Assimilation of Blended In Situ-Satellite Snow Water Equivalent into the National Water Model for Improving Hydrologic Simulation

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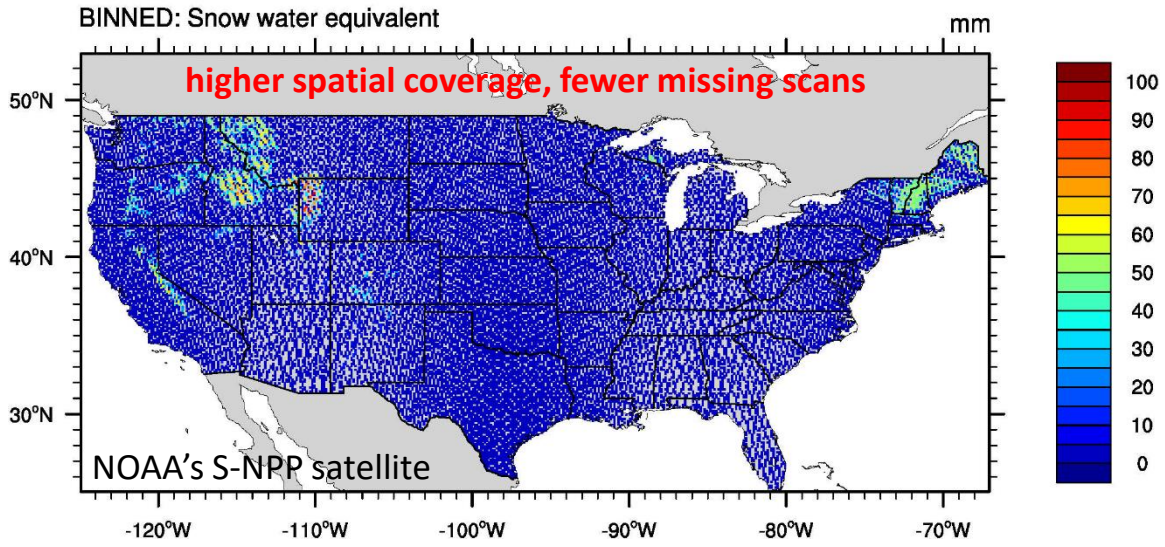
This work was supported by the National Oceanic and Atmospheric Administration (grant #NA18OAR4590410)

Objectives of the Research

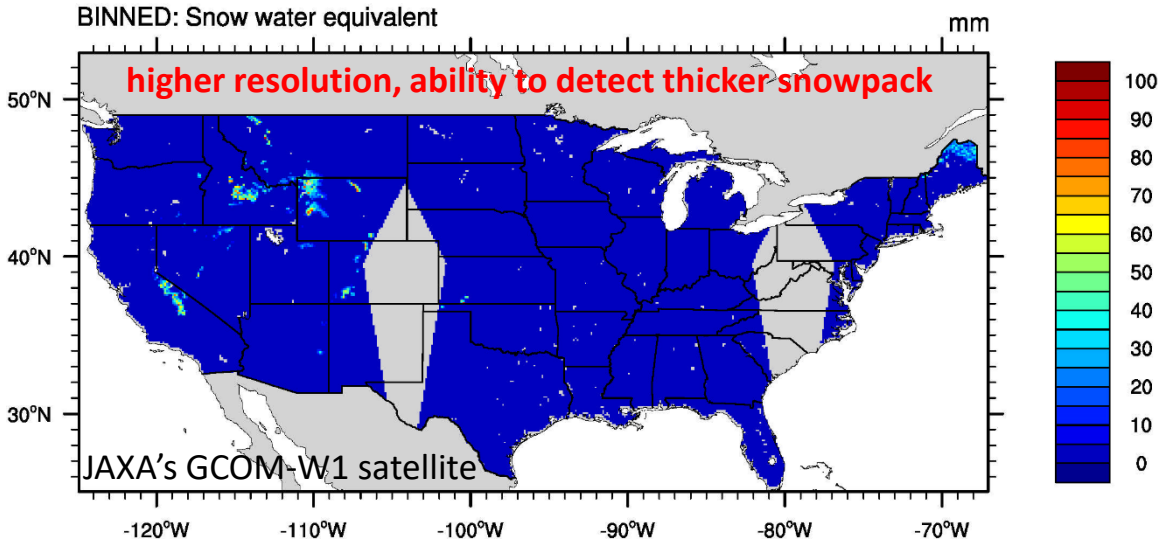
- Overarching goals
  - Develop a blended in situ-satellite snow water equivalent (SWE) product for CONUS
  - Develop capability for the National Water Model (NWM) to assimilate snow products
  - Assess impacts of assimilating blended in situ-satellite SWE on snowpack and streamflow
- Benefits to NOAA/NESDIS Satellite Programs
  - Facilitate transition of NOAA satellite products to hydro operation
  - Inform algorithm developers on potential improvements
- Benefits to NOAA/OWP
  - Inform OWP effort of building snow DA capability for NWM
  - Inform OWP on strengths of different satellite and in situ snow products
  - Improve hydrologic prediction for snow-dominated basins

