

Modeling gaps in continental-scale snow estimation

as highlighted by land surface model intercomparison

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Snow CCI workshop

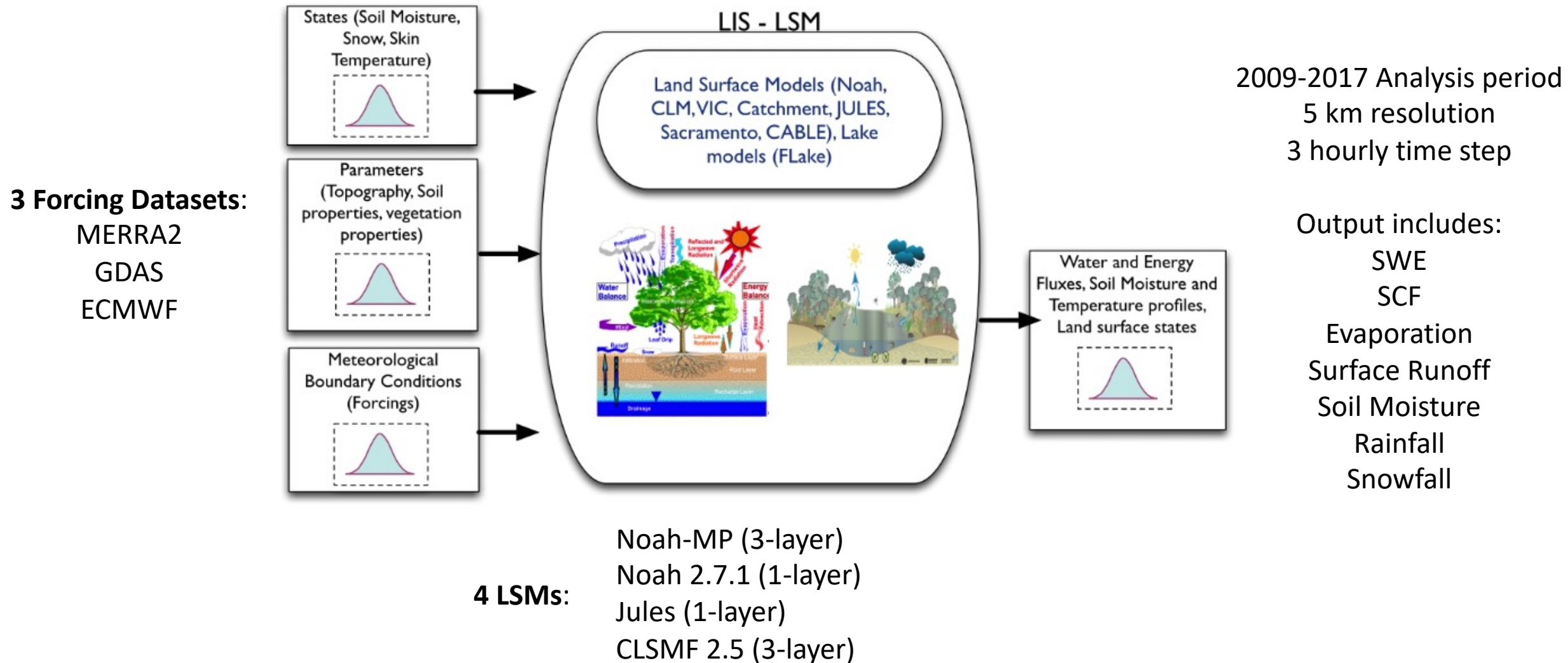
25 May 2021



Snow Ensemble Uncertainty Project (SEUP)

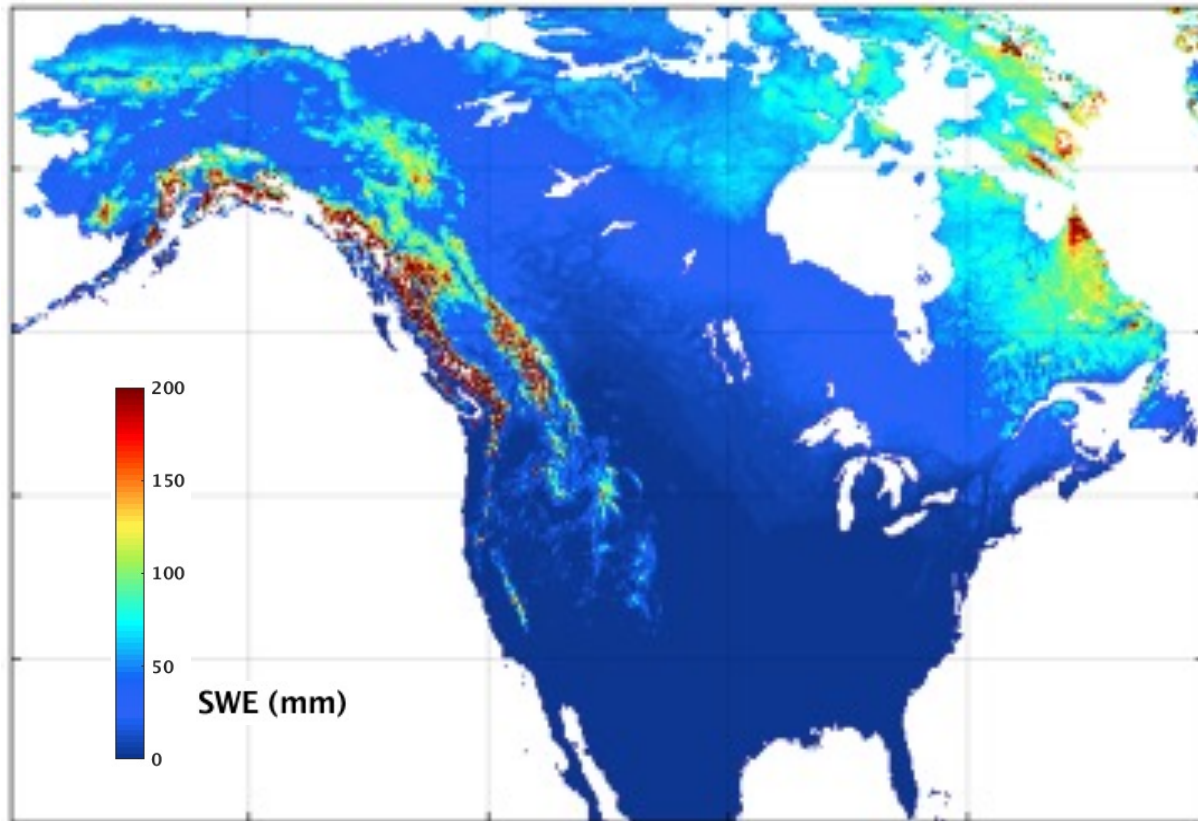
- Estimating spatially distributed snow water equivalent (SWE) is one of the largest challenges of snow hydrology
- Use ensemble of land surface models (LSMs) to establish a baseline estimate of SWE and related uncertainty
 - NASA's Land Information System (LIS) framework
 - Characterize SWE uncertainty across North America to identify regions and temporal periods with high variability
- Can use LSM ensemble and uncertainty in a data assimilation framework

