SNOWCLIM: HIGH RESOLUTION SNOW MODEL AND DATA FOR THE WESTERN UNITED STATES

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EXTENDED ABSTRACT

Seasonal snowpack shapes the climatic, hydrologic, ecological, economic, and cultural characteristics of many global regions. In many mountain regions, recent decades have seen less precipitation falling as snow, lower peak snow water equivalent (SWE), shorter snow duration, and earlier snowmelt runoff as a result of anthropogenic climate change (Knowles et al., 2006; Mote et al., 2018; Choi et al., 2010; Fritze et al., 2011). These developments are expected to continue in the coming decades, resulting in substantial declines (>50%) in seasonal snowpack for areas such as the western US and significant impacts to human and natural systems (Fyfe et al., 2017; Huss et al., 2017).

Understanding these changes and their implications often requires snow models and modeled snow data products (hereafter snow data) that satisfy at least one of several criteria. These criteria might include that the data is a) simulated with physics-based representations of energy and mass transfer processes, b) spatially continuous, c) high spatial resolution, d) large extent, e) multivariate, and f) multitemporal. There are two major hurdles to the development of a snow dataset that meets these criteria: computational cost and appropriate forcing data.

To address the first hurdle, we developed a computationally efficient physics-based snow model that has a flexible model structure and can be run in the cloud (hereafter SnowClim). The model retains the most important components of physically based models, including the complete energy balance and internal snowpack energetics (e.g. cold content and refreezing), while omitting more computationally expensive components such as horizontal transport, multiple layers, and iterative solutions for snow surface temperature. The model incorporates some simplifications in the interest of computational efficiency. For example, snow surface temperature is modeled as a function of dewpoint temperature. Key processes such as albedo and turbulent fluxes are modularized to allow evaluation of alternative process representations. These processes and others are controlled by thirteen tunable parameters.

To address the second hurdle, we statistically downscaled climate forcings from the Weather Research and Forecasting model (WRF; Liu et al., 2017) for the western United States. Downscaling entailed application of locally estimated lapse rates to correct for elevation and terrain-corrections in the case of solar radiation. To balance the competing ambitions of high spatial resolution and computational feasibility over the western US domain, we used variable spatial resolutions. Regions of complex terrain were modeled at 210m (hereafter ‘fine’). Regions of less complex terrain were modeled at 1050m (hereafter ‘coarse’). This resulted in approximately 30% of the domain being modeled at coarse resolution.

The raw WRF data consisted of 4km spatial resolution hourly simulations for 1 October 2000 to 30 September 2013 that used initial and boundary conditions from ERA-Interim (Dee et al., 2011). A pseudo-global warming run was also performed by perturbing ERA-Interim by the CMIP5 multimodel mean change between 1976-2005 and 2071-2100 under the RCP 8.5 scenario (Liu et al., 2017). Coarse resolution climate data for a preindustrial period was created by applying a multi-model mean delta from CMIP5 to the historical WRF simulations to represent conditions during 1850-1879. This resulted in 4-hourly downscaled climate forcings for 13 years for each of three periods: preindustrial, historical, and future.

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The SnowClim model was parameterized at 170 SNOTEL sites. Climate forcings for the parameterization runs consisted of the historical WRF data downscaled to SNOTEL sites using similar procedures to those described above. Parameterization entailed running the model for each possible combination of parameters. Model performance was assessed using the mean absolute percent error (MAPE) of annual maximum SWE (maxswe), the MAPE of annual snow duration, and the root mean squared error (RMSE) of daily SWE at each site. Snow duration was defined as the duration (in days) of the longest period of consecutive days with SWE > 0. RMSE was computed when observed SWE exceeded 10mm. The optimal parameter set was selected using Pareto preference ordering (Khu and Madsen, 2005) based on the median of each statistic across stations. The parameterization selected a single best parameter set which had station median MAPE of max SWE, MAPE of snow duration, and daily RMSE of 15.5%, 8.86%, and 62.2mm, respectively (spatial structure of errors is shown in Figure 1).

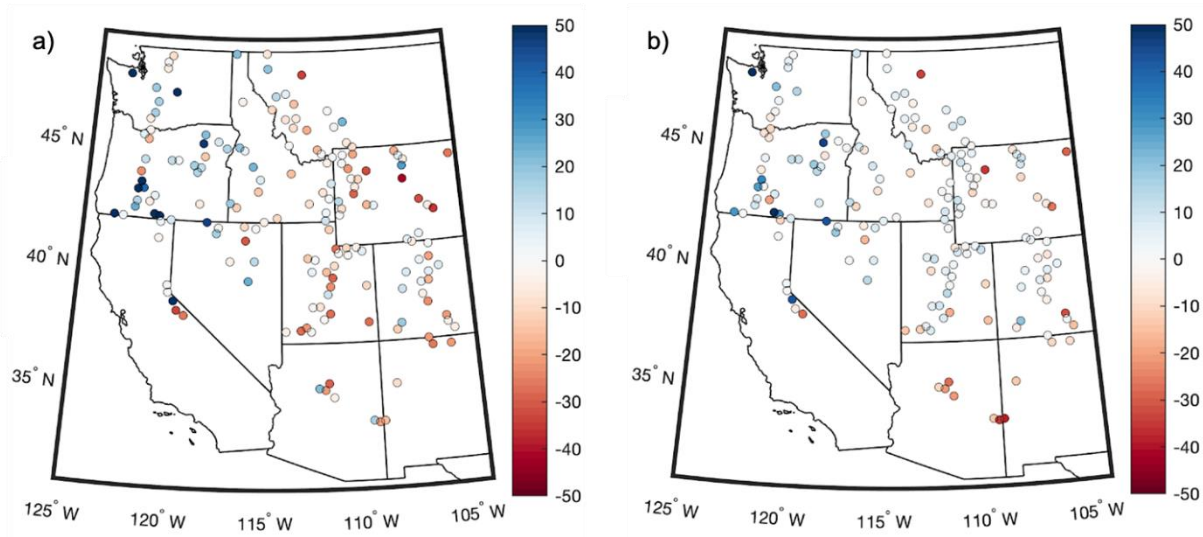

Figure 1. a) Mean percent error in maximum SWE at SNOTEL sites and b) mean percent error in snow duration at SNOTEL sites for the model parameterization selected by Pareto preference ordering

