Climate-change resilient snowpack estimation in the Western United States

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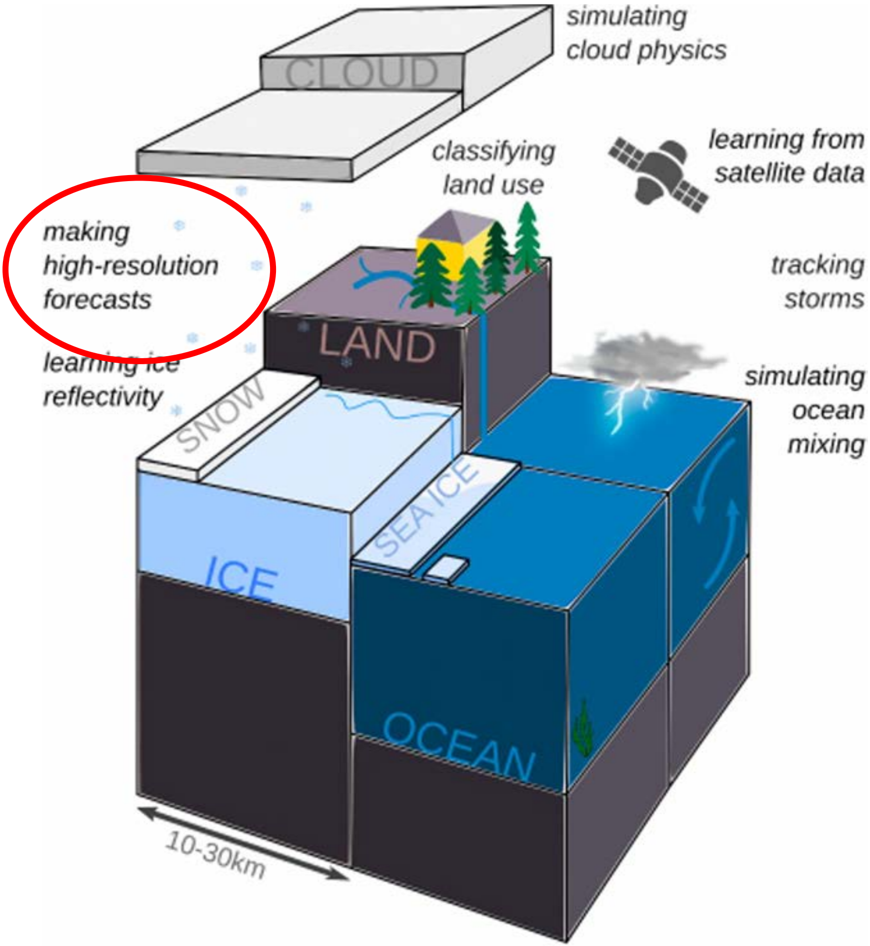
Photo: Jeremy Snyder




POLICY FORUM

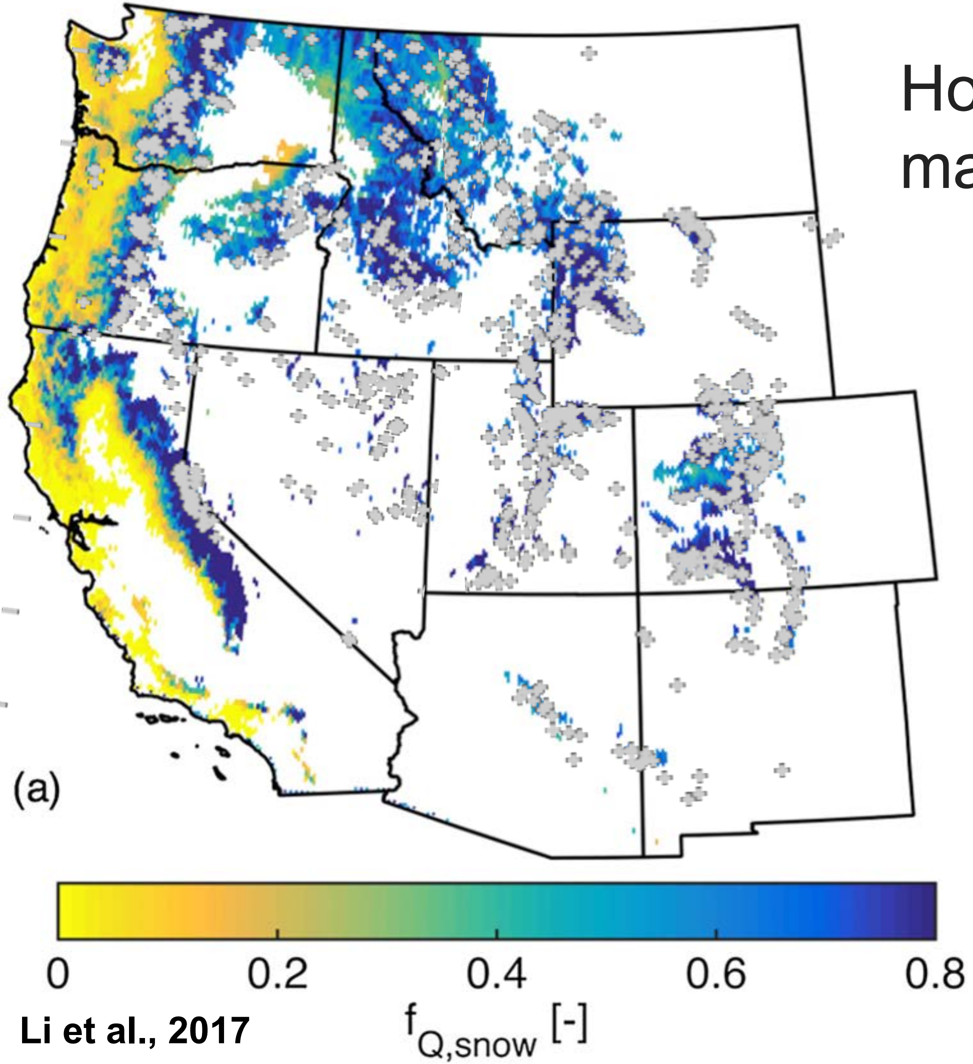
Stationarity Is Dead: Whither Water Management?

P. C. D. MILLY, JULIO BETANCOURT, MALIN FALKENMARK, ROBERT M. HIRSCH, ZBIGNIEW W. KUNDZEWICZ, DENNIS P. LETTENMAIER, AND RONALD J. STOUFFER Authors Info & Affiliations

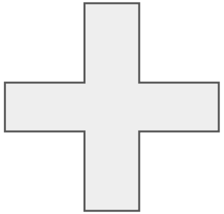
SCIENCE • 1 Feb 2008 • Vol 319, Issue 5863 • pp. 573-574 • DOI: 10.1126/science.1151915

Rolnick et al. "Tackling climate change with machine learning." *ACM Computing Surveys (2022)*

How do we measure and manage snowfall and snowpack?



Li et al., 2017



Snow Telemetry (SNOTEL) network in the Western US

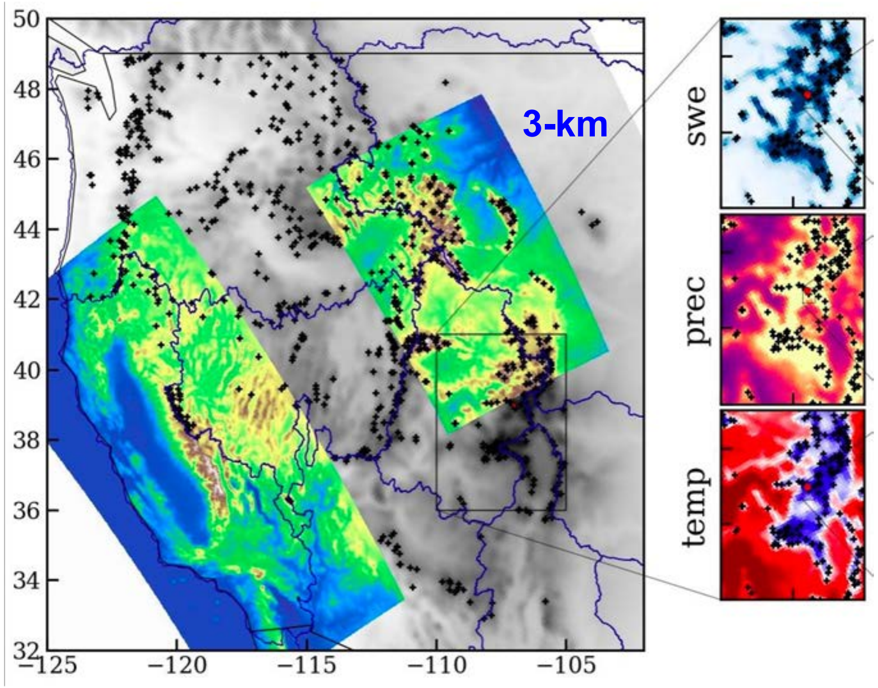
What about snow in the future? Models projections!

