



Predicting western US snowfall and runoff before the winter begins: a prospectus

Tom Hamill¹, Sarah Kapnick², Dave DeWitt³, Brian Gross⁴, John Lhotak⁵

¹ NOAA/OAR Earth System Research Lab, Physical Sciences Division, Boulder Colorado

² NOAA/OAR Geophysical Fluid Dynamics Laboratory, Princeton New Jersey

³ NOAA/NWS Climate Prediction Center, College Park, Maryland

⁴ NOAA/NWS Environmental Modeling Center, College Park, Maryland

⁵ Colorado Basin River Forecast Center, Salt Lake City, Utah

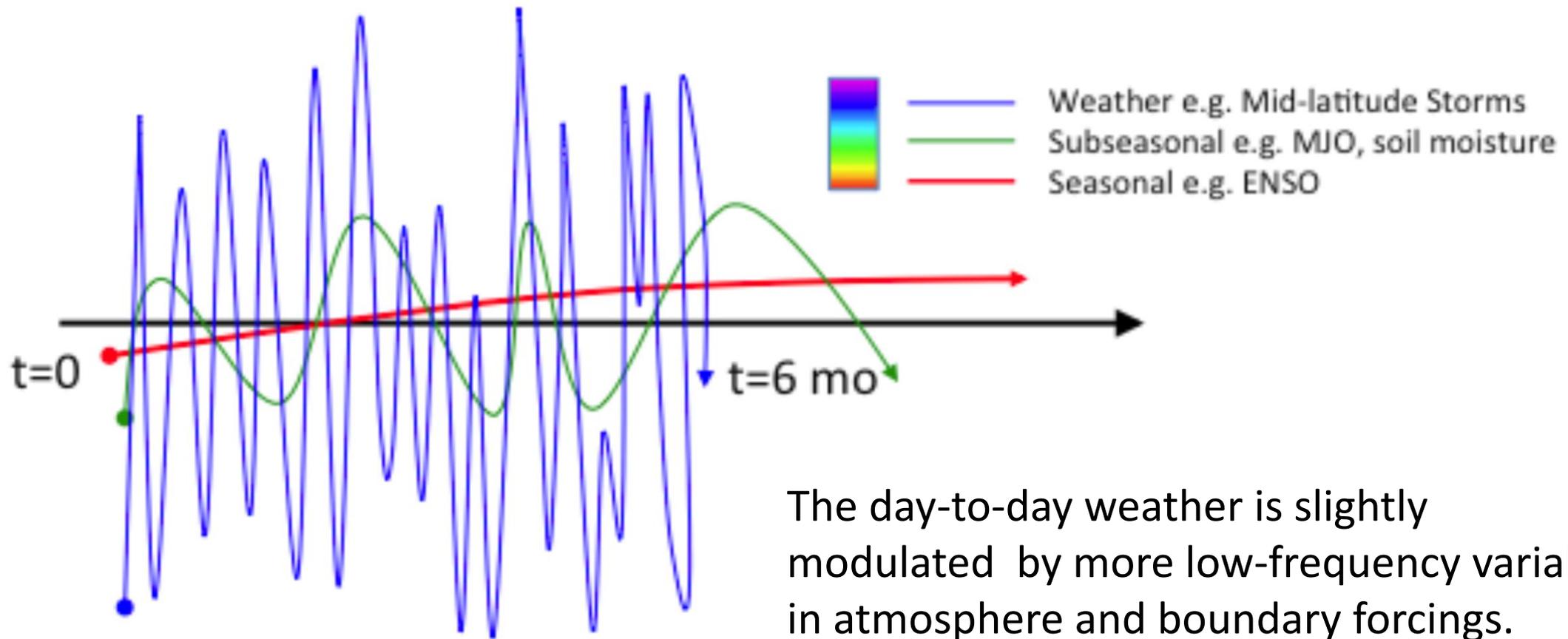
An aerial photograph showing a wide, winding river cutting through a rugged, brown, and arid landscape. The river meanders across the terrain, which is characterized by deep canyons and layered rock formations. The colors range from dark brown to light tan, with some green patches indicating sparse vegetation. The overall scene conveys a sense of a harsh, dry environment.

The need: managing an increasingly scarce resource

Is seasonal prediction
of wintertime snowfall
& runoff possible?

