Predicting Extremes

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Subject Matter Experts: Tom Hamill, Marty Hoerling, Matt Newman, Judith Perlwitz

NOAA Physical Sciences Laboratory Review
November 16-20, 2020

Physical Science for Predicting Extremes

Physical Sciences Laboratory

Users & Stakeholders

Observe

What extreme events have happened?
How can we measure the important processes?

Understand

How predictable is an extreme event?
What are the physical laws governing the processes?

Predict

Generate improved predictions, consistent with our understanding of the physical laws.
Predict the expected forecast skill in advance

Communicate

Convey what is known and not known about extremes in ways that facilitate effective decision making.

Initial focus in **Predicting Extremes** is on Subseasonal to Seasonal (S2S)

By design, PSL's activities are "**predicting** the nation's path through a varying and changing climate" consistent with NOAA's encompassing mission to "**understand and predict** changes in climate, weather, oceans, and coasts, and **to share** that knowledge and information with others."

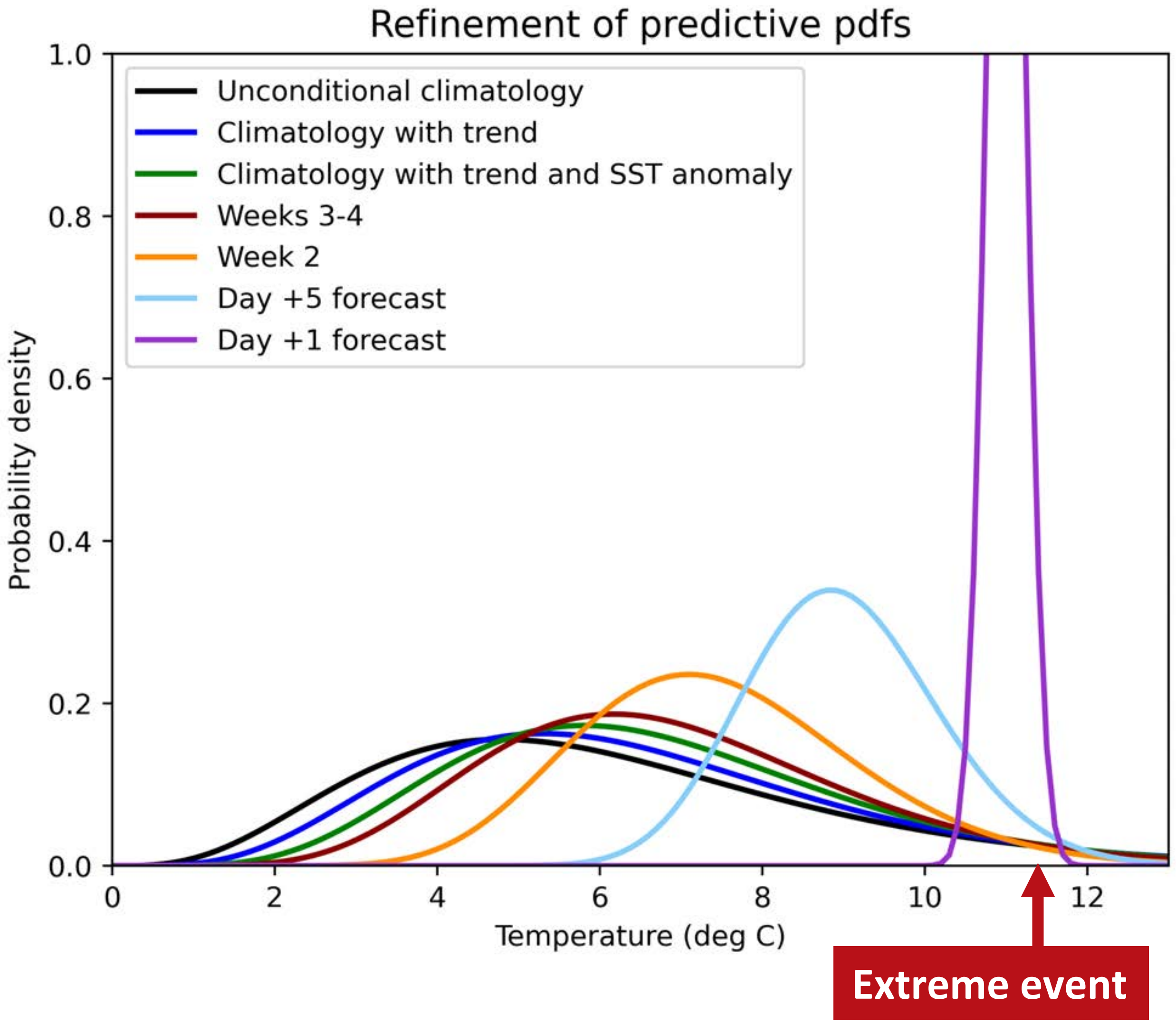
Goals for Predicting Extremes

- **Observe Extreme Events**
  - Advanced observations
  - Data assimilation
  - Reanalysis

- **Understand conditional and unconditional (climatological) distributions and their tails**
  - What is predictable at what leads?

- **Improve predictions of these distributions at all leads**
  - Even the mean is hard!
  - Only some forecasts may have useful skill – Need to identify "Forecasts of Opportunity"

- **Communicate new understanding and improved predictions to stakeholders and decision makers**



Highlights of PSL's Advances in the Prediction of Extremes

"Observe"

- **Unique 200-year atmospheric reanalysis** dataset for extremes
- **Reanalysis datasets** that initialize improved probabilistic predictions of extremes

Understand

- **Foundational contributions** to theory of extreme value distributions
- **Understanding extreme events**, their predictability and attribution
- **Innovative diagnostics** of climate variability and numerical weather and climate model errors

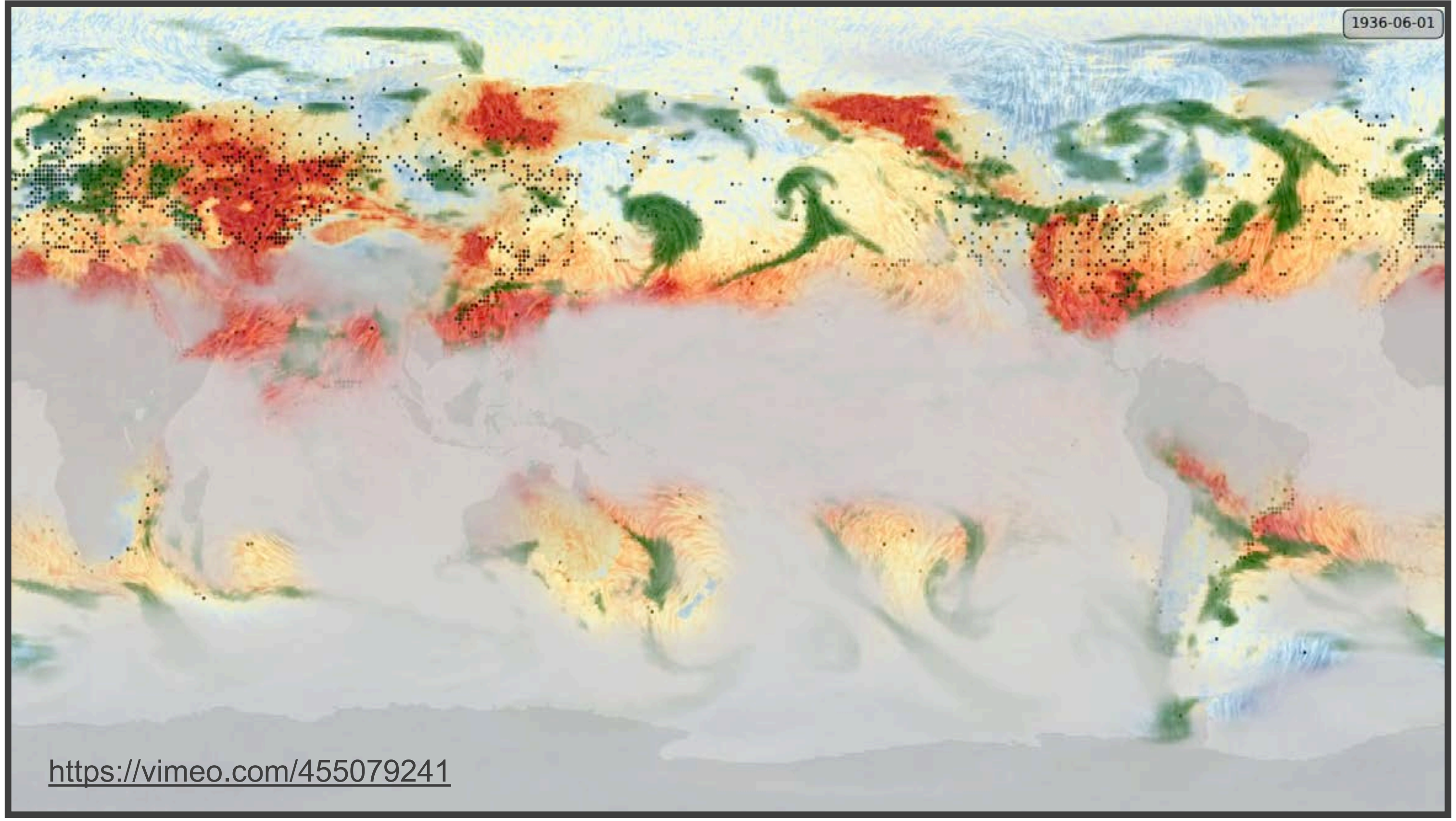
Predict

- **Identifying "forecasts of opportunity"**
- **New statistical forecast models**, e.g. LIM, for diagnosis and forecast benchmarks
- **Stochastic parameterizations** in NOAA global models improve simulation and forecasts of extremes
- **Reforecast datasets** that allow improved probabilistic predictions of extremes
- **Develop new forecast systems** to advance the prediction of extremes

The 20th Century Reanalysis (20CR) provides a global, 200-year history of sub-daily weather

by assimilating surface pressure observations into a modern NOAA weather model

Deadliest North American Heatwave June-August 1936
(20CRv3 weather, observations, and "fog of ignorance")



NOAA-CIRES-DOE
20th Century Reanalysis Version 3

- Global: 75km horizontal, 64 level grid
- 3-hourly resolution
- Spans 1836-2015 [1806-1835 experimental]
- Provides 80 estimates of temperature, wind, precipitation, pressure, humidity, & other variables, from the ground to the top of the atmosphere
- Used to, e.g., understand extreme weather and climate over the last 200 years, validate climate models.

Slivinski et al. 2019

Unique 200-year atmospheric reanalysis dataset

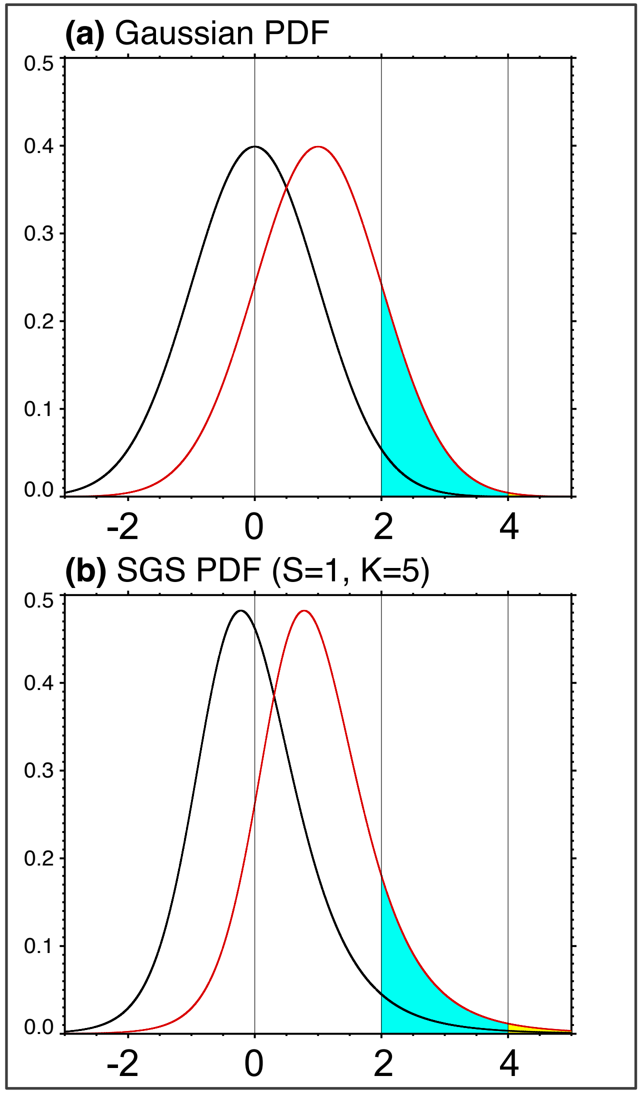
Stochastically-Generated Skewed (SGS) distribution compared to a Gaussian