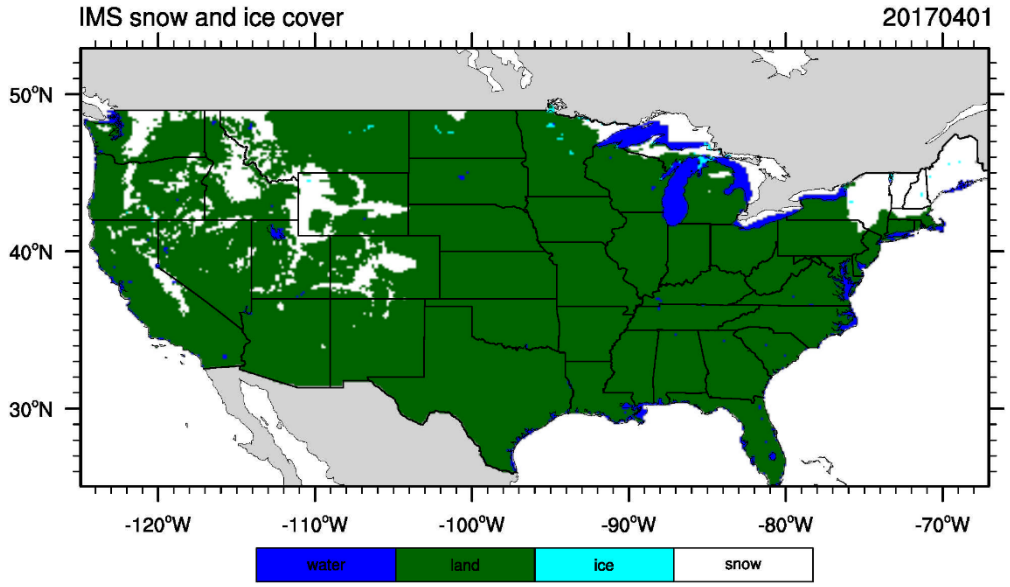
Creation of Blended SWE Product: Data Sources

