A comprehensive investigation of machine learning models for estimating daily snow water equivalent over the Western U.S.

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November 21, 2022

Abstract

Substantial progress on machine learning (ML) models and graphical processing units (GPUs) has stimulated emerging research in applications of ML to earth science. As snow is a vital component of the global hydroclimate system, precise snowpack prediction is of considerable value for science and society. In this work, we have trained three different ML models (LSTM, CNN and Attention) to predict daily snow water equivalent (SWE) with both dynamic and static features in the Western Contiguous United States from Snow Telemetry (SNOTEL) observations. Dynamic features include precipitation, minimum and maximum temperature, minimum and maximum relative humidity, specific humidity, solar radiation and wind velocity. Static features are latitude, longitude, elevation, diurnal anisotropic heating (DAH) index and topographic radiative aspect (TRASP) index. This choice of features allows us to produce high-resolution maps of regional SWE for a given set of input meteorological conditions. The importance and the sensitivity of input variables will be tested by several explainable AI methods including feature permutation and integrated gradient. The ML-based dataset is further up-sampled and compared with the 4km gridded SWE dataset from the National Snow & Ice Data Center (NSIDC), which is from a physical-based model. Future SWE estimates are also produced under climate conditions projected by CMIP class models, along with associated uncertainty estimates based on our sensitivity analysis. The ML models are demonstrated to be a fast and accurate method of producing high-resolution SWE estimates with minimal computing power.

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2021 AGU Fall Meeting

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Previous work on SWE estimation

- From reanalysis dataset: ANN model or random forest;
- From precipitation: cGAN;
- From precipitation and snow-related variables: LSTM.
- Not all models can be applied to projections.

- Idea: Use machine learning (deep learning) models for the SWE prediction and projection.
- The models should be able to handle time dependency.
- The models should mainly use atmospheric forcings for the projection purpose.

The task can be expressed as:

$$\mathrm{SWE}_t = f(P_t, P_{t-1}, P_{t-2}, \dots, P_{t-N+1}, T_t, T_{t-1}, T_{t-2} \dots, T_{t-N+1})$$

General Architecture

- Dynamic input variables: precipitation, temperature (min and max), solar radiation, specific humidity (min and max), relative humidity, vapor deficit and wind speed;
- Static input variables: latitude, longitude, elevation, diurnal anisotropic heat index (DAH) and solar radiation aspect index (TRASP).
- Output variable: SWE
- Input window size: 180 days.
- Models: Long-Short Term Memory (LSTM), Temporal Convolution Neural Network (TCNN), and Self-Attention model (Attention).

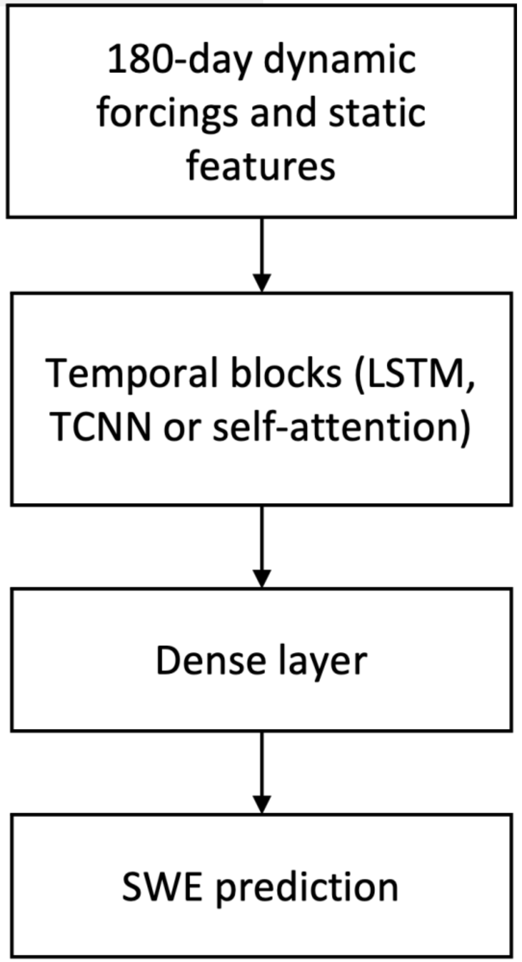


Figure: flow chart of our models.