Both P(0,1)
and shifted by
1 standard
deviation

Gaussian PDF

non-Gaussian SGS PDF

skewed and heavy-tailed with
Skewness S=1
Excess Kurtosis K=5



P(x ≥ 2) = 2.3%
and increases by
a factor of 7

P(x ≥ 4) = 0.003%
and increases by
a factor of 43

P(x ≥ 2) = 3.4%
and increases by
only a factor of 4

P(x ≥ 4) = 0.34%
and increases by
only a factor of 3

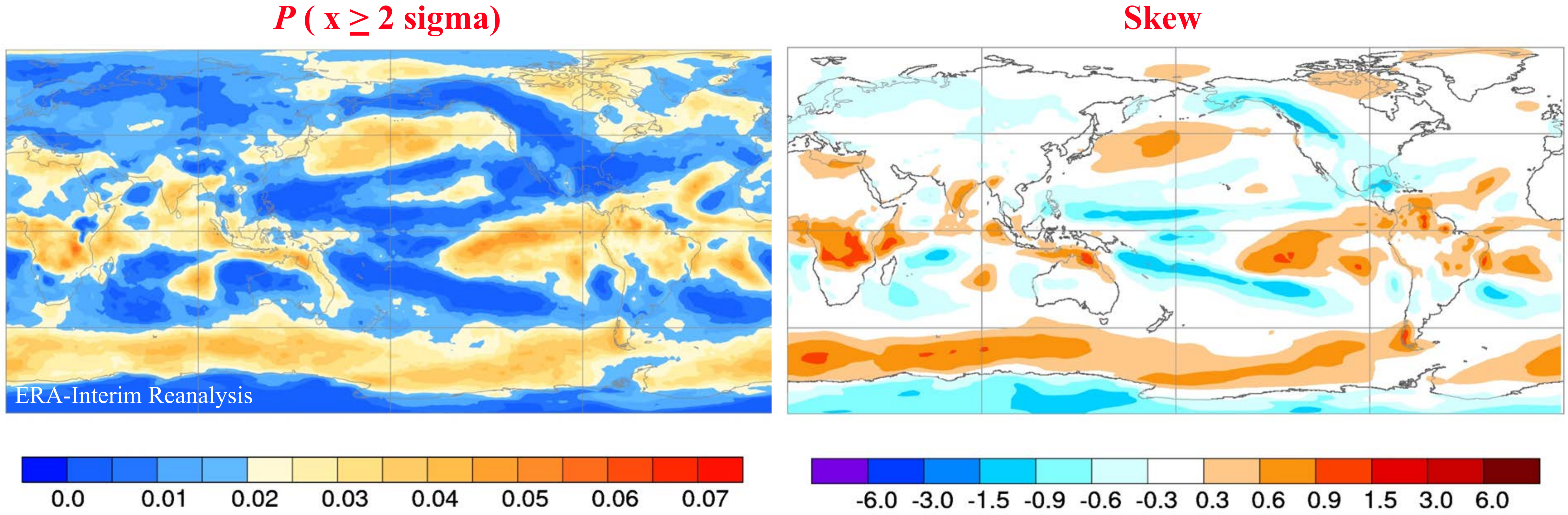
Risk Ratio for extremes is dramatically different in Gaussian and SGS

Using the wrong distribution can lead to gross misrepresentations of tail probabilities and their changes.
Note that observed distributions are much more like SGS distributions than Gaussian distributions.

Foundational contributions to theory of extreme value distributions

Sardeshmukh, Compo, Penland (2015)

Probability of 5-day mean 850 mb temperature anomaly exceeding +2 sigma compared to Skew (DJF 1980-2009)



This probability would be *0.022* if the distributions were Gaussian

The similarity of the exceedance probability P and skewness patterns is consistent with SGS theory

Useful forecasts of S2S Extremes need useful forecasts of mean and higher moments

Predict

- **What are predictability limits to S2S predictive skill?**
  - On average, S2S forecasts have low skill
  - We seek to identify “Forecasts of opportunity” *a priori*

- **What skill can (and should) we expect, and why?**
  - Is skill naturally higher for some places, variables, and times, either in the mean or in the distribution?
  - How might skill change with base state changes?
  - PSL tools such as Linear-Inverse Models provide a complement to the development of coupled ensemble prediction systems.

- **How to improve S2S forecast systems?**
  - statistical model development
  - model error simulation
  - statistical postprocessing
  - coupled data assimilation

Leading the development and application of a hierarchy of simplified models from Stochastic Parameterizations for nonlinear GCMs to Linear Inverse Models

GCM

$$\boxed{\frac{dx}{dt} = \underset{resolved}{A(x)} + \underset{parameterized}{P(x)}} + \underset{unparameterized}{R}$$

new GCM

$$\boxed{\approx A(x) + (1+r)P(x)}$$

Stochastic Parameterization specifying $R \sim r\,P(x)$, with r spatially correlated over $\sim$500 km, is an effective way to account for chaotic physics in GCMs

$x =$ state vector of interest, e.g., winds, temperature, humidity

$$\approx \{A_0 x + (S_{0A} + S_{1A}x)\xi_A\} + (1+r)\{P_0 x + (S_{0P} + S_{1P}x)\xi_P\}$$

$$\approx Lx + b\eta_1 + (Ex + g)\eta_2$$

This approximation adequately captures subseasonal anomaly dynamics, including the SGS non-Gaussianity of subseasonal anomalies

$$\approx Lx + S\eta$$

This approximation adequately captures S2S Gaussian anomaly dynamics and becomes a LIM

L and **S** are matrices determined from the τ-lagged and simultaneous covariance matrices of **observational fields** x to make the Linear Inverse Model (**LIM**), e.g., $e^{L\tau} = \langle x(\tau)x^T\rangle\langle xx^T\rangle^{-1}$.

Sardeshmukh, Penland, Newman, Compo, Whitaker, Bengtsson, Wang

Understand variations and deficiencies in seasonal SST skill:

We can determine which regions and years are more predictable than others, and why

Month 6 skill

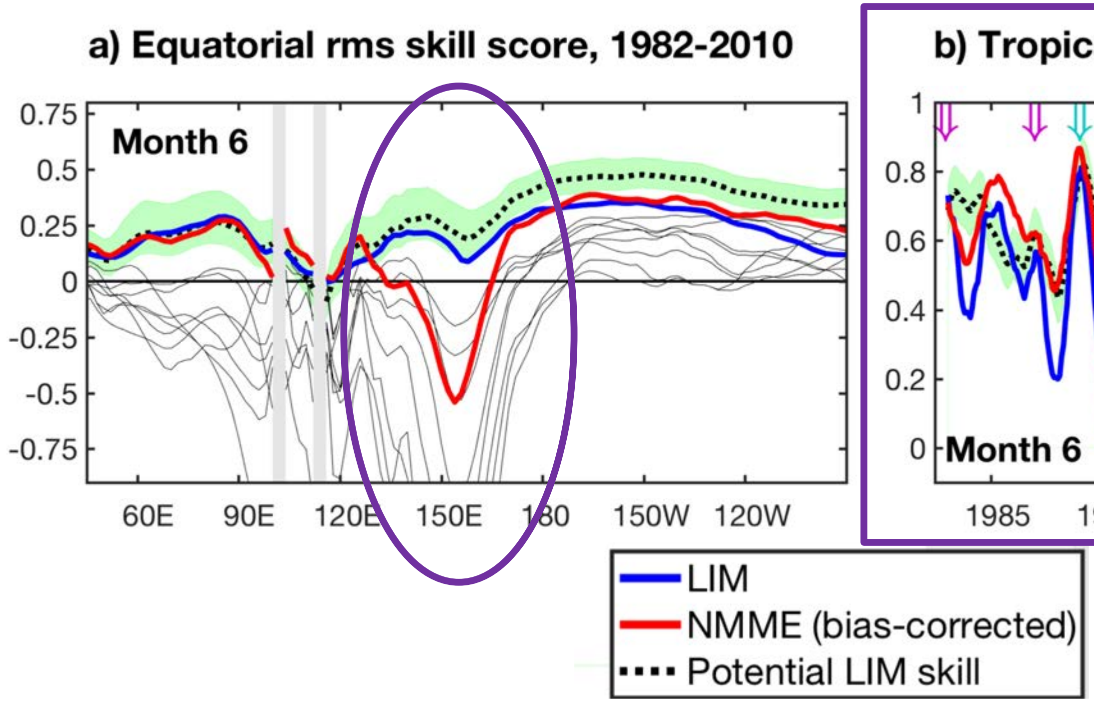
MONTHLY LIM:
***x* consists of SST, SSH, 200/850 hPa winds (1958-2010)**

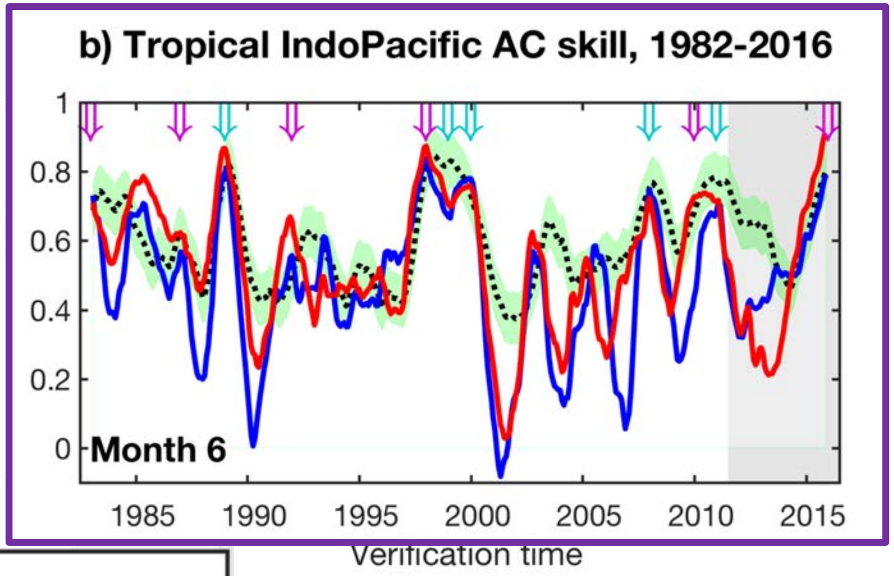
Left: Equatorial rms skill score (1 – standardized error)

Right: Monthly tropical IndoPacific pattern correlation skill, smoothed with 13-month running mean

Potential skill is found *a priori* from LIM forecast signal-to-noise ratio

North American Multi-Model Ensemble (NMME)
8 initialized coupled general circulation models