SEUP land surface model design with LIS

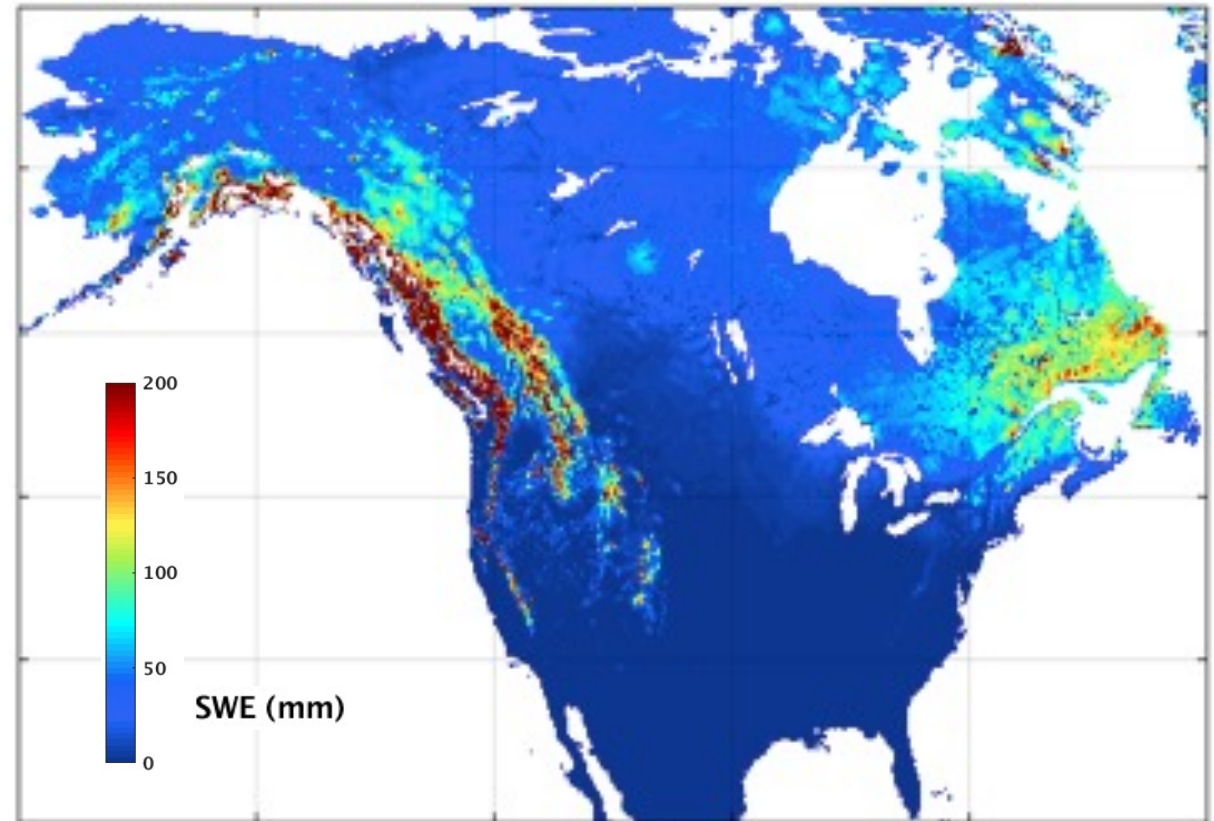


Largest SWE values in the mountains, but also large ranges between ensemble members

