H53D-1475 Analysis of Extreme Snow Water Equivalent Data in Central New Hampshire

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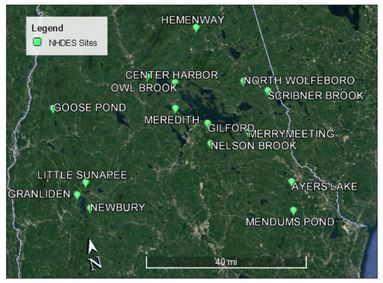
1. Background

Heavy snowfall and snowmelt-related events have been linked to widespread flooding and damages in many regions of the U.S.. Design of critical infrastructure in these regions requires spatial estimates of extreme snow water equivalent (SWE). In this study, we develop station specific and spatially explicit estimates of extreme SWE using data from fifteen snow sampling stations maintained by the New Hampshire Department of Environmental Services. The average record length for the fifteen stations is approximately fifty-nine years. A framework for probabilistic flood hazard assessment (PFHA) was employed to develop pointwise return levels and areal-based exceedance calculations for extreme SWE. Spatial dependence among the extreme data was explicitly handled via application of max-stable process models. This work will support the development and application of design scenarios for risk-informed cool season hydrologic analyses.

2. Study Area & Data

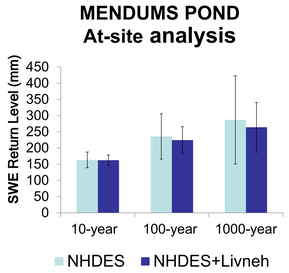
A region in central New Hampshire was selected to perform the analysis of extreme SWE, based on the potential for cold season flood events, the availability of snow data, and whether it is a region of interest to the NRC. The region has a maritime climate, is densely forested, and is generally snow covered during the winter months. Spring flooding due to snowmelt and rain on snow events accounts for a significant portion of the historical damaging floods in the state.



State and Federal agencies conduct bi-weekly snow surveys throughout the winter season in central NH

For this study, snow survey data from the New Hampshire Department of Environmental Services (NH DES), collected for over 50 years was used. The data record was expanded by including modeled SWE data from the Livneh (2013) data set. At each NH DES survey location, the Livneh data was compared for the overlapping period and bias-adjusted for the 103-year period of record.

Gridded geographical and climatological covariate data were used to inform the marginal model parameters. These covariate data include latitude, longitude, elevation, aspect (NED); PRISM temperature and precipitation (Daly et al 2002); and the NAO climate index (Trenberth et al 2016).



Example showing improved precision with the expanded data record. Error bars are 95% CI

3. PFHA Framework

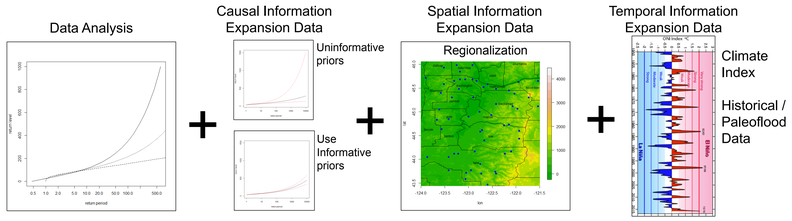
The analysis of extreme SWE involves application of a PFHA framework that involves application of one or more max-stable process model configurations to account for the spatial dependence among the extremes, remain in conformance with Extreme Value Theory for credible extrapolation, and generalize the uncertainty associated with model choice. The spatial process modeling leverages readily available and relevant spatially explicit covariate data. The noted additional max-stable process models also used the nonstationary winter North Atlantic Oscillation index as temporal covariate data, which has been observed to influence snowy weather along the east coast of the United States.

a) Test for spatial dependence

The extremal coefficient was calculated to evaluate spatial dependence among the extreme SWE. We employed five different simple max-stable models.

b) Combine data for *k* models

We combine causal information, spatial information, and temporal information expansion data to develop *k=35* max-stable models that leverage spatiotemporal covariate data.



