Accelerating research on seasonal hydroclimate forecasting

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CURRENT STATE OF GFDL'S GLOBAL CLIMATE MODELS FOR MULTI-SEASONAL PREDICTION APPLICATIONS

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GFDL Seasonal to Decadal Prediction and Research Systems

	Atmosphere resolution	Ocean resolution
CM2.1	200 km	1º
FLOR	50 km	1º
HIFLOR*	25 km	1º

- CM2.1 and FLOR: run each month as part of the **North American Multi-Model Ensemble (NMME)**

- Output provided to NCEP (National Hurricane Center and Climate Prediction Center) to inform their seasonal outlooks
  - FLOR and HIFLOR[1] for hurricanes
  - CM2.1 and FLOR for other climate outlooks, including **ENSO**, precipitation and temperature

- Ocean reanalysis also provided to NCEP for Multiple Ocean Reanalysis Project

Key point: **These prediction systems are made possible through harvesting the fruits of a decades long research effort on INITIALIZATION SYSTEMS and MODEL DEVELOPMENT.**

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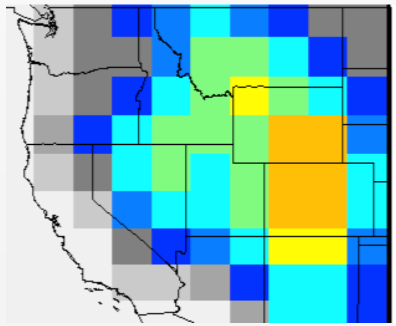
* Due to computational cost, HIFLOR is not run routinely

Seasonal Forecasting
Dynamical Model Research and Predictions at GFDL

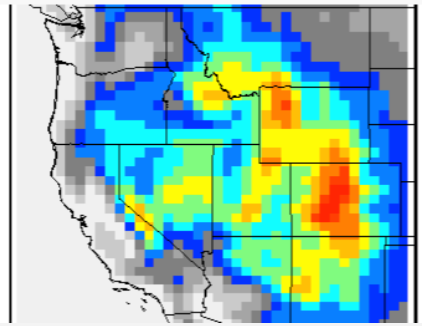
Research and Operations:
Part of the **NMME**

Primarily Research

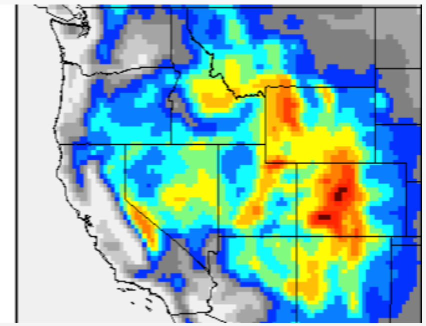
CM2.1



FLOR



HiFLOR

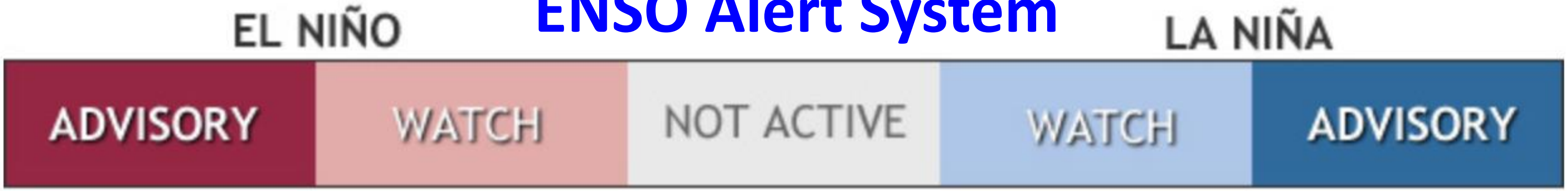


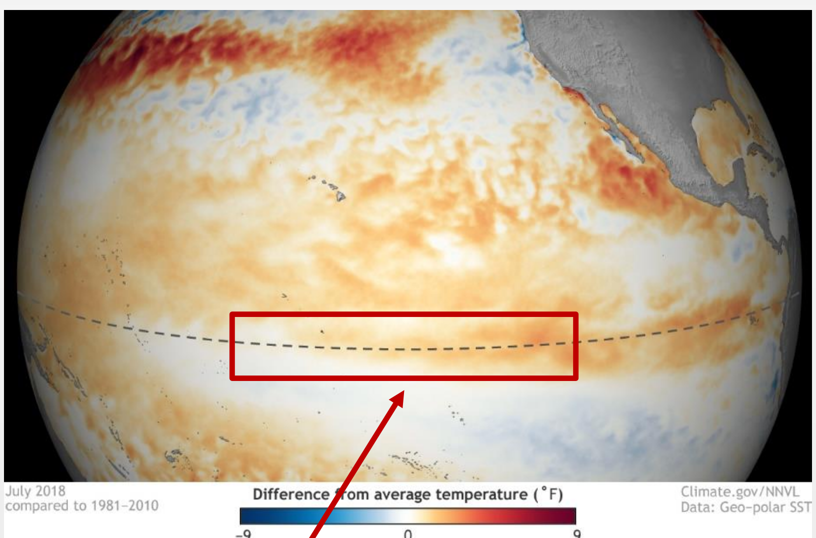
Atmospheric/Land Grid Size	***200 km***	***50 km***	***25 km***
Ensemble members	*10*	*12*	*12*

GFDL’s contribution to the NMME and NOAA’s operational ENSO forecasts

- Each month an 11-member team is responsible for (a) updating the status of ENSO (the Alert System) and (b) probabilistic forecast for the coming 9 months.

ENSO Alert System





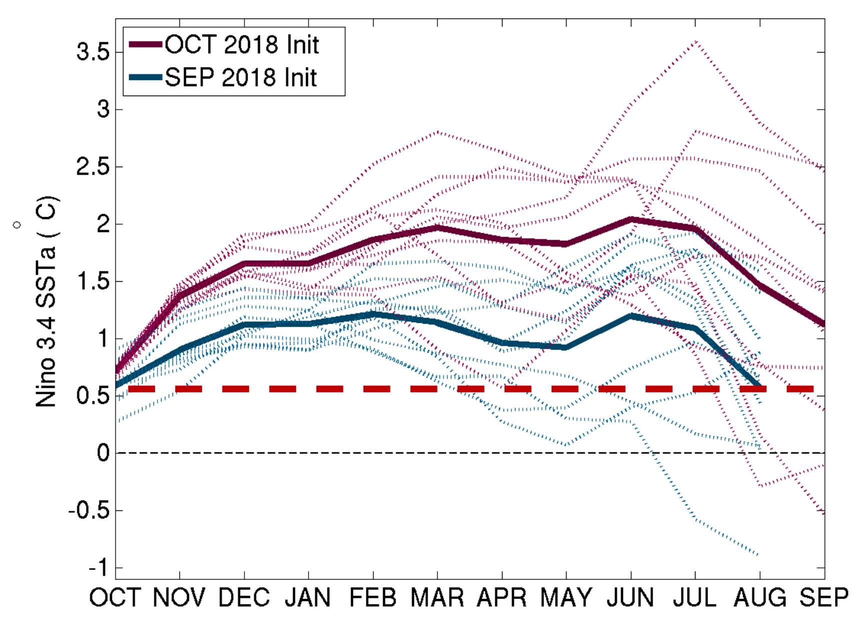
Niño 3.4 region

- State of ENSO primarily monitored through the Niño 3.4 SST index
- NMME ENSO forecasts provide a valuable source of guidance

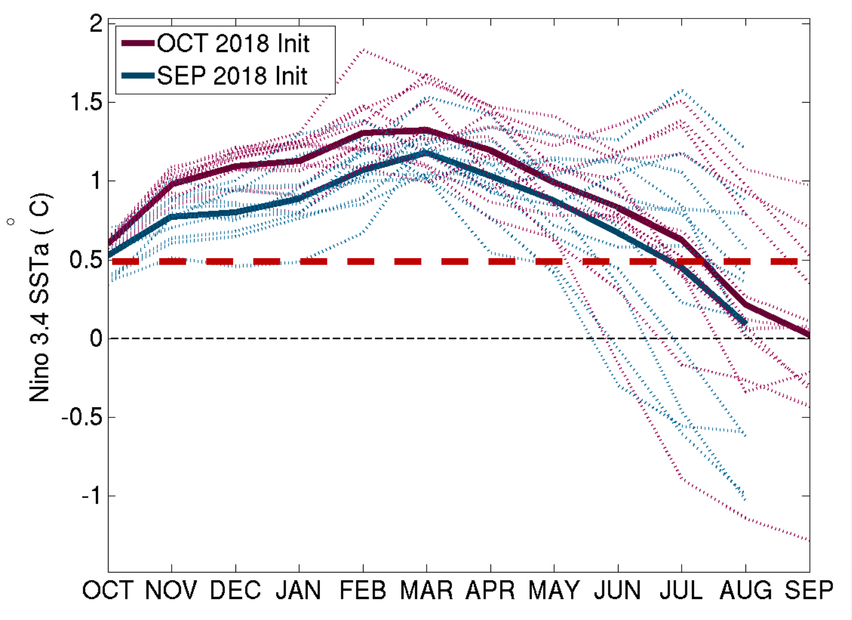
GFDL's contribution to the NMME and NOAA's operational ENSO forecasts