Ensemble mean SWE

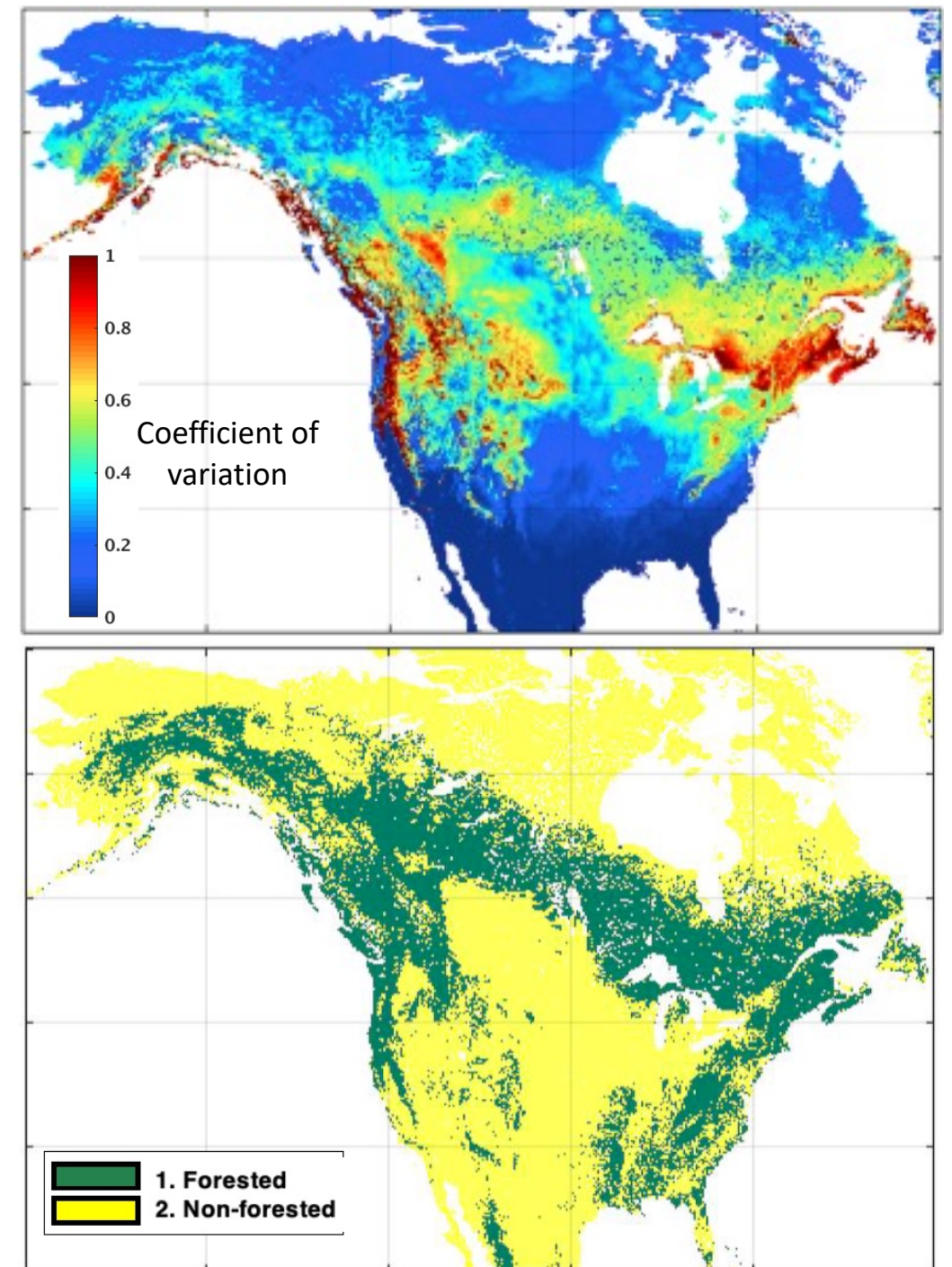


Range of ensemble mean SWE



High variability in SWE between LSMs in boreal forest

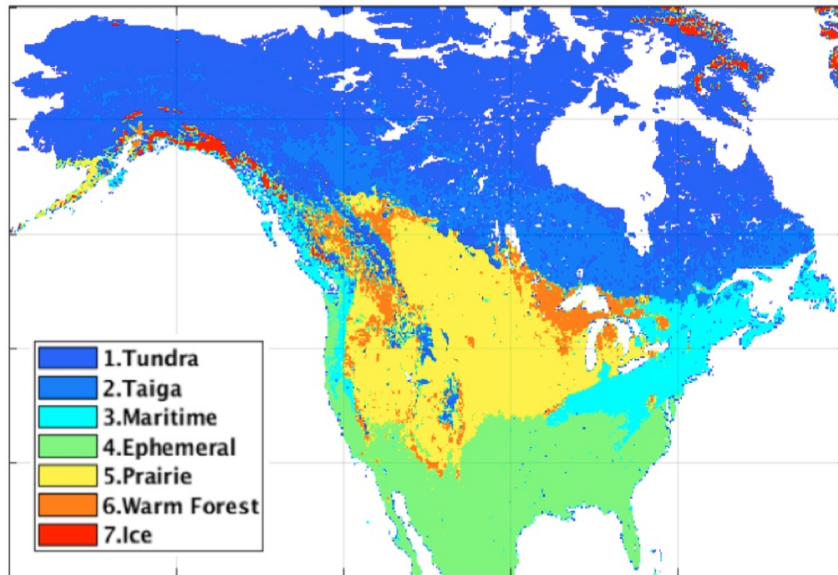
- Snow-vegetation interaction drives model spread, highlighting the need for improved model parameterizations in forested areas
- Need additional observational constraints in forested regions to reduce uncertainty in models
 - High resolution observations (within forests)



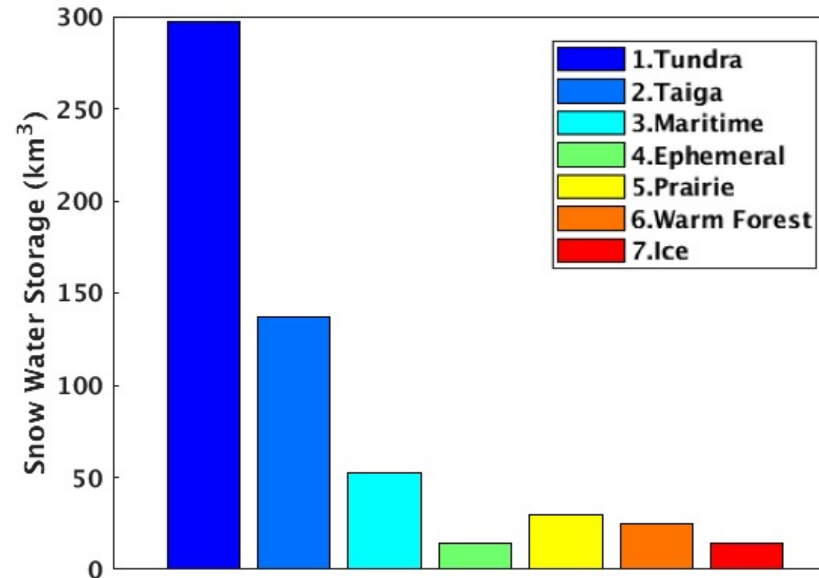
Tundra and taiga account for majority of North American snow storage, but both have high variability between ensemble members.

Since tundra/taiga covers such a large area, accurate observations in shallow snow regions is essential for improved global-scale snow estimates

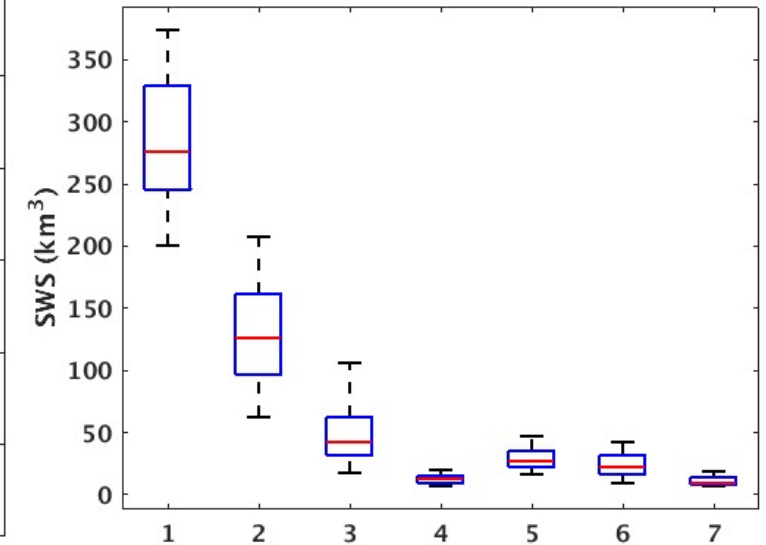
Snow Classes



Total Snow Water Storage



SWS Ensemble Spread



SEUP Phase 2 – Observing System Simulation Experiment (OSSE)

Snow-focused OSSE to evaluate the impact of data collected from proposed missions.

- Assess potential mission designs
- Quantify utility of observation beyond immediate variable of interest (in this case, beyond snow)

