NOAA's Subseasonal-to-Seasonal (S2S) Forecasting Overview

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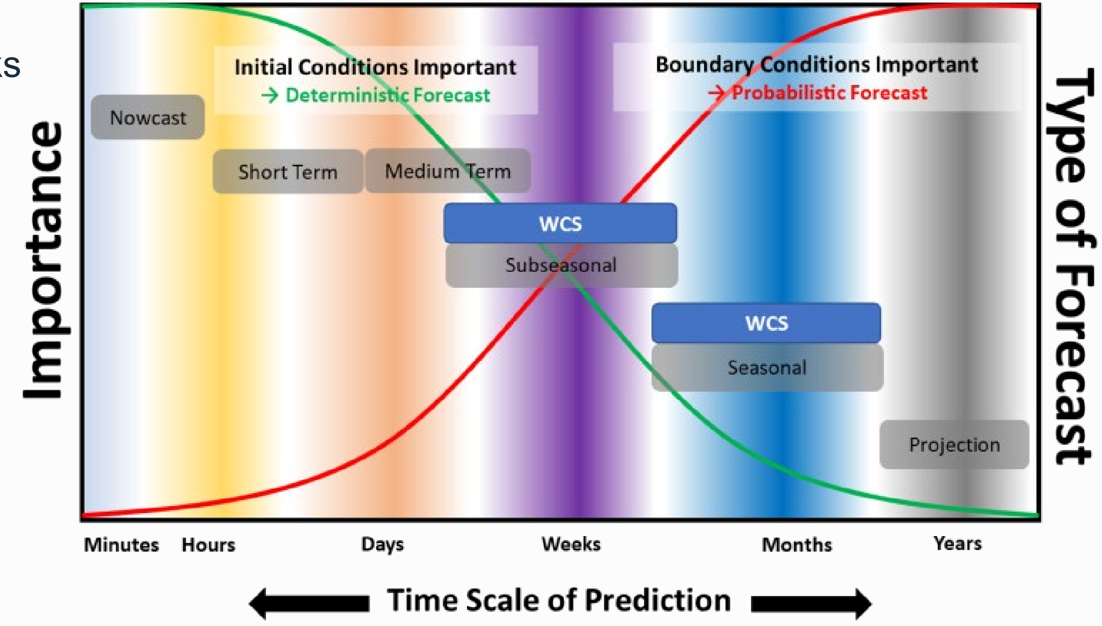
Defining the terms

- Nowcast: minutes to 1 hour
- Short-range: 1 hour to 48 hours
- Medium-range: 2 days to 2 weeks
- Sub-seasonal: 3-4 weeks
- Seasonal: 1 month to 1 year
- Decadal: 1 year to 15 years



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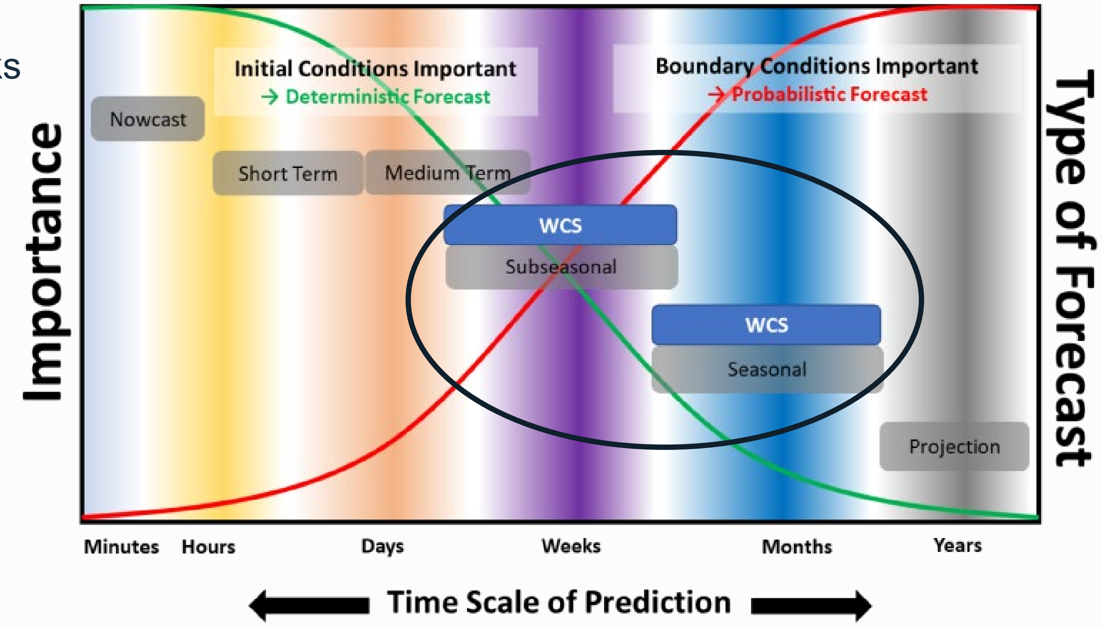
Land conditions very important (also vegetation)
Ocean conditions very important



