Update on NOAA's High-Resolution Rapid Refresh Forecast Models

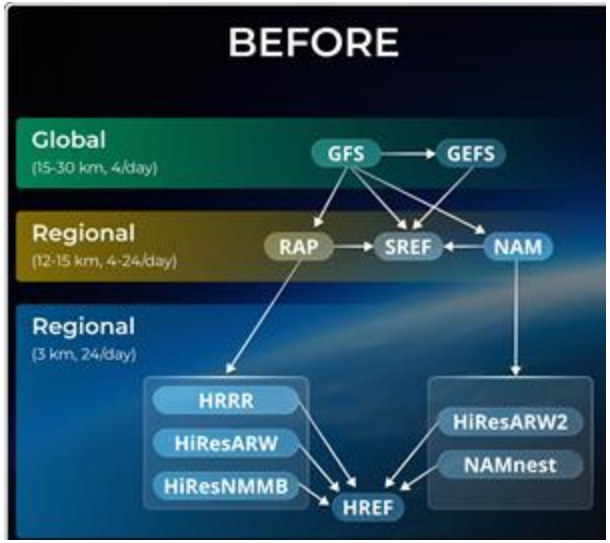
NOAA Atmospheric Science for a Resilient Environment Program
Global Systems Lab, Physical Sciences Lab, Global Monitoring Lab, Chemical Sciences Lab
Contribution from National Lab of Rockies too

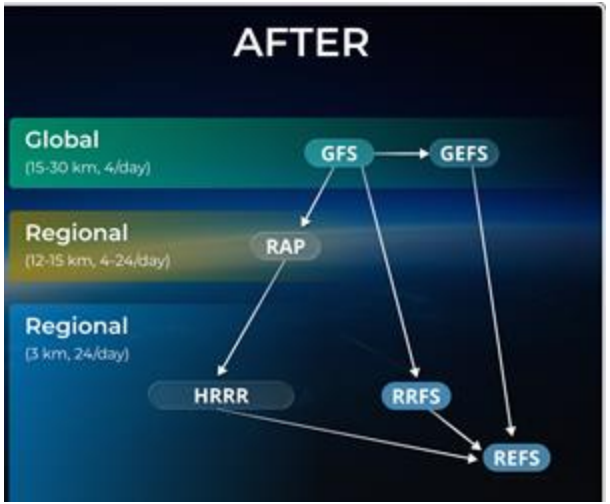
Dave Turner, Senior Scientist NOAA

Update on RRFS

Rapid Refresh Forecast System

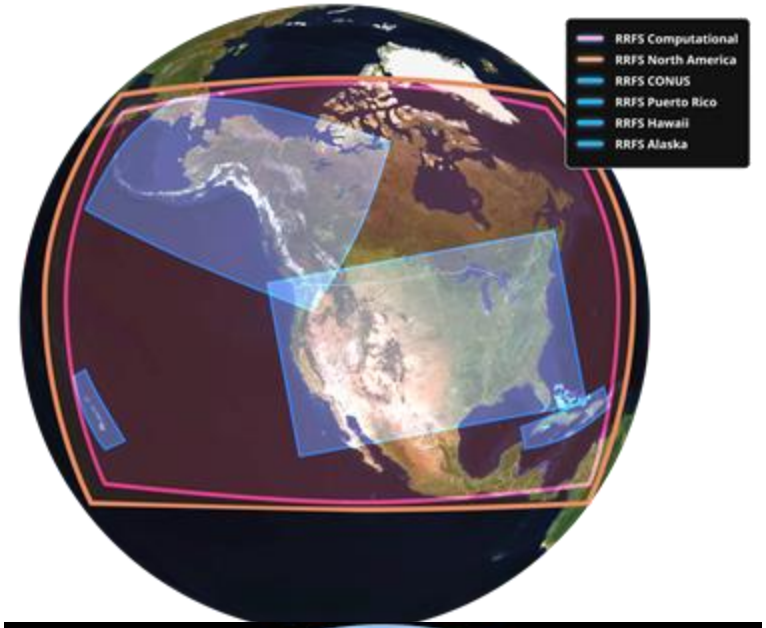
- 3-km grid, rapidly updating model
- Goal: simplify the operational modeling suite, and thus these models will be retired
  - NAM / NAM-nest, HREF, SREF, and HiresW
  - Additional info in NWS Service Change Notice 26-48
- RRFS has a deterministic member, and a 5-member ensemble (REFS)
- Will become operational 31 August 2026 at 12z (unless there is inclement weather)
- The HRRR and RAP will continue to be run operationally !!

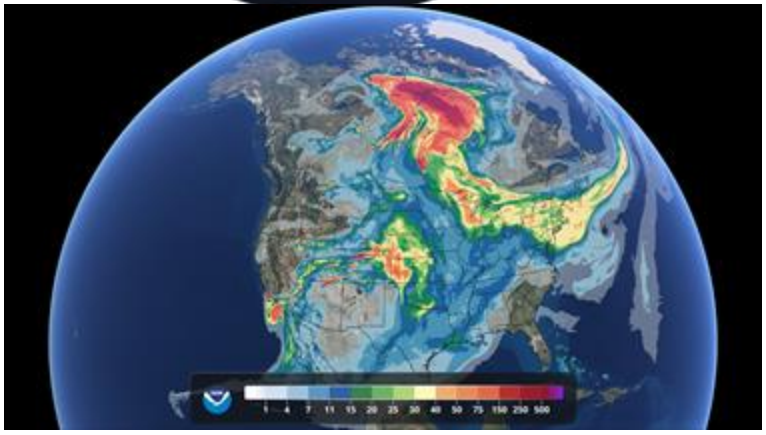




Update on RRFS

- RRFS – 18 h forecasts every hour, with 84 h forecasts for 00/06/12/18 UTC
- REFS – 60 h forecasts at 00/06/12/18 UTC
  - 5 members with physics diversity, and the HRRR (so 7 members total)
  - Adds a 6- time-lagged forecasts also
- Domain is full North American domain at 3 km
  - Data volume of RRFS and REFS, all variables over entire domain for all forecast hours, is 80 TB/day
  - Cut-outs over CONUS and Alaska at 3 km
  - Cut-outs over Hawaii and Puerto Rico
- Data will be on the NOAA Open Data Dissemination (NODD) cloud platform
- Smoke and dust forecasts in control member
- There is a 30-min time-lag issue in the RRFSv1 SWdown radiation!





