

NOAA's Precipitation Prediction Grand Challenge

David Novak
Director
NOAA/NWS Weather Prediction Center

Wayne Higgins, Jin Huang, David Dewitt, Brian Gross, Robbin Web,
Dorothy Koch, Ram Ramaswamy, and many others





Imperative to Improve Precipitation Forecasts

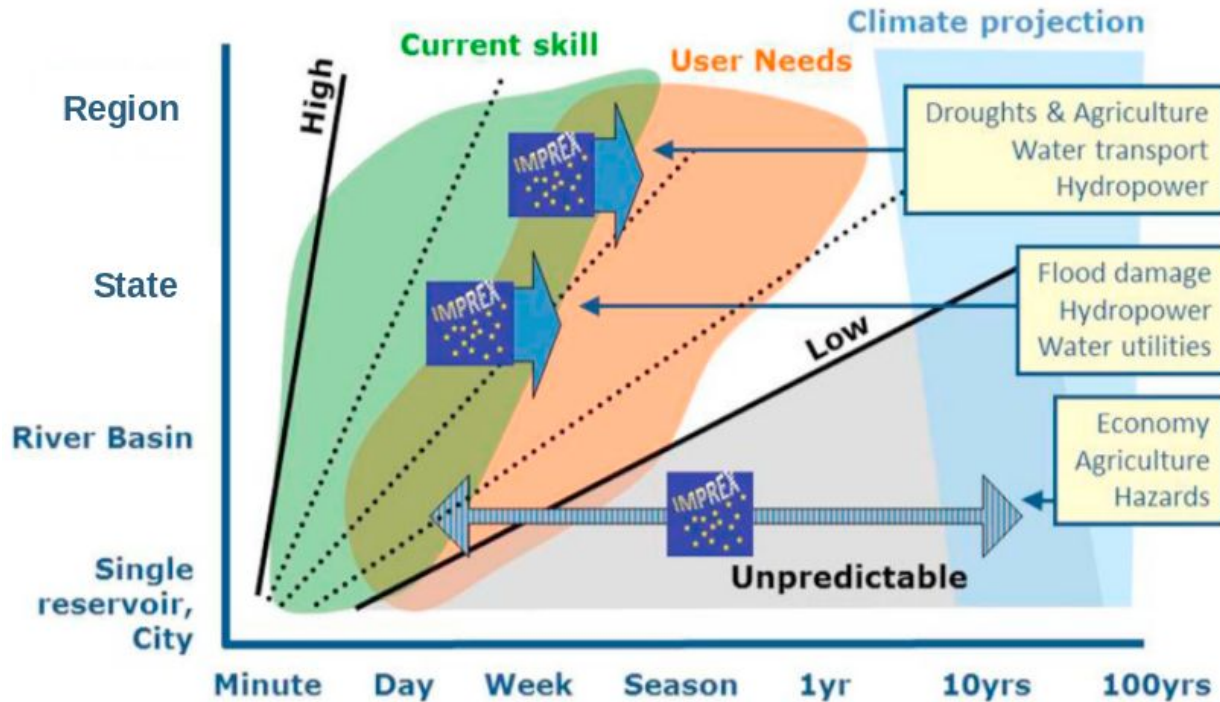
Deadly and damaging threat from too much or too little water - exacerbated by climate change



Progress in flood and drought forecasting largely dependent on improved precipitation forecasts



Imperative to Improve Precipitation Forecasts

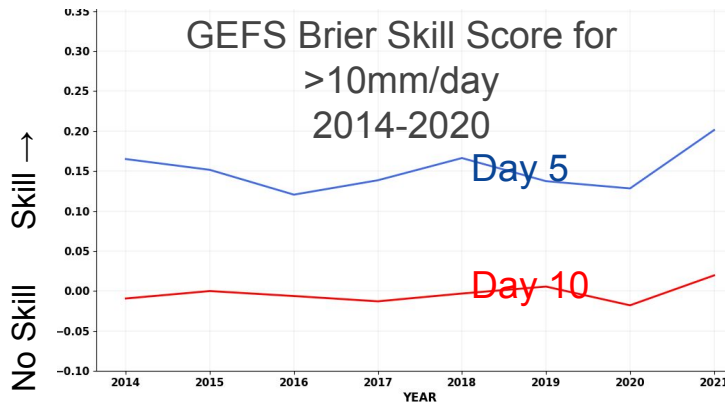
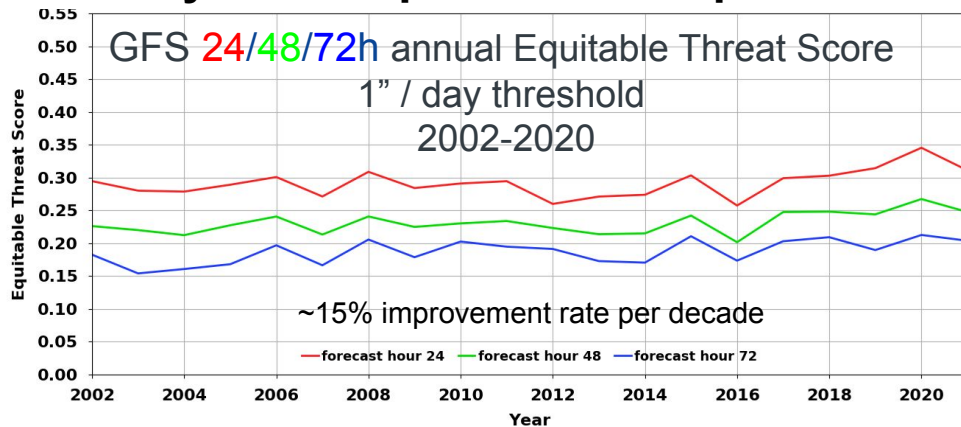


Great opportunity to aid decisions from days to seasons

Fig. 1. Predictability of weather and climate models across spatial and temporal scales (ranging from “High” to “Low”): a mismatch between current forecast skill and user needs persists. (Hunink et al. 2016)

Imperative to Improve Precipitation Forecasts

Painfully slow improvement in past



Priorities for Weather Research Report

“Unfortunately, precipitation forecast skill has not improved substantially over decades and remains one of the major technical challenges in atmospheric sciences.

Poor prediction skill for flood and drought has an inordinate impact on disadvantaged communities”



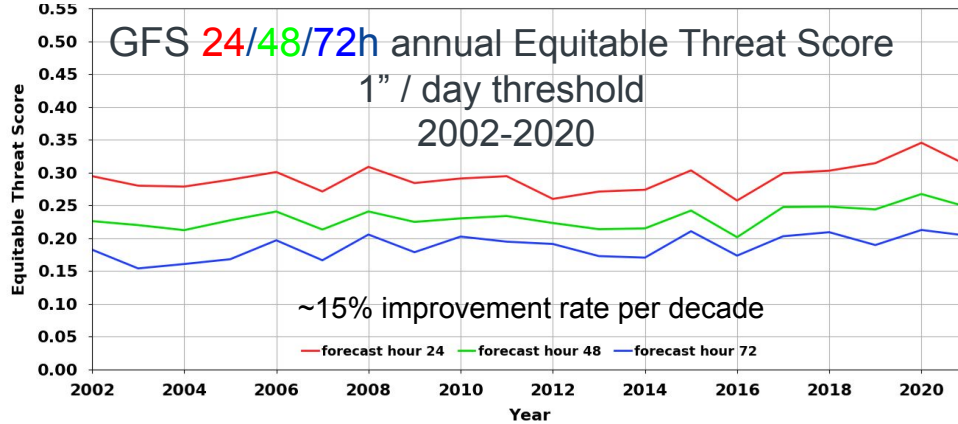
Precipitation Prediction Grand Challenge

Provide more accurate, reliable, and timely precipitation forecasts across timescales, from mesoscale weather, through week 3-4, S2S, to S2D through the development and application of a seamless, fully coupled Earth System prediction model.

