Advancing atmosphere-wave-ocean coupling to improve surface wind and wave forecasts for maritime shipping

Stephen G. Penny - Head of Weather

Sofar Team:
Colin Grudzien, Wolfgang Langhans, Miguel Solano
Moriah Cesaretti, Ciara Dorsay, John Orcutt, Camille Teicheira

Collaborators:
Tim Smith (NOAA), Tse-Chun Chen (PNNL), Jason Platt (UCSD), Mike Goodliff (RIKEN), Kylen Solvik (CU Boulder), Stephan Hoyer (Google Research), Lucas Harris & FV3-SHiELD team (GFDL)

ECMWF 50th Anniversary - 9 Apr 2025
Surface process coupling and its interactions with the atmosphere

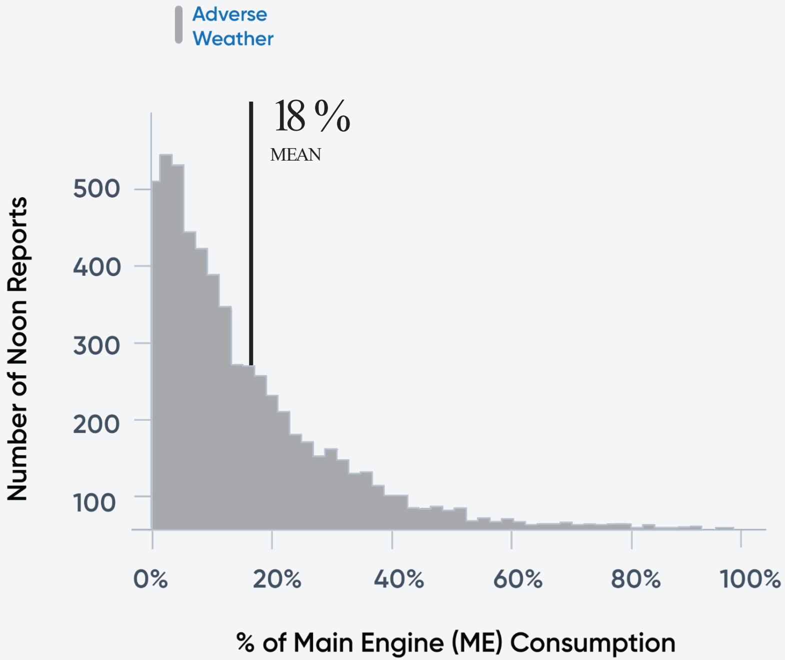
The Cost of Weather Uncertainty

The cost of adverse weather for a **single** Capesize Bulk Carrier per year:

18 % of main engine fuel consumption

~5,730 MT CO_2 emissions per year

~$920,000 Cost per year (at current prices)



70% utilization rate (at sea time) per year at an average ME consumption of 40 MT/day at an estimated bunker price of $500/MT