For this study, we use 9 CMIP6 GCMS

- Bias-corrected
- Dynamically downscaled with WRF

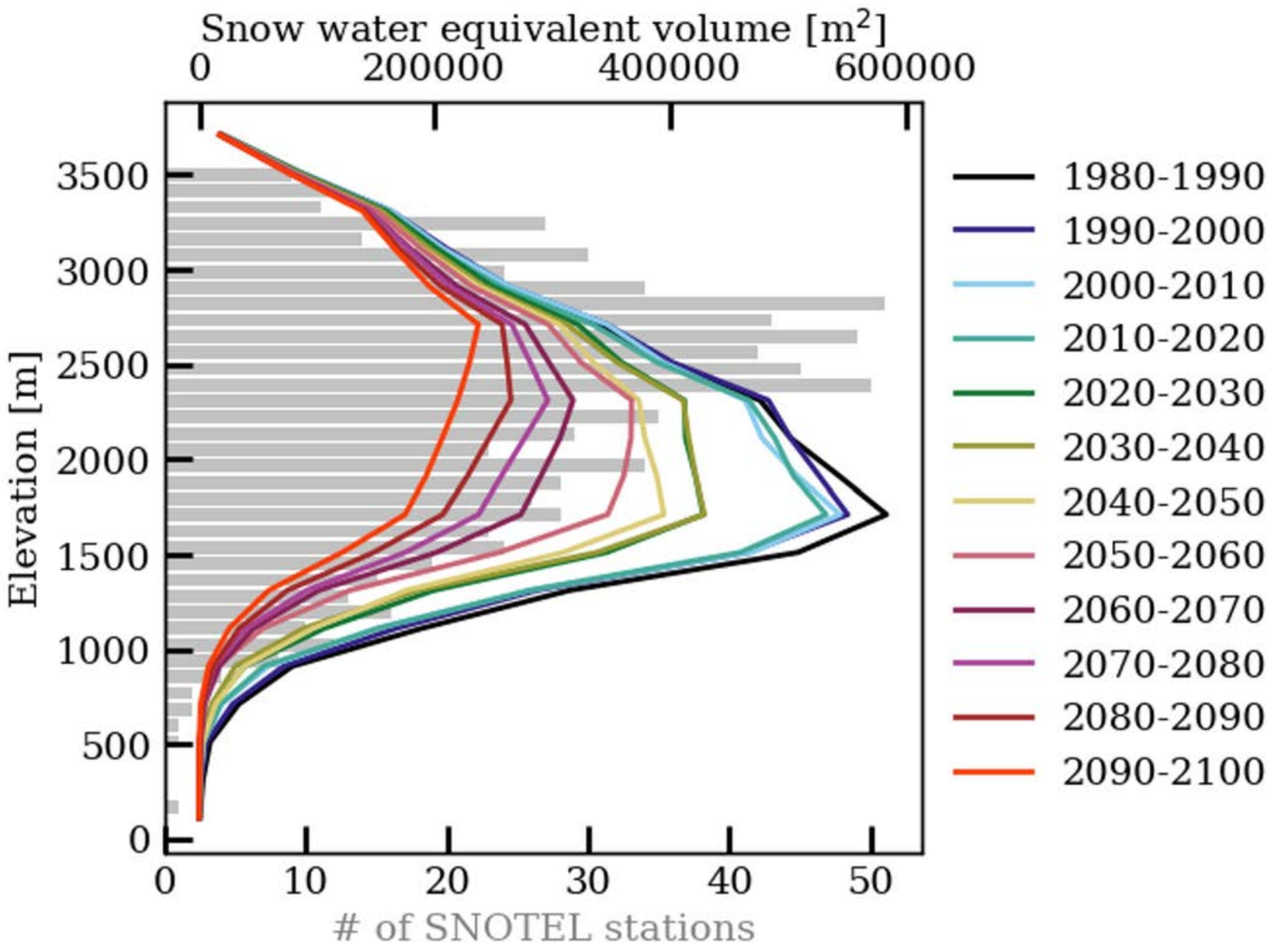
= high spatial resolution, any physical variable, any frequency, ensemble

9-km

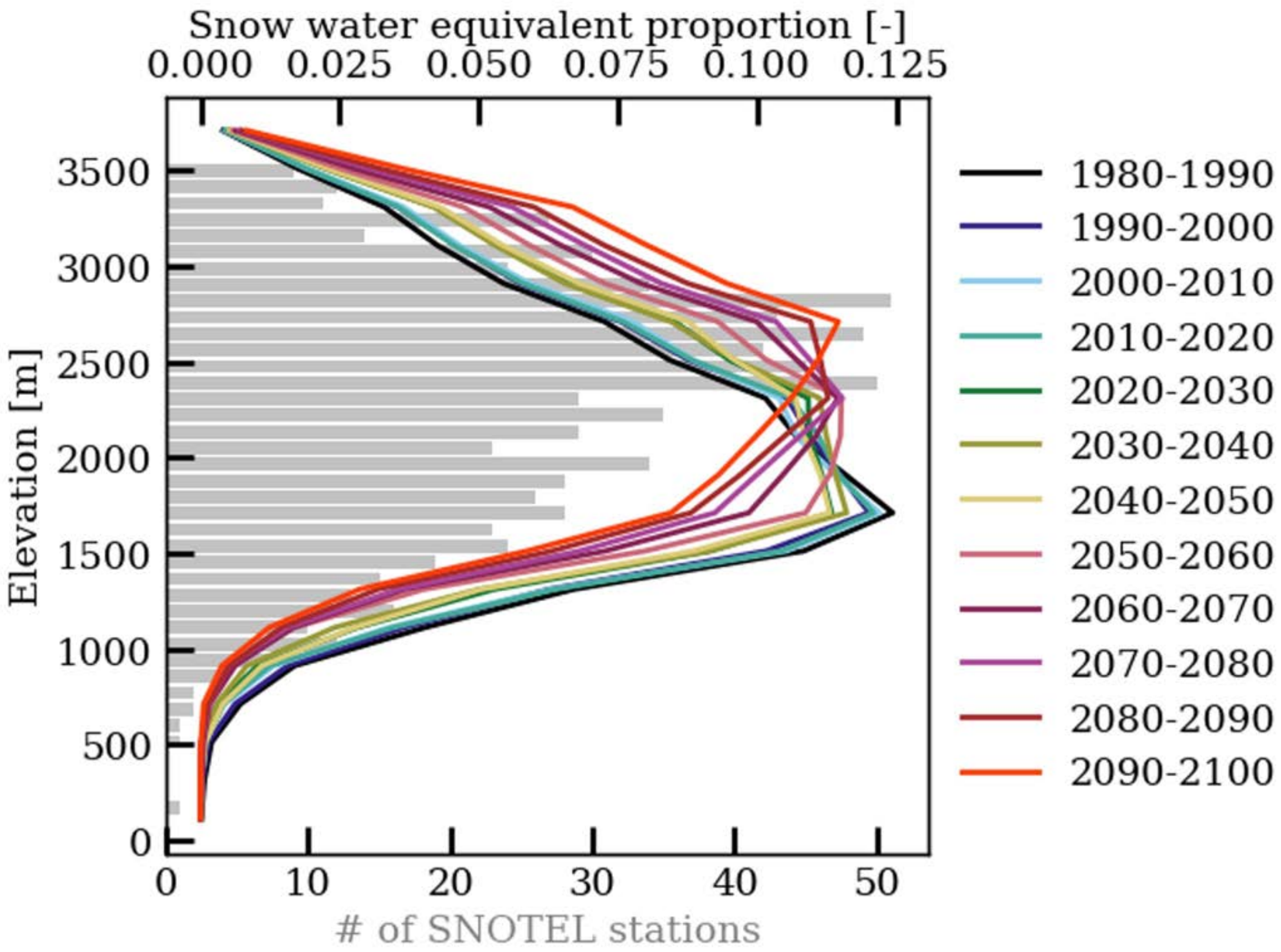


Downscaled reanalysis data: *Rahimi et al. (2022)*
Downscaled CMIP6 ensemble: *Rahimi et al., Submitted*

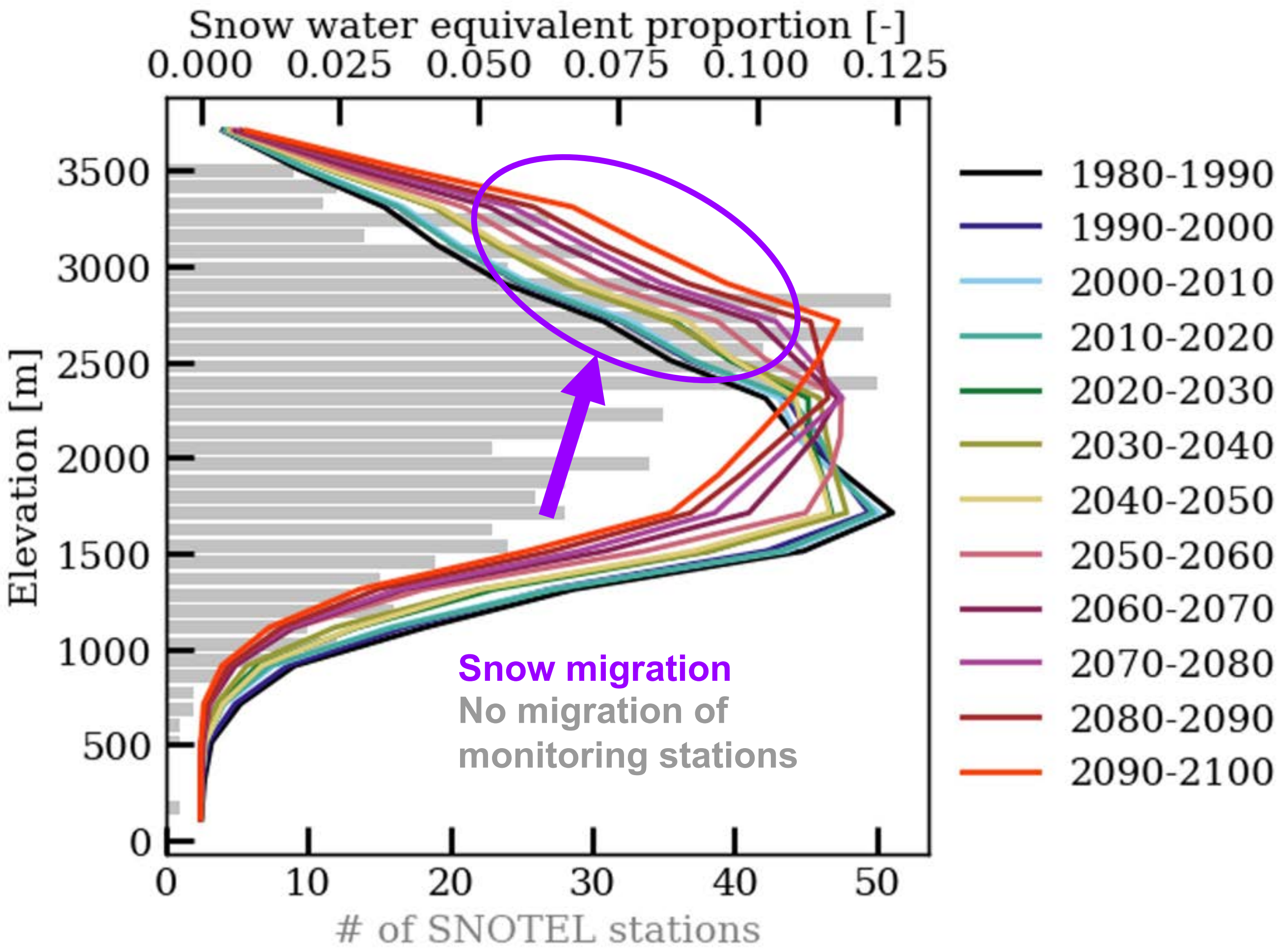
Snow distribution by decade from downscaled projections in **volume** units