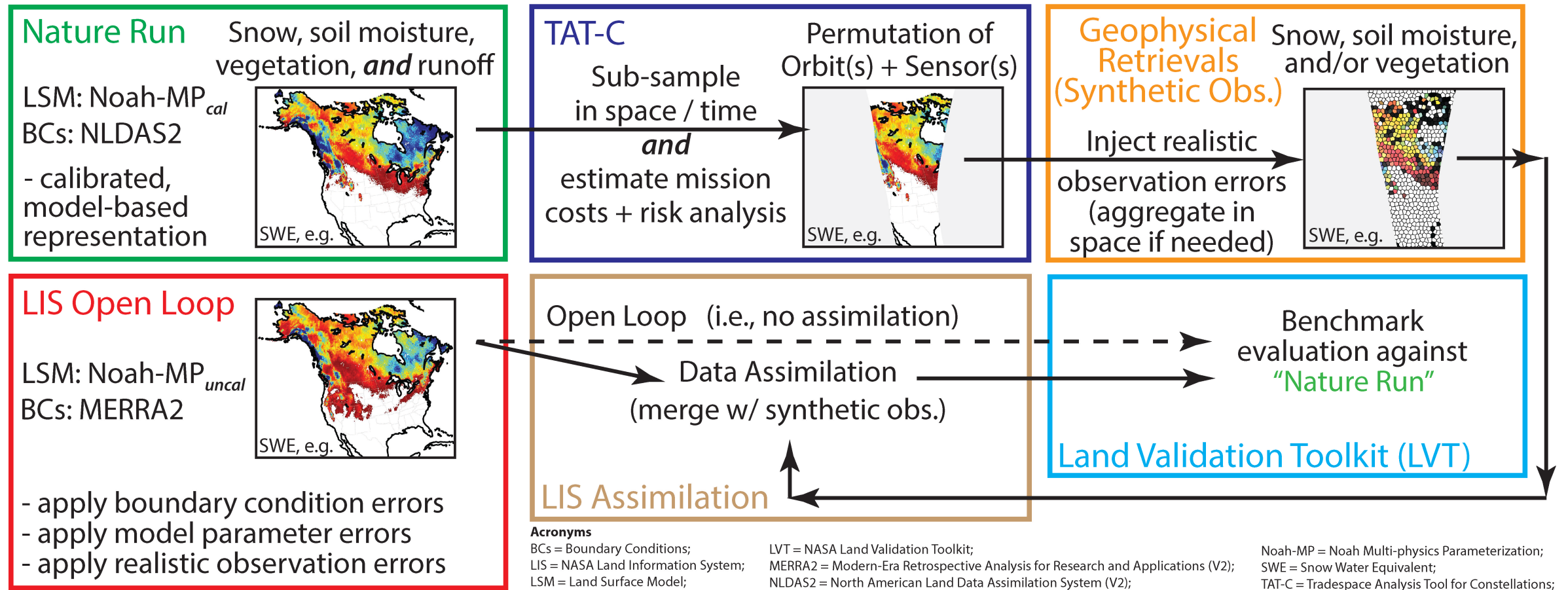
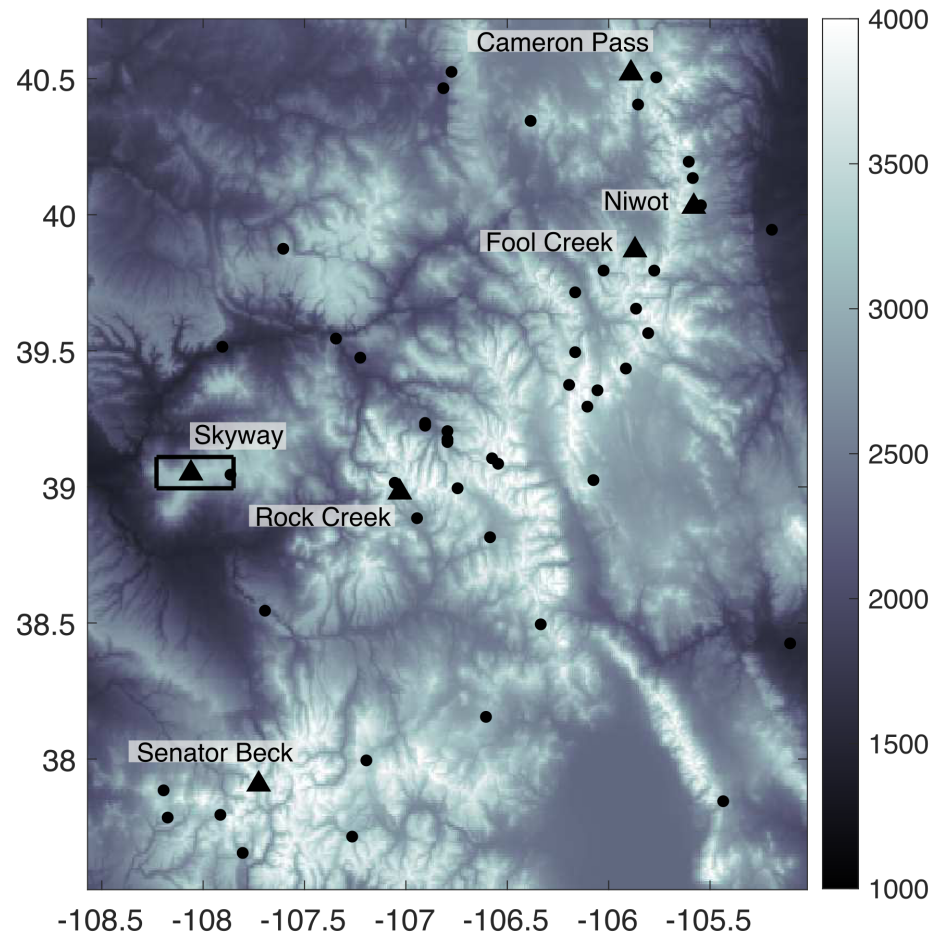
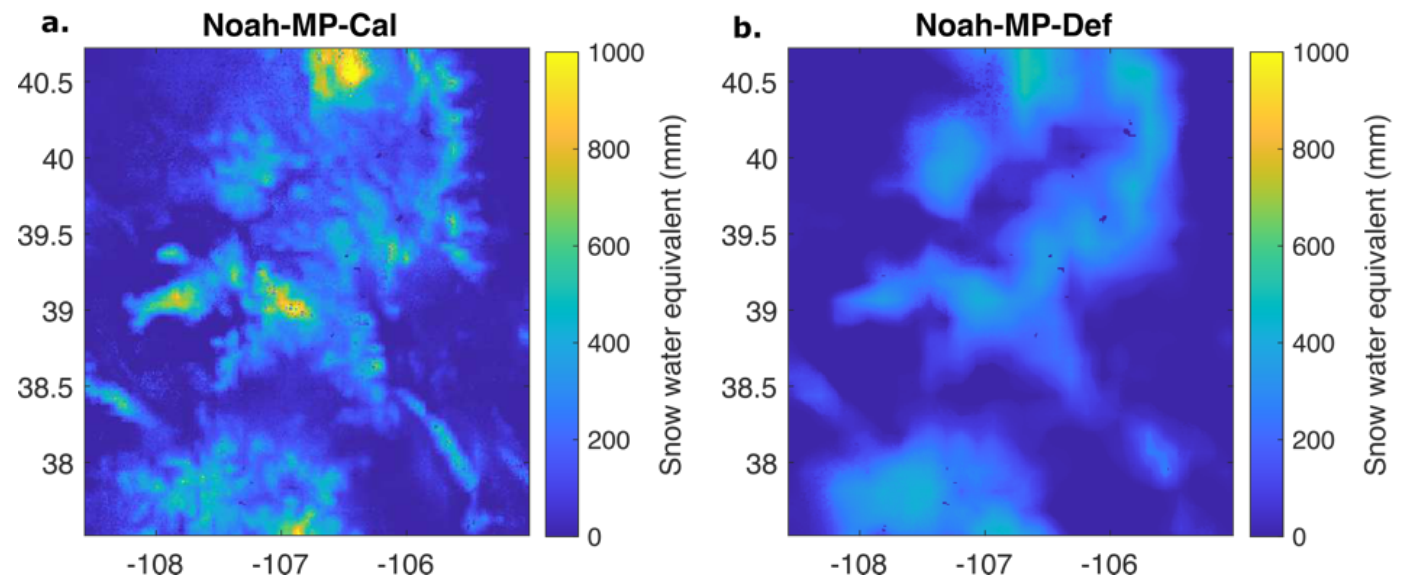


