Improving Snow Simulation in the Upper Colorado River Basin through the National Water Model: The Role of Forcing and Parameterization

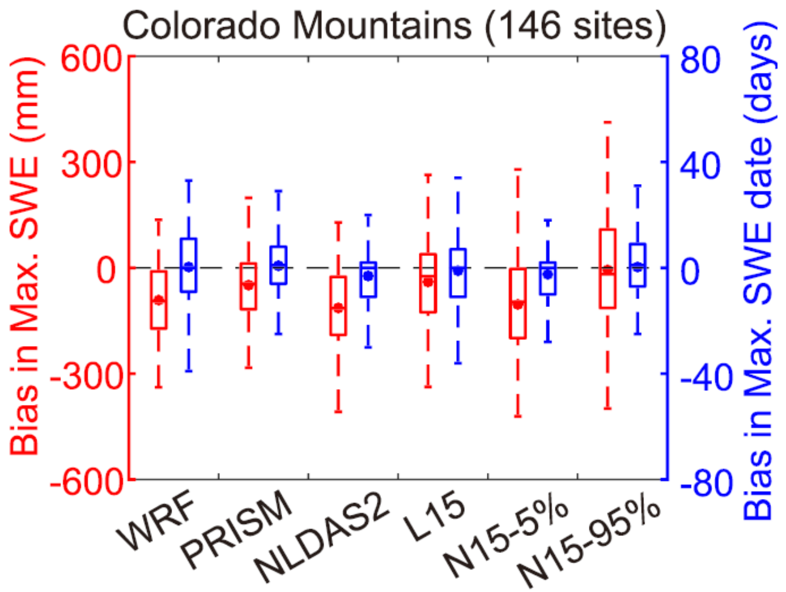
Yanjun Gan[1], Yu Zhang[1], Cezar Kongoli[2], Ming Pan[3]

1. Department of Civil Engineering, University of Texas at Arlington
2. Earth System Science Interdisciplinary Center, University of Maryland, College Park
3. Center for Western Weather and Water Extremes, University of California, San Diego

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

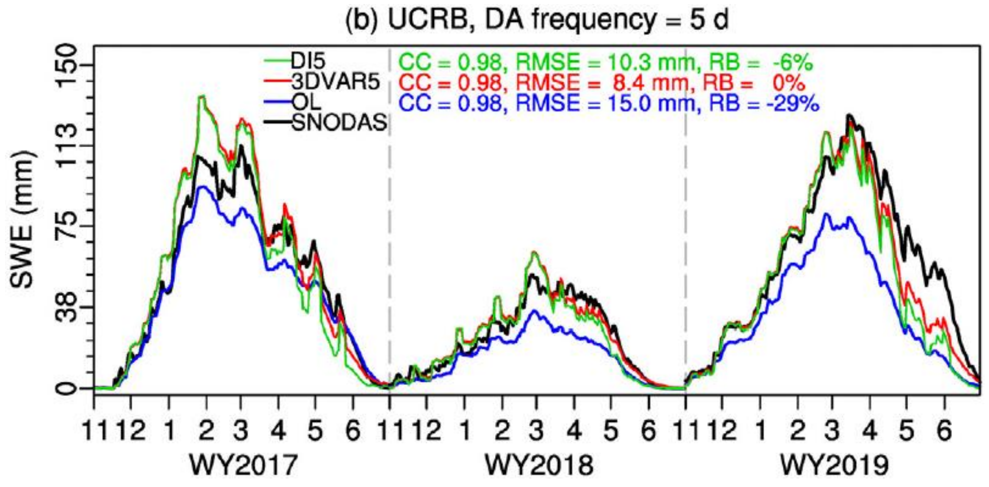
Background

Noah-MP



(He et al. 2019)

NWM

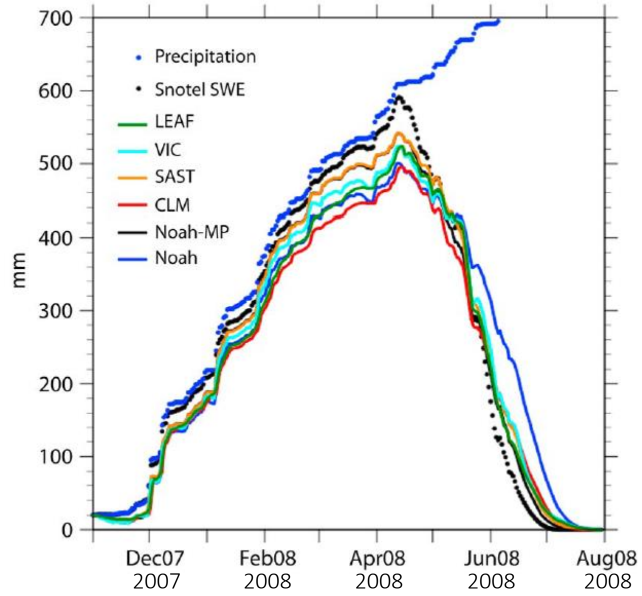


OL: open loop; 3DVAR: 3D variational; DI: direct insertion

(Gan et al., 2022)