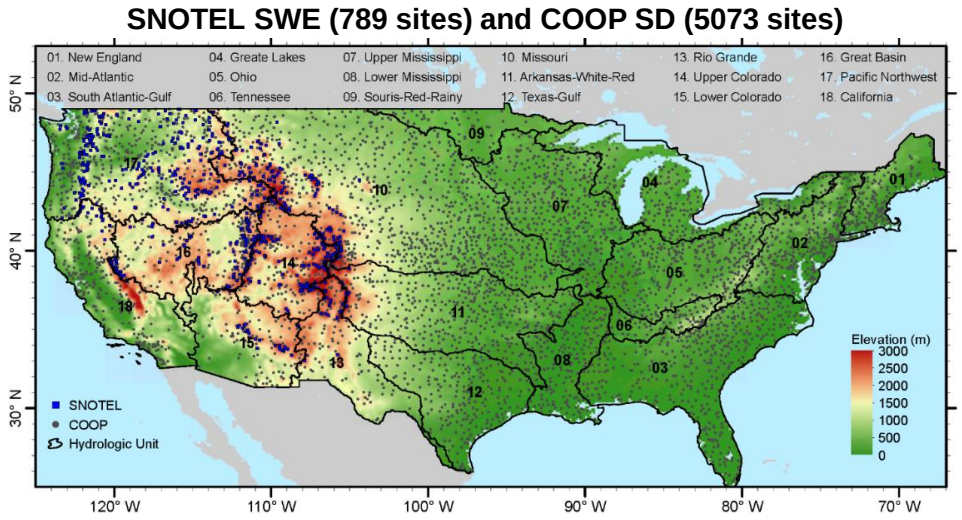
ATMS: 2017/04/01



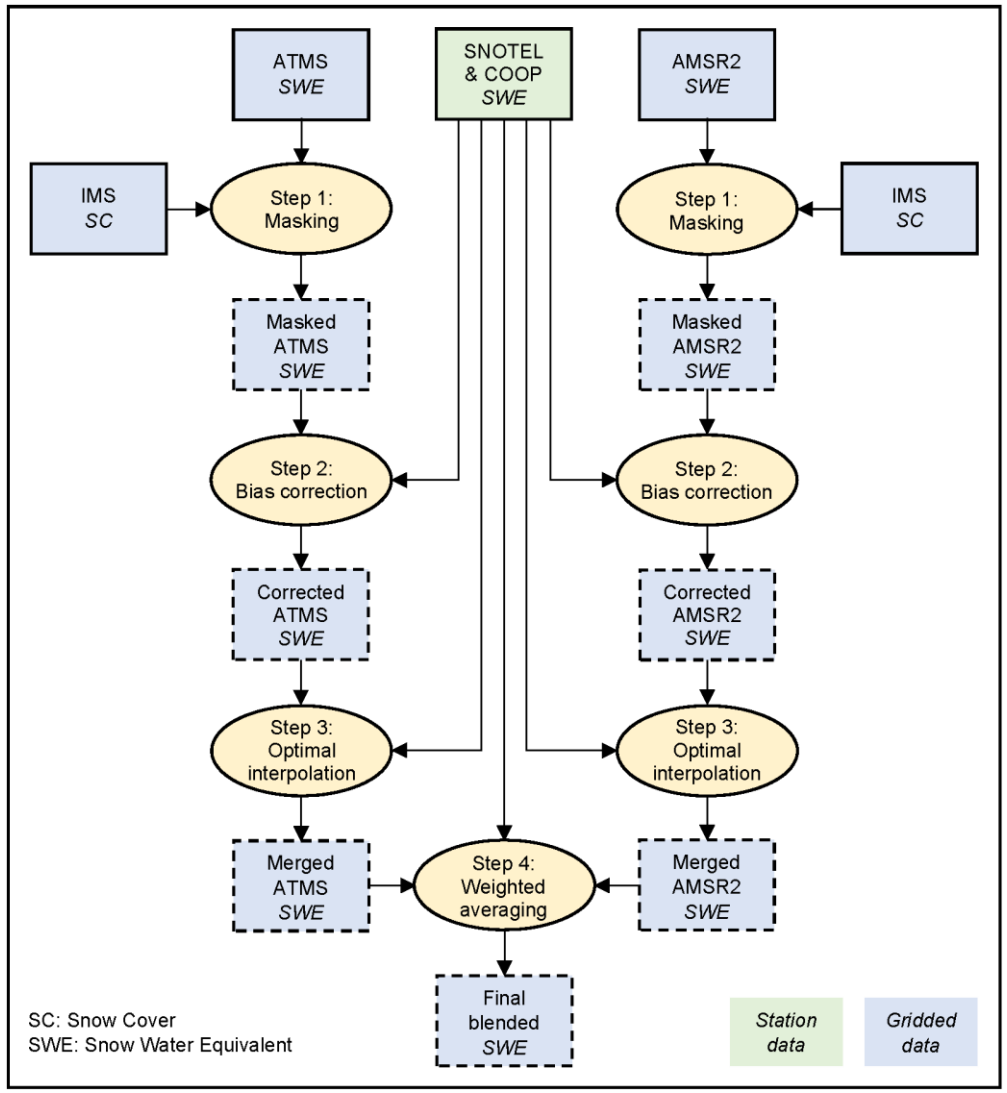
AMSR2: 2017/04/01







Creation of Blended SWE Product: Blending Algorithm

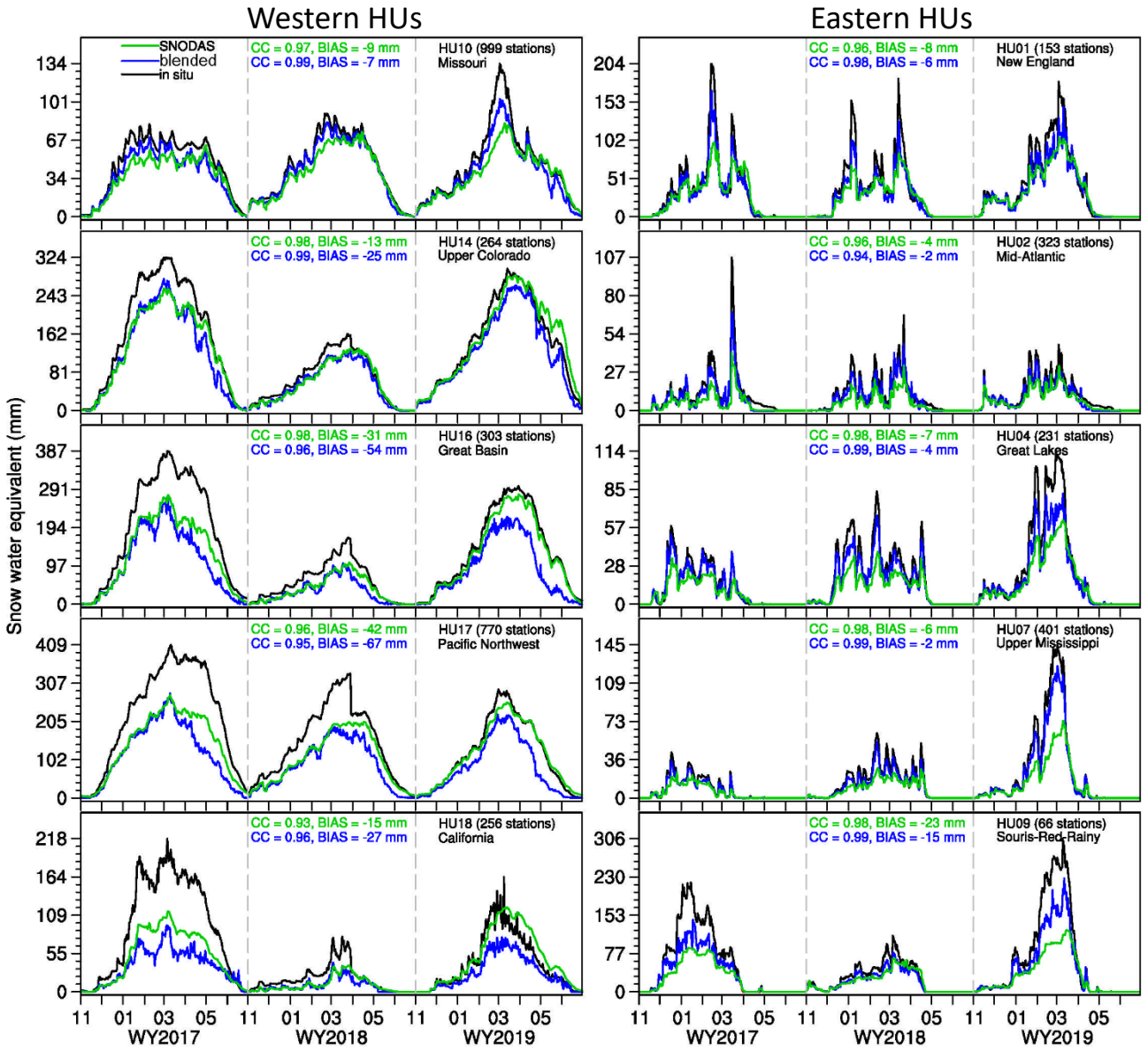


- **Masking**
  - Use IMS snow cover data to identify pixels with false detection and missing snow
- **Bias correction**
  - Match the CDF of satellite SWE retrievals with that of in situ SWE observations
- **Optimal interpolation**
  - Merge each corrected satellite retrieval with in situ observations
- **Weighted averaging**
  - Combine two blended products