Figure from Bart Forman

OSSE Nature Run

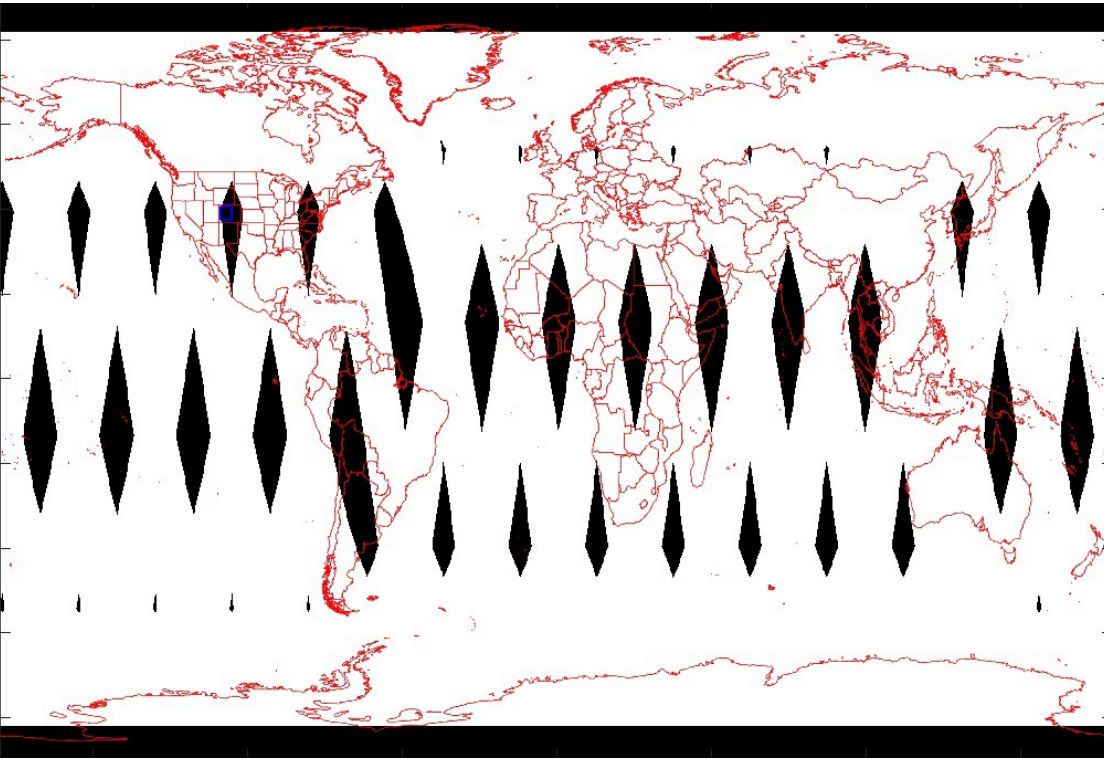


- Western Colorado domain that includes multiple SnowEx study sites
- Noah-MP with NLDAS2 meteorological forcing
 - ~1 km spatial resolution
- September 2009 through July 2020
- Calibrated against snow depth from the University of Arizona gridded data product

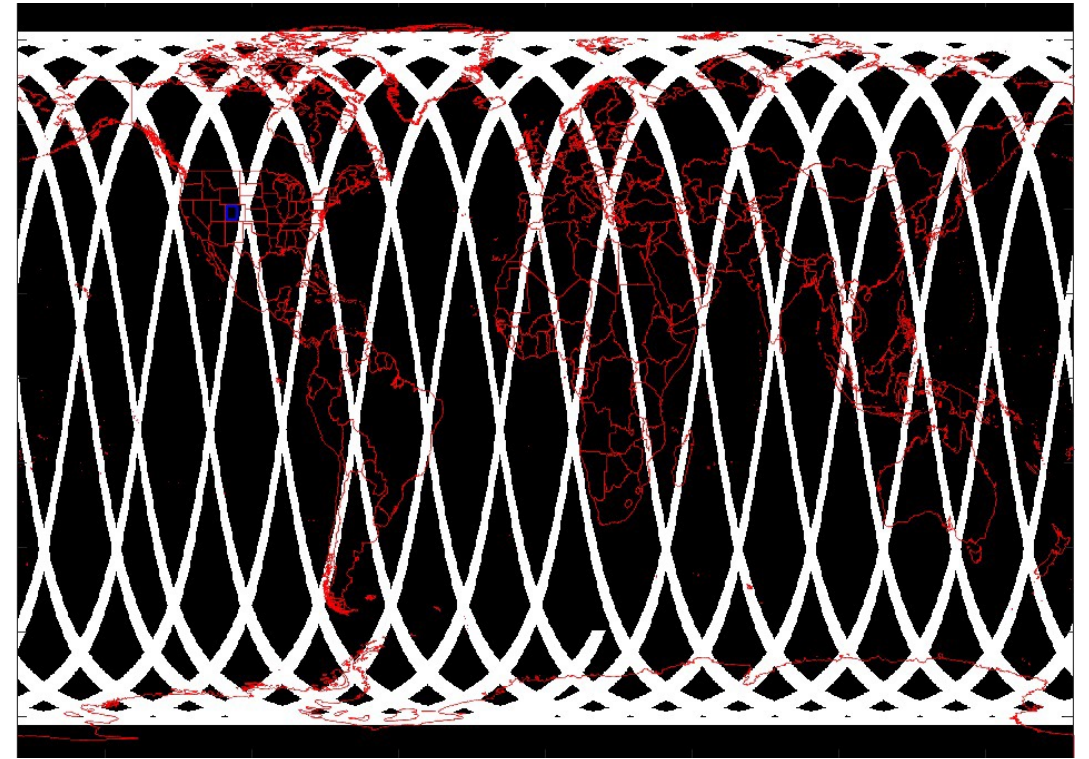


Realistic orbits for current/proposed sensors will be used to generate synthetic observations from Nature Run simulation

AMSR-2 one-day orbit
1450 km swath width



Sentinel 1A one-day orbit
250 km swath width



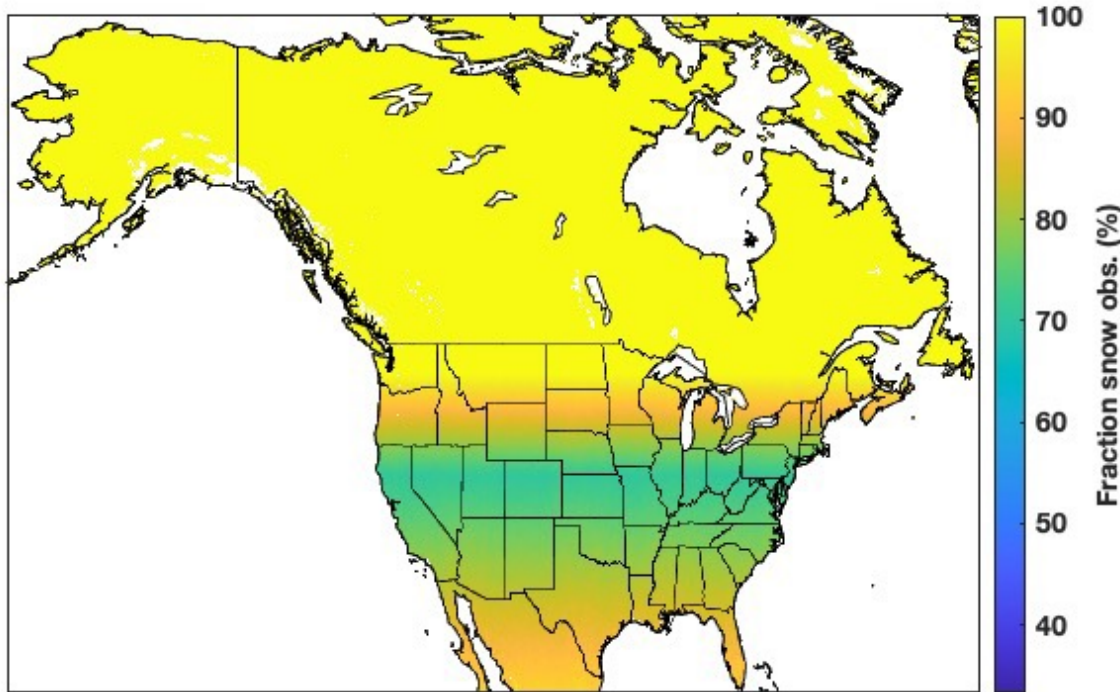
Orbits created with the Trade-space Analysis Tool for designing Constellations (TAT-C)

Use orbits+swaths to estimate annual coverage for each sensor, considering limitations.

