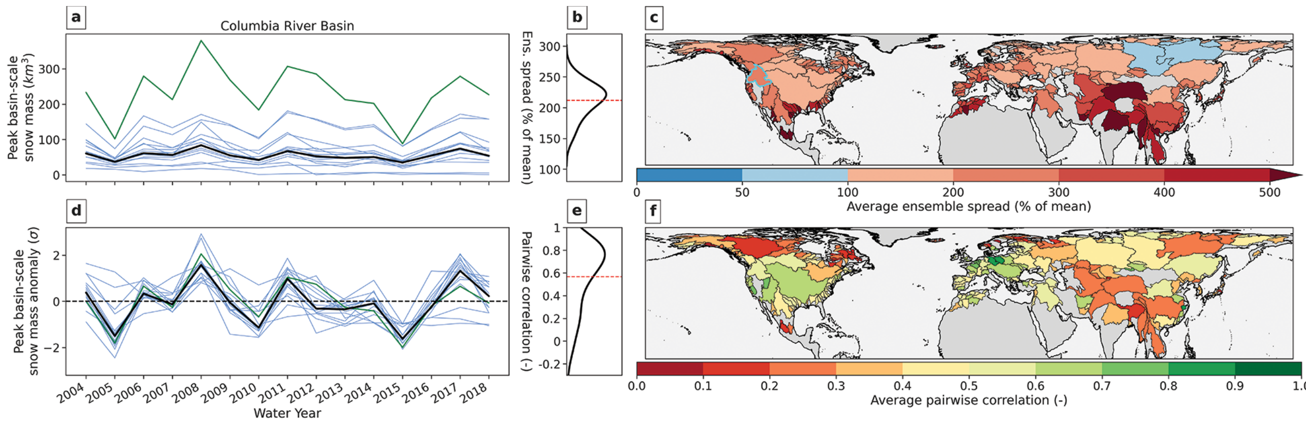
Snow Drought & Its Impacts

Insights from Quantifying and Sourcing Specific Uncertainties

Key messages from "Observing, Measuring, and Assessing the Consequences of Snow Drought," by **Alexander R. Gottlieb** (Dartmouth College) and **Justin S. Mankin**. Published online in *BAMS*, April 2022. For the full, citable article, see **https://doi.org/10.1175/BAMS-D-20-0243.1**.

Warm temperatures accelerate snow loss, raising questions about how anthropogenically forced snowpack declines will shape water availability in snow-dependent regions, particularly those without in situ snow data. Motivated by these concerns, recent research examines "snow droughts," or periods of exceptionally low snowpack, suggesting that they raise the risk of extremes such as droughts, heat waves, and wildfires in the following warm season. Yet considerable analytical hurdles remain in connecting snow droughts to their consequences and therefore identifying where snow droughts pose unique risks: For example, what constitutes a snow drought? Given observational uncertainty in snowpack data, how do we reliably quantify snow droughts? And lastly, what are the best practices for connecting snow droughts to their downstream impacts?



Characterization of observational uncertainty in snowpack data. (a) Time series of peak water year (WY, October–September) snow water equivalent (SWE) in the Columbia River basin [cyan outline (c)] from 15 gridded data products (blue lines) and an estimate from in situ SNOTEL network assuming stations are representative of the elevation at which they sit (green line). Black line denotes ensemble mean. (b) Distribution of the 16-member observational ensemble spread in the Columbia River basin (max–min estimate for each WY) as percentage of the WY ensemble mean. Red dotted line denotes the average spread across all WYs, indicating observational uncertainty in peak SWE is over 200% in a typical winter. (c) Average ensemble spread [as calculated in (b)] for all Northern Hemisphere river basins with seasonal snow cover. (d) As in (a), but for standardized anomalies. (e) Distribution of pairwise Spearman's rank correlations of anomalies for all combinations of data products. Red dotted line indicates the average correlation, or the expected level of agreement between two randomly selected data products. (f) As in (c), but for average correlation of anomalies across all combinations of data products. Greener colors indicate strong agreement on interannual variability across the ensemble, while redder colors indicate weak agreement.

Our work begins to resolve these issues by examining how observational and definitional uncertainty shapes snow drought assessment, and by extension, identified linkages to warm-season impacts like droughts. We create a new observational ensemble of 16 hemispheric snowpack datasets and evaluate this ensemble against 6 common snow drought definitions. In contrast to analyses that use one snowpack dataset or one drought definition, we show the value of leveraging observational and definitional uncertainty to more robustly identify snow droughts and connect those events to their downstream impacts.