Deep Learning Models for Time Series

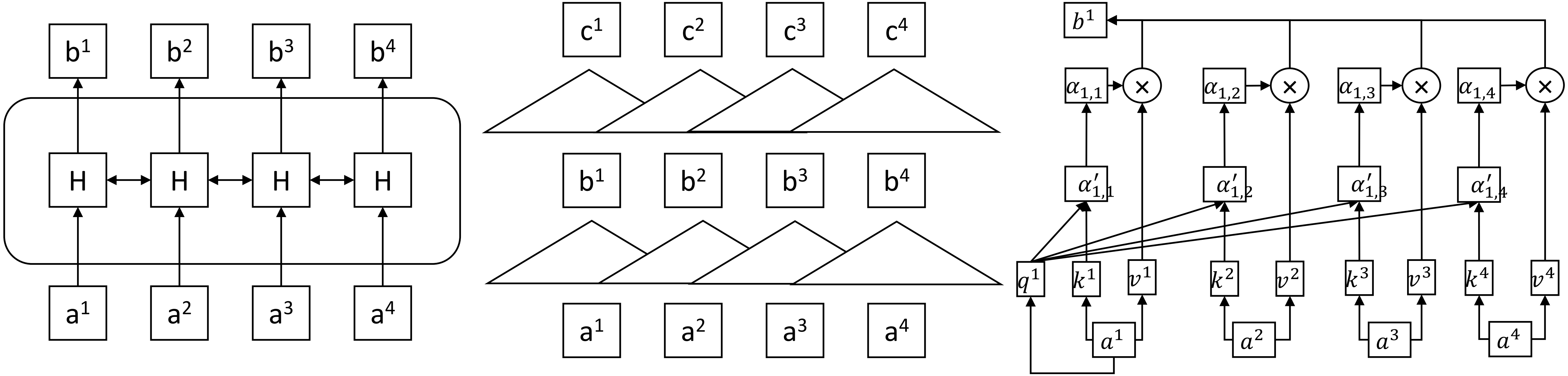


Figure: LSTM, TCNN and Attention model architecture.

Training, Testing and Validation

- 581 SNOTEL stations are used to train the model. The variables are normalized with the mean and standard deviation from all the stations.
- Hyperparameters are determined with the validation data.
- Train each model 10 times and get the ensemble mean prediction.
- The training time for LSTM is 5 hours, 10 hours for TCNN and 26 hours for Attention with 1 RTX2080Ti GPU.

Experiment Settings	
Loss function	Mean squared error
Training	1980-10-01 to 1999-09-30
Validation	1999-10-01 to 2008-09-30
Testing	2008-10-01 to 2018-09-30

SNOTEL Prediction Results

- Quantify the performance by Nash-Sutcliffe mode efficiency coefficient (NSE) or R square score.
- The median NSE values for LSTM, TCNN and Attention are 0.909, 0.878 and 0.874, respectively.
- We also compared with the NSIDC-UA dataset, which has a median NSE value as 0.861.