Closing the Ocean Data Gap

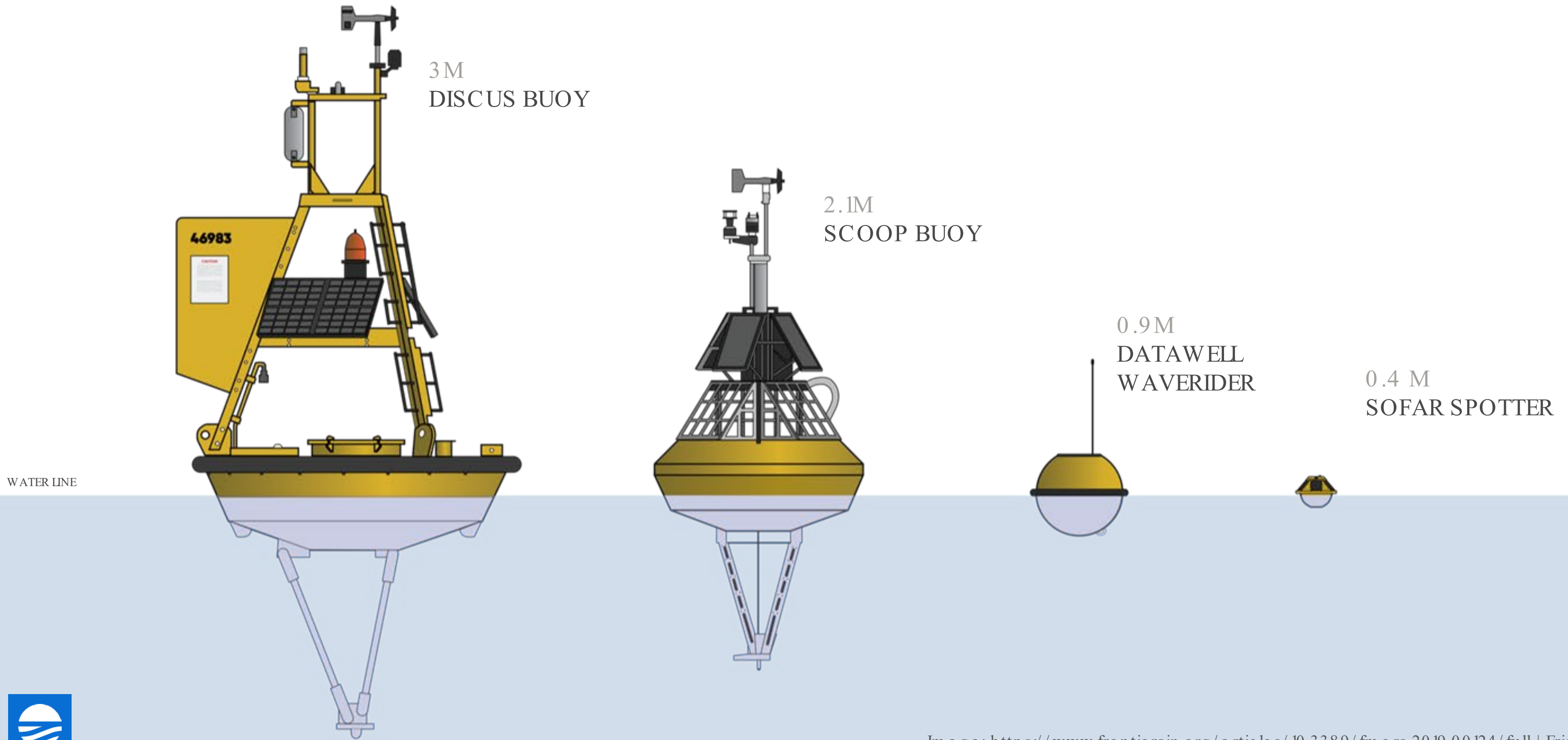
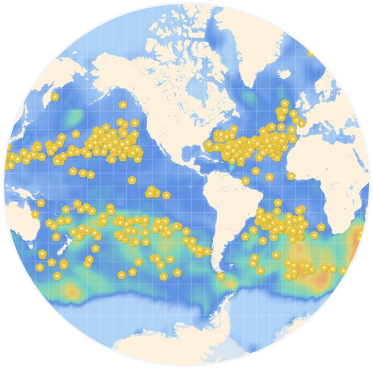


Image: https://www.frontiersin.org/articles/10.3389/fmars.2019.00124/full | Eric Gay

Sofar Capabilities

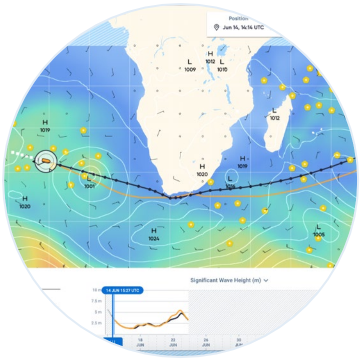
Spotter Platform

Extensible ocean sensing
platform deployed globally



Weather

Weather forecasts powered by
real-time data assimilation



Wayfinder

Voyage safety and guidance
with the best weather forecasts

Spotter Platform

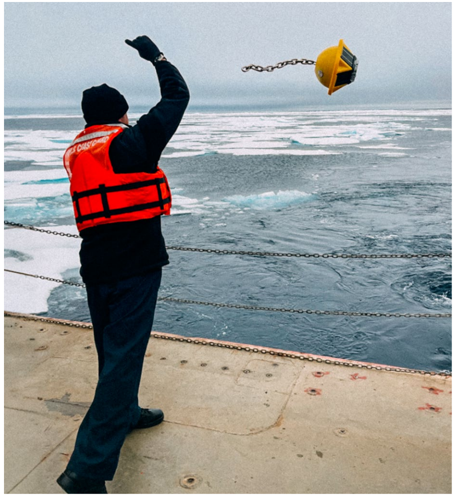
An extensible ocean sensing platform delivering real-time surface and subsurface data. Includes air-deployable and quick-deploy options.