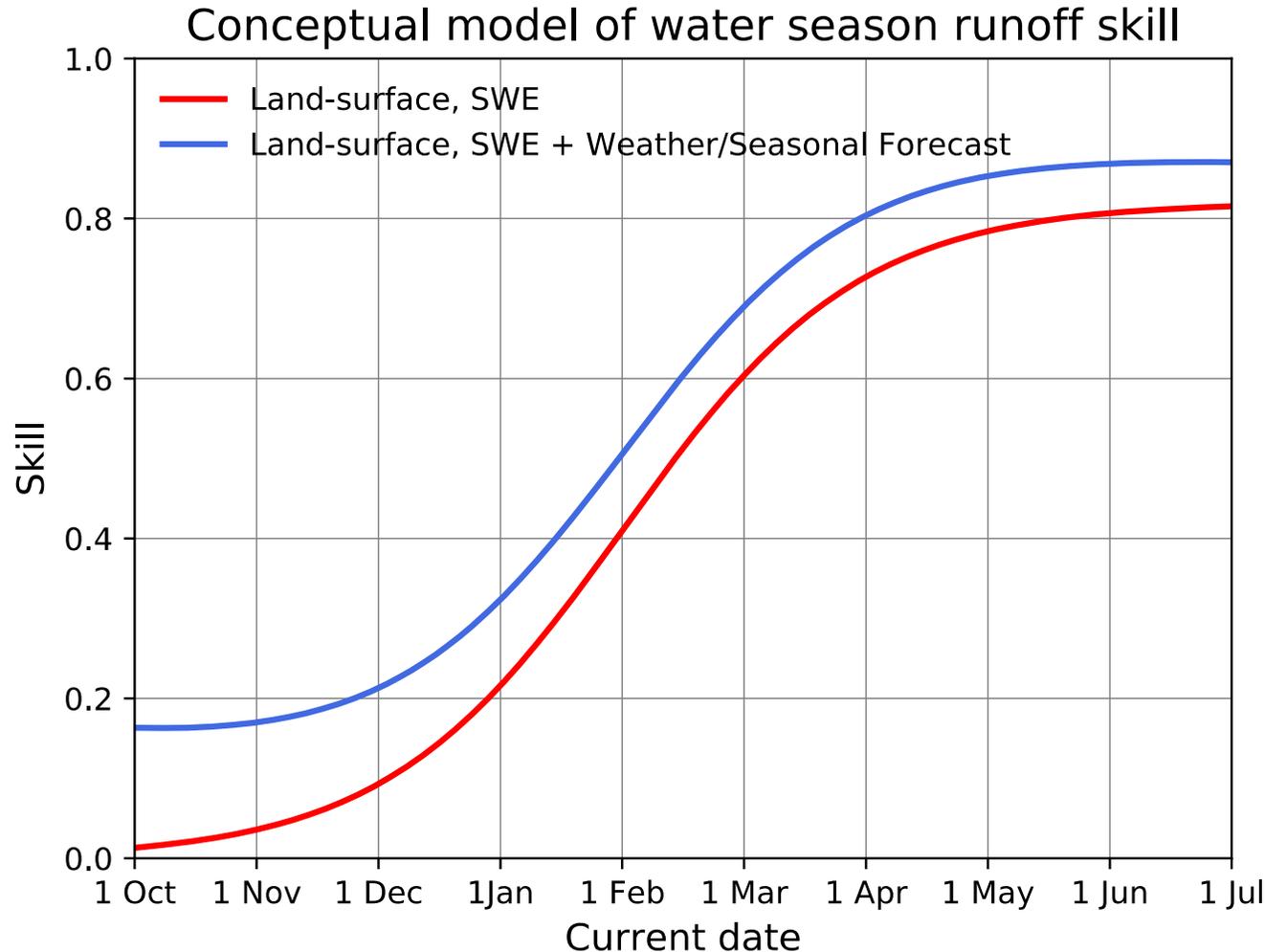


Weather, sub-seasonal, and seasonal variations.



The day-to-day weather is slightly modulated by more low-frequency variability in atmosphere and boundary forcings. That's all that will be predictable at seasonal time scales.

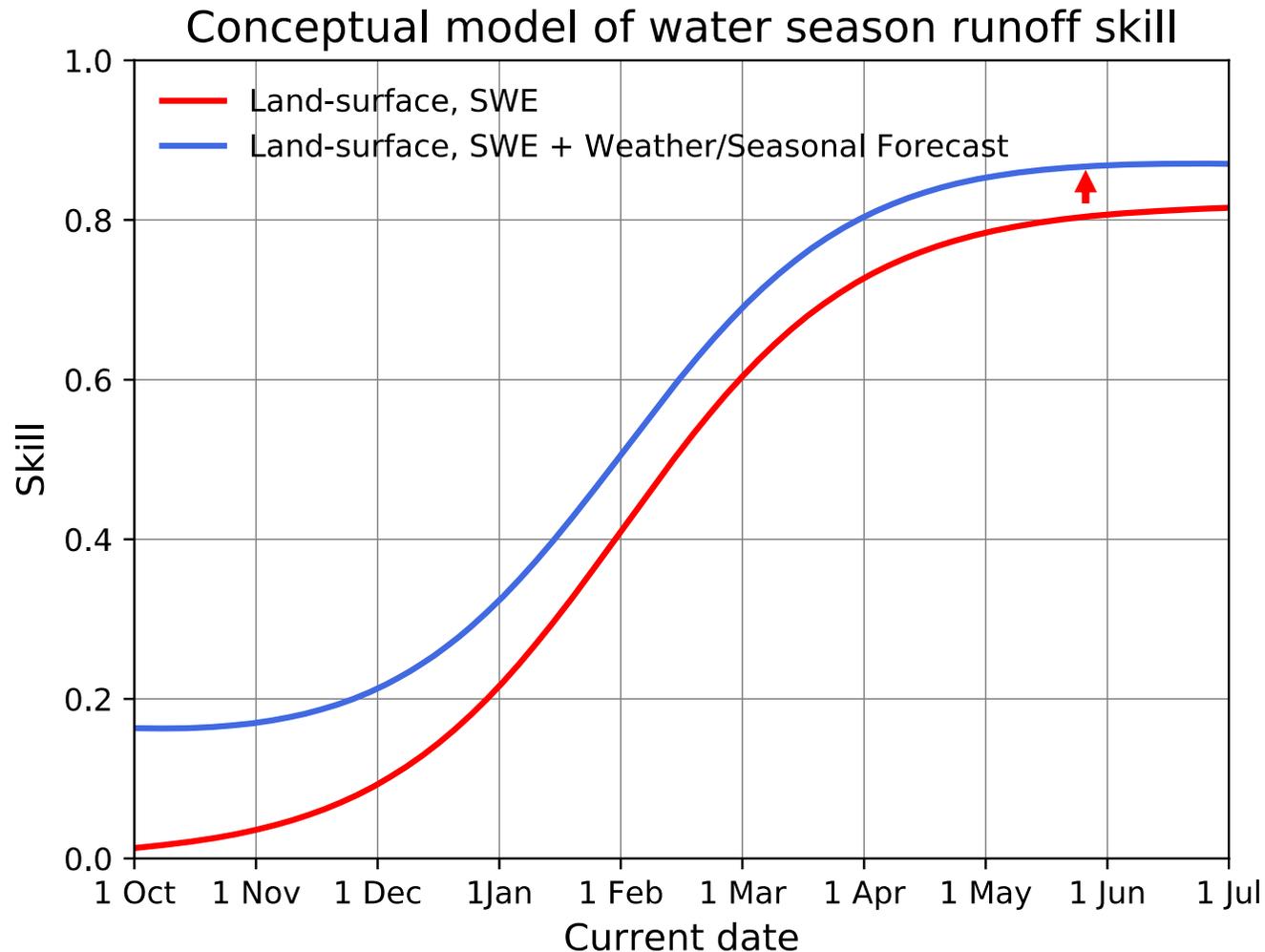
Two sources of seasonal predictive skill: forecasts of the weather, and the state of the land surface



The absolute value of skill here depends on factors such as:

- (a) the inherent ability to predict – is the phenomenon predictable?
- (b) the ability of the prediction system to perform up to the physical limits of predictability.
- (c) the ability to model changes to the snow pack during the season..
- (d) the metric one uses for evaluation.

