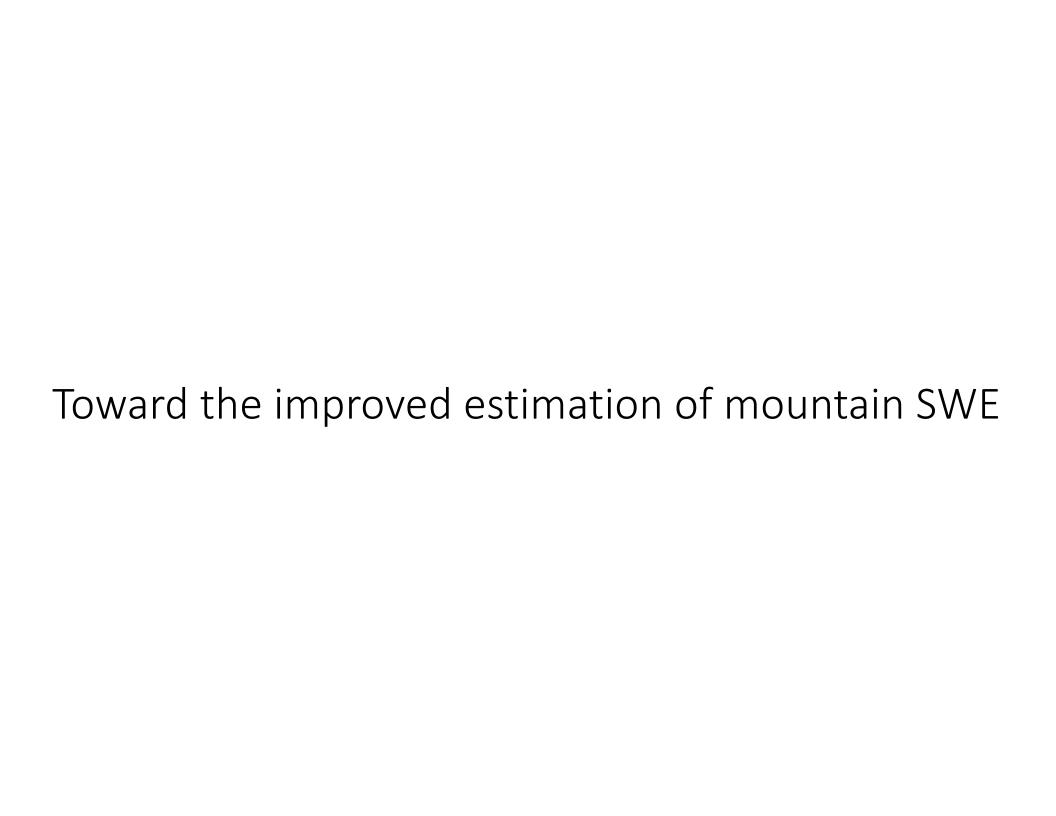
Lack of mountain SWE observations mean estimates of snow storage and fluxes are mostly model-based

How well do models estimate mountain SWE?





- Uncertainty is ~60% of mean (generally higher outside of WUS)
- Which (if any) of these estimates are correct?
- Need to observationallyconstrain model estimates