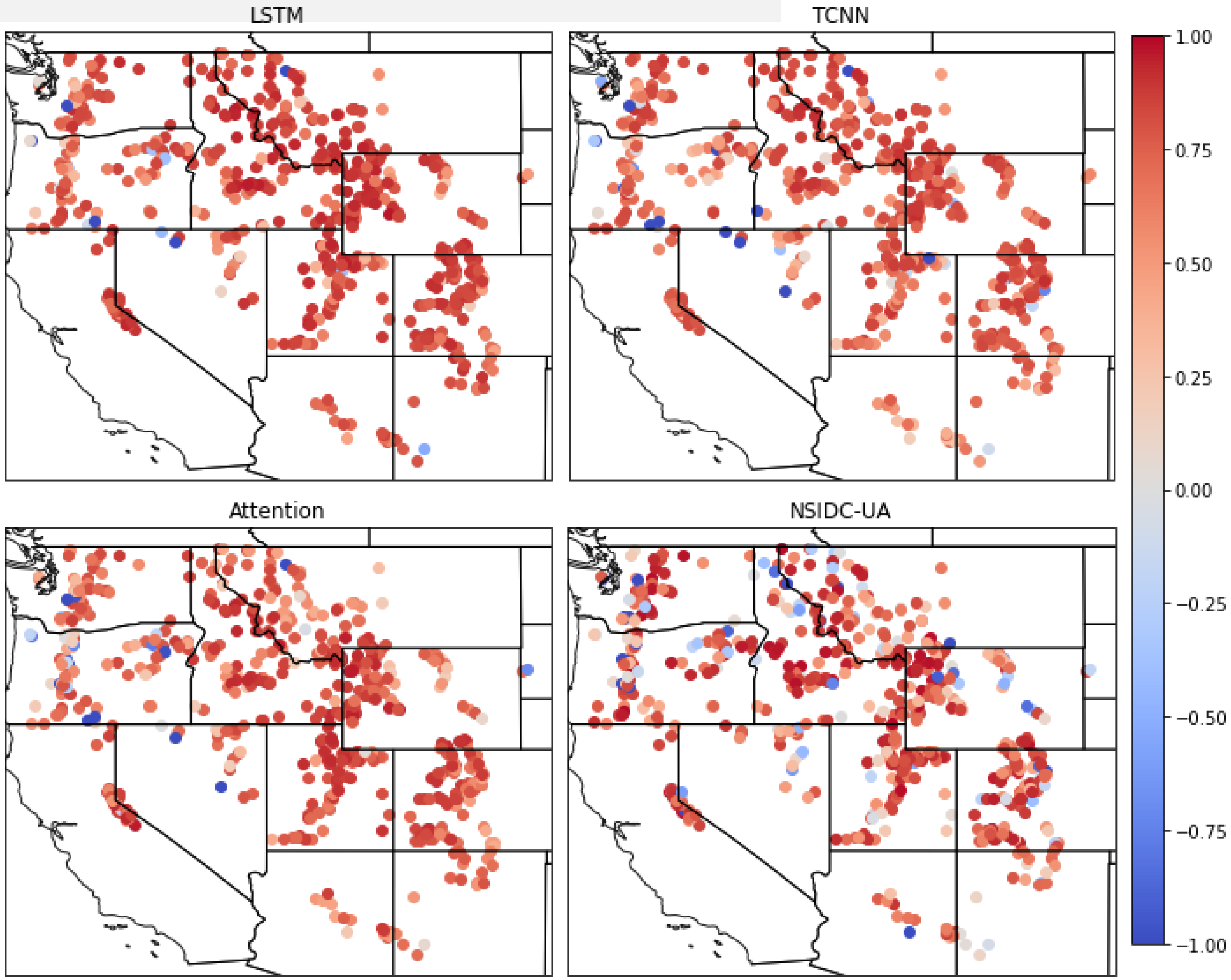
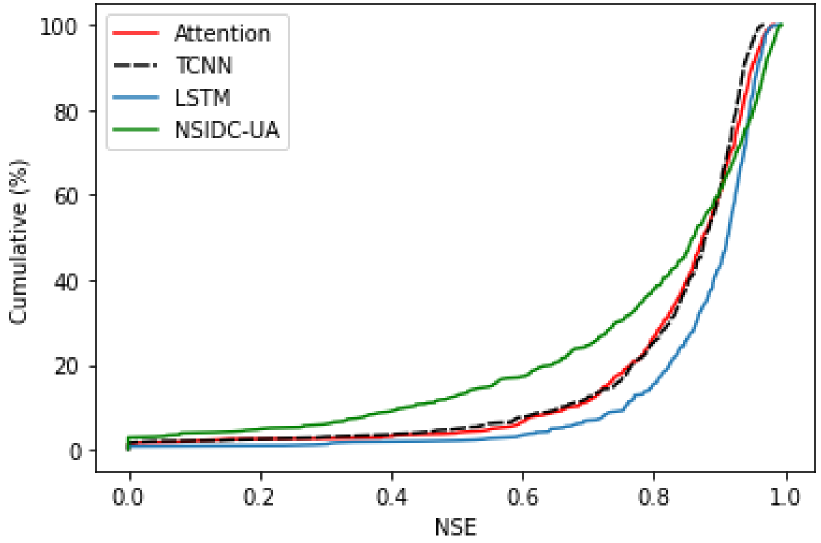