Different LSMs

112 SNOTEL sites
in Colorado River Headwaters



(Chen et al. 2014)

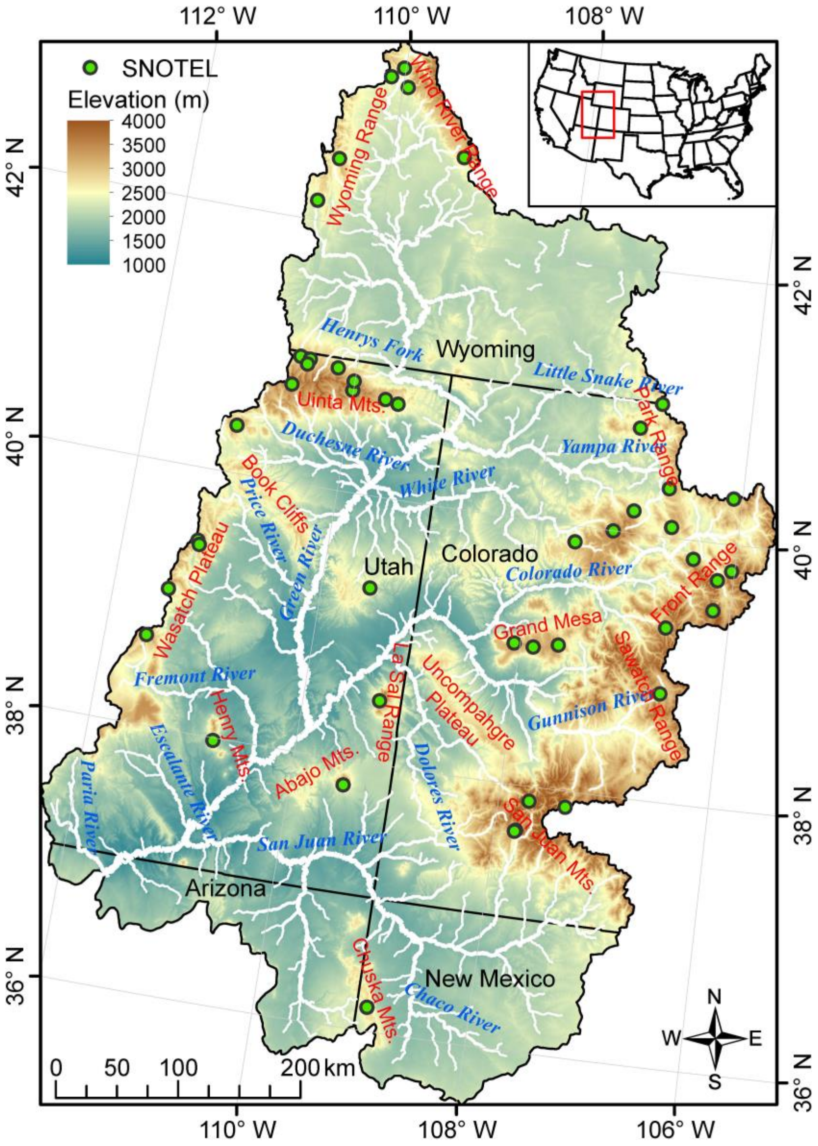
- LSMs underestimate snow accumulation and hence peak SWE in Upper Colorado River Basin (UCRB)
- Sources of uncertainty: Forcing errors and model deficiencies (structure and parameter)

Research questions

- Forcing data impact
  - How do errors in forcing data (precipitation and air temperature) affect snowpack simulations?
- Model parameterization influence
  - What is the relative impact of different model parameterization schemes on snowpack simulation accuracy?
- Enhancing predictability in complex regions
  - Can optimal parameterization schemes, combined with bias-corrected forcing data, enhance snowpack predictability in UCRB?

Gan, Y., Zhang, Y., Kongoli, C., & Pan, M. (2024). The role of forcing and parameterization in improving snow simulation in the Upper Colorado River Basin using the National Water Model. *Water Resources Research*. (Under review)