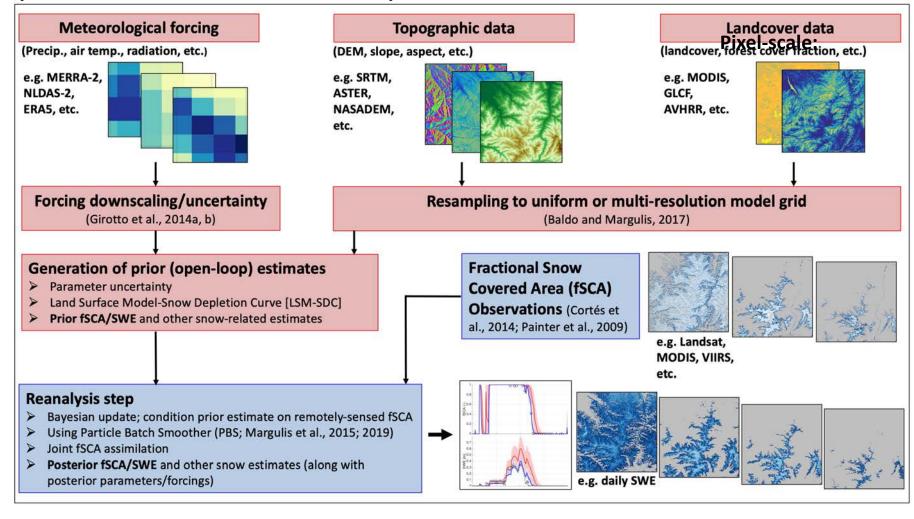


Data assimilation as an enabling estimation tool

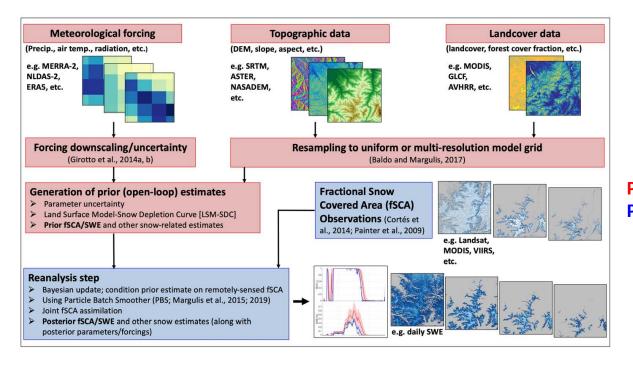
- Probabilistic (Bayesian) estimation approach
 - provides mathematical framework for merging disparate information with varying space-time scales/uncertainties
- Measurements (e.g., remote sensing):
 - characterized by their distribution (i.e., including measurement error)
 - often indirectly related to state variable of interest (e.g., fSCA vs. SWE) → a direct "retrieval" approach does not always work well
- Physically-based models provide prior estimate
 - inputs are key source of auxiliary information; physics embedded in estimates
 - model propagates uncertainty and relates modeled state to measured state
- Posterior estimate obtained by conditioning prior on measurements
 - examples: Kalman or particle filtering/smoothing
 - sometimes referred to as "reanalysis" methods

Utilizing the historical 30+ year optical record of fractional snow-covered area (fSCA) measurements