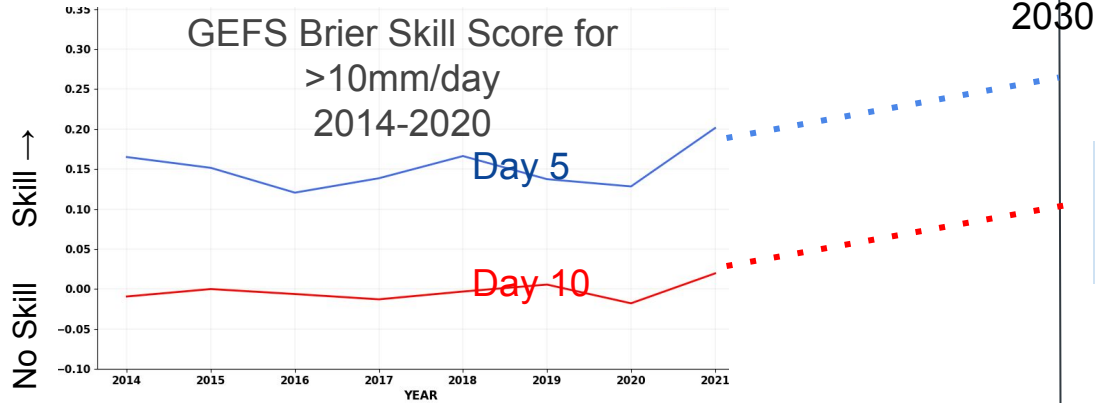
Imagine...

Painfully slow improvement in past

could be...



* DOUBLE the historical rate of improvement, adding 2 days of lead time.



From 'no skill' to 'some skill' at Day 10



Interconnected Objectives

- Enhance and sustain user engagement
- Advance understanding of precipitation predictability
- Improve process-level understanding and modeling
- Sustain, enhance, and exploit observations
- Improve prediction systems for precipitation
- Improve precipitation prediction products and applications

Improve prediction systems for precipitation



- Improve Unified Forecast System (UFS) precipitation forecasts by addressing errors from **initialization**
 - Understand and quantify error growth in UFS models and its attribution to the inaccuracy and gaps of initial conditions
- Improve UFS precipitation forecasts by addressing errors in **model biases**
 - Implement innovative physics packages (e.g., scale-aware convective parameterizations, sophisticated microphysics and boundary layer schemes)
- Improve physics in **coupled** models by emphasizing co-development of all model components, focusing on UFS

Precipitation Prediction Grand Challenge & UFS Applications

NPS Modeling System	Current Version	Q4FY21-Q3FY22 Moratorium	Q4 FY 22	Q1 FY 23	Q2 FY 23	Q3 FY 23	Q4 FY 23	Q1 FY 24	Q2 FY 24	Q3 FY 24	Q4 FY 24	Q1 FY 25	Q2 FY25	Q3 FY25	Q4 FY 25	Q1 FY 26	Q2 FY26	Q3 FY26	UFS Application
Global Weather, Waves & Global Analysis	GFS/ GDASv16.1											Coupled Reanalysis and S2S Reforecast Production					UFS Medium Range & Sub-Seasonal (w/Marine and Cryosphere)		
Regional Weather (Parent Domain)	NAMv4											GFSv17/ GDASv17/ GEFv13/ RTOFSv4/ GODASv3							
Regional Weather (Parent Domain)	RAPv5											GFSv17/ GDASv17/ GEFv13/ RTOFSv4/ GODASv3							
Global Ocean Analysis	GODASv2											GFSv17/ GDASv17/ GEFv13/ RTOFSv4/ GODASv3							
Global Ocean & Sea-Ice	RTOFSv2											GFSv17/ GDASv17/ GEFv13/ RTOFSv4/ GODASv3							
Global Weather and Wave Ensembles, Aerosols	GEFSv12		Coupled SubX Reforecasts w/Replay Technique									GFSv17/ GDASv17/ GEFv13/ RTOFSv4/ GODASv3							
Short-Range Regional Ensembles	SREFv7		Coupled SubX Reforecasts w/Replay Technique									GFSv17/ GDASv17/ GEFv13/ RTOFSv4/ GODASv3							
Seasonal Climate	CDAS/ CFSv2		Coupled SubX Reforecasts w/Replay Technique									GFSv17/ GDASv17/ GEFv13/ RTOFSv4/ GODASv3							
Regional Hurricane 1	HWRFv13		Coupled SubX Reforecasts w/Replay Technique									GFSv17/ GDASv17/ GEFv13/ RTOFSv4/ GODASv3							
Regional Hurricane 2	HMONv3		Coupled SubX Reforecasts w/Replay Technique									GFSv17/ GDASv17/ GEFv13/ RTOFSv4/ GODASv3							
Regional High Resolution CAM 1	HIRes Window v8										RRFSv1					UFS Short-Range Regional HIRes CAM & Regional Air Quality			
Regional High Resolution CAM 2	NAM nests/ Fire Wxv4										RRFSv1								
Regional High Resolution CAM 3	HRRRv4										RRFSv1								
Regional HIRes CAM Ensemble	HREFv3										RRFSv1								
Regional Air Quality	CMAQv6										RRFSv1					UFS Air Quality & Dispersion			
Regional Surface Weather Analysis	RTMA/ URMA v2.8										3DRTMA/ URMA v1								
Atmospheric Transport & Dispersion	HySPLITv7	HySPLITv8									HySPLITv9					UFS Coastal & Regional Waves			
Coastal & Regional Waves	NWPSv1.3	HySPLITv8									HySPLITv9								
Great Lakes	GLWUv1.0.3										GLWUv4					UFS Lakes			
Regional Hydrology	NWMv2.1										GLWUv4								
Space Weather 1	WAM/PEv1										WAM/PEv1					UFS Space Weather			
Space Weather 2	ENLILv1										WAM/PEv1								





Prediction System Gaps

Short to Extended Range





Common Model Systematic Errors

- Underestimation of heavy rain & overestimation of light rain
- The diurnal cycle of precipitation, with maxima too early in the day
- Initiation of convective precipitation
- Slow or non-physical propagation of convection
- Phase speed of mid-latitude troughs
- Sub-seasonal tropical variability (MJO representation)
- Double ITCZ



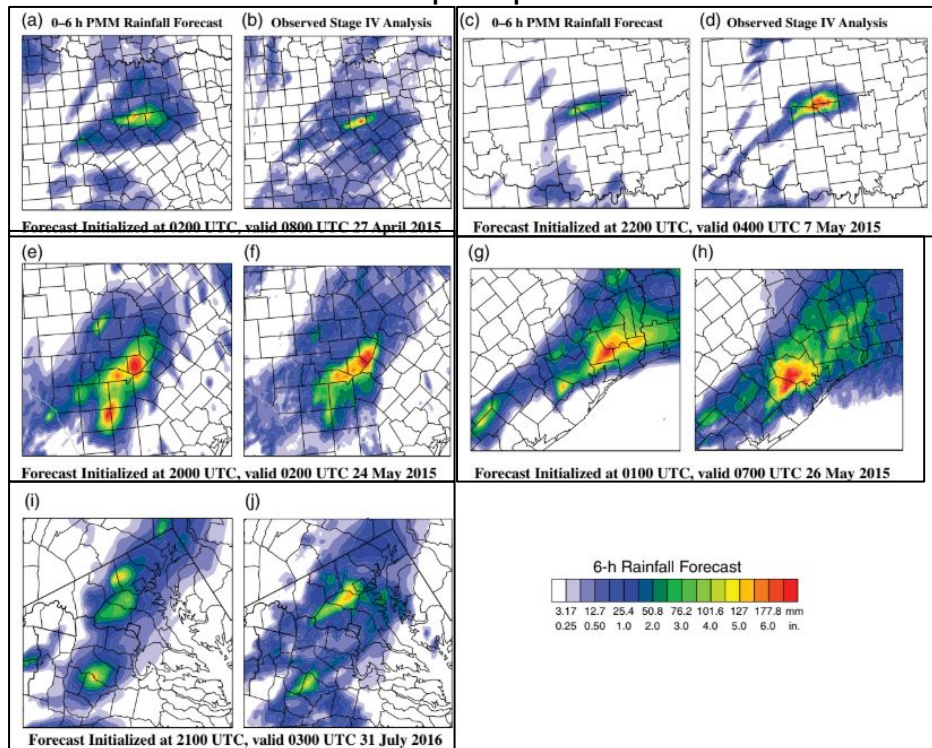
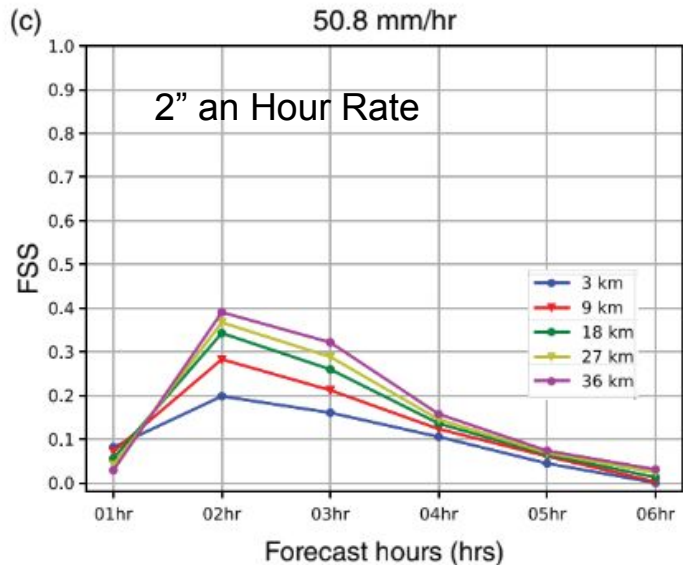
**These Systematic Errors can lead to Ensemble Underdispersion
-TOO confident in the WRONG solution**