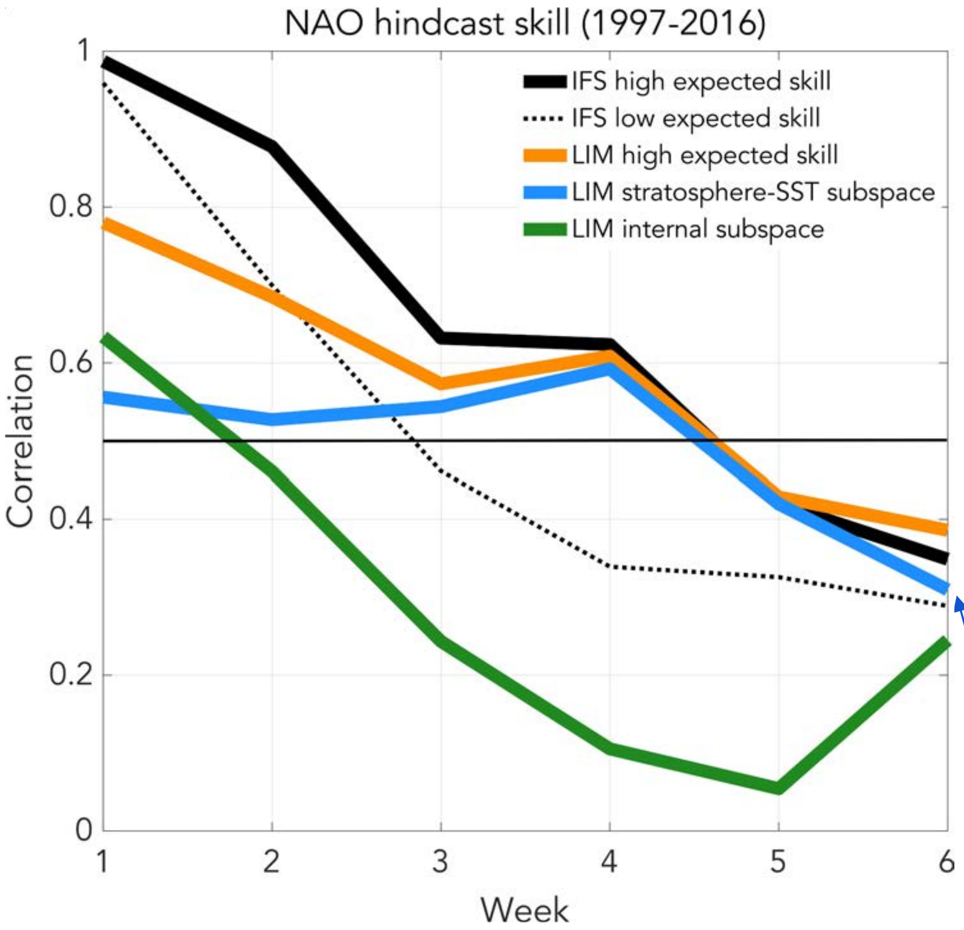


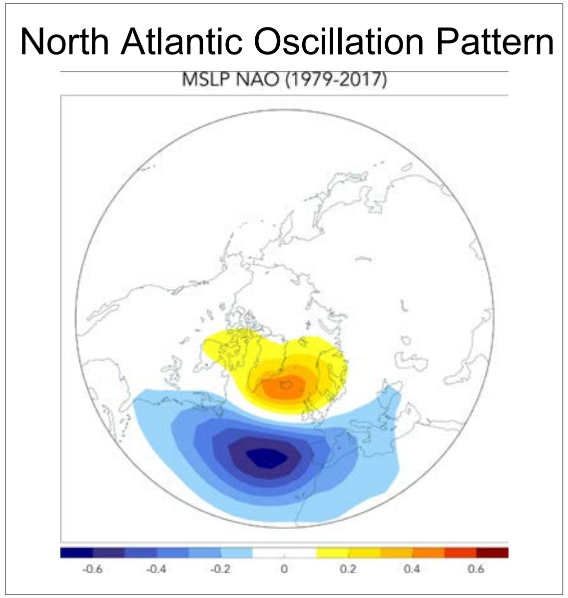
RMSSS=1 perfect skill
RMSSS=0 climo skill
RMSSS<0 worse than climo

r(NMME,LIM)=0.9/0.8
r(LIM potential,LIM)=0.9/0.7

Benchmarking, Diagnosing, and Forecasting S2S Forecast skill

LIM can successfully predict ***a priori*** which **ECMWF IFS forecasts** and which **LIM forecasts** will be more skillful.





Most of the skill predicting the North Atlantic Oscillation (NAO) at Week 3 and beyond from the LIM comes from **tropical SST and stratosphere variations**.

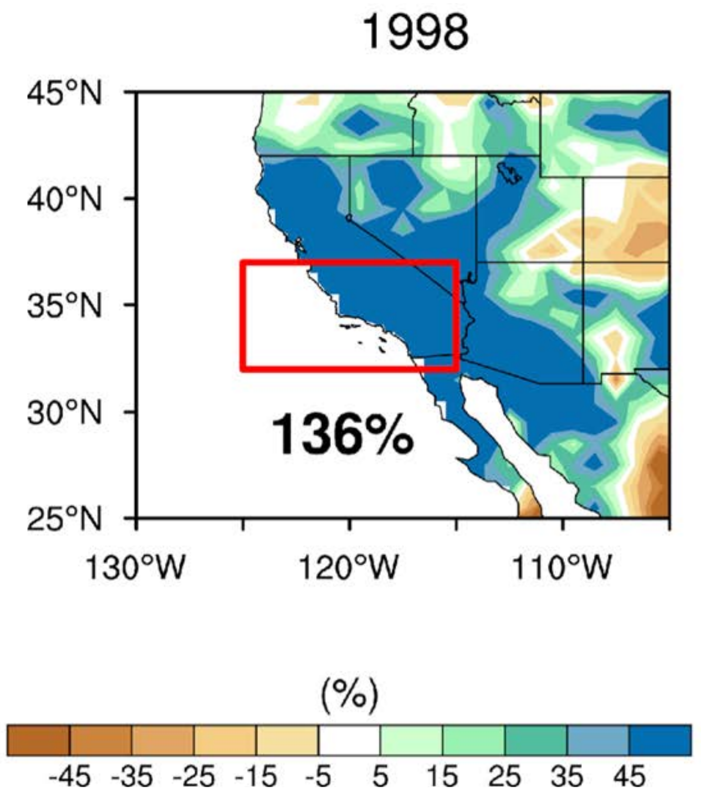
Impact of stratosphere-SST and internal subspaces on NAO predictability.
NAO hindcast skill for the IFS and LIM for the upper 15% of expected skill (by the LIM) hindcasts, skill from hindcasts given initial conditions filtered to only include the **stratosphere-SST (blue)** or **internal (green)** subspace portions of the LIM state vector.

Exploiting a “forecast of opportunity” for California as the 2015/2016 El Niño was developing

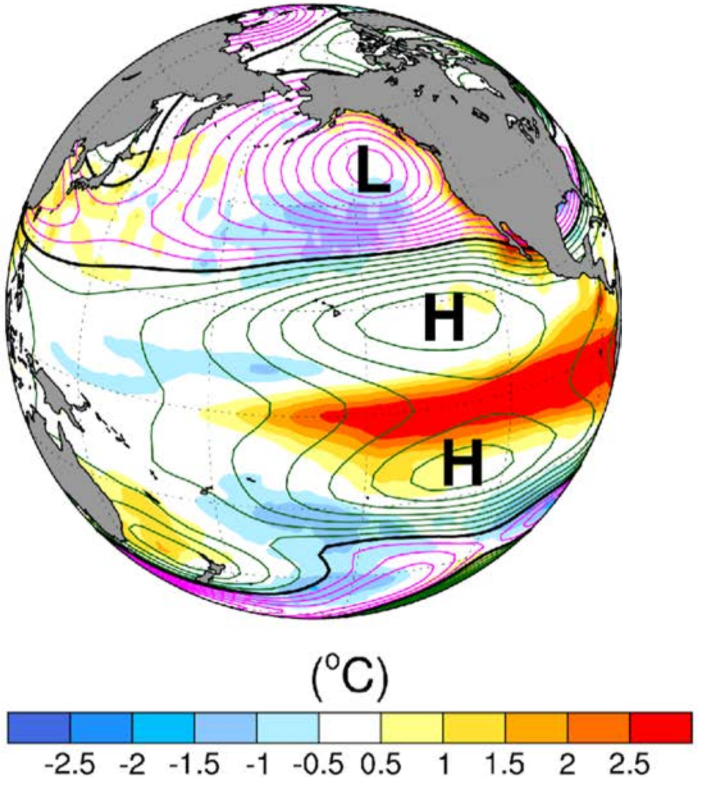
Dec 1997 to
Feb 1998

Observed
Anomaly
Conditions

Precipitation



200 hPa Geopotential Height/SST



Based on 1998 super El Niño, many anticipated extreme Wet conditions for winter 2016 in southern CA in large part because the Oceanic Nino Index in the equatorial Pacific was as extreme as in 1998.

What happened and why?

Zhang, Hoerling,…, Eischeid,…, Hoell, Perlwitz, Quan, Barsugli (2018)

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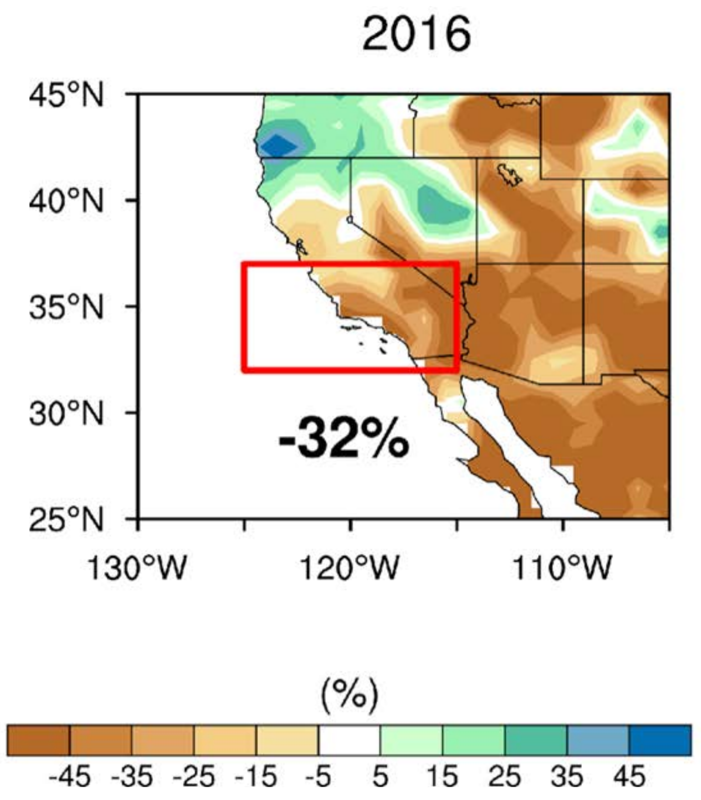

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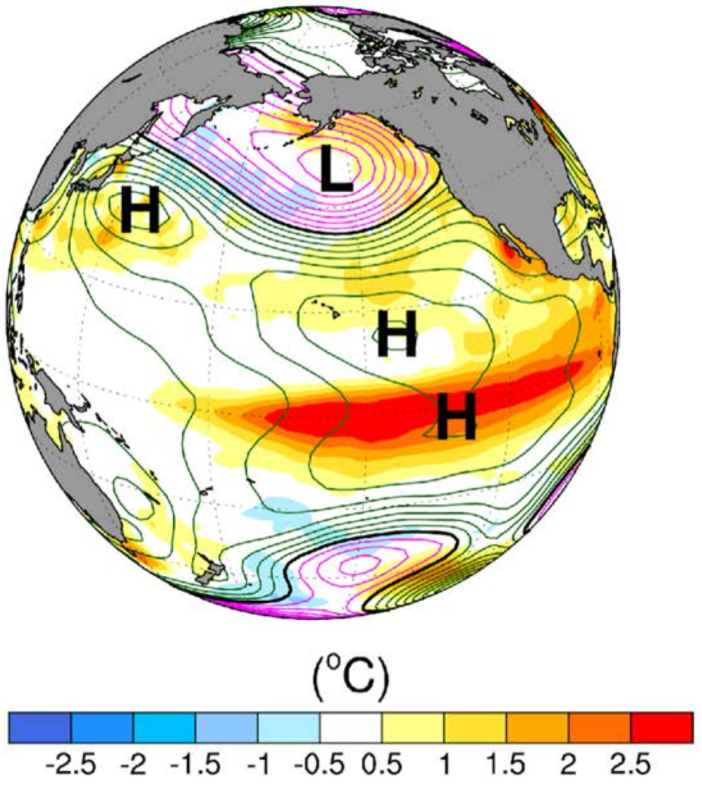
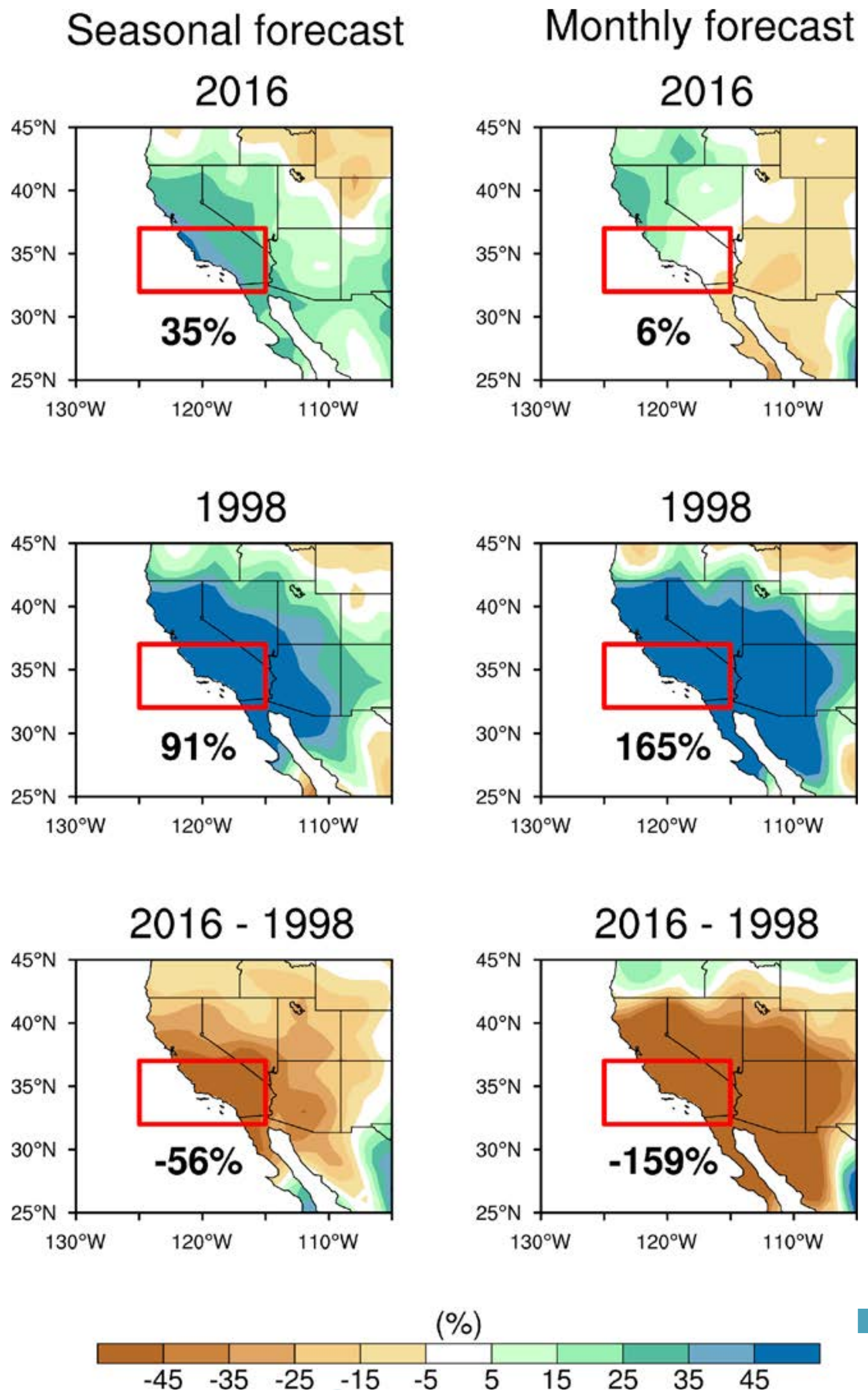