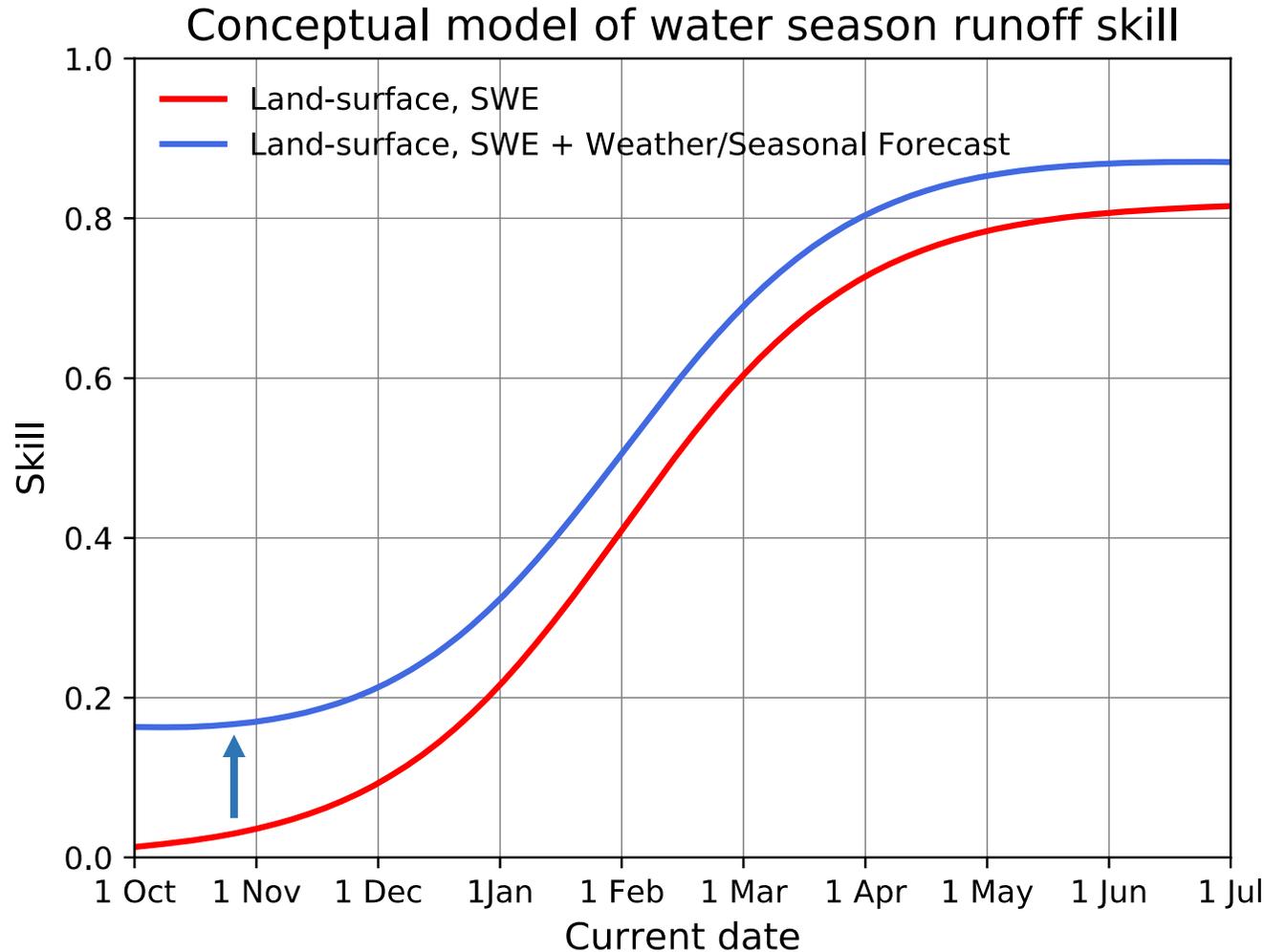
Two sources of seasonal predictive skill: forecasts of the weather, and the state of the land surface



The skill contributed by the accumulated snowpack grows as the water season progresses.

Skill could be improved slightly with better procedures to estimate the snow pack and with better land-surface and hydrology models to predict changes in the snow after it has fallen (melting, sublimation, etc.)

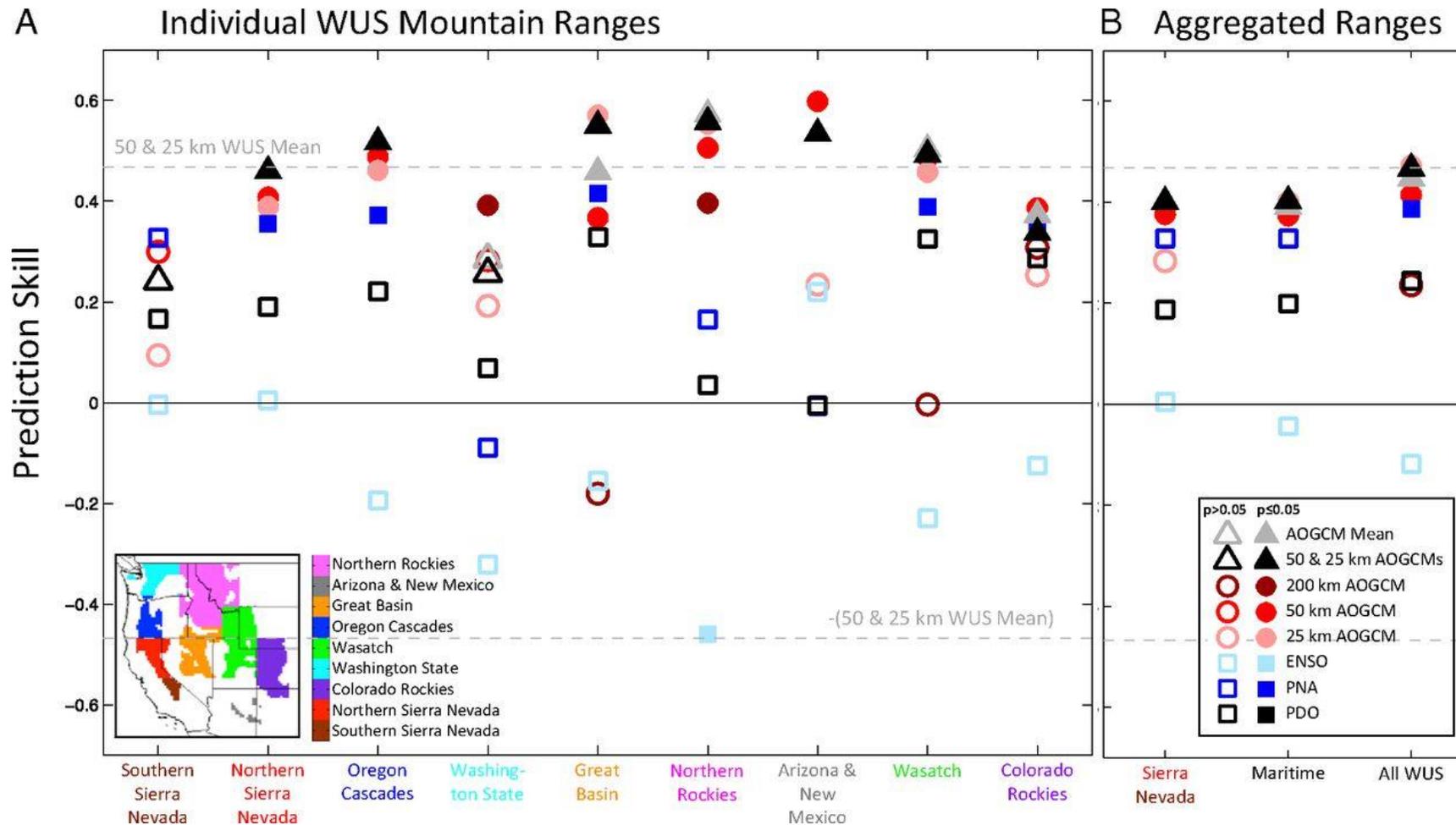
Two sources of seasonal predictive skill: forecasts of the weather, and the state of the land surface