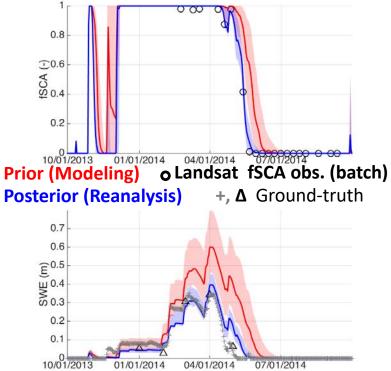
Bayesian Snow Reanalysis Framework



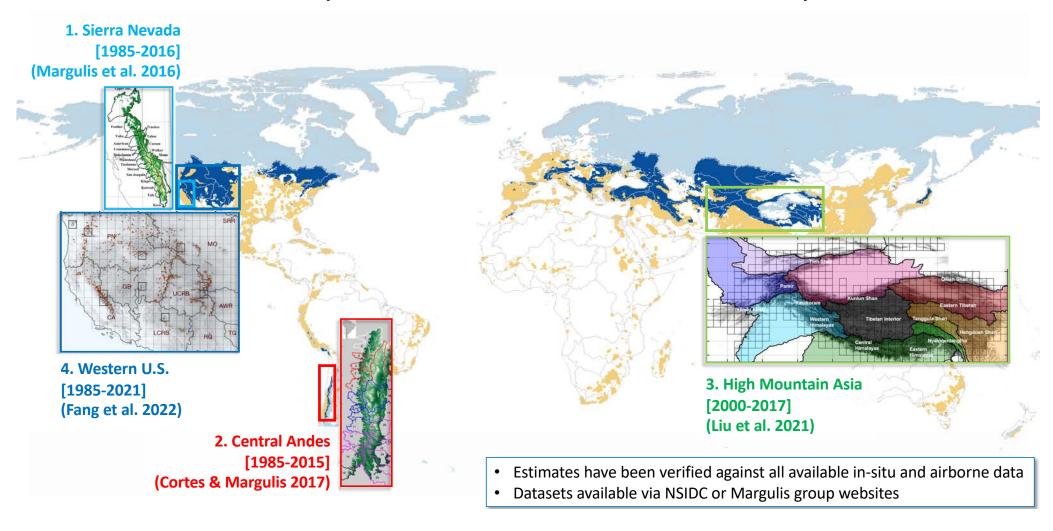
Bayesian Snow Reanalysis Framework







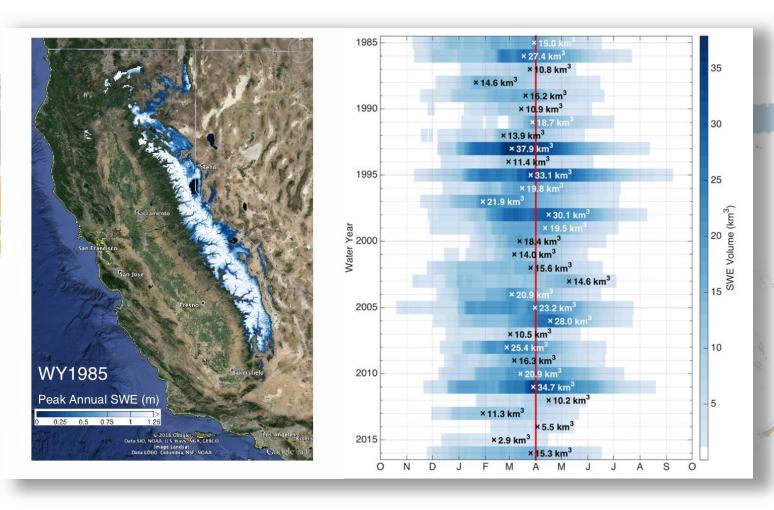
Method development and dataset history



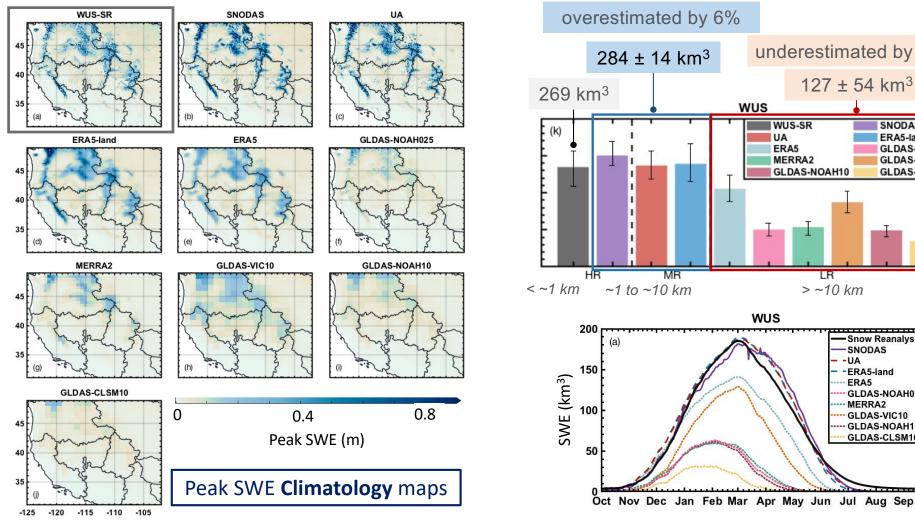
Datasets provide new physical insight

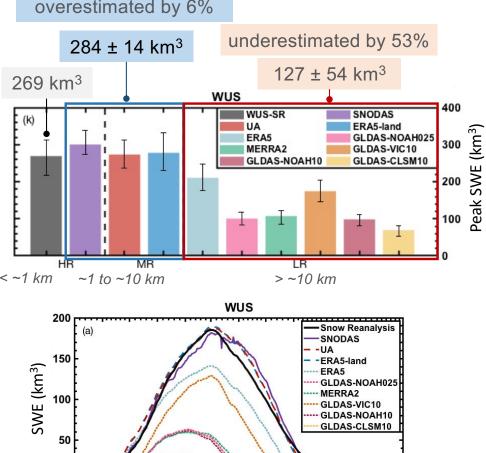
1. Sierra Nevada [1985-2016] (Margulis et al. 2016)