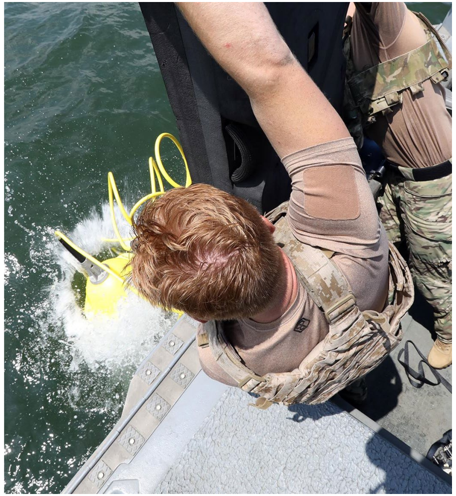
Surface Capabilities

- Wave & Wave Spectra
- Wind
- Sea Surface Temperature
- Atmospheric Pressure

Subsurface Capabilities

- Temperature
- Water level
- Current
- Development Kit
- Sound
- Water Quality






Andrew Reed, WHOI
WORK VEST
ONLY


April 2019
April
2019
September
2021

RAPID RESPONSE NETWORKS

Hurricane Ian

Rapid network augmentation through airdropped Spotters, demonstrating value of rapid-response capability

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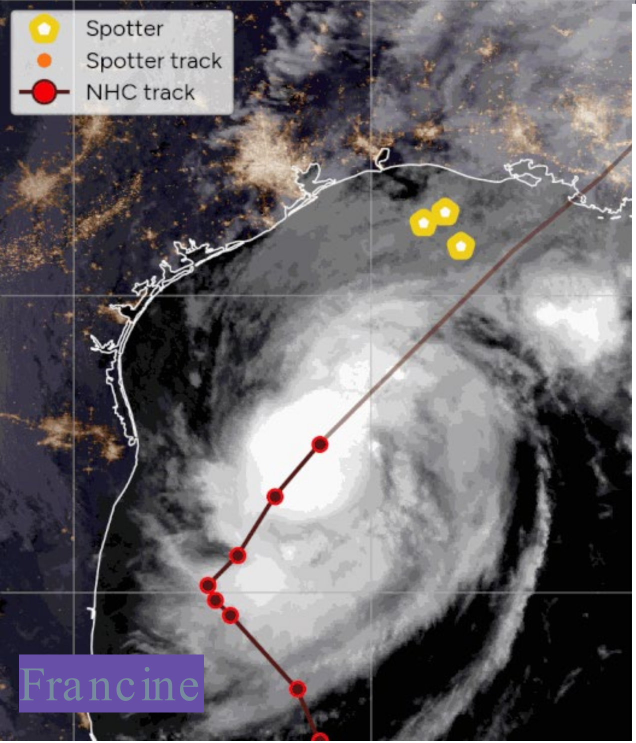
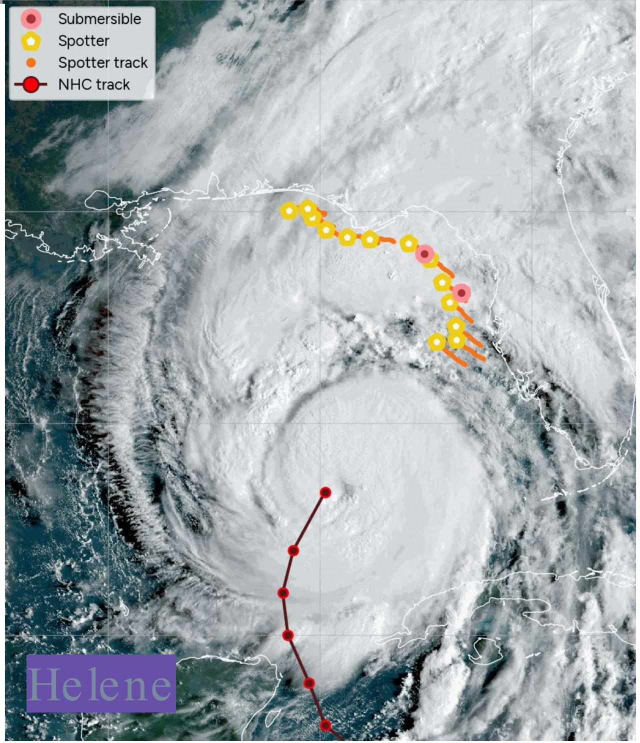


