Constraining process-based snow hydrology using a deep learning snow model

Photo credit: Jeff Steele

Justin Pflug

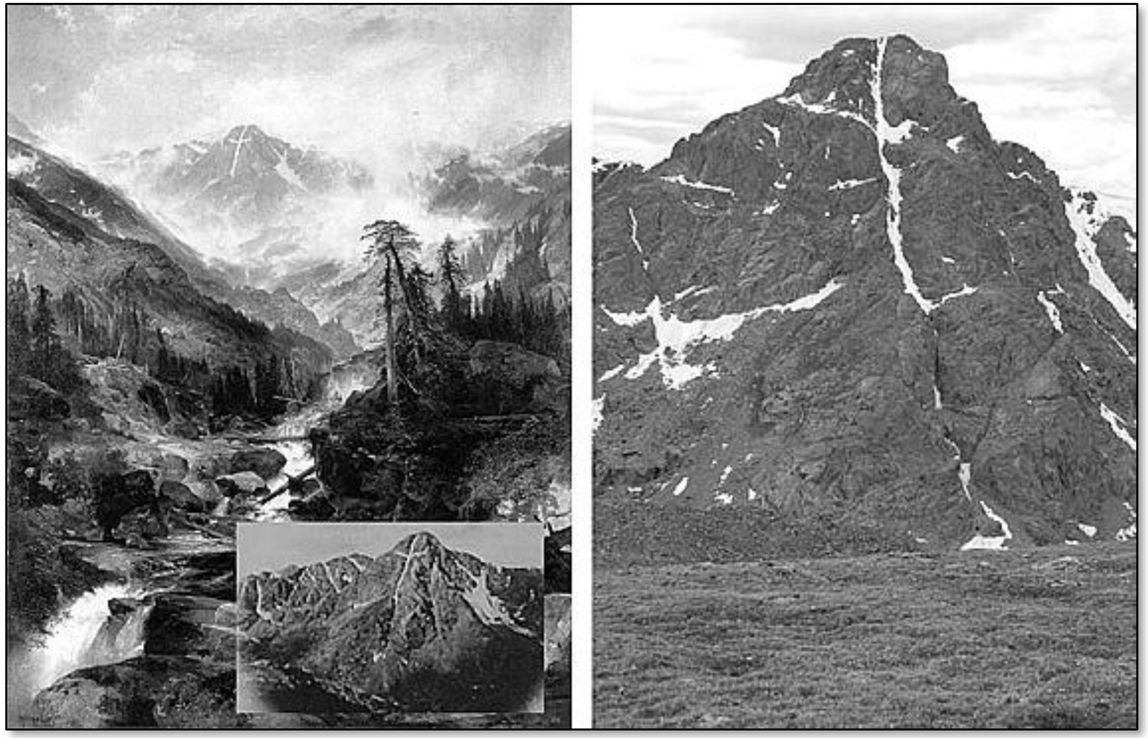
Associate Research Scientist
University of Maryland
Earth System Science Interdisciplinary Center
and NASA Goddard

***Coauthors**: Sujay Kumar, David Melissa Wrzesien, David Mocko, Kim Locke, Sarith Mahanama, Wanshu Nie, Ziheng Sun, Dorothy Hall, George Riggs, Goutam Konapala, Kristen Whitney, Kristi Arsenault*

WWAO, Connecting the Drops Webinar
25 June, 2026

The informative power of snow cover

Mountain of the Holy Cross, Colorado (127 years apart)



Sturm and Wager, 2010. *Using repeated patterns in snow distribution modeling: An arctic example*

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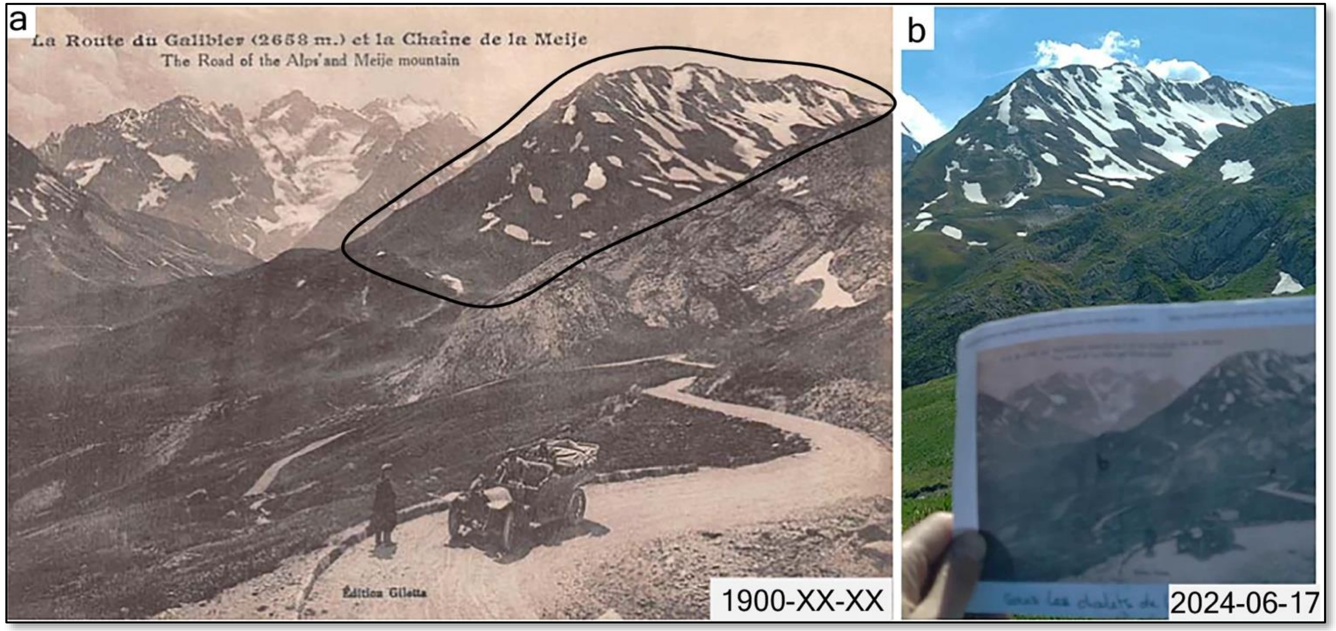

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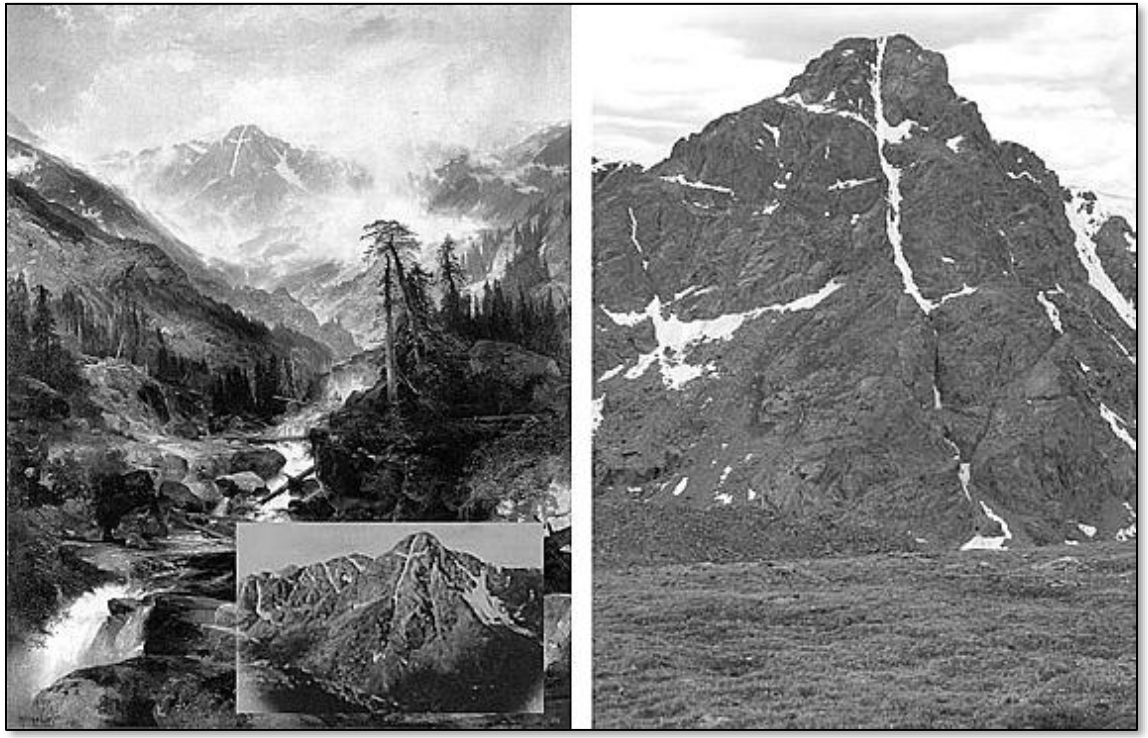

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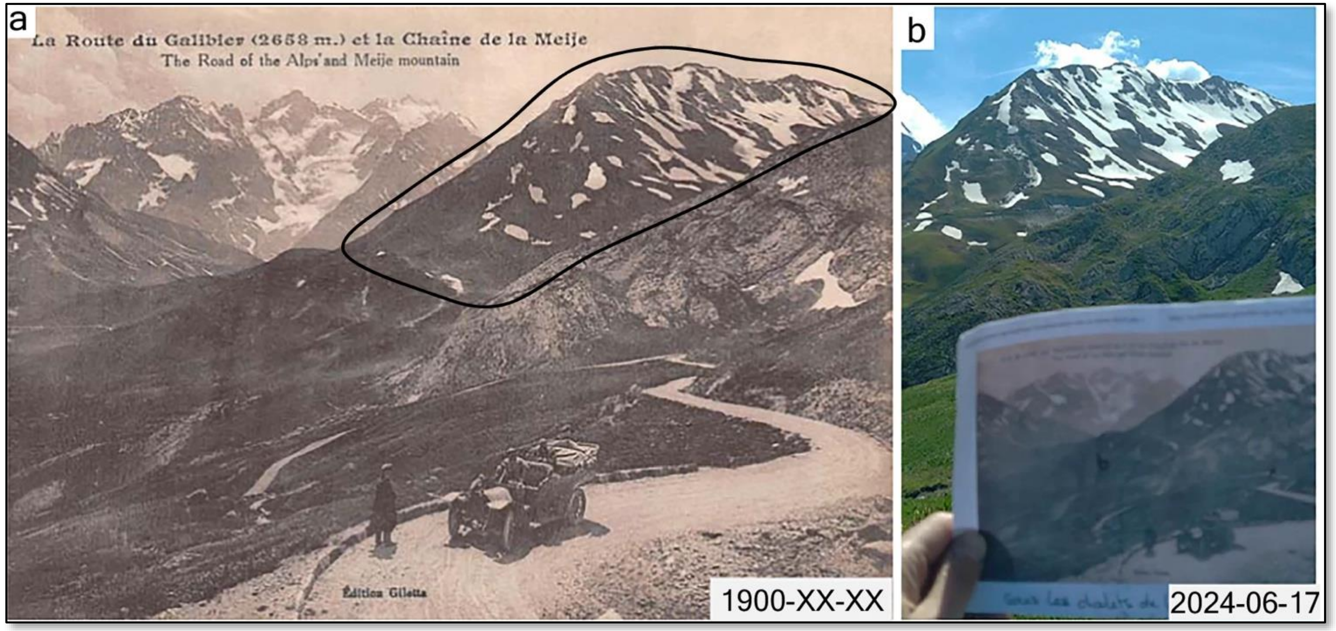
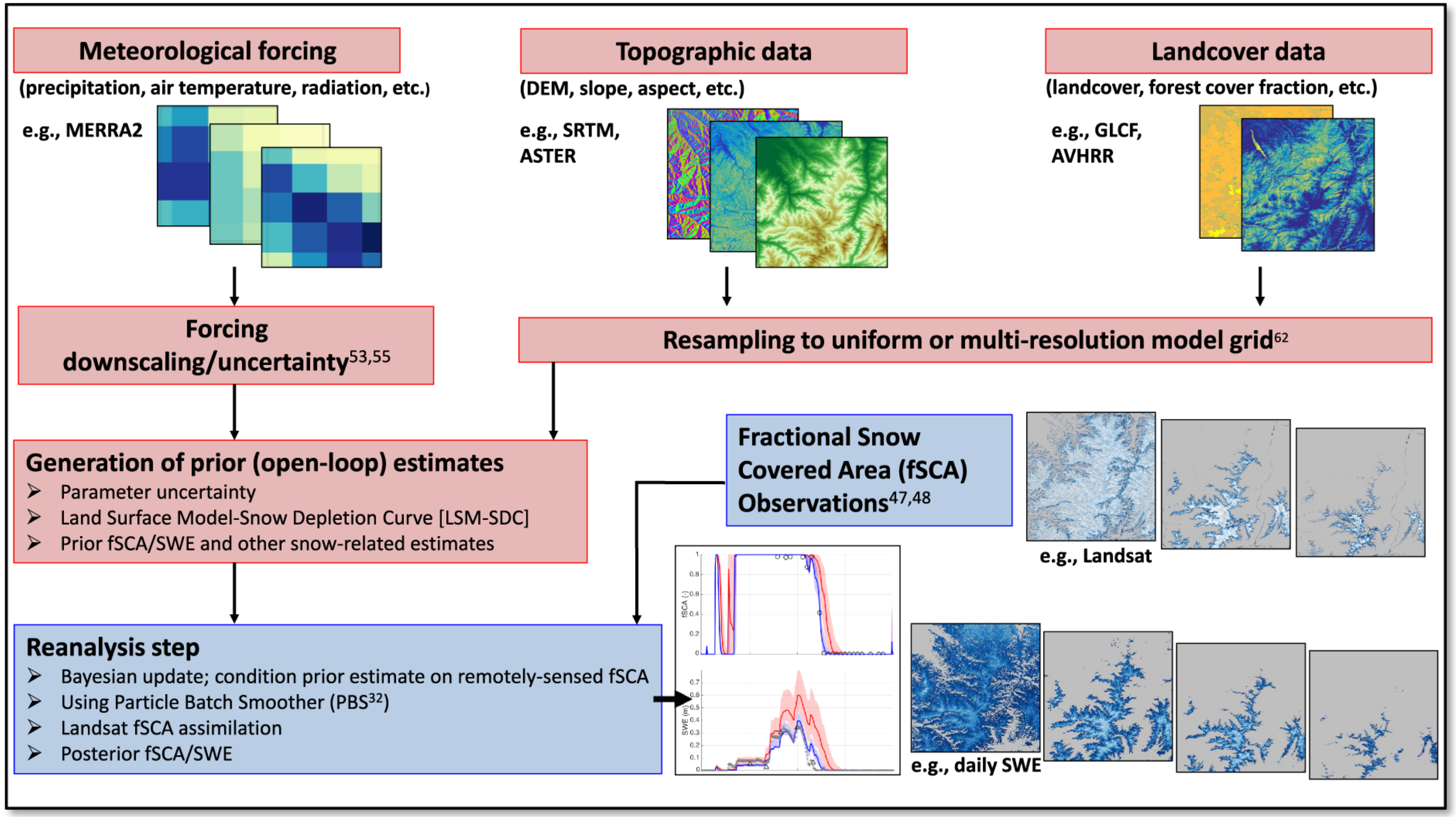


Choler et al. *2025. Legacy of snow cover on alpine landscapes.*

Yukigata (*noun*): recurring patterns formed by lingering patches of snow and exposed rock on mountainsides during spring snowmelt.

***Before there were written calendars in Japan**, farmers used the snow patterns on the hillsides and mountain slopes as a guide to the seasons…They gave these shapes whimsical names like the monkey or the snake. **When certain shapes emerged, they knew it was time to plant crops** (Sturm and Wagner, 2010)*

Western US Snow Reanalysis ("WUS-SR" – or – "UCLA")



Meteorological forcing
(precipitation, air temperature, radiation, etc.)
e.g., MERRA2

Topographic data
(DEM, slope, aspect, etc.)
e.g., SRTM, ASTER

Landcover data
(landcover, forest cover fraction, etc.)
e.g., GLCF, AVHRR

Forcing downscaling/uncertainty[53,55]

Resampling to uniform or multi-resolution model grid[62]

Generation of prior (open-loop) estimates
- Parameter uncertainty
- Land Surface Model-Snow Depletion Curve [LSM-SDC]
- Prior fSCA/SWE and other snow-related estimates

Fractional Snow Covered Area (fSCA) Observations[47,48]

e.g., Landsat

Reanalysis step
- Bayesian update; condition prior estimate on remotely-sensed fSCA
- Using Particle Batch Smoother (PBS[32])
- Landsat fSCA assimilation
- Posterior fSCA/SWE

e.g., daily SWE

Fang et al. 2022. *A western United States snow reanalysis dataset over the Landsat era from water years 1985 to 2021*

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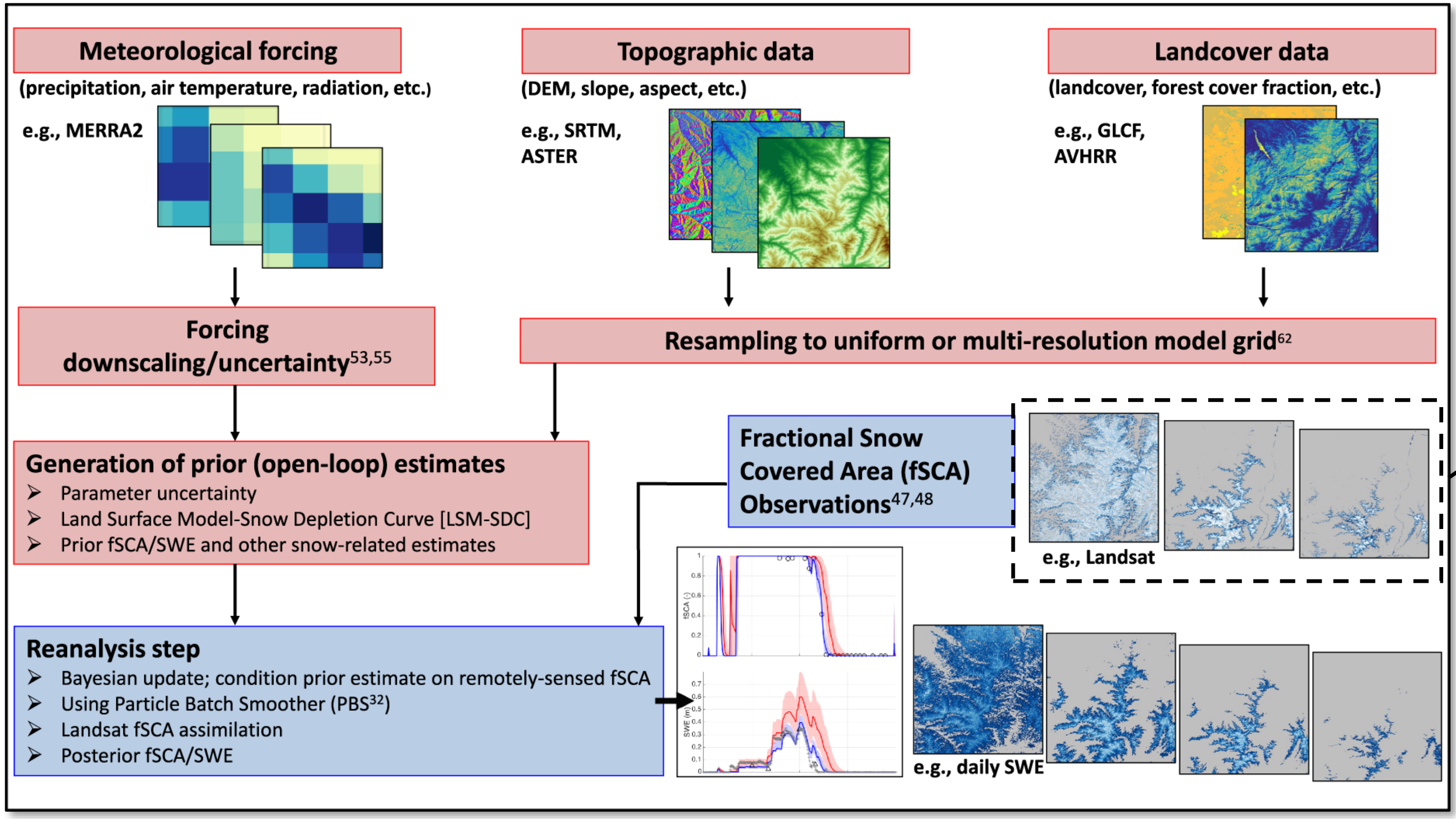