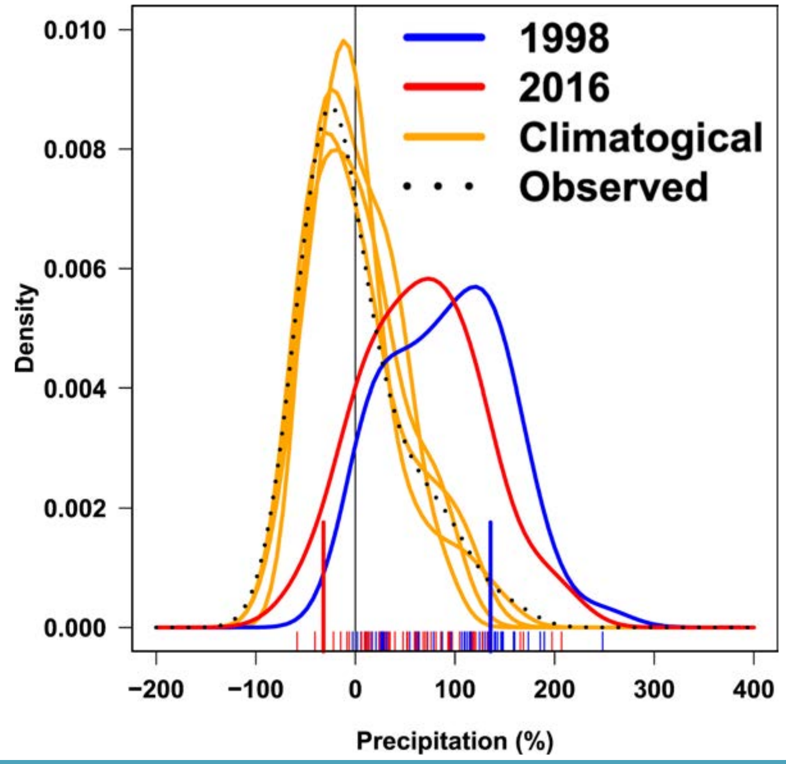
Warm equatorial Pacific SST anomalies were further to the west – into NINO4 region – than in 1998.
Despite the very strong El Niño, southern CA had **Dry conditions** for winter 2015/16.
Did numerical forecasts anticipate this?

Zhang, Hoerling,…, Eischeid,…, Hoell, Perlwitz, Quan, Barsugli (2018)



Different Modulation of winter climate by 1998 (east Pac) vs 2016 (central Pac) ENSO

- Model (CFSv2) predicted **drier [less-wet]** winter in 2016 than 1998 (left).
  -Important sensitivity to El Niño flavor ([Zhang et al. 2020](#))
- Weather driving (right) captured in sub-seasonal forecasts accentuated drying.



Precipitation in Southern California region has a skewed PDF that is well-represented in **simulated climatological PDF**.

Forecast 2016 PDF shows the greater risk of dry conditions (<0 anomaly).

Understanding extreme events

Zhang et al (2018)

Useful forecasts of S2S Extremes need useful forecasts of mean and higher moments

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  - PSL tools such as Linear-Inverse Models provide a complement to the development of coupled ensemble prediction systems.
- **How to improve S2S forecast systems?**
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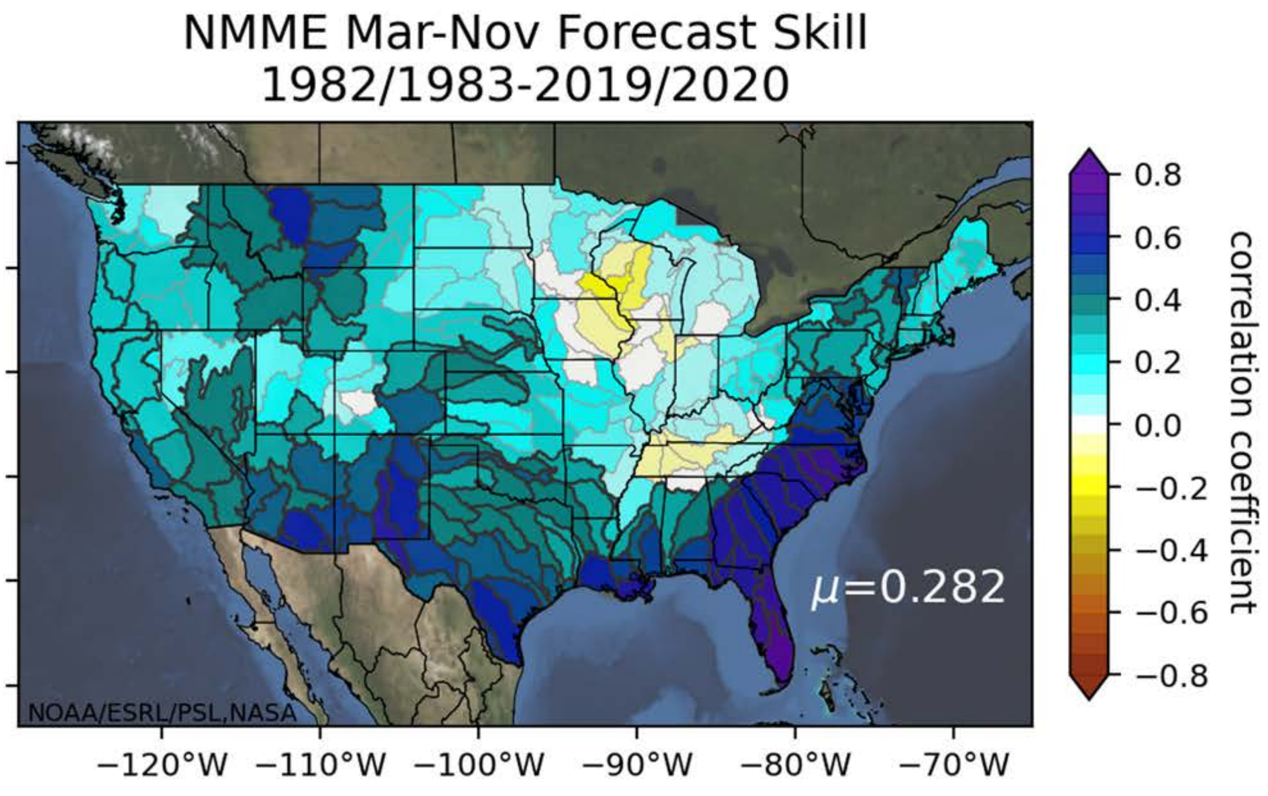
  - statistical postprocessing
  - coupled data assimilation

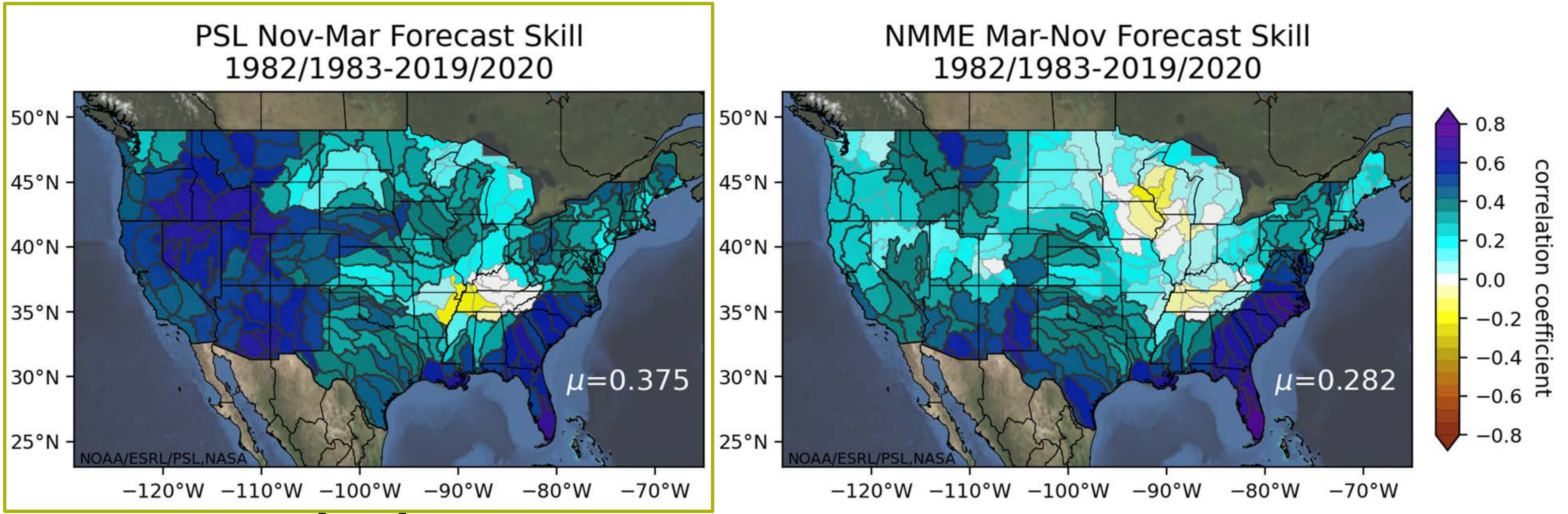
Benchmarking Extended Winter Season (Nov-Mar) Precipitation Forecasts



North American Multi Model Ensemble (NMME)

Switanek, Barsugli, Scheuerer, Hamill (2020)

Benchmarking Extended Winter Season (Nov-Mar) Precipitation Forecasts



SST (preceding 18 months)

SLP (preceding 2 months)

WNDS (preceding 2 months)

Merge various statistical forecast predictors

This PSL forecast is provided to California Department of Water Resources as experimental forecast guidance.