Evaluation of Solar Forecasts from RRFS

- Shaw, Larson, and Turner – in review *Solar Energy*
- Evaluated experimental RRFS SWdown forecasts from 1 Mar - 8 July 2024
- HRRR and RRFS control are pretty comparable
- Some ensemble members are much worse (physics diversity)
- Ensemble mean provides most skill

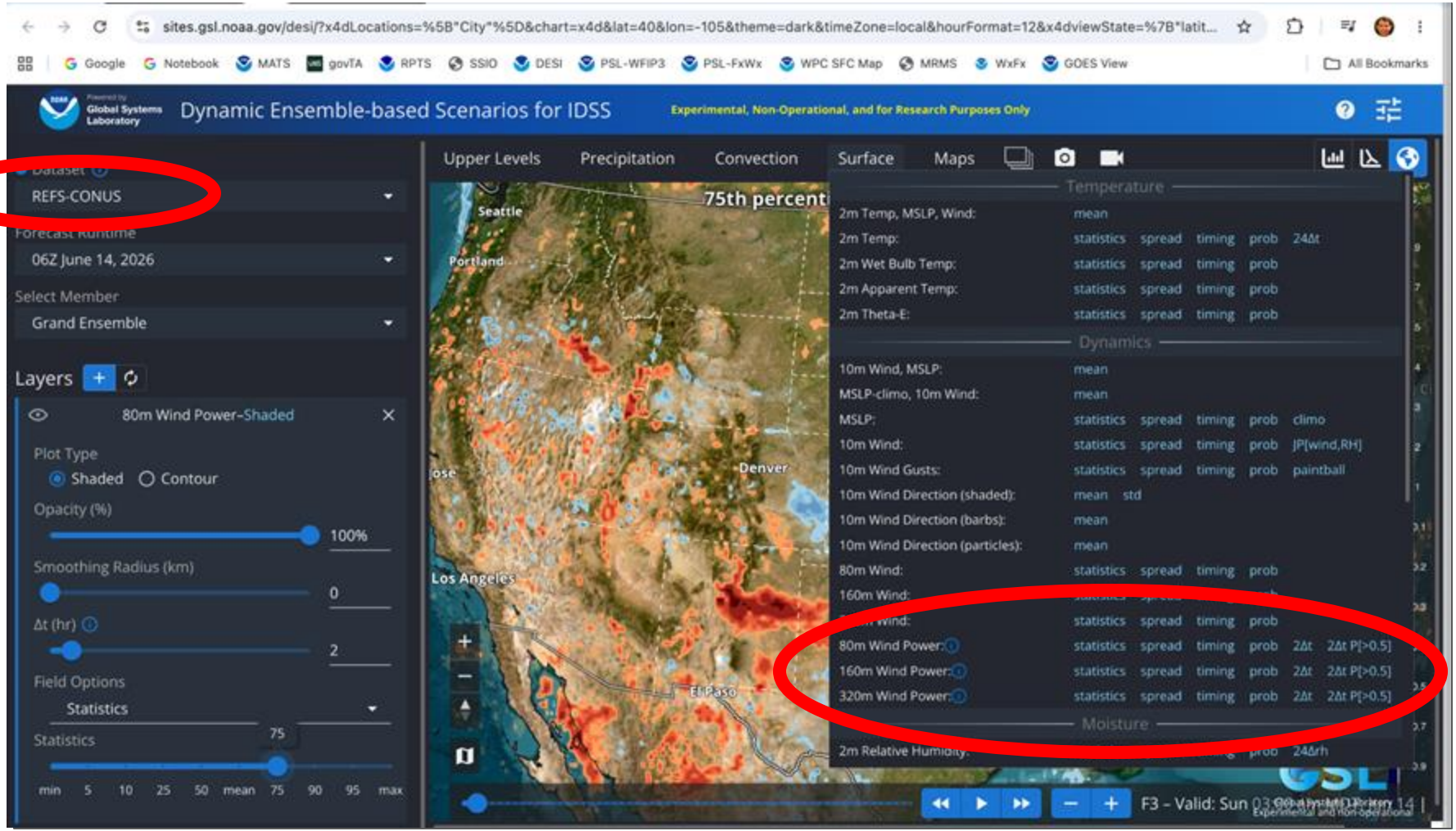
Location	HRRR	RRFS Control	RRFS mem1	RRFS mem2	RRFS mem3	RRFS mem4	RRFS mem5	Ens. Mean
BON	**158.1**	169.0	192.9	164.3	179.4	190.2	172.4	140.8
DRA	91.6	92.9	97.0	**89.3**	89.9	105.3	89.6	82.1
FPK	163.4	**157.9**	167.6	163.2	171.3	187.0	171.4	136.5
GWN	**160.2**	168.2	192.2	172.1	173.9	207.2	163.8	139.5
PSU	**153.5**	167.0	193.2	164.5	160.7	198.9	165.7	135.0
SXF	157.0	**154.0**	178.8	154.7	165.7	182.5	160.8	124.0
TBL	180.3	172.9	189.6	**170.4**	182.7	195.4	188.2	151.7

Jonah Shaw (CU), David Larson (formerly EPRI)

Ramp Events with RRFS and DESI

- Ensemble allows probabilistic and timing info to be determined
- RRFS includes wind output at 80 m (like HRRR), but also 160 and 320 m
- DESI provides way to interrogate the RRFS ensemble (denoted REFS)
  - https://sites.gsl.noaa.gov/desi