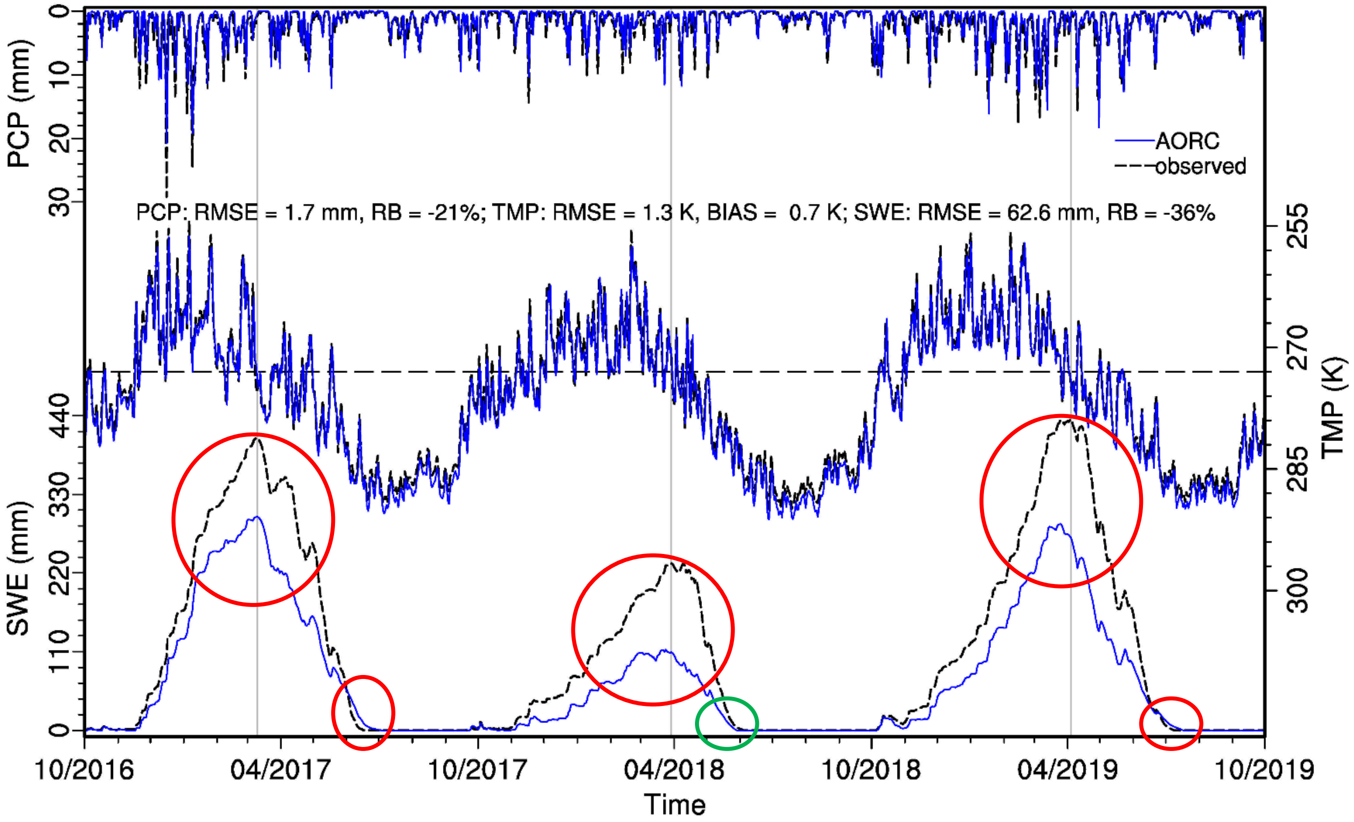
Study area and data



- Model: NWM v2.1 (1-km resolution for the Noah-MP)
- Static data: Obtained from the National Water Center (NWC) and subset for the UCRB (870×603 1-km grid cells)
- Forcing data: 1-km hourly AORC forcing data (Fall et al., 2023) for water years (WYs) 2016–2019
- Observation data: Bias-corrected and quality-controlled (BCQC) SNOTEL data for 46 sites (Yan et al., 2018; Sun et al. 2019; https://www.pnnl.gov/data-products)

Evaluation of AORC driven SWE

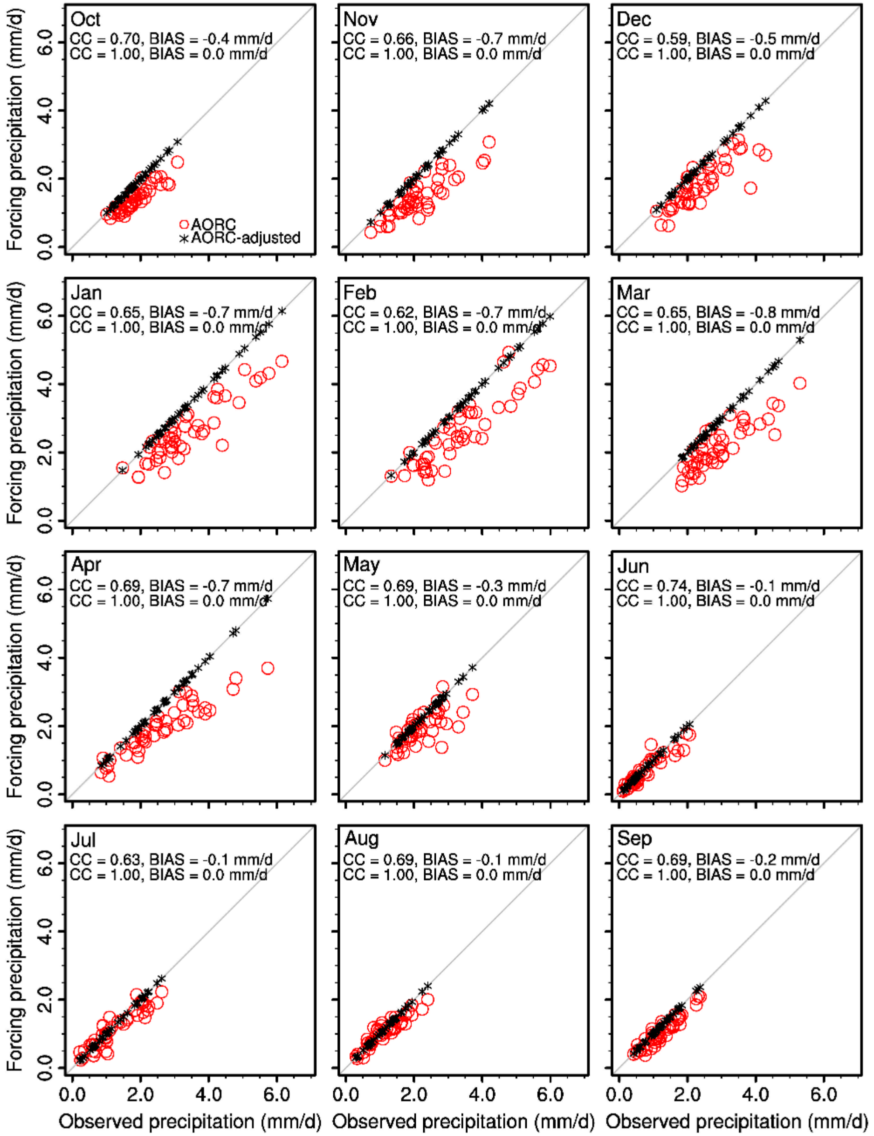
Experiment ID	Experiment name	Adjusted forcing variables	Scheme combination
1	CTL	none	default