Observing and defining snow drought

The two major sources of uncertainty in snow drought we considered were observational and definitional. Observational uncertainty emerges because snow water equivalent (SWE) is difficult to measure at hydrologically meaningful scales. Estimation is typically done by aggregating in situ data, remotely sensed observations, or reanalyses. These approaches produce different estimates of SWE measures, like its peak water year (WY, October–September) value. We quantify the uncertainty in SWE by calculating the agreement across our observational ensemble. Consistent with previous work, we find peak SWE uncertainty exceeds 100% of the ensemble mean nearly everywhere. And while examining standardized anomalies shows more reasonable consistency across datasets, there are many snow-dependent regions, such as high-mountain Asia, where we do not know

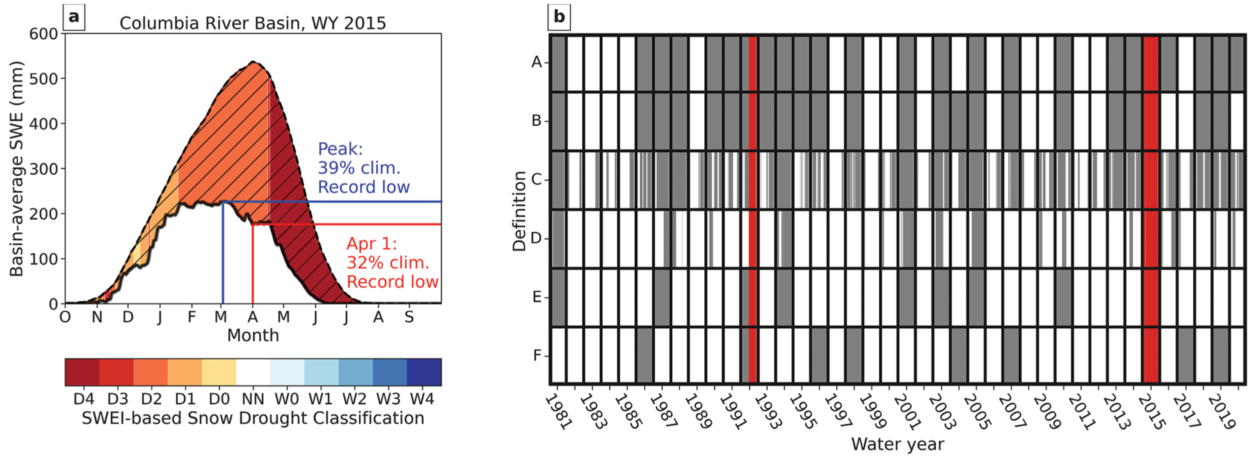


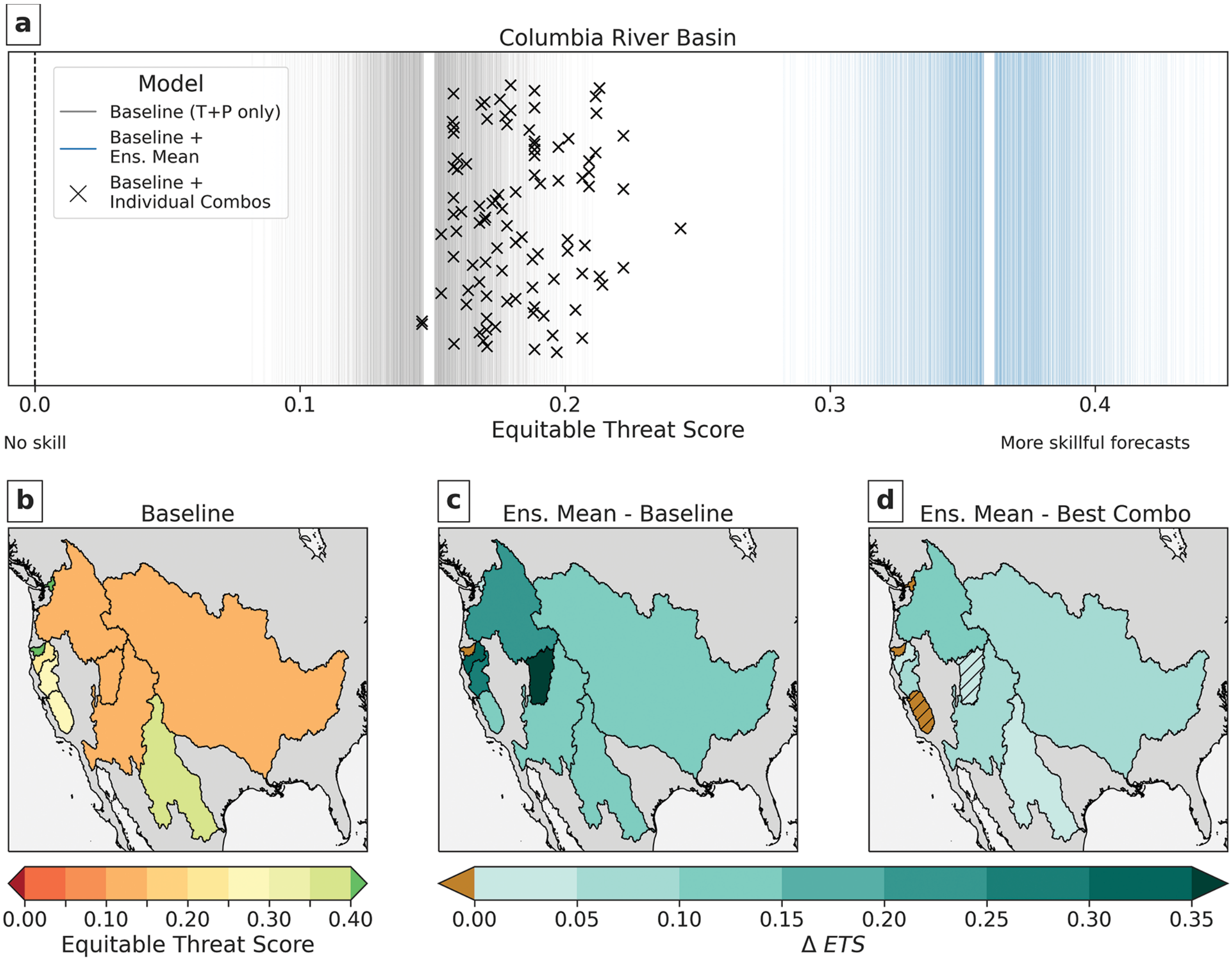
Illustration of definitional uncertainty in identifying snow droughts. (a) Common definitions of snow drought from the literature applied to SNOTEL data from WY 2015 in the Columbia River basin. For the area-weighted average across Columbia River basin SNOTEL sites, the dotted line indicates daily climatological median snowpack while the solid line indicates the daily-scale snowpack in WY 2015. This example illustrates different ways to assess the 2015 snow drought: (1) Hatching highlights periods of SWE below the climatological median; (2) color contours indicate snow droughts diagnosed using a standardized SWE index on the US Drought Monitor D-scale; (3) the date and magnitude of peak SWE ("Peak," in blue); and (4) the magnitude of 1 April snowpack ("Apr 1," in red). (b) Identification of historical snow droughts (in