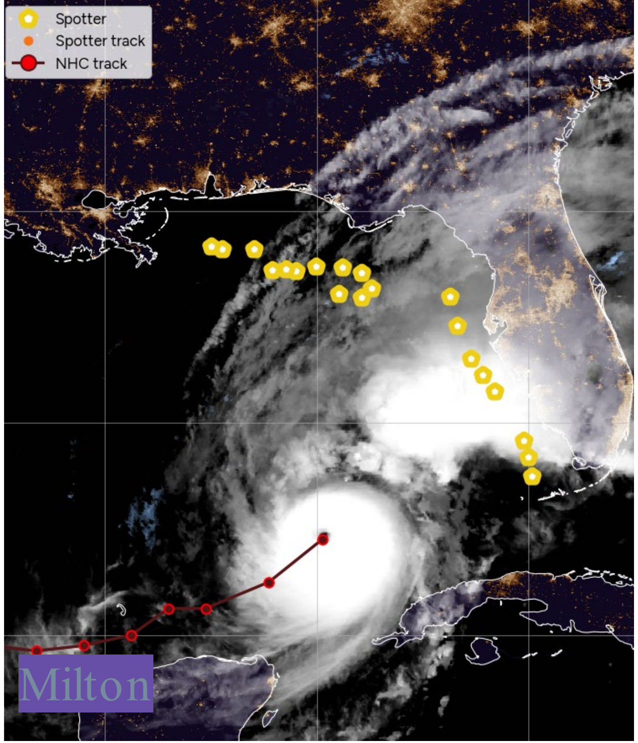
	Deployed	Active
	6	**5**

Mon, Sep 9, 2024 –
Thu, Sep 12, 2024



	Deployed	Active
	14	**12**

Tue, Sep 24, 2024 –
Fri, Sep 27, 2024



	Deployed	Active
	8	**8**

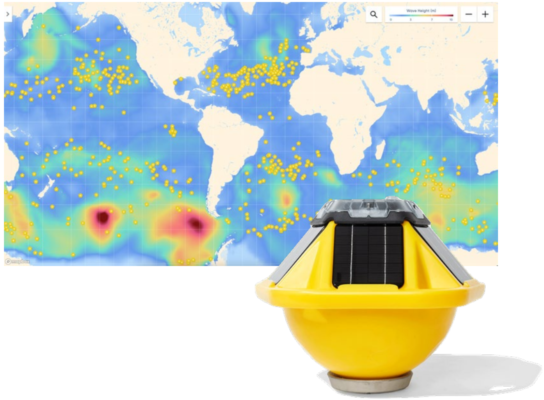
October 5, 2024 –
October 10, 2024

SOFAR

We own and operate the largest private in situ global ocean sensor network powering the world's most accurate marine weather forecasts.

- 2,500+ active sensors deployed globally
- 100,000+ unique daily ocean weather updates
- 10+ million device ocean hours

Assimilation of the Sofar Spotter Network



Data assimilated into WW3 model *hourly* to improve forecast skill.