GFDL's NMME Niño 3.4 SST forecast plumes

CM2.1



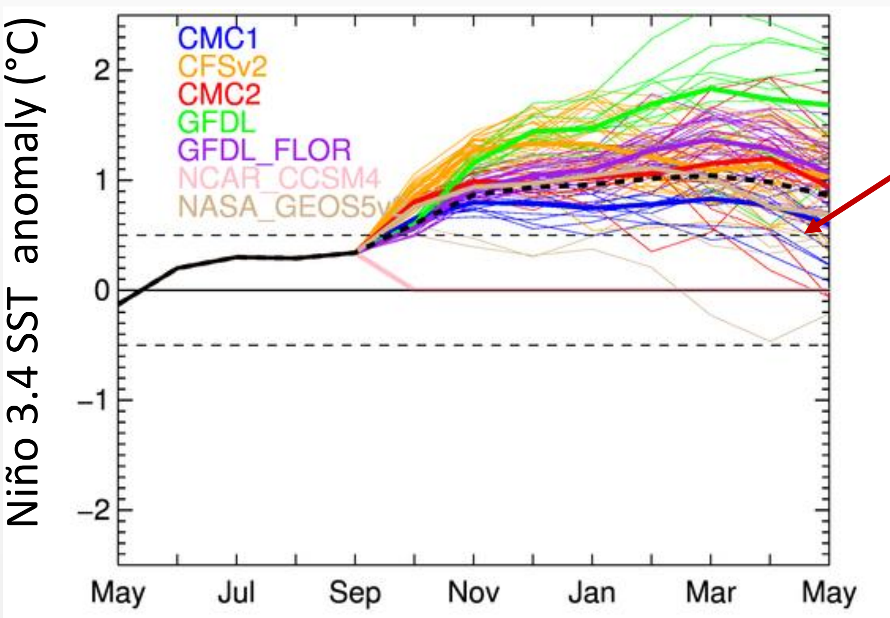
FLOR B01



Consolidating NMME forecast guidance for NOAA's operational ENSO forecasts

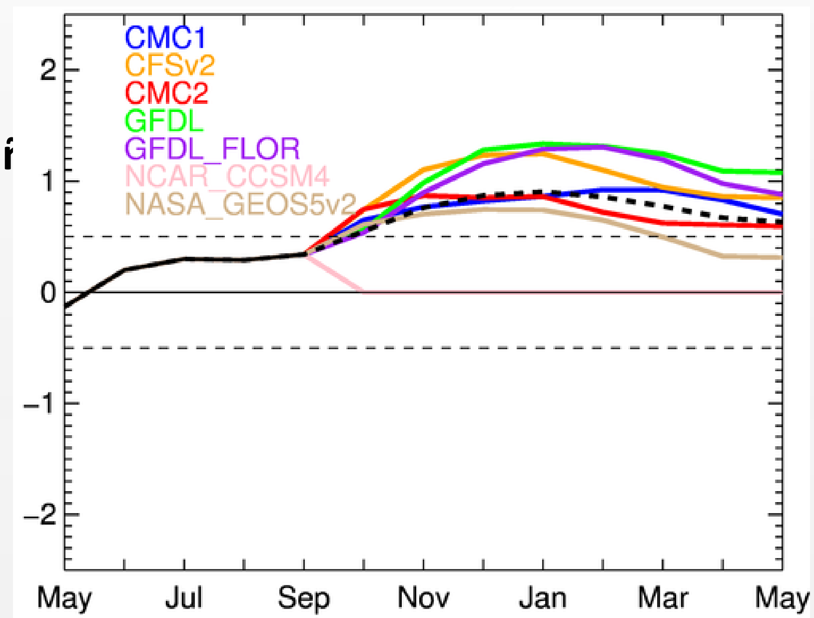
Full NMME Niño 3.4 SST forecast plume
NMME mean Niño 3.4 SST forecast plume

October Init



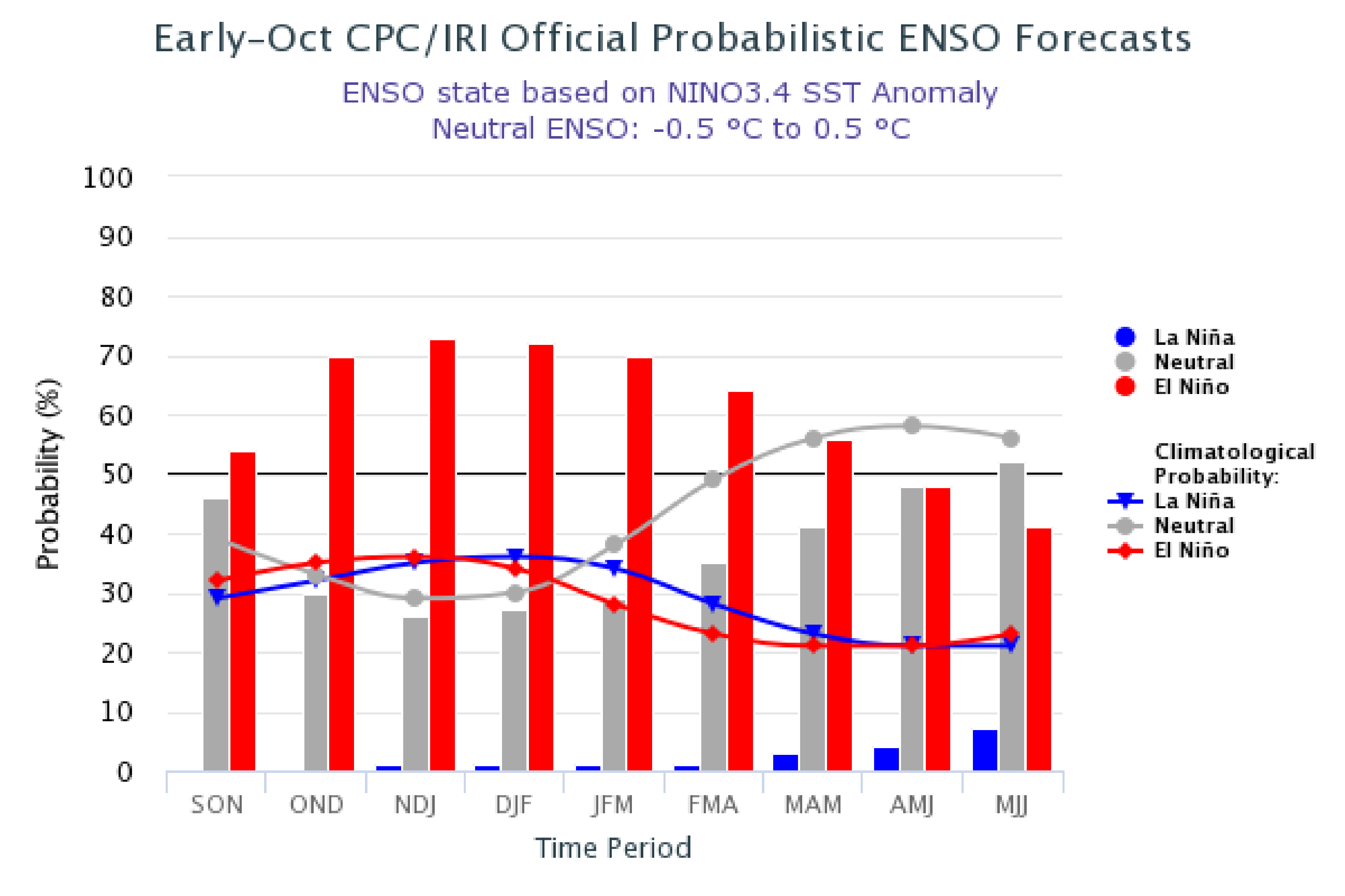
El Niñ

RESCALED



Courtesy of Emily Becker, NOAA CPC

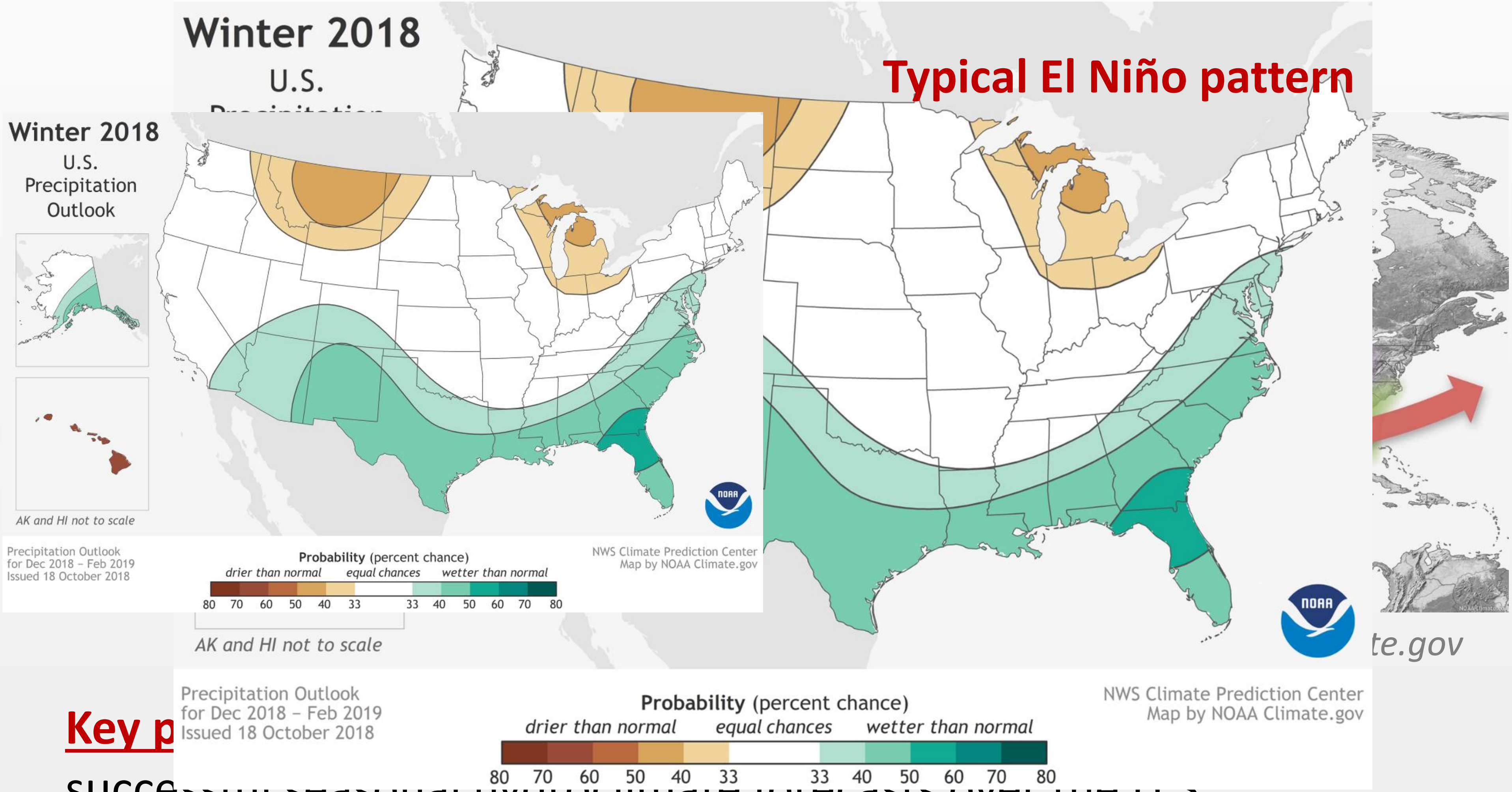
Current ENSO Alert System Status: El Niño Watch



https://iri.columbia.edu/our-expertise/climate/forecasts/enso/current/

http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/enso_advisory/ensodisc.shtml