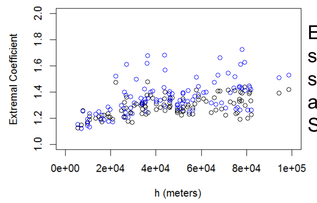
c) Apply multi-model averaging technique

Information Criterion Averaging:

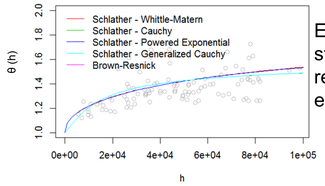
$$\beta_k = \frac{\exp\left(-\frac{1}{2} I_k\right)}{\sum_{k=1}^{K} \exp\left(-\frac{1}{2} I_k\right)}$$

4a. Results: Spatial Dependence

The observed extreme SWE data demonstrates moderate spatial dependence for distances up to 100km. Five different simple max-stable process models were employed to account for the spatial dependence.



Example results showing moderately strong dependence among the extreme SWE data



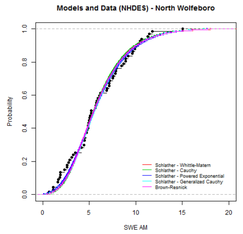
Example max stable model results fitted to extreme data

Test	Model Spatial Covariates
1	X, Y
2	X, Y, Z
3	X, Y, Z, Aspect
4	X, Y, Z, Aspect, P_A
5	X, Y, Z, Aspect, T_A
6	X, Y, Z, Aspect, P_A, T_A
7	X, Y, Z, Aspect, P*
8	X, Y, Z, Aspect, T*
9	X, Y, Z, Aspect, P*, T*

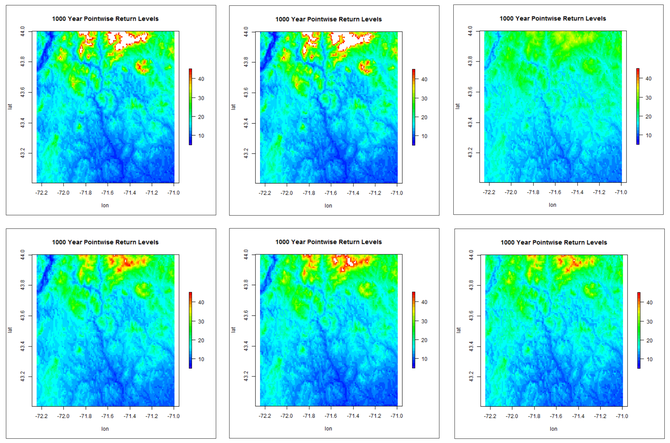
Model covariates employed. Each test was run with NAO *Winter mean (Dec to Mar). A, Annual means (Jan to Dec)

4b. Results: Max-stable Model Fit and Prediction

Trend surface modeling analysis of GEV marginals for test configurations 3-9 resulted in approximately equal information criteria scores. The five max-stable models with these seven configurations are the basis for the *k*=35 general max-stable process models to fit for framework application. The ten fitted general max-stable models with trend surface configurations 8 and 9 had the lowest information criteria scores. These top ten models were averaged for framework application.



Fitted max-stable models at the North Wolfeboro station

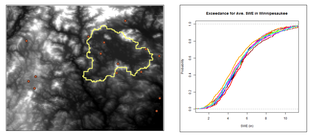


Top 6 models averaged for NHDES + Livneh data – representing epistemic uncertainty associated with model choice

4c. Results: Areal-based Exceedance Probability

With max-stable process applications, additional more complex areal assessments of risk can also be evaluated.

$$\Pr\left\{\int_{\mathcal{B}} \Upsilon(x)dx > z_{crit}\right\}$$



Exceedance probability of Avg SWE in the Winnepesauke Basin

5. Conclusions

We account for the spatial dependence among the extreme SWE data to develop multiple max-stable process models which leverage spatio-temporal covariates to predict pointwise return levels and more importantly areal-based exceedance probability calculations while remaining in conformance with the extremal paradigm. We generalize model selection via application of multi-model averaging to complete development and demonstration of a framework for PFHA with application to a specific relevant cool season flood hydrology process.

Acknowledgements

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ERDC
US Army Engineer Research and Development Center

U.S.NRC
United States Nuclear Regulatory Commission
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