Model physics development

- Most model physics development takes place for systems run on timescales of global weather (< 2 weeks), or even shorter: not as much at S2S+ timescales
  - Why? Mostly practical: shorter timescales = more/faster runs
- Physics development for S2S out to climate scales evolves much more slowly, and separately from NWP (weather) timescale
- Paradigm shift (at least at operational centers): consolidate modeling systems (dynamical cores, andsubgrid-scale physics) to run across many timescales– "minutes-to-millenia"
- Leverage paradigm shift to look at model physics atsubseasonal timescales

Paradigm shift at NOAA: Moving to UFS…

- NOAA is moving its modeling suite to the Unified Forecast System (UFS)
  - Replaces multiple models / domains / time-ranges / DA methods with single systems
  - Current applications are: hurricane, short-range, medium-range, seasonal-range
- Currently in operations in NOAA:
  - Medium-range: out to 16 days done by **atmosphere+wave** GFS/GEFS
  - Seasonal-range: out to 45 days (and beyond) done by **fully-coupled** CFSv2
- By FY2024, all of NOAA's operational global Earth system prediction for lead times from **0-35+ days** will be consolidated into a **single UFS-based model** (GEFSv13)
  - Challenge: Ensure model has "reasonable" skill from daily to subseasonal time scales

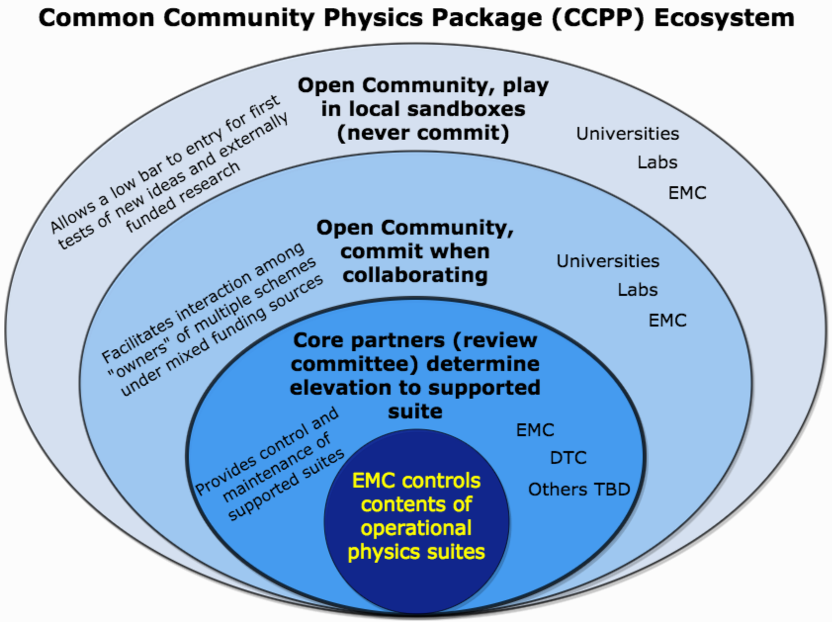
NPS Modeling System	Current Version	Q4 FY 22	Q1 FY 23	Q2 FY 23	Q3 FY 23	Q4 FY 23	Q1 FY 24	Q2 FY 24	Q3 FY 24	Q4 FY 24	Q1 FY 25	Q2 FY25	Q3 FY25	Q4 FY 25	Q1 FY 26	Q2 FY26	Q3 FY26	UFS Application
Global Weather, Waves & Global Analysis	GFS/ GDASv16.1																	
Global Weather and Wave Ensembles, Aerosols	GEFSv12	Coupled Reanalysis and SubX Reforecast Production							GFSv17/ GEFSv13									UFS Medium Range & Sub-Seasonal
Short-Range Regional Ensembles	SREFv7												Seasonal Reforecast Production				GFSv18/ GEFSv14/ SFSv1	
Global Ocean & Sea-Ice	RTOFSv2				RTOFSv3													UFS Marine & Cryosphere
Global Ocean Analysis	GODASv2				GODASv3													
Seasonal Climate	CDAS/ CFSv2																	UFS Seasonal