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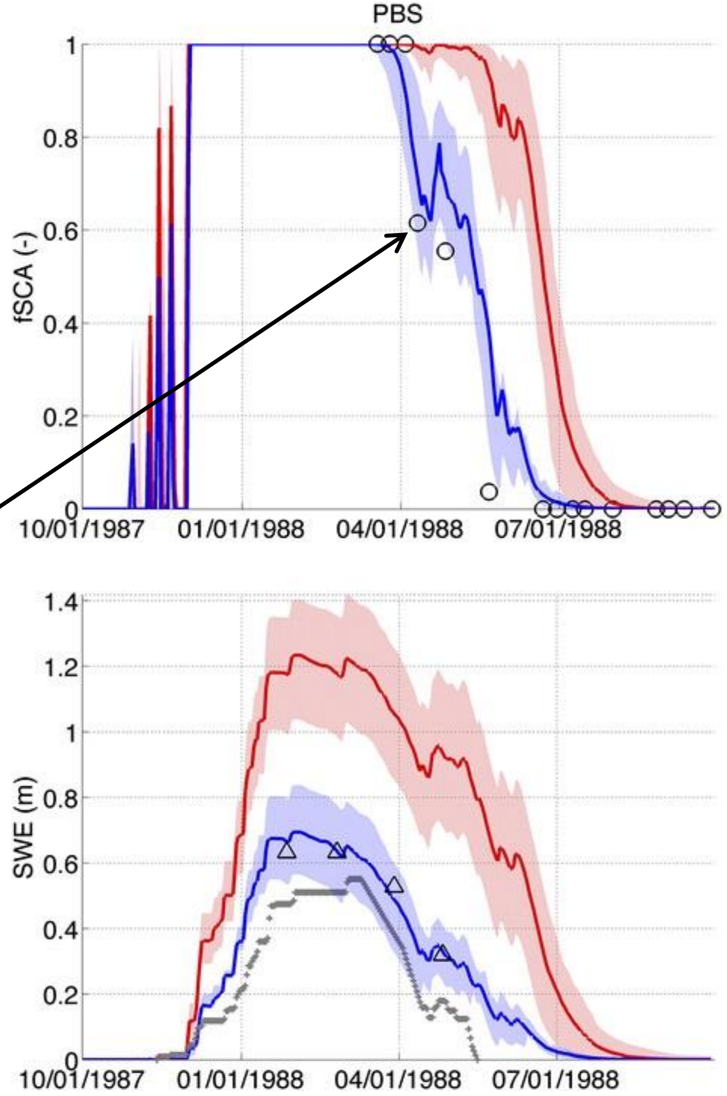
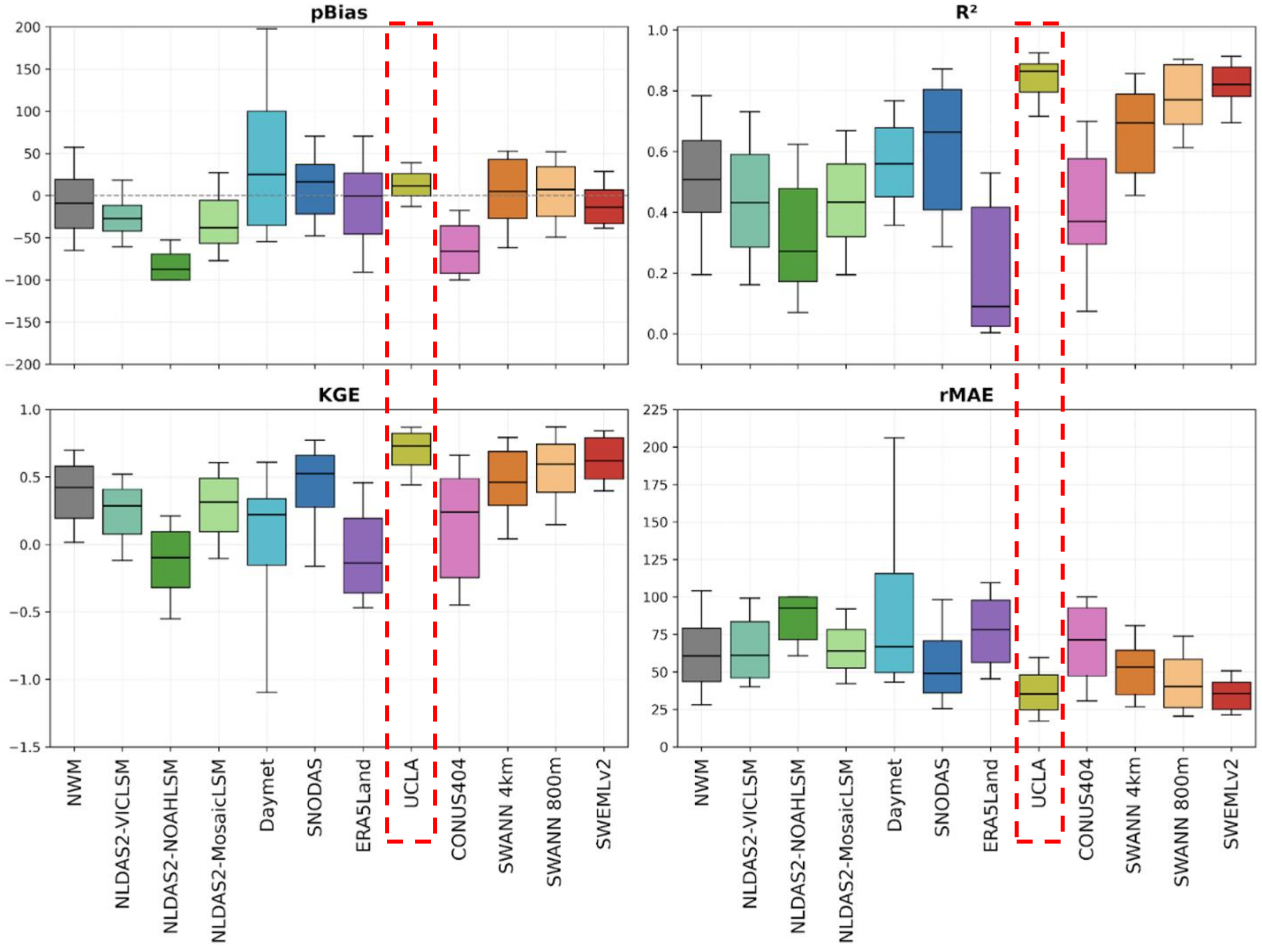
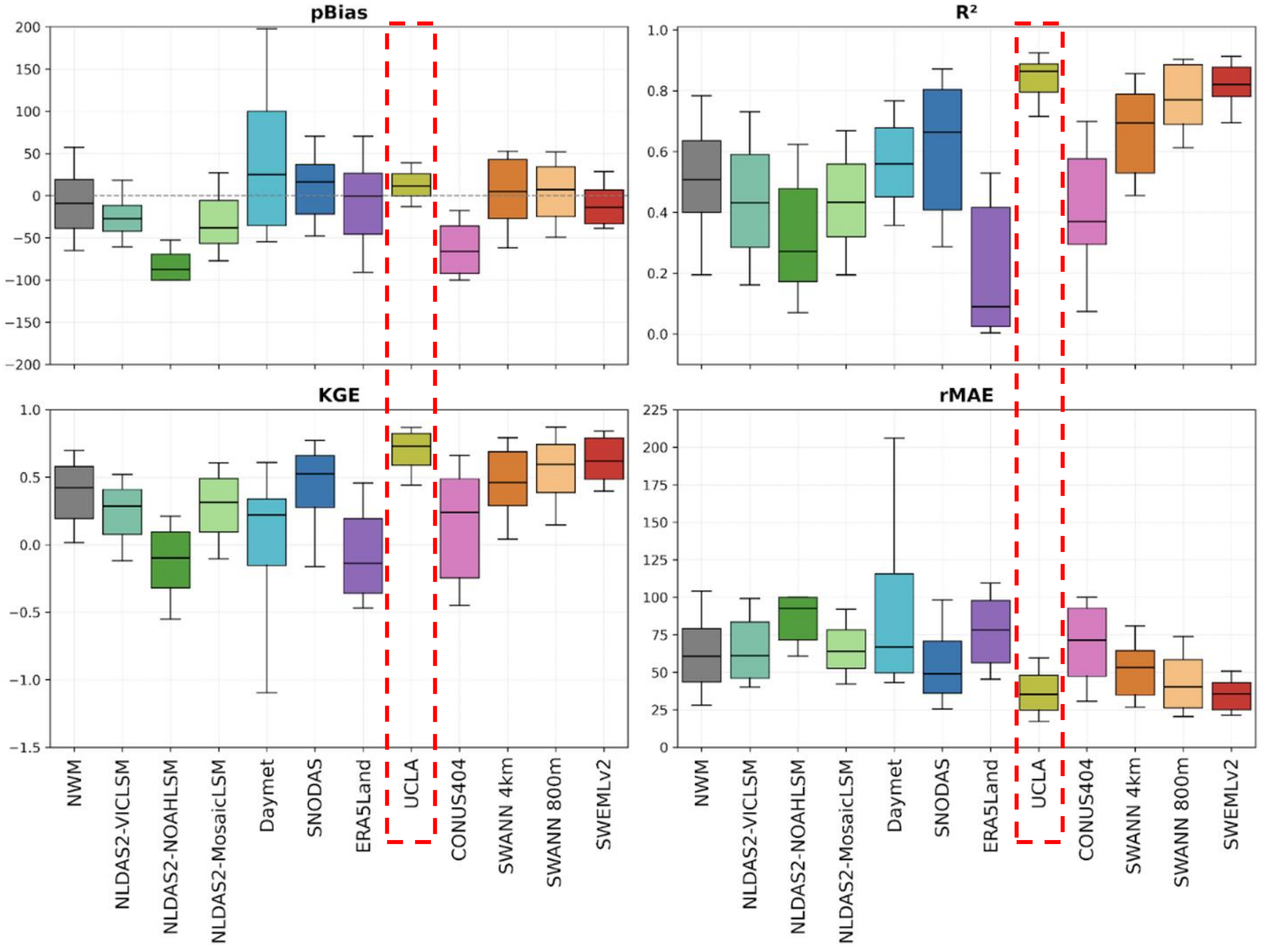


Western US Snow Reanalysis



Ritchie et al. *Benchmarking catchment-scale snow water equivalent datasets and models in the western United States [in review]*

Western US Snow Reanalysis



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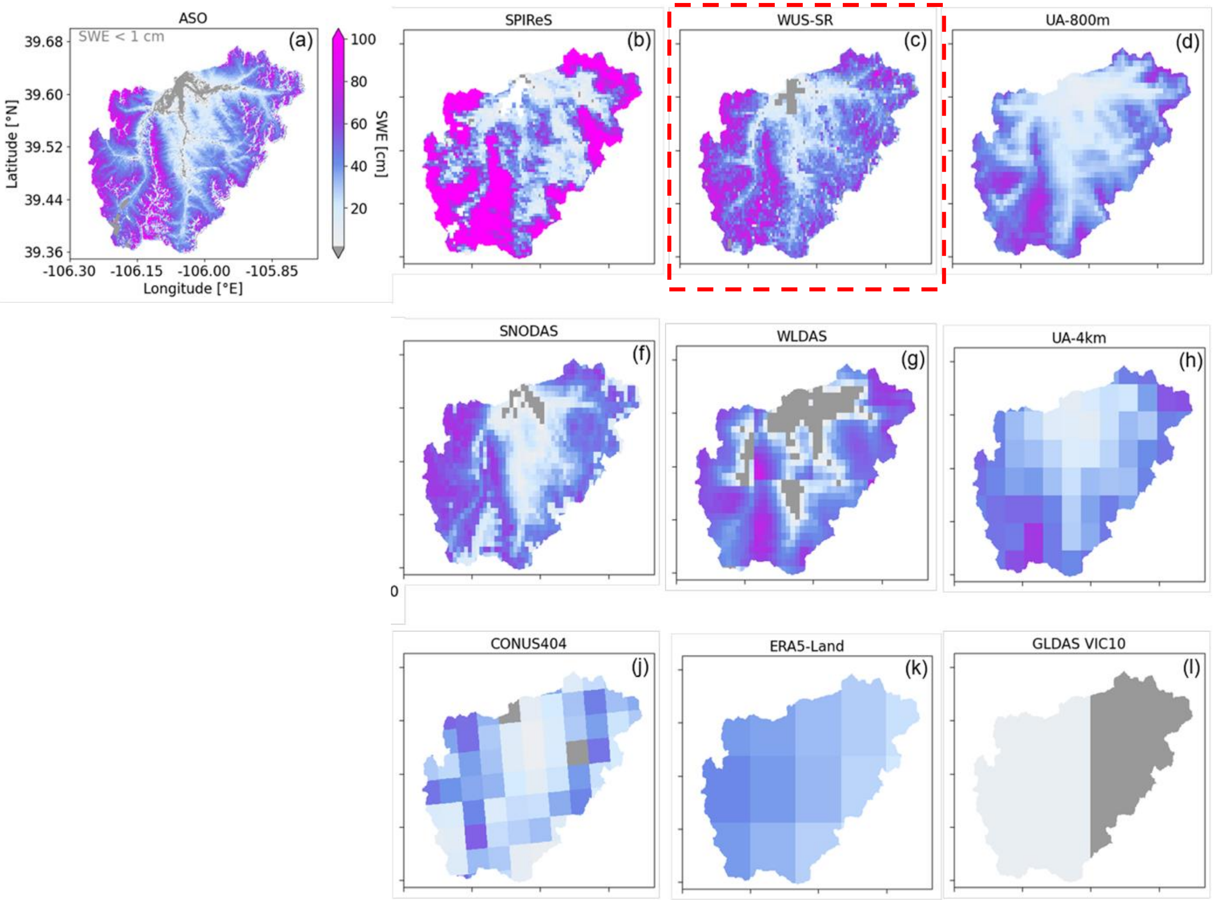
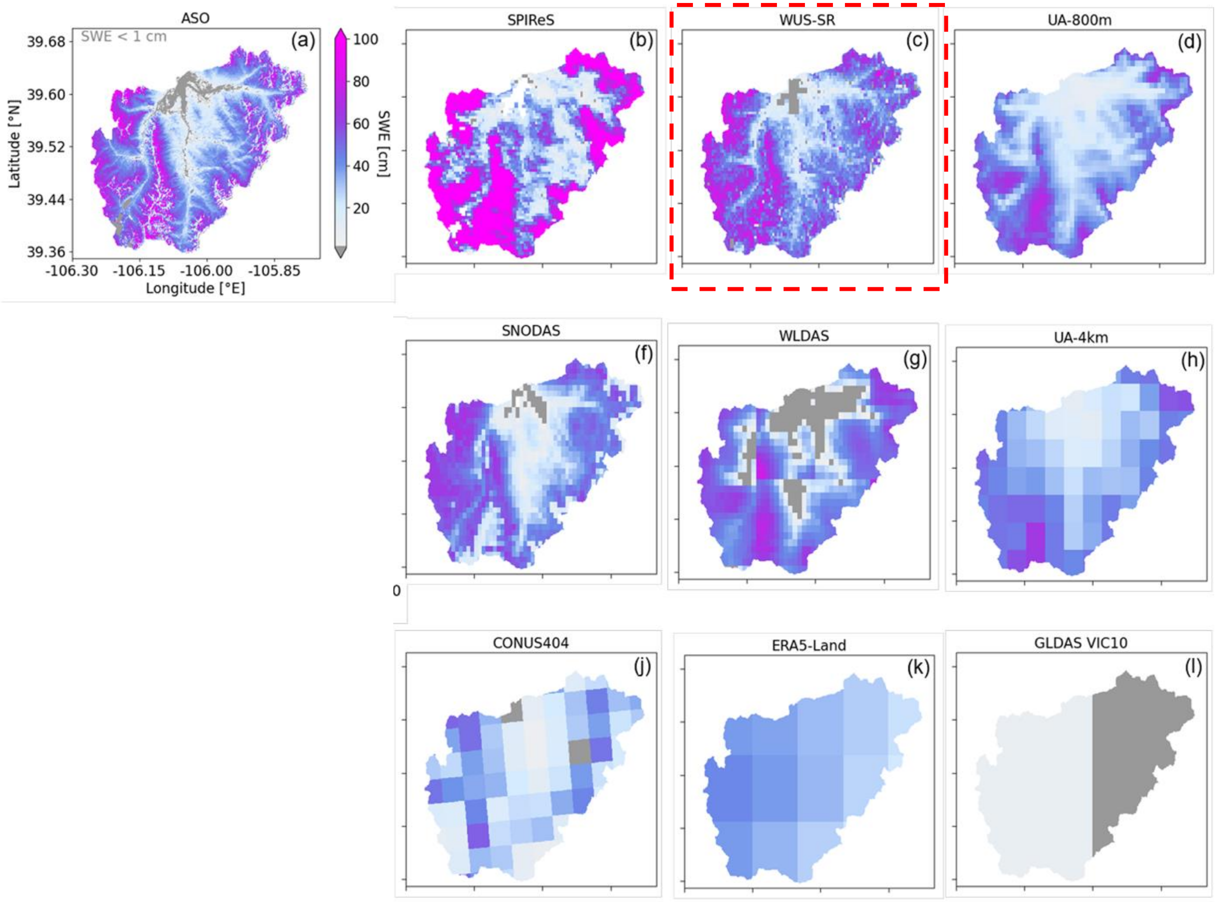


Lundquist et al. *Snow what? Comparing snow products to reveal what works, where, and why [in review]*

Western US Snow Reanalysis

Challenges for large-scale and real-time applications:

- Based on a large-ensemble of snow simulations
- Available for select years and regions
- WUS-SR snow cover assimilation requires snow disappearance before reanalyzing SWE → not available in real-time



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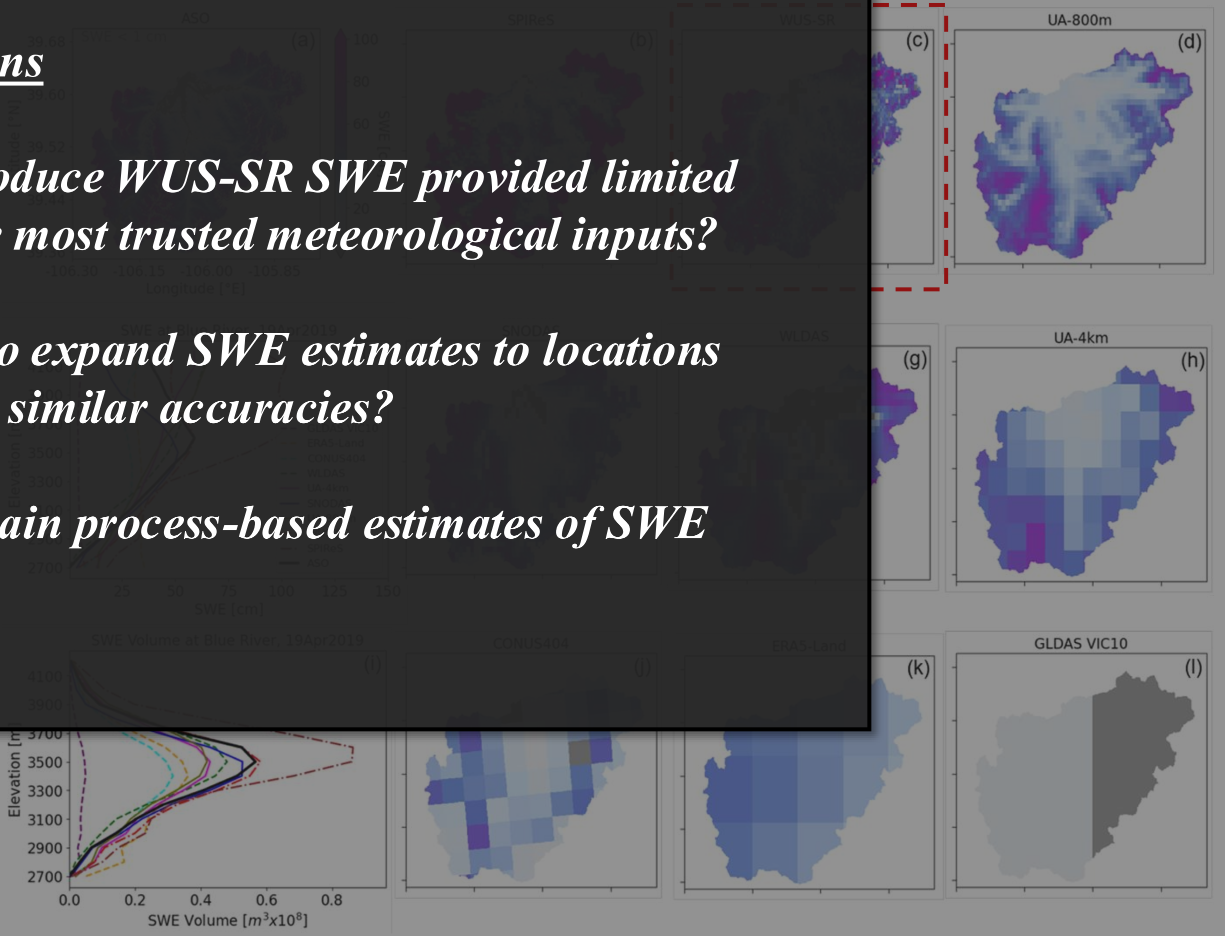
Western US Snow Reanalysis (WUS-SR)

However, there are challenges to using this data for real-time and global applications:

- Based on a large-ensemble of snow simulations
- Available for select years and regions
- WUS-SR snow cover assimilation requires snow disappearance before reanalyzing SWE → not available in real-time

Questions

1. ***Can a deep-learning model learn to reproduce WUS-SR SWE provided limited remote sensing observations and only the most trusted meteorological inputs?***
2. ***Can the model be generalizable enough to expand SWE estimates to locations outside of the Western United States with similar accuracies?***
3. ***How can this deep learning model constrain process-based estimates of SWE and snow driven hydrology?***



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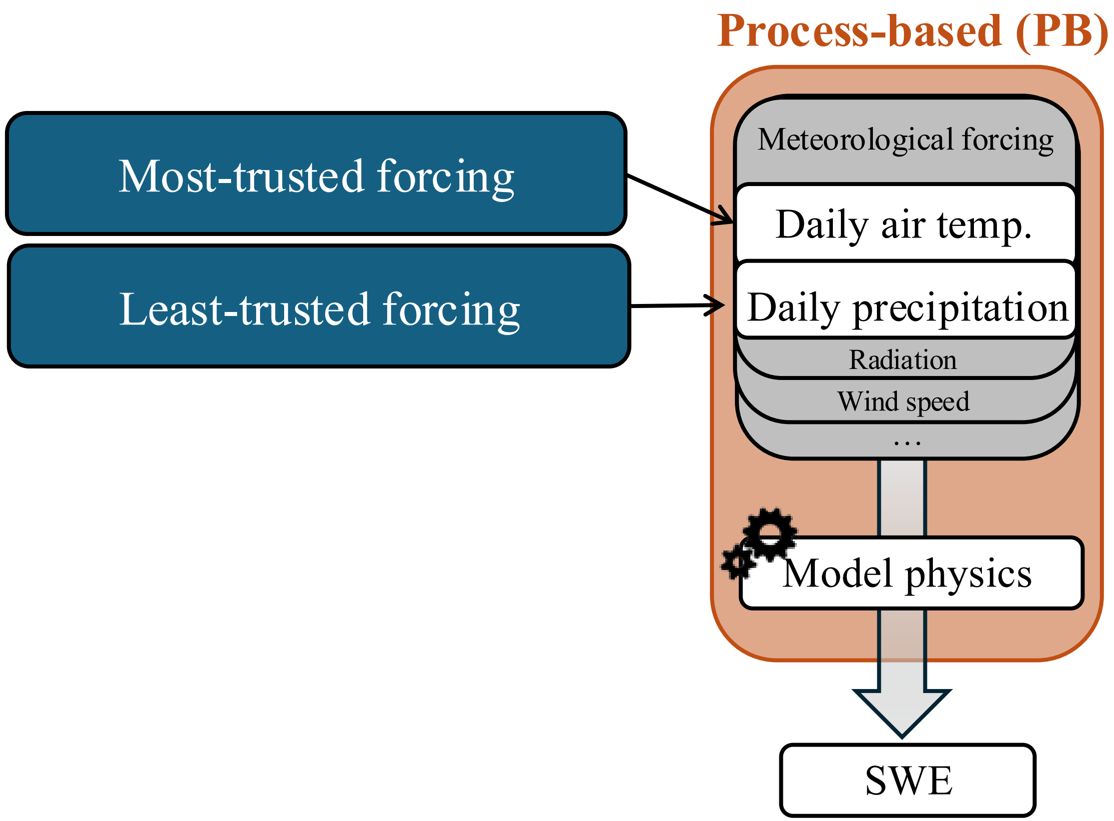
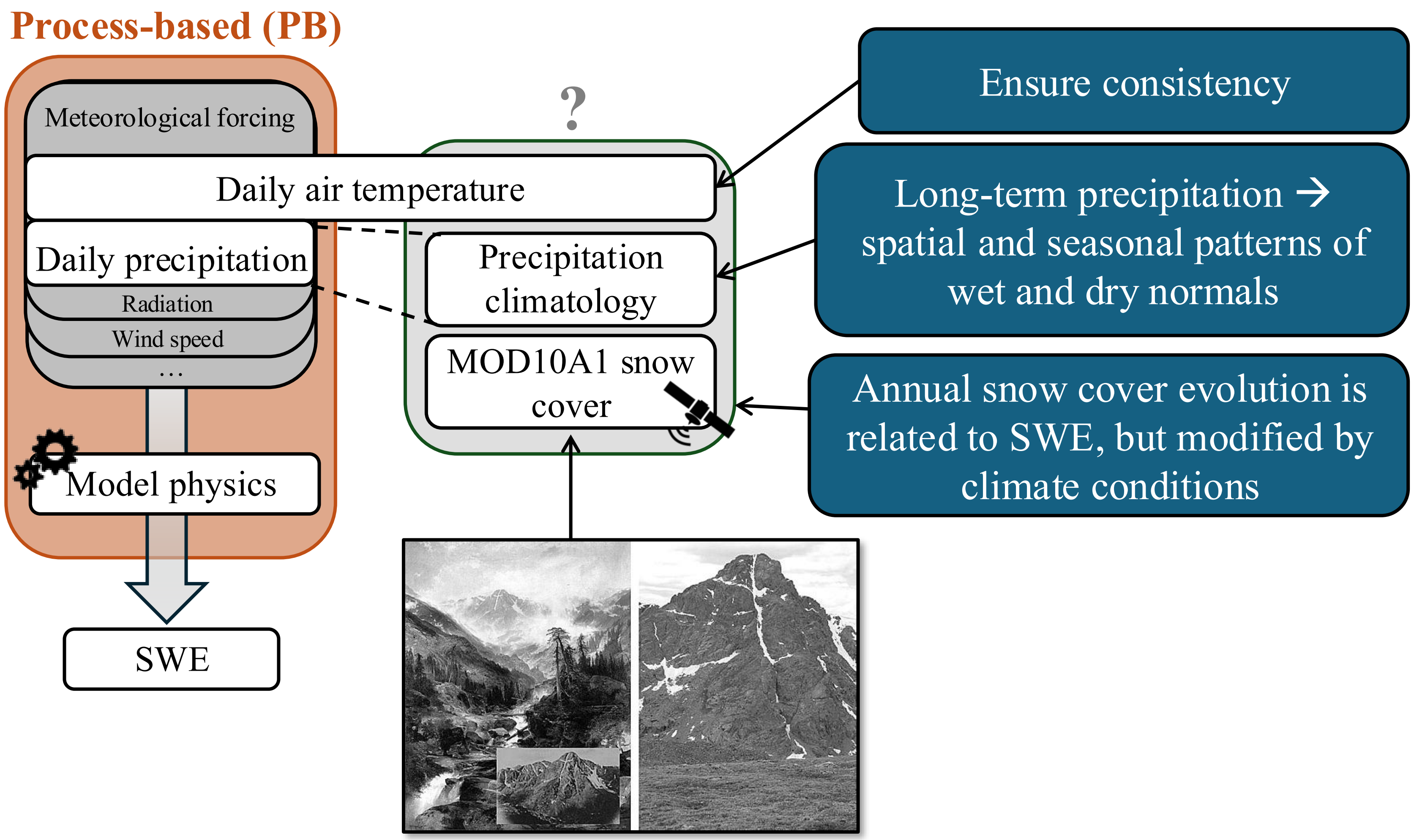
Process-based snow modeling



Data-driven snow modeling



Process-based (PB)

Meteorological forcing

Daily air temperature

Daily precipitation

Radiation

Wind speed

…

Model physics

SWE

?