0.125-deg daily blended in situ-satellite SWE product for CONUS

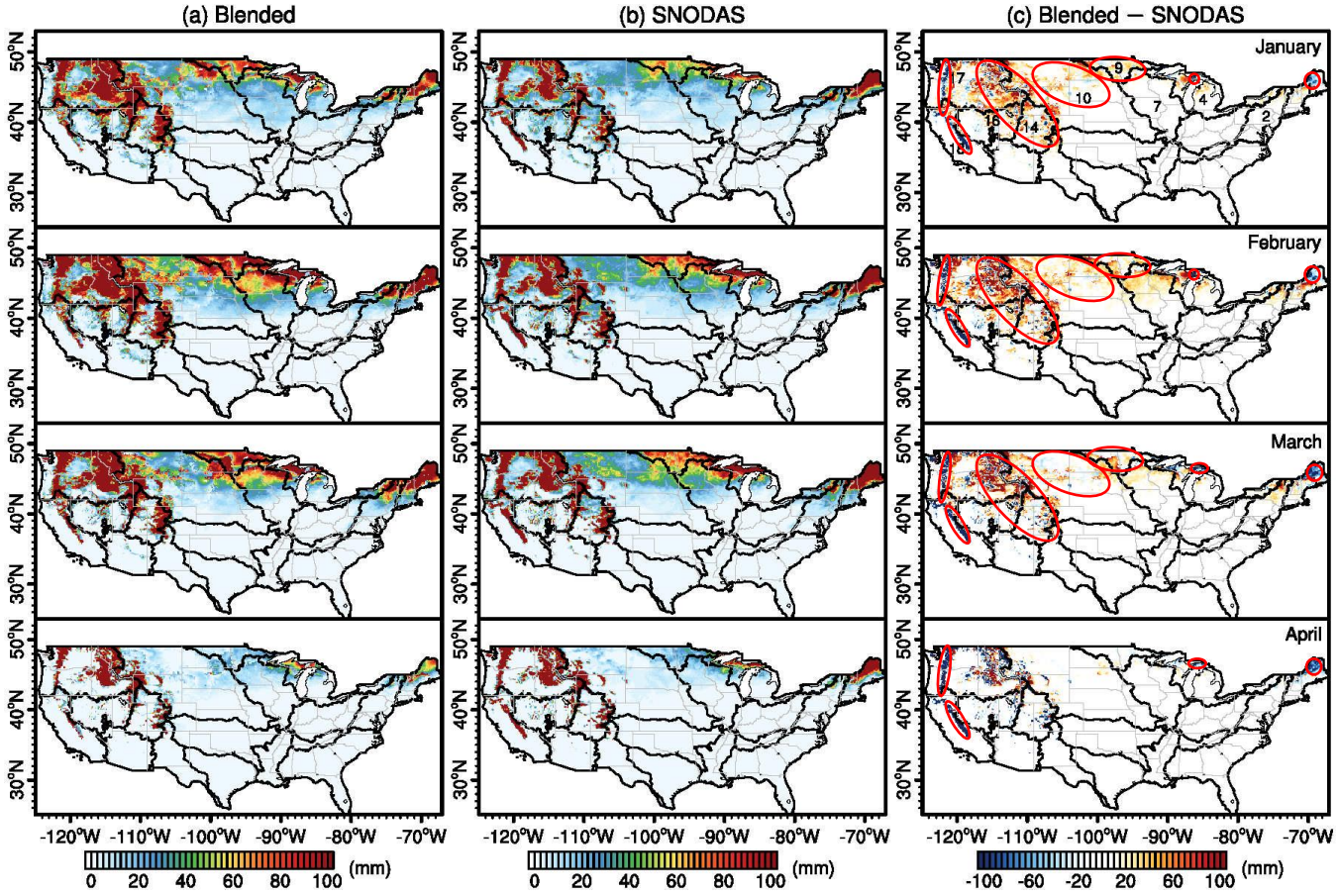
Gan, Y., Zhang, Y., Kongoli, C., Grassotti, C., Liu, Y., Lee, Y., Seo, D-J, 2021. Evaluation and blending of ATMS and AMSR2 snow water equivalent retrievals over the conterminous United States. Remote Sens. Environ. 254, 112280. https://doi.org/10.1016/j.rse.2020.112280.