Forcing

Observations

Initial Conditions
(Background)

WaveWatchIII®

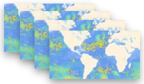
Data Assimilation

Analysis

Every 1-Hour

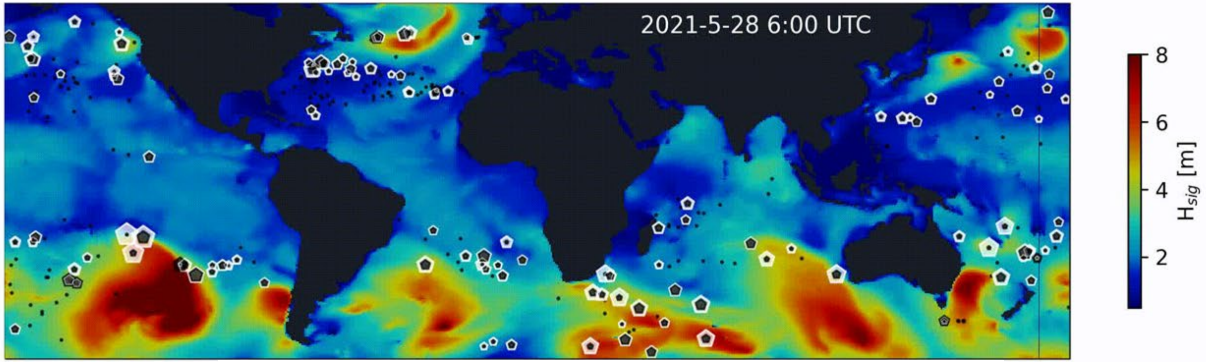
Every 6-Hours

15-Day Forecast

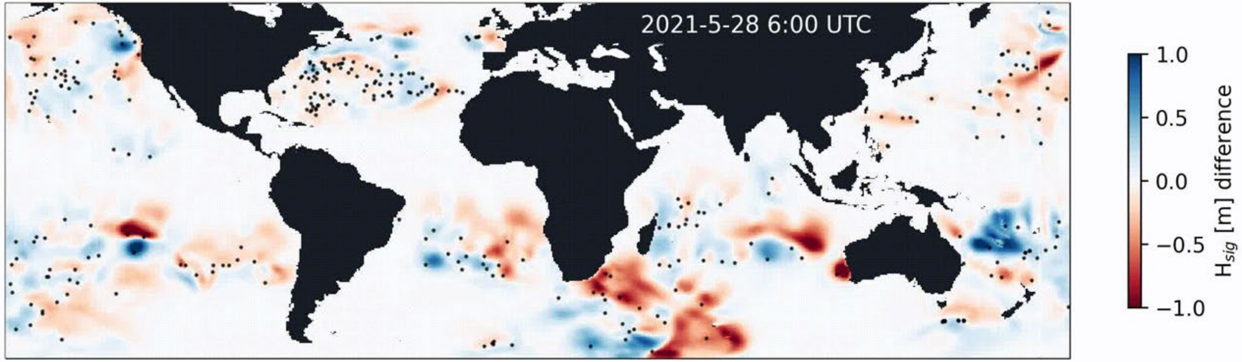


Models + Observations

Wave Model + Spotter size proportional to model error



Change to model after incorporating observations

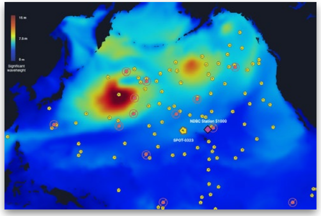


Assimilation of the Sofar Spotter Network

2021

Optimal Interpolation (OI) of Spotter significant wave height

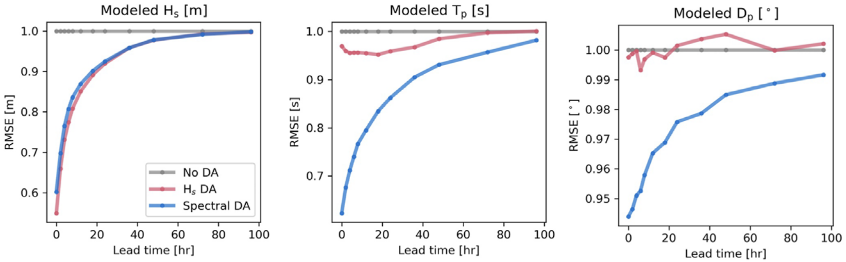
Smit, Houghton, et al. (2021). Assimilation of significant wave height from distributed ocean wave sensors. *Ocean Modelling*, 159, 101738.