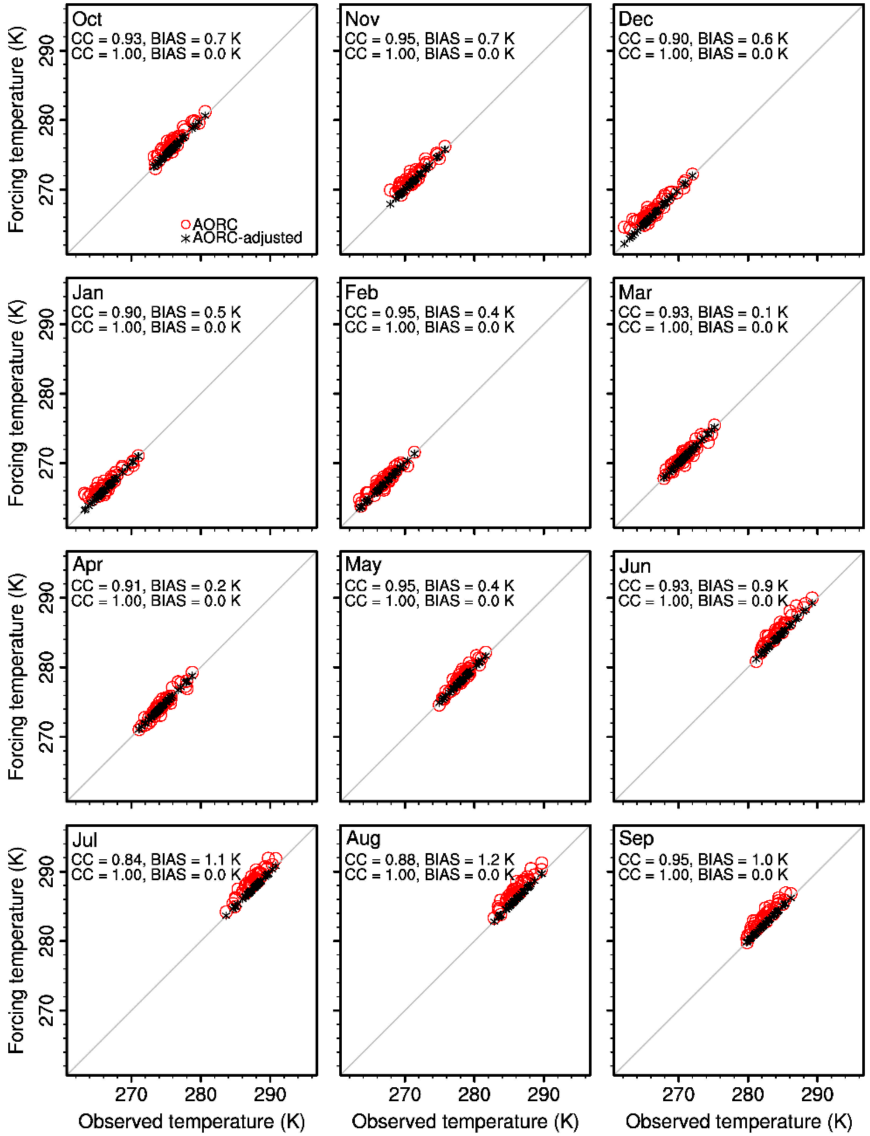
- NWM captures the overall temporal variation of SWE, but underestimates the magnitude by 36% (RMSE = 62.6 mm)
- Slower snow ablation is noted in WY 2017 and WY 2019, while faster snow ablation occurs in WY 2018
- Possible reasons
    - Errors in forcing data (e.g., a 21% precipitation underestimate and a slight air temperature overestimate of 0.7 K)
    - Model deficiencies in rainfall/snowfall partitioning and snow ablation physics (e.g., snow albedo and net radiation)