Evaluation of Blended SWE Product: Time Series



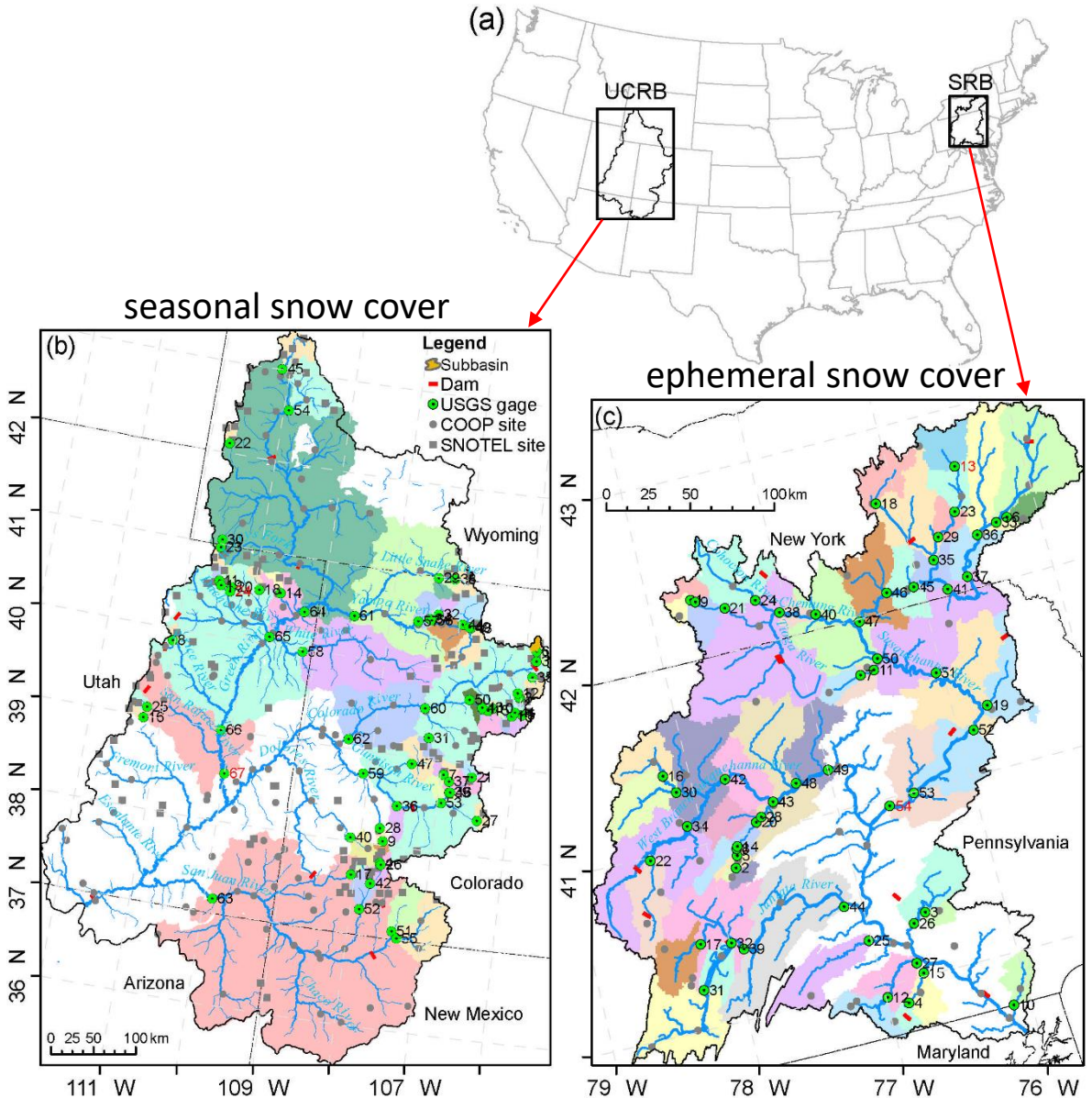
- Western HUs
  - Blended product performs comparably to SNODAS
  - SNODAS still does better in 2018-19 snow season
- Eastern HUs
  - Blended product exhibits smaller bias
  - Blended product shows higher correlation

Evaluation of Blended SWE Product: Spatial Distribution



- Blended product agrees well with the SNODAS analysis in spatial patterns.
- The overestimation of the blended product over the Rockies, Northern Plains, and Souris-Red-Rainy regions from January to March is reasonable
- The underestimation of the blended product over the Cascade and Sierra Nevada regions, as well as northern New England and the northern Great Lakes regions is due to the limited number of observation stations