Isn't it just a matter of resolution, ensembles, and data assimilation?

Yussouf and Knopfmeier (2019) - 36 member 3-km ensemble with rapid radar data assimilation run on 5 flash flood cases

0-6 hour forecast precip & observed

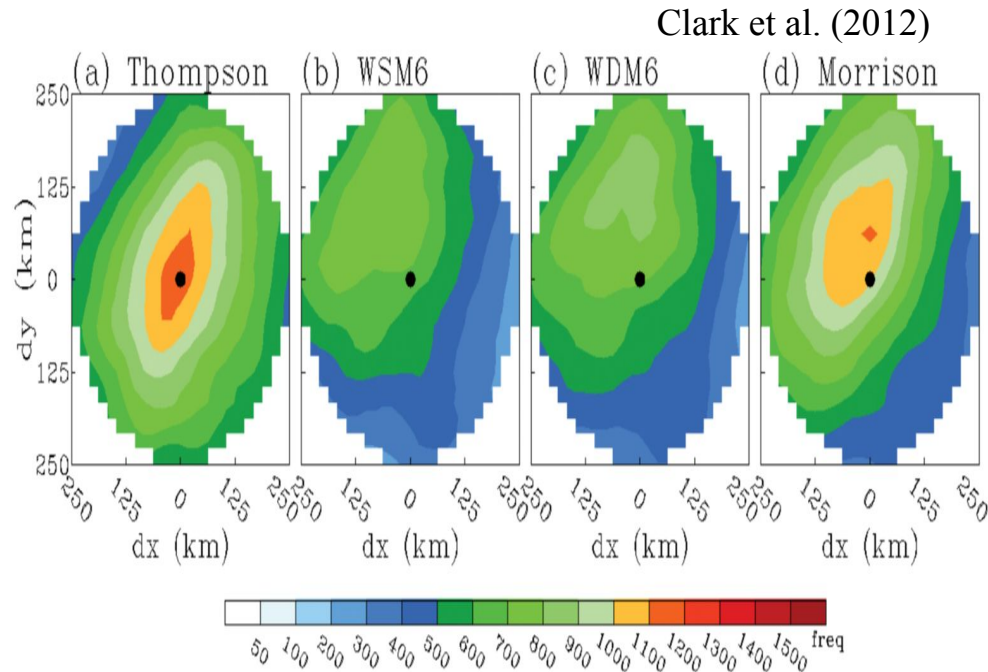


Some skill, but only out to 3 hours!



Model microphysics certainly Matter

Variation in precip amount and location depending on microphysics scheme



Composite frequencies of forecast (dot) and observed rainfall features (shading) at forecast hour 30 from 3 km convection allowing model forecasts

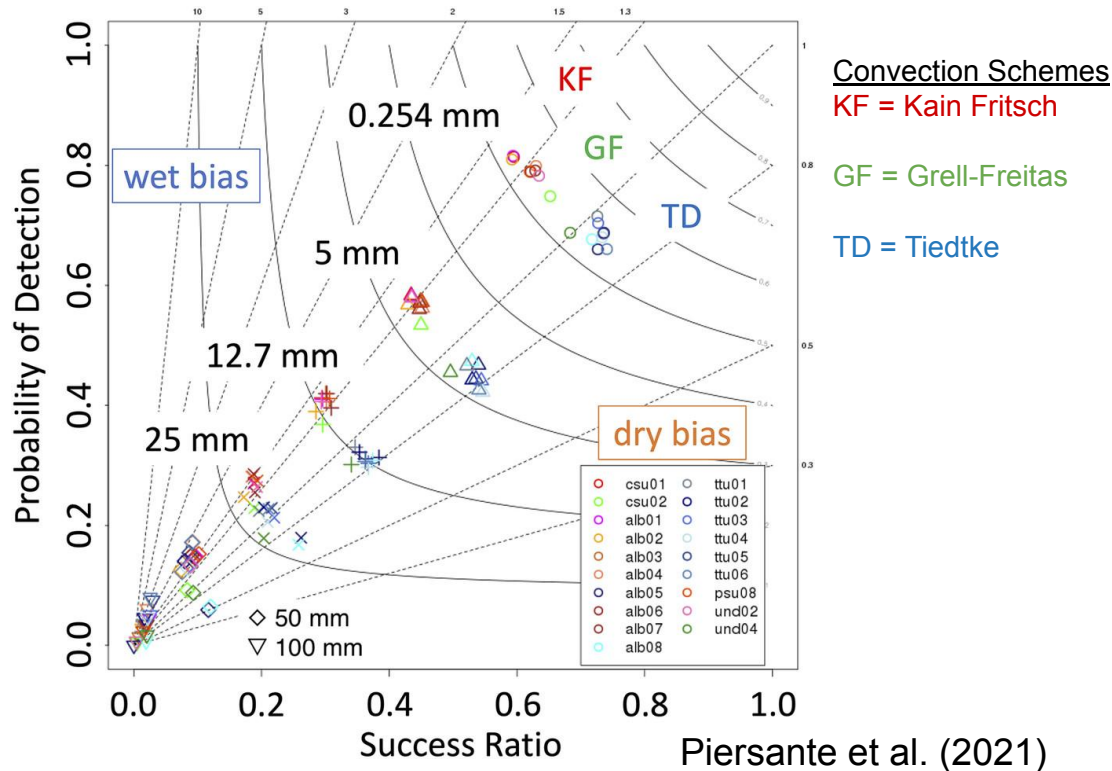




Convective Parameterization Certainly Matters



Precipitation skill clusters by convection parameterization



Convection Schemes

KF = Kain Fritsch

GF = Grell-Freitas

TD = Tiedtke

Performance diagram for precipitation over CONUS using 19 ensemble members with varied convection parameterizations, microphysics, and PBL schemes.

Clear clustering around the CP schemes



An Old Problem in a New Model

Grid-scale feedback largely solved in Global operational modeling systems through improved parameterizations.