Snow distribution by decade from downscaled projections by **proportion**



Snow distribution by decade from downscaled projections by **proportion**



$$Q = \sum_{i=1}^{n} a_i \mathrm{SWE}_i + e$$

“These predictions depend on the presence of **measurable snowpack**, as well as **a consistent relationship** between observed peak snow conditions and streamflow.” -Livneh and Badger 2020

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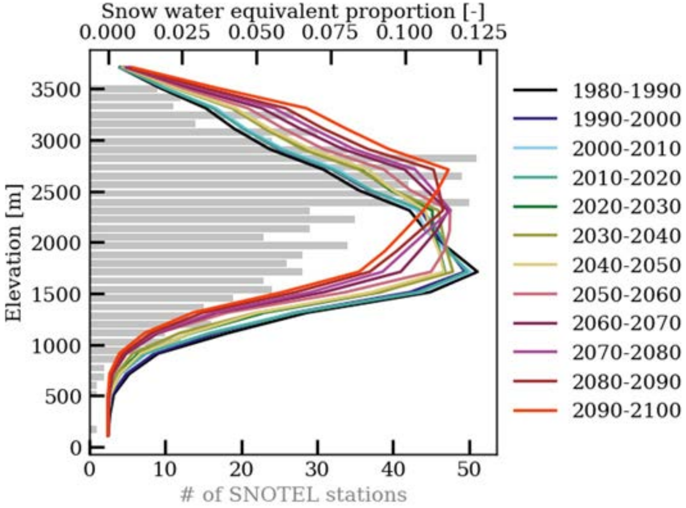

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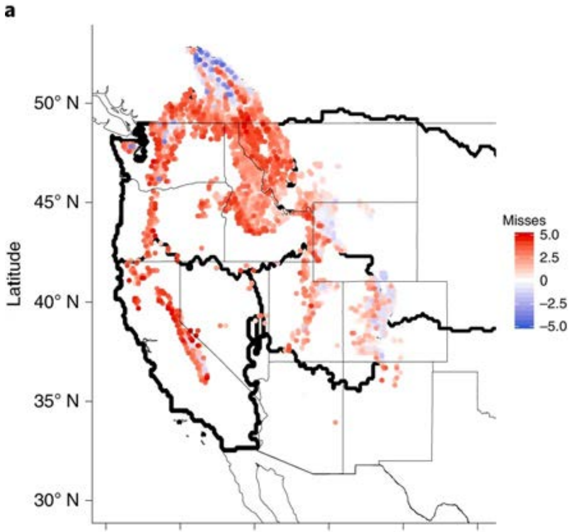

Article | Published: 20 April 2020

Drought less predictable under declining future snowpack

Ben Livneh & Andrew M. Badger

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Current management practices

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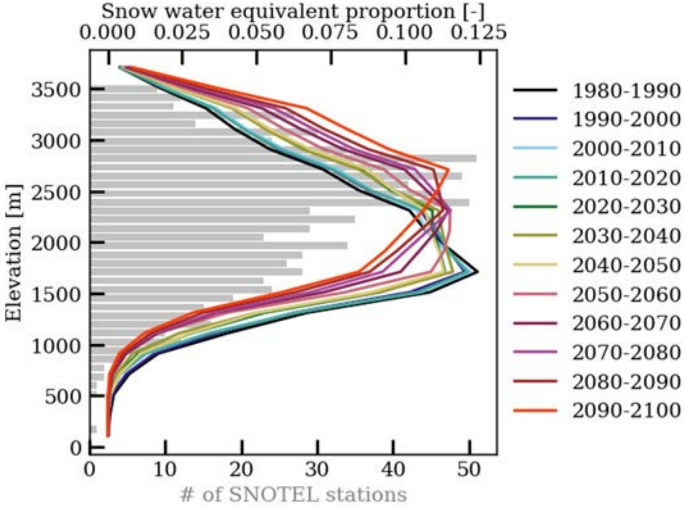

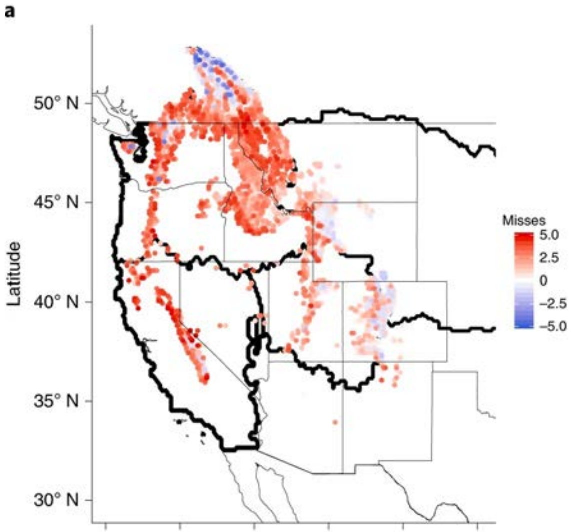

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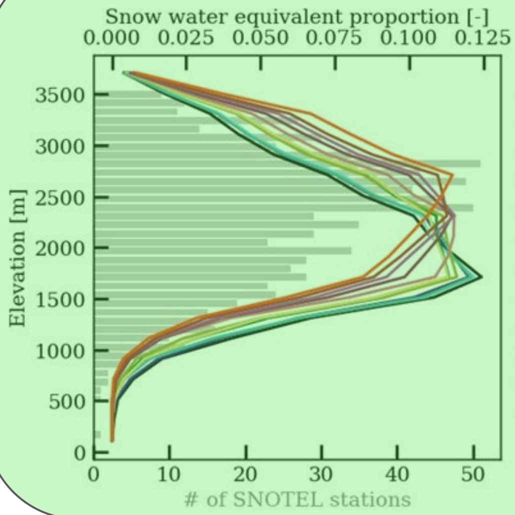
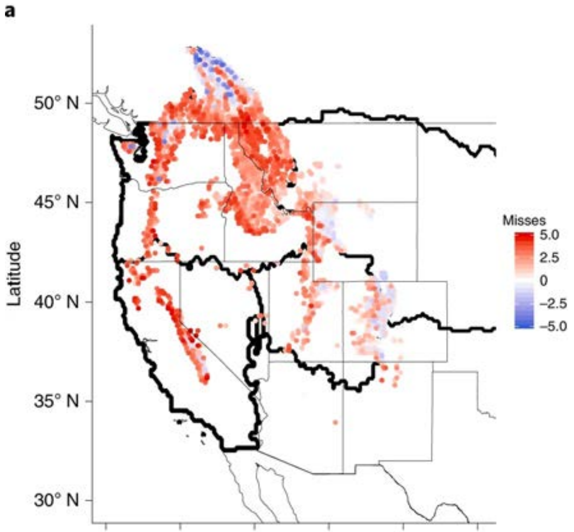
+

Expected future





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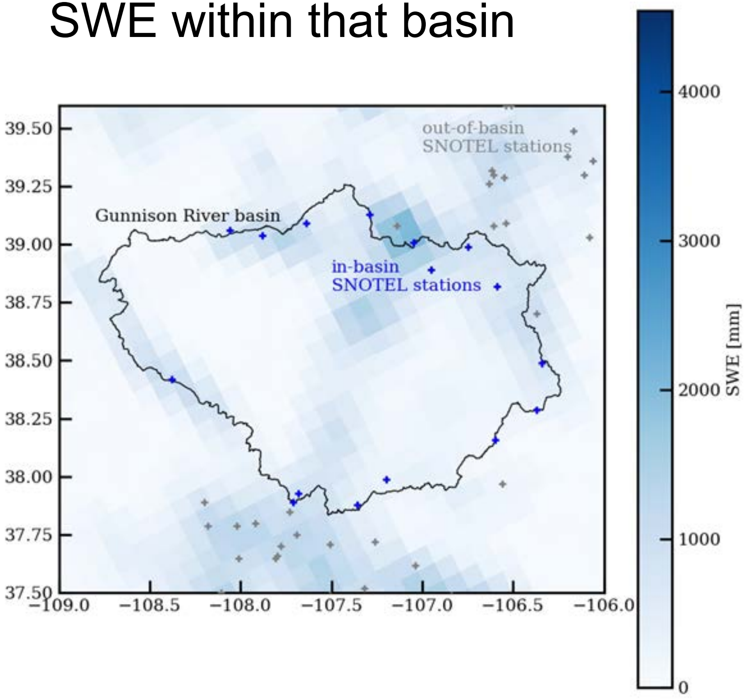
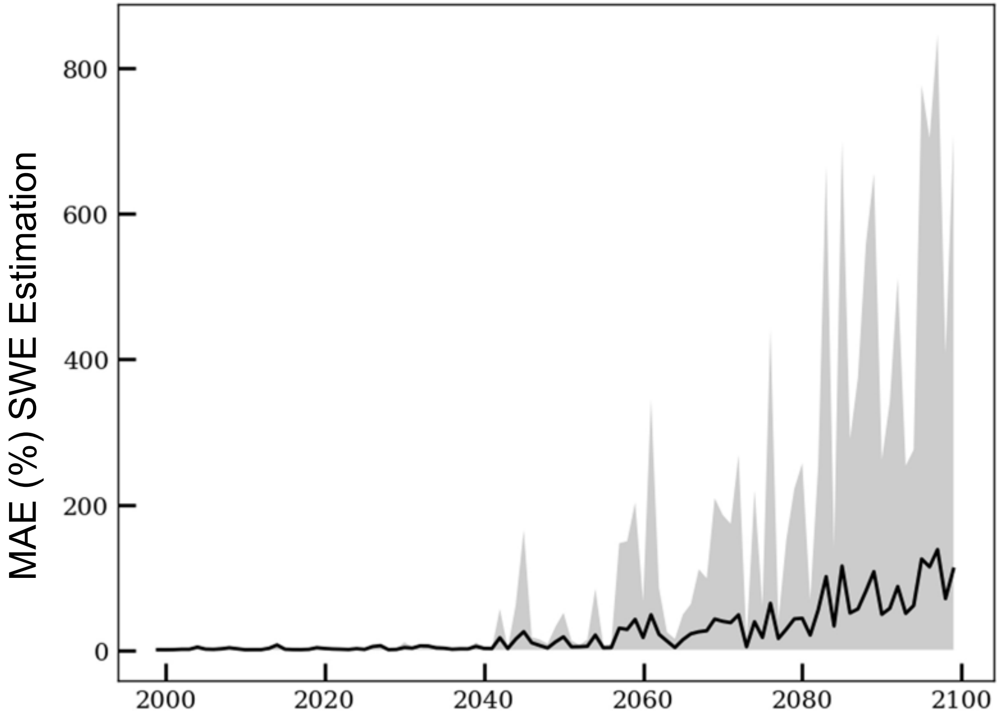
What do we do about this?