Paradigm shift at NOAA: Moving to UFS and CCPP

- Using Common Community Physics Package (CCPP) interface to couple physics to the dycore

- Strips (atmospheric) physics out of dynamical core; allows for easy replacement of physics *schemes* and entire physics *suites*

- Common framework used by operations (NOAA/EMC) and research partners



Standard output fields for Subseasonal Forecasts

On 500 and 200 hPa levels

Variable	CF Standard Name	Abbrev	Unit	Frequency
Geopotential Height	geopotential_height	zg	m	Average of Instantaneous values at 0,6,12,18Z

On 850 and 200 hPa levels

Variable	CF Standard Name	Abbrev	Unit	Frequency
Zonal Velocity	eastward_wind	ua	ms-1	Average of Instantaneous values at 0,6,12,18Z
Meridional Velocity	northward_wind	va	ms-1	Average of Instantaneous values at 0,6,12,18Z

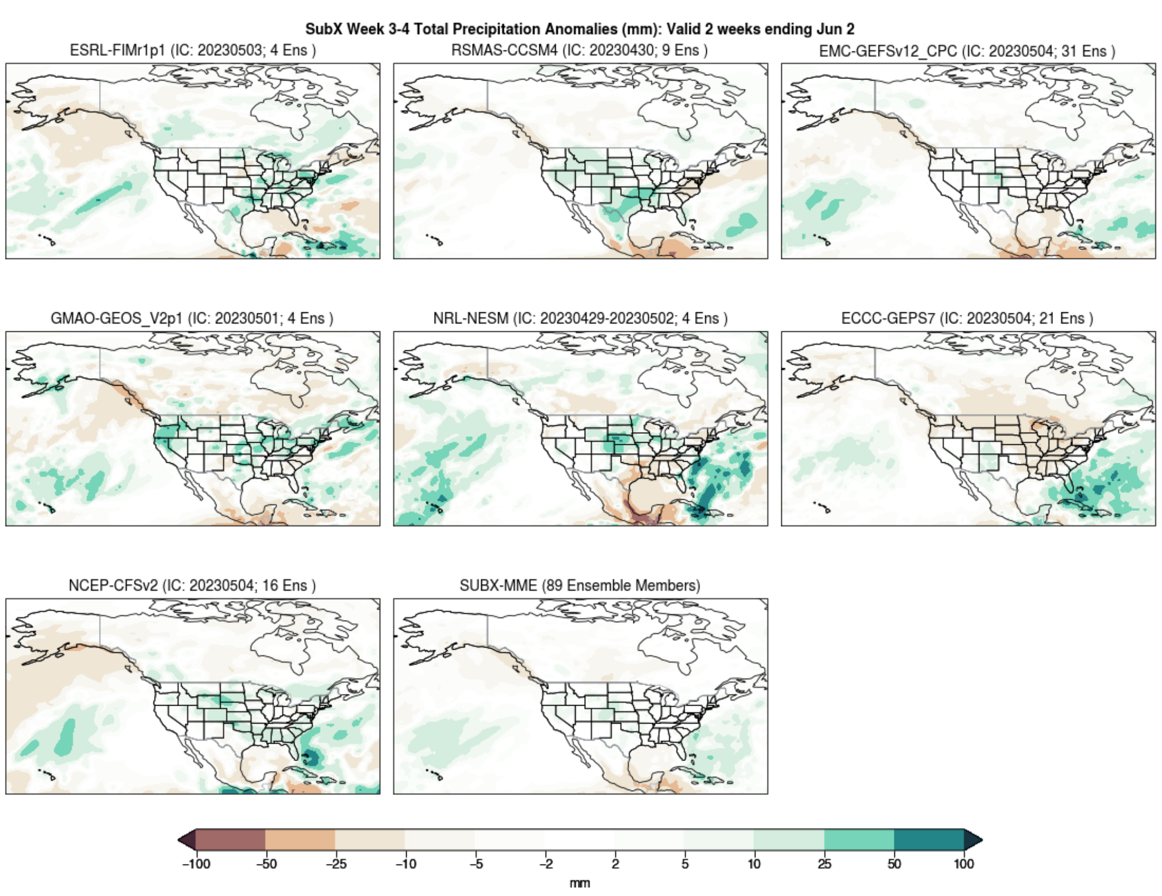
On a single level

Variable	CF Standard Name	Abbrev	Unit	Frequency
2m Temperature	air_temperature	tas	K	Daily Average
Precipitation	precipitation_flux	pr	kgm-2s-1	Accumulated every 24hrs
Surface Temperature (SST+Land)	surface_temperature	ts	K	Daily Average
Outgoing Longwave Radiation at top of Atm	toa_outgoing_longwave_flux	rlut	Wm-2	Accumulated every 24hrs