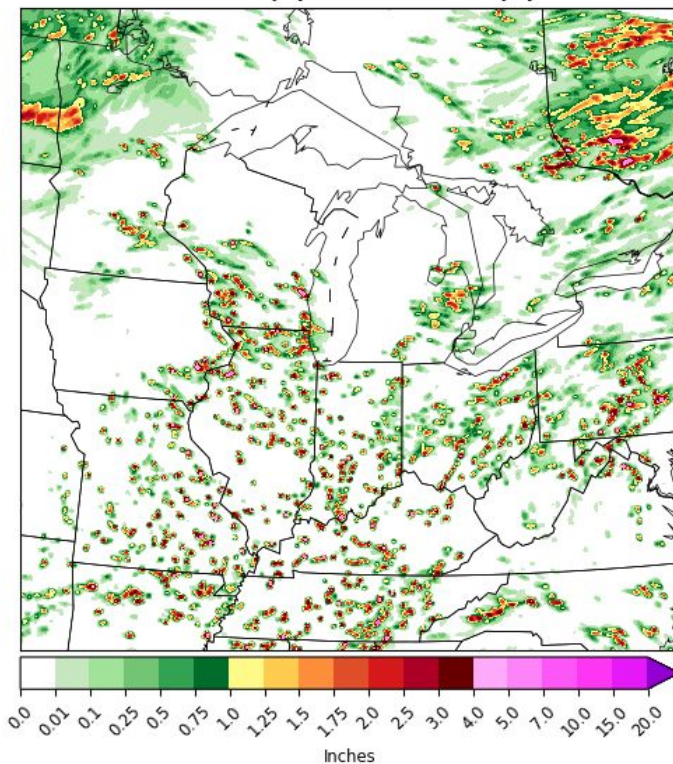
However, problem reappearing in FV3 CAMs

Current-generation parameterizations of deep convection have the following challenges:

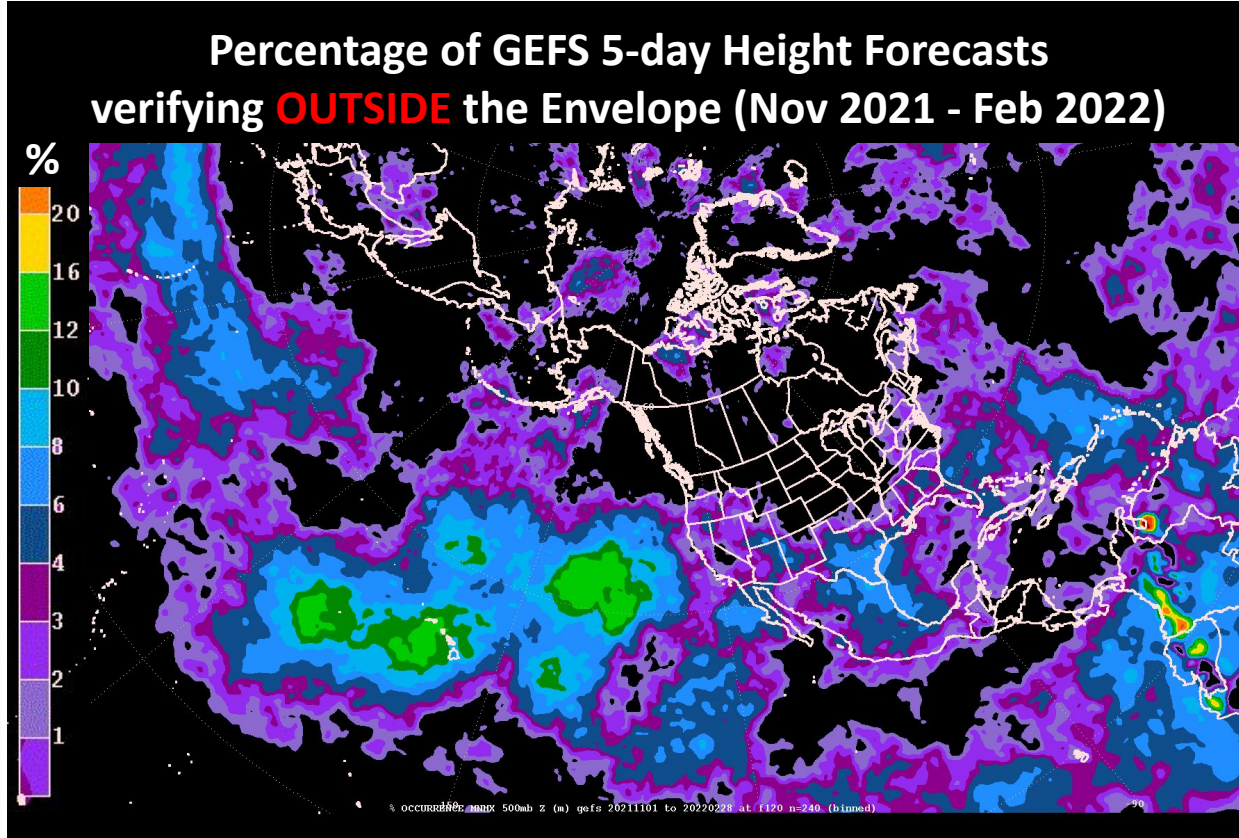
- local* convection is treated as independent from one grid column to the next.

- not scale-aware*, i.e., the statistics are not consistent when applied from finely resolved to coarsely resolved scales

GSL FV3-SAR4 24 h QPF 00z Initialization:
Valid 12 UTC 07 July 2020 to 12 UTC 08 July 2020



And we've solved the synoptic problem, right?



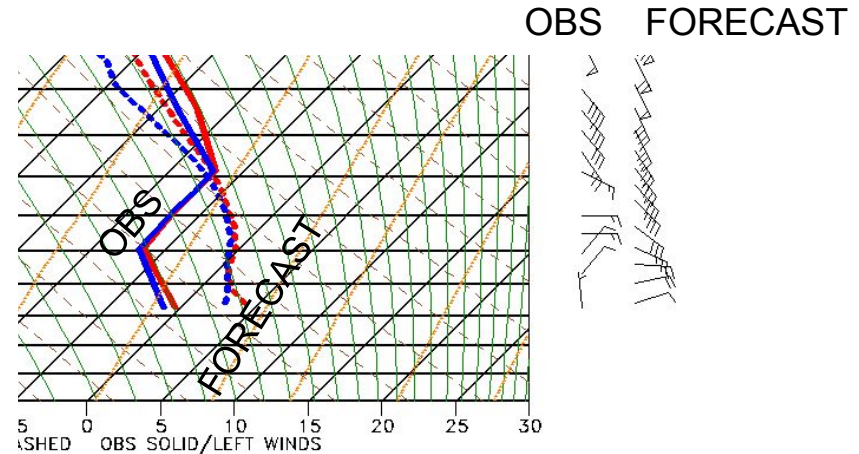
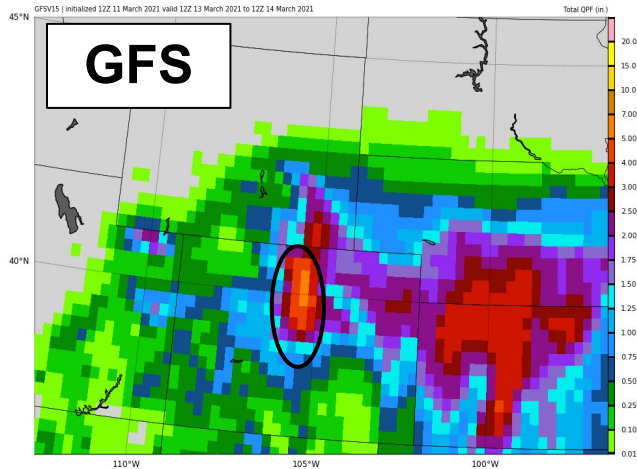
- Ensemble systems exhibit underdispersion
- Often run at coarser resolution than features of interest

And we've solved the synoptic problem, right?