1. Use SNOTEL locations to predict maximum annual SWE across the Western US from a dynamically downscaled multi-model CMIP6 GCM ensemble with a variety of models
2. Explore the characteristics and underlying assumptions behind successful and unsuccessful data models

Model 1: Linear regression

For each basin, use SNOTEL stations to predict SWE within that basin





Error explosion by end of 21st Century: Snowpack estimation is not currently resilient to expected changes in snowfall/snowpack

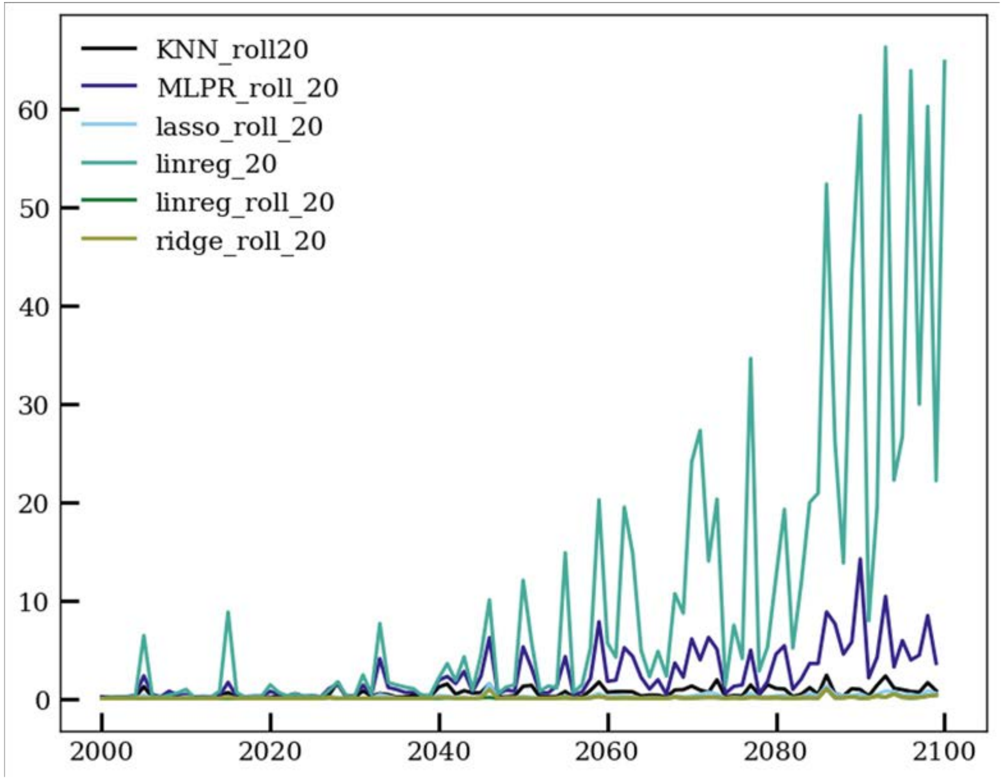
Data Model Complexity?

What else should we try?

What characteristics should data models have?

Do they need more data or do they need a different structure?

MAE (cm) SWE Estimation



Higher complexity data models reduce projection errors

Data + Model Complexity?

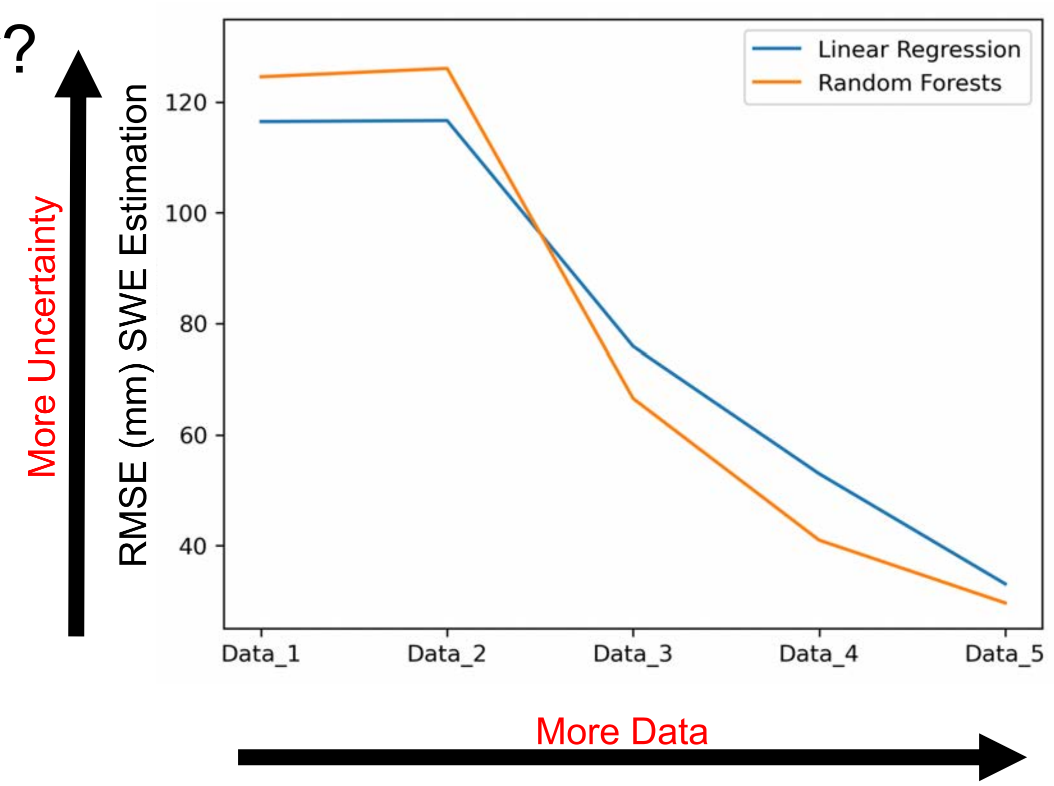
There are many observations that indirectly constrain snowpack.

What characteristics should data models have to constrain snowpack?

We find that more indirect observations reduce RMSE in SWE.

With minimal observations, a low complexity data model is needed. With more obs, a higher complexity model is needed. But when obs over-constrain SWE, the data model doesn't matter.

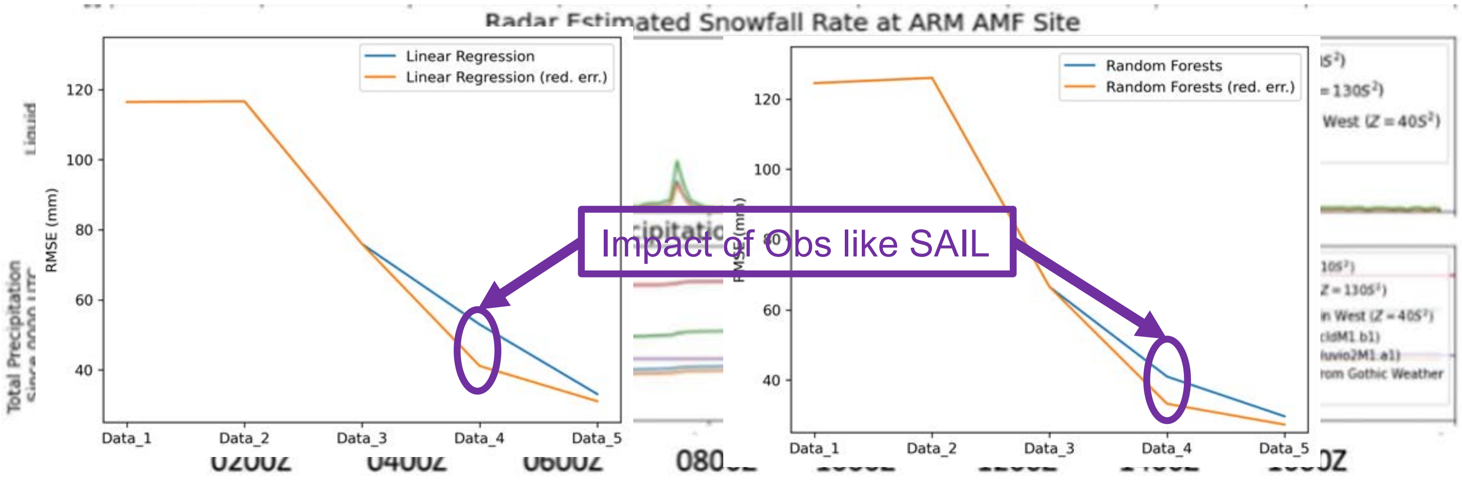
Western US SWE RMSE vs More Predictors




```
Data_1 = ['knn_snotel', 'Longitude', 'Latitude']
Data_2 = Data_1 + ['Elevation', 'Slope', 'Aspect', 'Veg-Type', 'Veg-Frac']
Data_3 = Data_2 + ['Cum-fSCA']
Data_4 = Data_3 + ['Cum-precip', 'Cum-snow', 'Mean-temp', 'PDD-sum']
Data_5 = Data_4 + ['ASO-proxy']
```

Connections to Field Campaigns like SAIL

- Field campaigns like SAIL show how well predictors of snowfall and snowpack can actually be constrained.
- Snowfall can be constrained to <10% of daily ground accumulation totals with direct observations, while there was >50% uncertainty without those obs.
- Where not over-constrained, SWE predictions improve with reduced precip uncertainty where



Feldman et al, BAMS, 2023

Attributes of climate-resilient snow estimation models

1. Represent nonlinear, nonstationary relationships
2. Resilient to loss of an input station
3. Take cautious advantage of out-of-basin information
4. Benefit from but do not require specialized observations

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We think the machine learning community has answers to this!