Figure: Prediction result from deep learning models and NSIDC UA dataset.

Prediction Results

- The LSTM is the best with the highest median NSE value and more concentrated distributions over high NSE value regimes.
- TCNN and Attention are similar, while Attention is better at high NSE value ranges.
- NSIDC-UA dataset has more stations in low NSE regions compared with deep learning models.
- There is a strong correlation among NSE values from different deep learning models. Pearson correlation is 0.945 between LSTM and TCNN and 0.818 between LSTM and Attention.



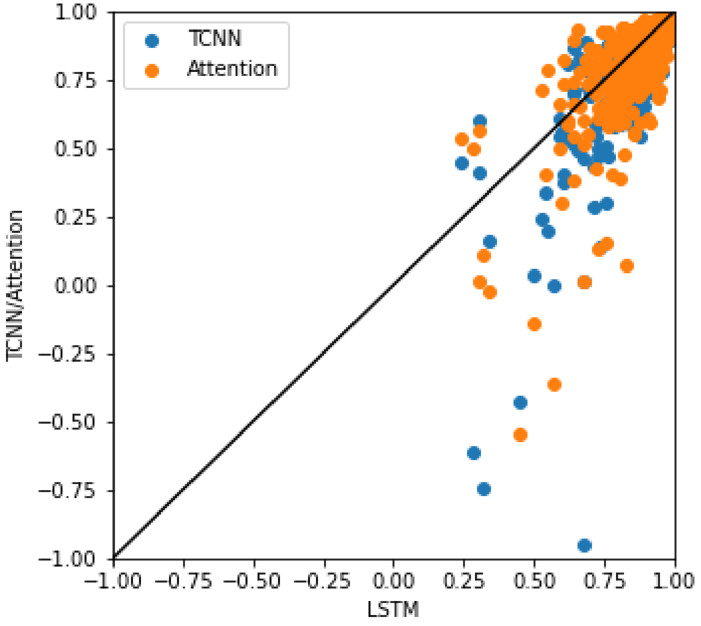


Figure: Probability distribution of NSE values (top) and correlation between NSE values (bottom).

Extrapolation

- Use the model trained on SNOTEL observations to generate a gridded SWE estimation.
- The statistic features of both input and output variables will be different. Models are in extrapolation regime.
- To deal with extrapolation, we focus on the seasonality of SWE instead of the actual SWE amount.