**Model forecast historic QPF
- that did not occur**

**Small errors in the synoptic flow resulted in
too deep and strong upslope flow in the
model forecast**

Day 3 forecast, valid March 14, 2021





Prediction System Gaps

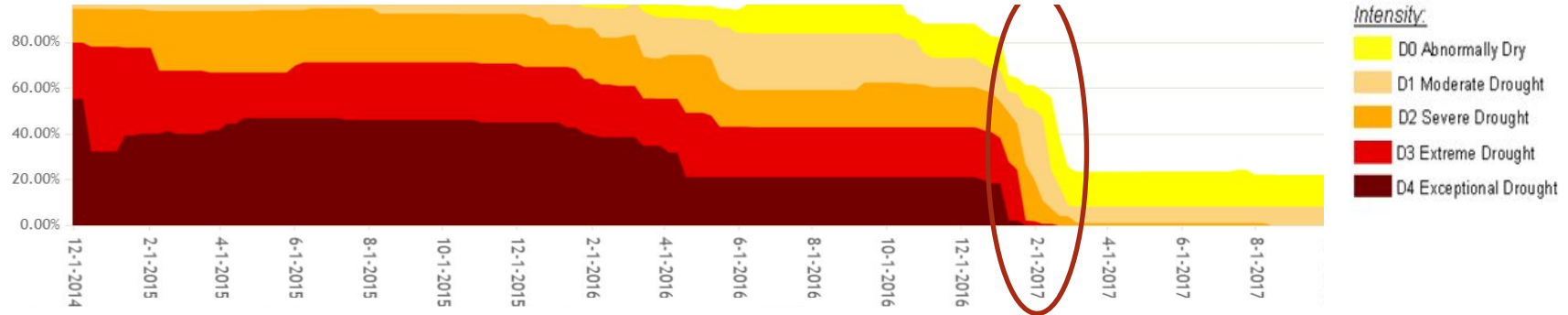
Seasonal-to-Subseasonal (S2S)



S2S Precipitation Prediction Challenge: Regime Transition

Failure to Predict Drought Amelioration

California Percent Area in U.S. Drought Monitor Categories



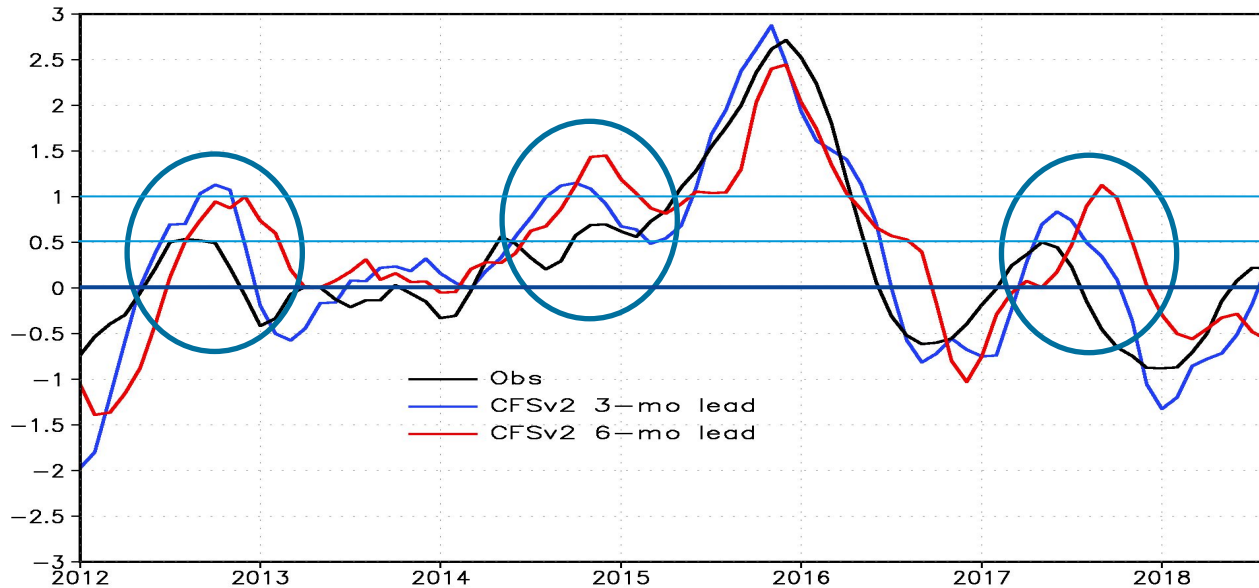
Transitioned from multi-year severe drought to near-normal conditions with record flooding over ~60 days

All models failed to predict this transition of the large scale atmospheric state and subsequent heavy rains beyond about two weeks lead.

- Why did the persistent west coast ridge break down despite La Nina conditions?
- What is potential role of other tropically-forced teleconnections?

Major Systematic Errors Limiting S2S Forecast Skill: El Nino False Alarms

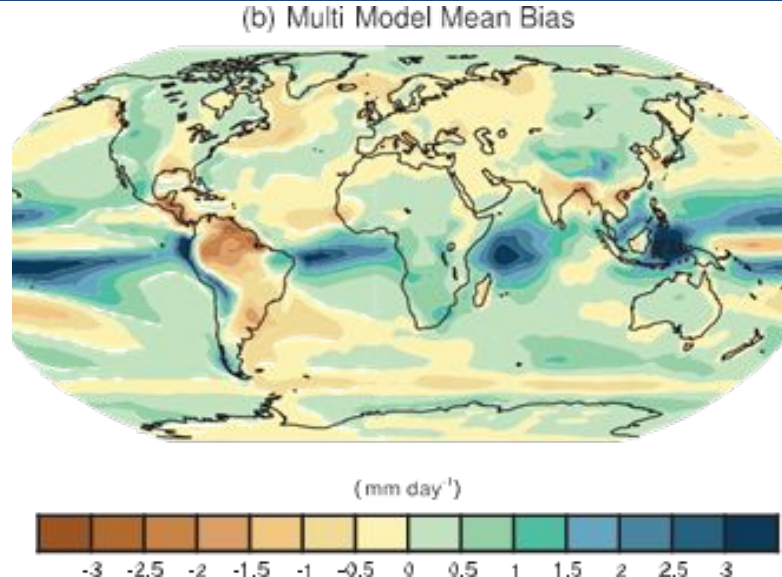
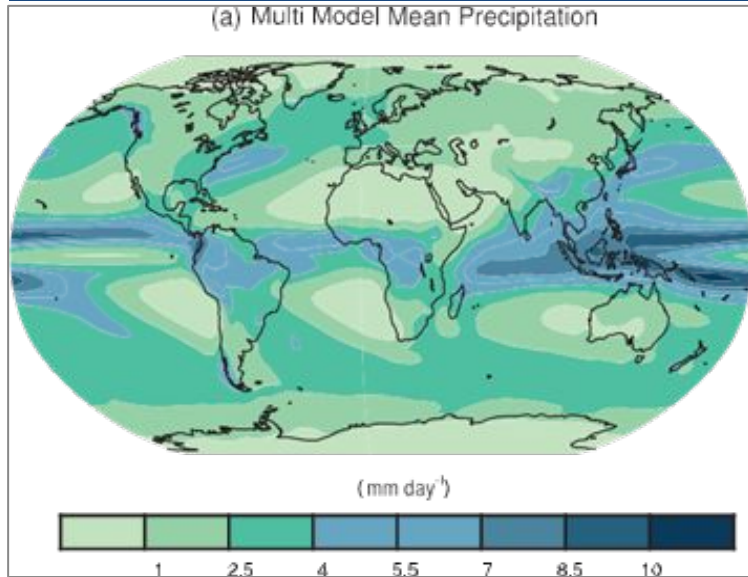
CFSv2 forecasts of SST for Nino3.4 at 3 month and 6 month leadtime



Current generation coupled models have large errors in timing and amplitude of S2S equatorial Pacific SST anomalies.

Systematic Precipitation Errors in CMIP5 Models (Flato et al., 2013)

Annual Mean Precipitation Rate (mm/day) for 1980 to 2005



Major errors in distribution of mean precipitation including the development of erroneous double ITCZ.