The role of forcing

Precipitation (forcing vs. observed)

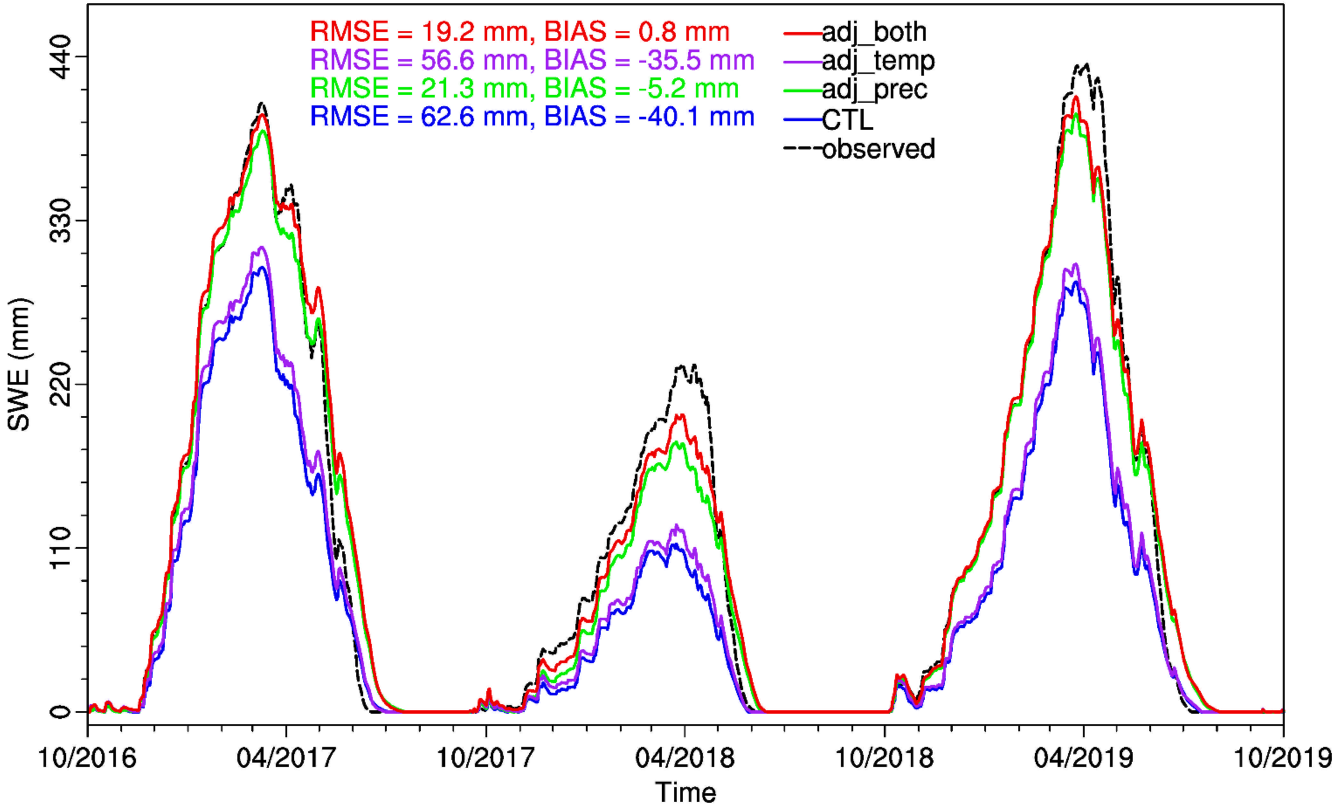


Temperature (forcing vs. observed)



The role of forcing

Experiment ID	Experiment name	Adjusted forcing variables	Scheme combination
1	CTL	none	default
2	adj_prec	precipitation	default
3	adj_temp	temperature	default
4	adj_both	precipitation and temperature	default



- adj_prec vs. CTL
  - Reduces RMSE by 66%
- adj_temp vs. CTL
  - Reduces RMSE by 10%
- adj_both vs. CTL
  - Reduces RMSE by 69%

The role of parameterization

2×2×3×2×3=72 combinations

Physical process	Parameterization schemes
Surface exchange coefficient for heat (SFC)	1. Monin–Obukhov (Monin & Obukhov, 1954; default) 2. Chen97 (Chen et al., 1997)
Snow surface albedo (ALB)	1. BATS (Yang et al., 1997; default) 2. CLASS (Verseghy, 1991)
Rainfall and snowfall partitioning (SNF)	1. Jordan91 (Jordan, 1991; default) 2. BATS (Dickinson et al., 1986) 3. Noah (Chen et al., 1996)
Lower boundary of soil temperature (TBOT)	1. Zero-flux (Niu et al., 2011) 2. Noah (Pan & Mahrt, 1987; default)
Snow/soil temperature time scheme (STC)	1. Semi-implicit (Yang et al., 2011) 2. Fully implicit (Pan & Mahrt, 1987) 3. Modified semi-implicit (Yang et al., 2011; default)