Travis Wilson, Ken Fenton (GSL)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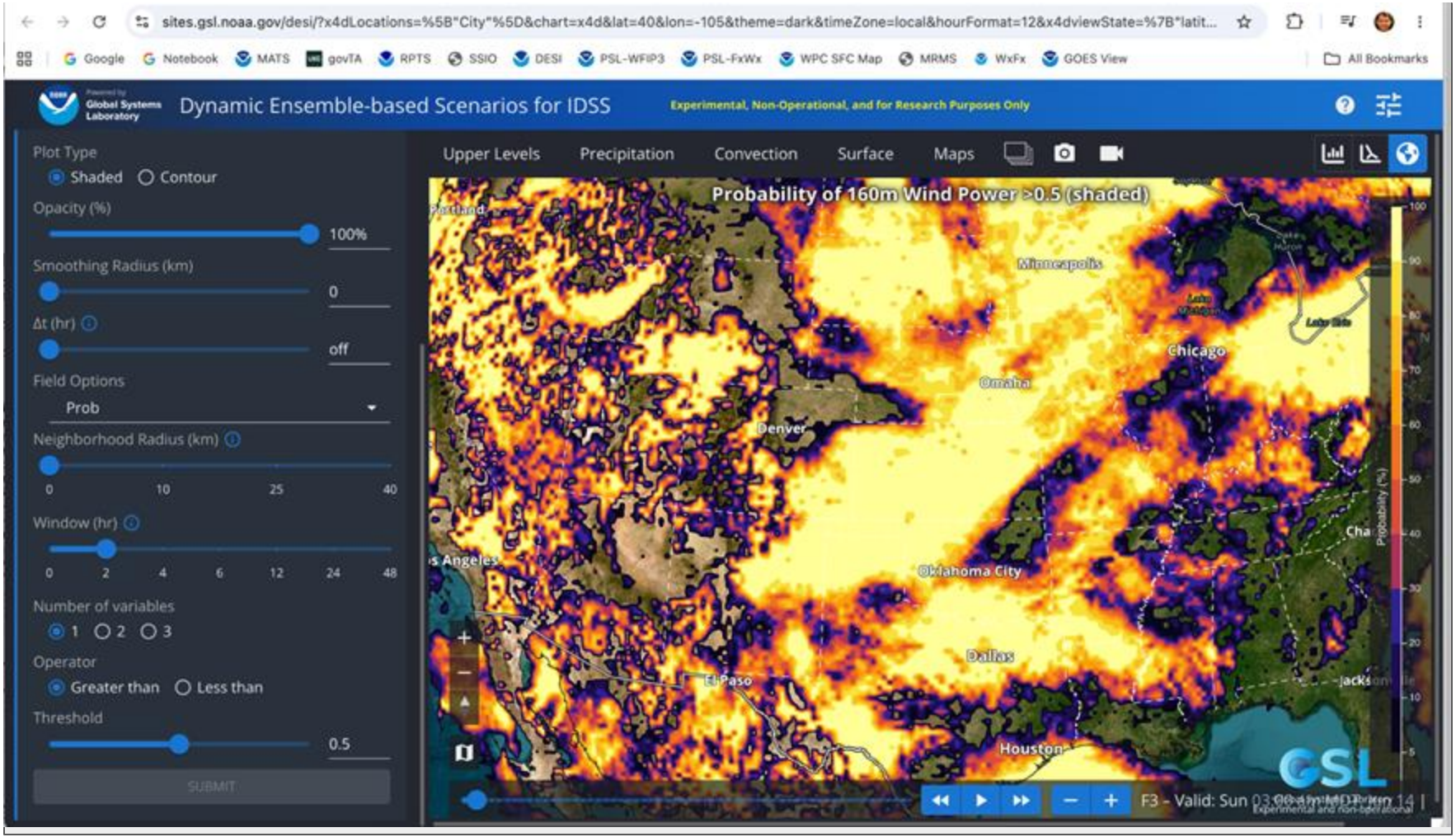
MATS
govTA
RPTS
SSIO
DESI
PSL-WFIP3
PSL-FxWx
WPC SFC Map
MRMS
WxFx
GOES View
All Bookmarks
Global Systems Laboratory
Dynamic Ensemble-based Scenarios for IDSS
Experimental, Non-Operational, and for Research Purposes Only
REFS-CONUS
06Z June 14, 2026
Grand Ensemble
Layers
80m Wind Power-Shaded
Plot Type
Shaded
Contour
Opacity (%)
100%
Smoothing Radius (km)
0
Δt (hr)
2
Field Options
Statistics
Statistics
75
min 5 10 25 50 mean 75 90 95 max
Upper Levels
Precipitation
Convection
Surface
Maps
75th percenti
Seattle
Portland
Denver
Los Angeles
El Paso
Temperature
2m Temp, MSLP, Wind: mean
2m Temp: statistics spread timing prob 24Δt
2m Wet Bulb Temp: statistics spread timing prob
2m Apparent Temp: statistics spread timing prob
2m Theta-E: statistics spread timing prob
Dynamics
10m Wind, MSLP: mean
MSLP-climo, 10m Wind: mean
MSLP: statistics spread timing prob climo
10m Wind: statistics spread timing prob JP[wind,RH]
10m Wind Gusts: statistics spread timing prob paintball
10m Wind Direction (shaded): mean std
10m Wind Direction (barbs): mean
10m Wind Direction (particles): mean
80m Wind: statistics spread timing prob
160m Wind:
Wind: statistics spread timing prob
80m Wind Power: statistics spread timing prob 2Δt 2Δt P[>0.5]
160m Wind Power: statistics spread timing prob 2Δt 2Δt P[>0.5]
320m Wind Power: statistics spread timing prob 2Δt 2Δt P[>0.5]