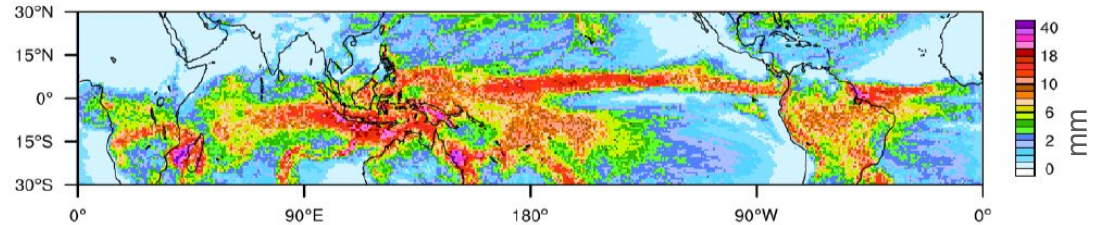
Coupled models used for S2S prediction have similar errors and these errors develop rapidly (order of 1 to 2 months).

40-day Convection-Permitting Global Run using an Exascale Earth System Model (Caldwell et al. 2021)

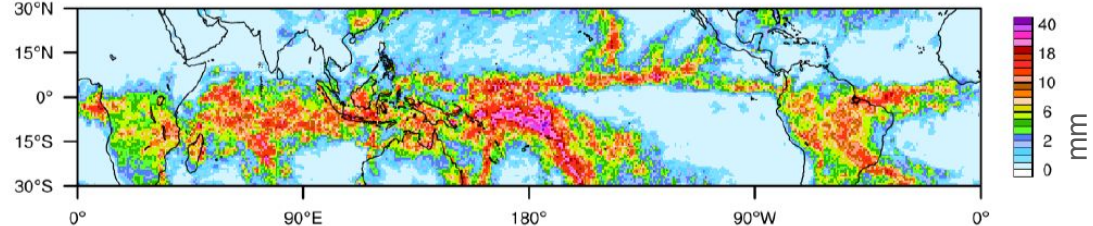
In exchange for huge computational expense, resolving deep convection improves many (but not all) long-standing climate model biases

Tropical precipitation biases persist

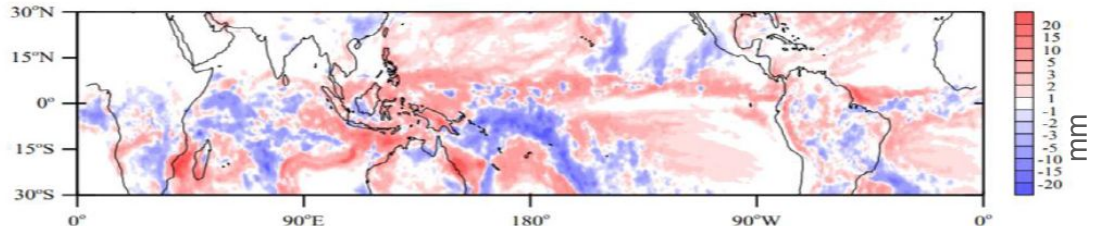
Model Forecast



GPM Observations



Difference



Modeling Aspects - No Silver Bullet

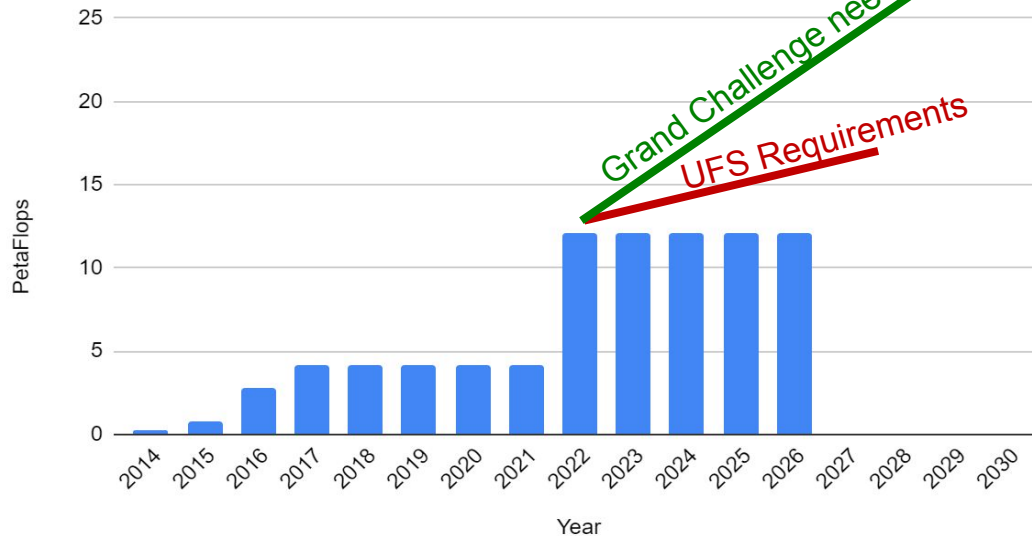
An Integrated System

- **Data Assimilation**
 - cited 241 times in Priorities for Weather Research report
- **Coupling**
- **PBL and Convective Parameterizations**
- **Microphysics**
- **Resolution**
- **Ensemble configurations**



Operational Computing Gaps

NOAA Operational Compute



- GEFSv13/GFSv17/RRFS/HAFS will FILL the Supercomputer
 - GEFSv13+GDAS/GFSv17: 110K cores (35% of Supercomputer)
 - HAFS: 72K cores (22.5% of Supercomputer)
 - RRFS/3DRTMA: 167K cores (58% of Supercomputer)
 - **Total 338K cores. This amounts to > 100% of Supercomputer**



Recent Progress in Improving Prediction Skill



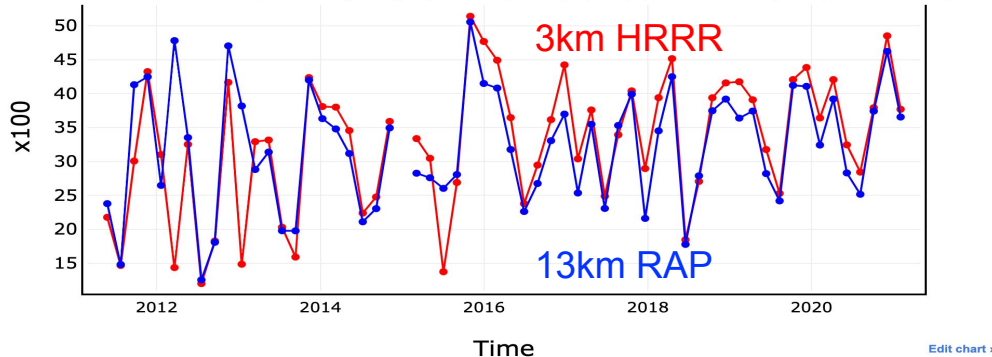
Some progress in short-range QPF

HRRR/RAP Equitable Threat Score 1" / day threshold – 60-day averages 2011-2021

24 Hour Precipitation : TimeSeries 05/18/2011 00:00 - 02/06/2021 12:00 : no diffs MATCHED [Close All Preview Windows](#)

Curve0 mean = 32.64, median = 33.36, stdev = 9.755
Curve1 mean = 32.15, median = 33.05, stdev = 8.686

— Curve0: HRRR_GSL in Eastern US (lon <= 100W), 1.00 (precip >= 1.00 in) 40 km grid, ETS (Equitable Threat Score), fcst_type: 2 12hr totalavg: 60D
— Curve1: RAP_GSL in Eastern US (lon <= 100W), 1.00 (precip >= 1.00 in) 40 km grid, ETS (Equitable Threat Score), fcst_type: 2 12hr totalavg: 60D

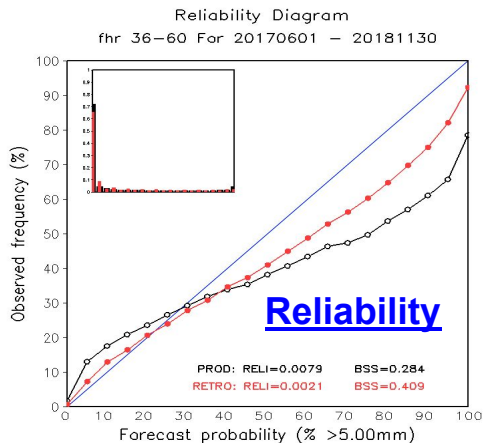


James et al 2022 (submitted to Wea. Forecasting)