New statistical forecast models as forecast benchmarks

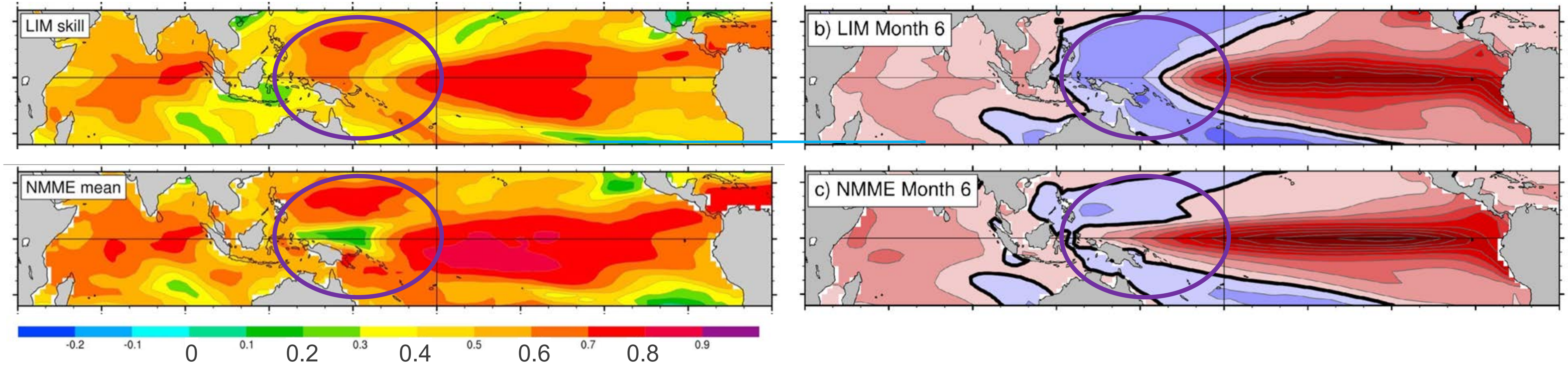
Switanek, Barsugli, Scheuerer, Hamill (2020)

Identifying important errors in the NMME related to global teleconnections:

One problem: ENSO pattern predicted by NMME extends too far west

SST Month 6 anomaly correlation skill

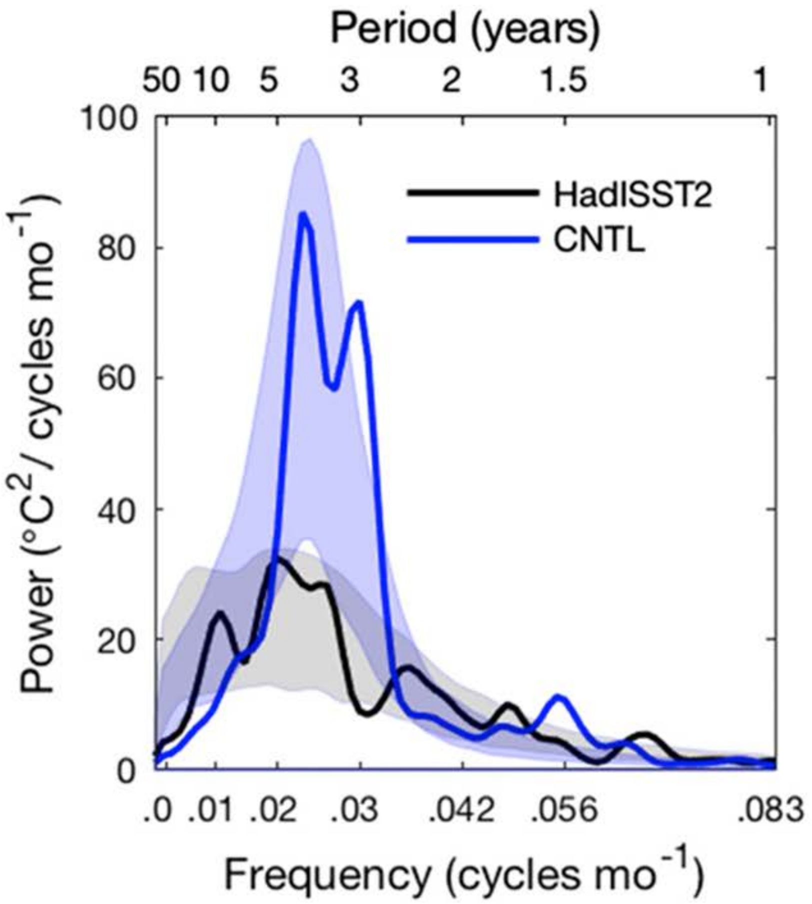
Leading EOF of Month 6 forecasts

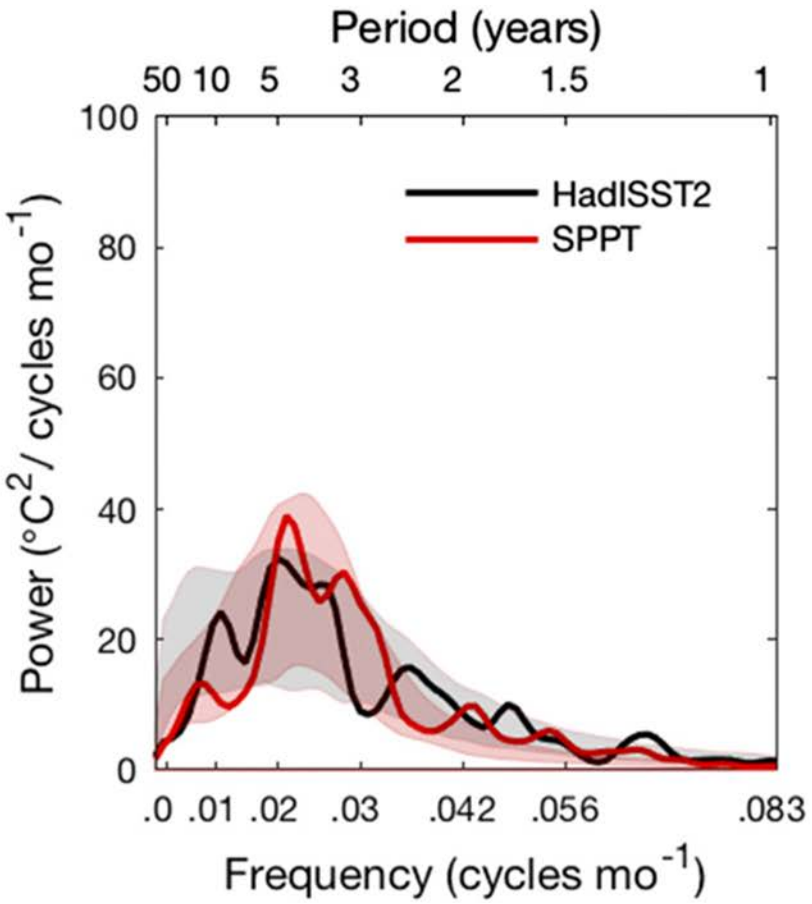


NMME forecast ENSO has a *loss of skill and an associated phase error in the western tropical Pacific, a sensitive region for forcing global and North American teleconnections*

Newman and Sardeshmukh (2017)

Adding Stochastically Perturbed Parameterization Tendency (SPPT) to CCSM4 improves ENSO variability





Curves: Spectra from SSTs in Nino3.4 region spanning 1870-2004

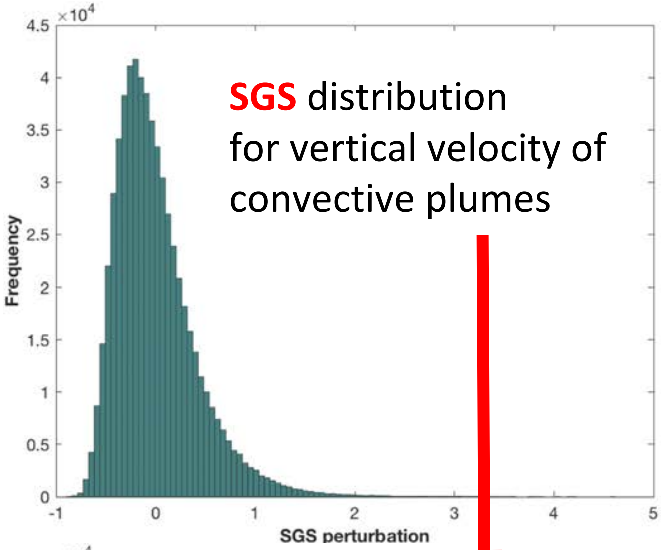
Shading: spectral range by sampling realizations from LIMs fitted to CNTL, SPPT, and HadISST2

Spectra of El Nino index from observed HadISST2 and CCSM4 coupled general circulation model (one of the NNME models) without (CNTL) and with (SPPT) stochastic parameterization

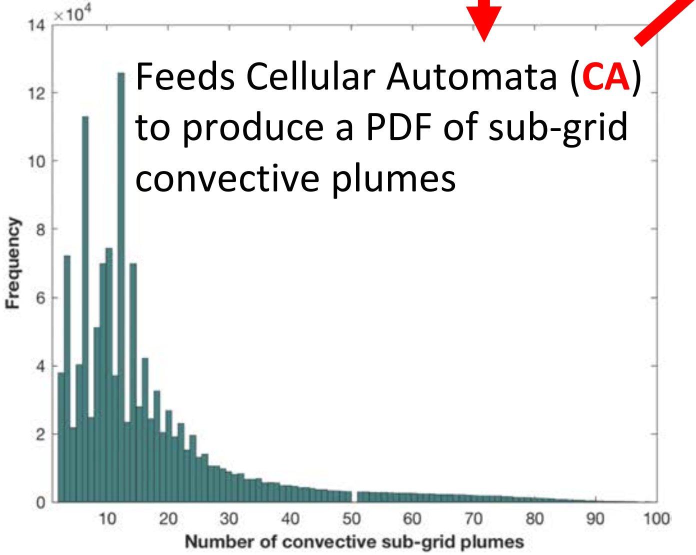
Berner, Sardeshmukh,… (2018)

Adding stochastic physics to improve NOAA numerical models

Example for convection

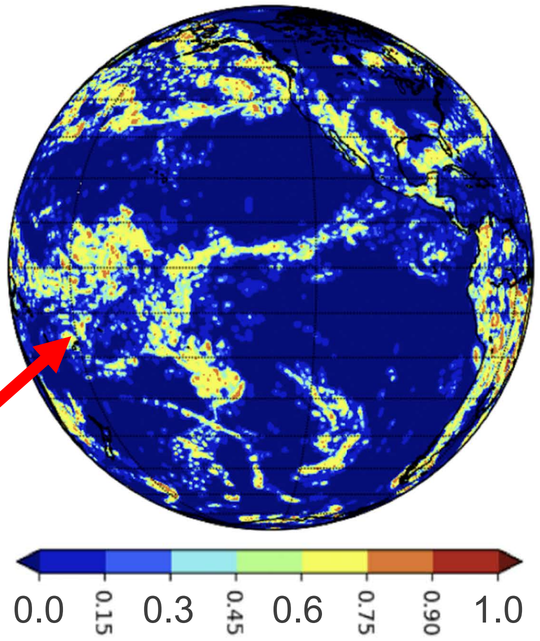


SGS distribution for vertical velocity of convective plumes



Feeds Cellular Automata (**CA**) to produce a PDF of sub-grid convective plumes

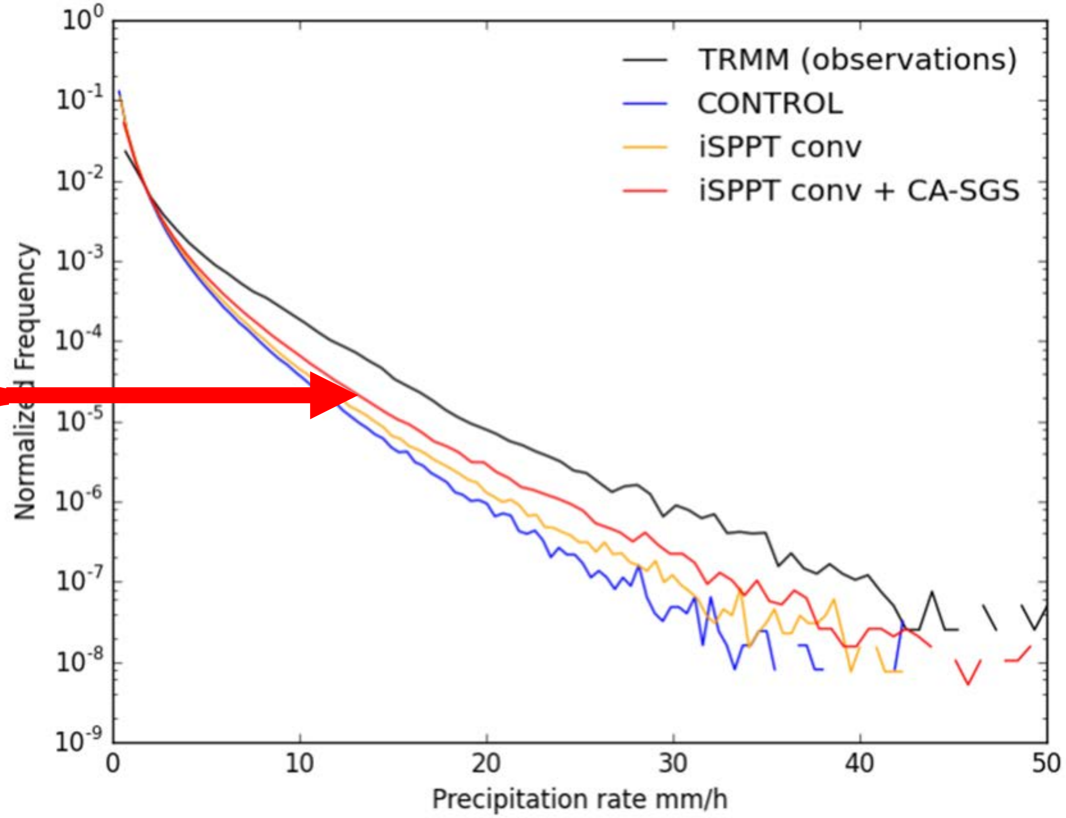
CA-SGS organizes fraction of convective cells



+

independent Stochastically Perturbed Parameterization Tendencies on convection only (iSPPT conv)

Frequency distribution of tropical precipitation. 3 months, January-March, 2016. GFS with C384.