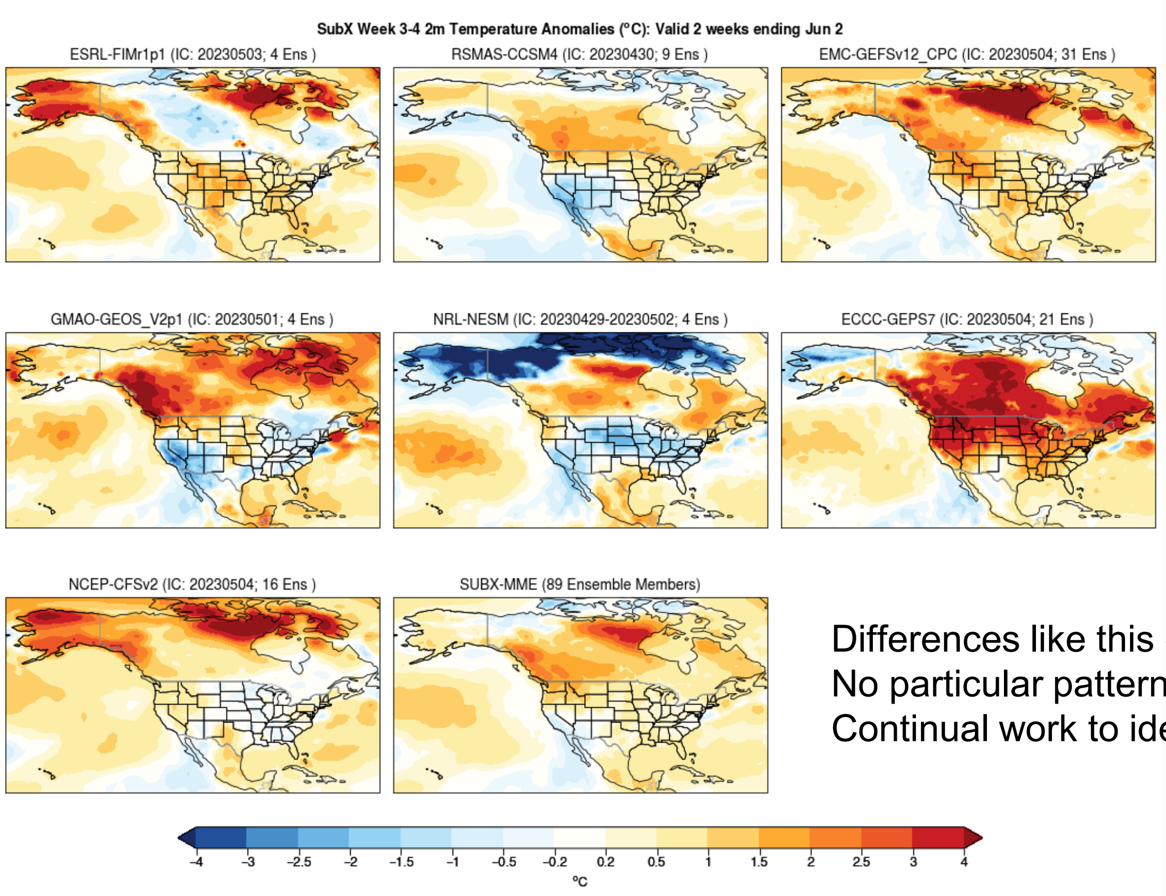
Sub-X Project

- Weeks 3-4 predictability for T2m (and especially QPF) is very low
- Mid-latitude subseasonal predictions rely heavily on teleconnections with tropics
- Mass/momentum biases might give some insight into global teleconnections
- Routine comparison of subseasonal (weeks 3-4) T2M and precip anomalies from multiple modeling groups (been doing this for multiple years)
- Ensembles important to provide probabilistic information