Contact: cowherd@berkeley.edu

Thank you!







EARTH & ENVIRONMENTAL SCIENCES

NSF

NCAR UCAR

UCLA Institute of the Environment & Sustainability

ESPM DEPARTMENT of ENVIRONMENTAL SCIENCE, POLICY, AND MANAGEMENT

DOE CSGF

SAIL Surface Atmosphere Integrated Field Laboratory

NERSC

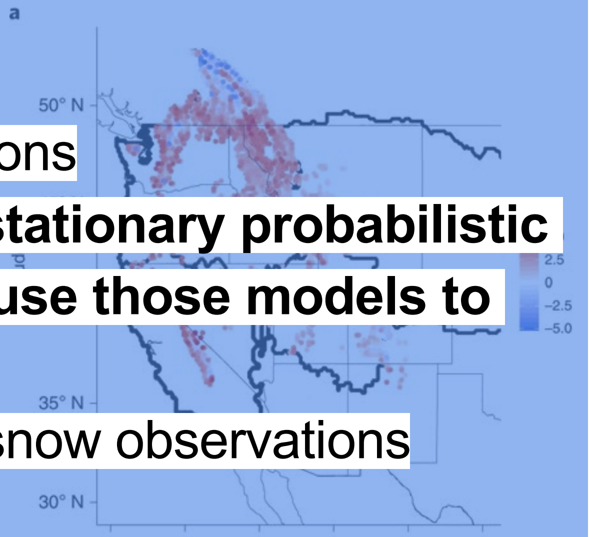
Berkeley | EECS Electrical Engineering and Computer Sciences

Jeremy Snyder

1: Increase the scale and resolution of direct observations

2: *“A successor.* We need to find ways to identify **nonstationary probabilistic models of relevant environmental variables** and to **use those models to optimize water systems**.”

+ AND takes into account the shifting availability of snow observations



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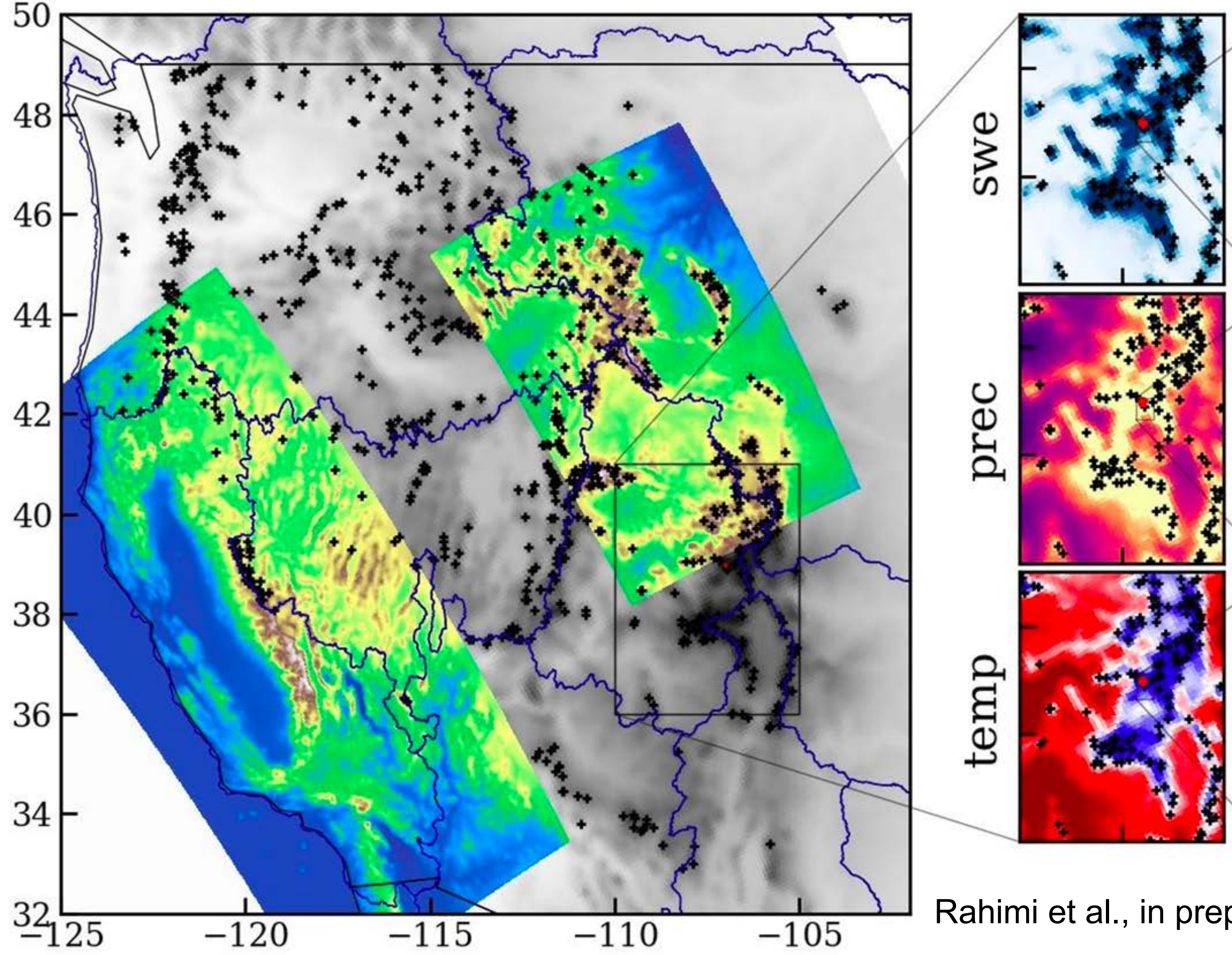
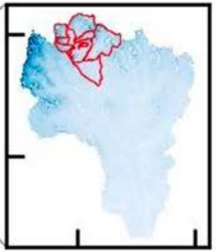
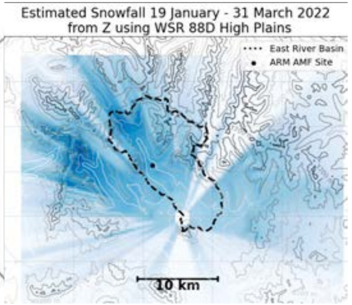


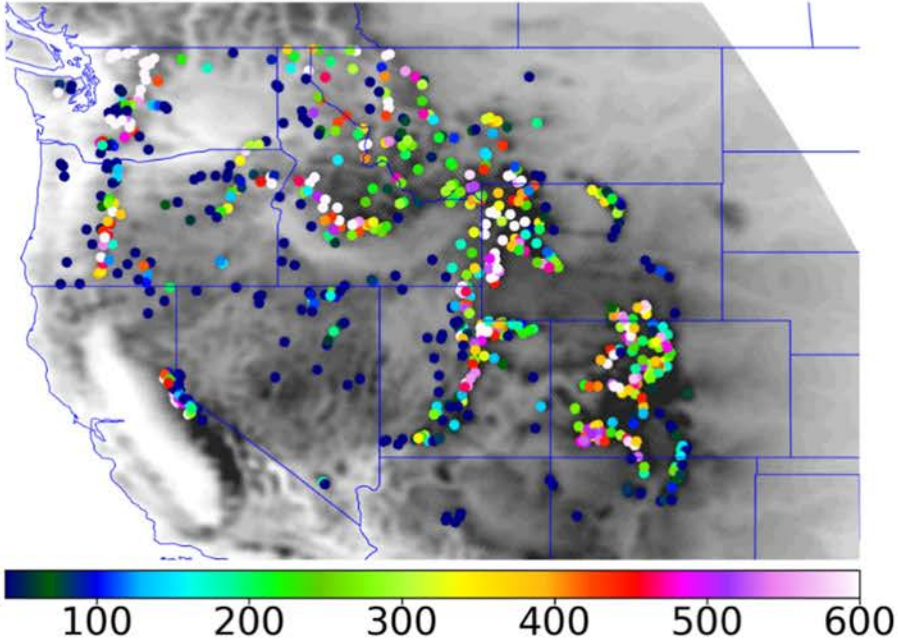


ASO SWE

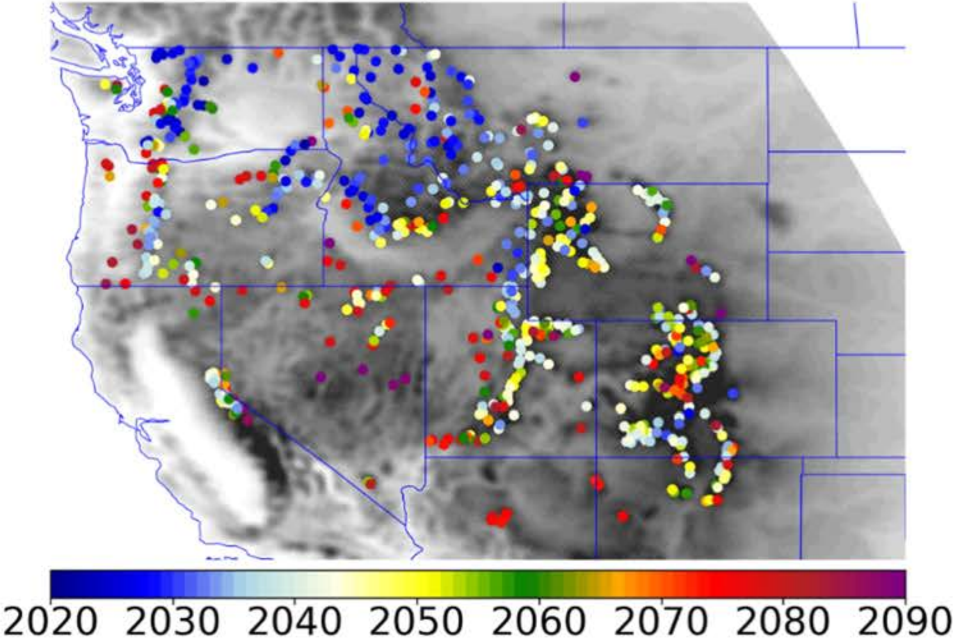


Rahimi et al., in prep

Ensemble-mean historical 10th percentile SWE [mm]