Precipitation climatology

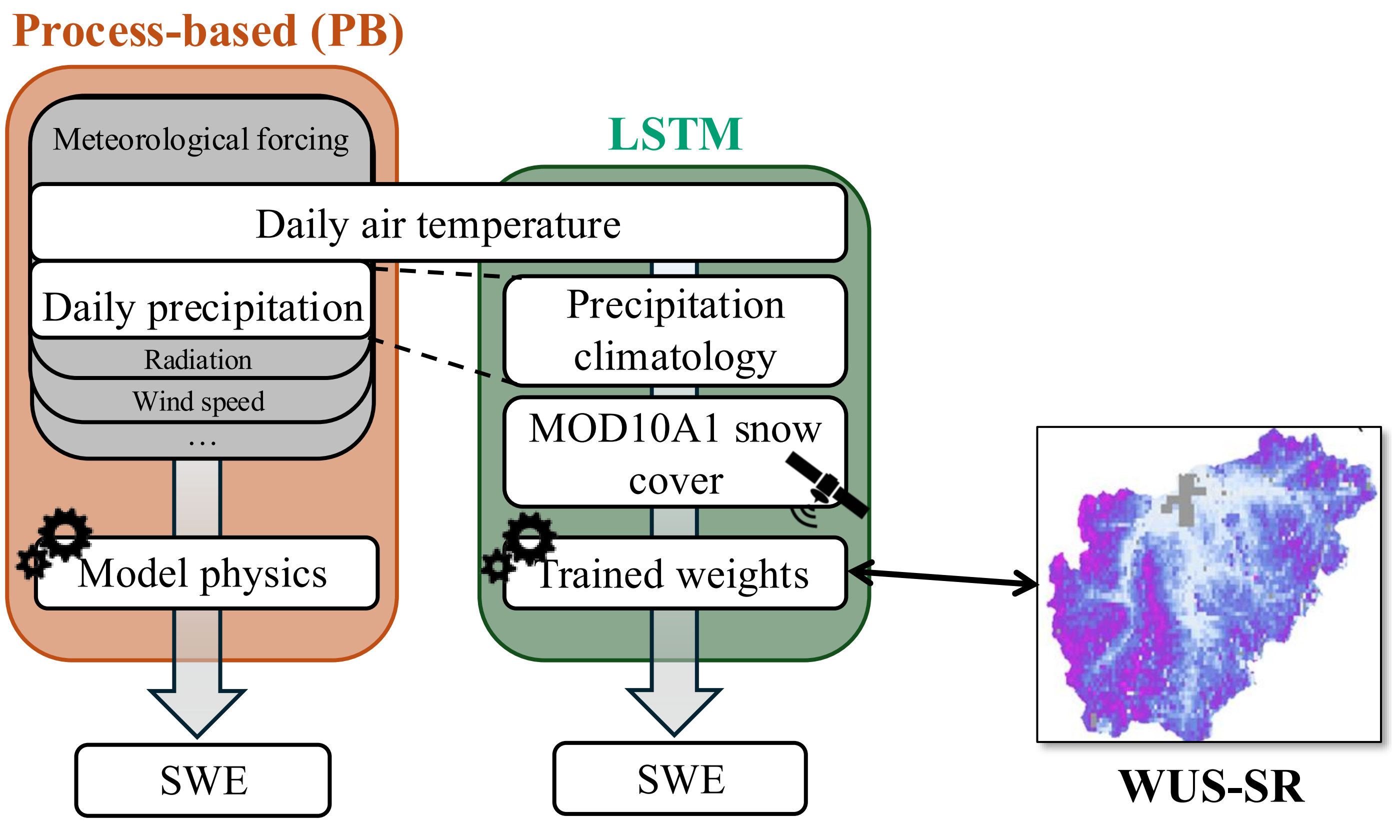
MOD10A1 snow cover

Ensure consistency

Long-term precipitation → spatial and seasonal patterns of wet and dry normals

Annual snow cover evolution is related to SWE, but modified by climate conditions

Data-driven snow modeling

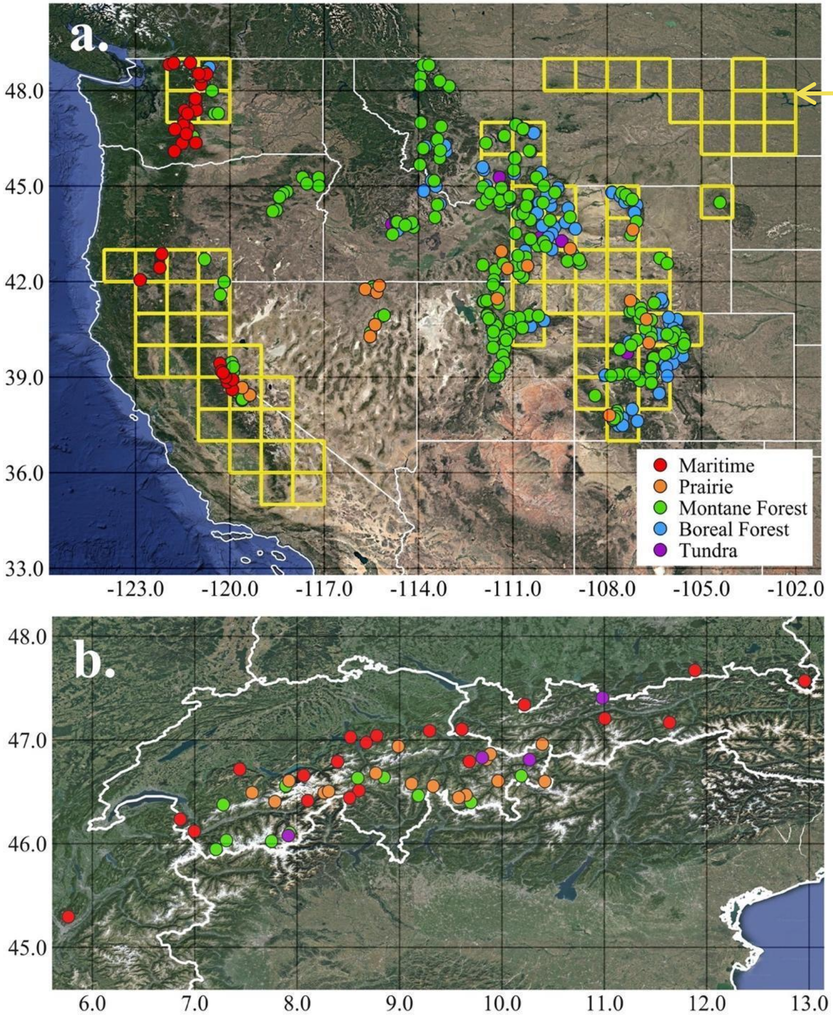


WUS-SR

LSTM

- Recurrent Neural Network (RNN)
- More effectively passes pertinent information for both long (e.g., seasonal) and short (e.g., daily) data lengths
- Good for time series of information, especially seasonal signals

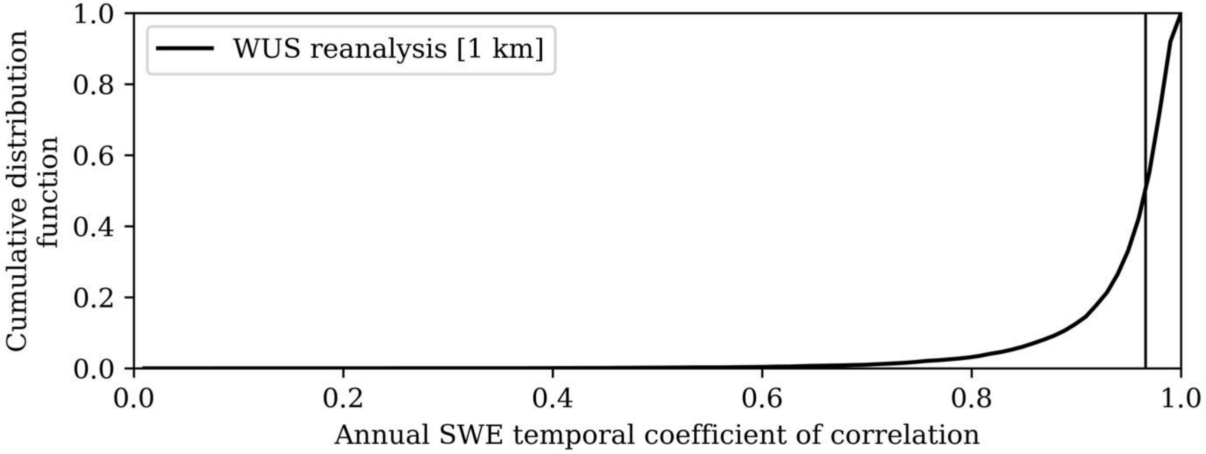
Data-driven snow modeling

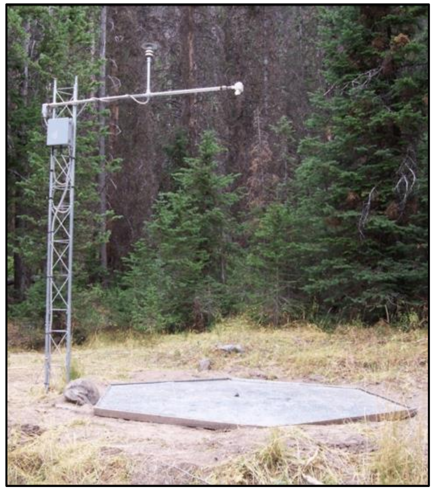


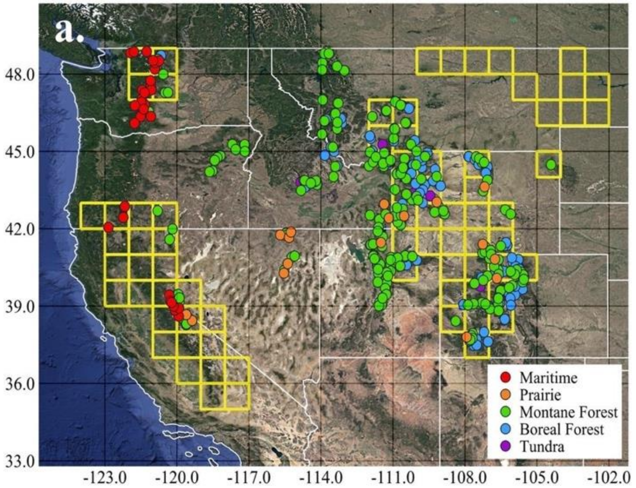
Pflug et al. 2025. Lightweight and regionally transferrable snow water equivalent estimation using a long short-term memory network.

- Aggregated model inputs and training targets to a 1 km and daily grid over WUS training regions:
  - **Input:** daily average air temperature from MERRA, downscaled to 5 km
  - **Input:** WorldClim 30-year monthly precipitation normals (30 arcsecond)
  - **Input:** MODIS fractional snow-covered area (fSCA, ~500 m), excluding cells/dates with cloud cover, and cells with snow pillows
  - **Training target:** WUS-SR SWE (~500 m)
  - **Excludes cells and years with ephemeral snow cover, glaciers, and an insufficient number of winter snow cover observations**

LSTM snow simulations



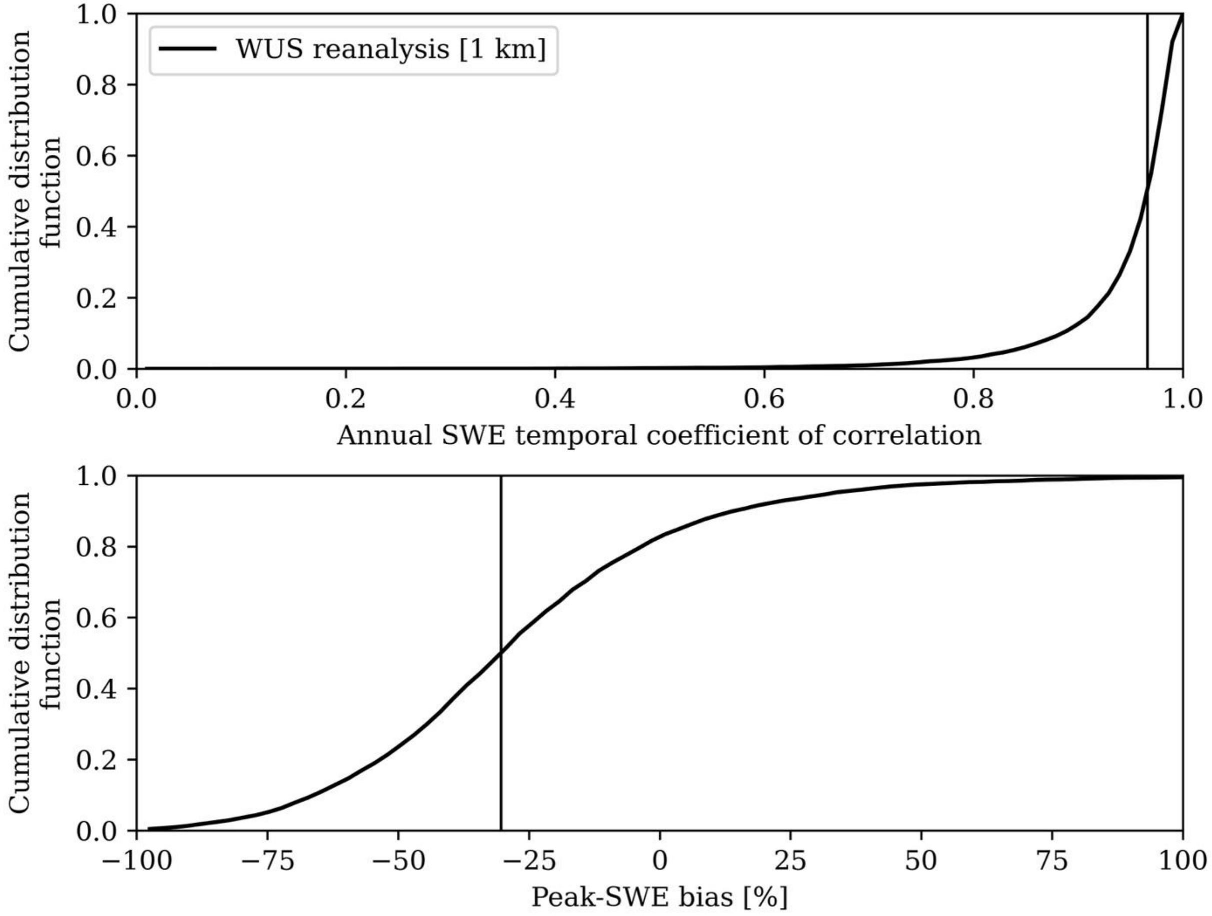


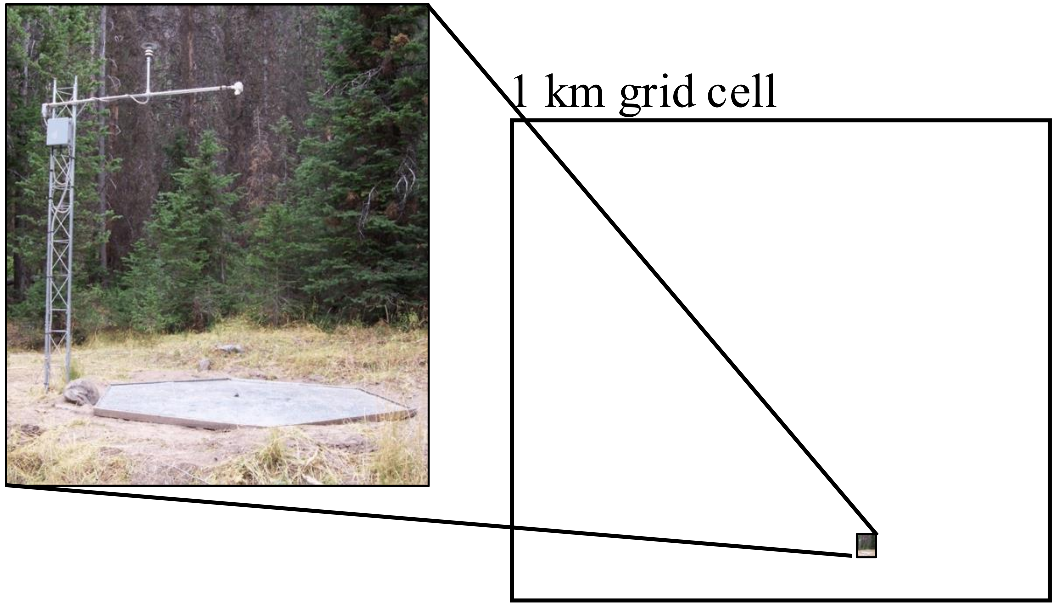


5501 comparisons

1 comparison = 330-day record of SWE observations and estimates at one snow pillow

LSTM snow simulations





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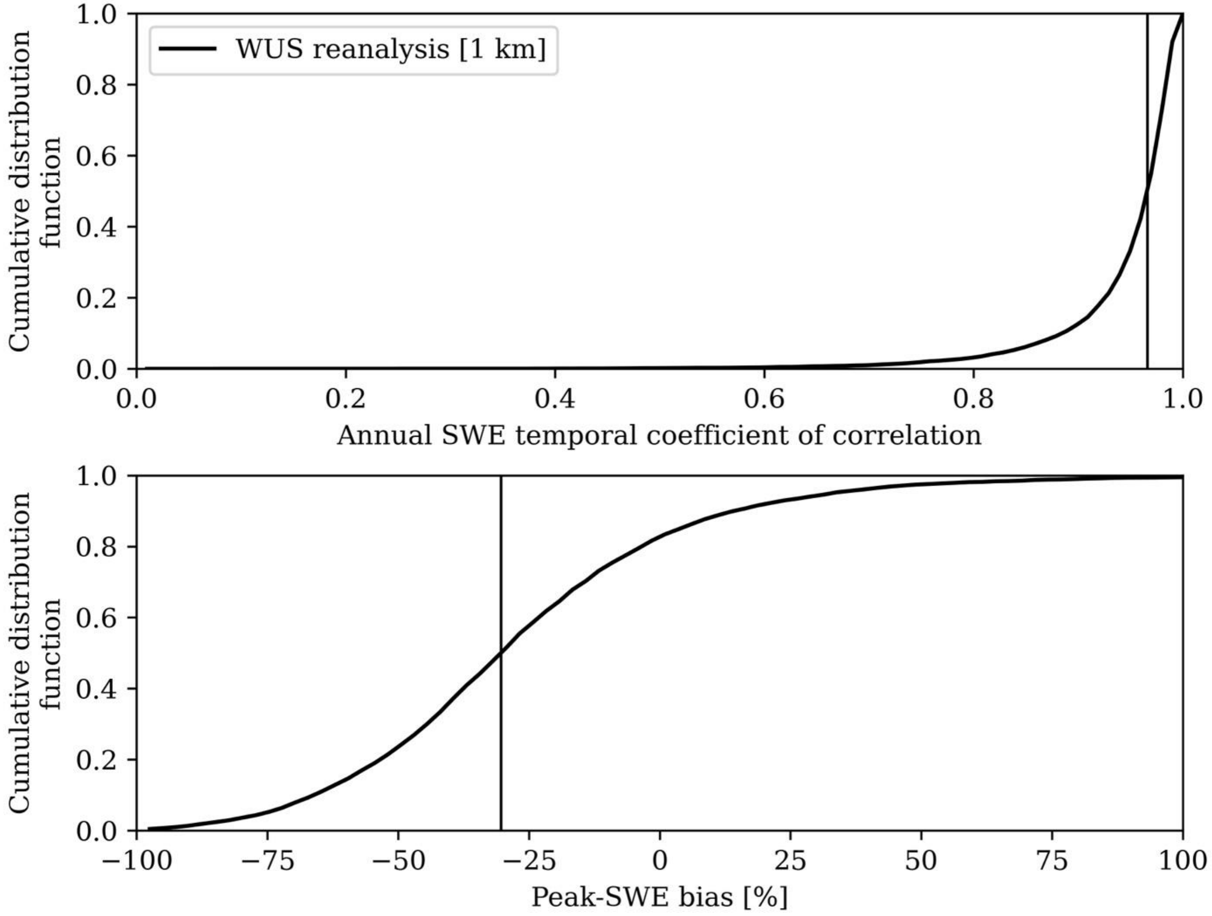

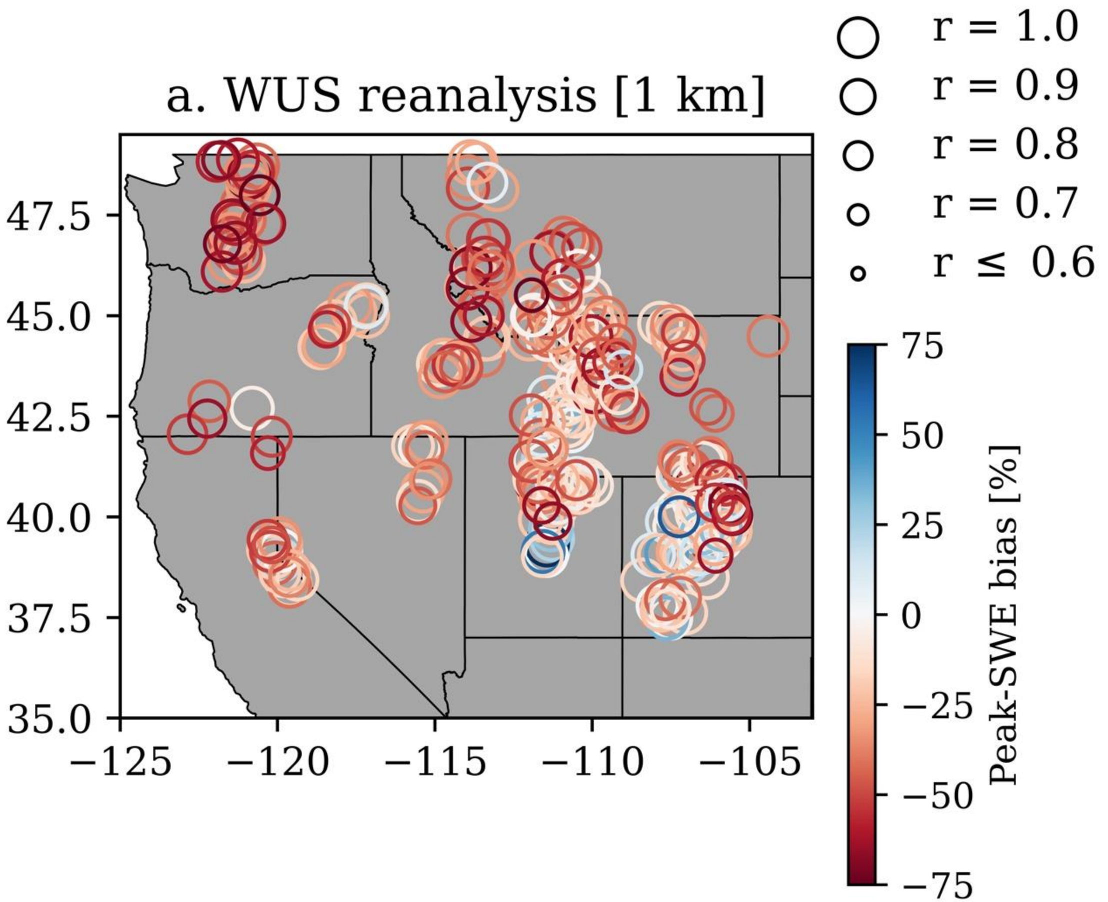

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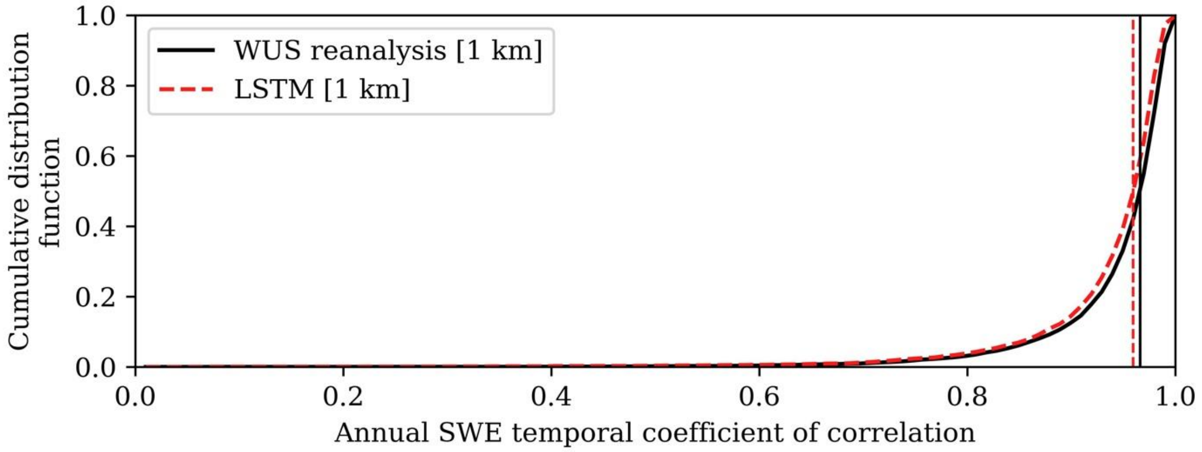