Given many critical decisions that need to be made far in advance, any potential skill in the forecasts of expected precipitation and temperature at the beginning of the water season are particularly helpful.

Is there any evidence of such skill?

Kapnick et al., PNAS 2018; July 1980-2015 prediction of March snow pack



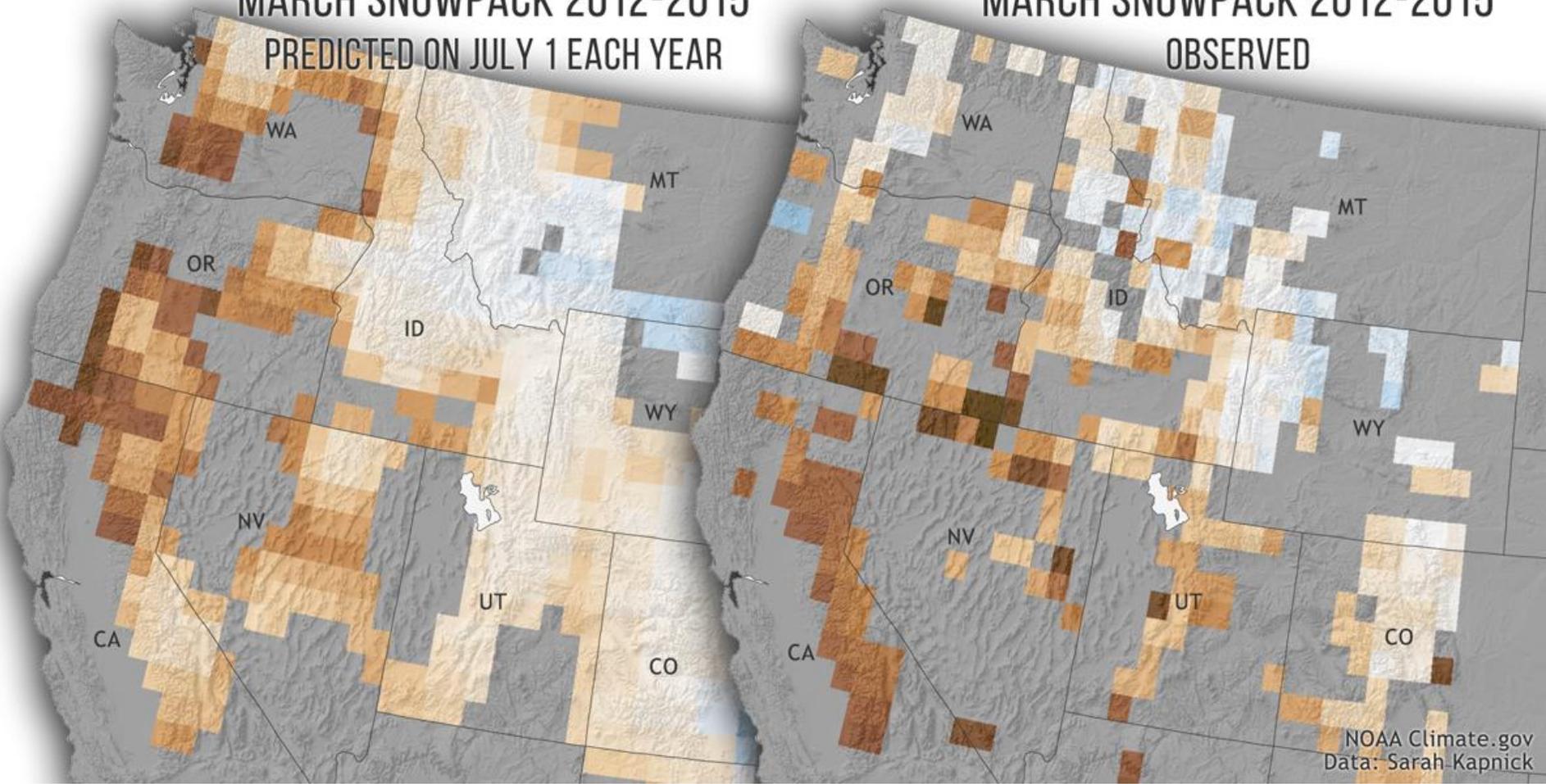
Mountain range snowpack prediction skill measured by correlations (Spearman) between observed March snowpack and predictors available July 1 from AOGCM models (triangles, circles) or climate indices (squares) where higher absolute values represent greater skill, shown for (A) various mountain ranges and (B) ranges aggregated in increasing scale. Dashed lines provided for the value of the higher-resolution multimodel (50 km and 25 km) prediction for snowpack over the entire mountainous WUS (0.48) and the negative value (-0.48) to provide a reference for correlations with climate indices. *Inset* provided for ranges in highest-resolution model; the 200-km model has no ranges for northern and southern Sierra Nevada, Oregon Cascades, or Arizona and New Mexico ([SI Appendix, Fig. S1](#)).