Year when mean SWE falls below historical 10th percentile



Bias corrected experiments only

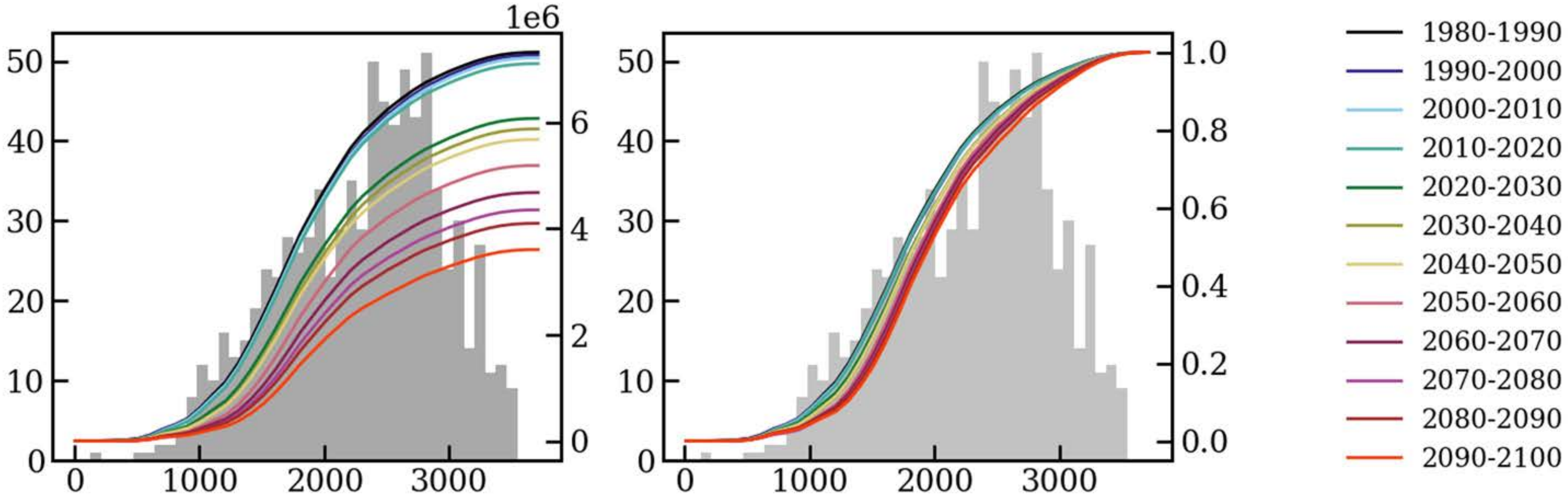
Correlation between emergence year and historical p10: -0.38
Correlation between p10 and WRF elevation: 0.19
Correlation between emergence year and WRF elevation: 0.07

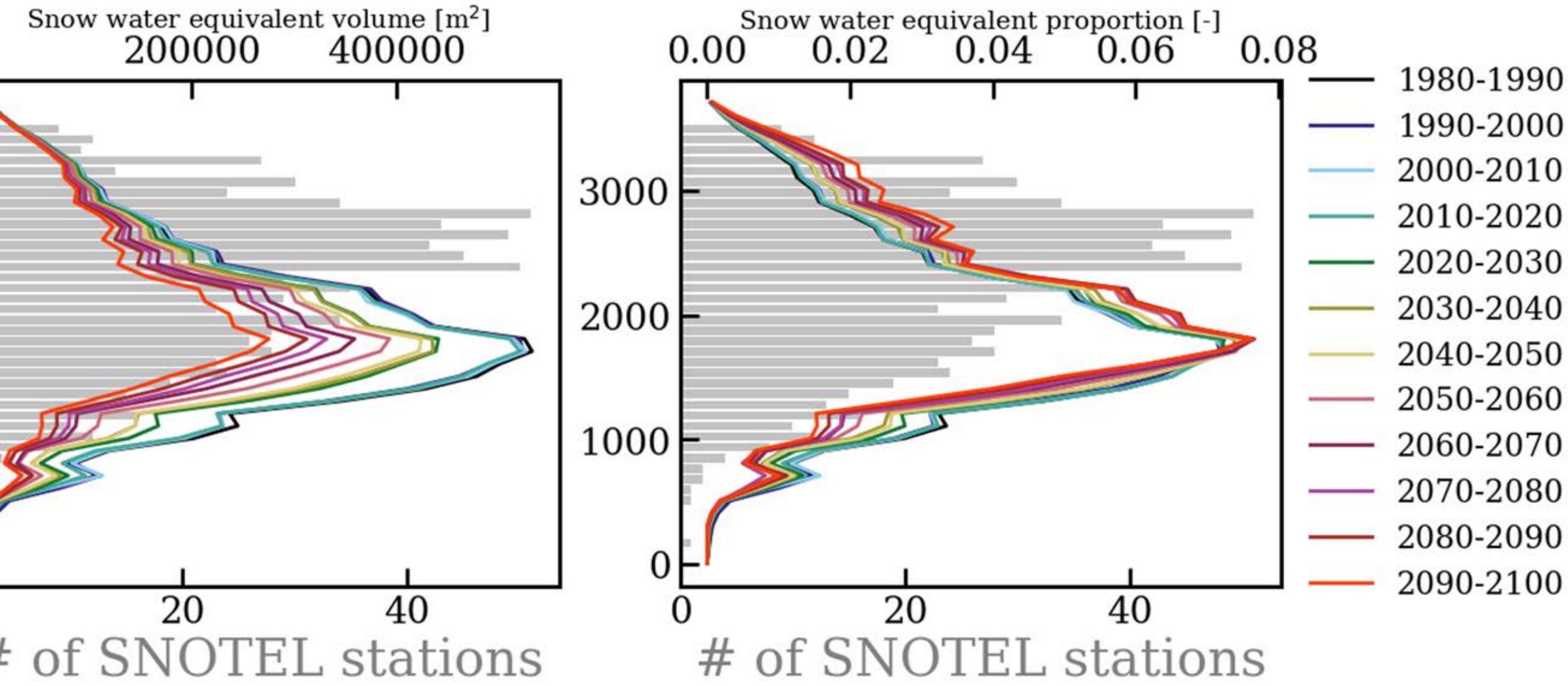
SAIL

How useful is the SAIL precip data?

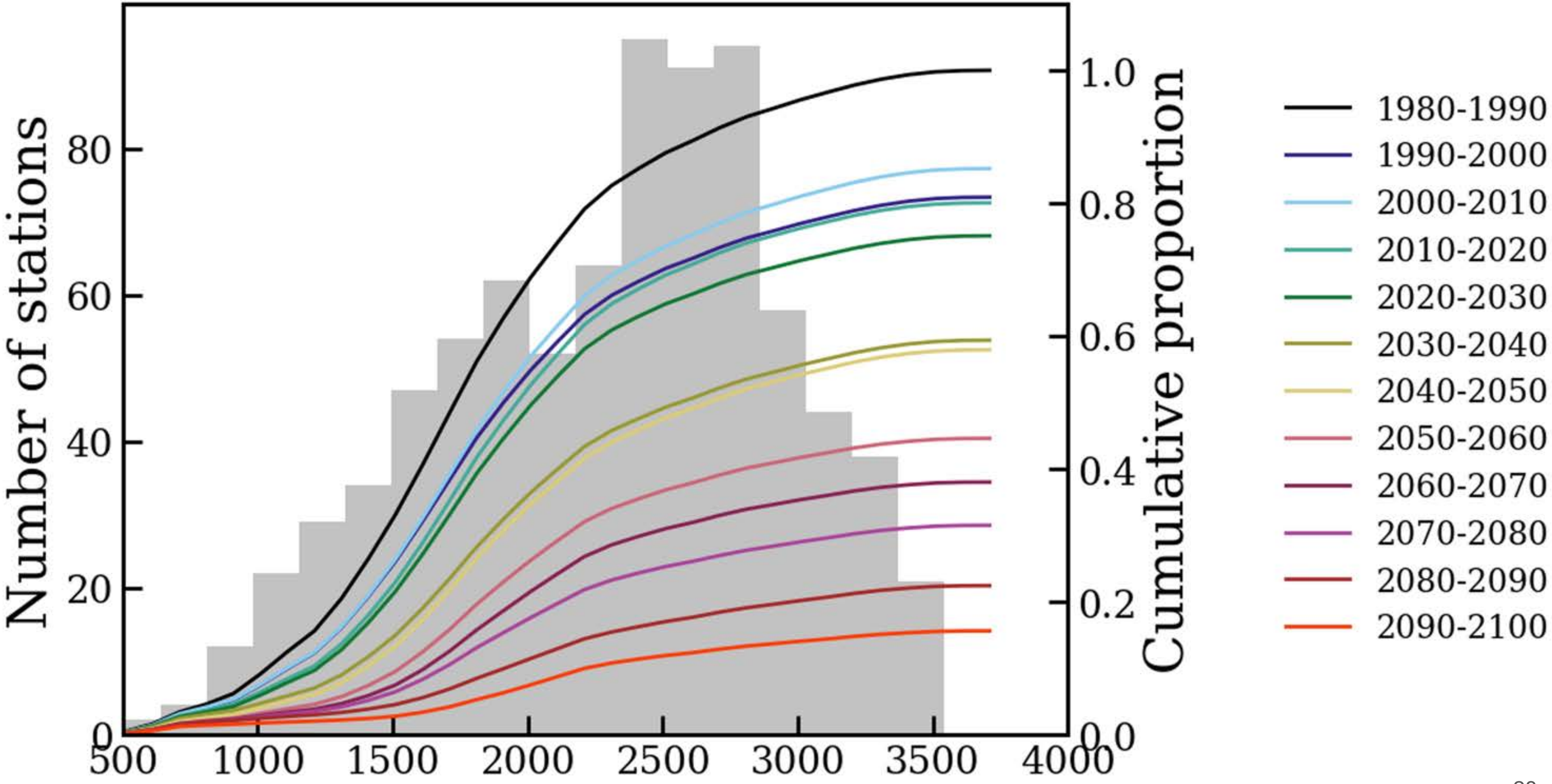
- Make a prediction of the ASO field using PRISM precip
- Repeat with SAIL precip data
- Should be better with the SAIL data because they are more accurate → this gives us an idea of how bad it is to use PRISM as a “good” source for precip (or daymet or whatever)
- → we can use a more complex model from more sparse data that are more certain in order to get a trustworthy idea of what snow looks like without relying on highly uncertain driving data