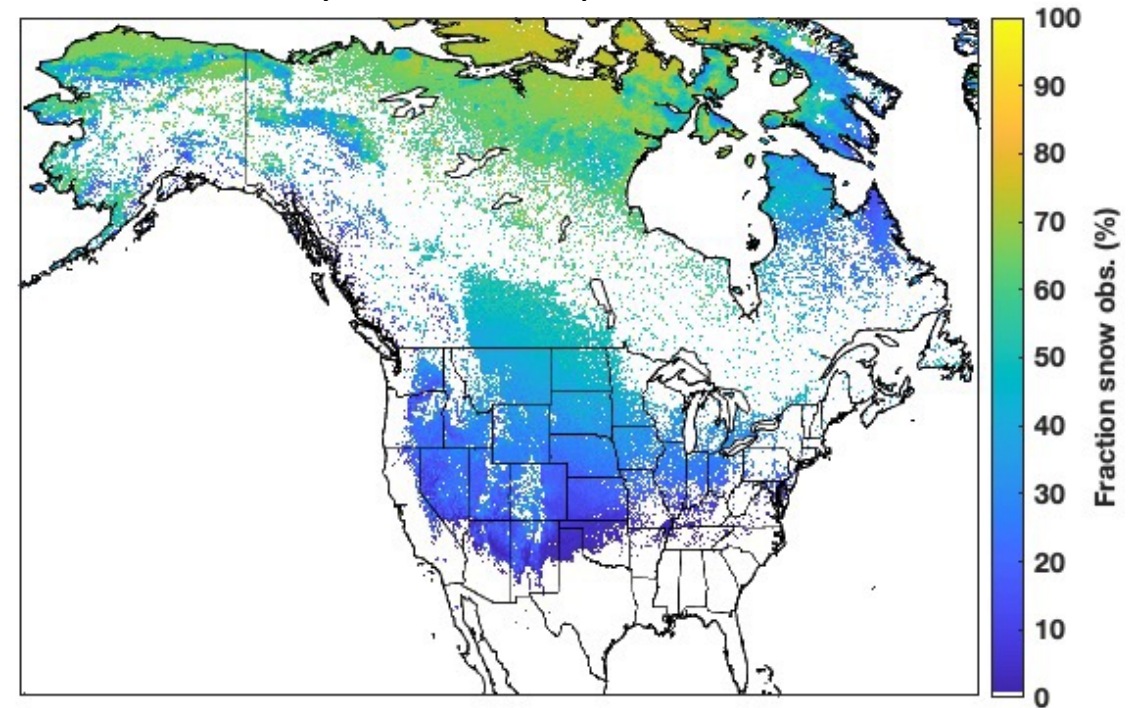
→ Optical sensors limited by clouds and polar night

→ SAR limited by dense forests and wet snow

AMSR2 coverage
No limitations



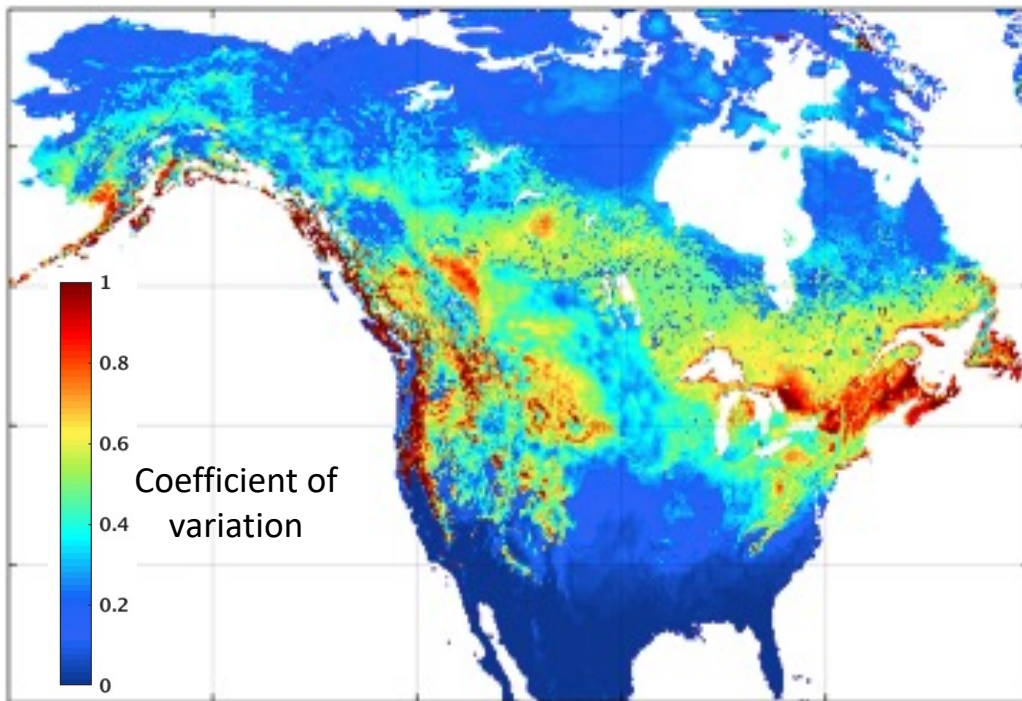
AMSR2 coverage
Limited by forests, deep snow, wet snow