  - Initial conditions, stocastic physics
  - Multi-physics
- Gain insights on the error characteristics, which can be addressed in the model physics

Example: Precip Anomaly: Valid 2-weeks ending 2 Jun 2023



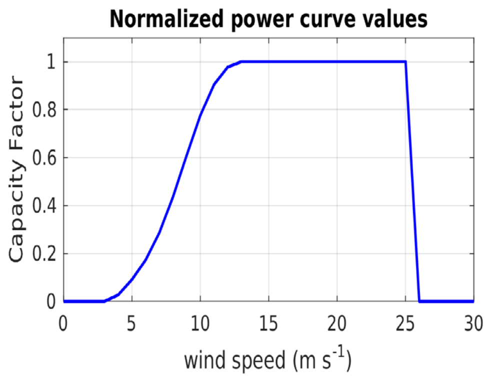
Example: T2m Anomaly: Valid 2-weeks ending 2 Jun 2023



Differences like this occur regularly!
No particular pattern among the models
Continual work to identify error sources

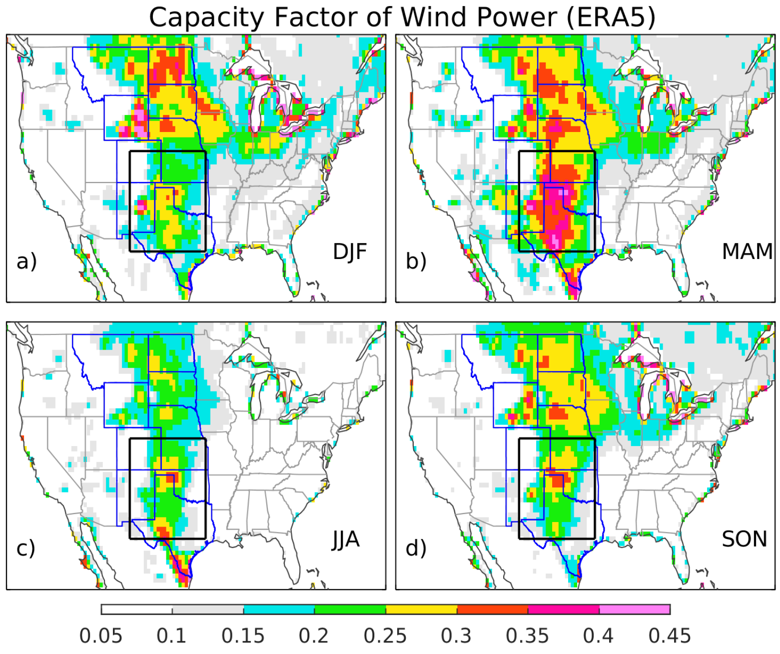
Changing Gears: Seasonal Wind Energy Forecasts