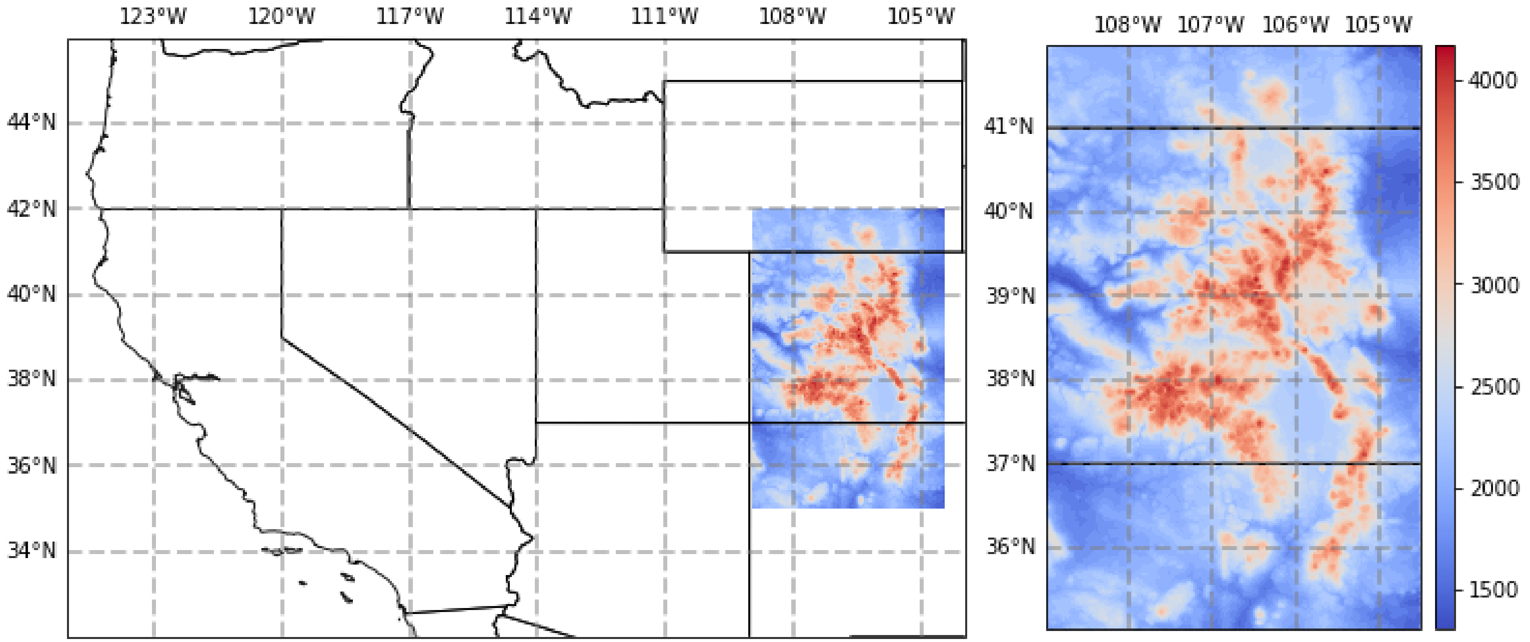


Figure: Rocky Mountain Domain (left) and elevation (right).

Extrapolation

- The seasonality itself will improve the generalization.
- By training another set of models, the generalization performance is much better.
- We lose the information of the actual SWE but gain the information in wider spatial domain. No free lunch.