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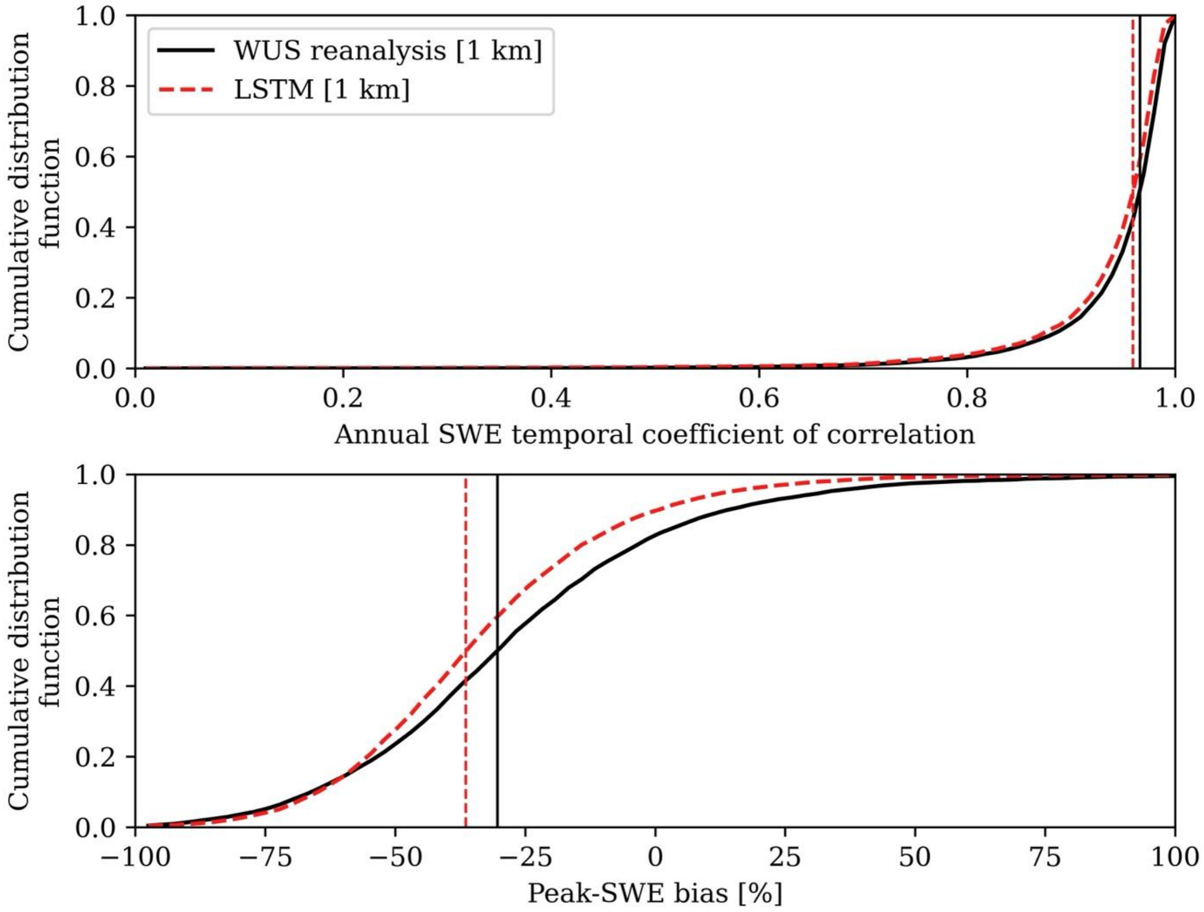

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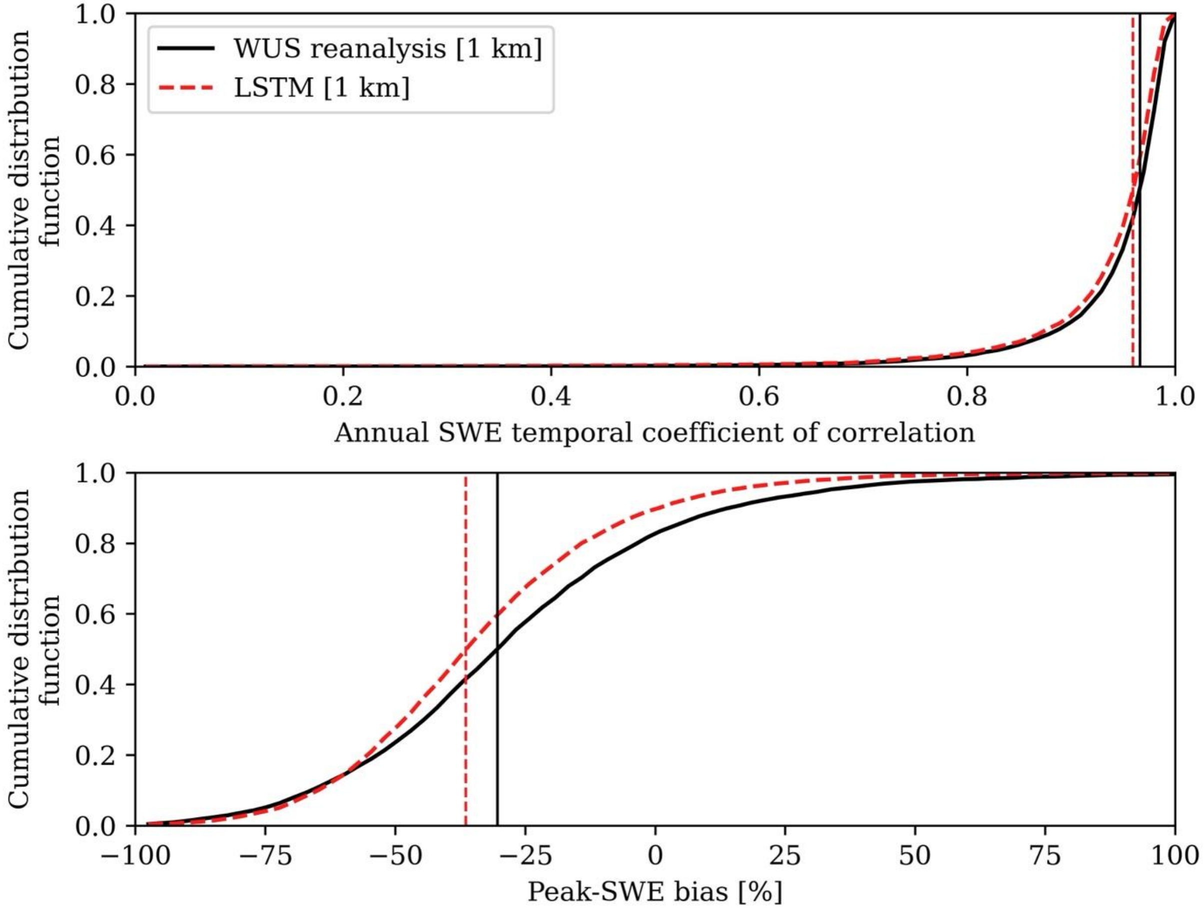

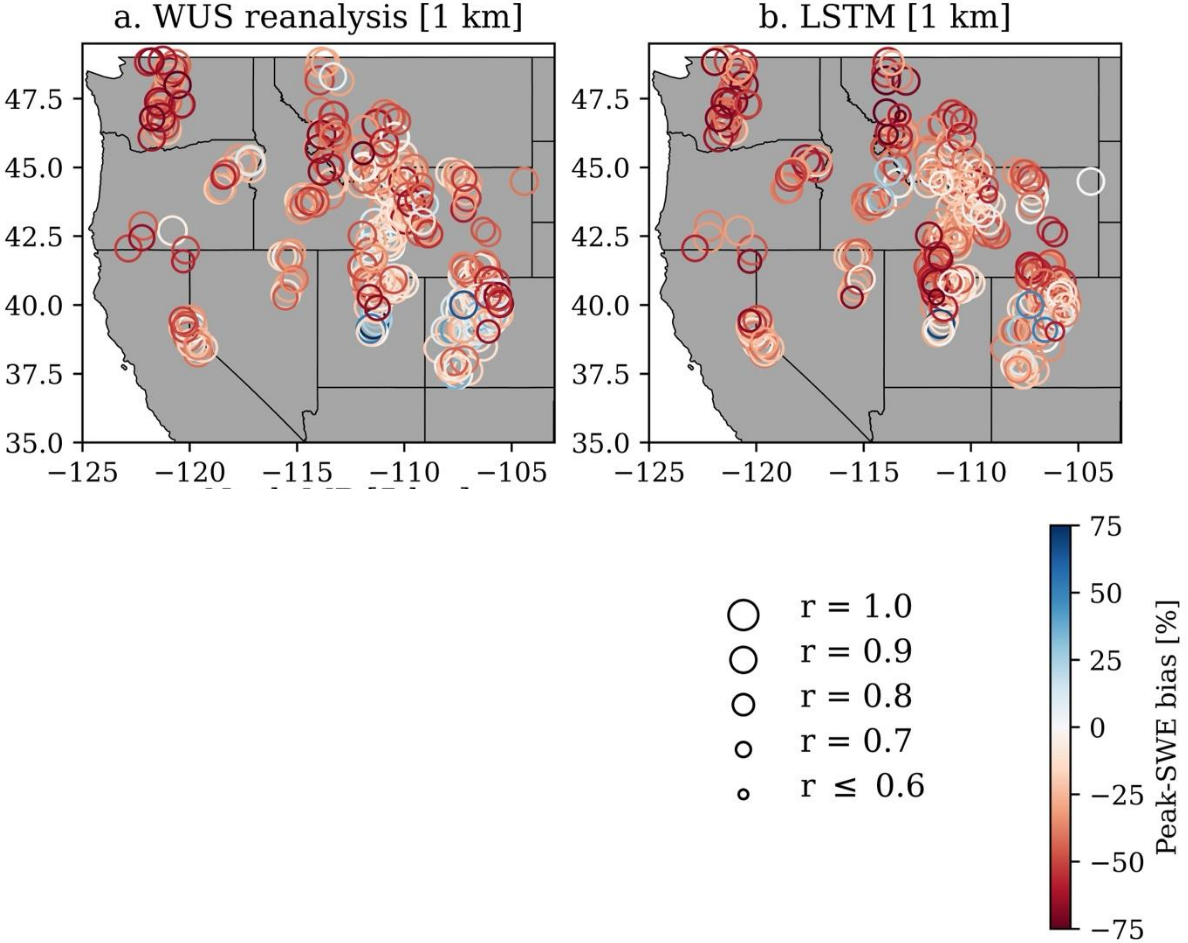

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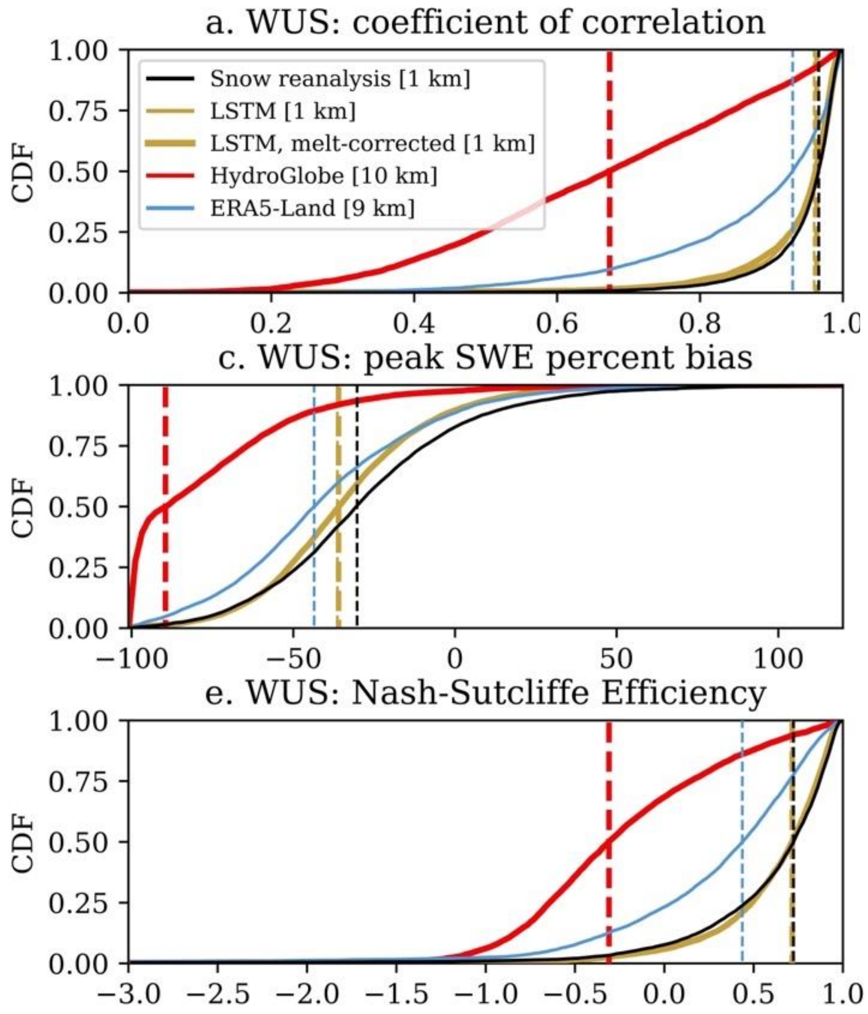

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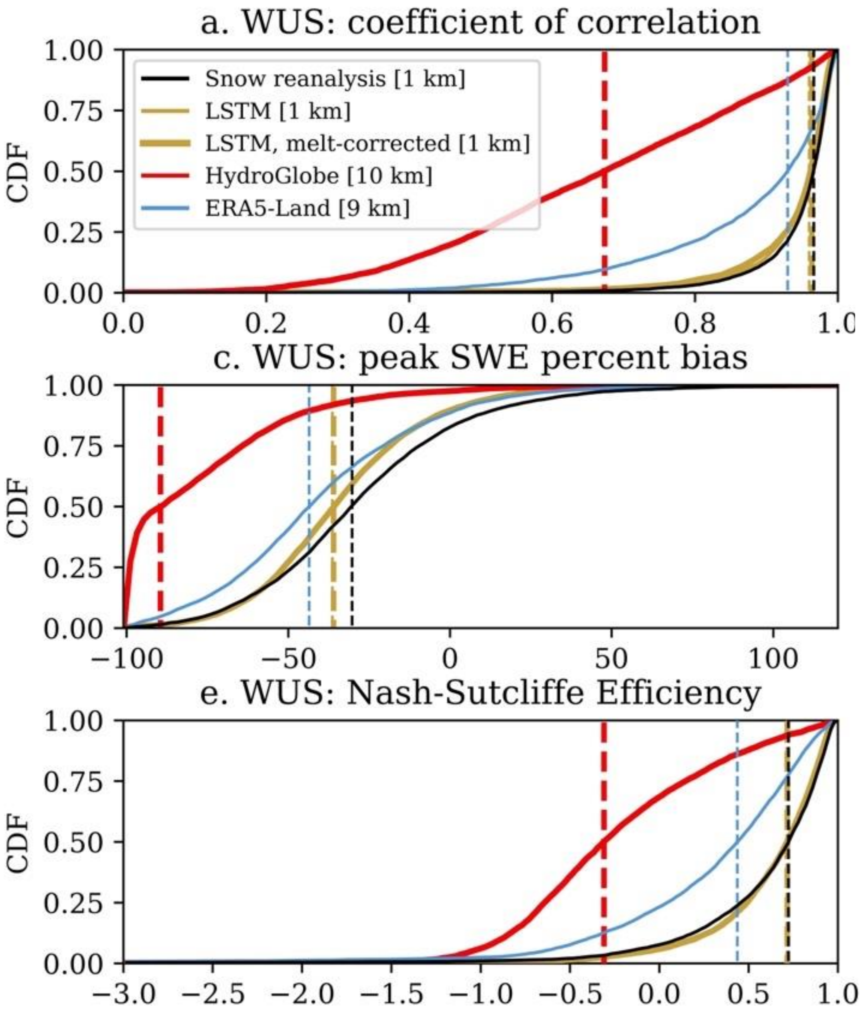
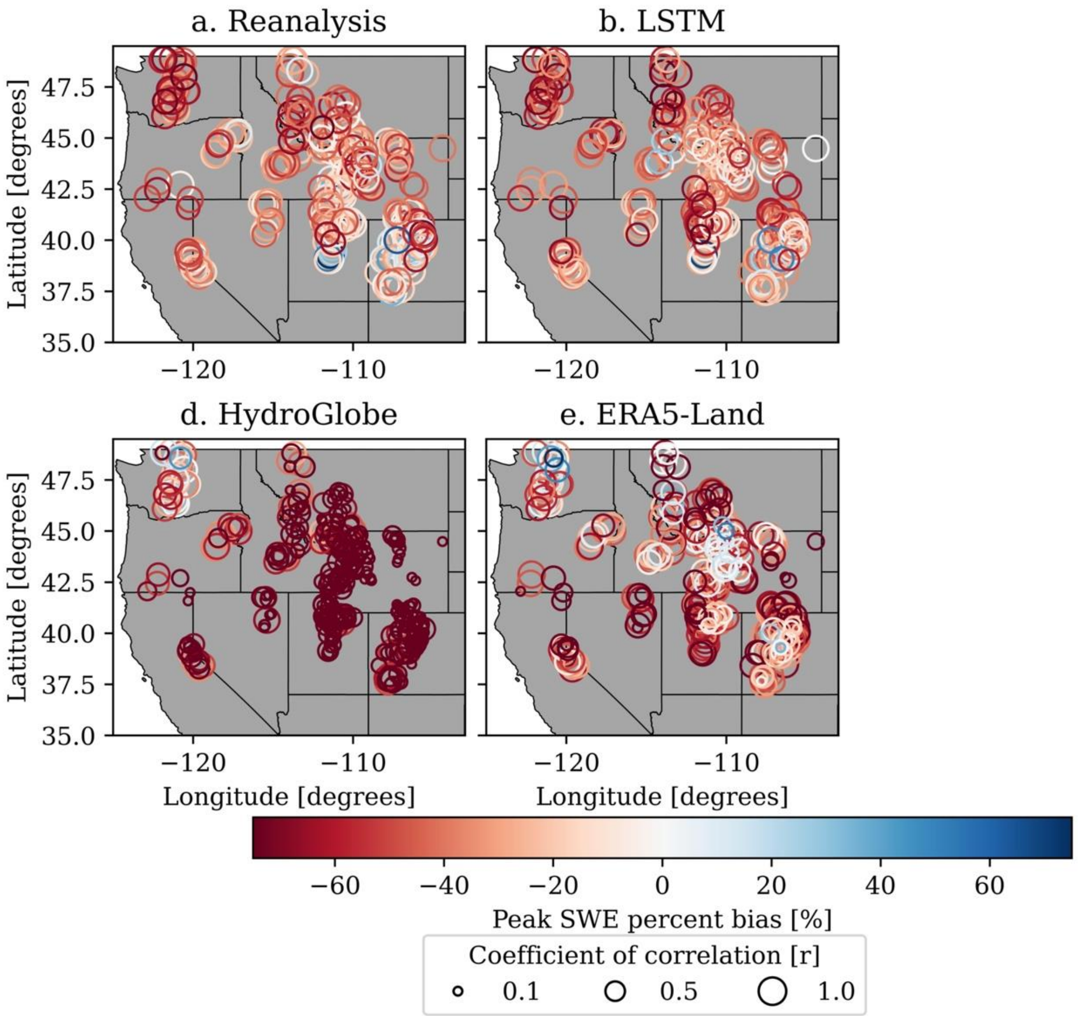
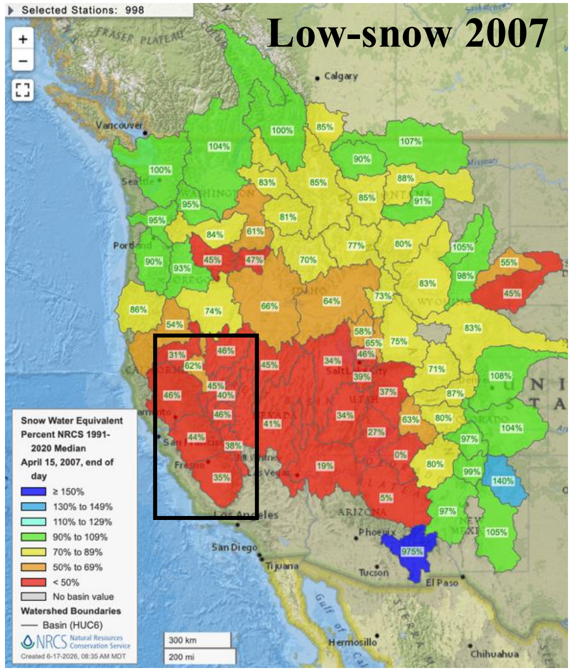
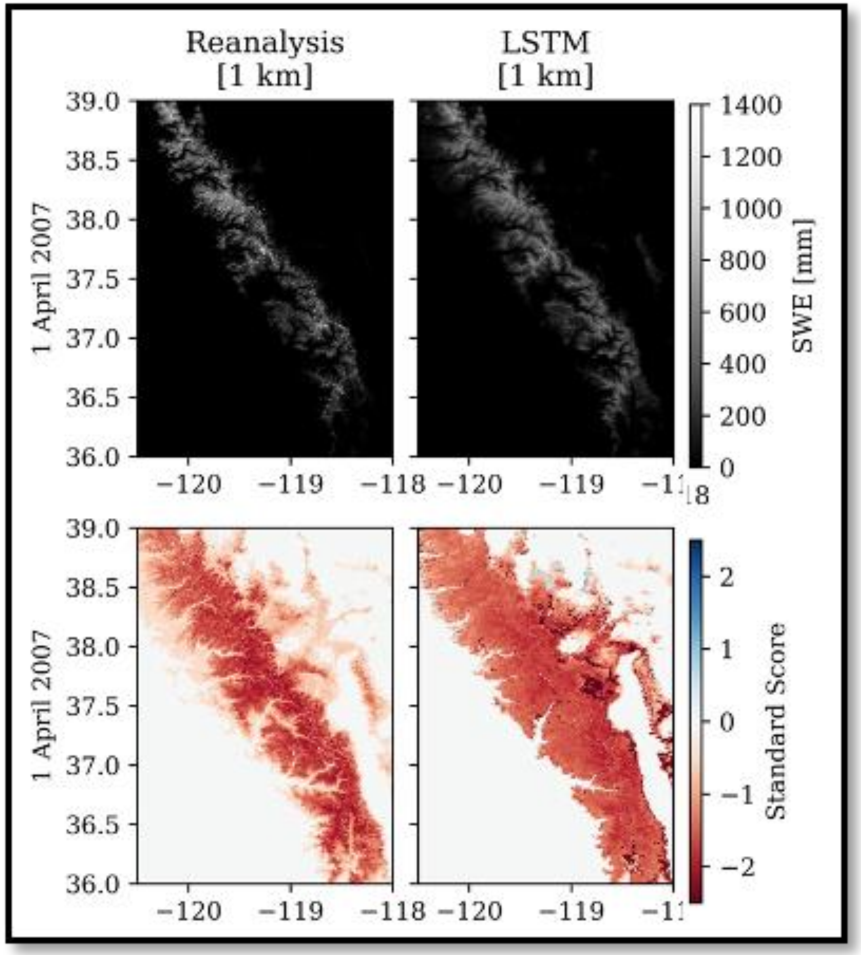