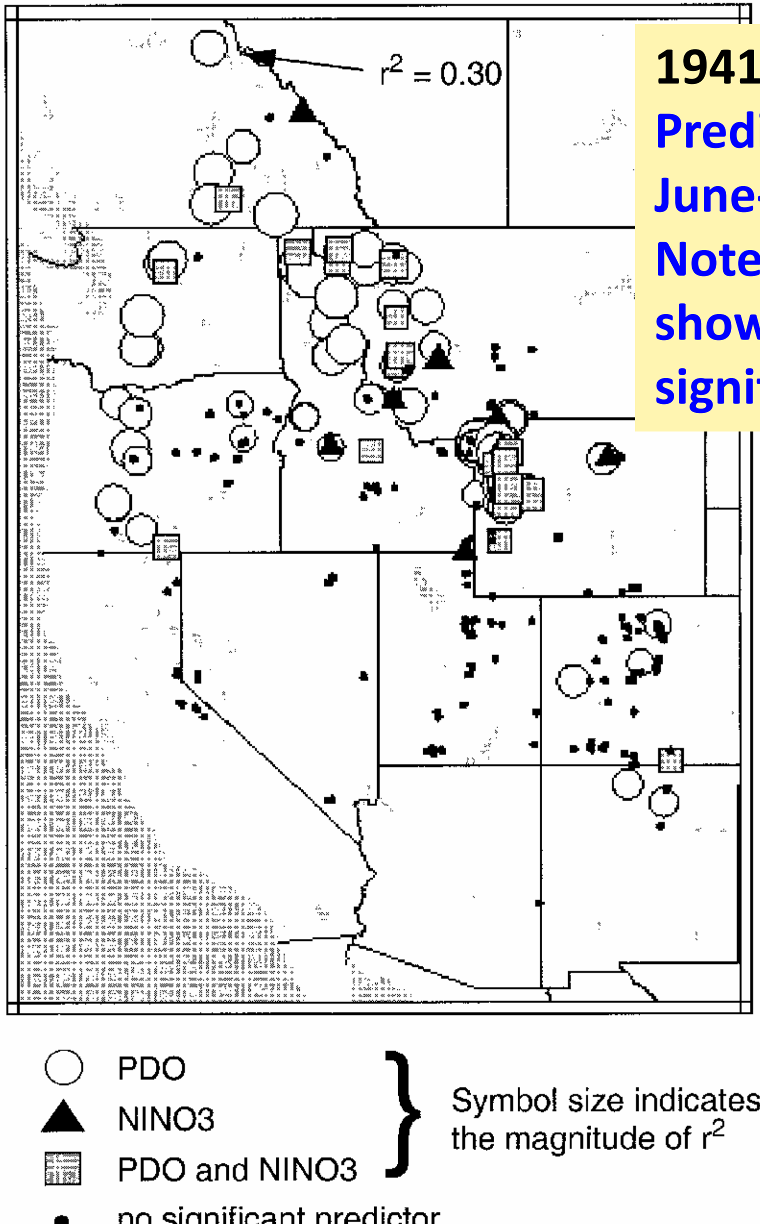
NOAA's 2018-19 Winter Outlook



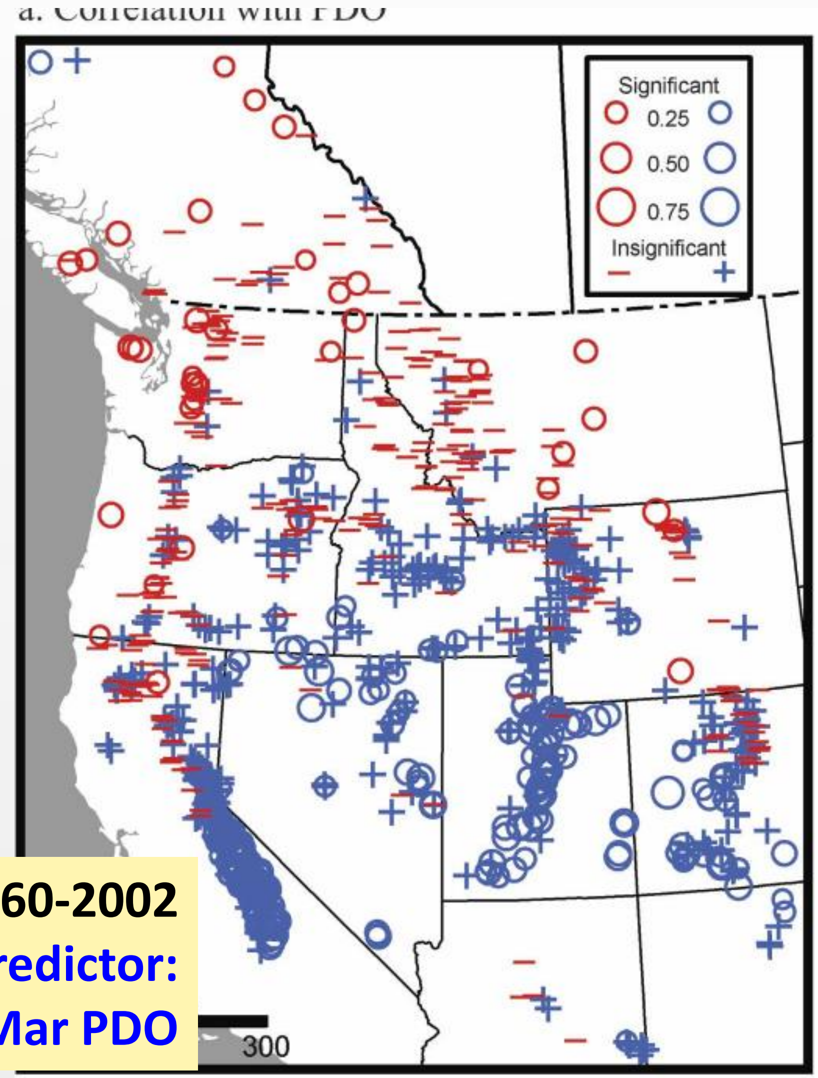
Key p

successful seasonal hydroclimate forecasts over the U.S.

Western U.S. Snowpack prediction: ENSO not a silver bullet



1941-90
Predictor: June-Nov
Note: 63% show no significance



1960-2002
Predictor: Oct-Mar PDO

Source: McCabe and Dettinger 2002; Mote 2006

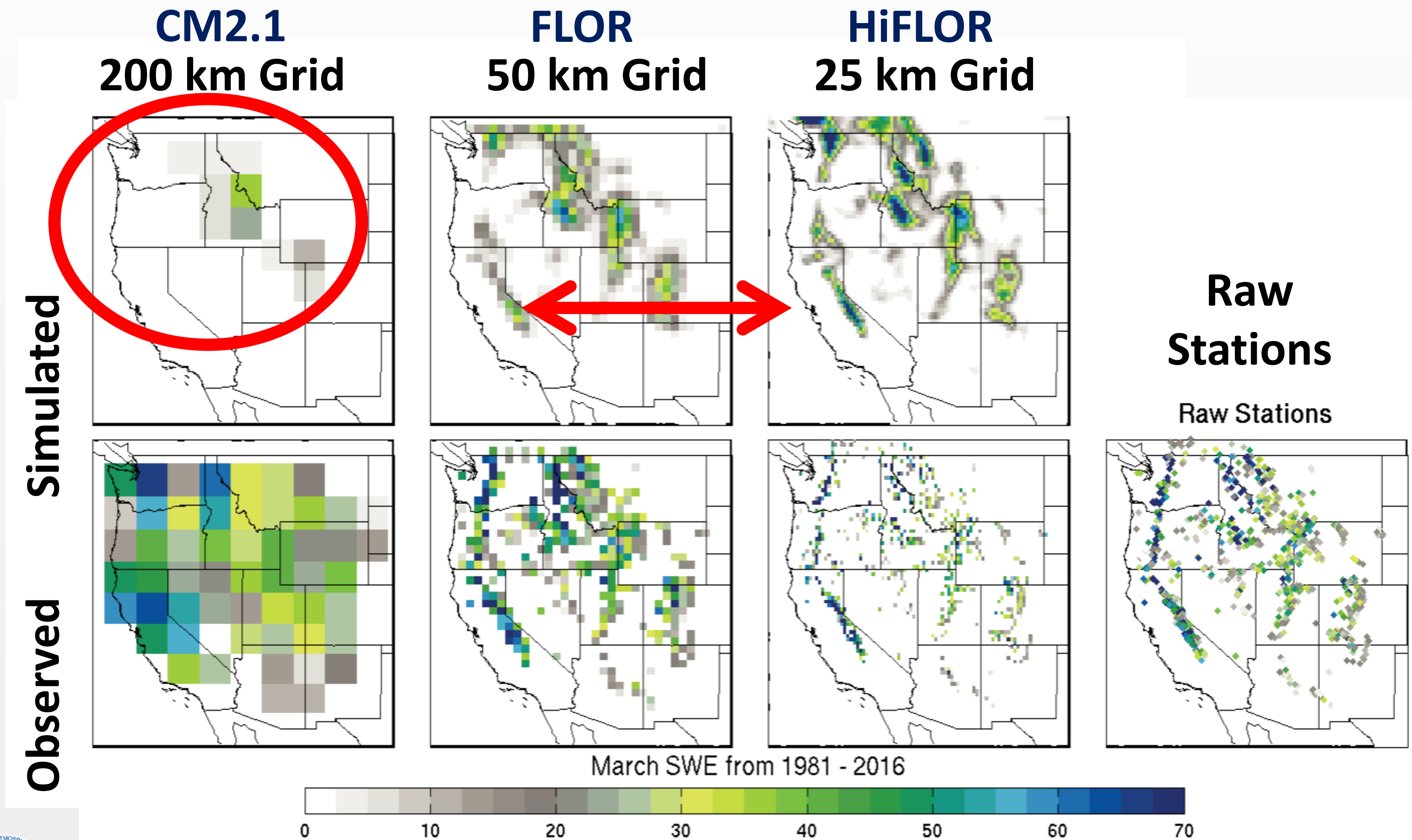
Developing a western U.S. prediction system

Scientific questions to ask

- *Why do we have mountain precipitation / snow?*
- *How does it vary?*
- *Can we predict it?*
- *What else are we missing?*
- *Are we asking the right prediction questions? (For science? For stakeholders?)*