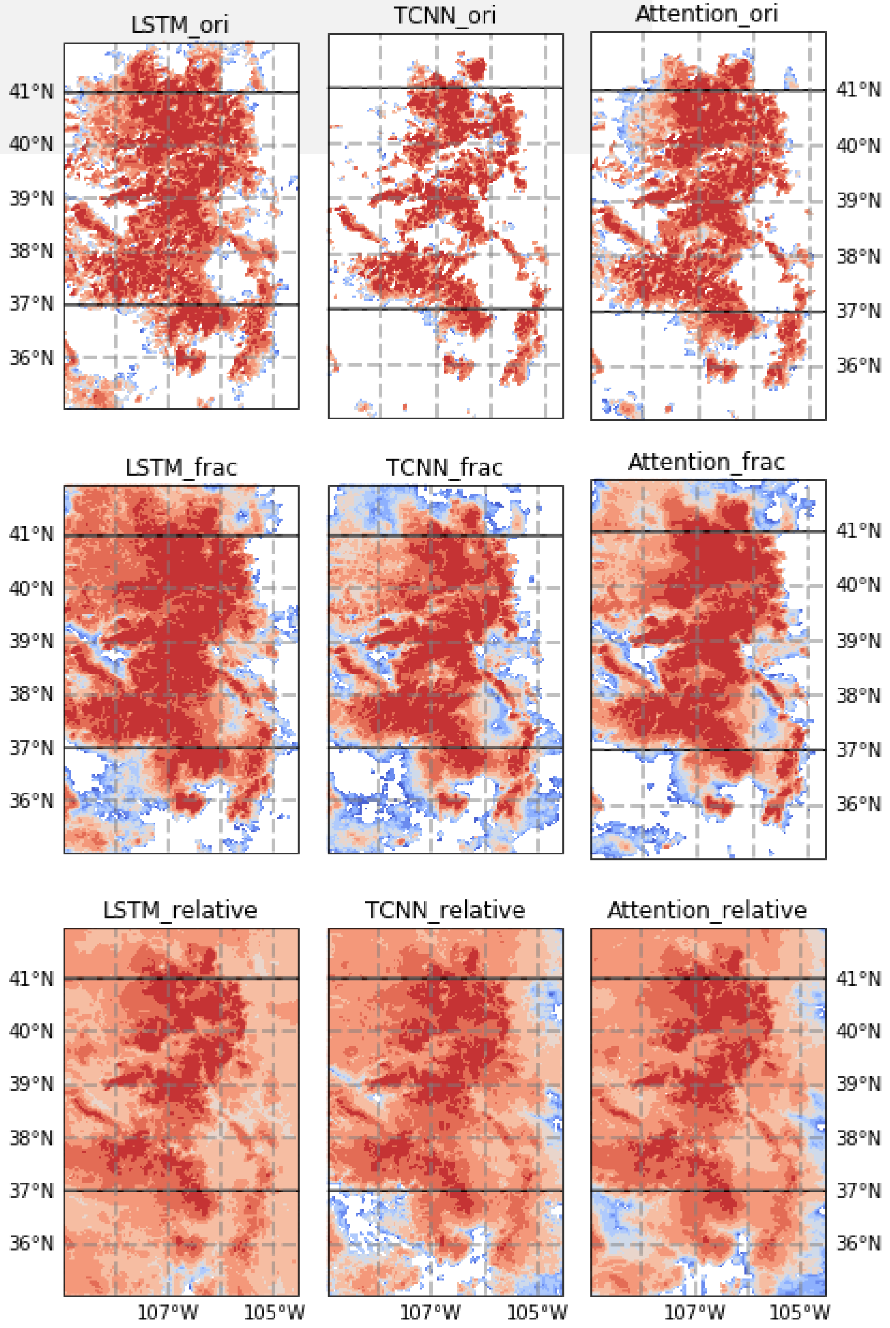


Figure: Extrapolation results.

Projection

- Continue with the SWE percentage and analyze the response of SWE to climate change.
- Use LOCA dataset as forcings. Select CESM-CAM5, CNRM-CM5, EC-EARTH, GFDL-ESM2M, HadGEM2-ES, and MIROC5.
- From the SWE seasonality, we used following metrics to assess the snowpack change.

Metric	Units	Assessment thresholds
Snowpack accumulation start date (SAD)	Days since Oct 1st	Day when SWE > 10% of maximum SWE
Snowpack peak accumulation date (SPD)	Days since Oct 1st	Day of maximum SWE
Complete melt date (CMD)	Days since Oct 1st	Day when SWE < 10% of maximum SWE
The length of snow season	Number of days	Sum of days from SAD to CMD