Moisture
2m Relative Humidity: prob 24Δrh
F3 - Valid: Sun 03
Experimental and non-Operational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WxFx
GOES View
All Bookmarks
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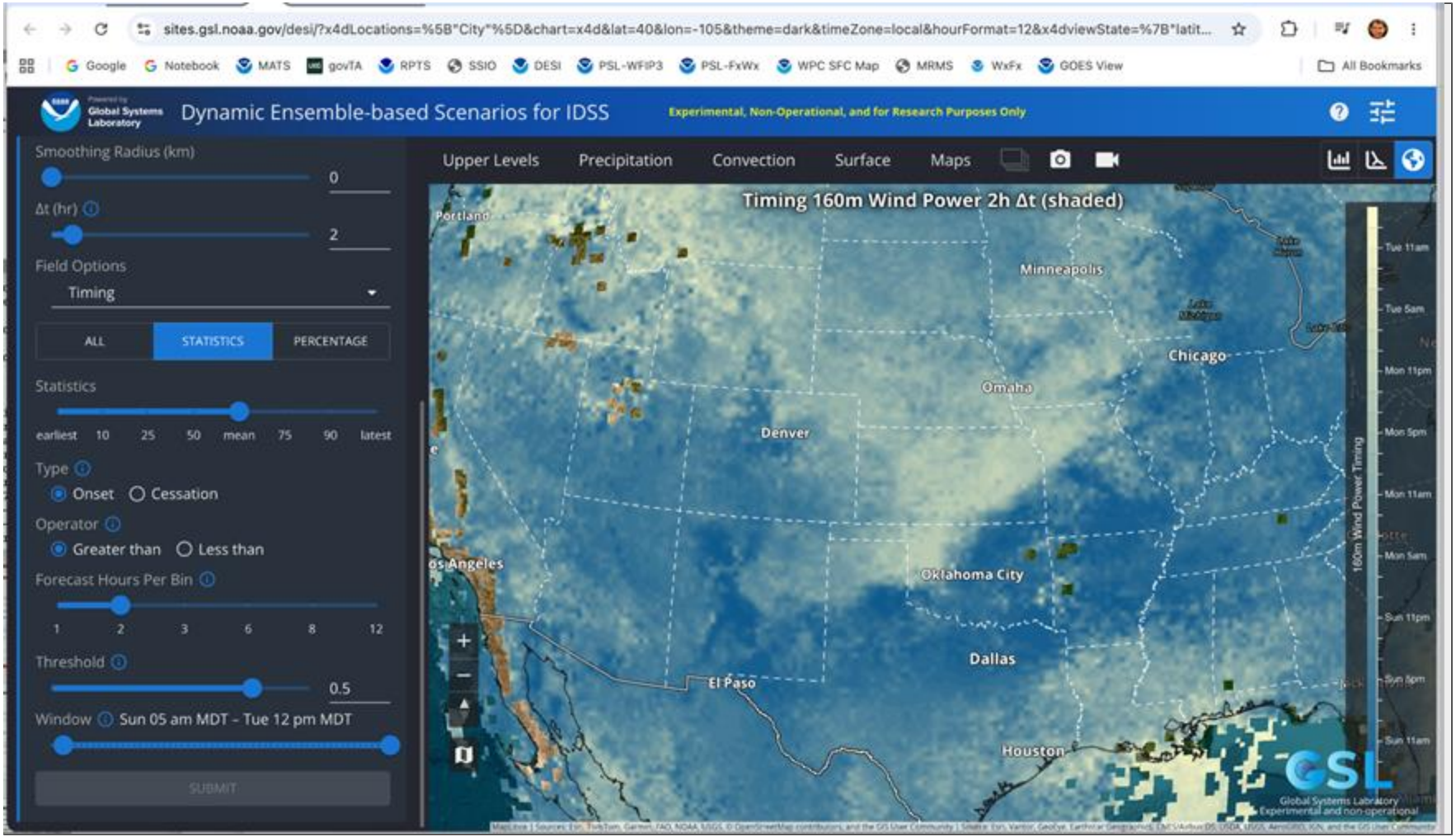
Plot Type
Shaded
Contour
Opacity (%)
100%
Smoothing Radius (km)
0
Δt (hr)
off
Field Options
Prob
Neighborhood Radius (km)
0
10
25
40
Window (hr)
0
2
4
6
12
24
48
Number of variables
1
2
3
Operator
Greater than
Less than
Threshold
0.5
SUBMIT
Upper Levels
Precipitation
Convection
Surface
Maps
Probability of 160m Wind Power >0.5 (shaded)
Minneapolis
Chicago
Omaha
Denver
Oklahoma City
Dallas
El Paso
Houston
Probability (%)
GSL
F3 - Valid: Sun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Google
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0
Δt (hr)
2
Field Options
Timing
ALL
STATISTICS
PERCENTAGE
Statistics
earliest 10 25 50 mean 75 90 latest
Type
Onset
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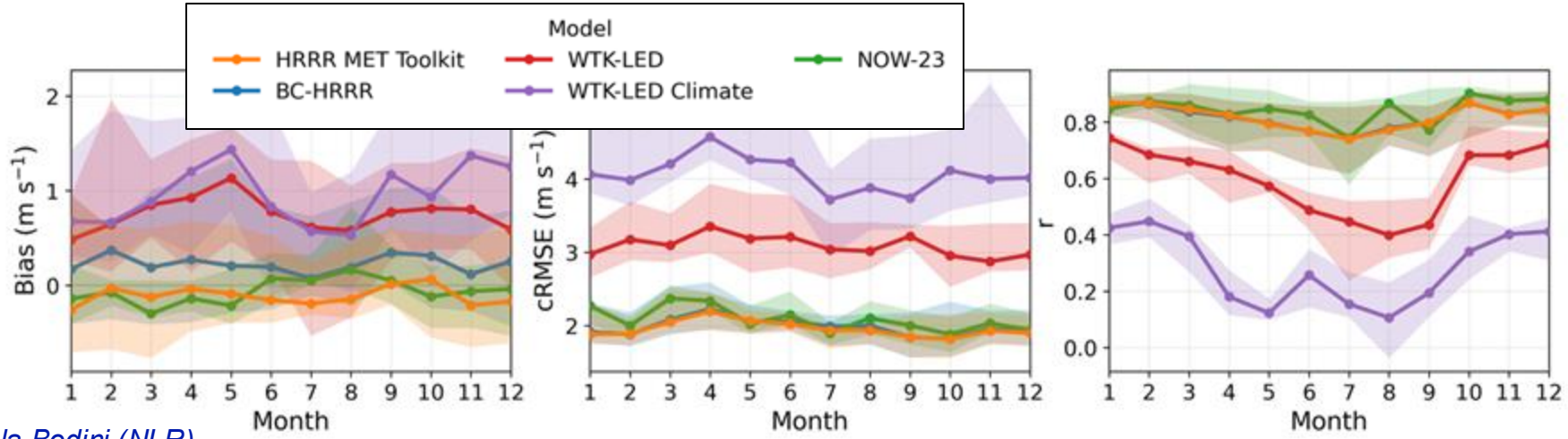
Operator
Greater than
Less than
Forecast Hours Per Bin
1 2 3 6 8 12
Threshold
0.5
Window
Sun 05 am MDT - Tue 12 pm MDT
SUBMIT
Upper Levels
Precipitation
Convection
Surface
Maps
Timing 160m Wind Power 2h Δt (shaded)
Portland
Minneapolis
Chicago
Omaha
Denver
Oklahoma City
Dallas
El Paso
Houston
160m Wind Power Timing
Tue 11am
Tue 5am
Mon 11pm
Mon 5pm
Mon 11am
Mon 5am
Sun 11pm
Sun 5pm
Sun 11am
GSL
Global Systems Laboratory
Experimental and non-operational