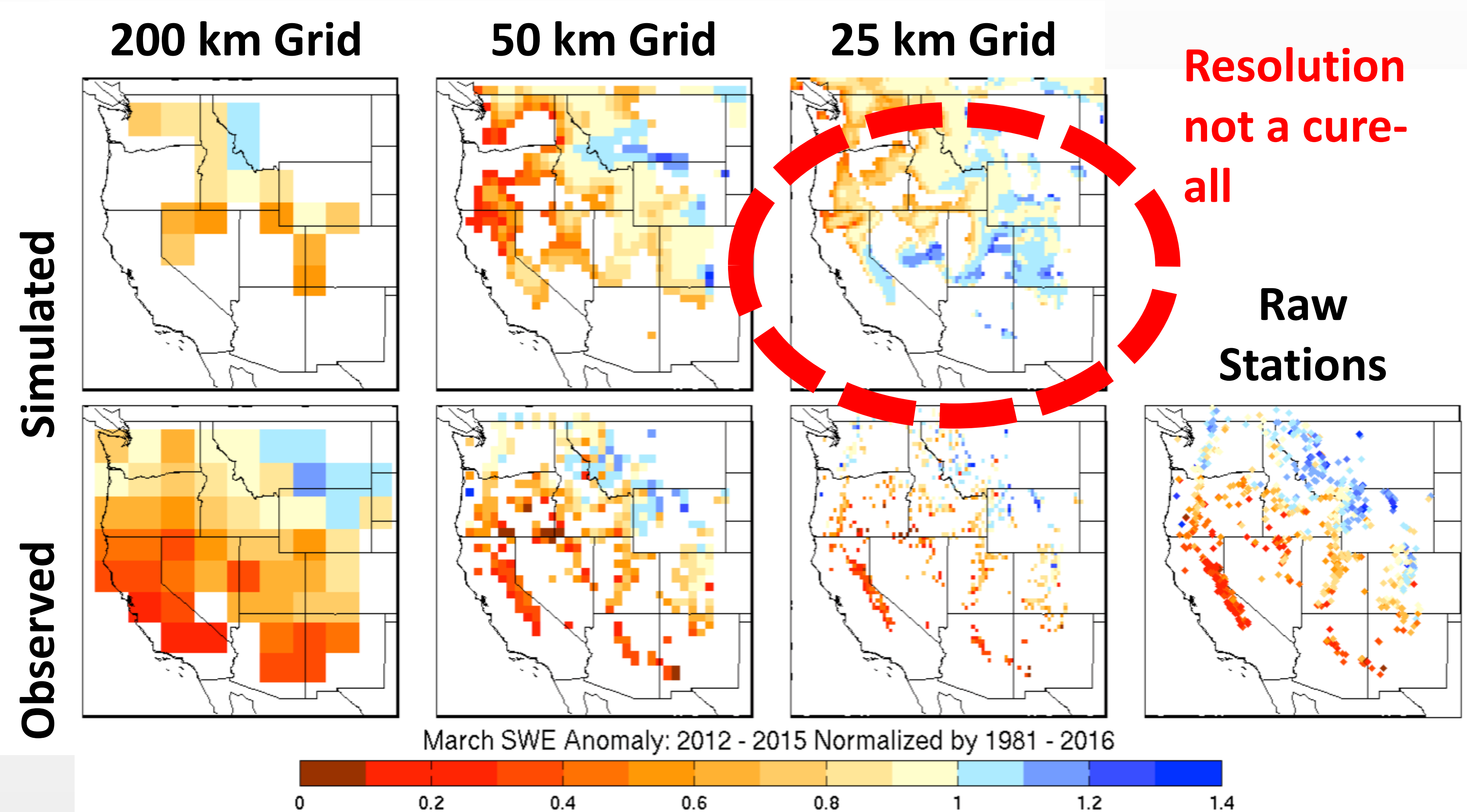
Climatology of western U.S. Snowpack

Model Initialized July 1: 8-mon prediction vs. Observed March



Source: *Kapnick et al., PNAS, 2018*

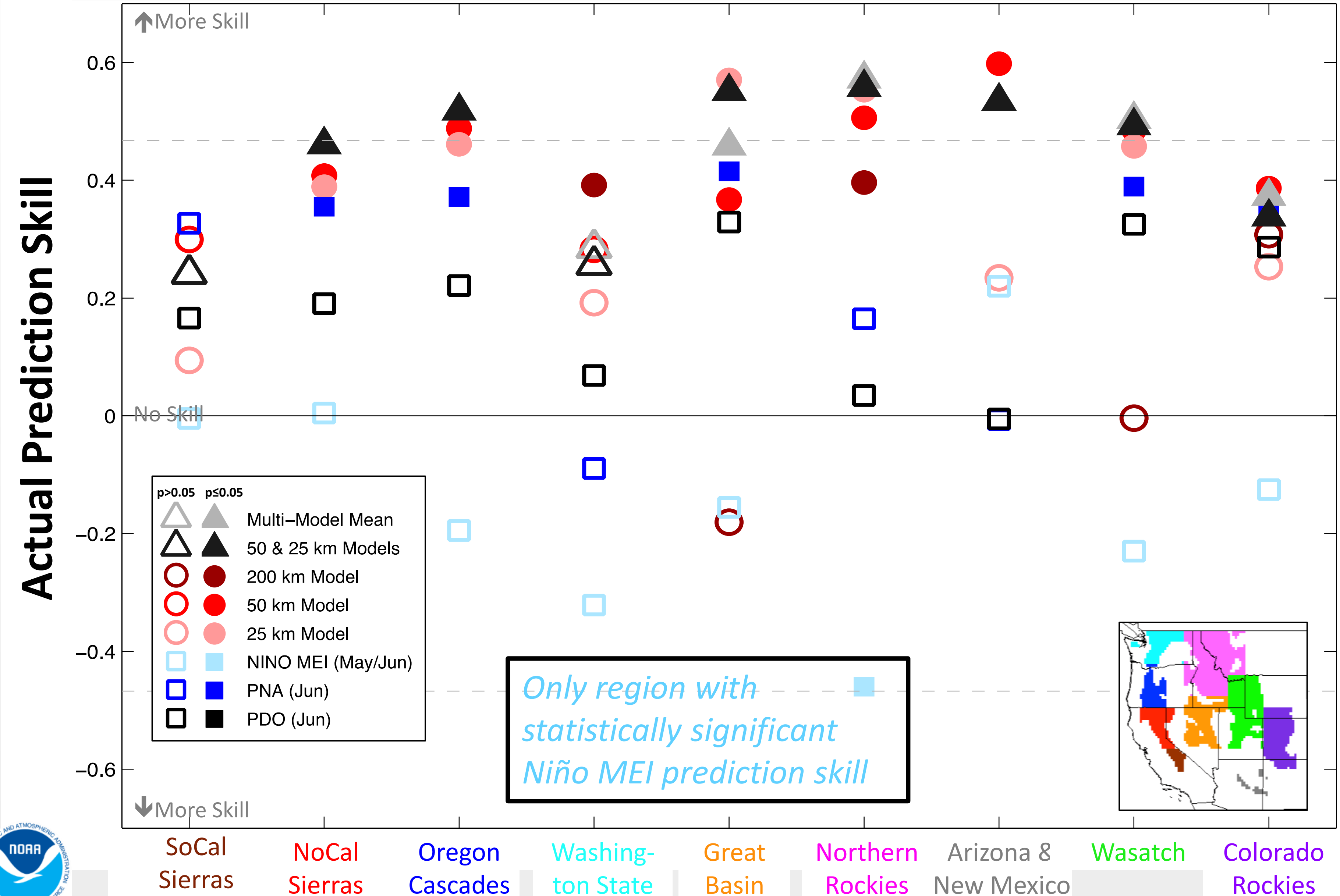
2012-2015 drought 8-m predictions annually



Source: Kapnick et al., PNAS, 2018

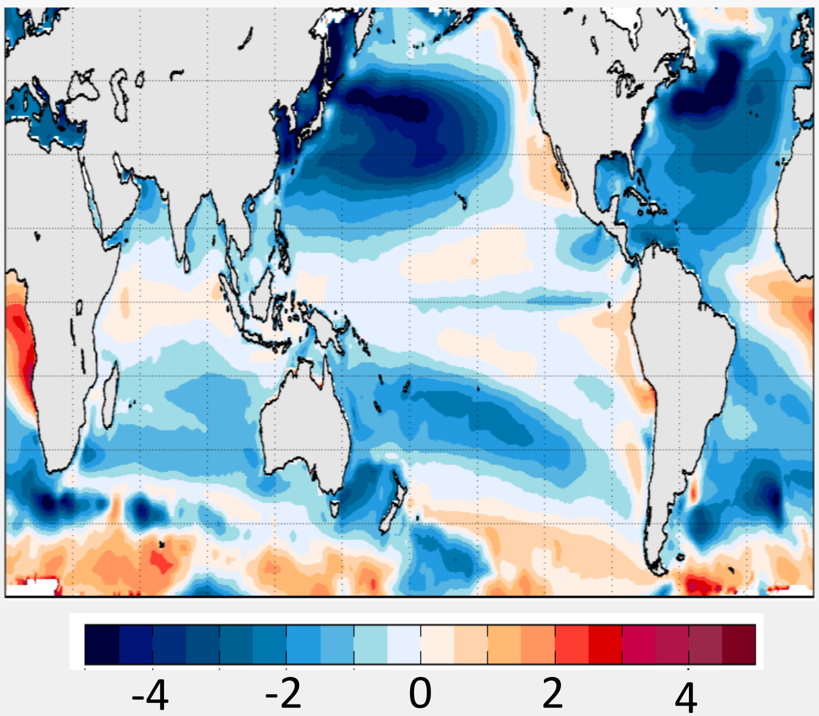
1981-2016 March prediction skill 8 months prior

March snowpack predicted on previous July 1 (Kapnick et al. 2018)

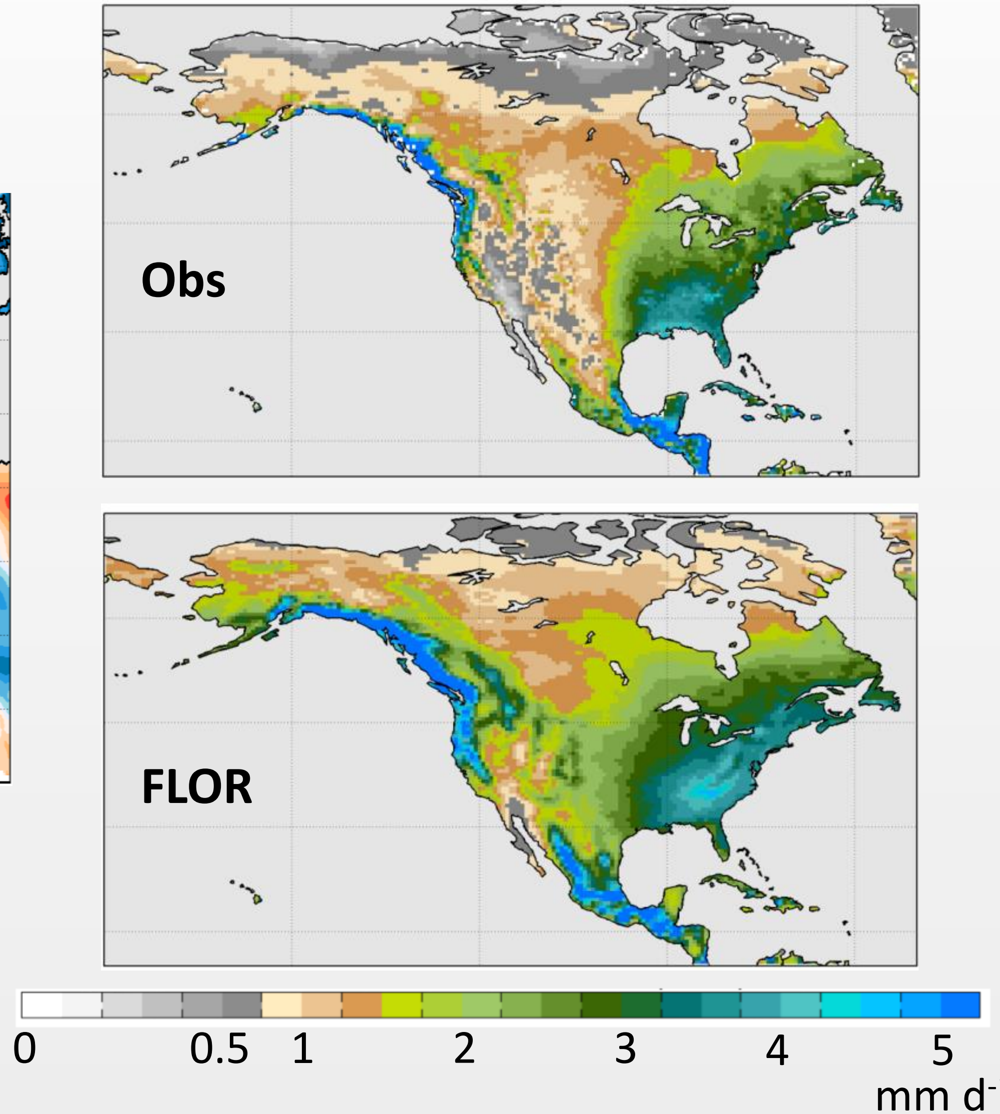


Current GCM shortcoming:
Excessive western U.S. precipitation and negative SST biases