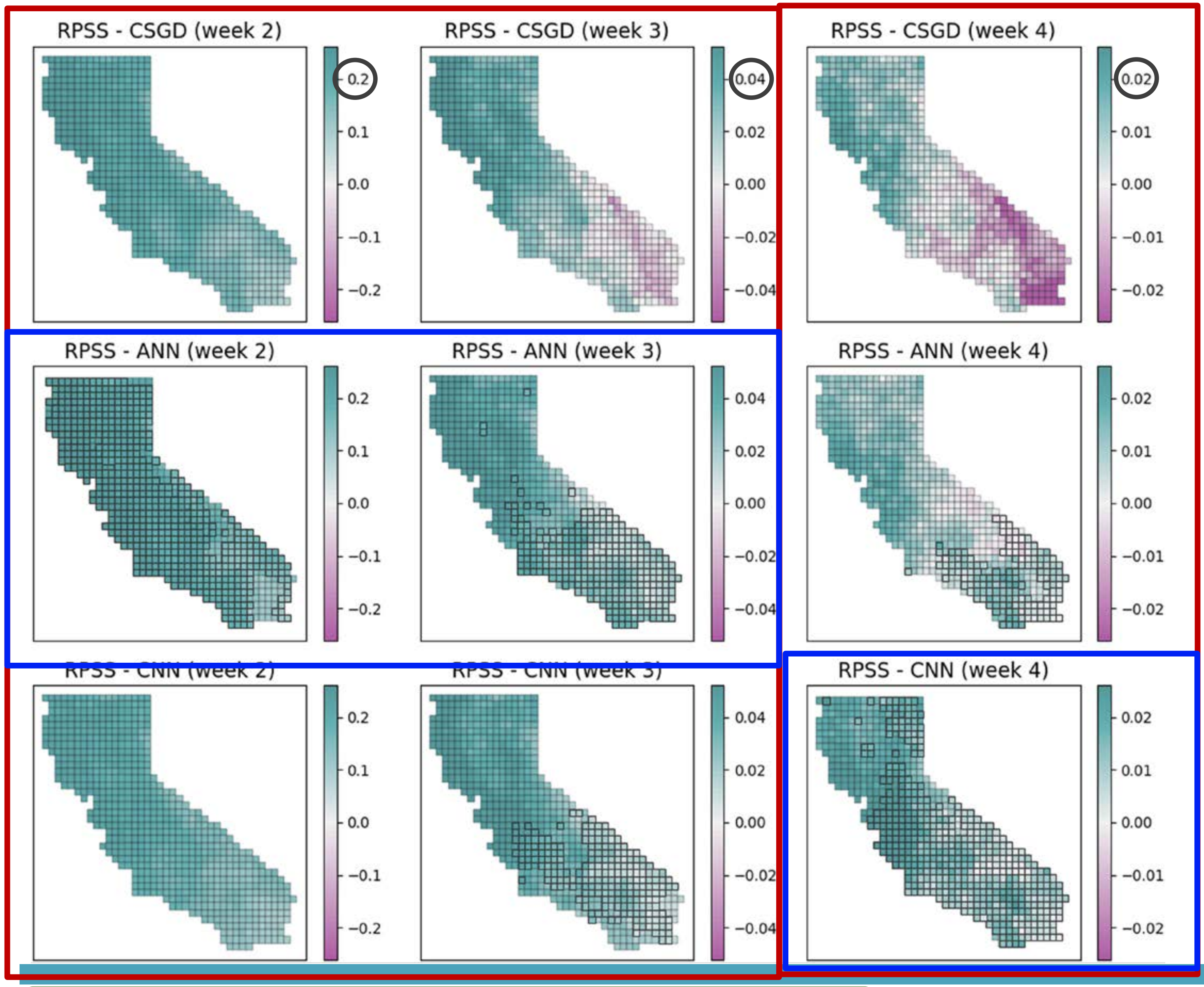


Stochastic physics can improve model variability and PDF tails.

Bengtsson, Bao, Pegion, Penland, Michelson, Whitaker (2019)

Improving NOAA numerical model output

Comparing statistical postprocessing approaches for weeks 2-4 tercile precipitation forecasts



top row: Ranked Probability Skill Score (RPSS) using a statistical postprocessing approach (Censored, shifted Gamma distribution; CSGD) (Scheuerer and Hamill 2015)

middle row: skills with Artificial Neural Network (ANN)

bottom row: skills with Convolutional Neural Network (CNN)

ANN has highest skill at week 2 and week 3.

CNN provides an advantage at week 4.

PSL scientists intend to adapt this method to CONUS-wide precipitation and transfer algorithm for operational use at the Climate Prediction Center.

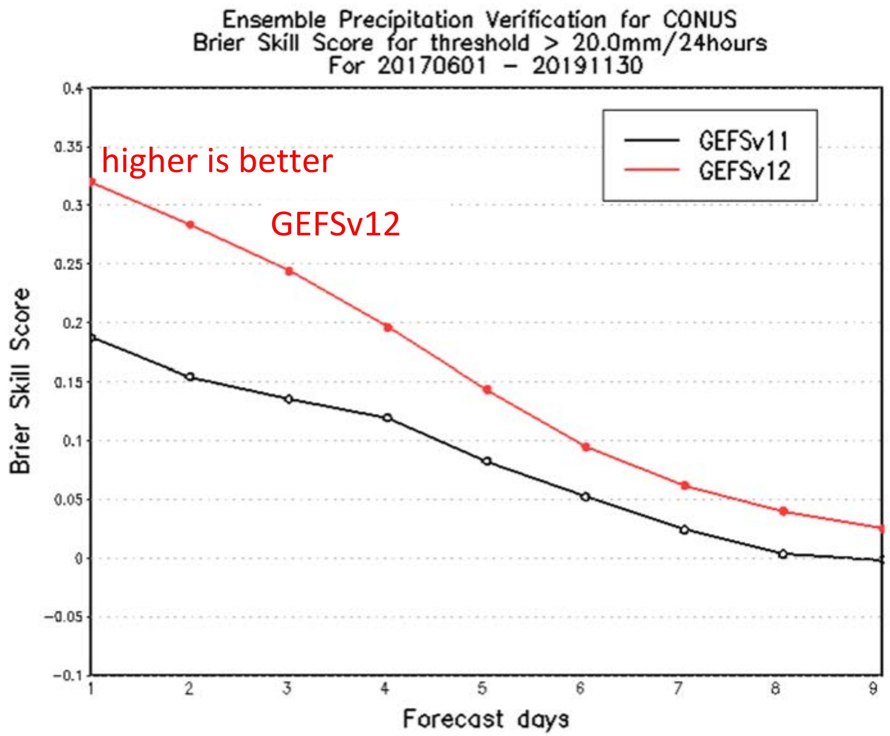
Improved probabilistic prediction of extremes

Scheuerer et al. (2020)

Improved Global Ensemble Forecast System (GEFS) v12 vs. v11

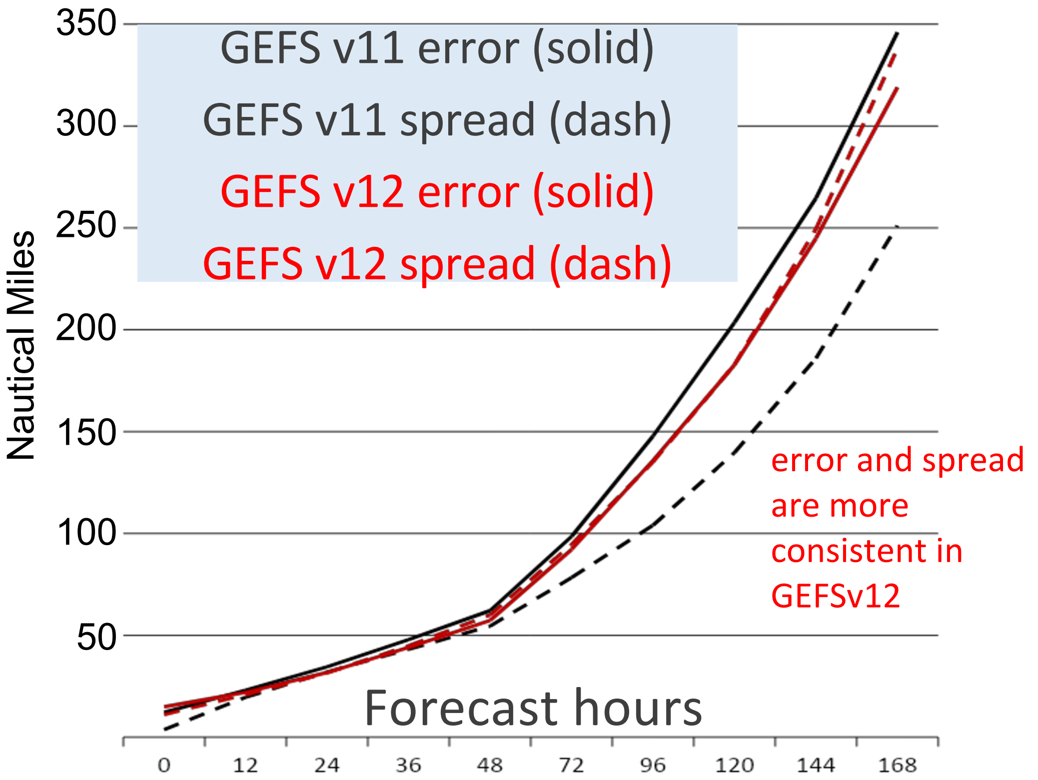
Years of PSL and collaborative research became operational product improvement

Probabilistic Precipitation forecasts



Stochastic physics in GEFSv12 improves forecasts of extremes

TC Tracks and Spread (2018)



GEFSv12 mean tropical cyclone track error reduced, ensemble standard deviation (spread) better represents error

Develop new forecast systems

Whitaker, Hamill, Pegion, Bengtsson

Example highlights for the next five years

"Observe"

- **Advance coupled data assimilation** for operational initialization and historical reanalyses

Understand

- **Improve attribution modeling methods** for understanding extremes
- **Improve understanding** of physical mechanisms underlying observed non-Gaussian distributions
- **Innovative diagnostics** of climate variability and weather and climate model errors

Predict

- **Develop coupled next-generation NOAA reforecasts**
- **Expand non-Gaussian approaches,** including additional sources of potential predictability
- **Further identify "forecasts of opportunity"**
- **Develop new physically-based stochastic parameterization** for improved uncertainty in UFS
- **Implement new Artificial Intelligence** algorithms to improve post-processing