9-model mean

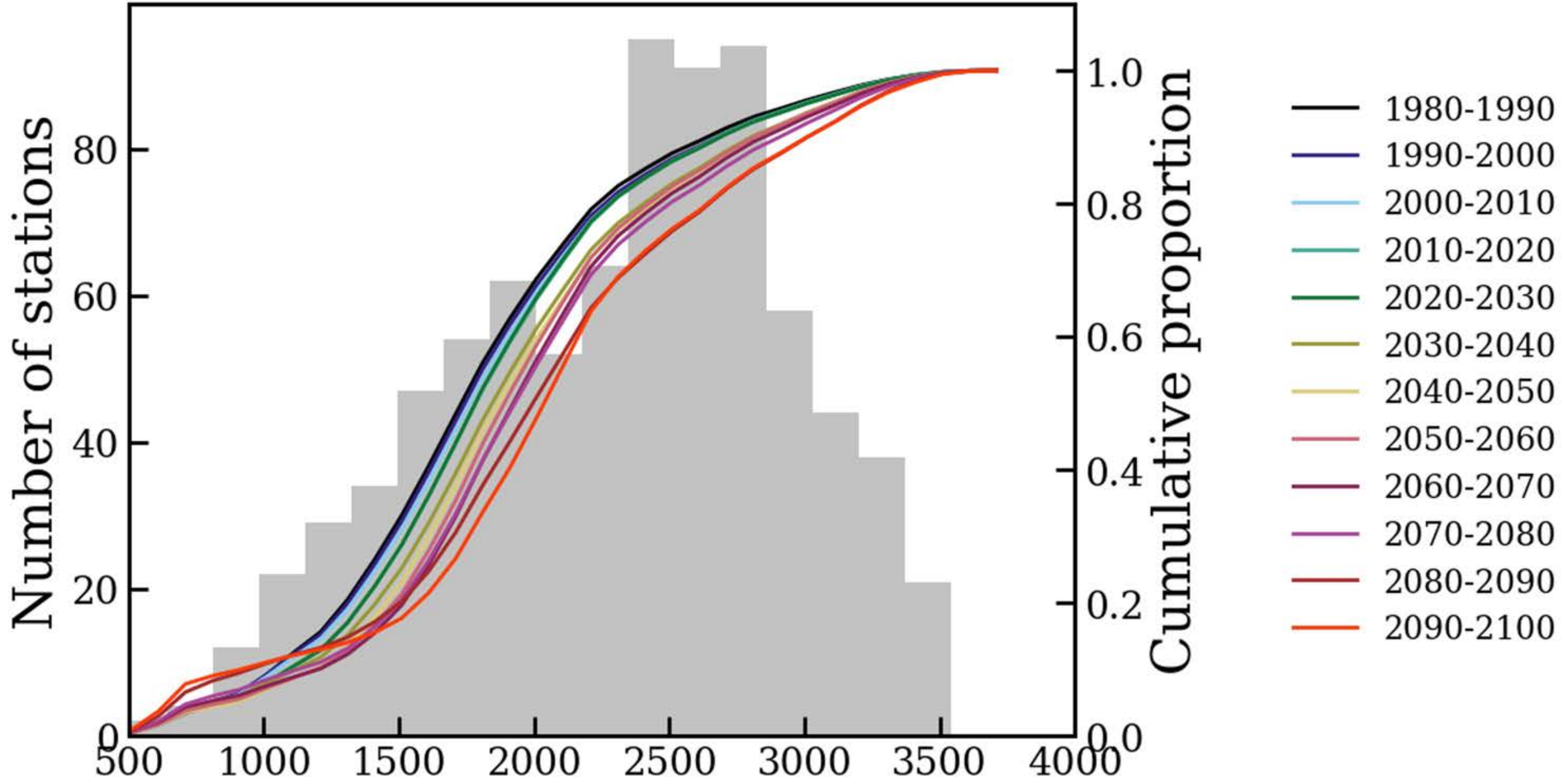

1e6
50
40
30
20
10
0
0
1000
2000
3000
6
4
2
0
1.0
0.8
0.6
0.4
0.2
0.0
1980-1990
1990-2000
2000-2010
2010-2020
2020-2030
2030-2040
2040-2050
2050-2060
2060-2070
2070-2080
2080-2090
2090-2100

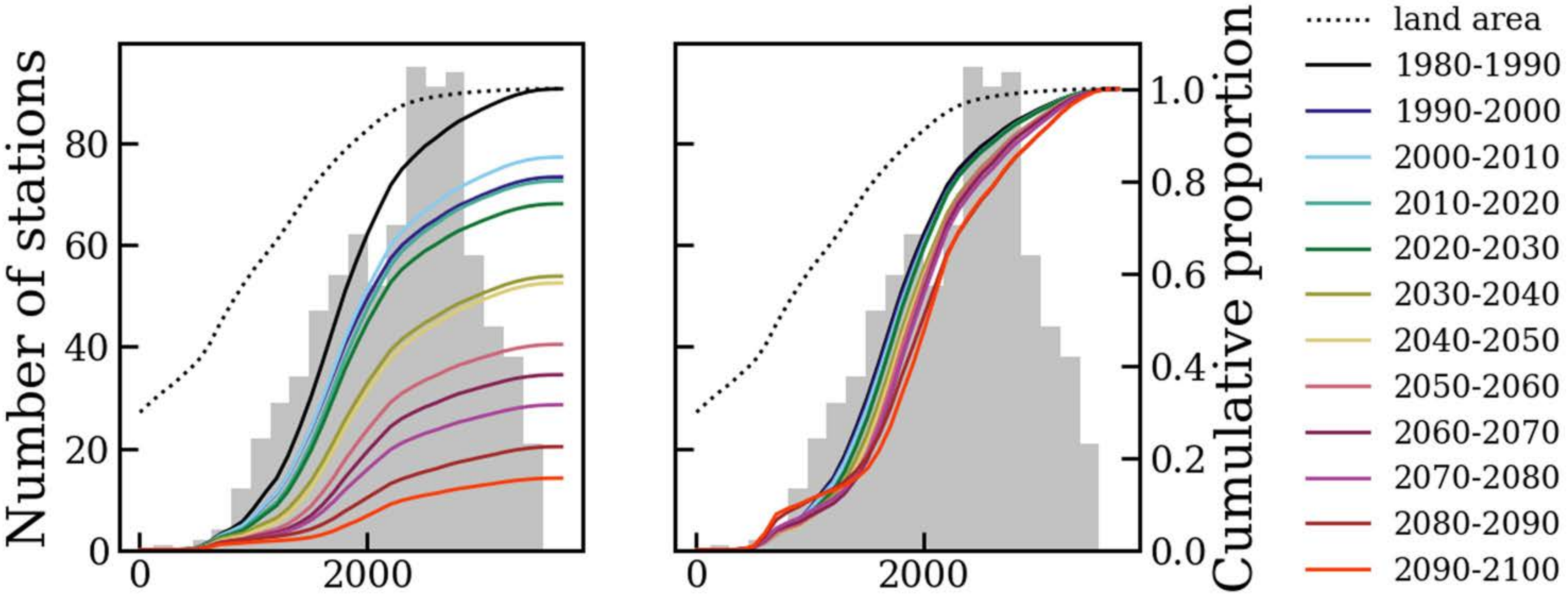


Snow water equivalent volume [m²]
200000
400000
20
40
# of SNOTEL stations
Snow water equivalent proportion [-]
0.00
0.02
0.04
0.06
0.08
3000
2000
1000
0
0
20
40
# of SNOTEL stations
1980-1990
1990-2000
2000-2010
2010-2020
2020-2030
2030-2040
2040-2050
2050-2060
2060-2070
2070-2080
2080-2090
2090-2100

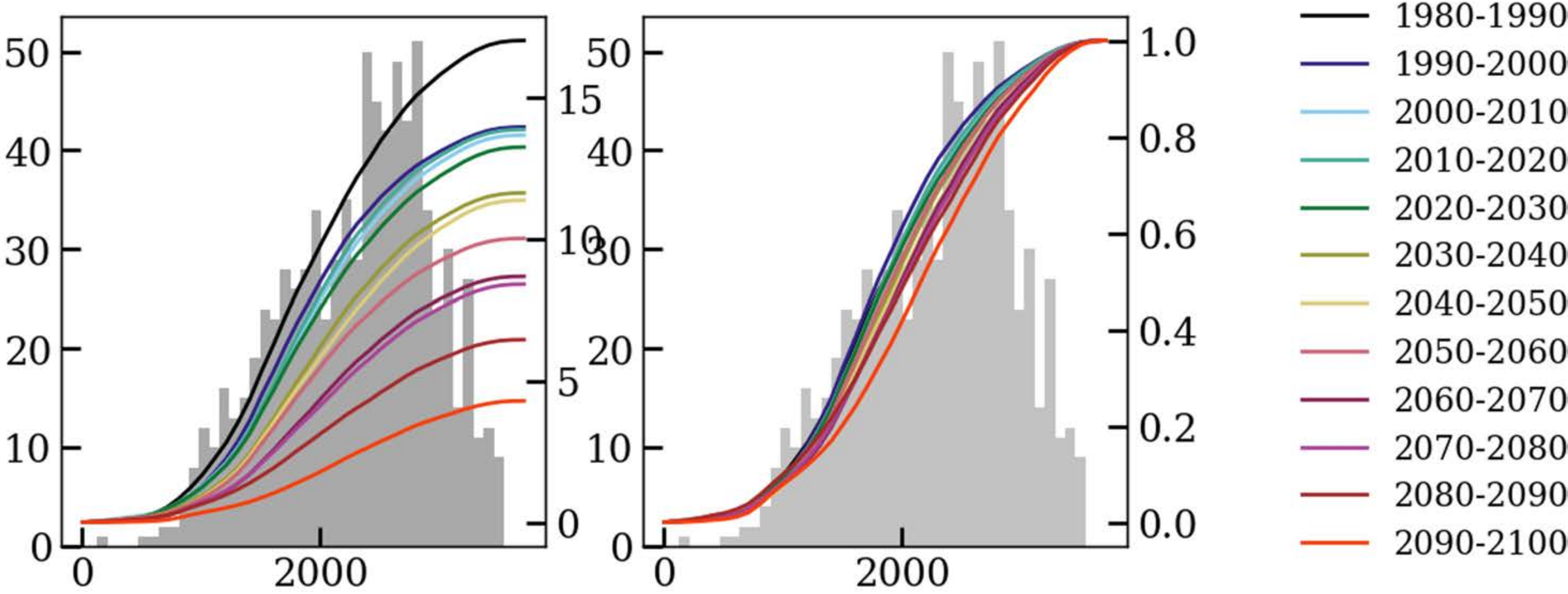


Number of stations
Cumulative proportion
0
20
40
60
80
500
1000
1500
2000
2500
3000
3500
4000
0.0
0.2
0.4
0.6
0.8
1.0
1980-1990
1990-2000
2000-2010
2010-2020
2020-2030
2030-2040
2040-2050
2050-2060
2060-2070
2070-2080
2080-2090
2090-2100