FLOR SST Bias (°C)



Climatological precipitation



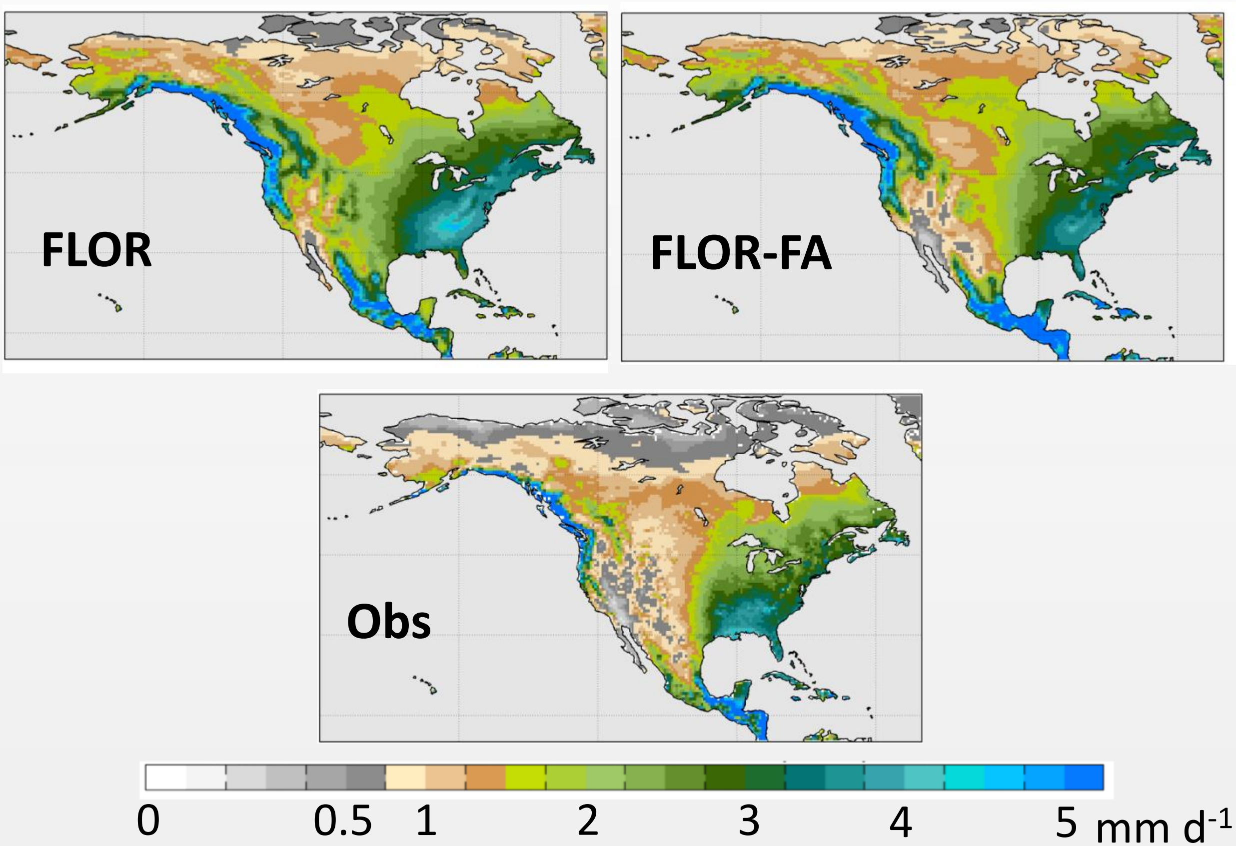
Flux-adjusted FLOR (FLOR-FA):
Correcting SST biases through flux adjustment

- Modifications of model’s momentum, enthalphy, and freshwater fluxes to greatly reduce SST biases (Vecchi et al. 2014)

- Substantially reduces western U.S. precipitation biases

- Experimental seasonal FLOR-FA predictions run routinely

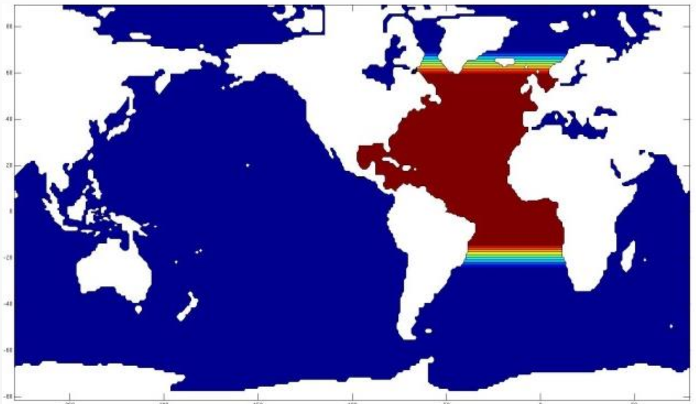
Climatological precipitation



FLOR-FA reduces U.S. region (25-50°N, 60-130°W) RMSE by:

- **18.3%** in October – March (cold season)
- **43.4%** in April – September (warm season)

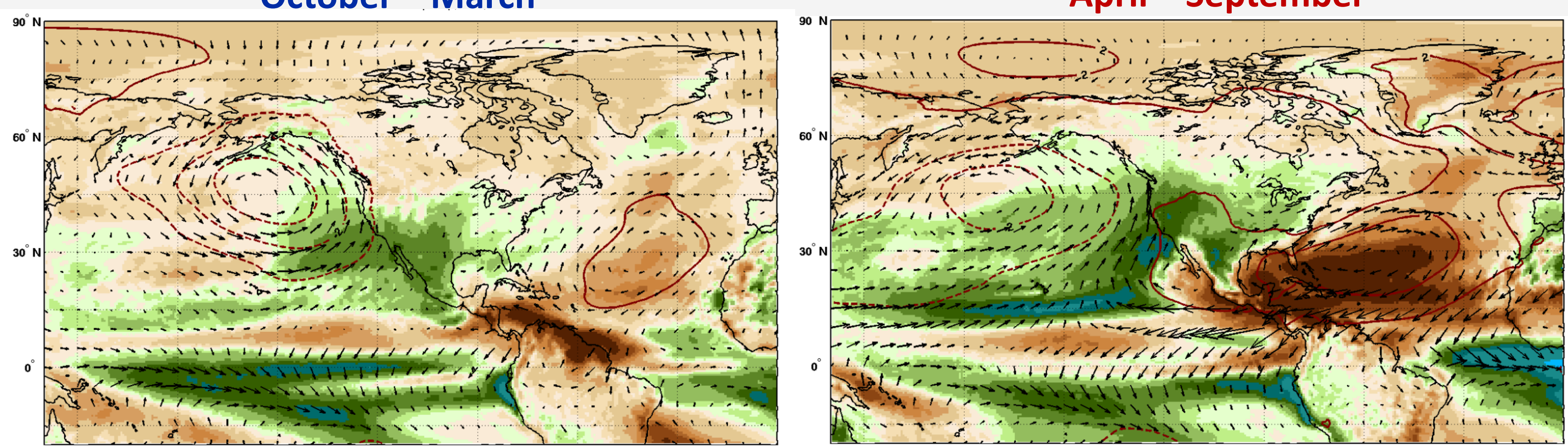
Atlantic SST biases responsible for a substantial portion of western U.S. precipitation biases in FLOR

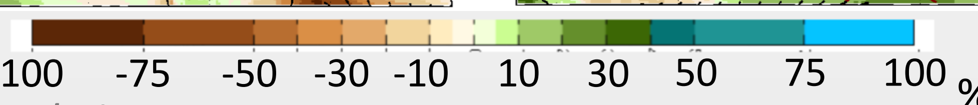


Experiment targeting Atlantic SST bias effects

Impact of Atlantic SST biases on precipitation (% difference), SLP, and winds

October – March **April – September**

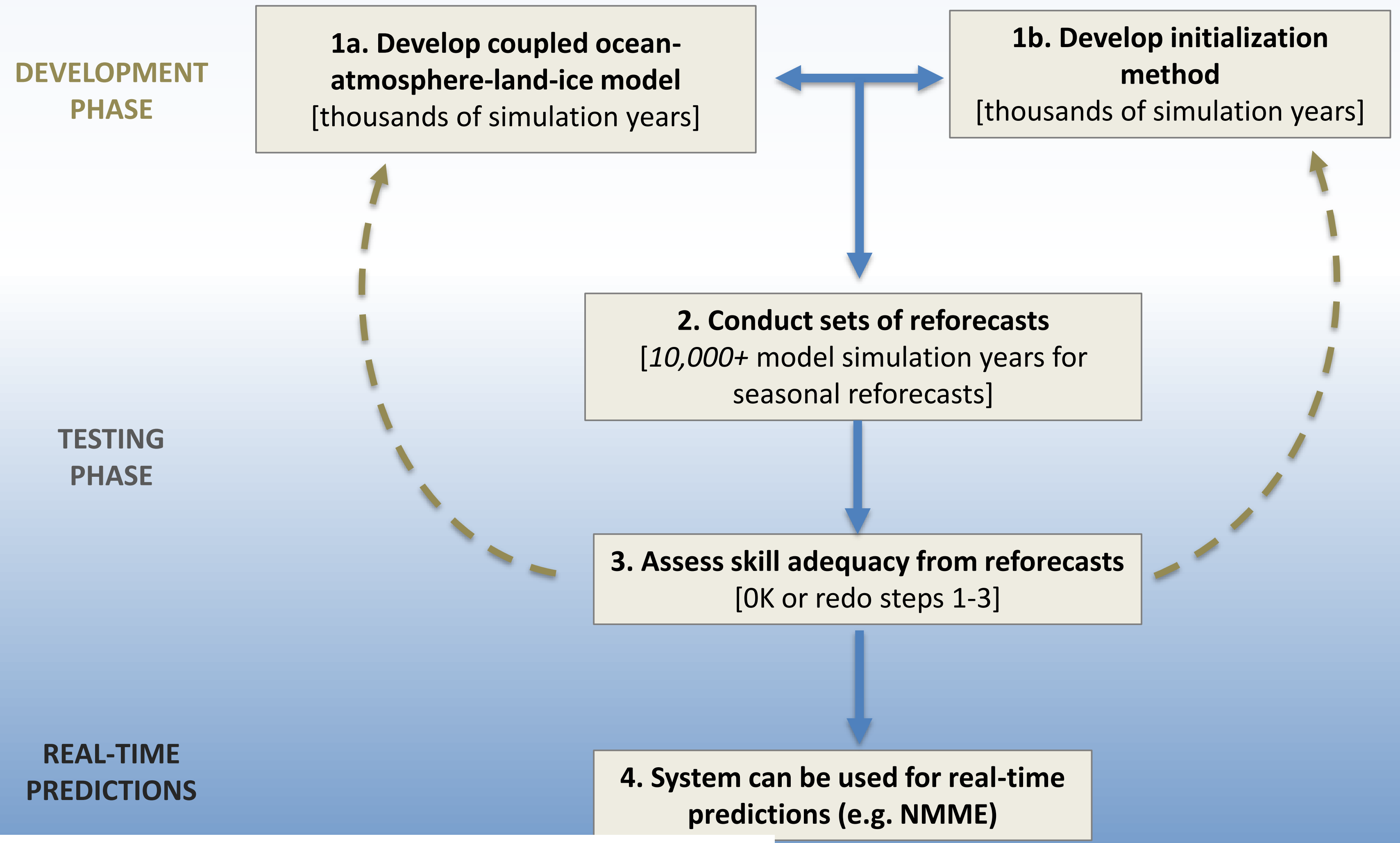




Source: Johnson et al., in prep.