HRRR-MET Dataset

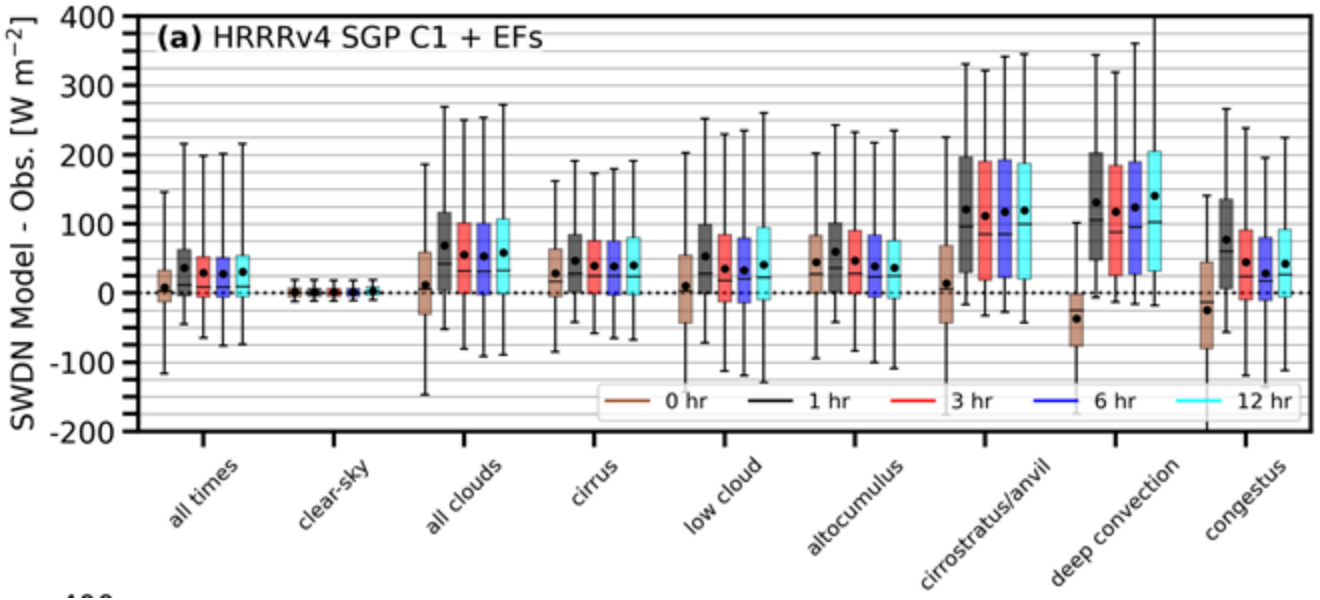
- National Lab of Rockies (NLR) repackaged HRRR 2h forecast data from 2015-2025 to be consistent in format with the Wind Tool Kit (WTK) data (2007-2013)
- Evaluated HRRR-MET (and two other WTK datasets) against observations
- HRRR-MET had best statistics; currently creating a HRRR-MET for Alaska now
- Bodini et al., *Wind Energy Science*, submitted



Nicola Bodini (NLR)

SWdown bias in the HRRR: Cloud type

- Utilize the NOAA SURFRAD network
- Apply ML-based cloud typing algorithm (Sedlar et al. JAMC 2021)
- Clear sky situations are well-modeled
- Initialization times also have small bias (skill of the cloud DA)
- Largest errors occur when we have the deepest clouds

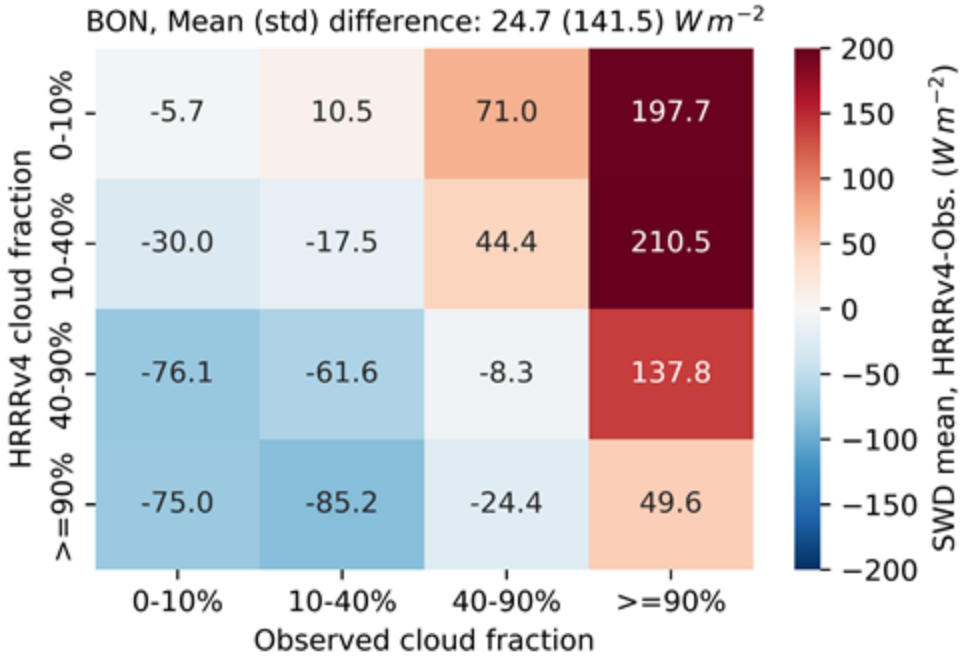


Kelly Balmes, Joe Sedlar (GML)

SWdown bias in the HRRR: Cloud fraction

- SWdown bias sensitive to both cloud fraction and cloud optical depth
- Separating results by cloud fraction demonstrates that largest issues are when we have overcast situations
  - Too little cloud fraction
  - Too little cloud optical depth (mass)
- Previous slide suggested the issue is that we have too little liquid water
- Why?

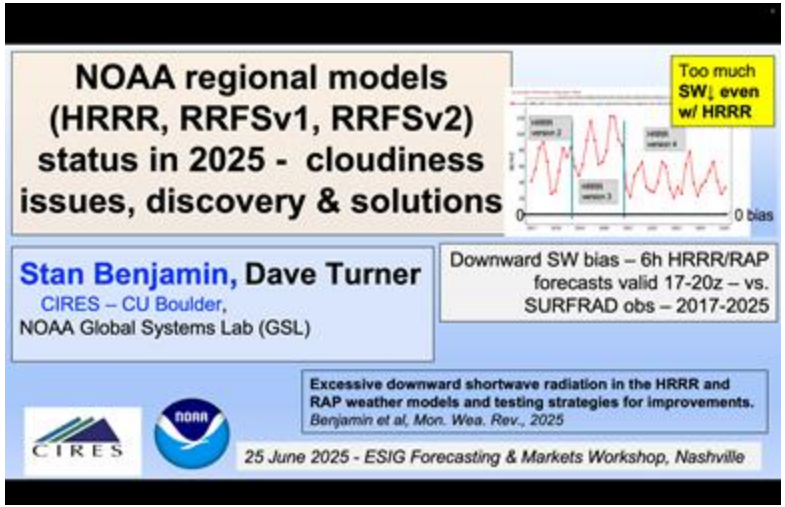
Example at SURFRAD site in Bondville, IL



Kelly Balmes, Joe Sedlar (GML)

Dry Bias and Cloudiness Issues in the HRRR

- Stan Benjamin spoke about this at last year's ESIG met workshop
- RRFS.v1 code is already frozen, but working on RRFS.v2
  - .v2 should become operational in ~2028
- Dry bias in model results in too few clouds, thus too much SWdown
- Continuing work to understand dry bias



Stan Benjamin, Eric James (GSL)