Communicate

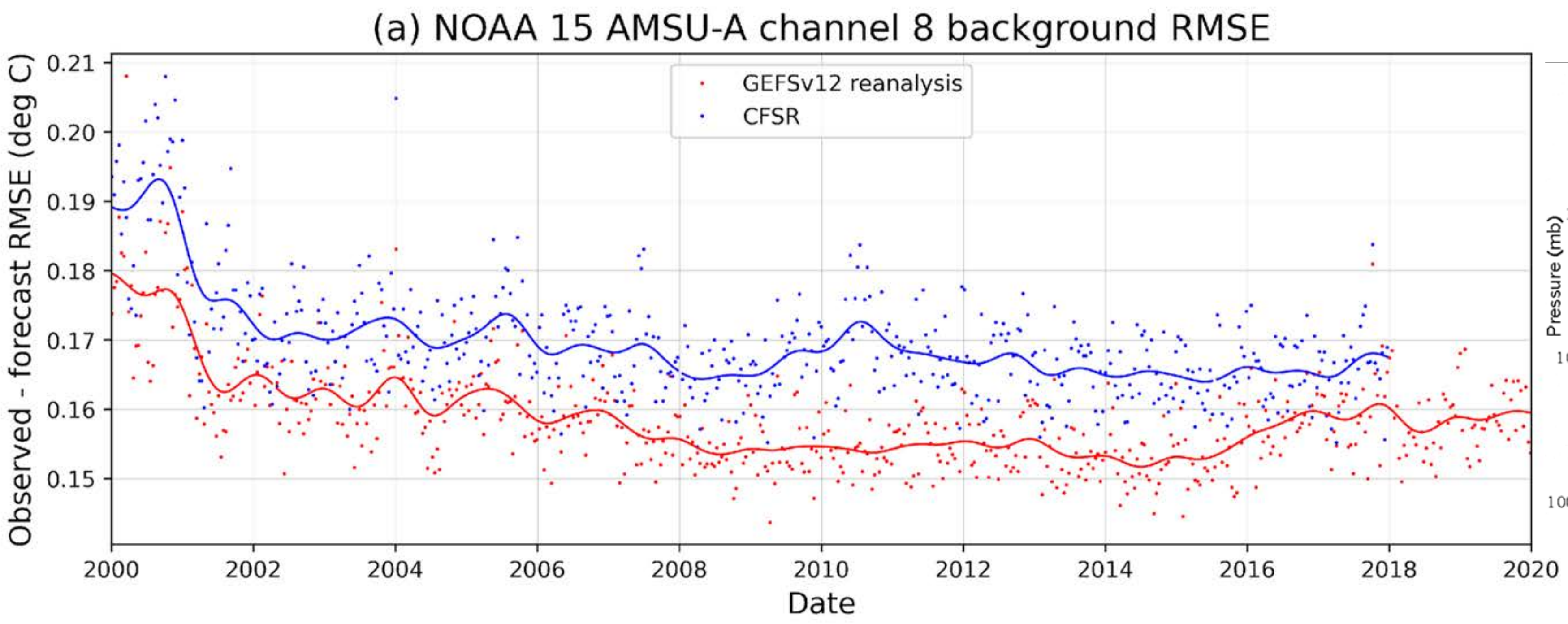
- **Develop experimental forecast products** for customer evaluation
- **Develop prototype** for NOAA real-time extreme event attribution

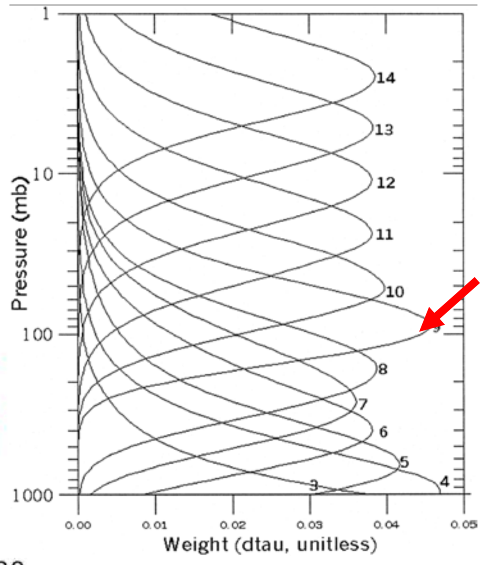
Supplementary slides

Physical Science Lab's new modern-era reanalysis for reforecast initialization

PSL scientists used the operational NOAA data stream and data assimilation system at reduced resolution and produced a reanalysis so that reforecasts would have statistically consistent initial conditions with the real-time GEFSv12 system. This is necessary to support statistical postprocessing

One measure of quality of the reanalysis is the fit of short-term forecasts to observations. The new reanalysis clearly has lower errors than the previous-generation CFSR.

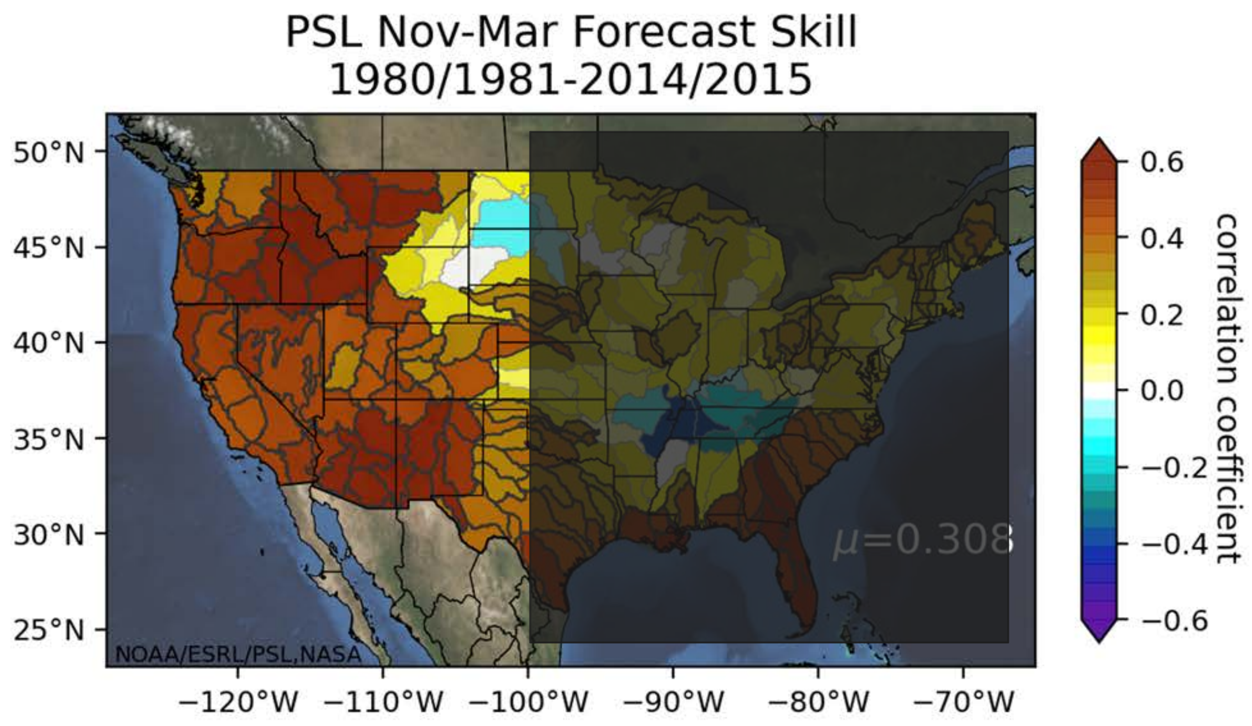




AMSU-A channel 8 peaks around 180 hPa.

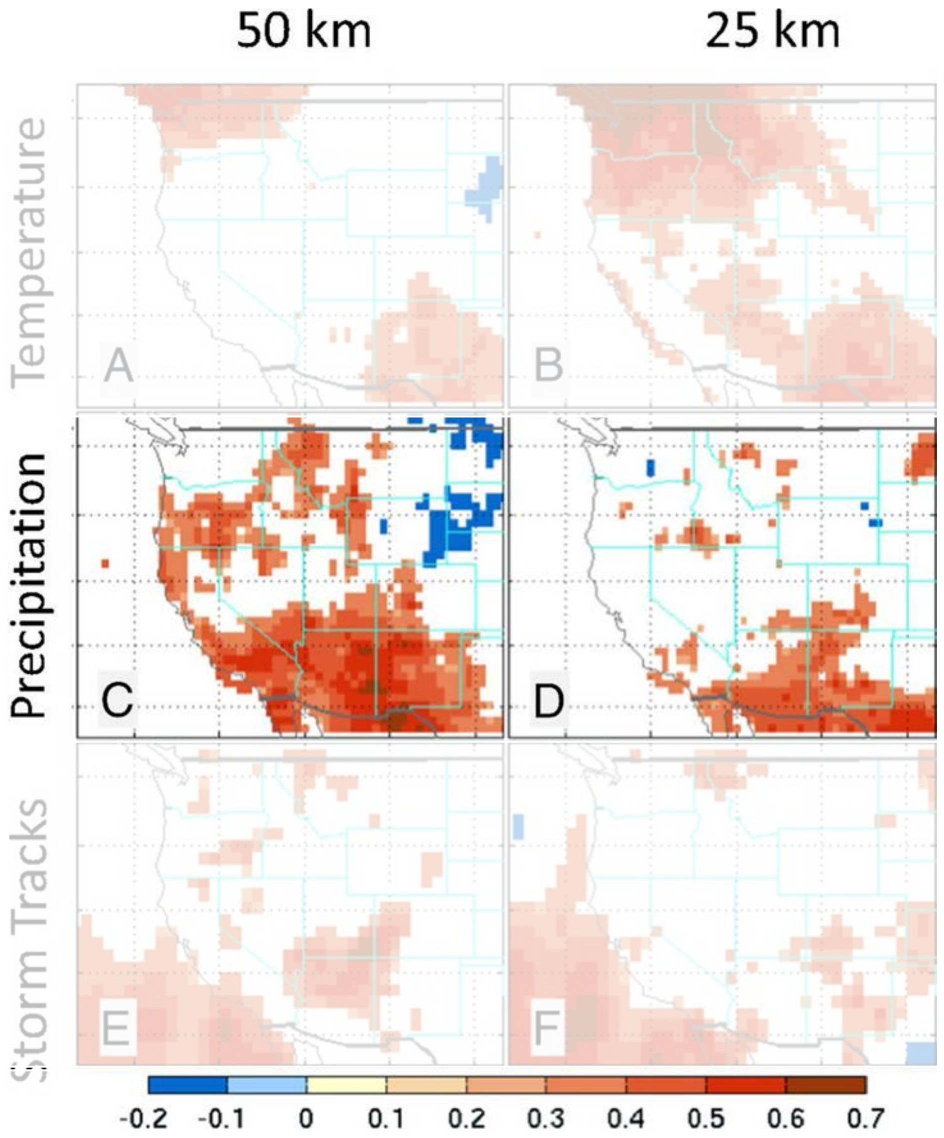
Summary Highlights of PSL's Advances in the Prediction of Extremes

- Foundational contributions to theory of extreme value distributions at the heart of understanding and predicting risks of extremes.
- Unique in having developed a 200-year global atmospheric reanalysis dataset at 3 hourly resolution to investigate how extremes have changed.
- Foundational contributions to understanding extreme events, their predictability and attribution.
- Pioneered statistical prediction models, e.g., Linear Inverse Models (LIM) that allow *a priori* identification of "forecasts of opportunity".
- Innovative diagnostics of weather and climate variability and numerical weather and climate model errors that affect predictions of extremes.
- Shown that developing and implementing stochastic parameterizations in NCEP global models improves simulation and forecasts of extremes.
- Generated reanalysis and reforecast datasets that allow essential re-calibration of forecast output to improve probabilistic predictions of extremes.
- Developed new forecast systems and improved existing NOAA systems to advance the prediction of extremes.



Colors are set to match approximately those of Kapnick et al. 2018.

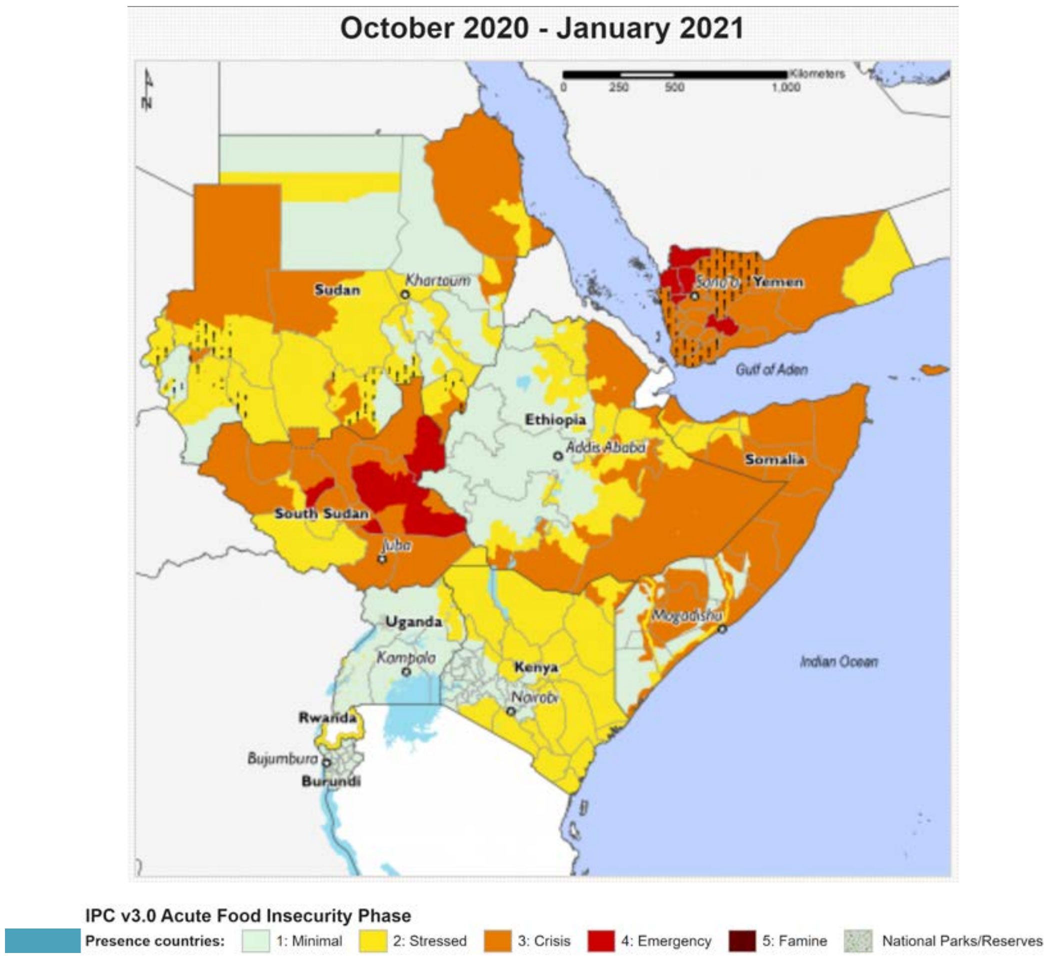
GFDL Nov-Feb Forecast Skill
1980/1981-2014/2015