- Research project at NOAA's Geophysical Fluid Dynamics Lab (GFDL)
- Using their Seamless System for Prediction and Earth System Research (SPEAR) model
- Resolutions: Atmos/Land (about 50km, 33 levels) and Ocean/Ice (about 1º, 75 layers)
- SPEAR's seasonal retrospective forecasts (Lu et al. 2020)
  - 12-month forecast initialized on 1st day each month from 1991 to present
  - 15 members
  - Real-time forecast for **North American Multi-Model Ensemble**
- Capacity factor (CF): an indicator of wind energy as a function of wind speeds at the turbine height (about 80-100 meters).
- Skill assessment
  - Target season: December-February (DJF), March-May (MAM) (1992-2022)
  - Verification data: the ERA5 reanalysis
- Predictability source analysis (major large-scale climate modes)
  - ENSO: leading source of boreal winter storm track predictability
  - North Pacific Oscillation (NPO): impact on winter SAT and storm tracks over North America
  - North Atlantic Oscillation (NAO): storm tracks over the far Northeastern United States and Canada

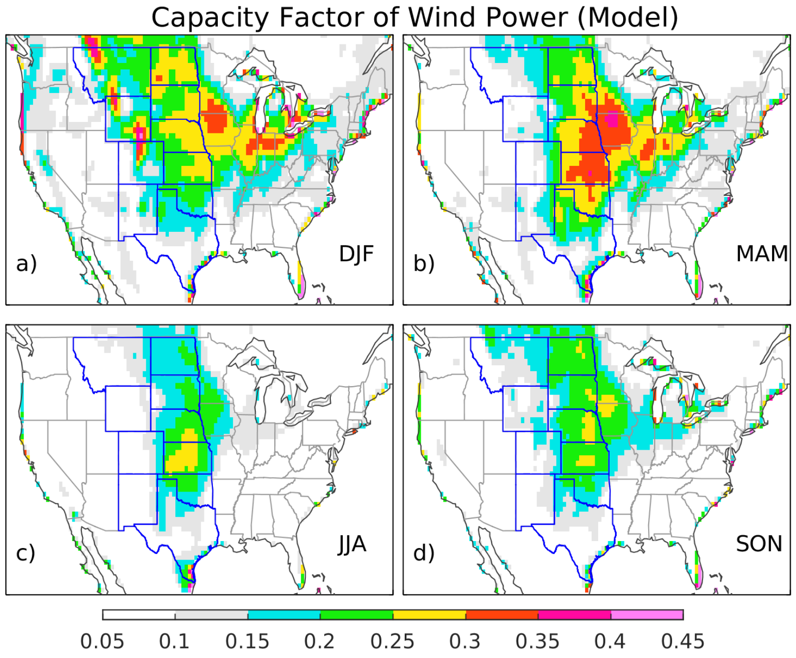


Predicting the Seasonal Climatology of Capacity Factor

Truth (from ERA5)