SWE estimates in abnormal years





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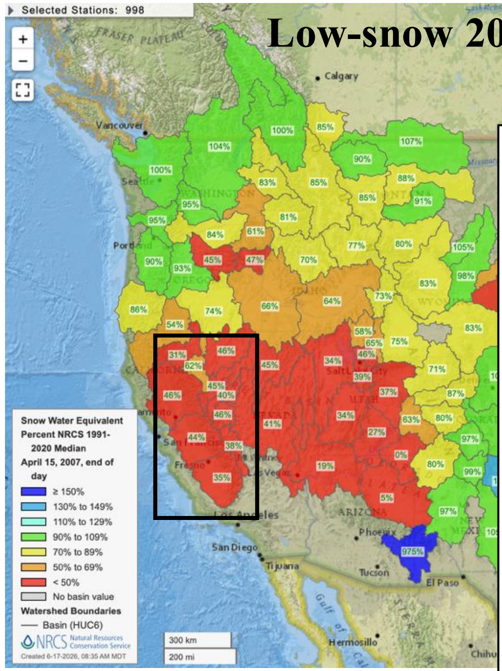

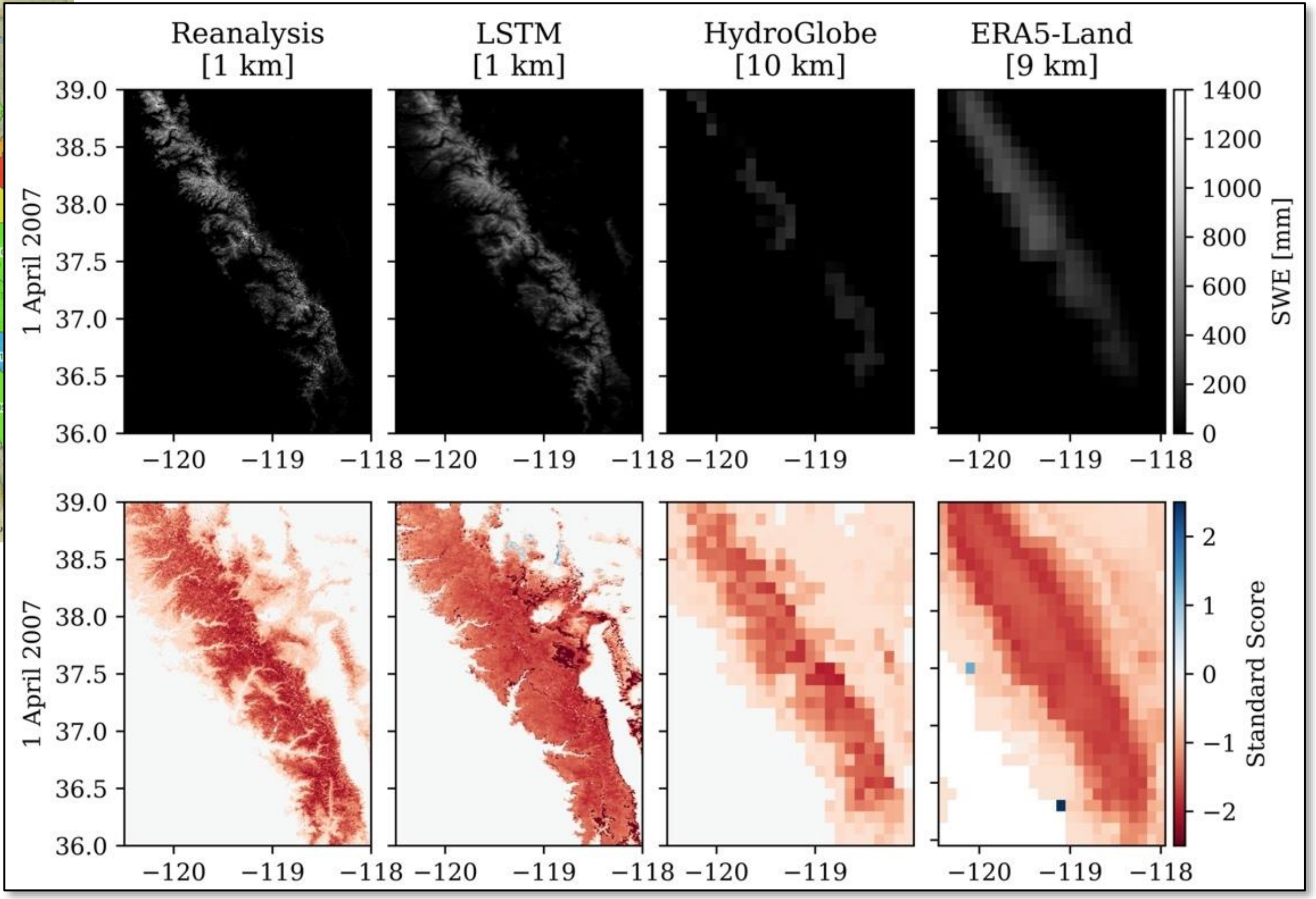

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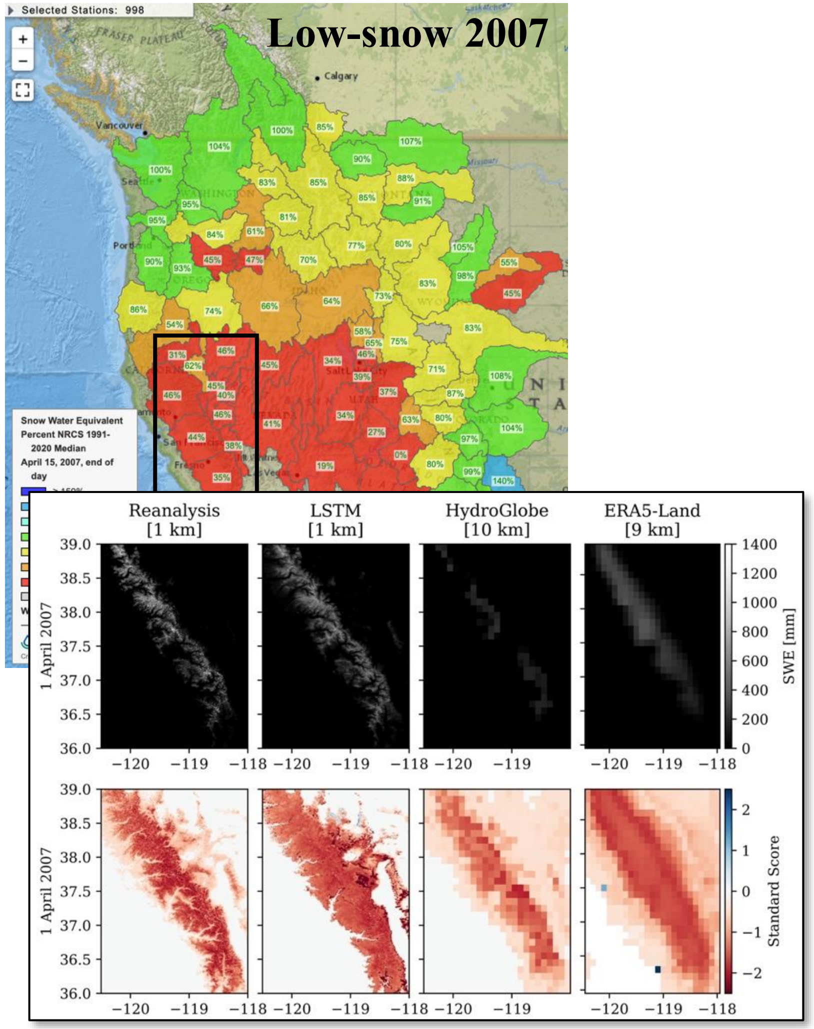
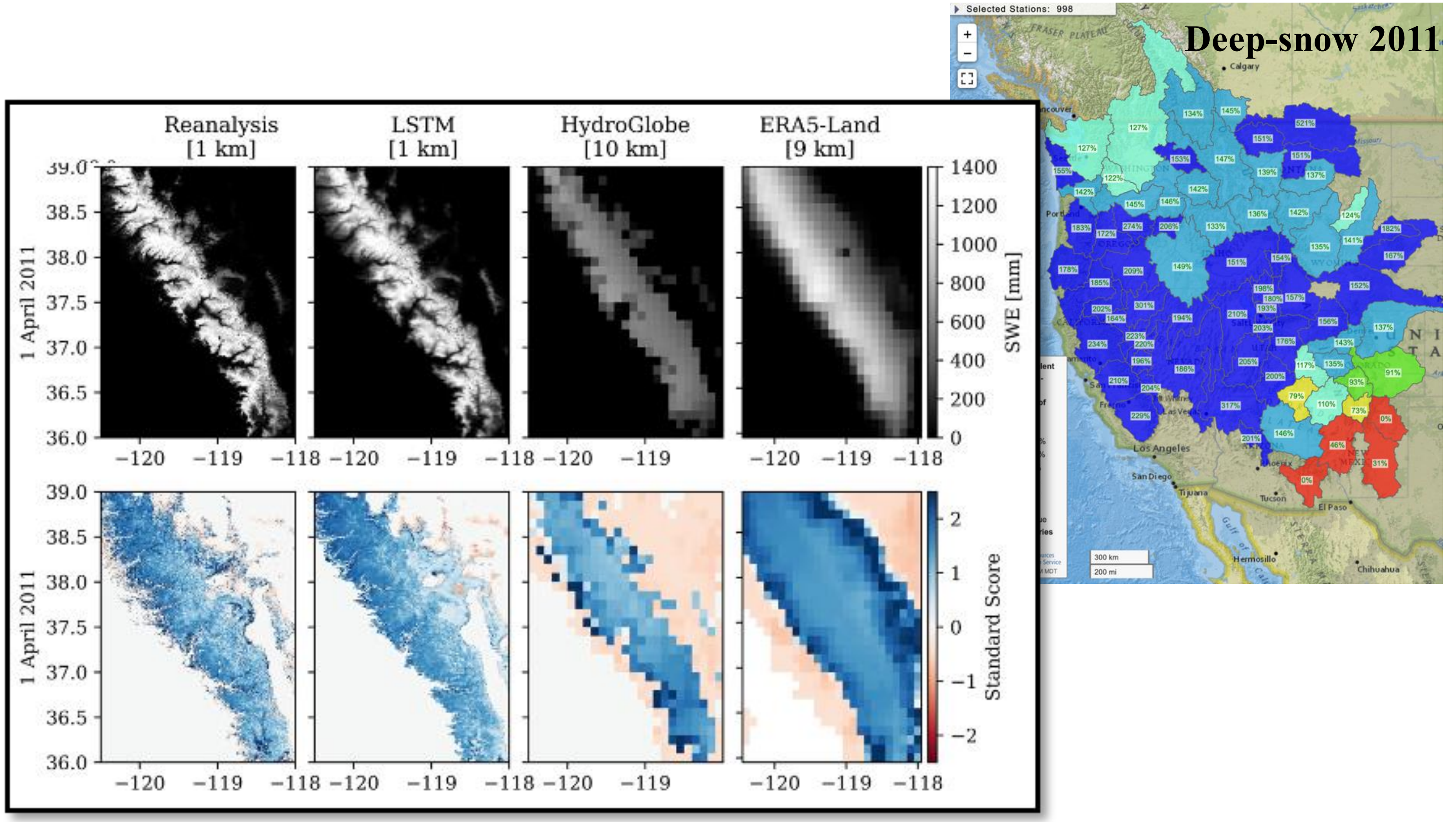
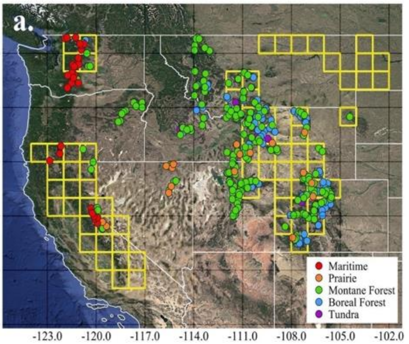
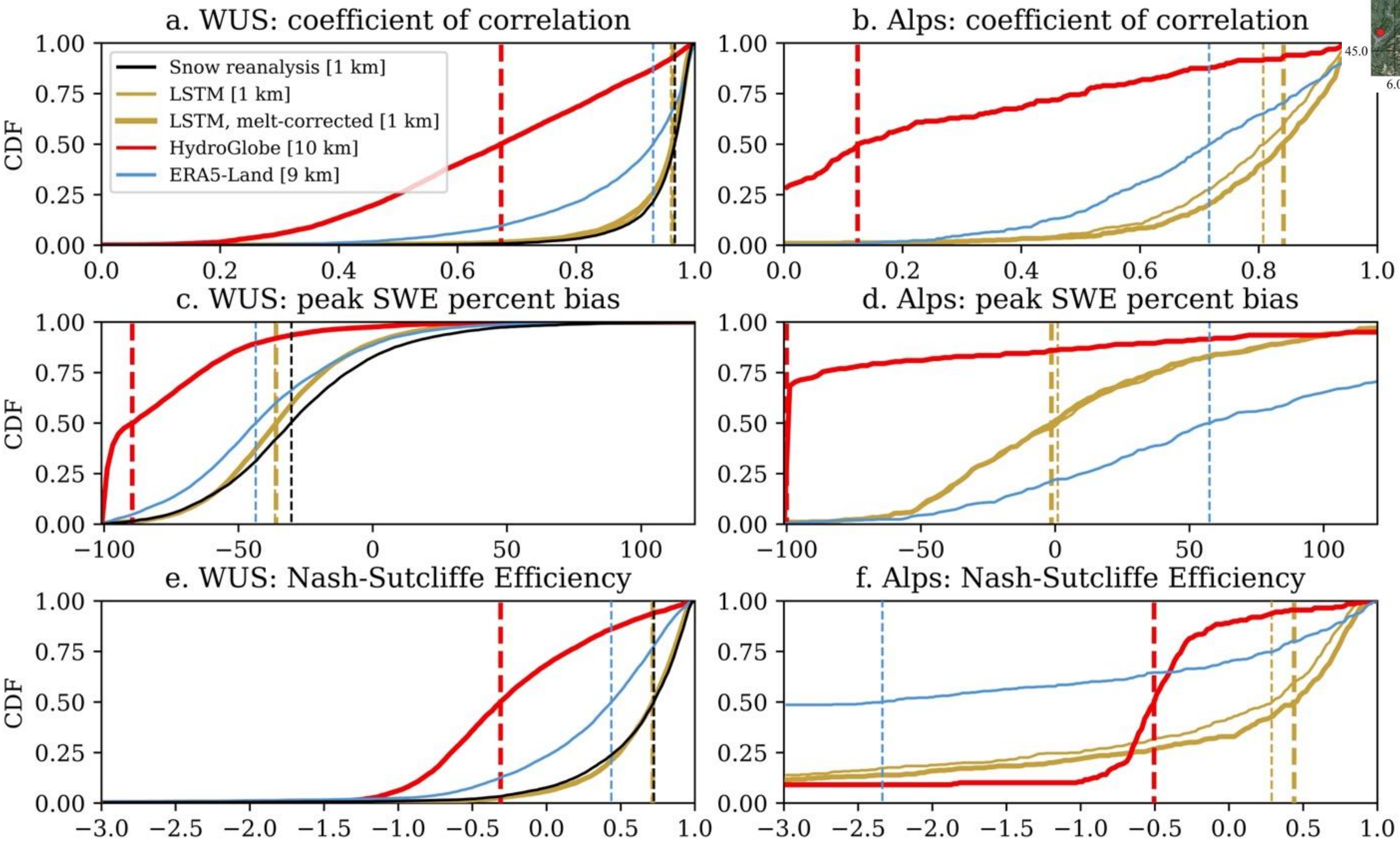
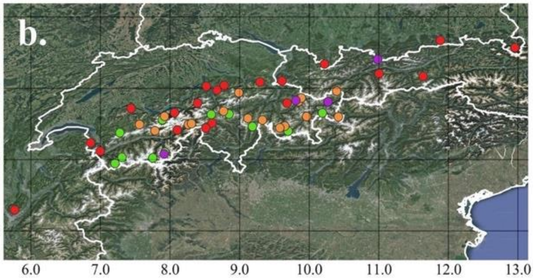




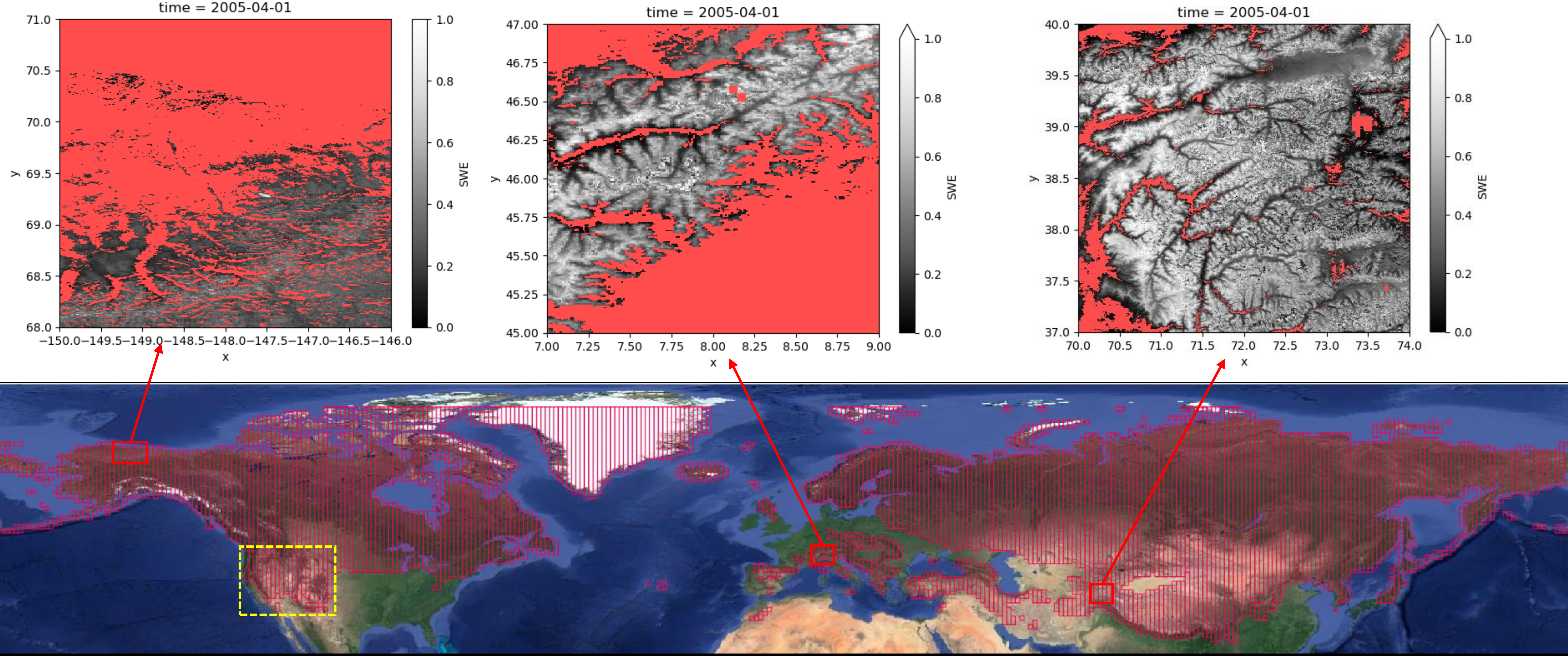
Regional transferability



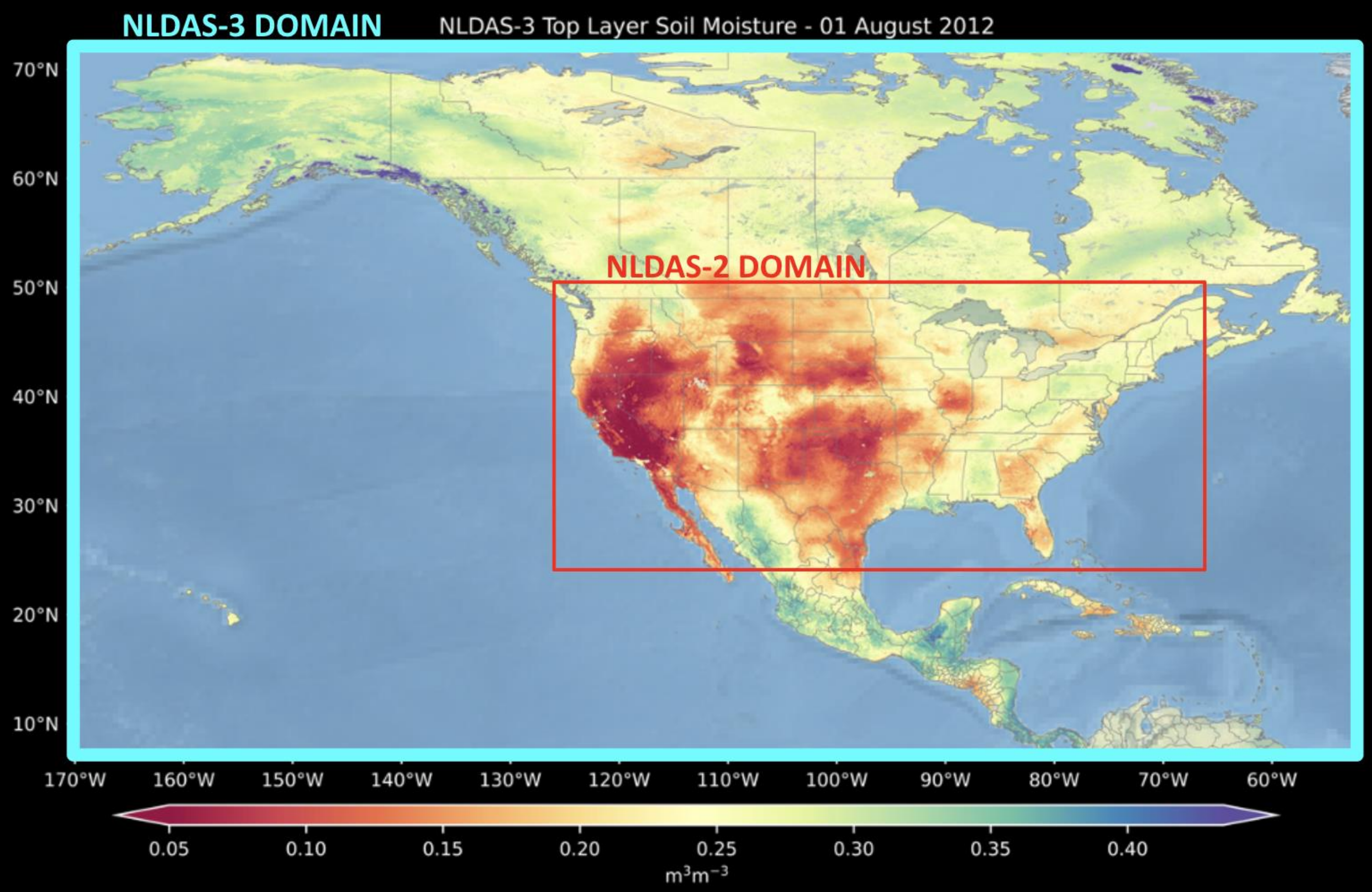




LSTM snow simulations: Global expansion



NLDAS-3 Upgrades at a Glance: Soil Moisture at 1 km over N. America



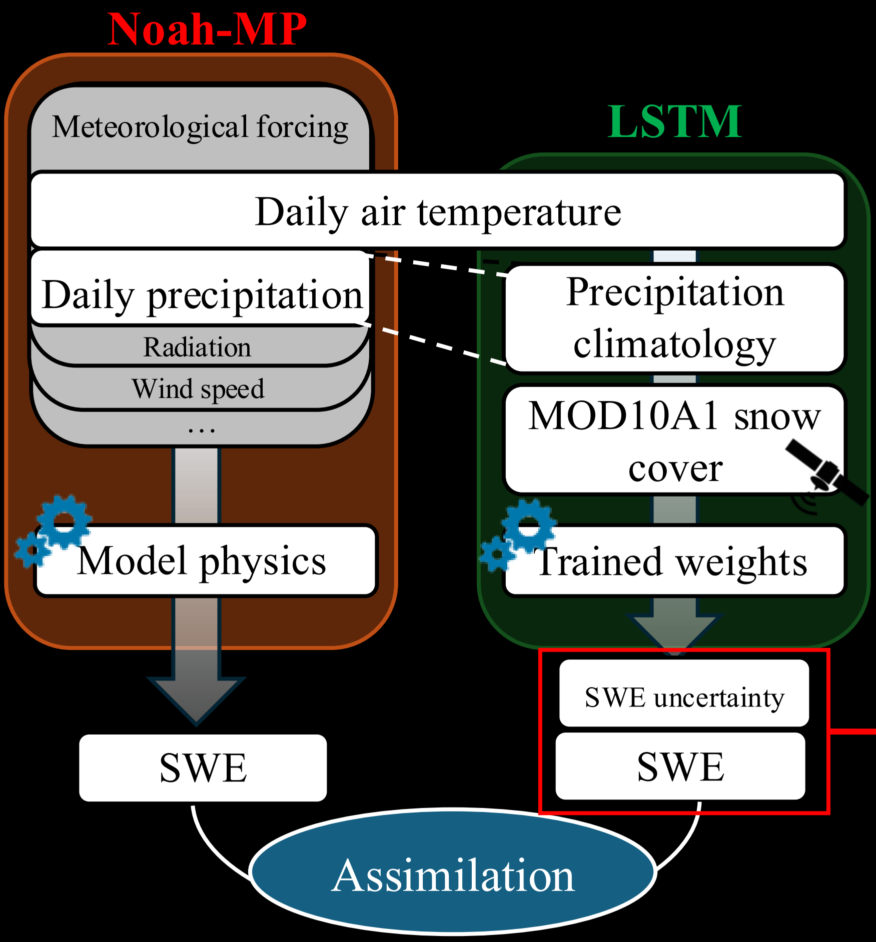
Larger domain: North America, Central America, & Caribbean (NLDAS-2 domain in red box)

Higher-resolution: 1 km for the entire domain

Land and water variables over North America in near real-time

Improved satellite data assimilation for better estimates of soil moisture, snow, water storage, ET, runoff, etc.