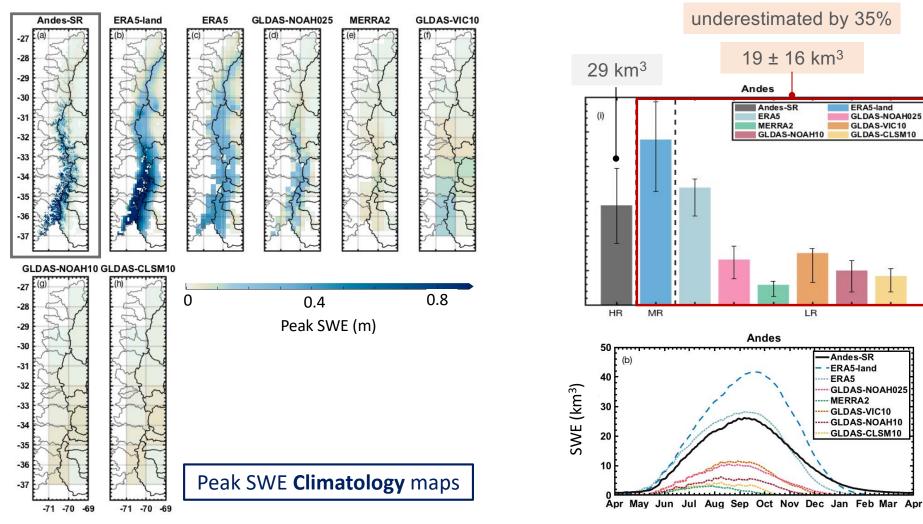
So how well do models estimate mountain SWE?



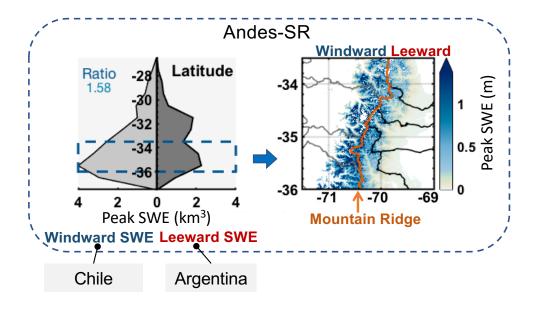


So how well do models estimate mountain SWE?

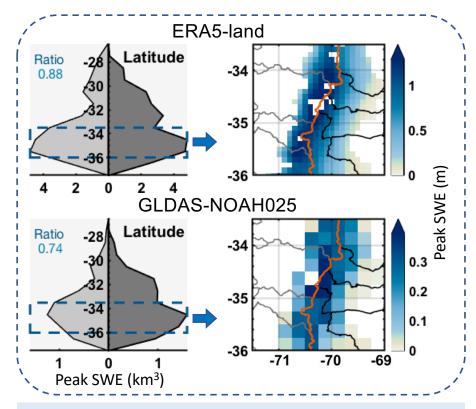
Peak SWE (km³)



Resolving key spatial features (Andes)



Ratio: Windward SWE Volume
Leeward SWE Volume



Distribute too much SWE in leeward basins

Ratios are overestimated by as much as 54% in GLDAS-NOAH025

Summary of recent work

- Developed multi-decadal retrospective mountain SWE datasets over WUS, HMA, and Andes using data assimilation framework with longterm fSCA record
 - ➤ Snow storage, snow drought, snowfall climatology, orographic enhancement and atmospheric rivers impact on snow storage in **Sierra Nevada** (*Margulis et al., 2016a,b; Huning and Margulis, 2017; 2018; Huning et al., 2017*)
 - Impacts of El Nino/La Nina on inter-annual **Andes** snow accumulation (*Cortes and Margulis, 2017*) and impacts of atmospheric rivers on intra- and interannual snow storage (*Saavedra et al., 2020*)
 - ➤ Evaluation of climatology, spatial patterns, and global reanalysis snow storage products over **High Mountain Asia** (*Liu et al., 2021; 2022*), **WUS and Andes** (*Fang et al., 2023*)

Future Work

- Expanding retrospective applications using historical fSCA data to global harmonized data products
 - ➤ <u>Goal</u>: Global harmonized midlatitude mountain snow reanalysis datasets in at the end of each water year
- Learning from historical observation-constrained datasets to improve forecasting/projection models
 - ➤ <u>Goal</u>: Use new datasets, that more realistically represent space-time dynamics of mountain snow, to better inform existing models and/or develop new ones
- Developing new satellite measurement capabilities for near-real-time SWE estimation
 - ➤ Goal: Develop the first-ever SWE-focused satellite mission concept (e.g., "SnoWatch" using existing signals of opportunity from communication satellite in collaboration with JPL)
 - ➤ <u>Goal:</u> Use other satellite missions (e.g., C-band ESA Sentinel-1), L-band NISAR) to provide potential new measurements useful for SWE characterization

Questions?

Work supported by:



THP, NEWS, HMA, IDS Programs



Hydrologic Sciences Program

Jet Propulsion Laboratory

Key contributors: Manuela Girotto, Michael Durand, Gonzalo Cortes, Laurie Huning, Yufei Liu, Yiwen Fang, Haorui Sun, and many others