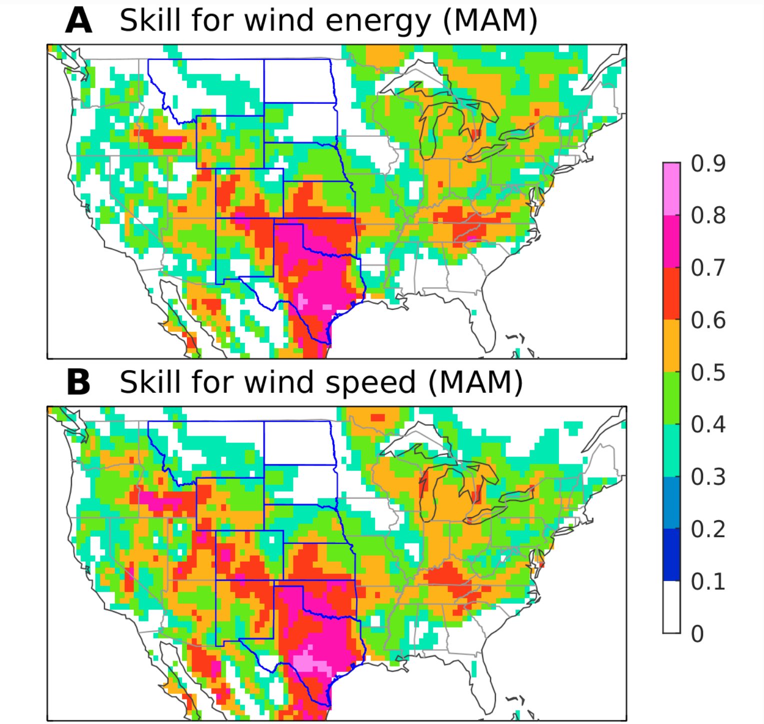
Seasonal Predictions from SPEAR



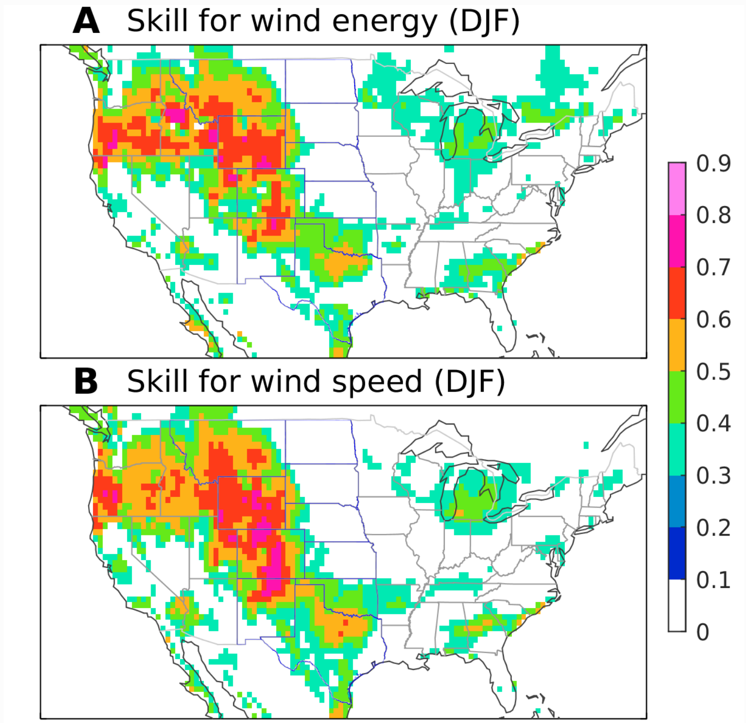
Statistics computed over 30 years

Correlation (skill) in predicting wind and capacity factor

Spring Season



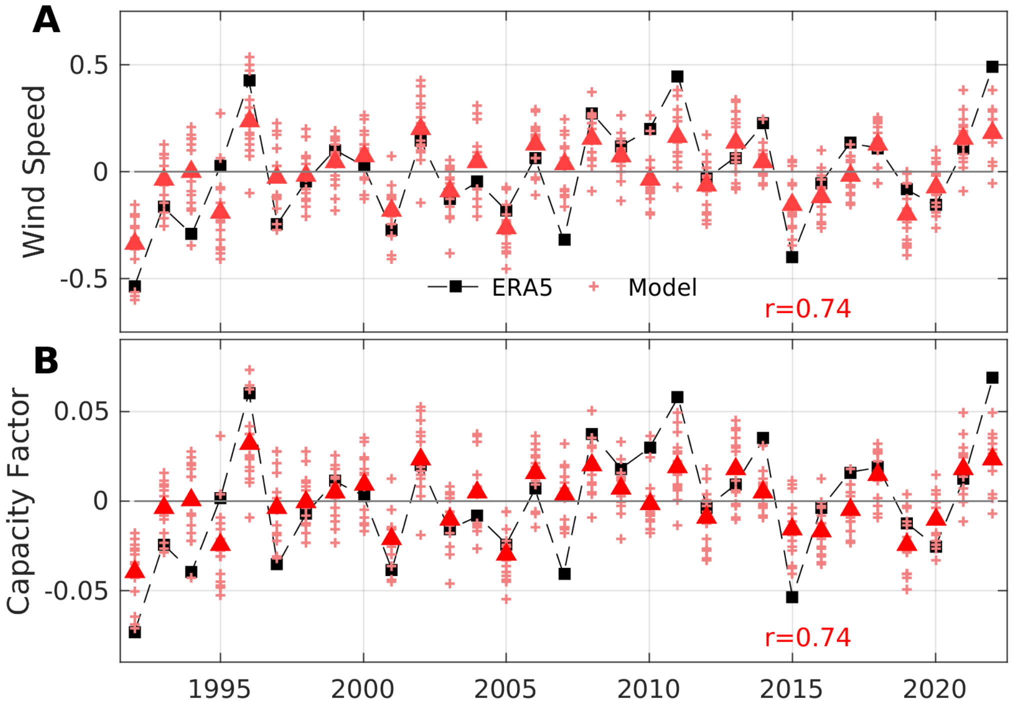
Winter Season



Statistics computed over 30 years
Correlation between (ERA5 reanalysis) vs (SPEAR Seasonal Predictions)

Seasonal prediction of CF over the Southern Great Plains

- Over the southern Great Plains, the CF is highly predictable with a correlation skill of 0.74.
- The CF over the southern Great Plains is significantly correlated with ENSO (r=0.61).
- Other significant contributions from PNA and NAO.



What do we need from S2S outlooks for wind energy?

- S2S forecasts need to be used at larger spatial scales
  - How do we imagine these outlooks will be used?
- Knowing how the 3-4 week (or 2 to 12 month) forecasts will be used will help with both
  - Outlook verification
  - Model development
- Example: Wind droughts for planning
- Almost never evaluate S2S models using contingency tables
- Need to consider conditional verification, wherein we evaluate outlooks as function of driver
  - E.g., state of the ENSO
- Post-processing (e.g., bias correction) and use of machine learning approaches should help extract extra value

Summary

- NOAA is splitting the subseasonal-to-seasonal forecast needs into two systems
  - Subseasonal (3-4 weeks outlooks): By the UFS medium-range forecast system
    - Very active research on improving physics and building a skillful ensemble
  - Seasonal (2 months to 2 years): Starting a new effort to create a Seasonal Forecast System (SFS)
    - Will ultimately replace the current operational CFS for seasonal outlooks (planned for FY 2026)
- Predictability at these longer (S2S) time ranges is low
  - Some variables show some predictability based upon global teleconnection patterns
  - ENSO (seems very important), Pacific North American (PNA), North Atlantic Oscillation (NAO)
  - SPEAR seasonal wind outlooks show some skill at predicting turbine capacity factor (very experimental)
  - Ensembles will be key to quantify probabilities
  - Machine learning techniques are providing clues to when these models have more skill (not shown)
- Verification is key to improving these modeling systems and outlooks
  - No one model seems better than another at either subseasonal or seasonal outlooks
  - Errors depend on variable (phenomenon) of interest, geographic location, lead time
  - Many errors at these longer time-range are due to compound events (e.g., rain followed by drydown)
  - Need more methods to evaluate these longer forecasts, esp for compound events