Assimilation of Blended SWE Product: Experimental Setup



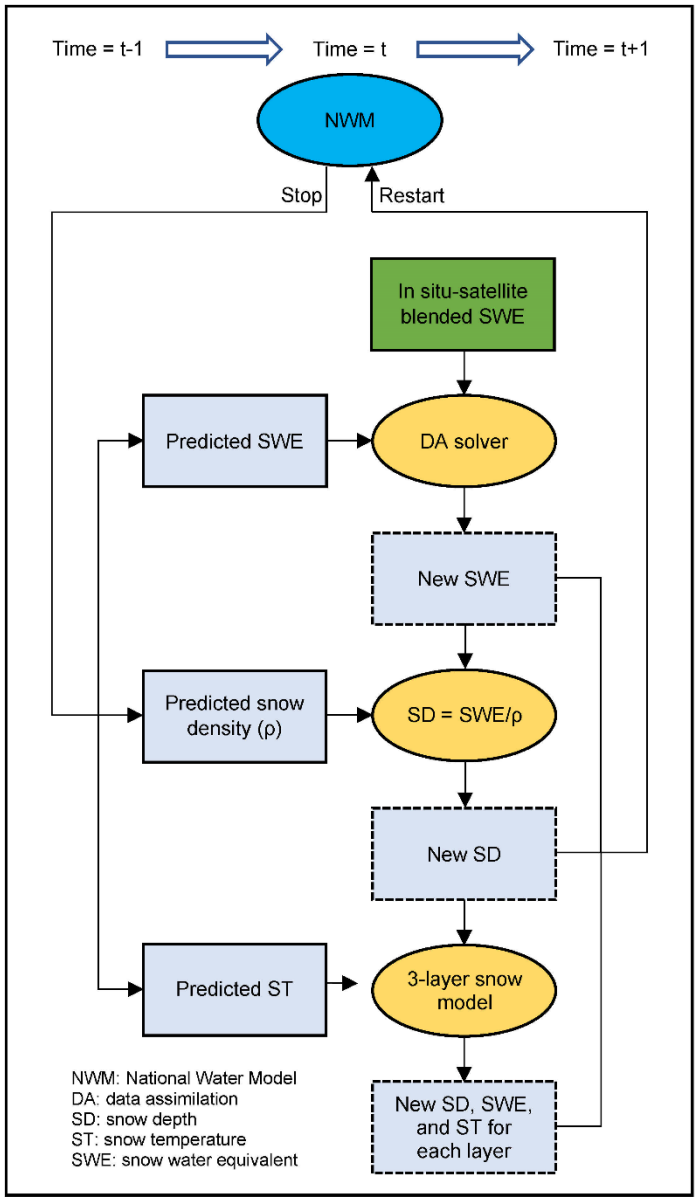
- Model
  - NWM v2.0 (1 km × 1 km)
- Domains
  - Upper Colorado River Basin (UCRB): 67 subbasins
  - Susquehanna River Basin (SRB): 54 subbasins
- Data

Data category	Data name	Spatial resolution	Temporal resolution
Static data	Land-related data	1 km	N/A
	Routing-related data	250 m	N/A
Forcing data	NLDAS-2 forcing	1/8°	hourly
Observation data	Blended in situ-satellite SWE data	1/8°	daily
Reference data	SNODAS SWE	1 km	daily
	USGS streamflow	gauge	daily

- Simulation period: 10/01/2015 – 09/30/2019 (spin-up for 20 years)

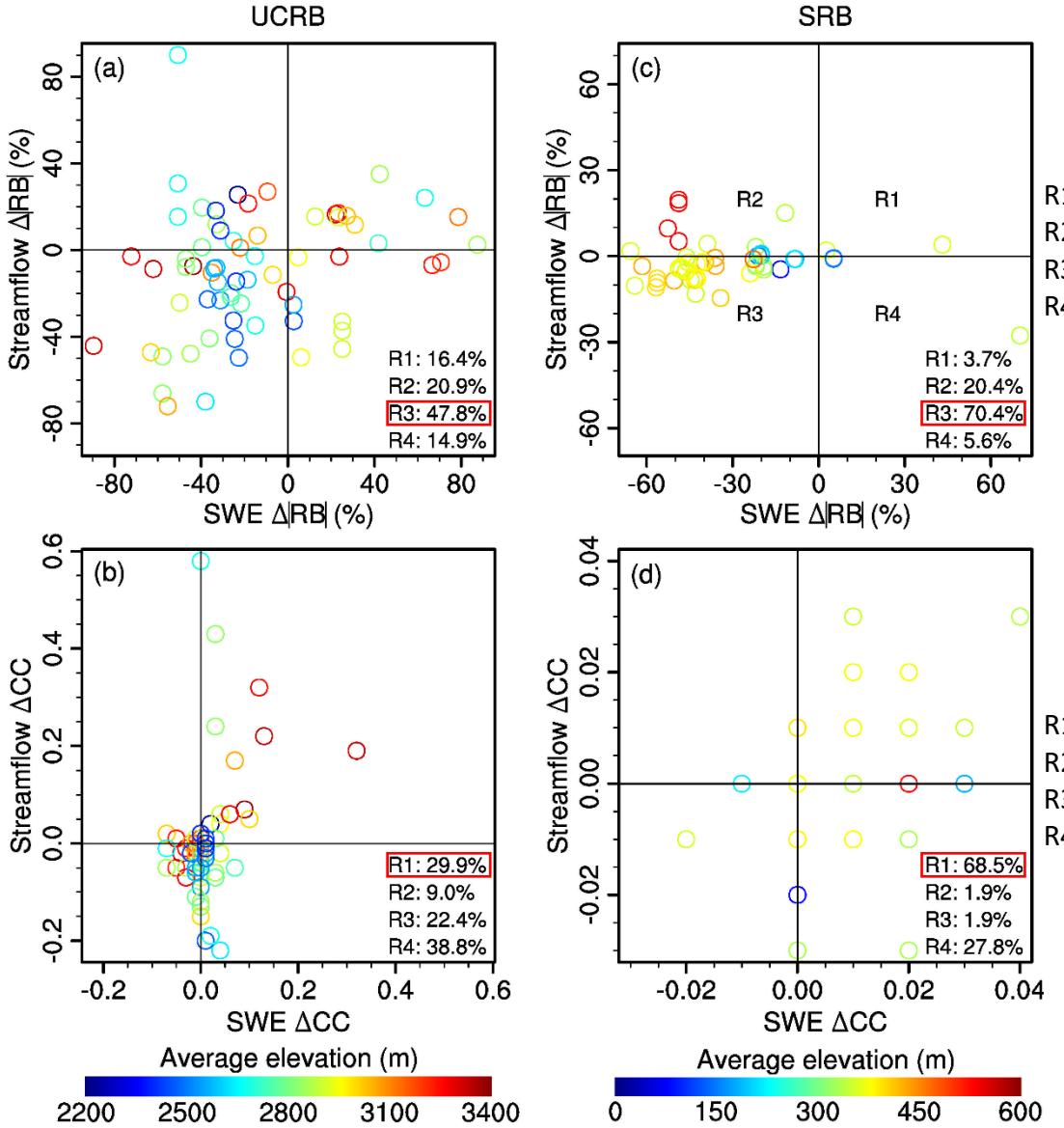
Gan, Y., Zhang, Y., Liu, Y., Kongoli, C., Grassotti, C., 2022. Assimilation of blended in situ-satellite snow water equivalent into the National Water Model for improving hydrologic simulation in two US river basins. Sci. Total Environ. 838, 156567. https://doi.org/10.1016/j.scitotenv.2022.156567.