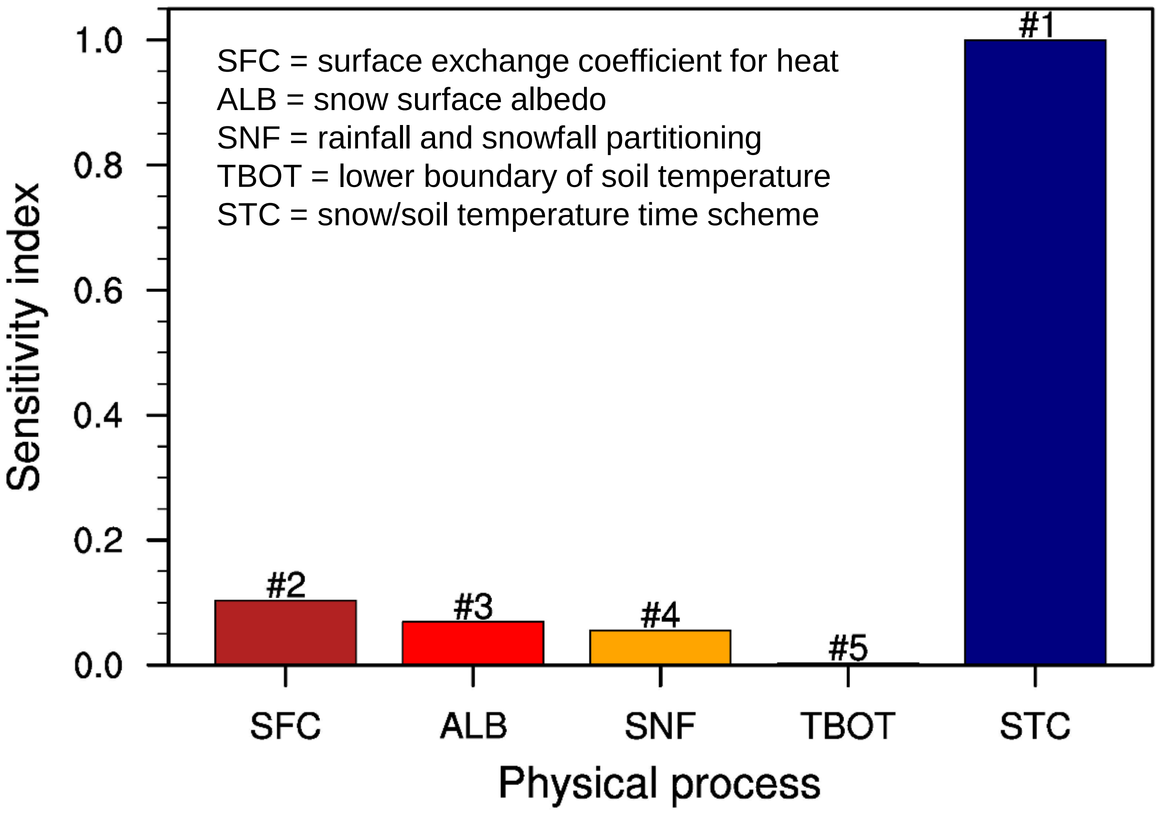
72 experiments driven by adjusted AORC forcings (both precipitation and temperature)

Sensitivity analysis of the physical processes

Assume that there are m distinct physical processes (here $m = 5$), each with various parameterization schemes (2 or 3 for different processes). The mean value of the evaluation metric (RMSE) for each specific scheme j ($j = 1, 2, \cdots$) within a given process i ($i = 1, 2, \cdots, m$) can be represented as $\bar{Y}_j^{(i)}$. We defined an index to quantify the sensitivities of these physical processes as follows:

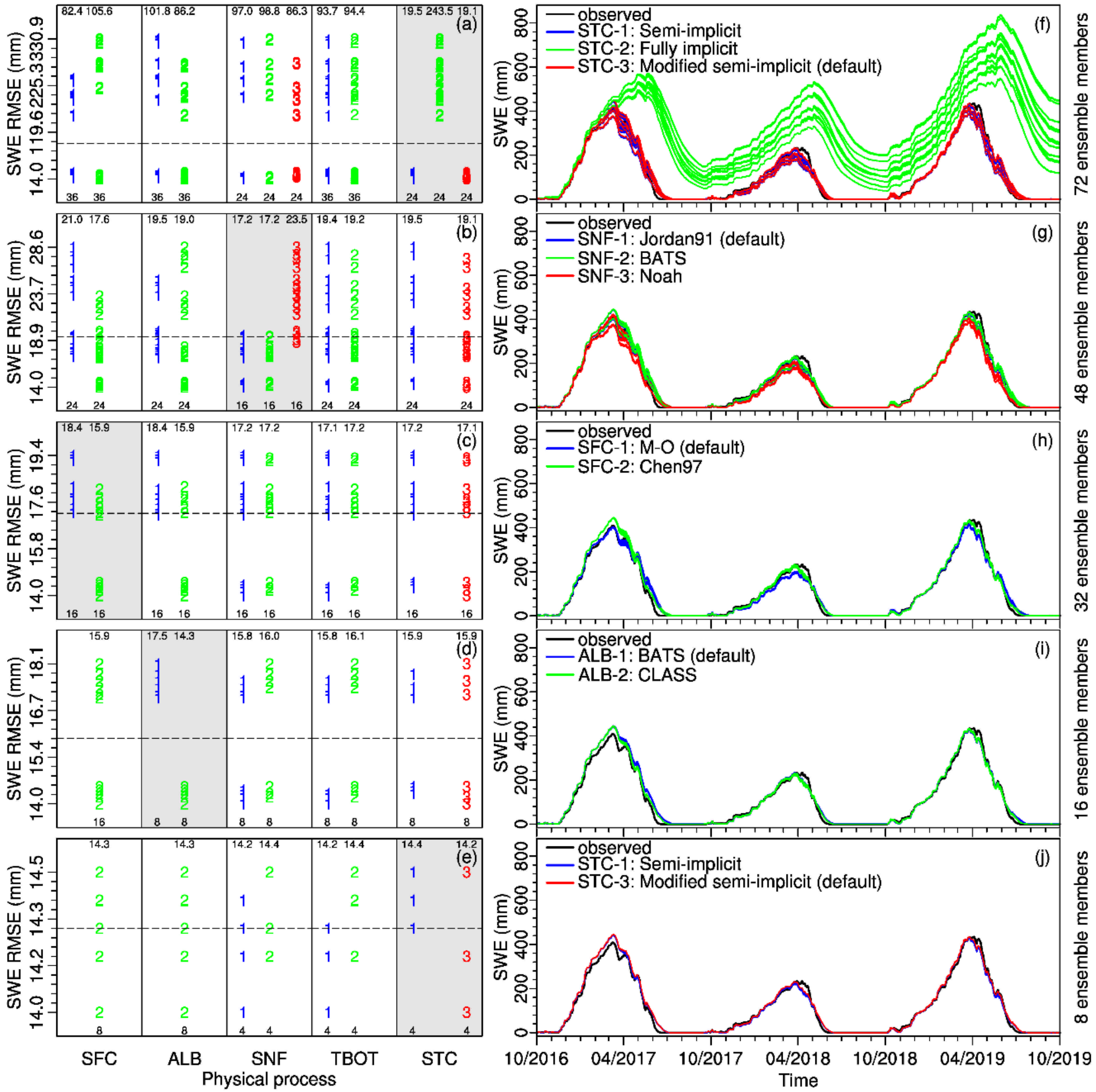
$$S_i = \frac{\Delta\bar{Y}^{(i)}}{max\{\Delta\bar{Y}^{(1)}, \Delta\bar{Y}^{(2)}, \cdots, \Delta\bar{Y}^{(m)}\}}$$

where $\Delta\bar{Y}^{(i)} = \bar{Y}_{max}^{(i)} - \bar{Y}_{min}^{(i)}$ is the difference between the largest and the smallest mean values of the evaluation metric (RMSE) for the ith process.



STC > SFC > ALB > SNF > TBOT

Combinatorial optimization of the schemes



- STC-2: Tends to generate larger coefficients B in the thermal diffusion equation, resulting in smaller increments for the snow surface temperature, which leads to more extensive snow cover and delayed snow ablation
- SNF-3: Partitions less precipitation into snowfall due to its lower air temperature threshold
- SFC-1: Produces a larger negative bias during the snow accumulation period and a larger positive bias during the late snow ablation period, because it produces a lower C_H, which results in a less efficient land surface ventilation and higher surface skin temperature (Niu et al., 2011)
- ALB-1: Produces a slightly higher snow surface albedo and, consequently, retaining more snow than the ALB-2 (CLASS) scheme, primarily due to its weaker snow aging effects (Niu et al., 2011)
- STC-1: Sets the whole grid cell to freezing temperature, while STC-3 only sets the snow-covered part to freezing temperature, producing more realistic ground surface temperature