Dry Bias and Cloudiness Issues in the HRRR

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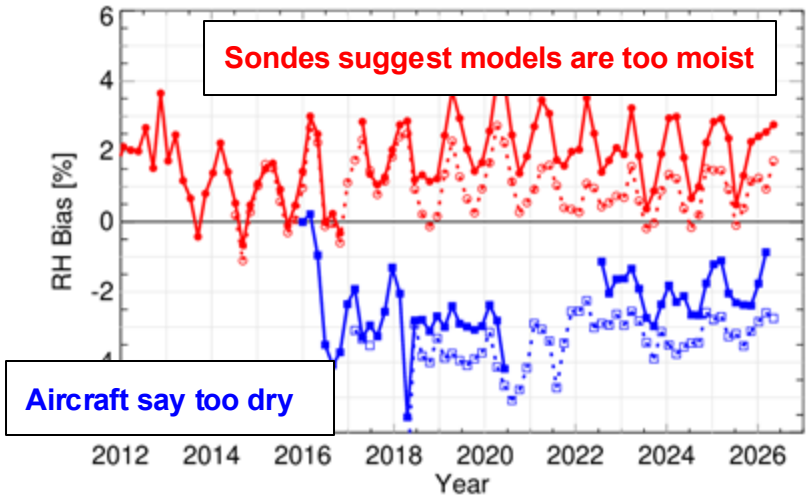
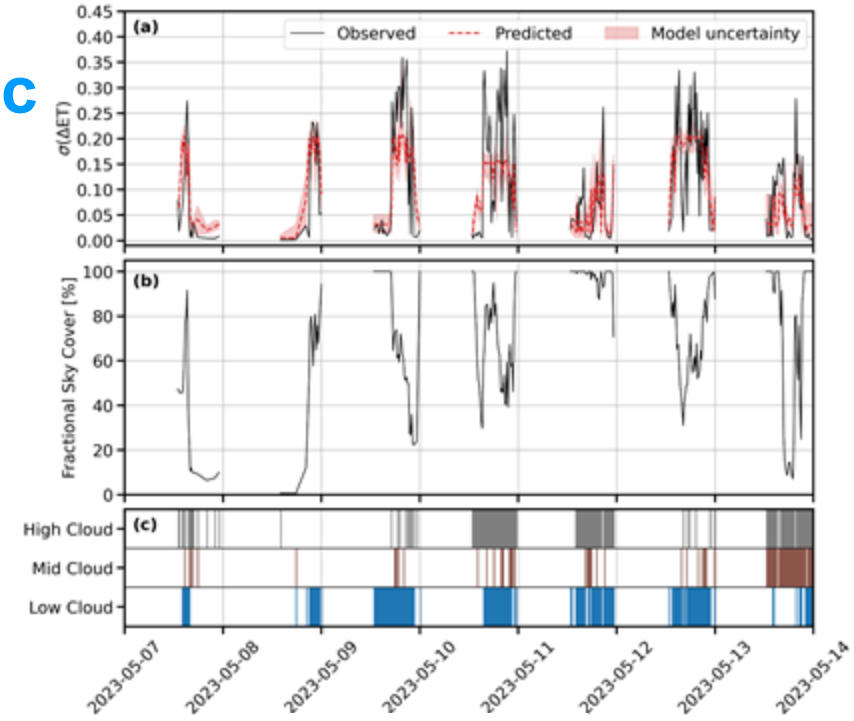
  - .v2 should become operational in ~2028
- Dry bias in model results in too few clouds, thus too much SWdown
- Continuing work to understand dry bias
- NWS radiosondes suggest models are too moist, but AMDAR aircraft say models are too dry
- Been able to show sondes have an RH bias issue when RH is close to saturation!
- Benjamin et al., BAMS, in preparation

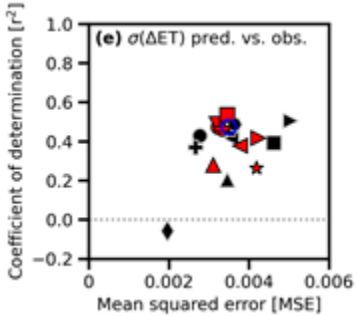


Stan Benjamin, Eric James (GSL)

SWdown variability diagnostic

- New paper recently published in *Solar Energy (Balmes et al. 2026)*
- Machine learning (ML) model was developed to predict solar variability from cloud cover and cloud type
- The ML model was evaluated at 16 NOAA SURFRAD and DOE ARM sites across CONUS and globe
- The ML model was found to be largely generalizable and could be used with NWP model output to forecast day-ahead solar variability