Assimilation of Blended SWE Product: Workflow



- DA methods: 3DVAR and DI
- DA procedure
  - The predicted SWE at each grid cell is updated with the blended SWE using different DA methods
  - SD is adjusted based on the physical relationship of the updated SWE and model-predicted snow density
  - The updated SWE and SD are redistributed to different snow layers following Noah-MP's three-layer snow model
  - Snow temperature of each layer is updated based on the following rules: 1) when snow is observed and predicted by the model in that layer, snow temperature is same as the model predicted; 2) when snow is observed but not predicted by the model in that layer, snow temperature is set to that of the lower neighboring layer or the ground when there is no predicted snow.

Assimilation of Blended SWE Product: Evaluation



3DVAR vs. OL (|RB|)

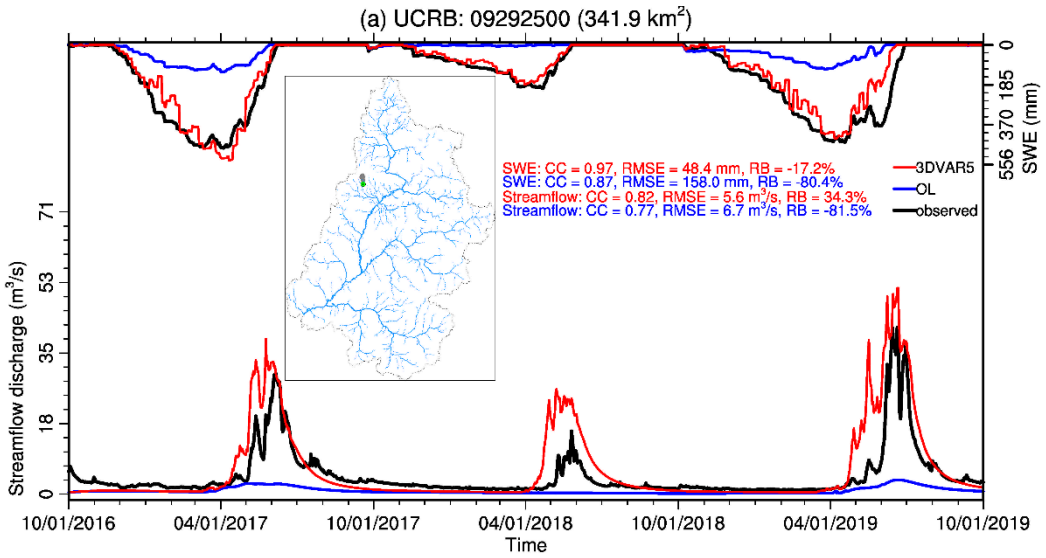
R1: degraded SWE + degraded streamflow
R2: improved SWE + degraded streamflow
R3: improved SWE + improved streamflow
R4: degraded SWE + improved streamflow

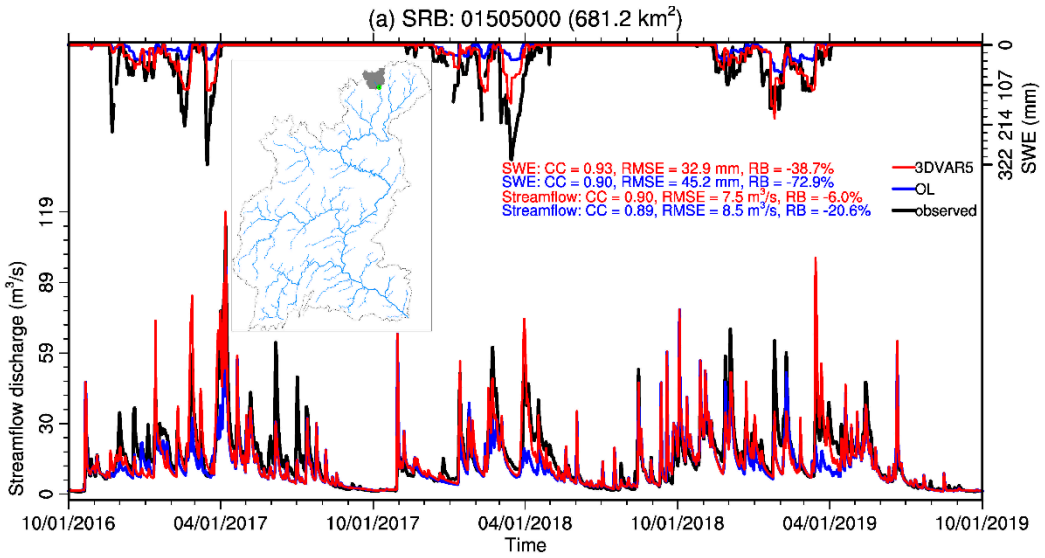
3DVAR vs. OL (CC)