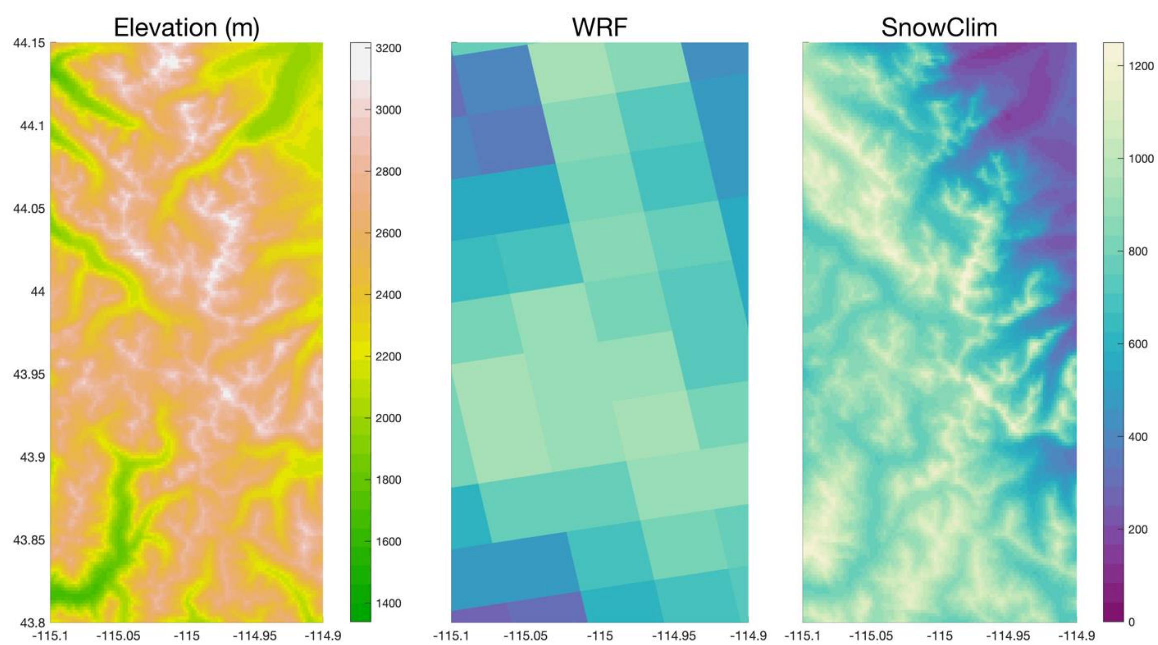

Figure 2. For an area of the Sawtooth Mountains in Central Idaho, a) terrain elevation (m), b) average historical SWE in the month of April as modeled by WRF at 4km resolution, and c) average historical April SWE (mm) as modeled by SnowClim at 210m/1050m resolution. The color scale is the same for b) and c).

The SnowClim model was applied to the western US using the parameterization identified above, a temporal resolution of 4 hours, and a variable spatial resolution. Here, we define the western US as the continental US west of 104°W. The model was run in parallel on a high-performance computer with 34 cores. The computation time was approximately 3.5 days per time period (e.g. historical). The SnowClim model resolves the effects of topography on snowpack with much more detail than currently available large-extent snow datasets such as WRF (Figure 2).

Downscaled climate forcings and snow model outputs were aggregated to monthly and annual climatologies for each of the three time periods (preindustrial, historical, and future) to create the SnowClim dataset (Table 1). These data will be made publicly accessible on the CUAHSI HydroShare website (https://www.hydroshare.org) in the coming months. In addition, the SnowClim model code will be hosted on HydroShare where it can be run in the cloud using MATLAB online. Additional data is available upon request.

Table 1. Summary climate and snow variables included in the SnowClim dataset

Climate Data	**Snow Data**
Monthly temperature (min, max, and mean)	Monthly SWE
Monthly precipitation	Monthly depth
Monthly solar radiation	Monthly snow cover days
Monthly dewpoint temperature	Monthly snowfall
Annual number of freeze/thaw cycles	Annual size and date of maximum SWE
	Annual size and date of largest snowfall event
	Annual snow duration
	Date of first and last snow
	Number of days without snow between first and last snow

Given its high spatial resolution, large extent, and physics basis, we anticipate that the SnowClim dataset will enable unprecedented analyses of changing hydroclimate and its implications for human and natural systems. At present we are aware of projects in a range of disciplines including glaciology, wildlife, and agriculture that are interested in using this data. We expect it to be particularly useful to species distribution modeling since it provides compatible, high resolution climate data as well. The relatively short run time of the model compared to other physics based snow models may prove useful in modeling snow in other global areas. Going forward, further model evaluation is needed at elevations below where SNOTELs are typically located and we may consider incorporating additional processes such as interactions with vegetation and the effect of aerosol deposition on snow albedo.
(KEYWORDS: Snow modeling, climate change, gridded data)

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