NLDAS-3 snow constraints



Noah-MP

Meteorological forcing

Daily air temperature

Daily precipitation

Radiation

Wind speed

…

Model physics

SWE

LSTM

Precipitation climatology

MOD10A1 snow cover

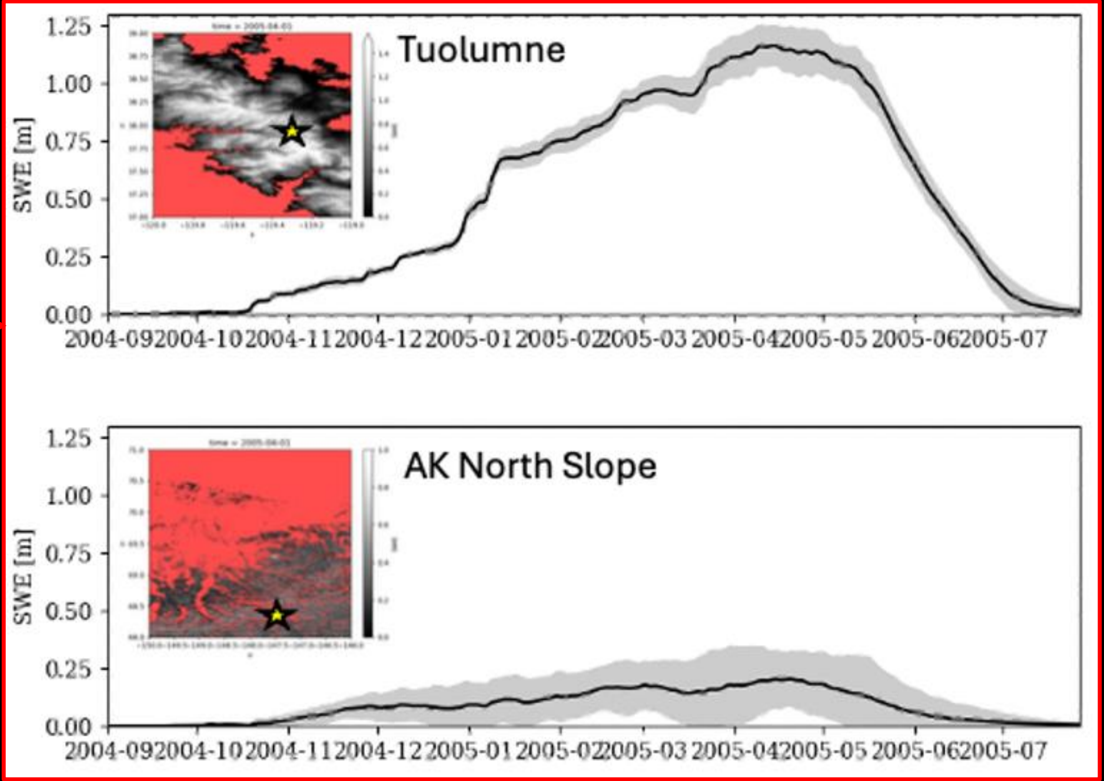
Trained weights

SWE uncertainty

SWE

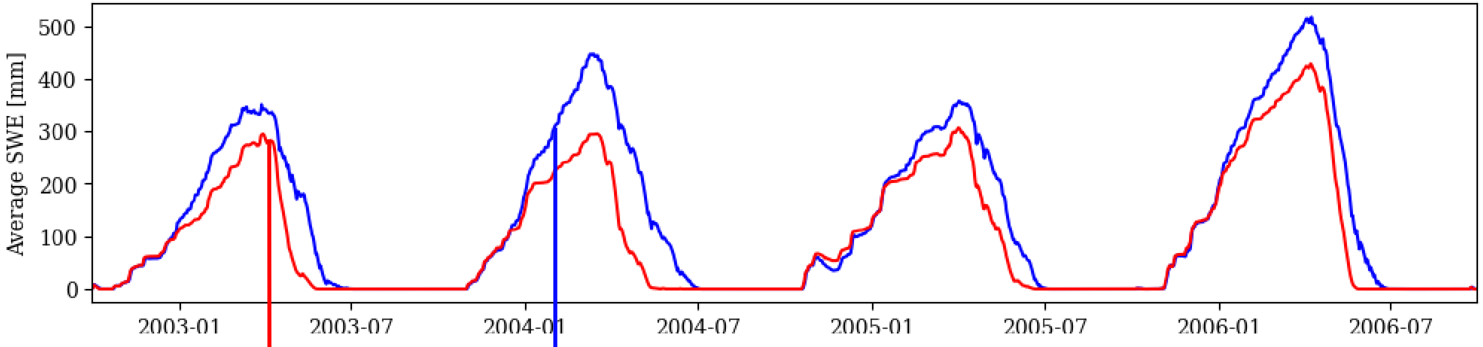
Assimilation

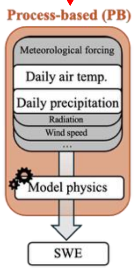
Allow SWE uncertainty prescribed by the LSTM model to define where/when to prescribe high faith to the LSTM estimates, or lean on the process-based simulations more



NLDAS-3 in snowy basins

Southern Wyoming Range





Process-based (PB)

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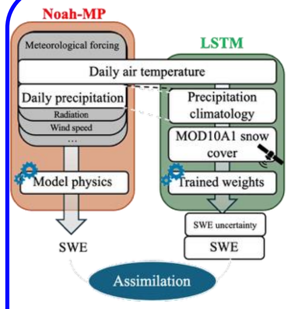
Daily air temp.
Daily precipitation
Radiation
Wind speed
…
Model physics
SWE



Noah-MP

Meteorological forcing
Daily air temperature
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Precipitation climatology
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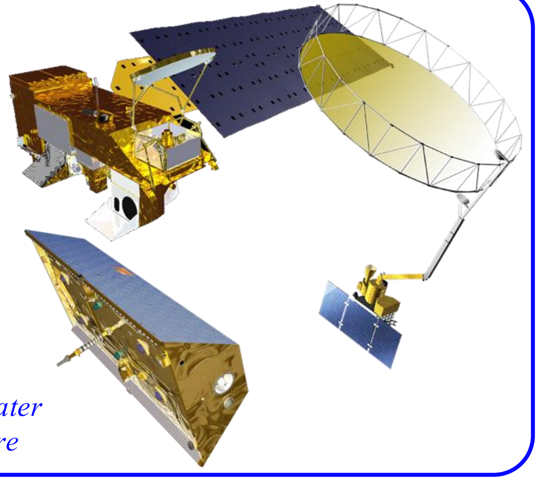
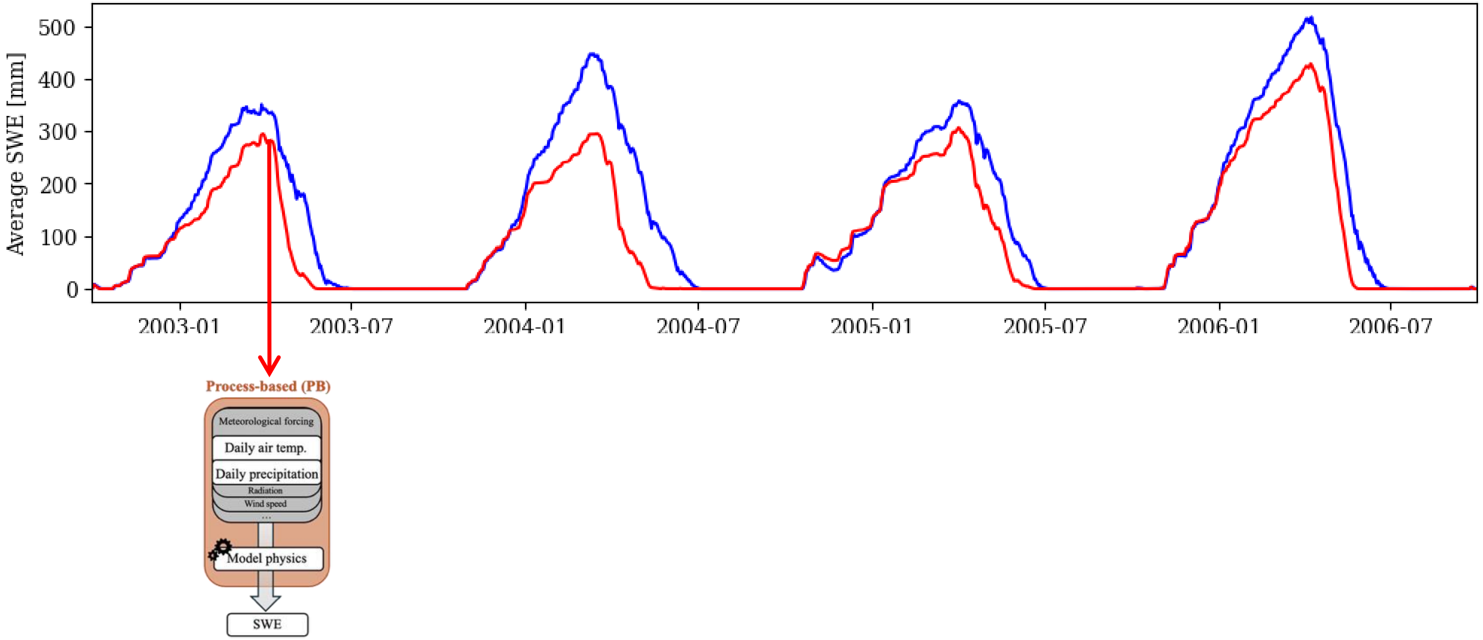


Assimilating SWE, vegetation, terrestrial water storage, and soil moisture

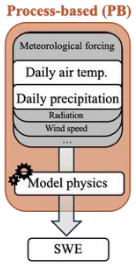
NLDAS-3 in snowy basins

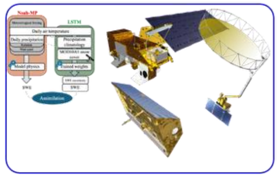
Southern Wyoming Range

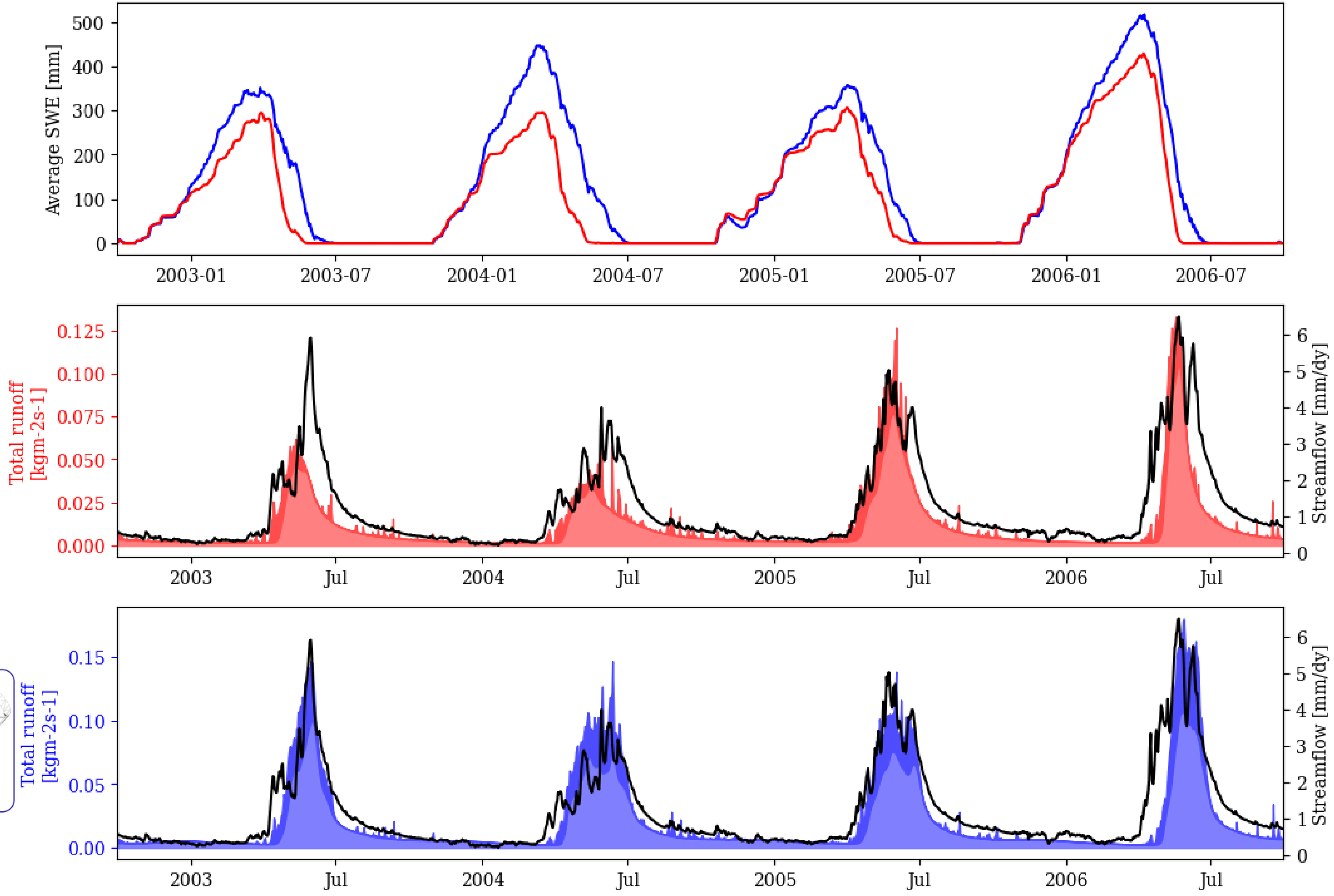


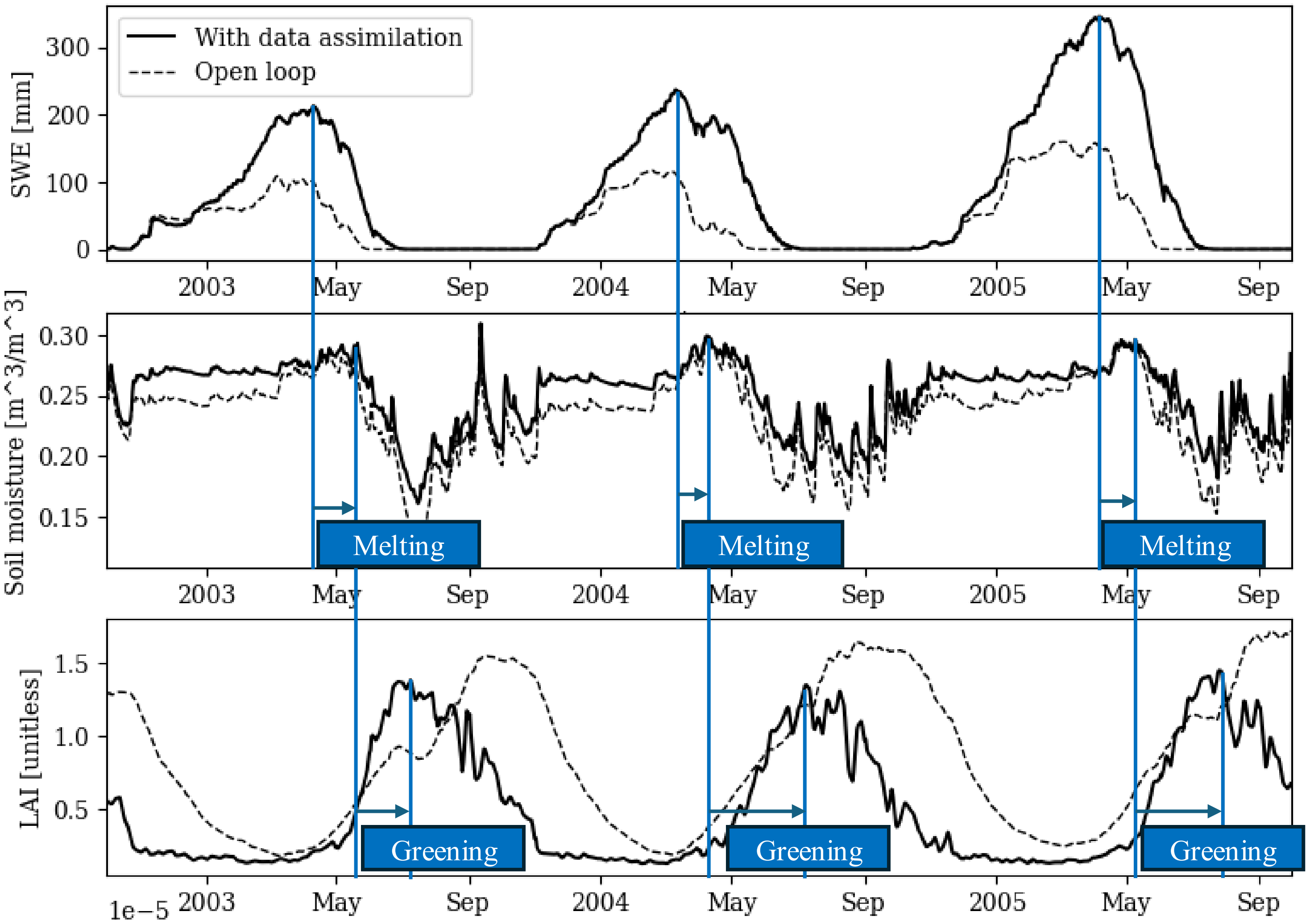
NLDAS-3 in snowy basins

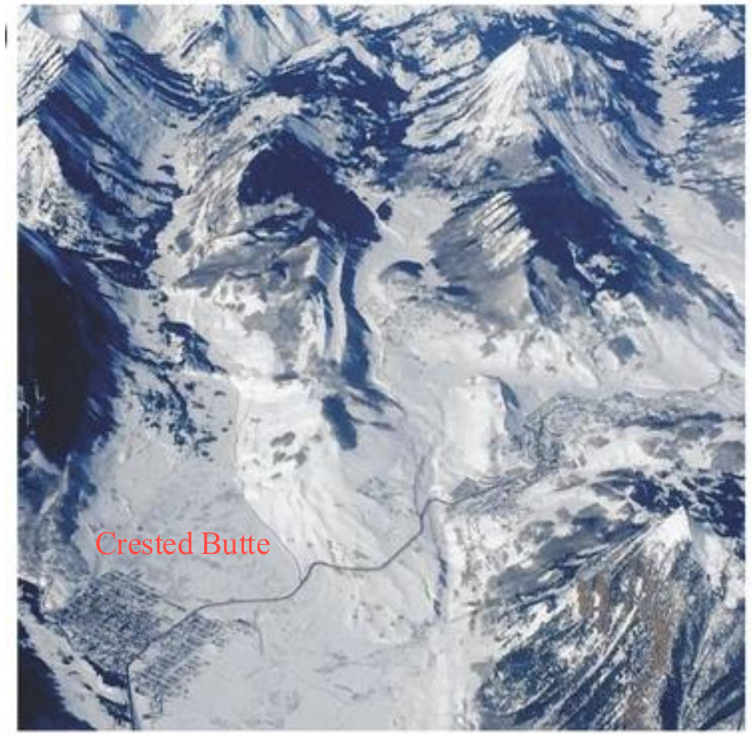
Southern Wyoming Range








With data assimilation
Open loop
SWE [mm]
300
200
100
0
2003
May
Sep
2004
May
Sep
2005
May
Sep
Soil moisture [m^3/m^3]
0.30
0.25
0.20
0.15
Melting
Melting
Melting
2003
May
Sep
2004
May
Sep
2005
May
Sep
LAI [unitless]
1.5
1.0
0.5
Greening
Greening
Greening
1e−5
2003
May
Sep
2004
May
Sep
2005
May
Sep


Crested Butte

Conclusions

Can a deep-learning model learn to reproduce WUS-SR SWE provided limited remote sensing observations and only the most trusted meteorological inputs?

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- Since location-specific information (e.g., terrain, vegetation, coordinates) was excluded, the model was computationally efficient and could be used to estimate SWE in multiple snow climate
- The LSTM trained in the WUS had a high coefficient of correlation (0.81), low bias (< 1%, on average), and low root mean squared error (0.11 m) relative to point observations in the European Alps

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How can this deep learning model constrain process-based estimates of SWE and snow driven hydrology?

- The model was developed to provide estimates of both SWE and SWE uncertainty, making traditional assimilation approaches with process based models possible
- Initial results from NLDAS-3 show improvements to WUS snow evolution and runoff

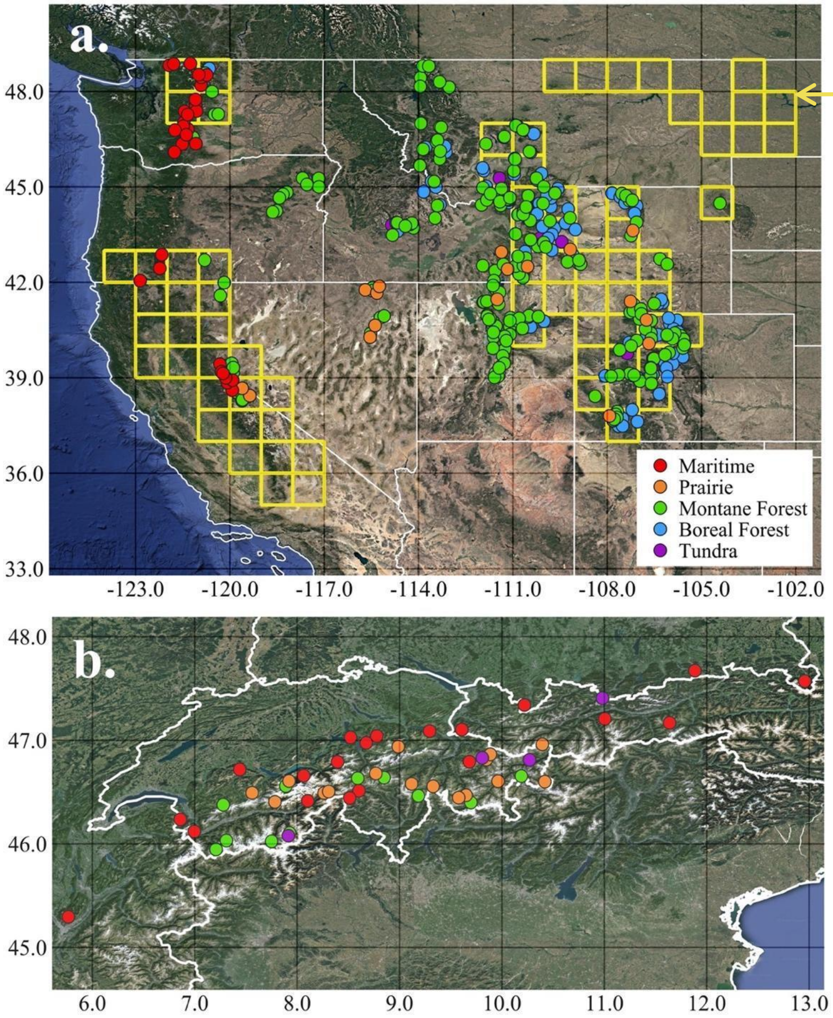
Thank you!