DEVELOPMENT OF GFDL’S NEXT GENERATION SEASONAL-TO-DECADAL PREDICTION SYSTEM

Building a seasonal to decadal prediction system



CURRENT SYSTEM IN USE: CM2.1/FLOR/HIFLOR

NEW SYSTEM IN DEVELOPMENT: SPEAR

Towards a **S**eamless System for **P**rediction and **EA**rth System **R**esearch "SPEAR"

➔ Using latest generation component models to build next generation seamless prediction system. The building blocks are AM4/FV3 (atmosphere), MOM6 (ocean), SIS2 (sea ice), LM4 (land)

Drivers:

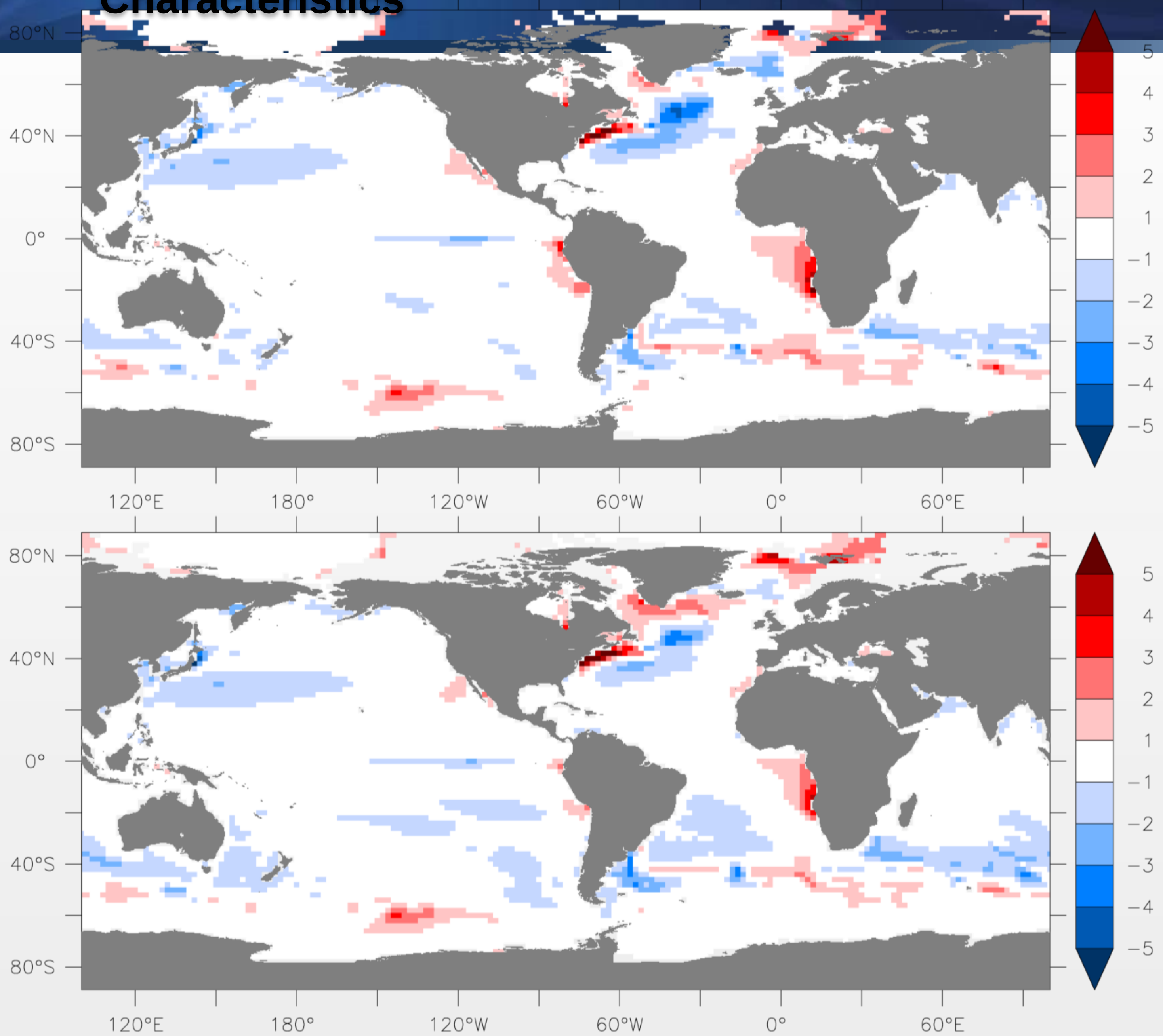
- Advances in scientific understanding, physics, and numerics
- User needs for improved predictions across scales, especially for extremes and regional scales

	Atmosphere res	Ocean res	Status of Development	Reforecasts
SPEAR_LO	100 km	1°	**Completed**	Planned next 6-9 months
SPEAR_MED	50 km	1°	**Completed**	Planned next 6-12 months
SPEAR_HI	25 km	1°	**In development**	Very limited set planned due to computational costs

NOTE: There are clear benefits to moving to higher resolution (25 km+), however HPC is presently a limiting factor. We will work to develop higher resolution versions, but progress and transition to operational forecasts is limited

4. Model Simulation Characteristics

SST BIAS (annual mean)
Control, 2010 forcing

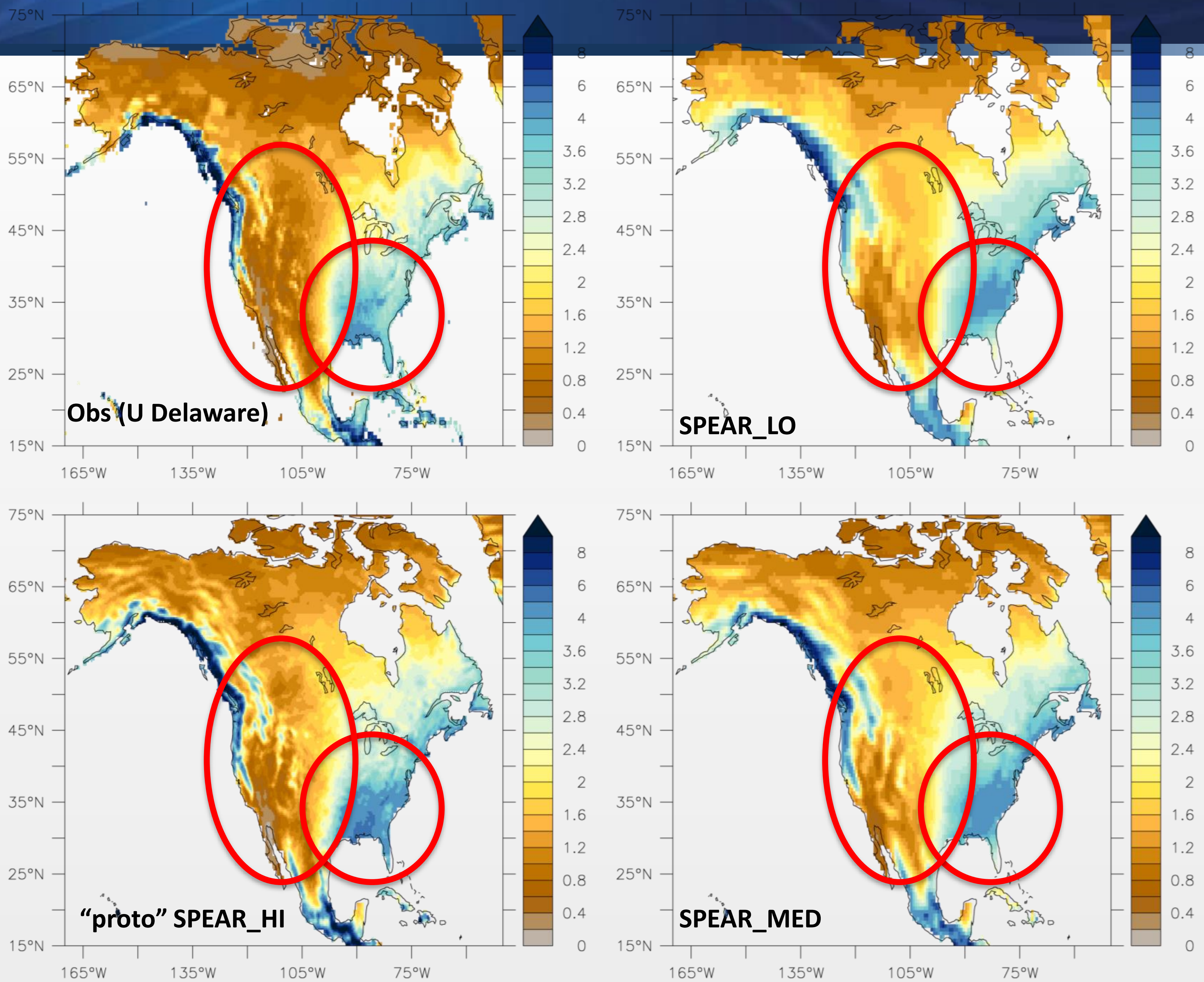


SPEAR_LO
rmse = 0.84

SPEAR_MED
rmse = 0.86

PRECIPITATION (annual mean, units are mm day^{-1})

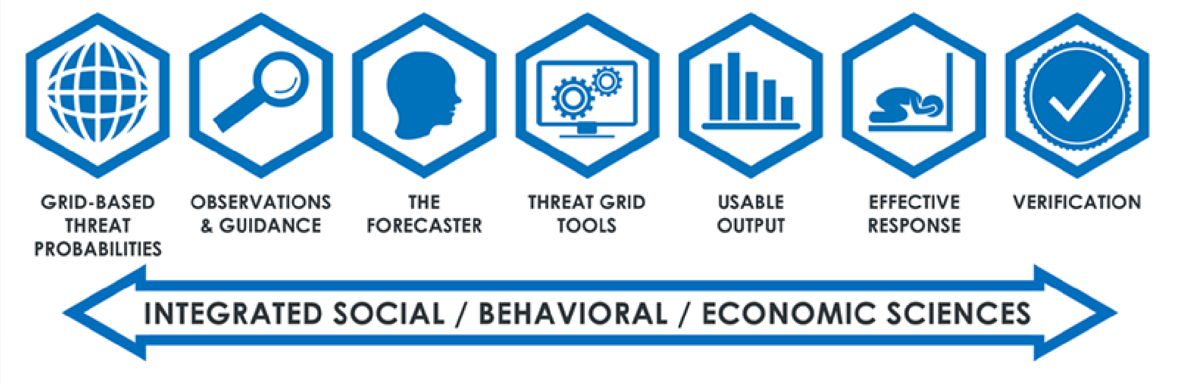
Control, 2010 forcing



Potential future pathways in S2D hydroclimate forecasting

- Investigating predictable deviations from canonical ENSO influence
- Decadal hydroclimate predictability?
- Understanding inherent snowpack predictability in poorly forecast regions (e.g., Coastal California mountains) and the impact of improvements in dynamical models and initialization systems
- Probabilistic hazard information on hydroclimate extremes tailored to user needs (flexible, adaptable to new information)

Forecasting a Continuum of Environmental Threats (FACETs)



A GFDL FACETs postdoc will focus on probabilistic seasonal prediction of hydroclimate extremes

Key takeaways

- **GFDL's coupled climate models** actively engaged in **S2D research and operations**
  - Providing guidance for NOAA's ENSO, temperature and precipitation, and hurricane outlooks
- **Snowpack prediction skill exists 8 months in advance** in a dynamic coupled modeling system
  - Prediction in this system comes from the ocean state on July 1 (initialization) & dynamic coupled evolution of weather / climate (prediction from the global coupled model simulating the ocean, atmosphere, and land as it evolves in time)
- **The new frontier:** At the GFDL we are developing a next-generation prediction system (SPEAR) to tackle S2D prediction challenges. We are also trying to better engage with stakeholders and regional experts on prediction problems

EXTRA SLIDES

With a study showing the present feasibility of snowpack prediction, how do we advance prediction further? How do we deliver operational products?