gray) based on definitions from the literature (A: peak SWE < climatological mean; B: 1 Apr. SWE < climatological mean; C: daily SWE < climatological median; D: SWEI < −0.8; E: peak SWE < 25th percentile; F: date of peak SWE < 25th percentile). Red shading indicates periods in which all six definitions agree that a snow drought occurred.

the true water content of the snow on the ground or whether snowpacks are above or below average in a given year.

Definitional uncertainty asks: How do we identify snow droughts? Analytical choices such as the appropriate snow metric (e.g., peak or April 1st snowpack) or snow drought threshold (e.g., 25th percentile, z-score < −1) influence the sample of snow drought events a researcher might consider. This means researchers can come to very different conclusions about the historical frequency and intensity of snow droughts, and by extension, the set of impacts attributed to them. To illustrate this uncertainty we apply six different snow drought definitions to one high-quality 40-year snowpack dataset and find that only two years show consilience across all measures.

Connecting snow drought to its warm-season impacts

Given these uncertainties, what can we claim about snow droughts and their consequences? To address this question, we use a simple forecast framework in which we retroactively predict warm-season droughts using statistical models with and without snow drought information. We evaluate a) a naive "baseline" model with no snow drought information, only cold-season temperature and precipitation; b) models that additionally include snow drought based on a single snowpack dataset and snow drought definition from our observational-definitional ensemble; and c) a model that includes the mean snow drought assessment across our ensemble.