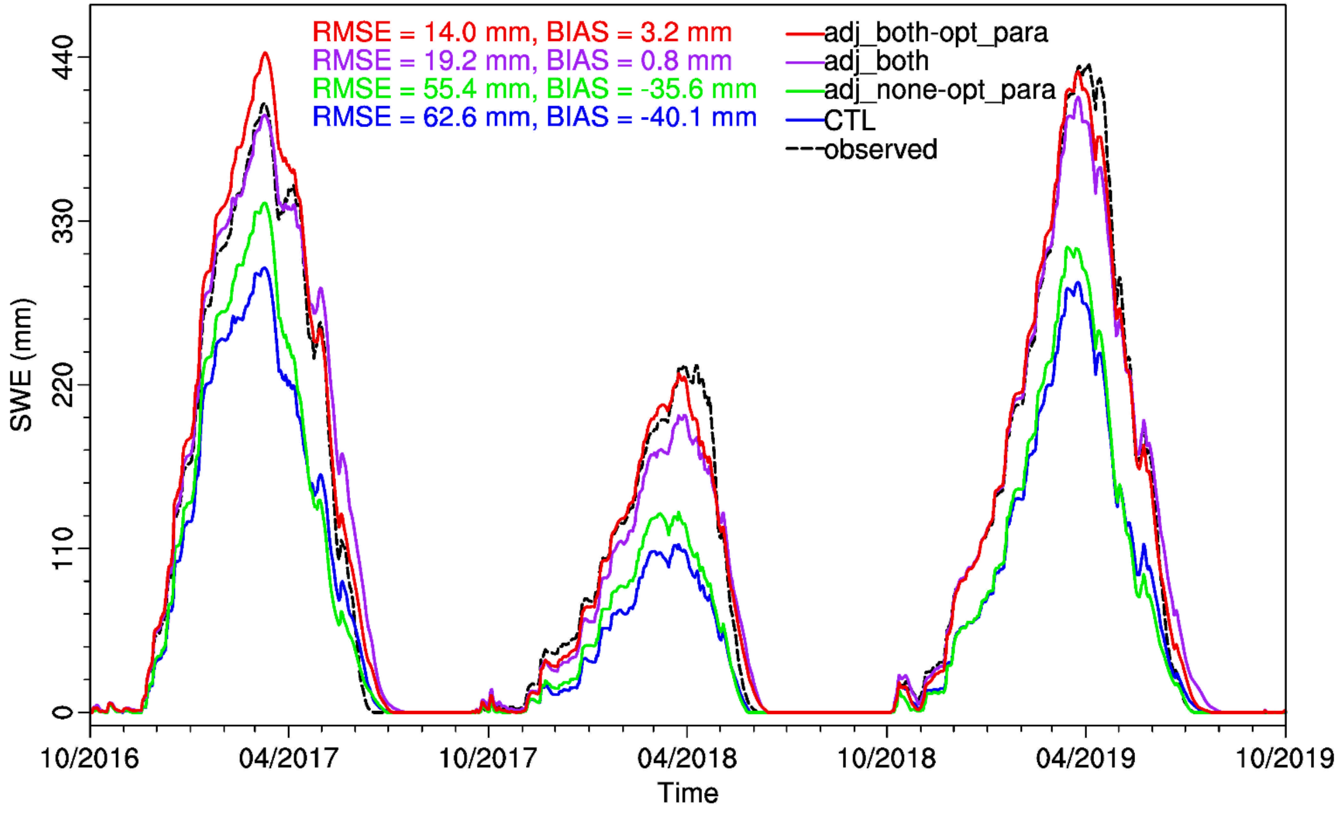
Optimal vs. default scheme combinations

Default scheme combination: SFC-1, ALB-1, SNF-1, TBOT-2, and STC-3
Optimal scheme combination: SFC-2, ALB-2, SNF-1, TBOT-1, and STC-3

Physical process	Parameterization schemes
Surface exchange coefficient for heat (SFC)	1. Monin–Obukhov (Monin & Obukhov, 1954; default) 2. Chen97 (Chen et al., 1997)
Snow surface albedo (ALB)	1. BATS (Yang et al., 1997; default) 2. CLASS (Verseghy, 1991)
Rainfall and snowfall partitioning (SNF)	1. Jordan91 (Jordan, 1991; default) 2. BATS (Dickinson et al., 1986) 3. Noah (Chen et al., 1996)
Lower boundary of soil temperature (TBOT)	1. Zero-flux (Niu et al., 2011) 2. Noah (Pan & Mahrt, 1987; default)
Snow/soil temperature time scheme (STC)	1. Semi-implicit (Yang et al., 2011) 2. Fully implicit (Pan & Mahrt, 1987) 3. Modified semi-implicit (Yang et al., 2011; default)

Optimal vs. default scheme combinations

Experiment ID	Experiment name	Adjusted forcing variables	Scheme combination
1	CTL	none	default
2	adj_none-opt_para	none	optimized
3	adj_both	precipitation and temperature	default
4	adj_both-opt_para	precipitation and temperature	optimized



- adj_none-opt_para vs. CTL
  - Reduces RMSE by 12%
- adj_both-opt_para vs. adj_both
  - Reduces RMSE by 27%
- adj_both-opt_para vs. CTL
  - Reduces RMSE by 78%

Takeaways

- Forcing data impact
  - Adjusting AORC precipitation reduced SWE RMSE by 66%, adjusting temperature trimmed it by 10%, and adjusting both decreased it by 69%
  - SWE simulations are more sensitive to AORC precipitation adjustments than to adjustments in air temperature
- Model parameterization influence
  - Sensitivity: STC > SFC > ALB > SNF > TBOT
  - Optimization of parameterization scheme combination led to a 12% reduction in SWE RMSE
  - When combined with bias-corrected AORC precipitation and temperature, parameterization optimization achieved a remarkable 78% reduction in SWE RMSE
- Enhancing predictability in complex regions
  - Improve the quality of forcing data, especially precipitation, by incorporating more in-situ observations
  - Optimize model structures and mitigate model parameterization uncertainties
  - Improve physical processes such as rainfall/snowfall partitioning and snow ablation

Thank you!

Questions and Comments?

yanjun.gan@uta.edu