Public Law 115–25
115th Congress

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.

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

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

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

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:

Note: These questions directly relate to the *Weather Research and Forecast Innovation Act of 2017*

What might a coordinated NOAA effort look like?

1. Produce a new prediction system based on research advancements from the last 5-10 years on seasonal prediction
2. Create snow and mountain hydrometeorological data sets to improve regional water resource prediction (to validate the prediction system and train operational product development methods)
3. Develop post-processing methods to blend ensembles, reduce bias and deliver operational product(s)
4. Careful communication with designated stakeholders to develop targeted products

Major risk factors

- **HPC:** Availability of high performance computing for prediction system development
- **Communication & Engagement:** Need for sustained and careful management of communication between NOAA and WSWC to deliver products for stakeholder needs
- **Physics:** Physical constraints of the Earth System may limit our ability to improve prediction everywhere at every timescale (days to weeks to months to seasons to decades), but we can redefine the problem to deliver products that are useful
- **Synthesis:** Synthesizing improvements developed under this project with those from other projects

CM2.1: 200 km AM2 atmosphere, 1° MOM4 ocean, LM2 land
(IPCC AR4, AR5 model, and seasonal prediction model)

Circa 2004

Higher resolution

CM3/CM4

(CM2.2, CM2.3, CM2.4)

CM2.4: Farneti and Delworth, 2010; Farneti et al, 2010

Circa 2010

CM2.5: 50 km AM2 atmosphere, 0.25° MOM4/5 ocean, LM3 land
CM2.6: 50 km AM2 atmosphere, 0.1° MOM4/5 ocean, LM3 land

Delworth et al., 2012

(CM2.7, CM2.8)
But … these were too computationally expensive to use as seasonal to decadal prediction models

Circa 2013

CM2.5_FLOR: 50 km AM2 atmosphere, 1° MOM5 ocean, LM3 land

FLOR = Forecast Oriented Low Ocean Resolution

Also,
"**HIFLOR**": 25 km AM2 atmosphere, 1° MOM5 ocean, LM3 land

FLOR and HIFLOR are excellent seasonal prediction tools … FLOR is used in NMME.

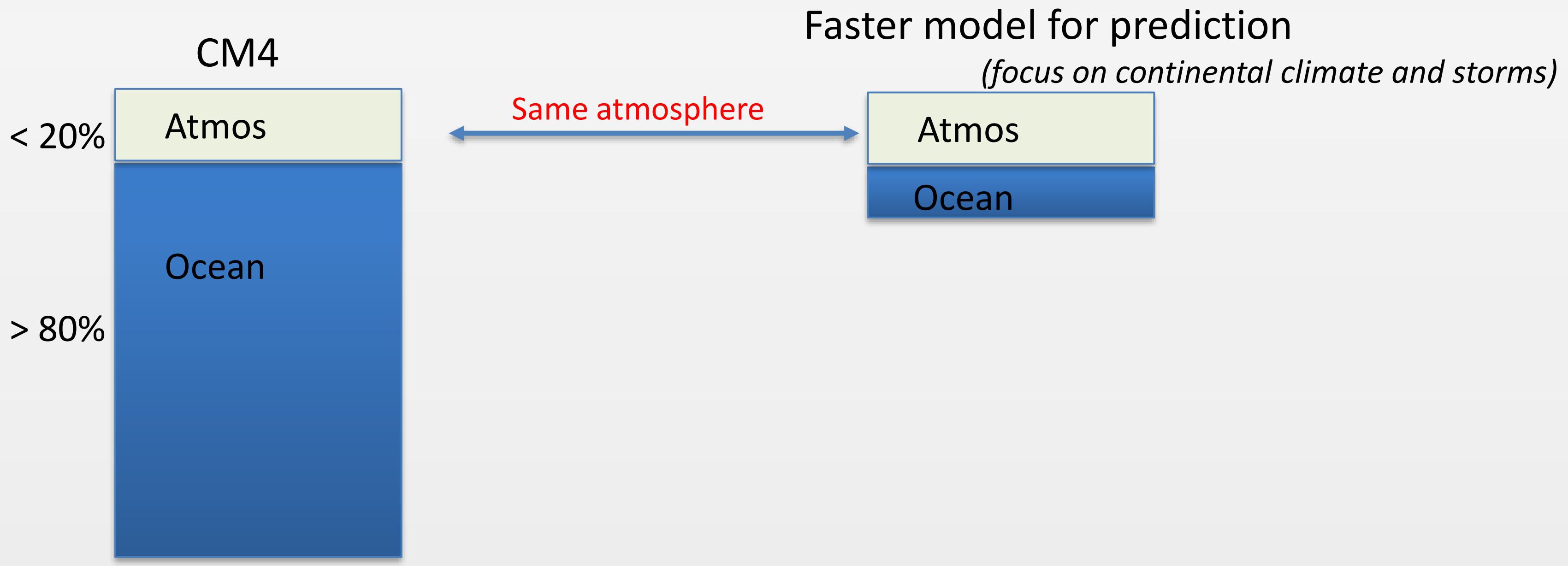
➔ To assess prediction models, need to run large number of reforecasts (also called hindcasts or retrospective forecasts) to assess skill of model.

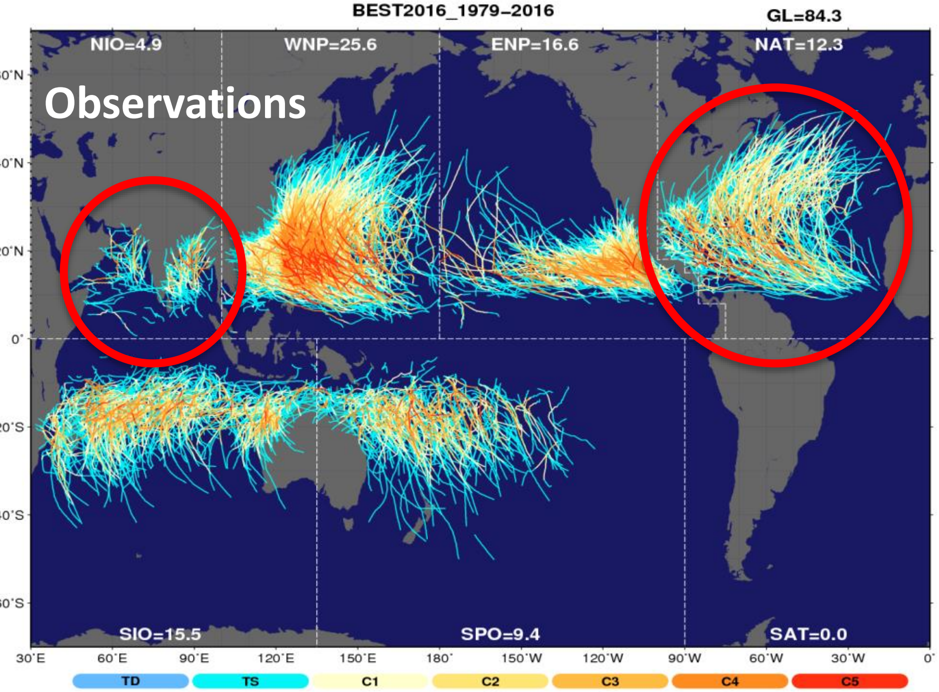
SEASONAL PREDICTION:
Seasonal retrospective forecasts for 1981 to 2017
37 years * 12 months per year * 30 ensemble members ➔ 37*12*30 = **13,320 model years**!

DECADAL PREDICTION:
Similar calculations show we need more than **5000 model years**!

CM4 takes around 10,600 cpu hours per model year.
➔ *using 10% of GAEA would only allow ~700 simulated years in a month*

If we want to use same atmosphere as CM4, only choice is to use lower ocean resolution.