Projection Results

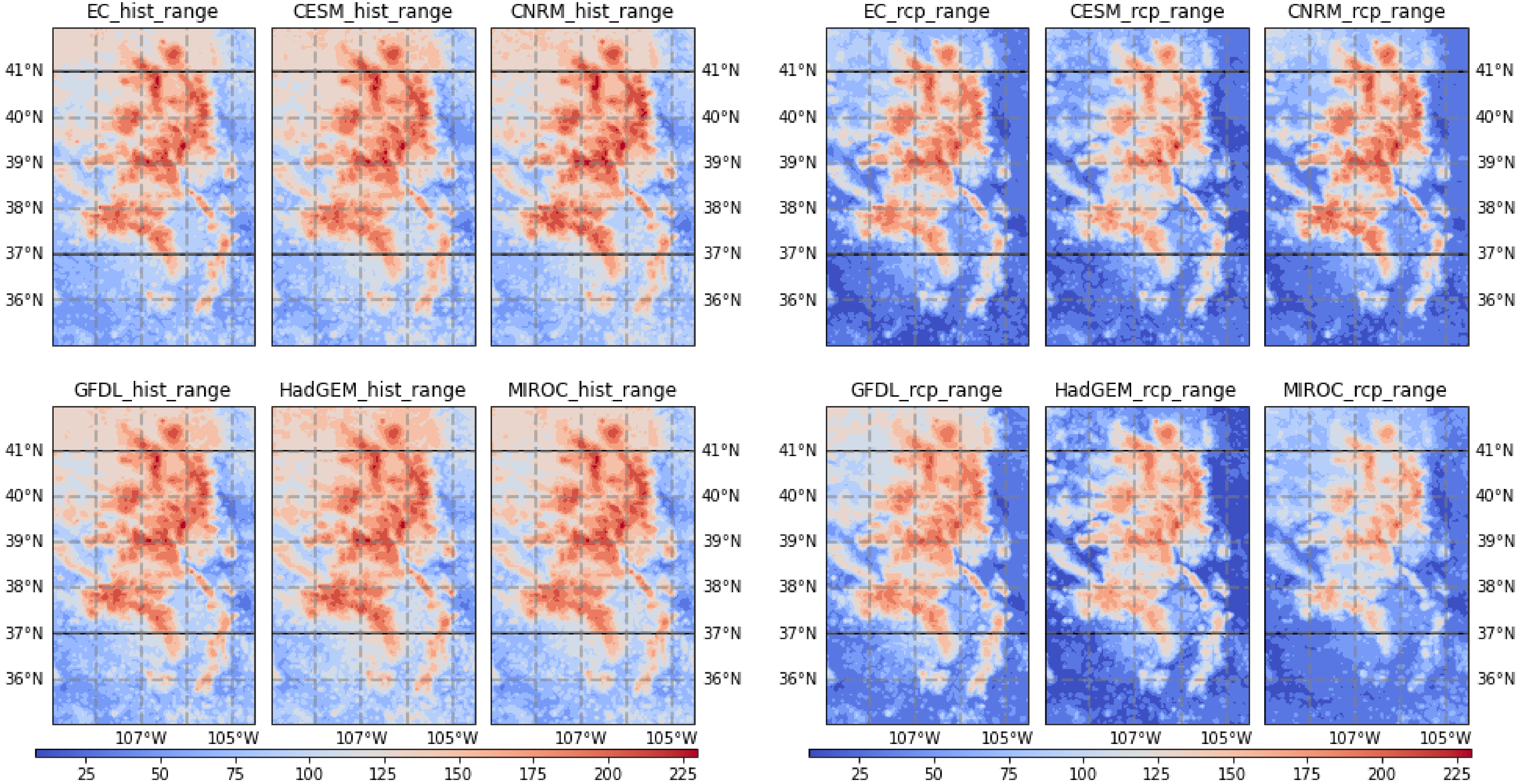


Figure: Historical (left) and RCP8.5 (right) projections of snow season length.