2022

OI of Spotter directional wave spectra

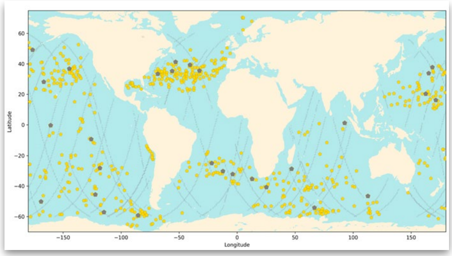
Houghton, et al. (2022). Operational assimilation of spectral wave data from the Sofar Spotter network. *Geophysical Research Letters*, 49.



2023

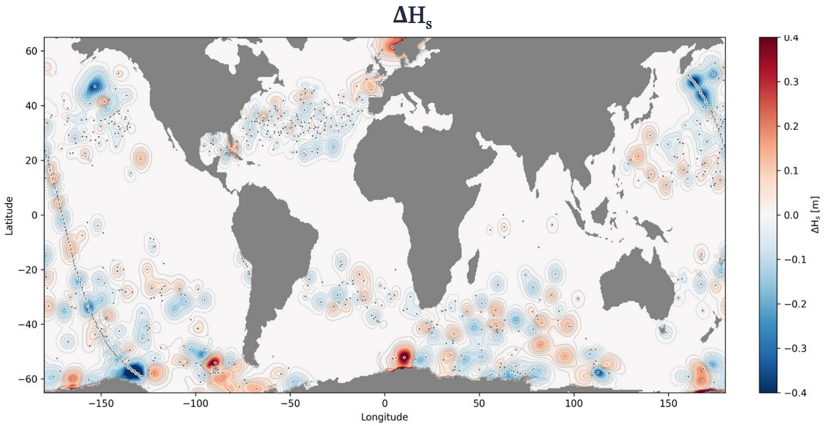
Ensemble-based DA of Spotter significant wave height

Houghton, et al. (2023). Ensemble-Based Data Assimilation of Significant Wave Height from Sofar Spotters and Satellite Altimeters with a Global Operational Wave Model, *Ocean Modelling*.

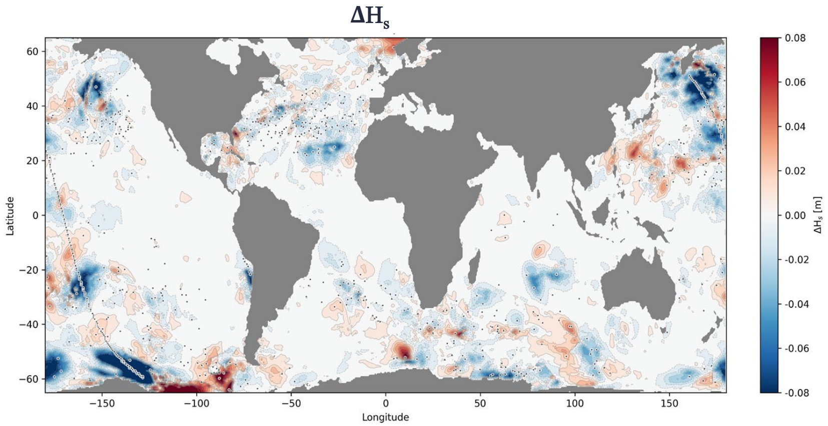


Optimal Interpolation vs. Ensemble-based DA

In traditional Optimal Interpolation, we assume homogeneous and isotropic error covariances statistics - i.e. a Gaussian parameterization of error covariance that decays with distance from observation.