Low March snowpack case study: 2012-15

Yearly predictions made July 1 (50 km model) vs. observed

MARCH SNOWPACK 2012-2015
PREDICTED ON JULY 1 EACH YEAR

MARCH SNOWPACK 2012-2015
OBSERVED



- Average of predictions for the 2012-2015 snowpack drought made every July 1 for the following March (8-month lead) using a 50 km model
- To put in perspective: The forecasts were made around the 4th of July holiday before the first snowflake of winter hit the ground

Snow water content



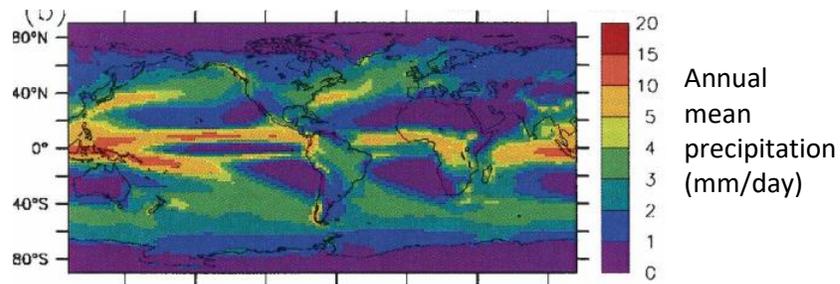
NOAA Climate.gov
Data: Sarah Kapnick



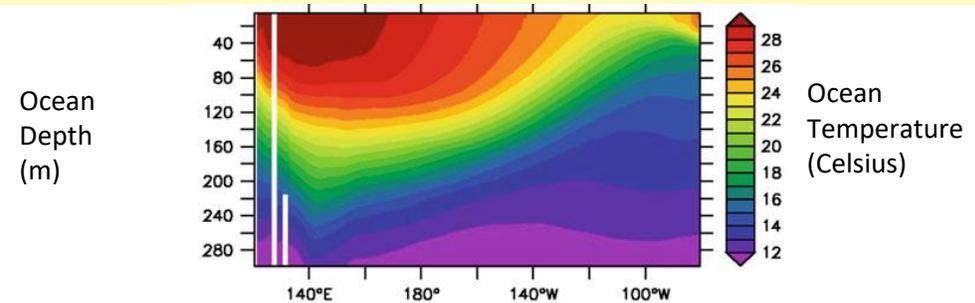
Source: Climate.gov image adapted from Kapnick et al., Proc. Natl. Acad. Sci. 2018

What led to the capability for 8-month snow prediction in Kapnick et al. 2018?

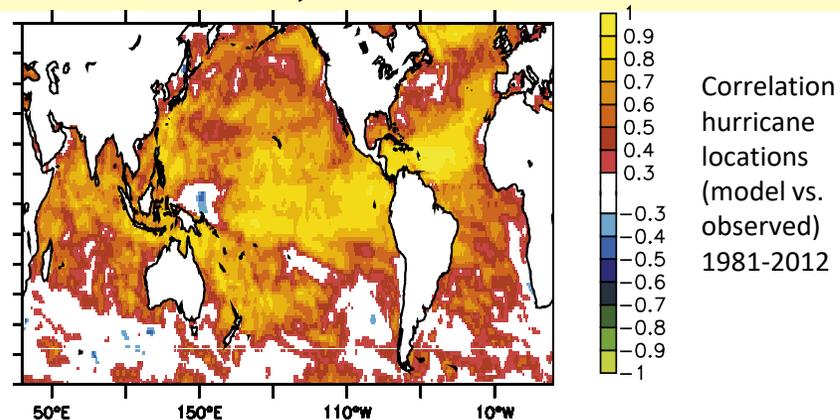
- 1) Global climate model developed at 200km resolution (*Delworth et al. 2006*)



- 2) Initialization system developed for (1) (*Chang et al. 2013*)



- 3) Develop a seasonal to multi-seasonal system with (1) & (2) (*Vecchi et al. 2014*)



- 4) To inform the development of a new prediction system from (3), we have analyzed various aspects of prediction skill & sources of skill

- Select examples of skill:
 - Precipitation & temperature skill (*Jia et al. 2015*)
 - Winter storm track skill (*Yang et al. 2015*)
 - Sea ice prediction (*Bushuk et al. 2017; 2018*)
- Select example sources of skill:
 - Stratospheric influence (*Jia et al. 2017*)
 - Role of initialization for western US precipitation (*Yang et al. 2018*)
 - Boundary condition role S. California 2016 winter (*Zhang et al. 2017*)

A proposed 5-year program to understand and predict western US snowfall.

- **Understand**: numerical experiments to define the upper end of predictive skill.
 - Also, understand the sources of predictive skill.
- **Test**: Explore with modern prediction systems how well precipitation, snow, and runoff predictions were made over the last several decades.
 - Develop a snow reanalysis as a basis for forecast verification.
 - Test GFDL's best system over several decades.
 - Test NWS's best system over several decades.
 - Apply statistical postprocessing to remove systematic errors.
 - Use NWS lumped "HEFS" system to predict streamflows.
- **Decide**: determine which parts of each system is best, and improve upon obvious problems.
- **Beta-test**: Start producing experimental guidance from GFDL and/or NWS.
- **Tech transition**: migrate the best system into operations.
- **Production**: Produce seasonal snow and runoff forecasts operationally across the western US.