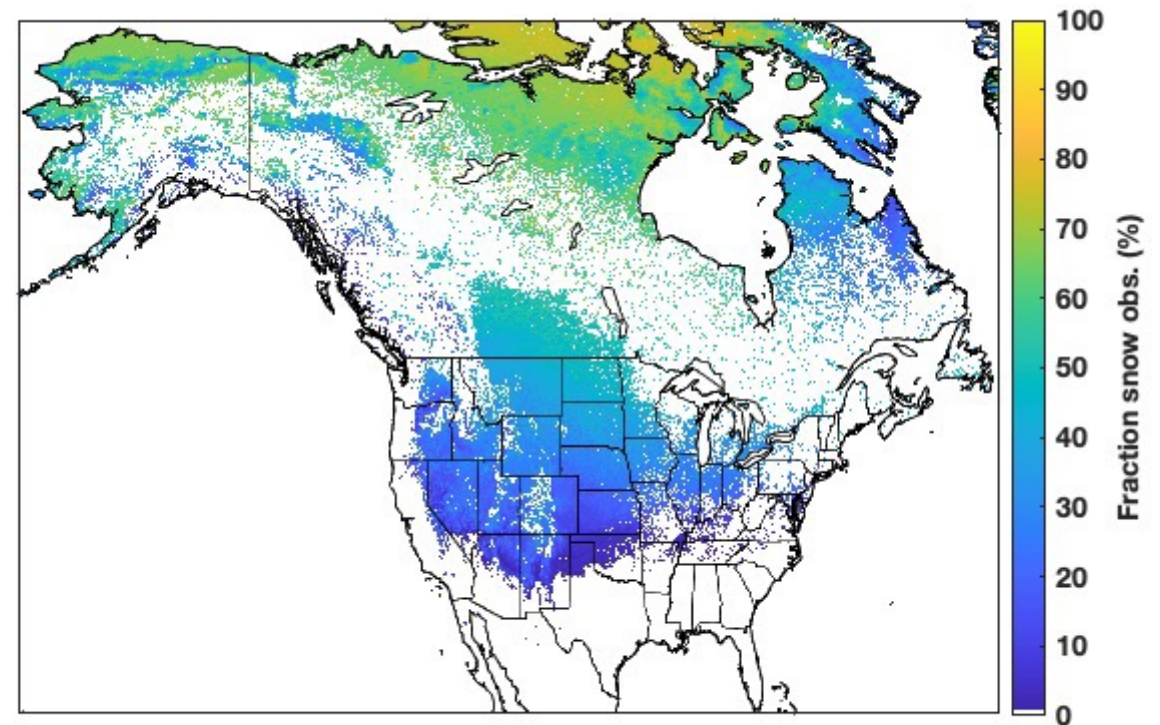
$$\text{Fraction snow obs (\%)} = \frac{\sum \text{days with observations \& snow cover}}{\sum \text{days with snowcover}} \times 100$$

Data masks help determine where we have satellite observations and where we are “blind” to the snow

From SEUP



AMSR2 coverage



AMSR2 limitations overlap where model uncertainty is high → proposed satellites should meet this need

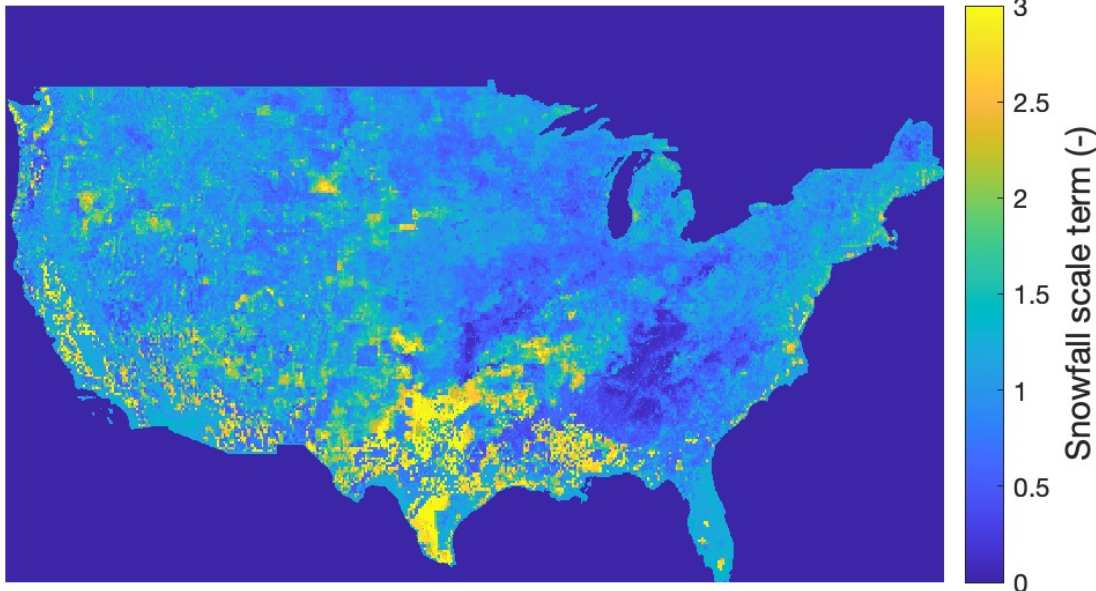
In summary, models constrained by observations through data assimilation likely the best path for global snow estimation. Models and satellite observations currently have critical gaps.

Model gaps

Forests, mountain areas, tundra/taiga

Can field observations constrain model uncertainty?

Can machine learning improve model parameterizations?



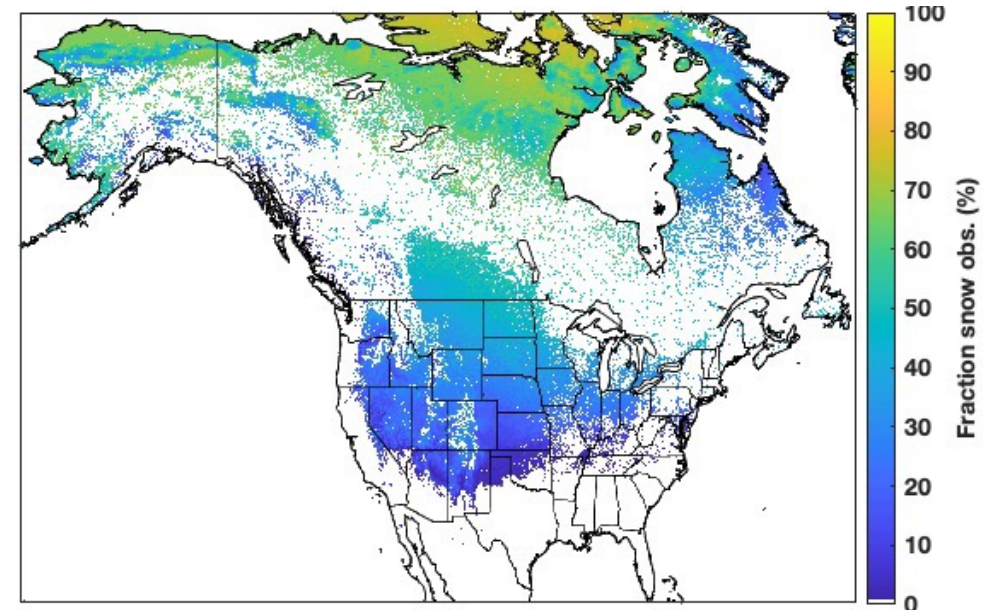
Remote sensing gaps

Forests, deep snow, wet snow

Where are current gaps when we consider all sensors?