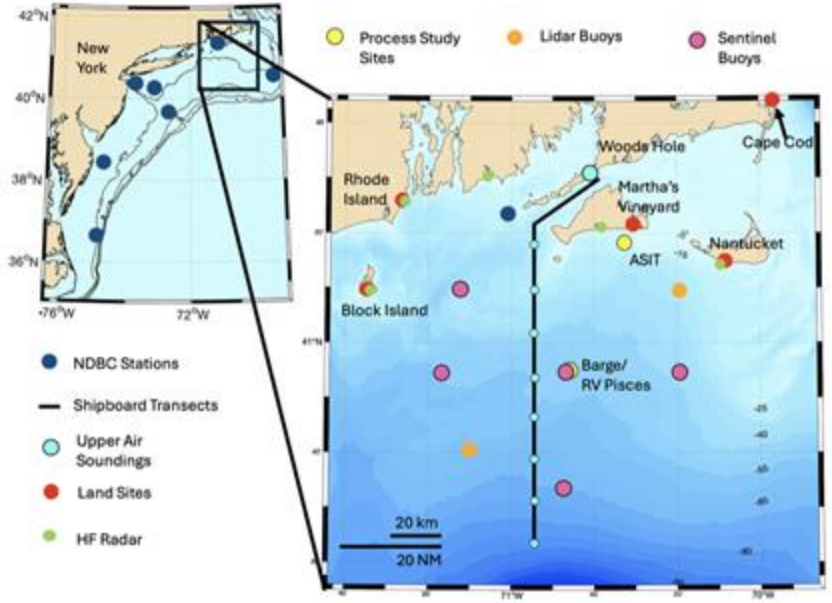




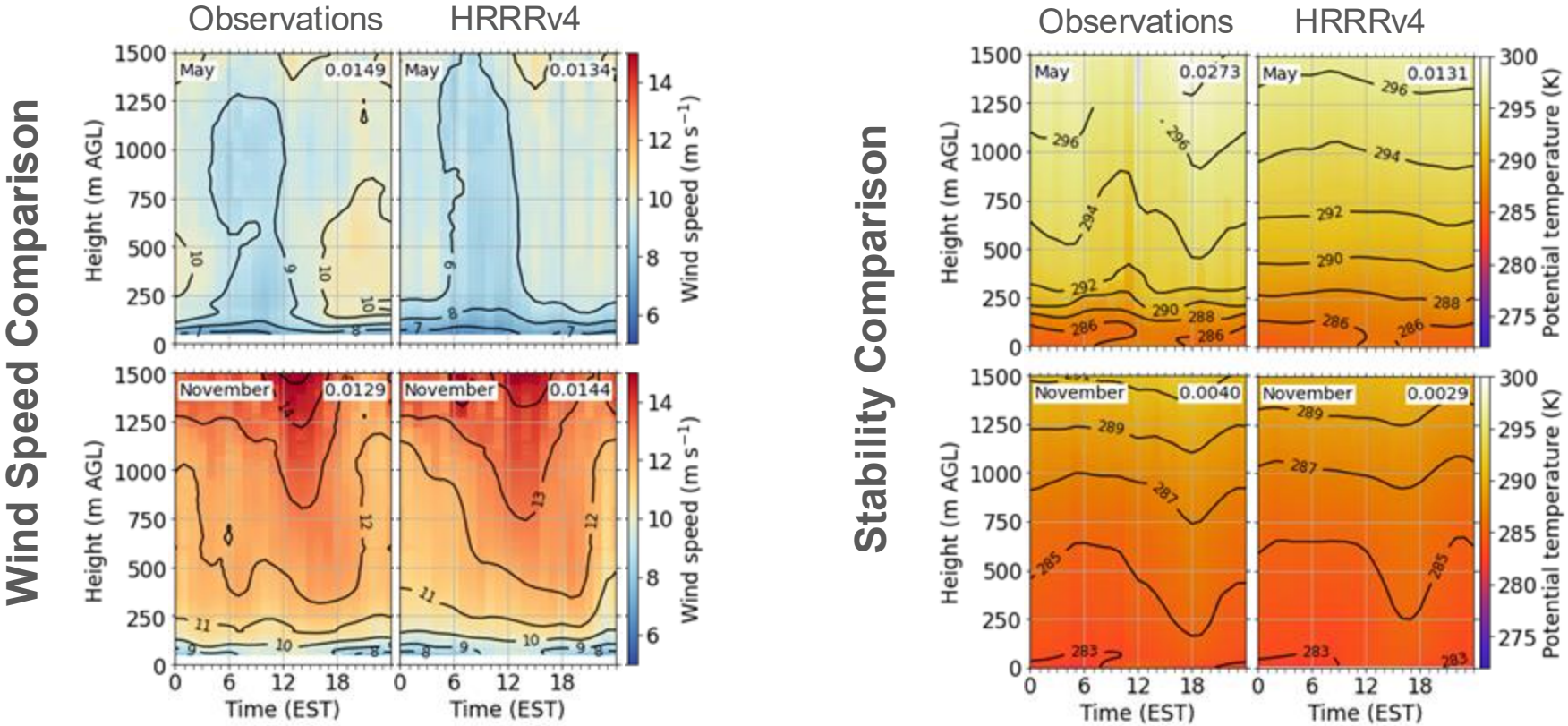
Kelly Balmes, Laura Riihimaki (GML)

3rd Wind Forecast Improvement Project (WFIP-3)

- Focused field campaign and analysis off the east coast of the US
  - Field campaign from Feb 2024 to August 2025
- QC'd data in DOE Wind Data Hub
- Overview in Kirincich et al. BAMS (in review)
- Many studies looking at various processes
- Evaluated HRRR offshore
  - Sensitive to boundary conditions (SST)
  - Able to capture stability well
  - Too weak LLJs (too much mixing)
- Improvements made to RRFS.v2
- Working on improving clouds now



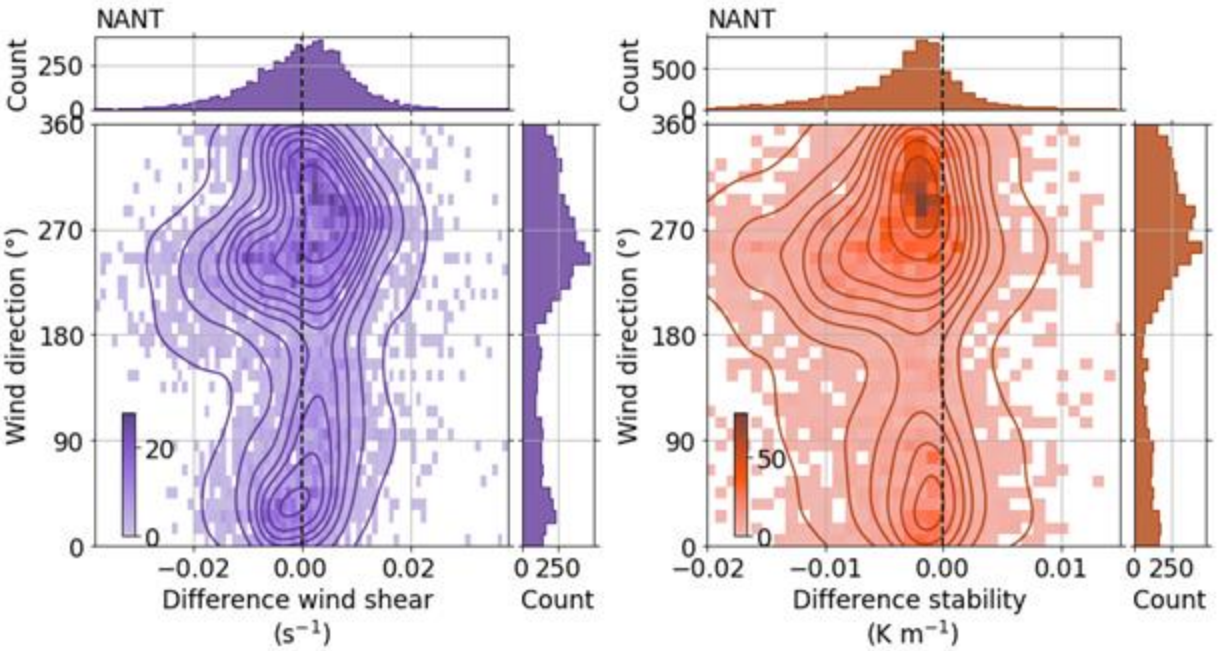
HRRR errors along the coast of southern New England