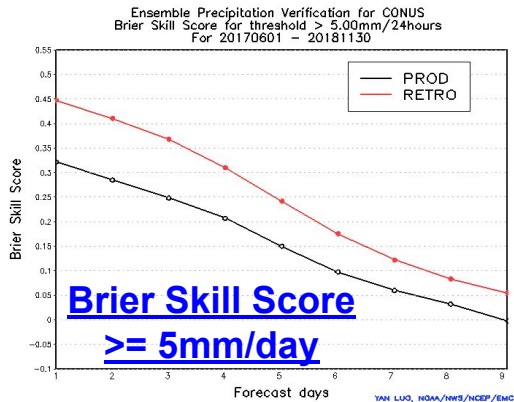
Long-term improvement for NOAA short-range rapidly updated model for QPF (summer and winter)

- Data assimilation – **improved use of radar, surface, cloud obs**
- Model – **better physical parameterizations**
- Improved representation of diurnal cycle

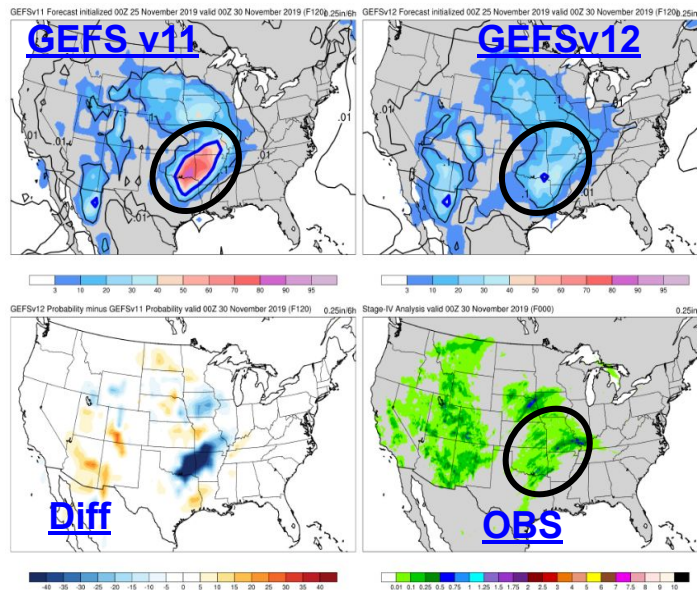
Some progress in medium-range QPF



Significant Improvement of Probabilistic QPF



Prob ≥ 0.25 inch/24 hours at 5 day forecast



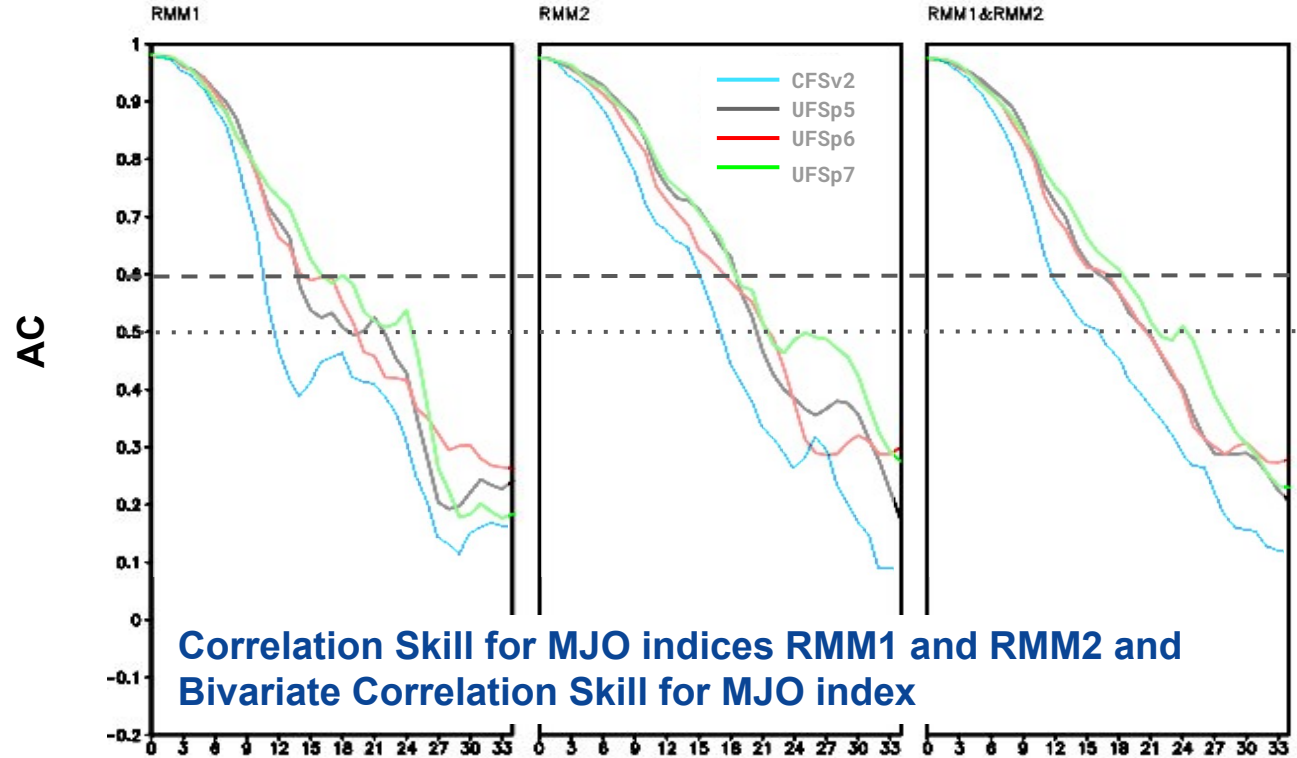
GEFS v11 is extremely overconfident while GEFSv12 has more reasonable (day 5) probabilities due to increased spread



Some progress in S2S-range

UFS-Coupled Improvements in MJO-Skill

Dramatically increased skill of MJO from improved UFS physics and coupling



Correlation Skill for MJO indices RMM1 and RMM2 and Bivariate Correlation Skill for MJO index

Progress in NOAA Testbeds

Hydrometeorological Testbed Experiments

Serve as forum to bring meteorologists, hydrologists, modelers, and academics together to improve precipitation forecasts

- Test new forecasting and verification techniques
- Evaluate deterministic and ensemble models
- Examine ways to better represent the hydrological aspects





Interconnected Objectives

- Enhance and sustain user engagement
- Advance understanding of precipitation predictability
- Improve process-level understanding and modeling
- Sustain, enhance, and exploit observations
- Improve prediction systems for precipitation
- Improve precipitation prediction products and applications



“Weather forecasts possess no intrinsic value. They only acquire value through their ability to influence the decisions made by users of the forecast”

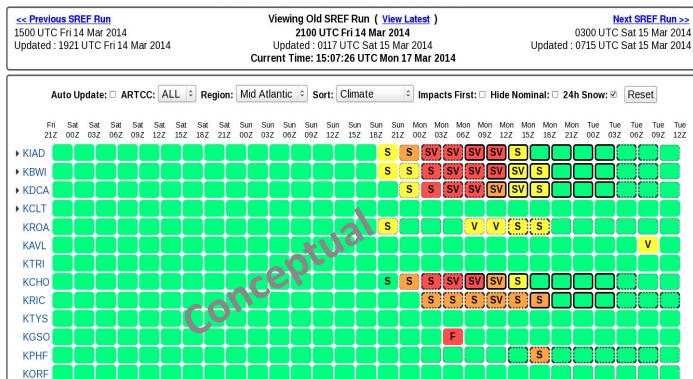
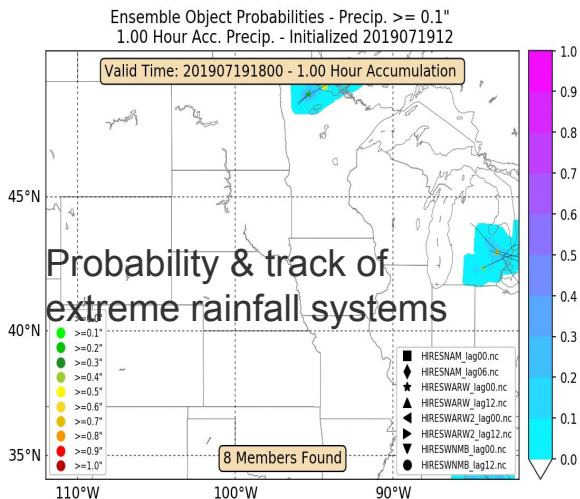
Allan H Murphy, *Weather and Forecasting*, June 1993



Improved Modeling Enables New Tools...