Tropical cyclone statistics

RMSE

FLOR: 0.58

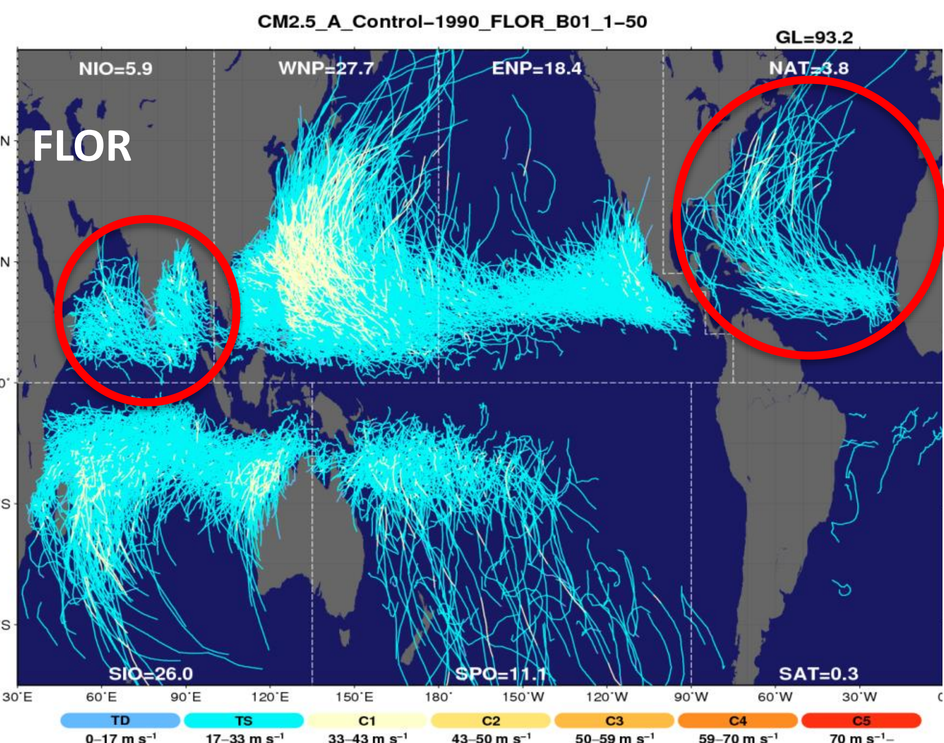
SPEAR_MED: 0.41

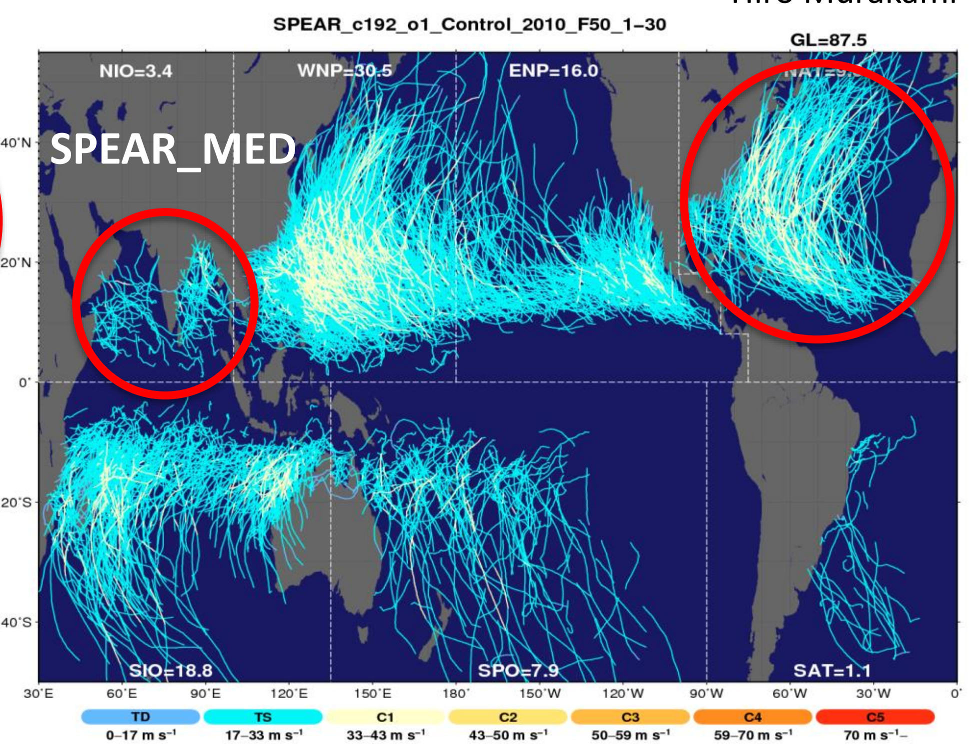
Correlations

FLOR: 0.80

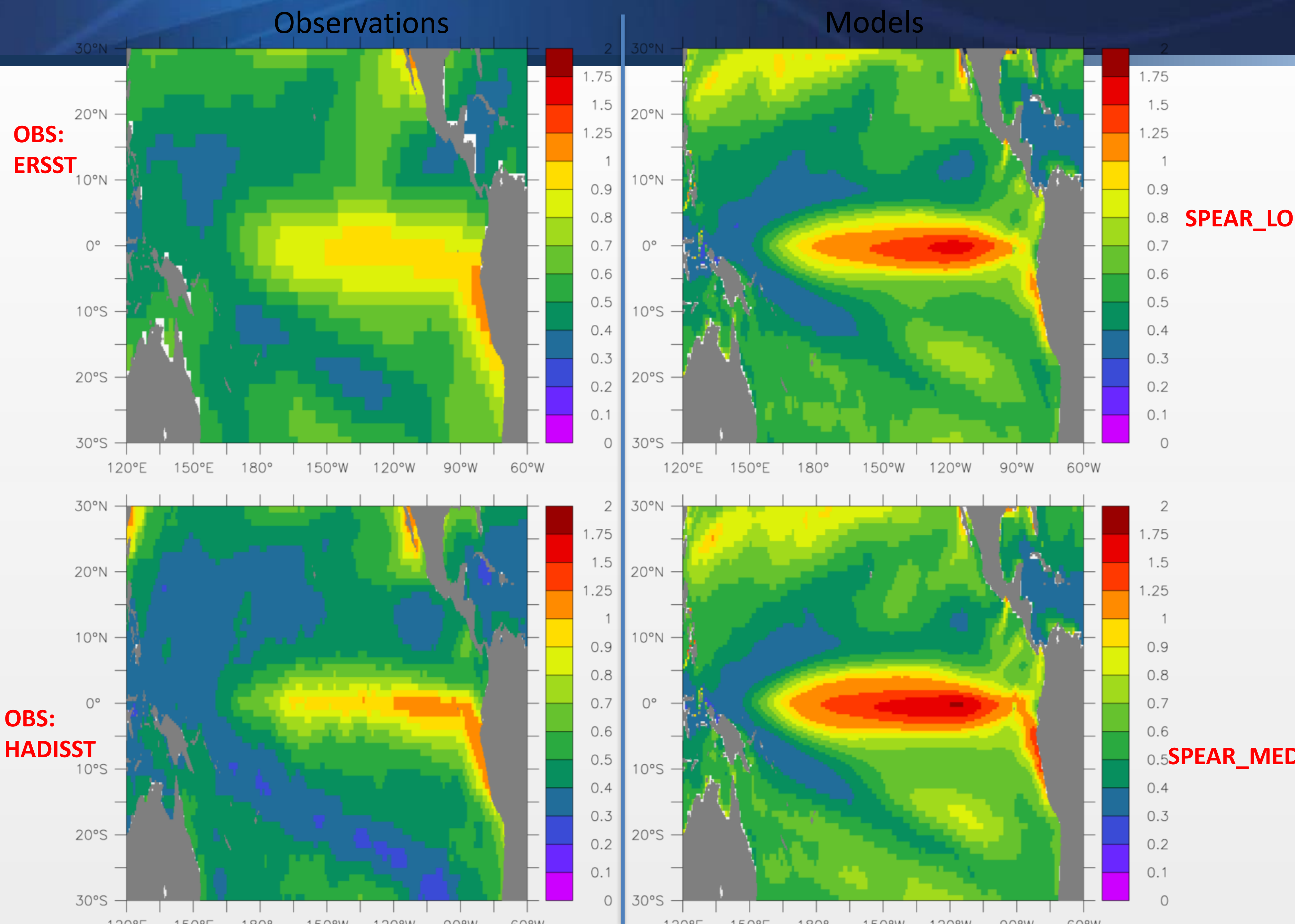
SPEAR_MED: 0.86

Courtesy
Hiro Murakami





Variability (as shown by standard deviation of monthly SST anomalies)



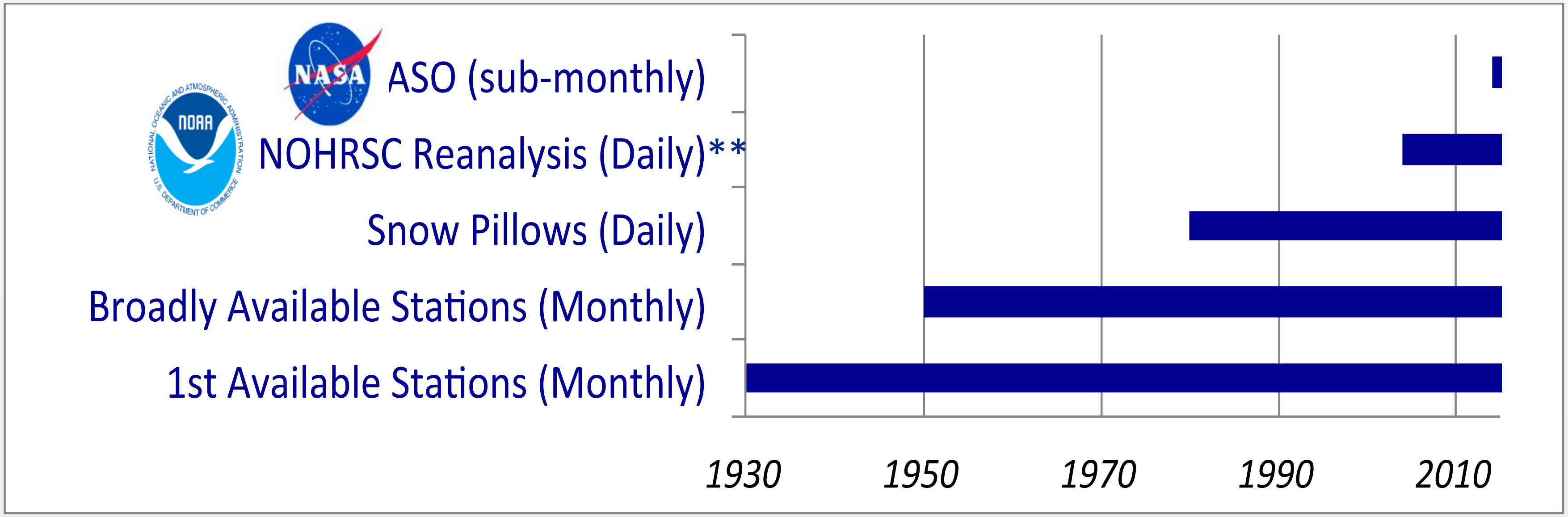
Selected accomplishments with CM2.1, FLOR, and HIFLOR

- **Simulation, prediction, attribution of hurricanes, including Cat 4/5** *(Murakami et al, 2015, J. Climate; 2016, J. Climate; , 2017, J. Climate)*
- **Seasonal sea ice prediction** *(Bushuk et al, 2017, Geophys. Res. Letters; 2017, J Climate)*
- **Seasonal prediction of winter storminess** *(Yang et al, 2015, J. Climate)*
- **Multi-annual to decadal prediction of Atlantic ocean temperature** (Yang et al., 2013, J. Climate)
- **Improved seasonal prediction of temperature and precipitation with improved initialization** (Jia et al, 2016, J Climate; 2017, J. Climate)
- **Decadal predictability of Southern Ocean** (Zhang et al, 2017a, J. Climate; 2017b, J. Climate)
- **Western US snow pack** (Kapnick et al, 2018, PNAS)
  - Skill in predicting western US snowpack 8 months in advance
- **Western US precip, 2015/2016 ENSO** (Yang et al, 2018, Climate Dynamics)
  - Impact of initialization system on seasonal prediction of precipitation
- **Attribution of causes of 2017 Major Hurricanes in Atlantic** (Murakami et al, in revision)
- **Causes of Southern Ocean trends in sea ice** (Zhang et al, in revision)

See https://www.gfdl.noaa.gov/bibliography/ for searchable database of GFDL papers

Case study: Observations critical for verification

- Longest records for precipitation, temperature & streamflow
  - Snow courses provide the longest record for snowpack verification
- Reanalysis products severely underrepresent snowpack (Kapnick & Delworth 2013, Wrzesien et al. 2017)
- Newly-developed gridded products (Margulis et al. 2016) confined to California or short records (NOHRSC); but could be expanded



***Note: NOHRSC does not perform well over all complex terrain and has an acceptance issue in the mountain cryosphere research community*