Differences in algorithmic rain-on-snow flood climatology across historical data products

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Abstract

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A common misconception is that RoS events are generated by warm rain providing heat to the snowpack. Multiple studies have found that the actual heat transfer between the liquid rain and surface snowpack is rather small and explains less than 5% of the observed snowmelt. In the northeastern United States, events such as the 1996 event are associated with a confluence of surface conditions, including anomalously high heat fluxes into the snow pack which are associated with stormy conditions.

Rapid snow ablation in regions with ephemeral snow have been shown to have a strong correlation with subsequent increases in basin streamflow. For example, SURIANO 2019 found that 75% of snow ablation events in the SRB (defined by daily decrease in snow depth in above-freezing conditions) yielded increased river discharge three days later.

While climatological studies such LORI W are critically important, event-level analysis has become increasingly important for stakeholders (CITE STORYLINES PAPERS). This becomes a complex challenge when working with gridded climate data, particularly for future model projections of which no observational reference exists. To extract information regarding singular extreme events and their corresponding statistics, algorithmic techniques which objectively analyze datasets without manual intervention need to be devised.

Here, we demonstrate a technique for generating an event database at the basin-scale in arbitrary climate datasets. We focus on the direct prediction of couple surface processes (i.e., snow water equivalent and surface runoff) to minimize issues with statistical or dynamical downscaling.

XXXXXX

To evaluate the suitability of historical products, we evaluate four products that seek to reproduce observed conditions, although each with a different form.

First, L15

Second, NLDAS-VIC4.0.5

Third, a full, global reanalysis JRA-55. Reanalyses are derived from running prognostic 3-D Earth system models while assimilating observational data as they are integrated. Therefore, they serve as a bridge between in-situ observational data and free-running climate models. More details re: reanalyses can be found in XXX.

Finally, a nudged version of the DoE E3SM model is run at 1° spatial resolution. This simulation is analogous to the majority of climate models in CMIP6. To constrain the large-scale meteorology to that observed, the simulation is nudged to ERA5 reanalysis at 6-hourly timescales, with acts as a crude assimilation technique. This nudging is performed above the boundary layer, which offers the advantage of reproducing patterns of 500 hPa geopotential height and sea level pressure while allowing the model to simulate grid-scale processes relatively freely (Sun et al., 2019). While E3SM is run on an unstructured cubed-sphere mesh, the simulation output is regridded to a 1°x1° regular latitude-longitude mesh using higher-order methods (Hill et al., 2004).

Three variables are extracted over the SRB. These include total precipitation (liquid and frozen, summed), surface snow water equivalent, and surface water runoff. All data is standardized to daily average values by temporally-averaging any subdaily (e.g., hourly) data. The SRB is defined using a shapefile (MORE INFO). Grid cells that have at least 50% of their area enclosed by the boundary of the SRB are kept, while those exterior to the SRB (<50%) are set to missing values. Results using a simple latitude-longitude box encompassing the SRB demonstrated similar results (not shown). A basin-wide timeseries is then constructed by spatially averaging the three fields for each calendar day (00Z to 00Z) and smoothing the resulting time series using a simple moving average to reduce day-to-day noise in the derived variables. We choose a 5-day window based on synoptic timescales (XXXXX), although perturbations to this averaging period didn't materially change any of the findings here. Rain-on-snow days are defined algorithmically by flagging coincident times of negative dSWE and surface runoff that both exceed certain thresholds in the smoothed SRB timeseries. We test two methods of thresholding; one uses fixed thresholds across all datasets and the other defines dataset specific thresholds by those exceeding 95% over the dataset. For fixed thresholds, we require an average dSWE of 1.4 mm/day and surface runoff rate of 1.4 mm/day. Note that while the majority of the events are associated with precipitation (e.g., rain-on-snow) we do not exclude a specific precipitation criterion, but rather, leverage surface runoff as a proxy for surface flooding.

(SOME EXAMPLE OF HOW ALL EVENTS FLAG WITH HIGH STREAMFLOW?)

This is clearly shown in Fig. XXXX, which shows PDFs of the three quantities for each of the four datasets. The shape of the

Findings

Table XXXX shows

To further explore the event climatology, we focus on results associated with a single water year across all datasets. In particular, we choose the 1995 water year since this includes the 1996 rain-on-snow floods over the SRB (LEATHERS). The 1996 event, broadly considered to be the event of record in the SRB, results in XXXXXXXXXXXXX. While focusing on a single water year provides

Fig. XXXX shows the time series of basin-integrated PRECT, ROF, and dSWE. Negative dSWE denotes snow melt. Shaded are events that were flagged by the snowmelt algorithm to be important.

How data is generated for forcing is critically important. Since RoS events in regions of ephemeral snow (e.g., SQ) can have surface forcing at hourly timescales (e.g., XXXXXX), using daily meteorological data to force offline LSMs will generally underpredict RoS frequency. Even at lower spatial resolutions, models coupled at shorter timescales (e.g., reanalysis, nudged coupled GCMs) produce more accurate land-atmosphere interactions, particularly at shorter weather scales.

While we do not downscale any datasets in this study, it is likely that using data from XXX to force a hydrological model will result in vastly different streamflows than XXXXX. From a stakeholder perspective, this is an important consideration when backtesting models, and, in particular, applying such models to evaluate tail risks (e.g., 1-in-100 year flood events and how they may change in the future.)

Mean climatologies are shown in S1. It is well-known that simulated runoff from different hydrologic models can be extremely variable, with regional differences between products reaching an order of magnitude in some cases (Gudmundsson et al., 2012; Sood

& Smakhtin, 2015; Beck et al., 2017). While there is less product-to-product variability in precipitation and snow water equivalent (SWE), it has been found that significant spread still exists in climate data products even for precipitation.

While spatial resolution is important, it appears that the time resolution of data is also critical for transient extremes, such as rain-on-snow flooding. This is particular important given that the synoptic variations in surface temperature and humidity that dictate snowmelt and precipitation phase occur on the order of hours at local scales.

Acknowledgments

Enter acknowledgments, including your data availability statement, here.

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