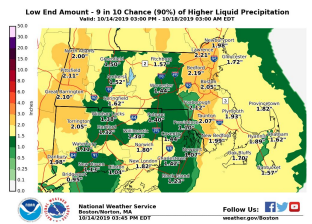
Translate model forecasts into actionable information for critical decisions

Urban Rainrate Dashboard: Probability of hourly rainfall rates exceeding stormwater design criteria for major cities.

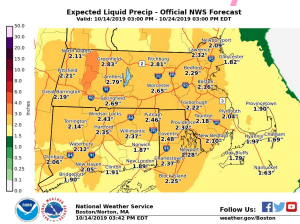


Extract Weather Scenarios

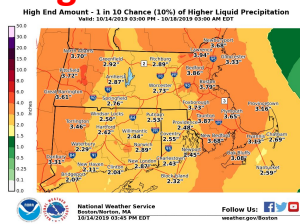
Low End Amount



Most Likely



High End Amount



Improved Modeling Enables New Products...

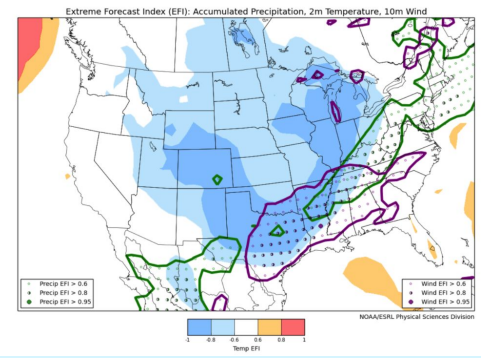
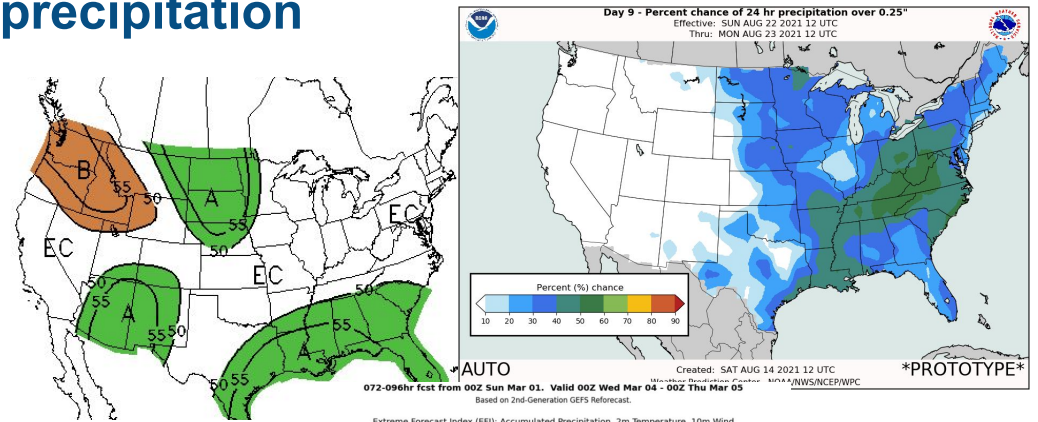
Translate model forecasts into actionable information for critical decisions

Day 8, 9, 10 probabilistic daily precipitation forecasts

Improved Week 3&4 forecasts

Flash Drought services

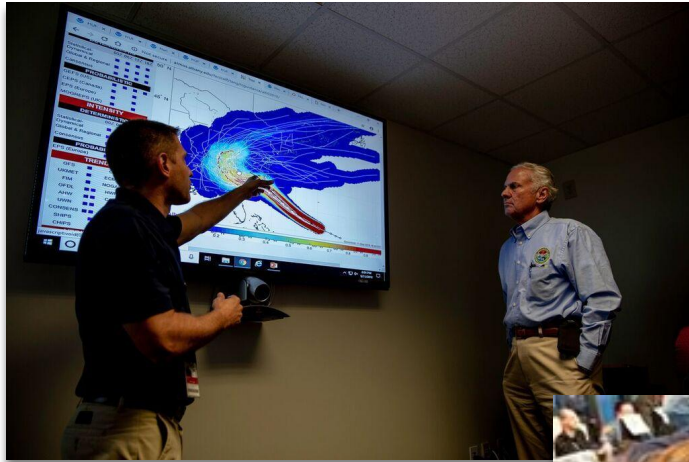
New tools based on reforecasts -
such as the Extreme Forecast Index,
AI-powered applications





...and Fuels Impact-based Decision Support Services

Translate model forecasts into actionable information for critical decisions





These Objectives accomplished by:

- Co-developing / partnering with NOAA's end-users
- Partnering with related initiatives, including UFS, S2S, EPIC
- Investing in reanalyses and reforecasts
- Exploiting machine learning and artificial intelligence tools
- Leveraging testbeds and other fora that bring communities together to transition new precipitation capabilities to operational implementation

Ongoing PPGC Efforts

FY22 Budget

Competitive Grants:

- Improve understanding of key physical processes
- Improve model representations of these processes
- Reduce the systematic biases in NOAA models

2022 Infrastructure Act

Modernized precipitation frequency (Atlas-14 dataset) and probable maximum precipitation studies

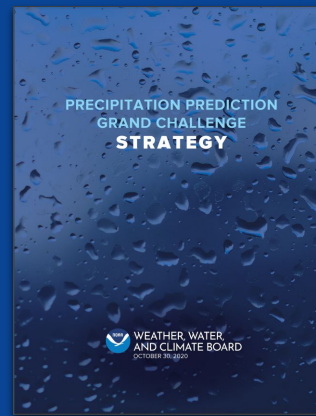
2022 Disaster Supplemental Improvements

- Social Science
- Process Studies
- Satellite data infusion
- Model Development
- Product / tool improvements

Bottom Line

The Precipitation Prediction Grand Challenge is an historic R20 opportunity to improve precipitation prediction skill

NOAA Precipitation Prediction
Grand Challenge Strategy ([LINK](#))





Gaps for medium-range precipitation forecast skill



- Medium-range (e.g., 3–14 days) precipitation forecast skill often dependent on the large-scale.
- Some states, such as blocking patterns, are susceptible to especially rapid error growth in association with nonlinear dynamical processes as well as moist-diabatic processes.
- **Improvements in data assimilation and physical parameterizations** could help to reduce forecast errors in low-skill situations.
 - **Improved techniques for assimilation of satellite all-sky radiance data** in under-observed and sensitive regions could provide better representation of wind, temperature, pressure, and humidity in model initial conditions.
 - **More realistic parameterizations of processes that affect latent heating** (e.g., cloud microphysics and convection) could be especially helpful in improving the representation of diabatic modification of the large-scale flow.



An Old Problem

Spurious grid-scale convection (aka. gridpoint storms, precipitation bull's eyes, and grid-scale precipitation bombs) typically develop in mesoscale models, particularly at grid spacings where convection needs to be treated as both a parameterized and grid-resolved process (approximately 10–50 km)

[Spurious Grid-Scale Precipitation in the North American Regional Reanalysis](#)

Gregory L. West¹, W. James Steenburgh¹, and William Y. Y. Cheng¹

<https://www.mdpi.com/2073-4433/12/9/1194/htm>

<https://www.osti.gov/pages/servlets/purl/1833211>