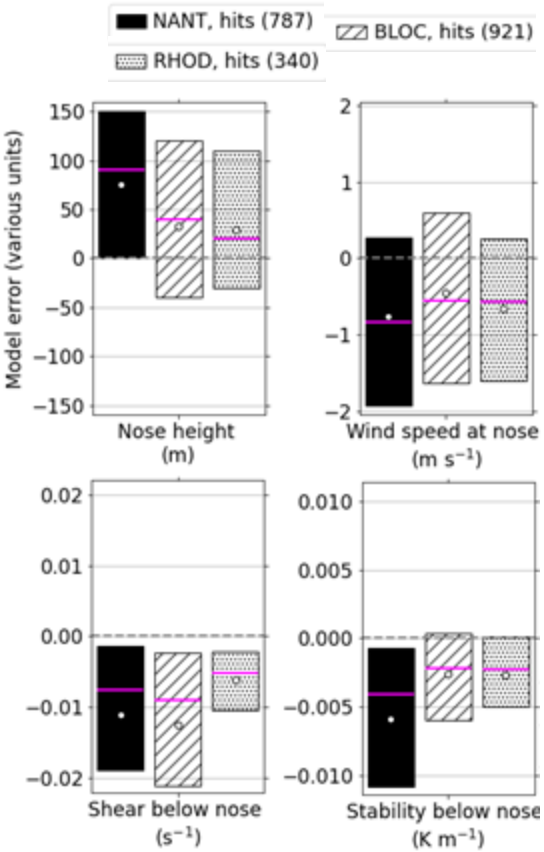


HRRRv4 overall does a good job in capturing the diurnal cycle of wind speed and stable stratification in the MBL

Bianca Adler and Laura Bianco (PSL)

Low-level shear and stability errors: Dependence on wdir

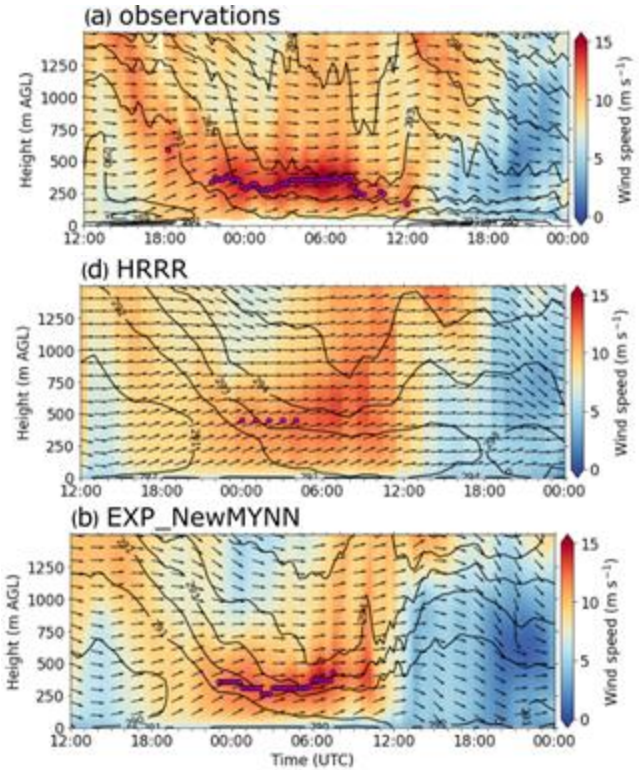




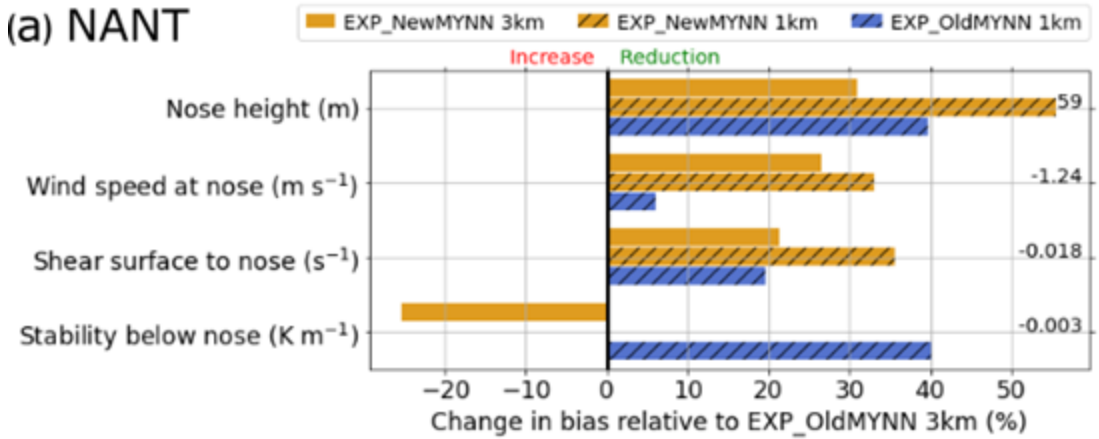
- HRRRv4 underestimates shear and stability especially for southwesterly flow during LLJs
- HRRRv4 errors are consistent at 3 sites along the coast

Bianca Adler and Laura Bianco (PSL)

Improvements to LLJ forecasts with new MYNN-EDMF



New MYNN-EDMF much better captures LLJ strength and structure in this example



Robust improvements of more than 20 % for nose height, wind speed and shear due to new MYNN-EDMF on average

This is the HRRR.v4

Joe Olson and Xia Sun (GSL) and Bianca Adler and Laura Bianco (PSL)

HRRRcast: AI-powered weather prediction

- HRRRcast was developed from the archived HRRR forecasts
- Goal: to provide a computationally inexpensive ensemble for the HRRR
- Started from GraphCast approach; however, moved toward our own method for number of reasons (computation efficiency during training, loss functions)
- Training method
  - Emphasizes accuracy in radar reflectivity (spread / skill)
  - Members do NOT have realistic storm structure (that was not the objective of the training)
  - Have not included focus on low level winds or solar irradiance
- .v1 described in Abdi et al. AIRES 2006; already have .v3 running
- Part of the NOAA Project EAGLE (Experimental AI Global and Limited-area Ensemble forecast system)

Daniel Abdi and Isidora Jankov (GSL)

Summary

- Continued to evaluate HRRR using range of observations to understand what drives bias in low-level winds and solar irradiance
- Improved understanding from above used to improve RRFS.v2
- RRFS.v1 code is frozen, and will become operational on 31 Aug 2026
  - Is an ensemble system (REFS), and will replace most operational regional modeling systems
  - HRRR (and RAP) will remain operational until RRFS.v2 becomes operational in ~2028
  - Experimental RRFS.v2 is beating the HRRR in the Hazardous Wx Testbed's Spring Forecast Experiment (done this twice in a row: 2025 and 2026)
    - First time that the HRRR's been beat in the HWT spring experiment since 2016
- AIWP is coming on strong within NOAA, but focus has been on convection and it may be another year or two before other applications have a focus
  - Many other AI applications being developed…

Questions? Dave.Turner@noaa.gov