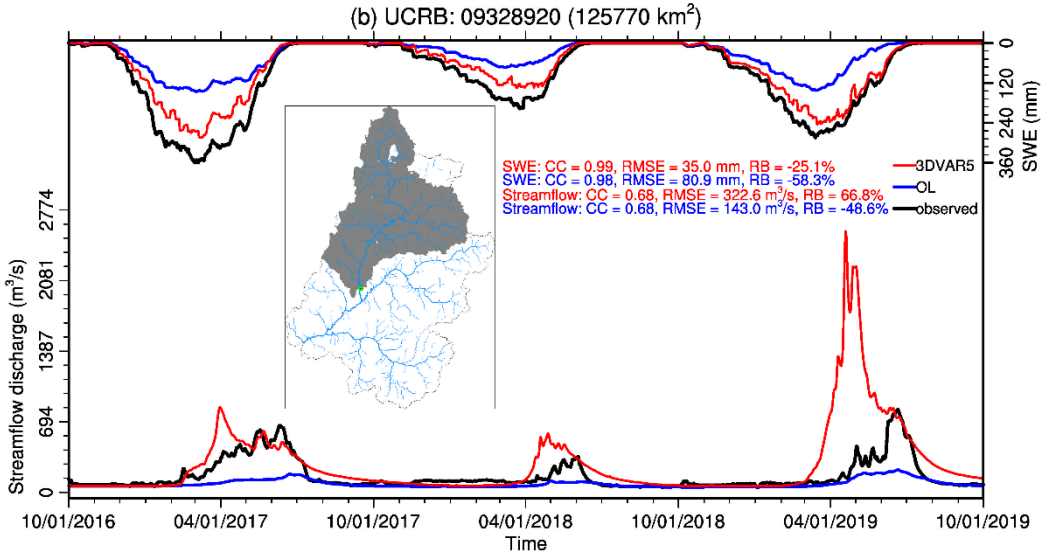
R1: improved SWE + improved streamflow
R2: degraded SWE + improved streamflow
R3: degraded SWE + degraded streamflow
R4: improved SWE + degraded streamflow

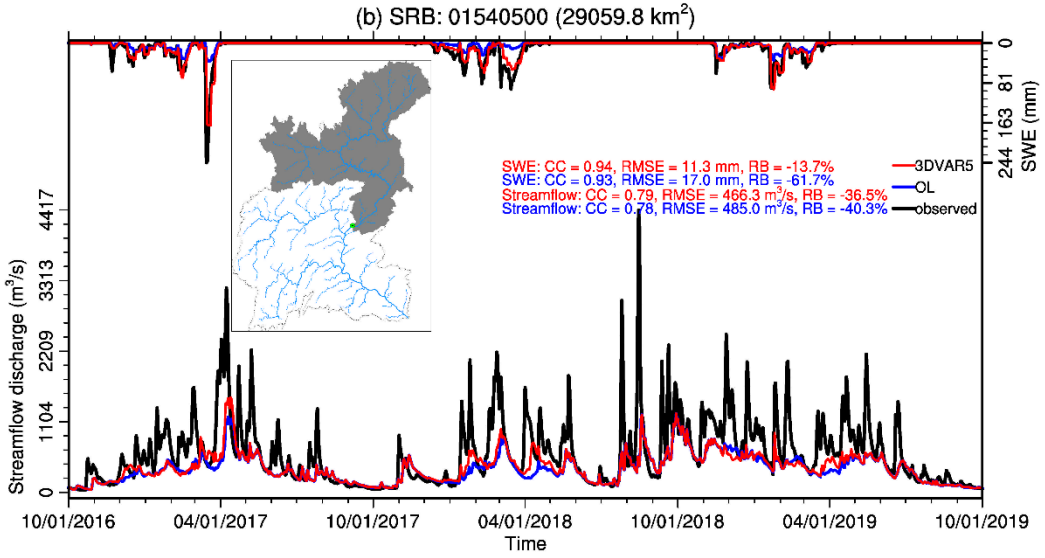
- Fewer subbasins experience improved streamflow than SWE, indicating that improved SWE does not always translate into improved streamflow.
- The percentage of subbasins with improved SWE and streamflow is higher for SRB than for UCRB, despite the degree of improvement (especially the CC) is smaller for the former.

Assimilation of Blended SWE Product: Evaluation









Key Lessons

- SWE retrieval blending
  - Blended in situ-satellite SWE product outperforms raw retrievals (ATMS and AMSR2) and blended products using each sensor alone
  - Blended product slightly outperforms SNODAS in some locations east of the Rockies
  - Deep snow over inter-mountain west is challenging to capture even with blending
- Data assimilation
  - Improves NWM snow analysis for both UCRB and SRB
  - Impacts on streamflow are mixed
    - UCRB: DA improves bias but degrades correlation
    - SRB: DA improves both metrics

Thank you!

Questions and Comments?

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