Using observational and definitional uncertainty in snow drought to improve warm-season drought forecasts. a) Forecast framework for evaluating utility of snow drought information for forecasting warm-season drought (as identified by the U.S. Drought Monitor), using the Columbia River basin to illustrate the underlying methods. Gray band (white line) indicates 95% confidence interval (median) of warm-season drought forecast skill from baseline model that uses only October–March average temperature and cumulative precipitation. Skill is measured with the commonly used Equitable Threat Score and is estimated from a repeated *k*-fold cross-validation process in which the model is fit on all but three years and used to make out-of-sample predictions for those unsampled years. Black x's indicate the median cross-validated estimate for models that include a binary snow drought classification for each year based on an individual snow drought dataset–definition combination. Blue band (white line) indicates 95% CI (median) of skill estimates of a model using the ensemble mean (across all dataset–definition combinations) snow drought identification (i.e., the fraction of combinations that identify a snow drought in a basin in a WY). b) Median cross-validation baseline forecast skill for 10 western U.S. basins (analogous to white line inside gray band in (a). c) Difference in forecast skill between ensemble mean model and baseline model [analogous to difference between white lines in (a)]. Darker greens indicate a larger forecast skill improvement from the inclusion of the ensemble mean snow drought identification. d) As in (c), but the change in forecast skill for a model with the ensemble mean model versus the best-performing individual dataset–definition combination model. Hatching in (c) and (d) indicates basins where the distributions of skill estimates are statistically indistinguishable ($p > 0.05$) by a two-sample *t*-test.

Most snow drought information, irrespective of source, increases warm-season drought forecast skill, consistent with previous findings showing the importance of snowpack as a source of skill in hydrologic forecasting. However, the greatest increase comes not from one of the 96 combinations of snow drought definitions and snowpack datasets; rather, it comes from the model that combines all dataset–definition combinations. This suggests that observational and definitional uncertainty do not undermine snow drought assessment, but rather strengthen it.

Conclusions and moving forward

Our analysis shows that quantifying and sourcing uncertainties can produce valuable insights about the character of snow droughts and their impacts. Our approach provides an analytical basis for future work on at least four fronts: (1) it allows us to more rigorously characterize historical snow drought occurrence and magnitude, particularly in regions without the benefit of in situ data; (2) it allows us to link snow droughts to their consequences, such as droughts, heatwaves, and wildfires; (3) it provides a crucial basis for identifying and exploring the biogeophysical mechanisms that link snow droughts to those consequences; and (4) it provides the grounds for evaluating individual snowpack datasets and snow drought definitions. Together, our work makes a compelling case for an analytical practice that integrates as many observational datasets and definitional measures as possible, not only for snow droughts, but for any Earth system variable whose variation and change pose differential risks to people and the managed and natural systems they care about.

METADATA

BAMS: What would you like readers to learn from this article?

Alexander Gottlieb (Dartmouth College): *Uncertainty isn't a dirty word or an excuse for inaction; it's a source of information that we can leverage to generate new scientific insights and inform more robust adaptation decision-making.*

BAMS: How did you become interested in the topic of this article?

AG: *I've lived in cold, snowy places my whole life, and there's an almost universal qualitative sense that winters have gotten shorter, warmer, and less snowy. The scientist in me has always wondered a) if the data corroborate that sense, and b) what the consequences of those losses are going to be in Pennsylvania, where I grew up; Colorado, where I lived for a time; Vermont, which I now call home; and all the other snow-covered regions of the world. It's clear that snow plays very different hydrological, ecological, cultural, and socioeconomic roles in different places, and understanding the differential impacts of changes to snow around the globe felt like a set of interesting and important questions.*

BAMS: What surprised you the most about the work you document in this article?

AG: *I was shocked at how substantial the gap in warm-season drought forecast skill was between the ensemble mean and the best-performing ensemble member in some basins. People who work with ensembles of climate models often observe the same performance improvement of the mean over constituent members, but it was fascinating to see the same hold true for observations. As we mention in the paper, there are likely many more practical and philosophical lessons from the climate modeling community that could offer valuable insights into observational ensembles.*

BAMS: What was the biggest challenge you encountered while doing this work?

AG: *This project was a massive exercise in data management. Getting 16 different snow water equivalent datasets—which are produced and hosted by different institutions, require different protocols to download, come in different data formats, and have different native spatial and temporal resolutions—into a format where I could make apples-to-apples comparisons of snow drought quantities was quite time- and computationally intensive. I'm deeply grateful to all the data providers, and to Dartmouth's Research Computing team, for providing and maintaining the infrastructure necessary for a project of this scale.*

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