A pathway to implementation

predictability studies, understanding

snowfall reanalysis development

generate GFDL retrospective simulations

generate NWS retrospective simulations

postprocess the simulations to
improve skill

Evaluate the skill of precipitation,
snow water equivalent, runoff

Model changes, synthesis with other
system improvements, re-testing

Adapt GFDL model components for NWS use

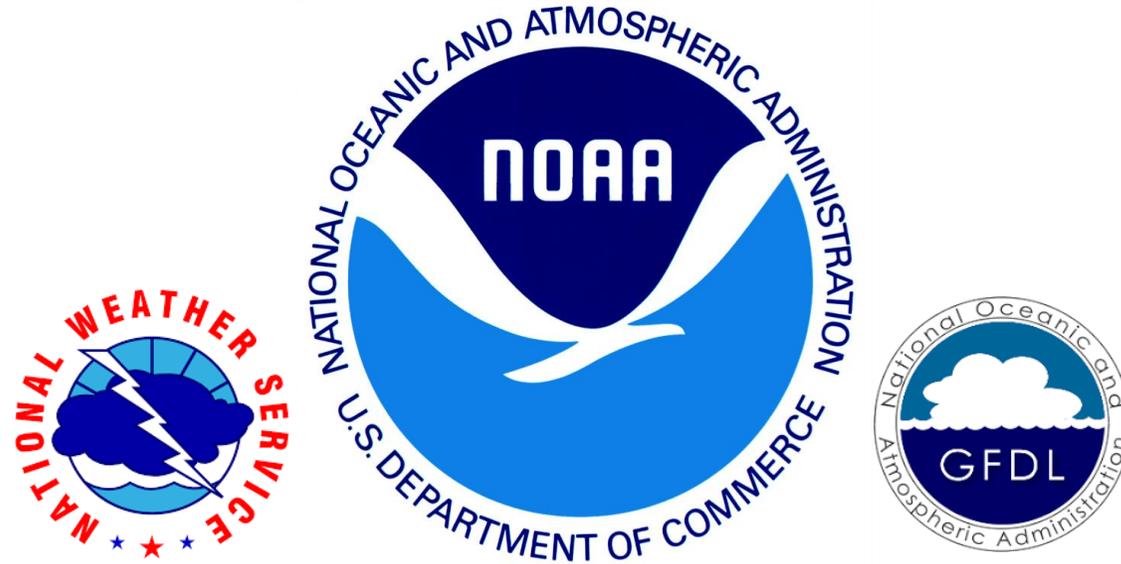
Produce real-time experimental forecast guidance

Pre-operational tests

implement

Start

Proposed core and possible external partners



Earth System Research Laboratory
Serving Society through Science



& others
that are
relevant

A precedent: upcoming California DWR funding for sub-seasonal prediction: three thrusts

- Statistically post-process sub-seasonal predictions to improve upon the raw numerical guidance from prediction systems.
- Since tropical thunderstorm clusters modulate landfalling atmospheric rivers, develop diagnostics to understand what's wrong with the prediction of tropical thunderstorm clusters.
- Improve the prediction system's representation of these tropical thunderstorm clusters (presumably improving the prediction of landfalling atmospheric rivers).

Challenges for a seasonal prediction initiative

- Are we confident in seasonal precipitation predictability?
- Funding to explore this. My team in ESRL/PSD is putting some skin (base funding) in the game.
- High-performance computing – NOAA is perpetually squeezed.
- Uniting NWS's previously separate weather and climate-change prediction infrastructure.
- Synthesizing improvements developed under this project with those from other projects.

Conclusions

- Responding to CDWR & Jeanine Jones, NOAA scoped out a possible activity to make operational seasonal snowfall predictions in the western US, especially the Upper Colorado River.
- NOAA would work collaboratively to achieve these seasonal snowfall predictions, including other partners when necessary.
- We look forward to discussing this. If it is possible to get this project off the ground, we can modify it so that it better meets the needs of Western Water.
- Next steps?

An Act

To improve the National Oceanic and Atmospheric Administration’s weather research through a focused program of investment on affordable and attainable advances in observational, computing, and modeling capabilities to support substantial improvement in weather forecasting and prediction of high impact weather events, to expand commercial opportunities for the provision of weather data, and for other purposes.

Be it enacted by the Senate and House of Representatives of the United States of America in Congress assembled,

SECTION 1. SHORT TITLE; TABLE OF CONTENTS.

(a) **SHORT TITLE.**—This Act may be cited as the “Weather Research and Forecasting Innovation Act of 2017”.

(b) **TABLE OF CONTENTS.**—The table of contents for this Act is as follows:

- Sec. 1. Short title; table of contents.
- Sec. 2. Definitions.

**TITLE I—UNITED STATES WEATHER RESEARCH AND FORECASTING
IMPROVEMENT**

- Sec. 101. Public safety priority.
- Sec. 102. Weather research and forecasting innovation.
- Sec. 103. Tornado warning improvement and extension program.
- Sec. 104. Hurricane forecast improvement program.
- Sec. 105. Weather research and development planning.
- Sec. 106. Observing system planning.
- Sec. 107. Observing system simulation experiments.
- Sec. 108. Annual report on computing resources prioritization.
- Sec. 109. United States Weather Research program.
- Sec. 110. Authorization of appropriations.

TITLE II—SUBSEASONAL AND SEASONAL FORECASTING INNOVATION 

- Sec. 201. Improving subseasonal and seasonal forecasts.

TITLE III—WEATHER SATELLITE AND DATA INNOVATION

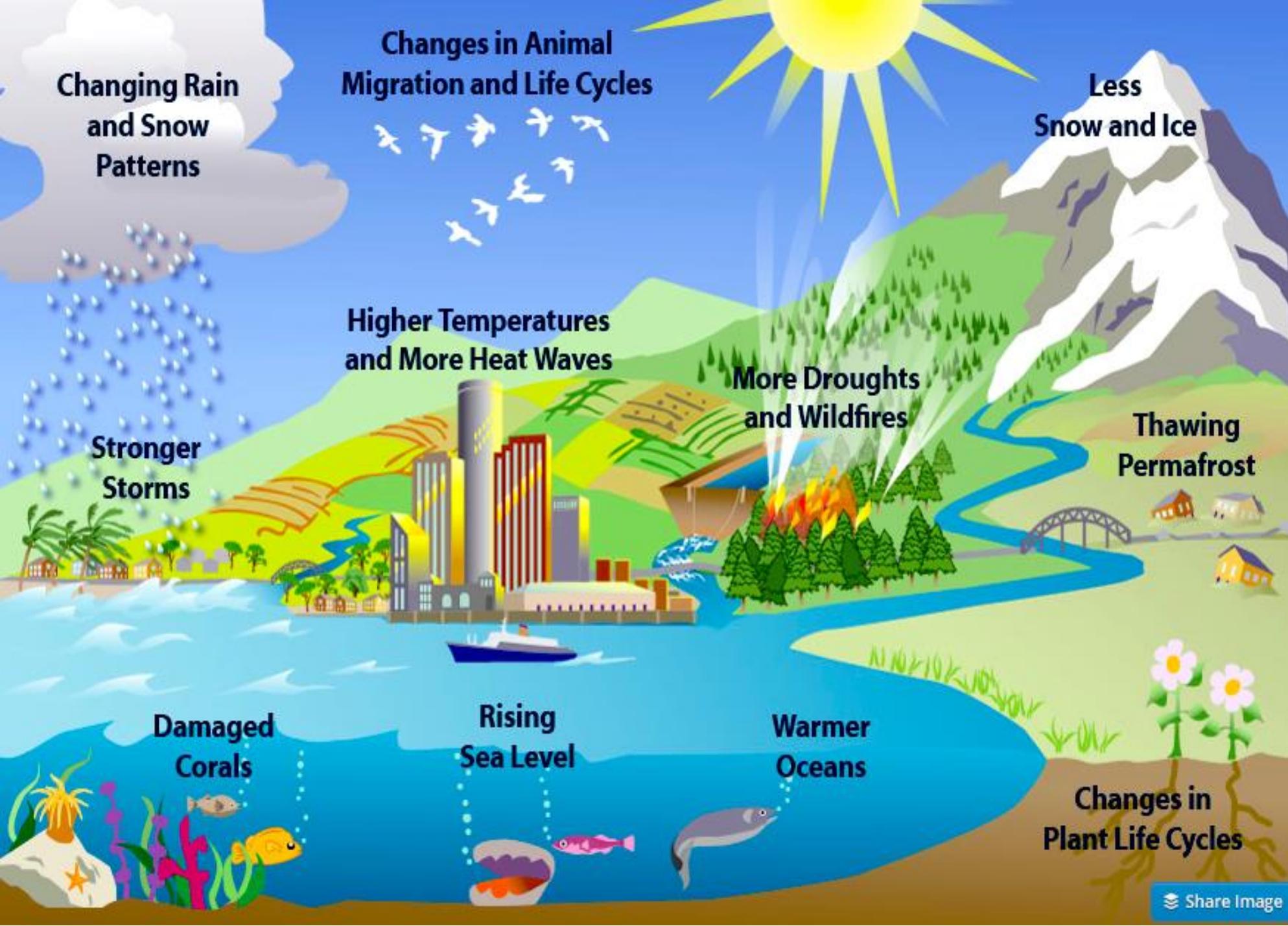
- Sec. 301. National Oceanic and Atmospheric Administration satellite and data management.
- Sec. 302. Commercial weather data.
- Sec. 303. Unnecessary duplication.