Justin Pflug
Associate Research Scientist, University of Maryland
NASA Goddard, Hydrological Sciences Laboratory
jpflug@umd.edu

Pflug et al. (2025)

NLDAS-3

Data-driven snow modeling



Pflug et al. 2025. Lightweight and regionally transferrable snow water equivalent estimation using a long short-term memory network.

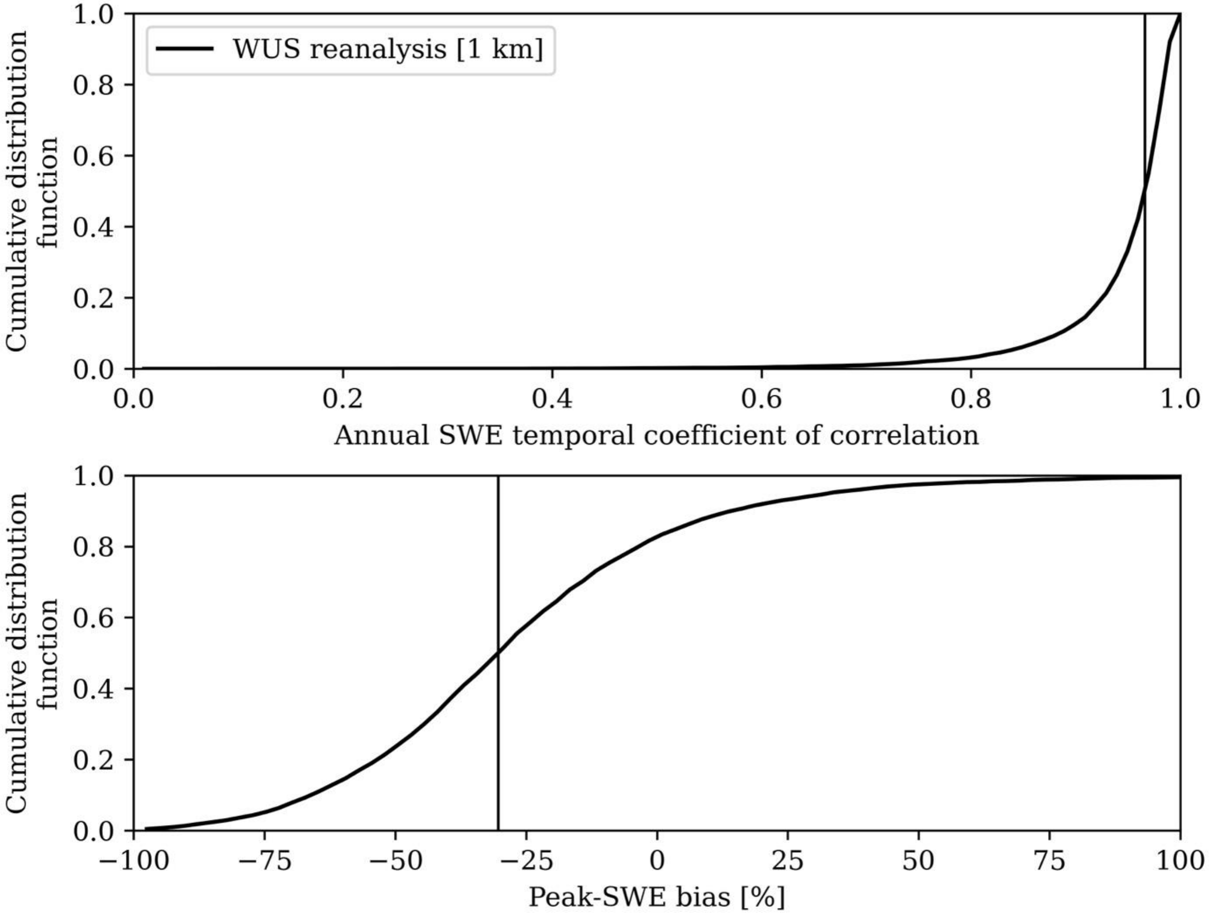
- Aggregated model inputs and training targets to a 1 km and daily grid over WUS training regions

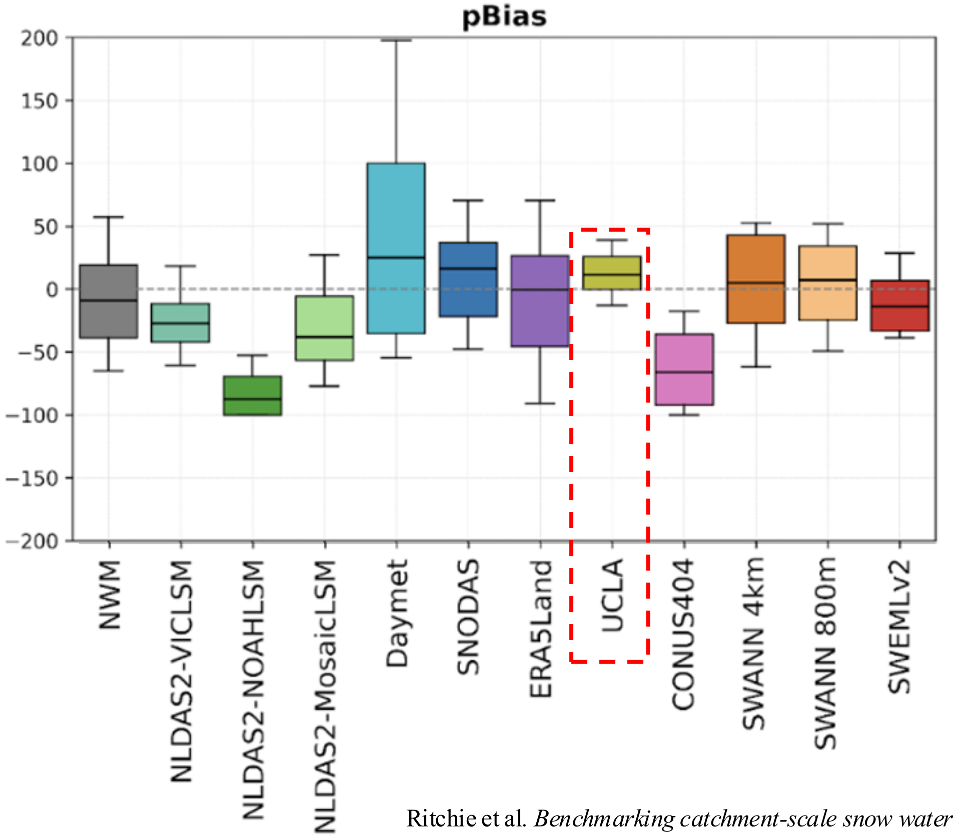
- Probabilistically sampled inputs to represent the full distribution of meteorological and snow conditions in the training regions (250,000 cells, ~4% of the data)

- Trained the LSTM using multiple folds of the prepared training. Used to parameterize model uncertainty

- Masking layers added for dates and cells where any MODIS fSCA observation that contributed to a 1 km grid cell failed quality control checks

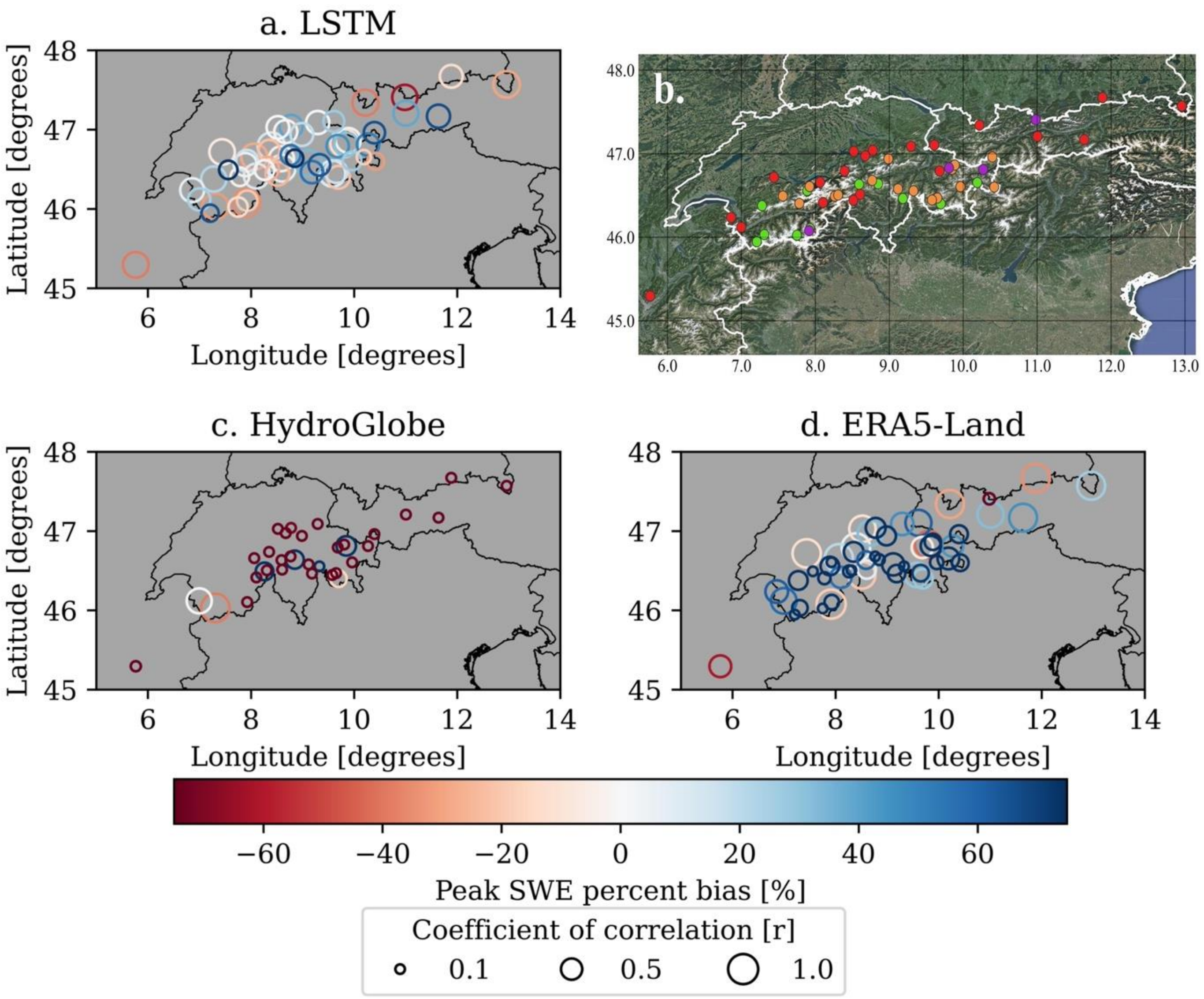
LSTM snow simulations



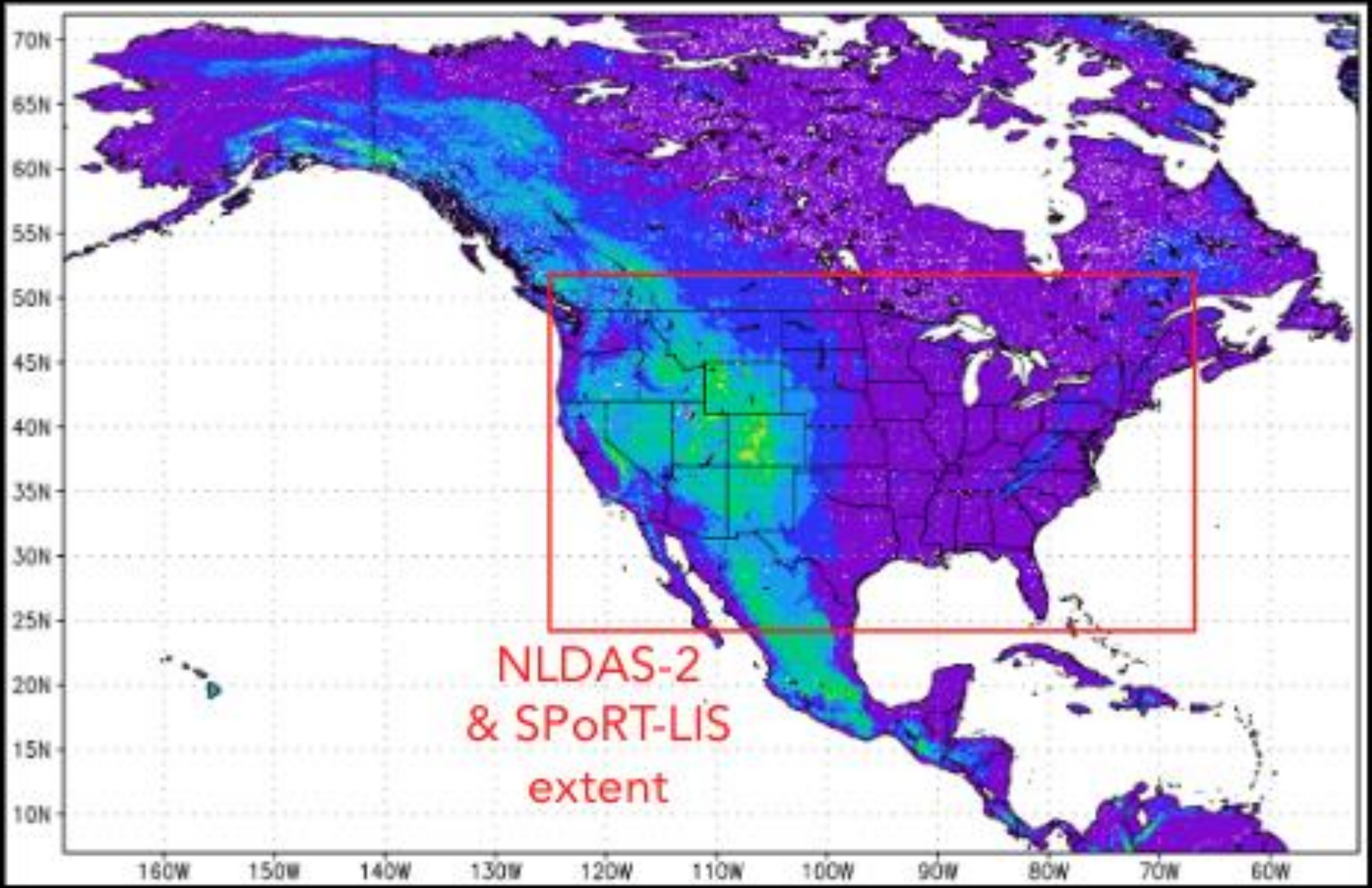


Ritchie et al. *Benchmarking catchment-scale snow water equivalent datasets and models in the western United States [in review]*

Regional transferability



NLDAS-2 vs. NLDAS-3 Comparison



NLDAS-2

Grid spacing: ~12.5 km
Domain: CONUS (25 to 53 N)
Land points: 76,088

NLDAS-3

Grid spacing: ~1 km
Domain: 7 to 72 N
169 to 52 W
Land points: 27,245,580

The very large increase in the number of land points for NLDAS-3, combined with the ensembles needed for data assimilation, requires significant computational resources!

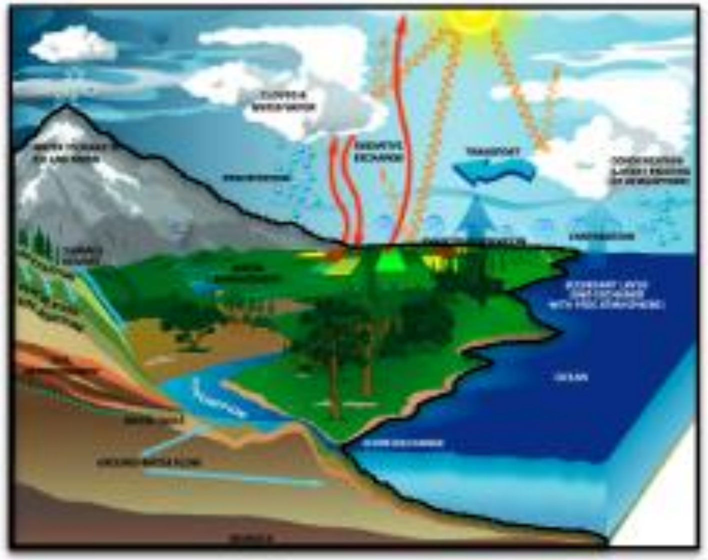
NLDAS-3 System Setup and Improvements

Improvements in red

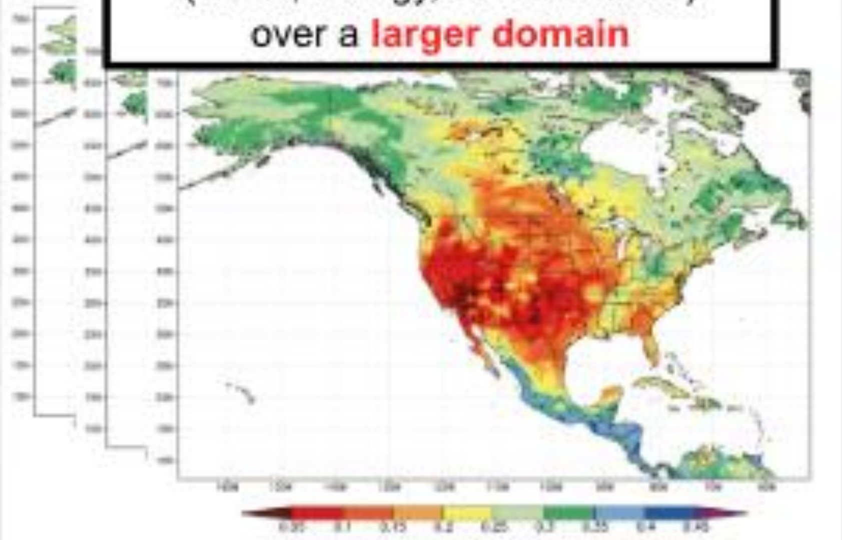
Satellite Data Assimilation
(soil moisture, snow,
terrestrial water, vegetation)

Blended meteorological inputs

Land Information System
Running Noah-MP model



High resolution outputs
(water, energy, carbon fluxes)
over a larger domain



Providing real-time cloud-based outputs
(with more variables) & analysis platforms

EARTHDATA
VEDA BETA
jupyter

NLDAS-3 Output Variables

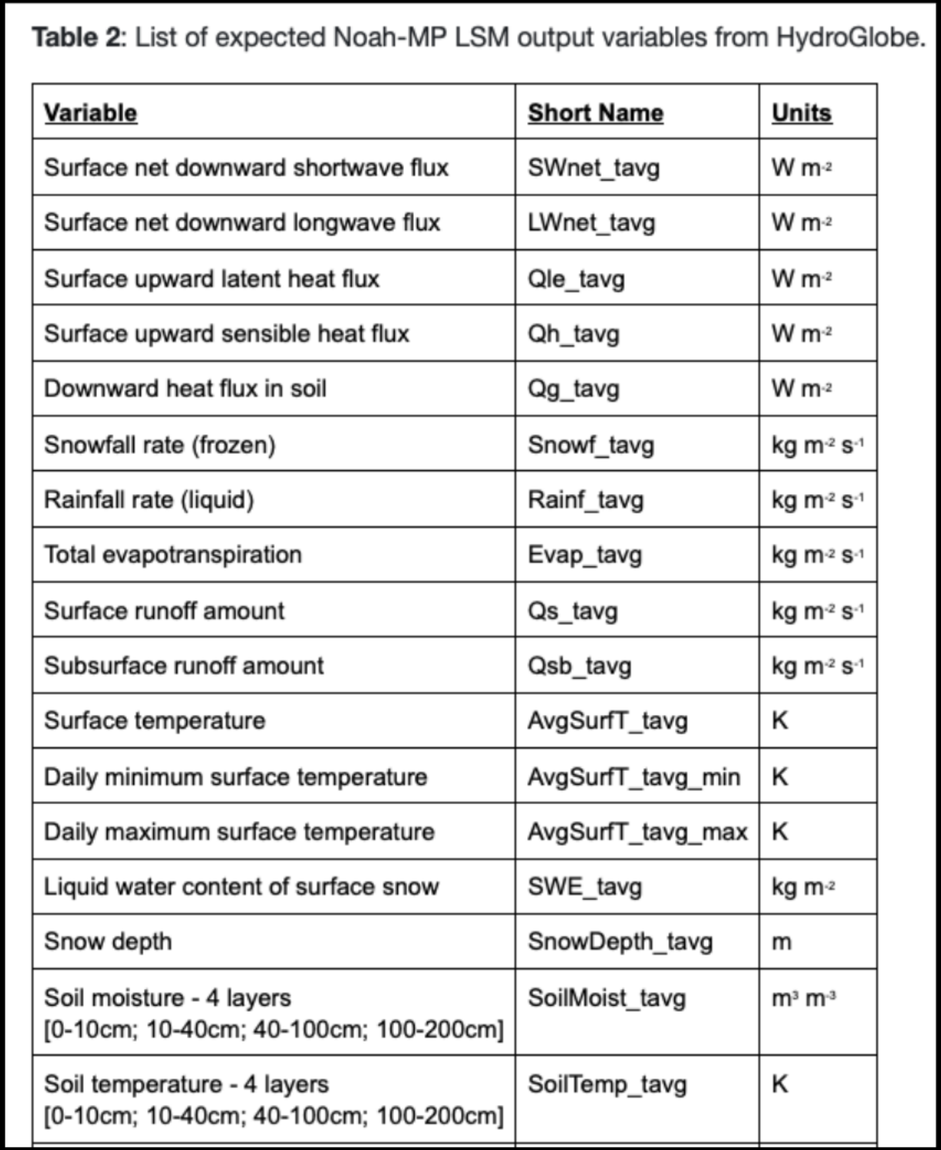
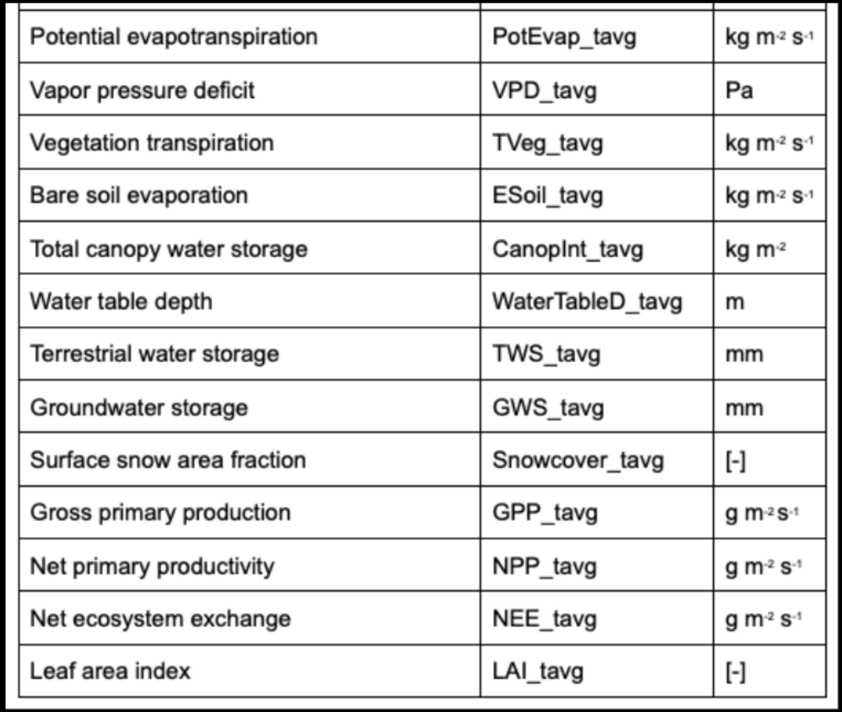
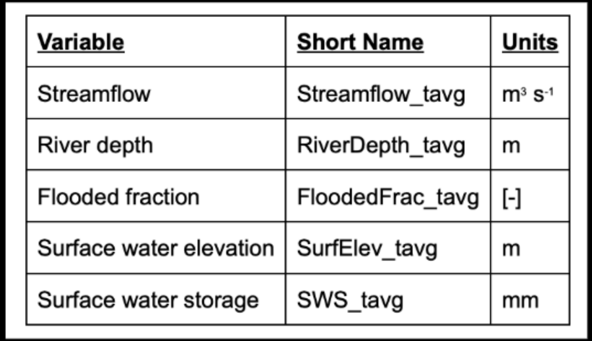


Table 2: List of expected Noah-MP LSM output variables from HydroGlobe.