Number of stations
Cumulative proportion
0
20
40
60
80
0.0
0.2
0.4
0.6
0.8
1.0
500
1000
1500
2000
2500
3000
3500
4000
1980-1990
1990-2000
2000-2010
2010-2020
2020-2030
2030-2040
2040-2050
2050-2060
2060-2070
2070-2080
2080-2090
2090-2100



Number of stations
0
20
40
60
80
0
2000
0
2000
0.0
0.2
0.4
0.6
0.8
1.0
Cumulative proportion
land area
1980-1990
1990-2000
2000-2010
2010-2020
2020-2030
2030-2040
2040-2050
2050-2060
2060-2070
2070-2080
2080-2090
2090-2100



50
40
30
20
10
0
0
2000
15
10
5
0
50
40
30
20
10
0
0
2000
1.0
0.8
0.6
0.4
0.2
0.0
1980-1990
1990-2000
2000-2010
2010-2020
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2030-2040
2040-2050
2050-2060
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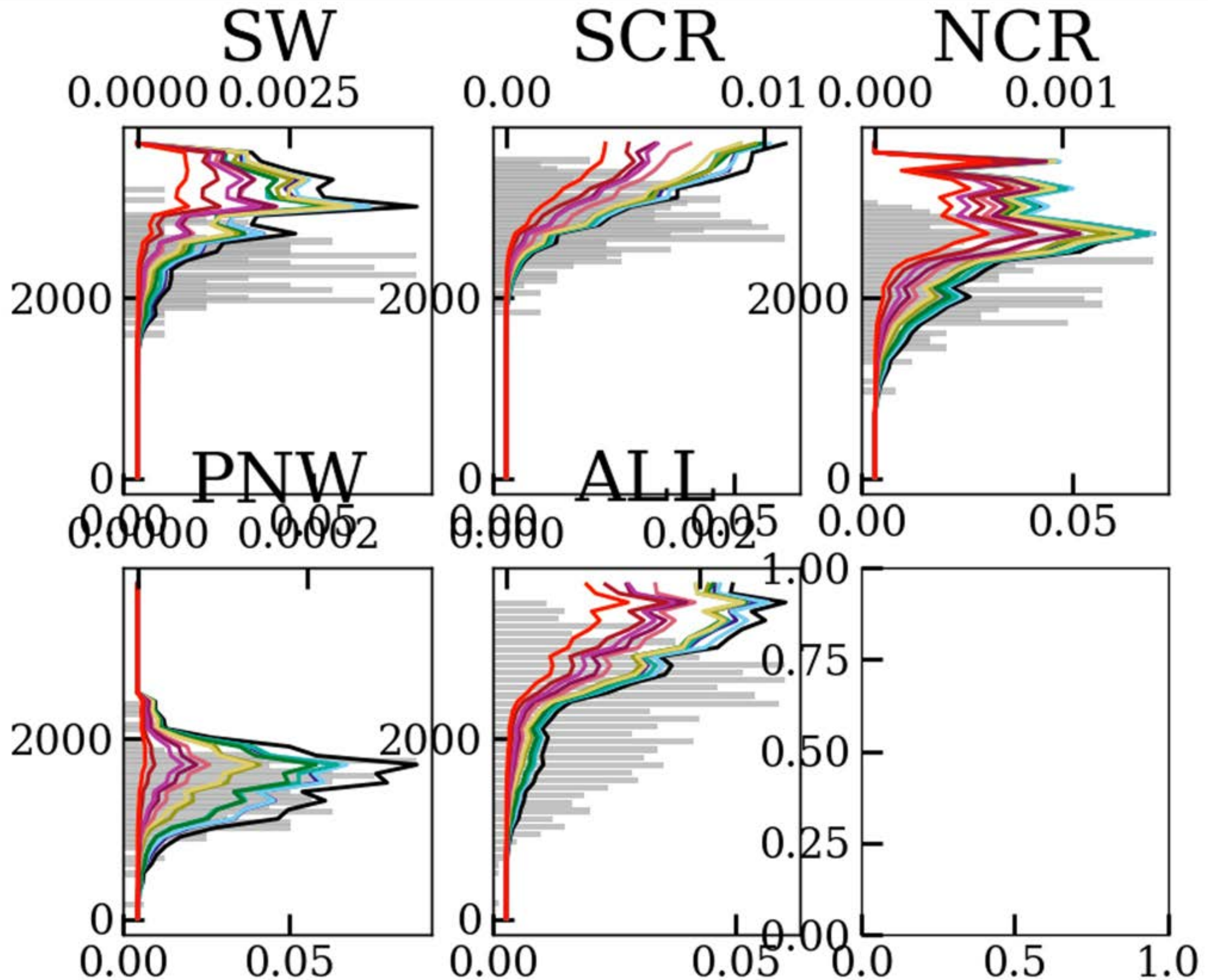
2080-2090
2090-2100


SW
SCR
NCR
PNW
ALL
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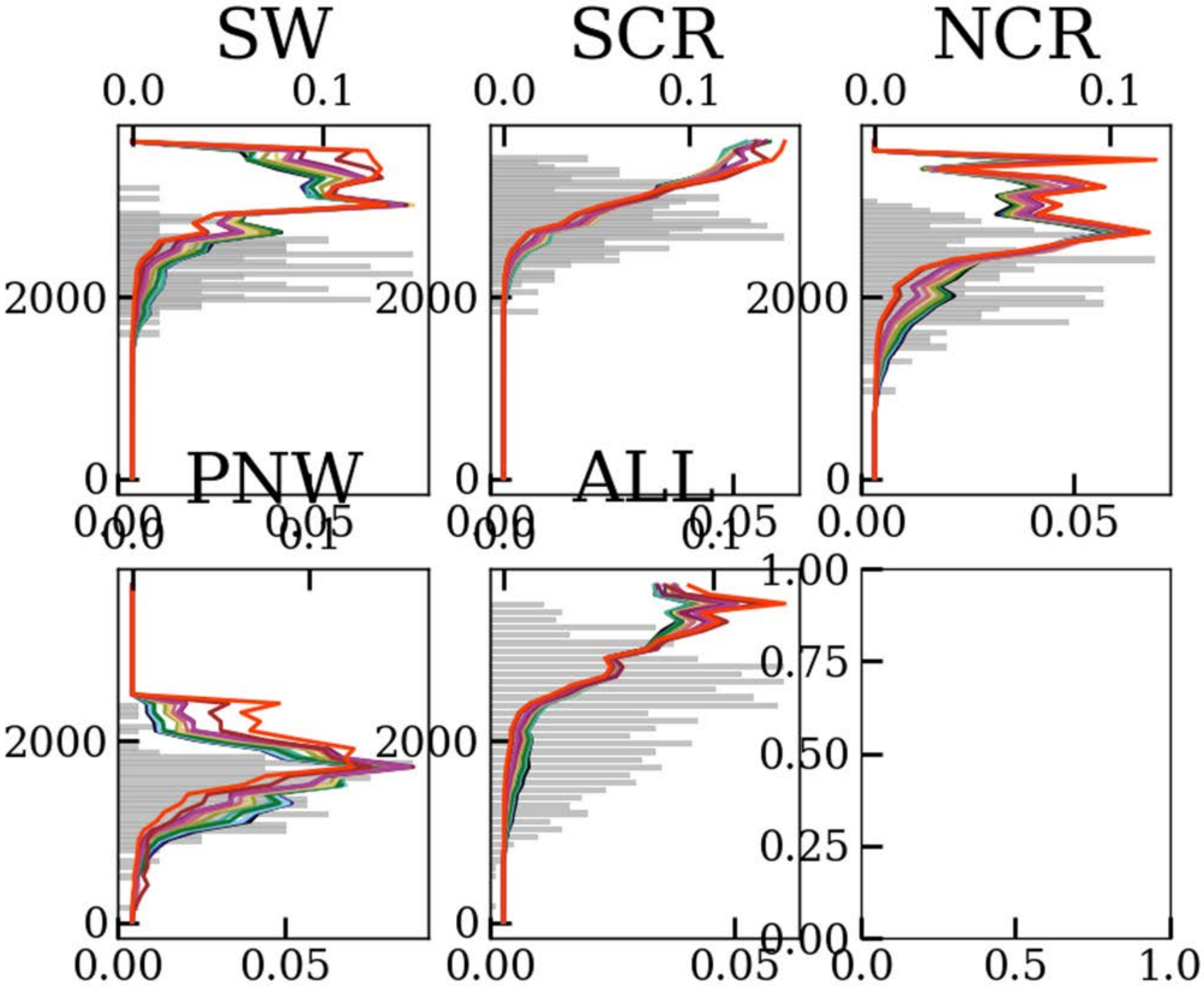
0.00 0.01
0.000 0.001
0.0000 0.0002
0.000 0.002
2000
0
0.00 0.05
1.00
0.75
0.50
0.25
0.00
0.0 0.5 1.0


SW
SCR
NCR
PNW
ALL
0.0
0.1
2000
0
0.00
0.05
1.00
0.75
0.50
0.25
0.5
1.0

Change in shared properties → change in correlation