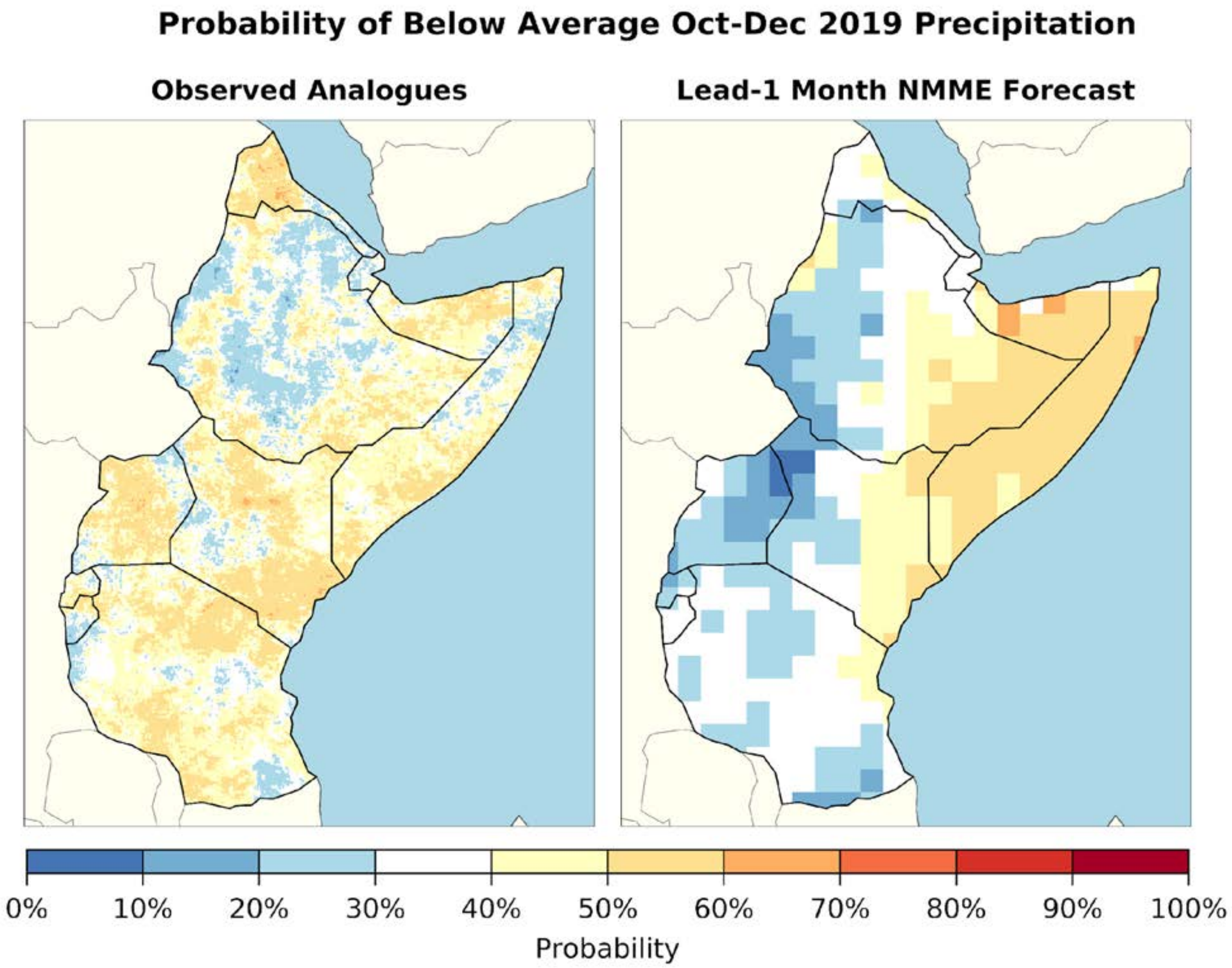


Kapnick et al., 2018

Support food security outlooks issued by the Famine Early Warning Systems Network by applying initialized forecasts and a predictive understanding of conditions relevant to agriculture

Food Insecurity Phase Classification

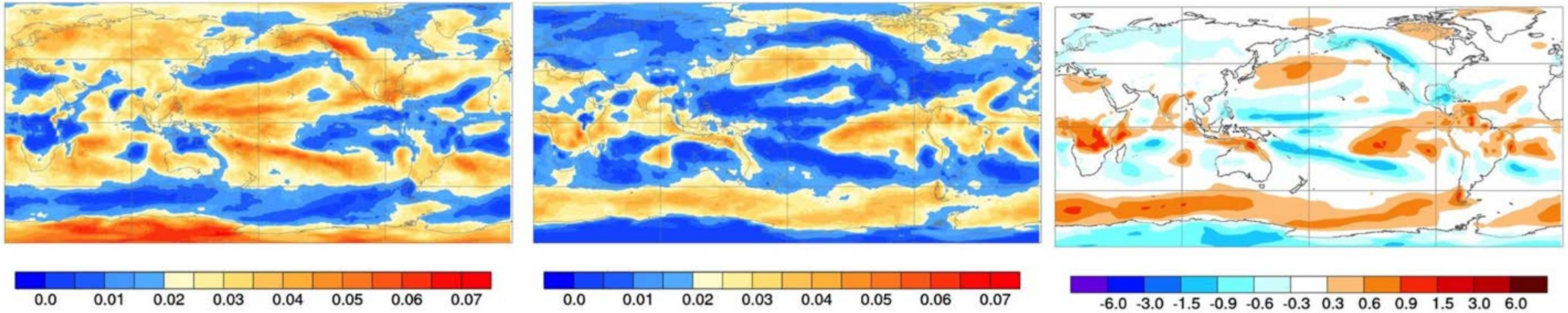




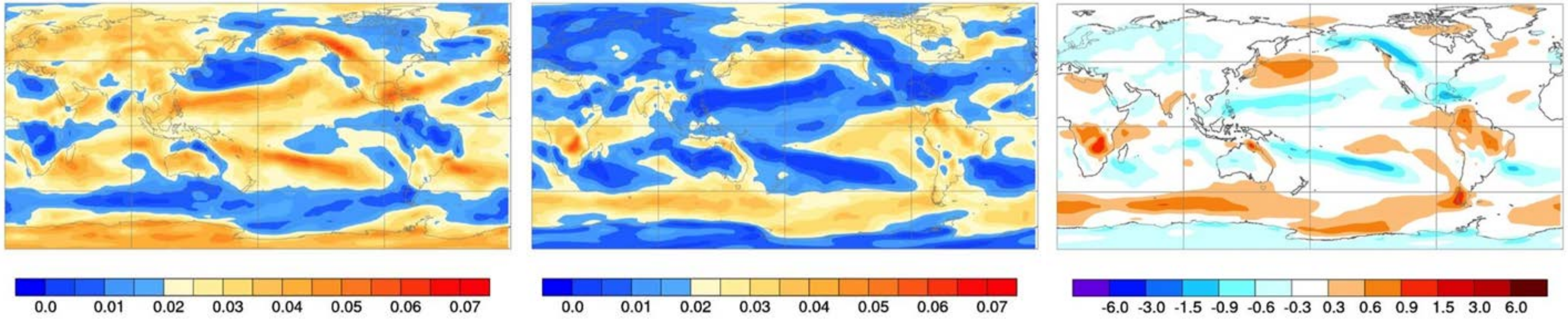
Probability of 5-day mean 850 mb temperature anomaly exceeding ± 2 sigma (DJF 1980-2009) *Both probabilities would be 0.022 if the distributions were Gaussian*

P **(x ≤ -2 sigma)** ***P*** **(x ≥ 2 sigma)** **Skew**

ERA-Interim Reanalysis



20CR-v2c Reanalysis



The similarity of the exceedance probability and skewness patterns is consistent with SGS theory

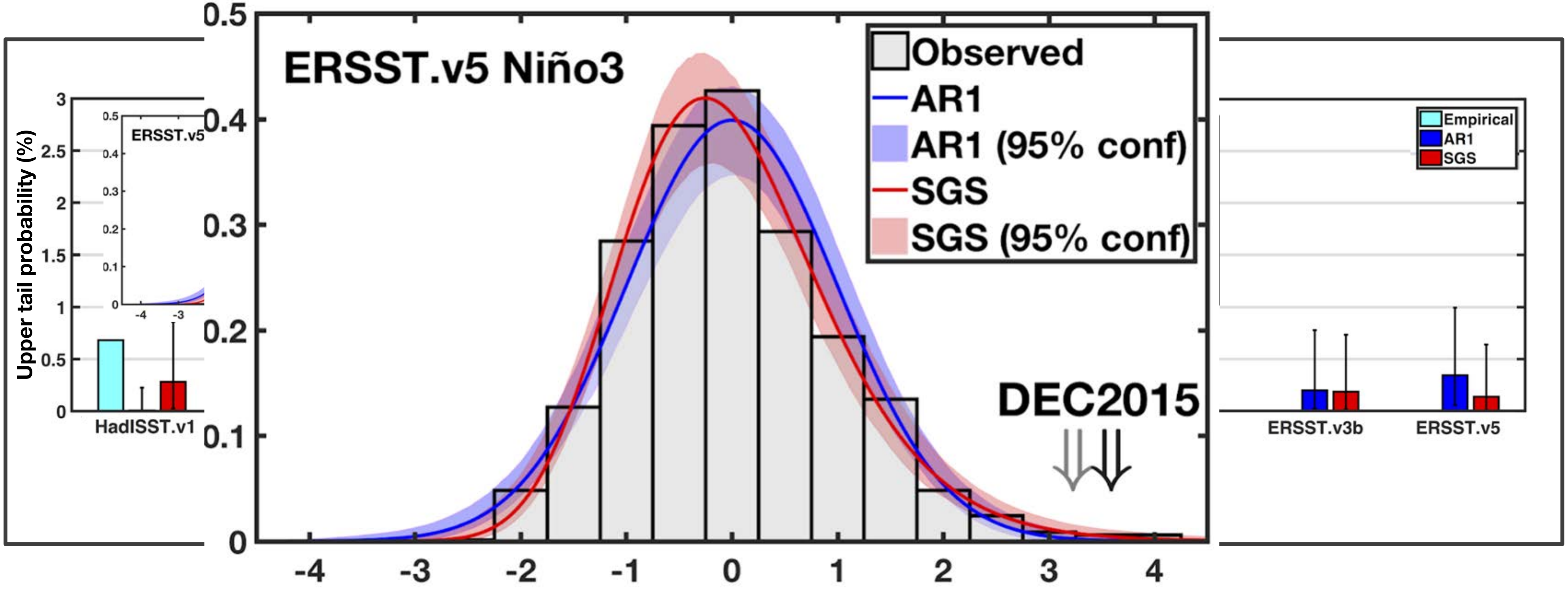
Sardeshmukh, Compo, Penland, McColl (2020)

How extraordinary was the 2015/16 El Nino compared to ENSOs of the 20th century?

Niño extremes relative to SGS instead of AR1 Gaussian distributions:

observed Niño3 extreme was ***more likely***

observed Niño4 extreme was ***less likely***



Niño3: **eastern equatorial Pacific warmth was strong but not unprecedented**, comparable to events every few decades or so.

Niño4: **central equatorial Pacific warmth was <u>unprecedented</u>** in all SST reconstruction datasets except ERSST.v4.

This exceptional warmth was unlikely entirely natural, and (compared to CGCM and LIM simulations) appears to reflect an anthropogenically forced trend.