Apr. 18, 2017
[H.R. 353]

Weather
Research and
Forecasting
Innovation Act
of 2017.
15 USC 8501
note.

Weather Research and Forecast Innovation Act of 2017

Regarding funding, Congress has authorized, has asked for a report, but has not yet appropriated funds, neither in general nor specifically to this project.



Global warming should not be ignored as a predictable factor in seasonal snowfall forecasts.

Generally, there will be less snow and more rain with each passing decade.

Runoff will occur earlier in the water year.

More on the testing the GFDL and NWS prediction systems

- Generate ensembles of predictions from 1 October to the end of the water year. With resources, generate forecasts from other initial dates (say, 15 Oct, 1 Nov, ...). This provides more confidence in the results and will indicate whether there is skill at leads shorter than 6-8 months.
- Test most up-to-date versions of the GFDL coupled prediction system (SPEAR) and the NWS Unified Forecast System (UFS). These share several components.
 - Same (ocean and atmosphere and sea ice “dynamical core”)
 - Different (land-surface, treatment of subgrid processes, coupling of state components)
- Evaluate precipitation and temperature forecasts at various lead times (e.g., 1 month, 2 months ... 8 months). Evaluate snow-water equivalent. Force the NWS Hydrologic Ensemble Forecast System with these precipitation and temperature forcings and evaluate runoff forecasts for accuracy.
- Since computations are expensive and global in nature, we might as well evaluate many basins (Upper Colorado, tributaries, Columbia River, etc.).

More details on components of the project

Predictability studies

- Commonly one generates an “ensemble” of simulations with a model in question and then uses one of the members of the ensemble to assess the predictability of the phenomenon. Is the range of scenarios predicted by the ensemble “sharper” (more specific) than the overall climatology of possible model states?
- After the fact, with analyses of past weather and the ocean, can nudge the predictions to analyzed data to examine the impact of near-perfect predictions of one part of the system (such as the El Nino).

Snowfall reanalysis generation

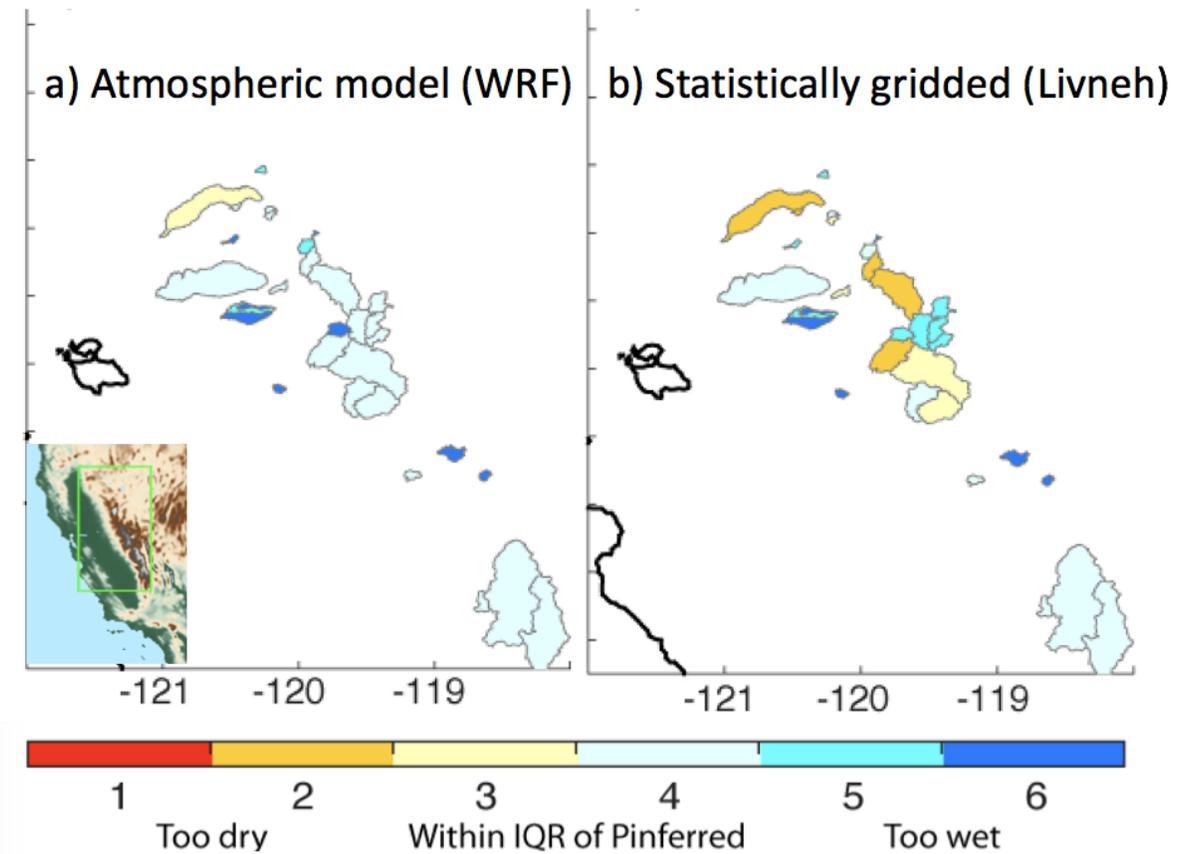
- Synthesize work of UCLA scientists such as Steve Margulis (<https://ntrs.nasa.gov/search.jsp?R=20180000648>) , Mimi Hughes (NOAA ESRL PSD - high-resolution WRF dynamical downscaling), and Andy Wood (NCAR, various statistical models).
- Use common modern data sources, in situ and remote, over period of reforecasts.