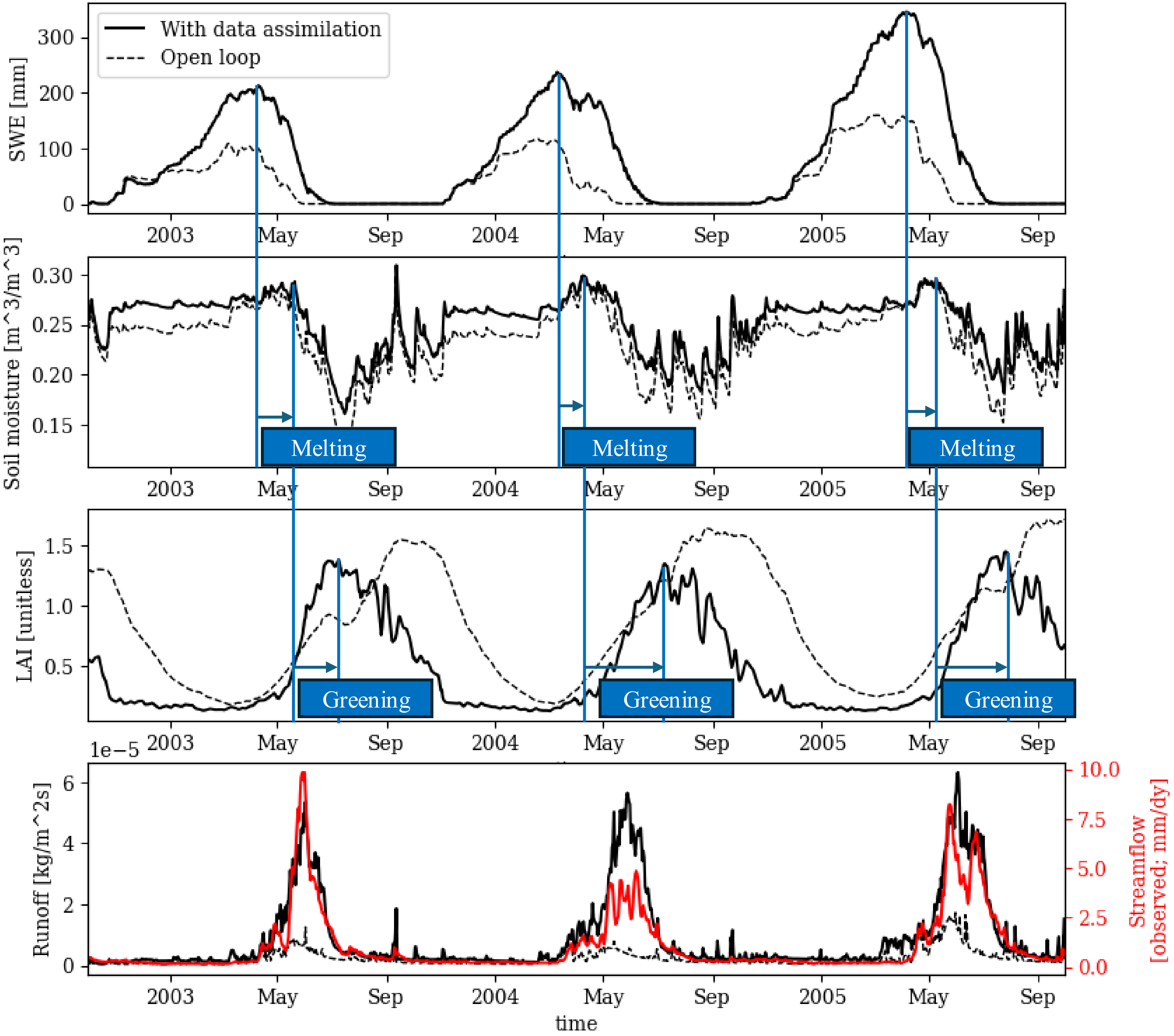
Variable	**Short Name**	**Units**
Surface net downward shortwave flux	SWnet_tavg	$\mathrm{W\ m^{-2}}$
Surface net downward longwave flux	LWnet_tavg	$\mathrm{W\ m^{-2}}$
Surface upward latent heat flux	Qle_tavg	$\mathrm{W\ m^{-2}}$
Surface upward sensible heat flux	Qh_tavg	$\mathrm{W\ m^{-2}}$
Downward heat flux in soil	Qg_tavg	$\mathrm{W\ m^{-2}}$
Snowfall rate (frozen)	Snowf_tavg	$\mathrm{kg\ m^{-2}\ s^{-1}}$
Rainfall rate (liquid)	Rainf_tavg	$\mathrm{kg\ m^{-2}\ s^{-1}}$
Total evapotranspiration	Evap_tavg	$\mathrm{kg\ m^{-2}\ s^{-1}}$
Surface runoff amount	Qs_tavg	$\mathrm{kg\ m^{-2}\ s^{-1}}$
Subsurface runoff amount	Qsb_tavg	$\mathrm{kg\ m^{-2}\ s^{-1}}$
Surface temperature	AvgSurfT_tavg	K
Daily minimum surface temperature	AvgSurfT_tavg_min	K
Daily maximum surface temperature	AvgSurfT_tavg_max	K
Liquid water content of surface snow	SWE_tavg	$\mathrm{kg\ m^{-2}}$
Snow depth	SnowDepth_tavg	m
Soil moisture - 4 layers [0-10cm; 10-40cm; 40-100cm; 100-200cm]	SoilMoist_tavg	$\mathrm{m^3\ m^{-3}}$
Soil temperature - 4 layers [0-10cm; 10-40cm; 40-100cm; 100-200cm]	SoilTemp_tavg	K

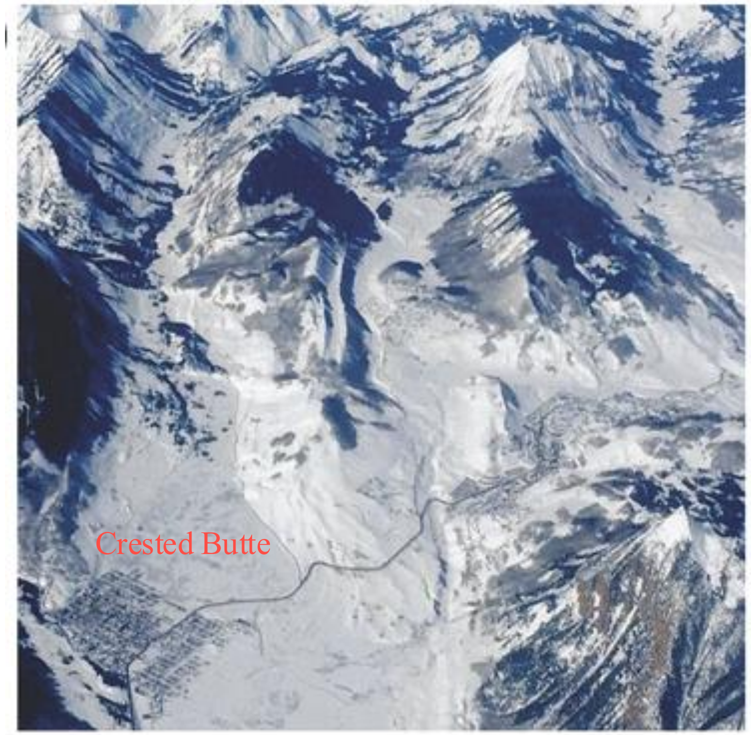


Potential evapotranspiration	PotEvap_tavg	$\mathrm{kg\ m^{-2}\ s^{-1}}$
Vapor pressure deficit	VPD_tavg	Pa
Vegetation transpiration	TVeg_tavg	$\mathrm{kg\ m^{-2}\ s^{-1}}$
Bare soil evaporation	ESoil_tavg	$\mathrm{kg\ m^{-2}\ s^{-1}}$
Total canopy water storage	CanopInt_tavg	$\mathrm{kg\ m^{-2}}$
Water table depth	WaterTableD_tavg	m
Terrestrial water storage	TWS_tavg	mm
Groundwater storage	GWS_tavg	mm
Surface snow area fraction	Snowcover_tavg	[-]
Gross primary production	GPP_tavg	$\mathrm{g\ m^{-2} s^{-1}}$
Net primary productivity	NPP_tavg	$\mathrm{g\ m^{-2}\ s^{-1}}$
Net ecosystem exchange	NEE_tavg	$\mathrm{g\ m^{-2}\ s^{-1}}$
Leaf area index	LAI_tavg	[-]



Variable	**Short Name**	**Units**
Streamflow	Streamflow_tavg	$\mathrm{m^3\ s^{-1}}$
River depth	RiverDepth_tavg	m
Flooded fraction	FloodedFrac_tavg	[-]
Surface water elevation	SurfElev_tavg	m
Surface water storage	SWS_tavg	mm


With data assimilation
Open loop
SWE [mm]
300
200
100
0
2003
May
Sep
2004
May
Sep
2005
May
Sep
Soil moisture [m^3/m^3]
0.30
0.25
0.20
0.15
Melting
Melting
Melting
LAI [unitless]
1.5
1.0
0.5
Greening
Greening
Greening
1e−5
Runoff [kg/m^2s]
6
4
2
0
Streamflow [observed; mm/dy]
10.0
7.5
5.0
2.5
0.0
time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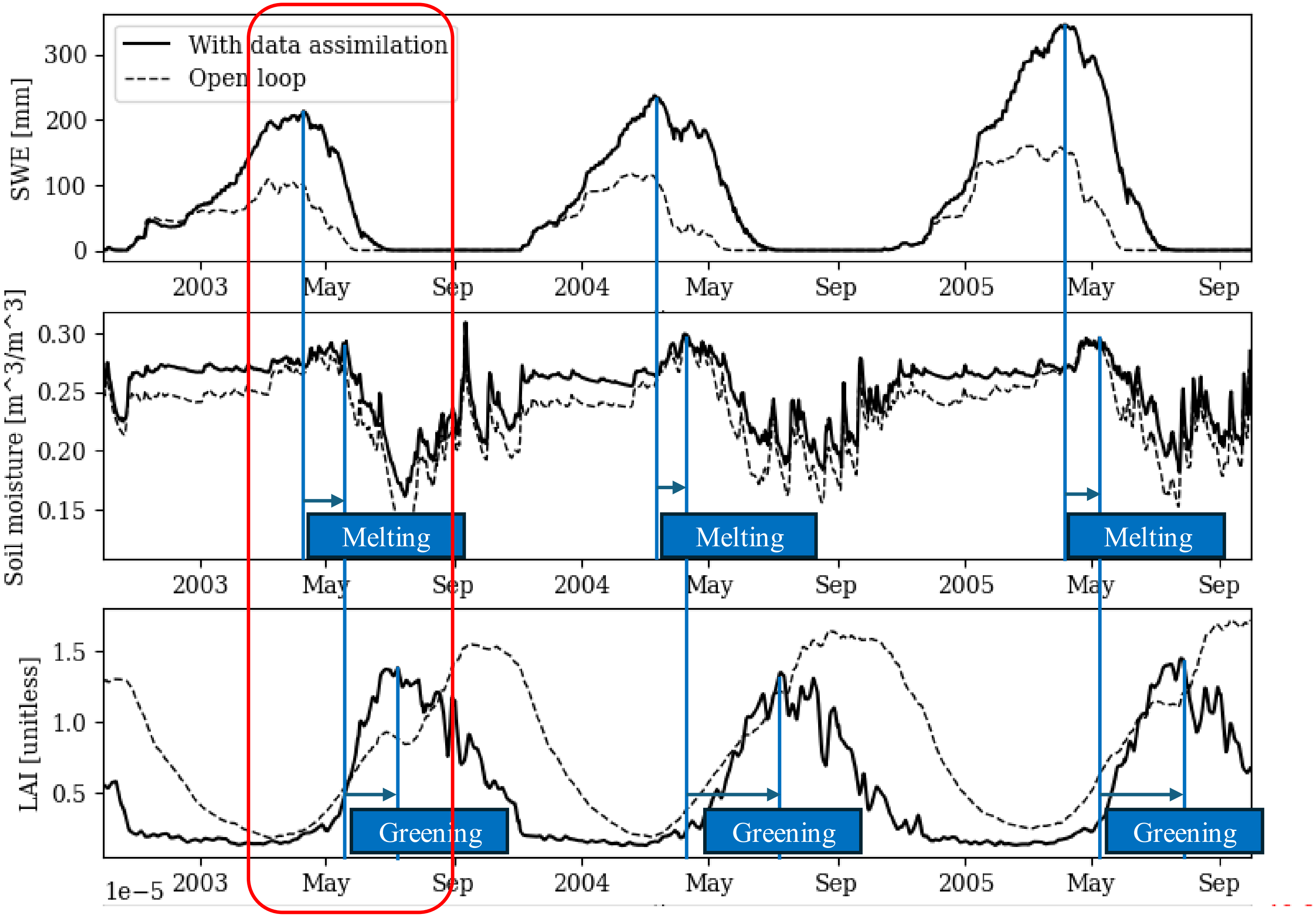
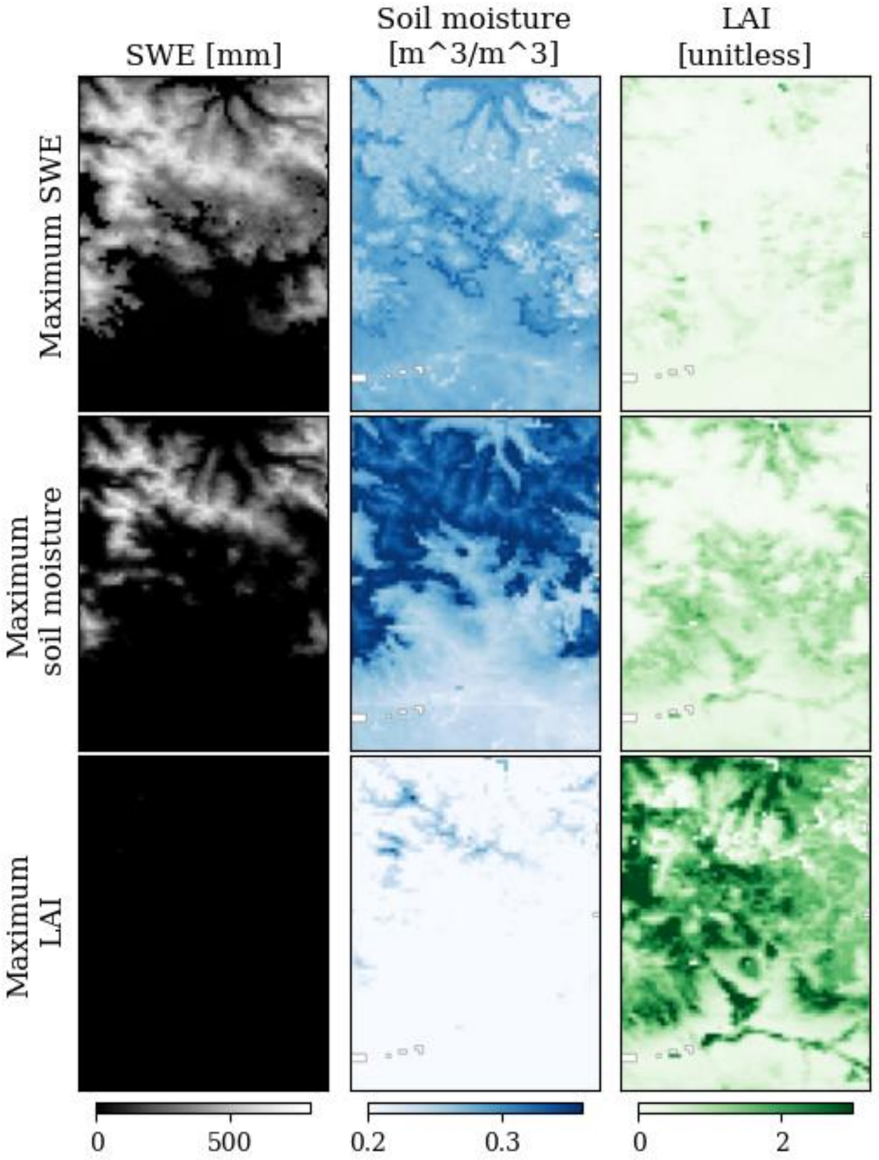
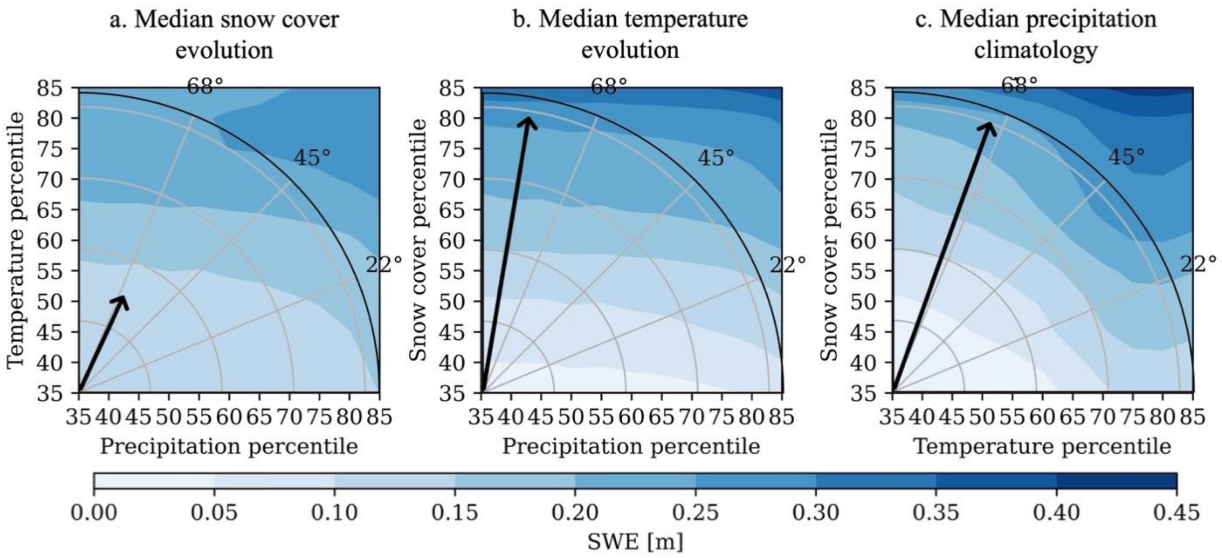

With data assimilation
Open loop
SWE [mm]
300
200
100
0
2003
May
Sep
2004
May
Sep
2005
May
Sep
Soil moisture [m^3/m^3]
0.30
0.25
0.20
0.15
Melting
Melting
Melting
2003
May
Sep
2004
May
Sep
2005
May
Sep
LAI [unitless]
1.5
1.0
0.5
Greening
Greening
Greening
1e−5
2003
May
Sep
2004
May
Sep
2005
May
Sep


SWE [mm]
Soil moisture [m^3/m^3]
LAI [unitless]
Maximum SWE
Maximum soil moisture
Maximum LAI
0
500
0.2
0.3
0
2

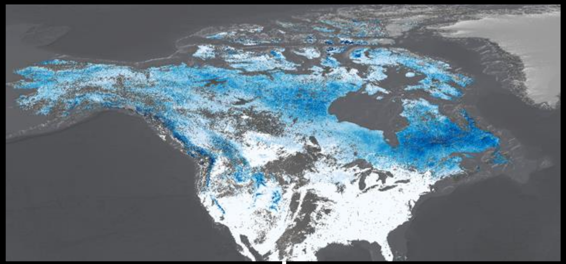


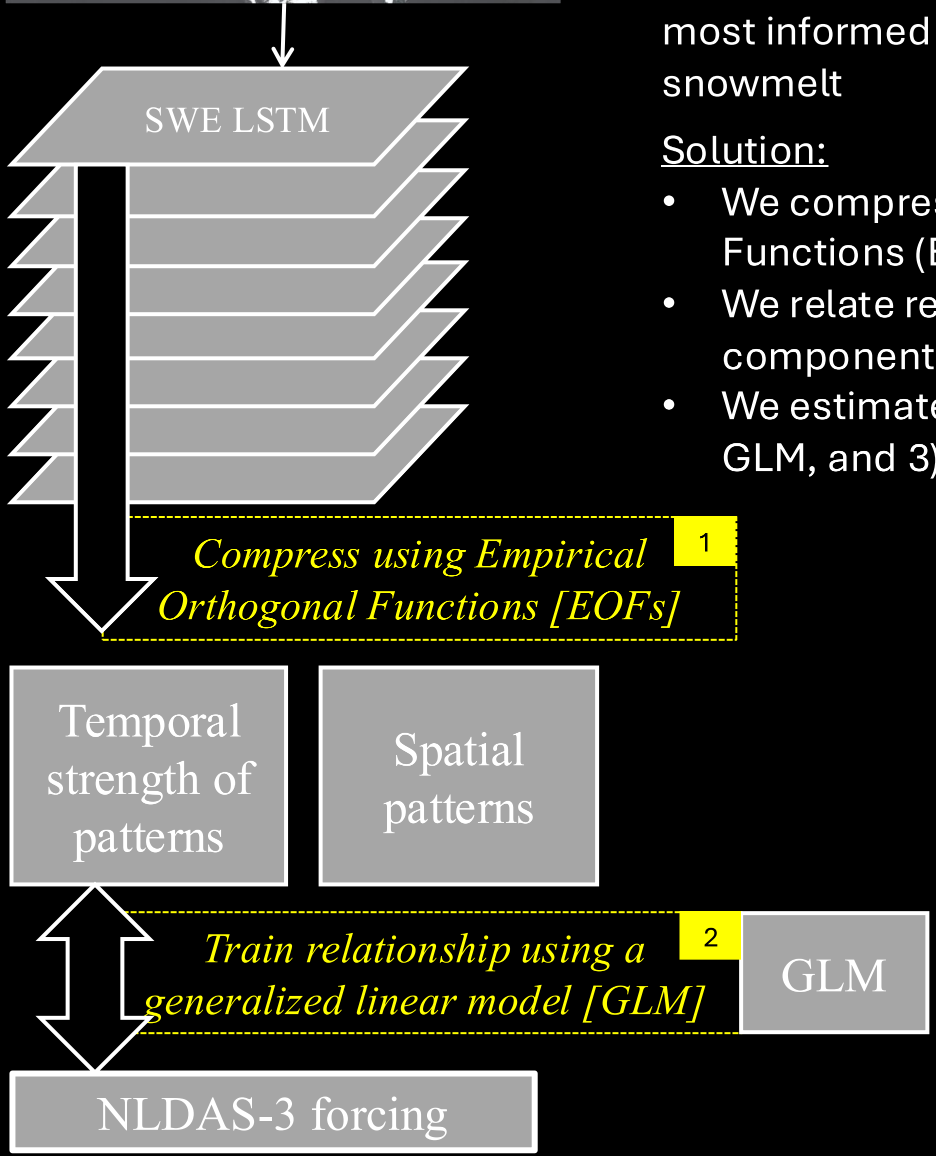
a. Median snow cover evolution

b. Median temperature evolution

c. Median precipitation climatology

Real-time SWE estimates using LSTM SWE patterns and NLDAS-3 regional forcing





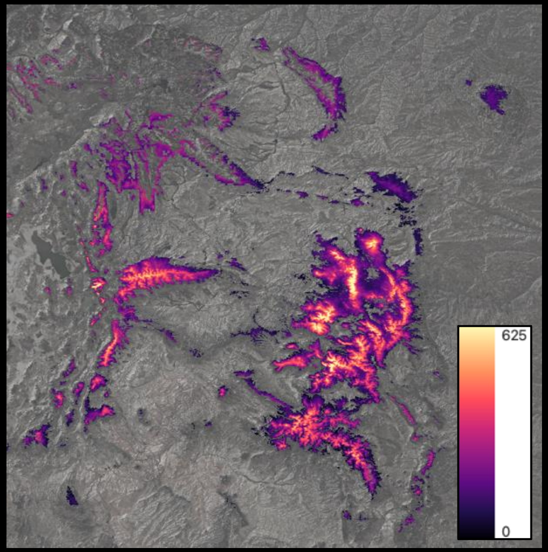
<u>Problem:</u> SWE estimates developed using a Long Short-Term Memory network (Pflug et al., 2025) are most informed by how snow cover changes during melt → SWE estimates can be uncertain before snowmelt

<u>Solution:</u>

- We compress the pattern of SWE on an end of winter date (e.g., 1 April) using Empirical Orthogonal Functions (EOFs) 1
- We relate regional and time-average meteorological conditions from NLDAS-3 to the temporal components of the EOFs using Generalized Linear Models (GLMs) 2
- We estimate SWE in years withheld from the EOF using 1) forcing from NLDAS-3, 2) the trained GLM, and 3) spatial patterns from the EOF analysis

CO/UT/WY Rocky Mountains

1 April 2009 EOF-based SWE estimate [mm]



1 April 2009 EOF-based SWE error [mm]