Projection Results

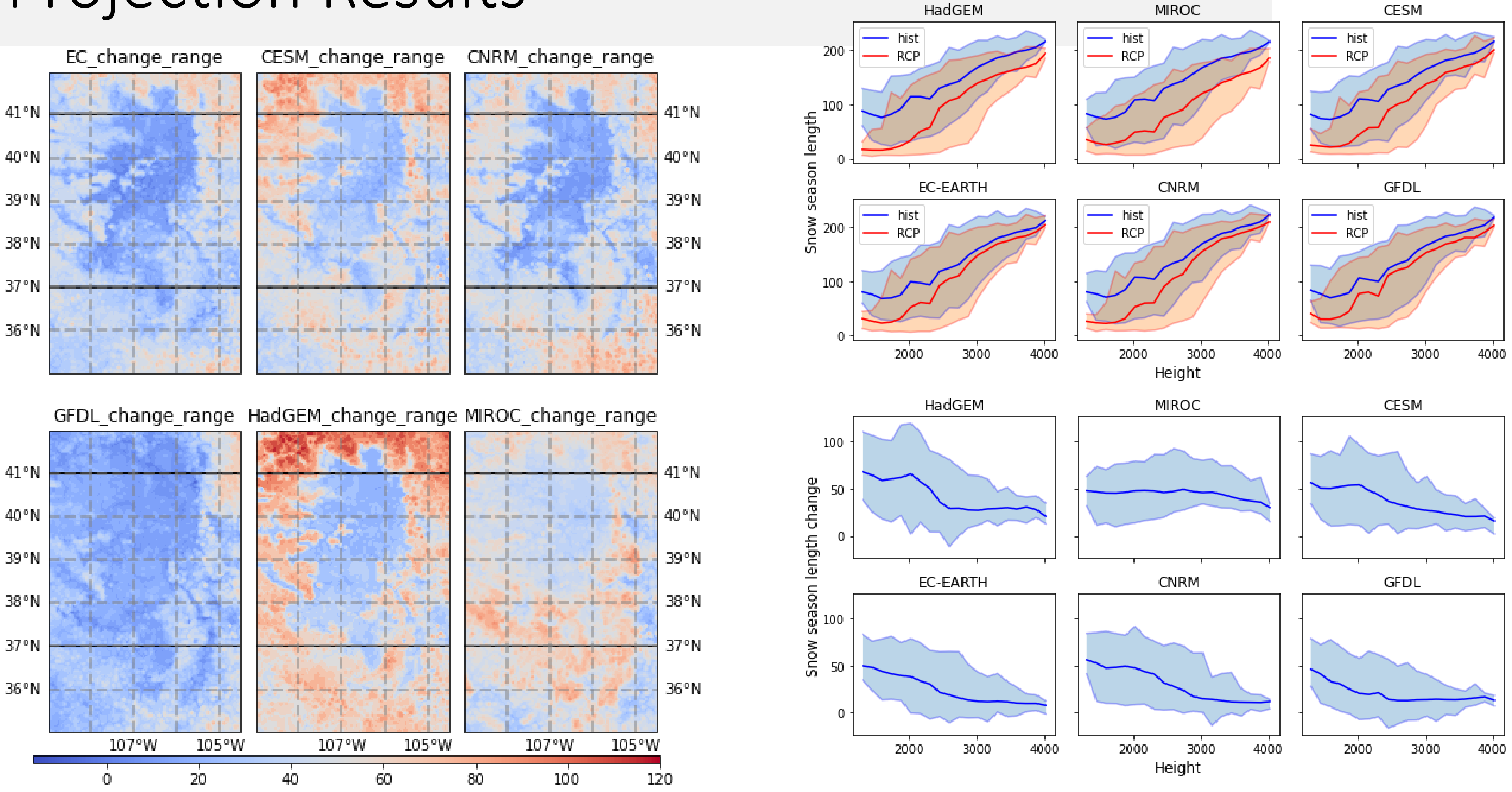


Figure: Snow season length changes in the future (left) and the height dependency (right).

Future Work

- Couple with physical-based models to deal with extrapolation problems;
- Data assimilation from satellite-based products for low-elevation area;
- Explainable AI method to analyze the physical impactors;
- Generalize to a wider area;
- Projections with CMIP6 models when LOCA data is available.

Thanks

- We would like to acknowledge the helpful discussion with Chaopeng Shen, Wen-Ping Tsai from Pennsylvania State University, David John Gagne from NCAR, Mark Risser, Alan Rhoades and Chris Paciorek from Lawrence Berkeley National Laboratory.

- The computational platform is Tempest GPU cluster at UC Davis. We also thank the Computational and Information System Lab for access to the Casper cluster through the Advanced Study Program at NCAR.

- Any further questions or suggestions, please contact at shiduan@ucdavis.edu