Estimating precipitation and other hydrologically relevant forcings with dynamical downscaling

High-resolution (~4 km) regional atmospheric models (e.g., WRF) forced by reanalysis datasets can outperform statistically gridded datasets in estimating annual high-elevation precipitation, particularly where in situ data is sparse^{1,2,3}.

A west-wide WRF reanalysis downscaling would serve as a training dataset for statistical postprocessing and also potentially as improved forcings for a second-generation SWE reanalysis.

Categorical Precipitation relative to precipitation inferred from streamflow for watersheds in California's Sierra Nevada

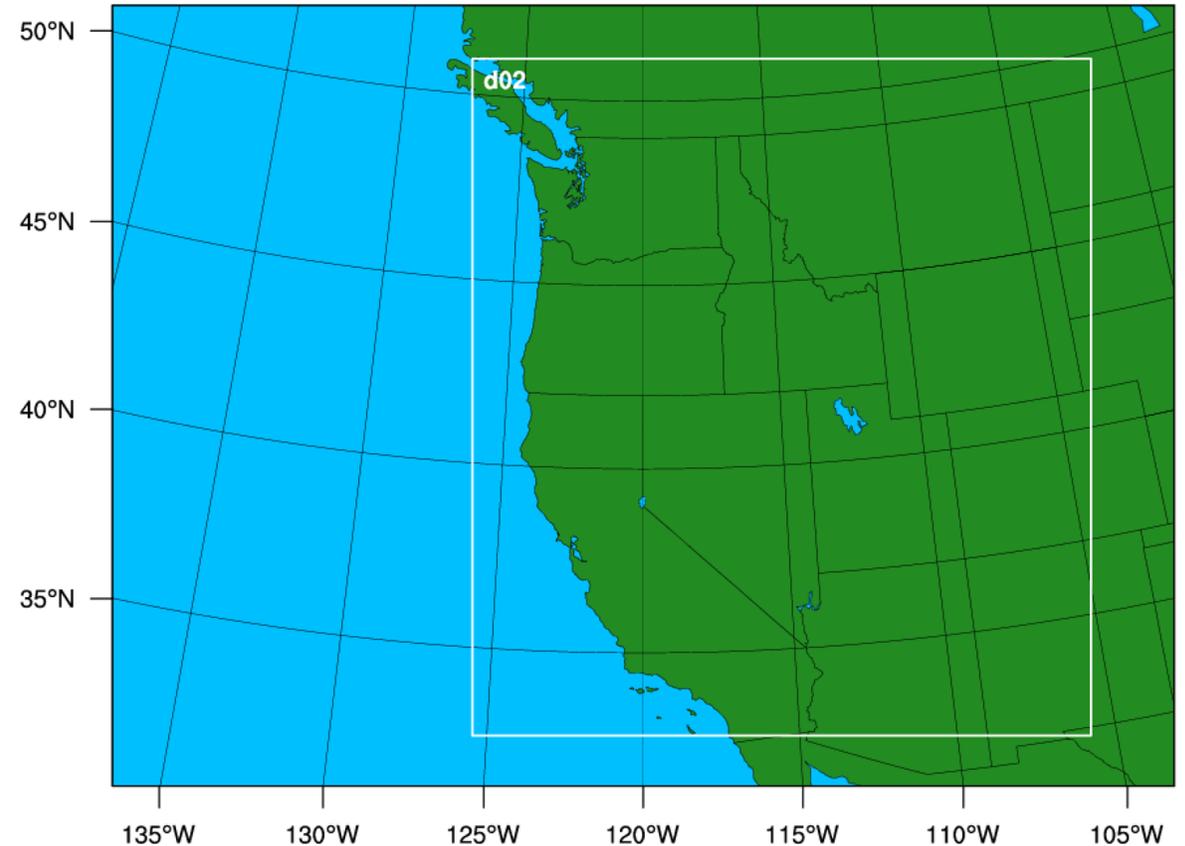


1. Gutmann et al. 2012; 2. Carrier et al. 2017; 3. Hughes et al. 2017

Supporting details on WRF downscaling

Quality depends strongly on configuration: ESRL scientists have experience in configuring these simulations for optimal precipitation estimates.

This dataset would not only give us high quality estimates of precipitation, but also Components that directly lead to SWE and its evolution at the surface (precipitation [amount and phase], temperature, SW/LW radiation at surface, and wind)



Example WRF configuration: inner domain would have 3 km grid spacing (within 9 km outer grid)

Postprocessing the prediction system output.

- Models can have systematic errors (too wet, too cold) and an unavoidable lack of spatial detail.
- Through comparisons of past forecasts and observations, it is possible to restore spatial detail in mountainous regions and correct bias.
- My organization, ESRL/PSD has significant experience in developing such techniques and making them operational in the NWS.
- If, say, GFDL conducts multiple simulations with their prediction system, one with a 50-km grid spacing and another with 25 km (which is much more computationally expensive), the 50-km + statistical postprocessing can be used as a benchmark for the 25 km.

Migrating the system to operations

- If the GFDL system is superior, then we would need to:
 - Test to isolate the causes. Is it the coupling technique? The land surface? The sub-grid parameterizations?
 - Test to determine whether their predictions are also superior with shorter-lead forecasts.
 - Adapt the GFDL components so that they can be used in the UFS community model that the NWS runs operationally and supports to the research community.