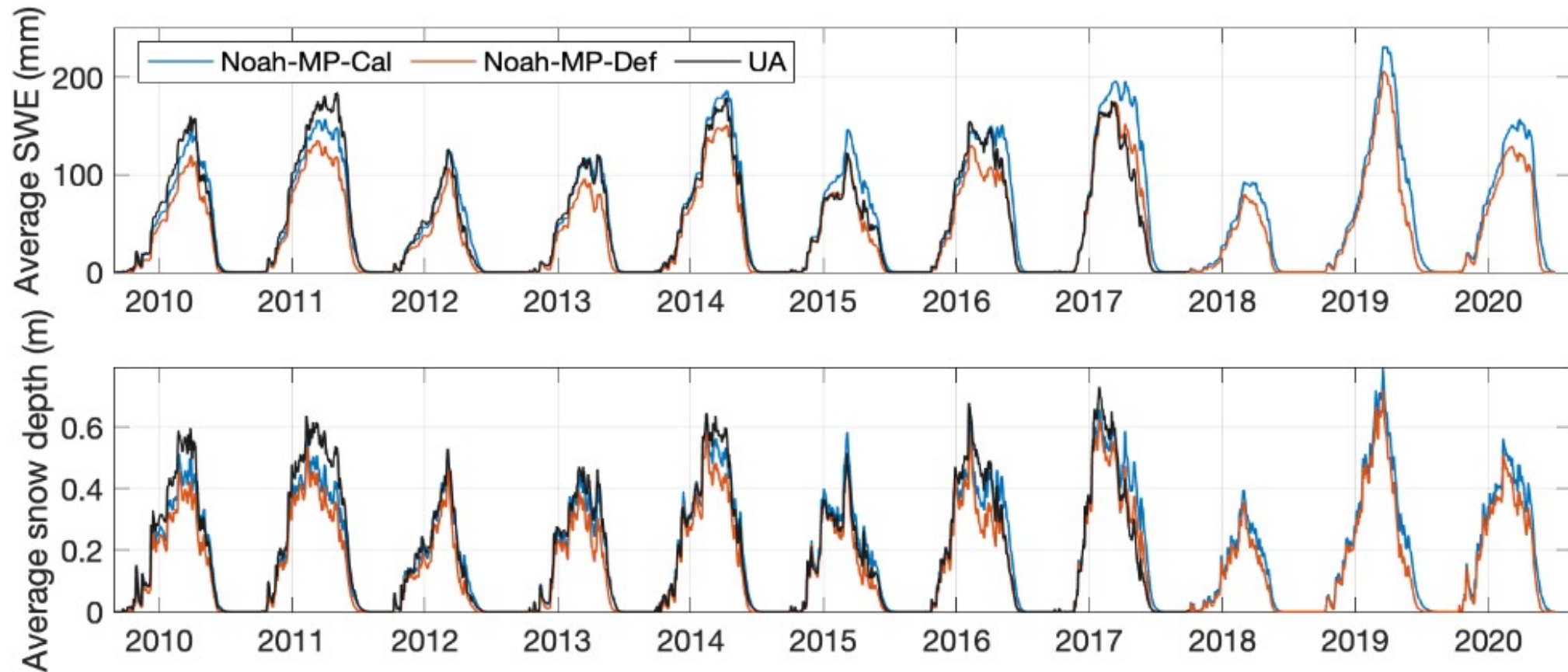
Can proposed sensors address the gaps?

What can we learn from the OSSE?

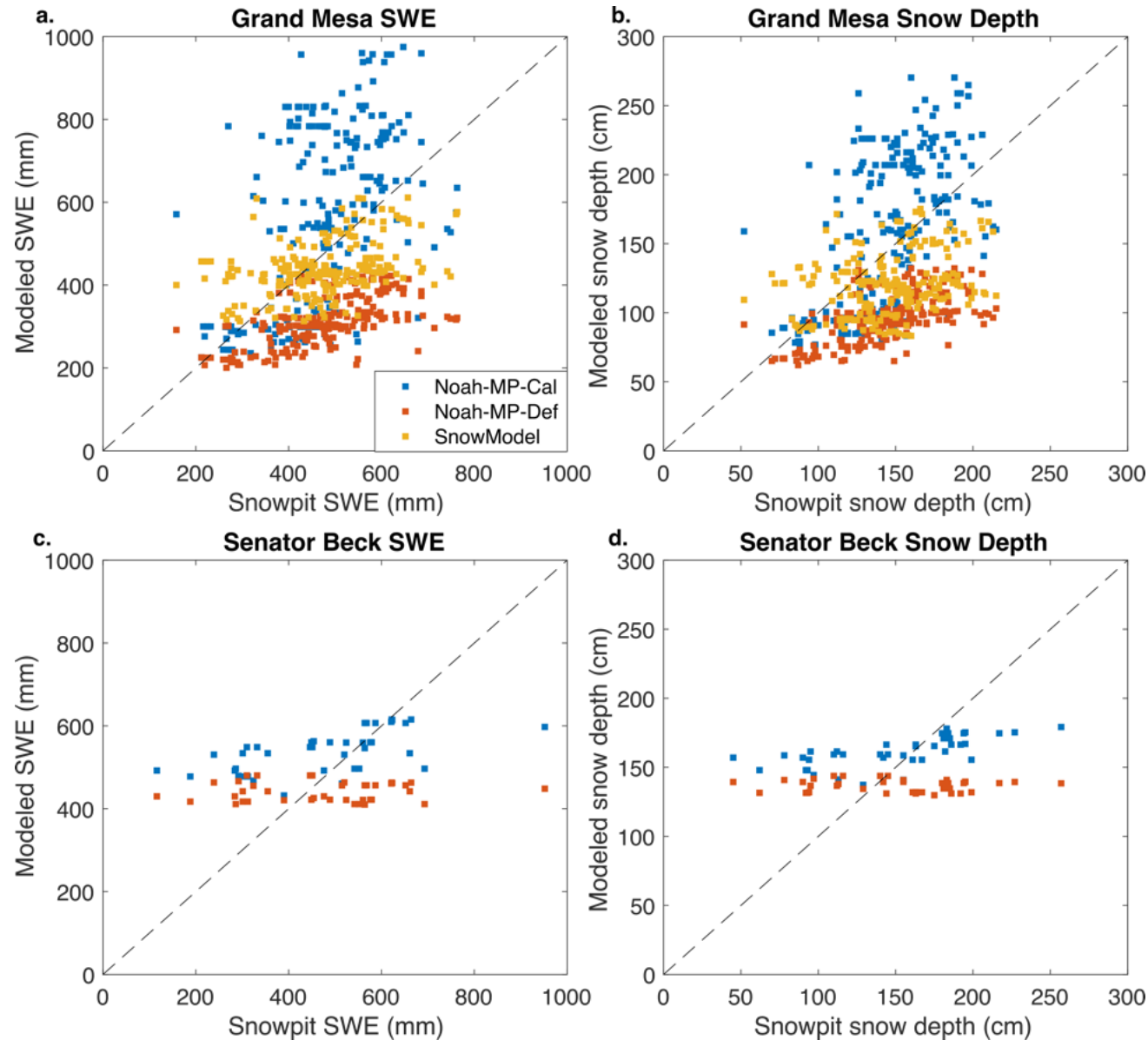


Additional slides

SWE and snow depth averaged over full domain for the 11-year **calibrated Nature Run**, compared to **default NoahMP** and **UA snow product**



Evaluation of Noah-MP estimates against SnowEx 2017 snow pit observations



Grand Mesa

Simulation	MAE for SWE (mm)	MAE for depth (cm)
Calibrated	169.0	39.6
Default	162.9	48.8
SnowModel	88.5	34.6

Senator Beck

Simulation	MAE for SWE (mm)	MAE for depth (cm)
Calibrated	115.4	33.1
Default	142.5	43.1

SnowEx 2017

Evaluation against

ASO snow depth