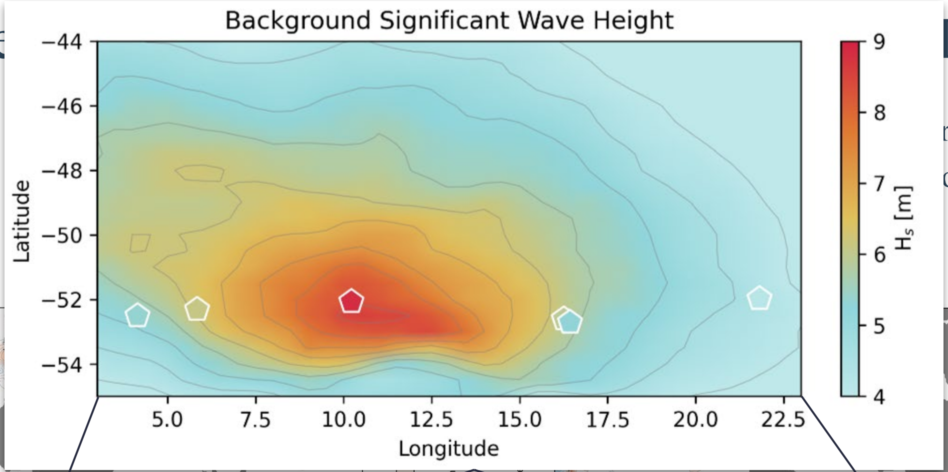
***Optimal Interpolation**: Blobby, local updates out of balance with wave model and wind forcing*

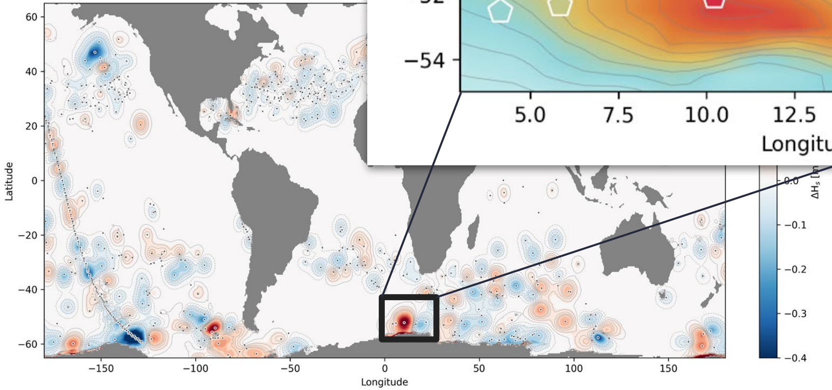


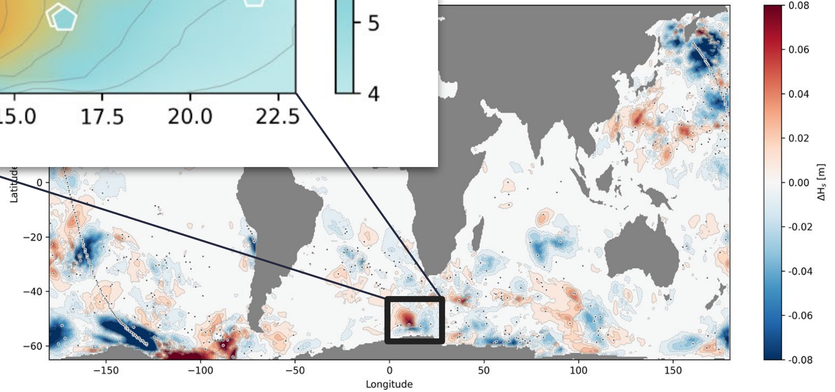
***LETKF**: Coherent, physically realistic updates balancing model uncertainty with observations*

Optimal Inte… DA

In traditional Optimal … r covariances statistics - i.e. a Gaussian param… om observation.





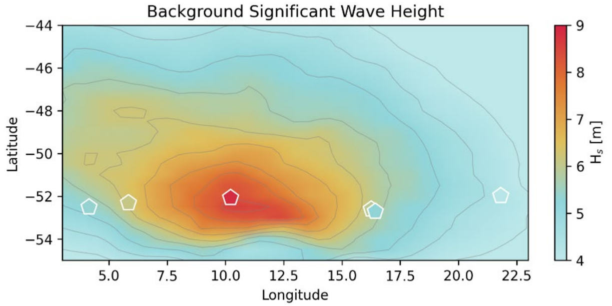


Optimal Interpolation: Blobby, local updates out of balance with wave model and wind forcing

LETKF: Coherent, physically realistic updates balancing model uncertainty with observations

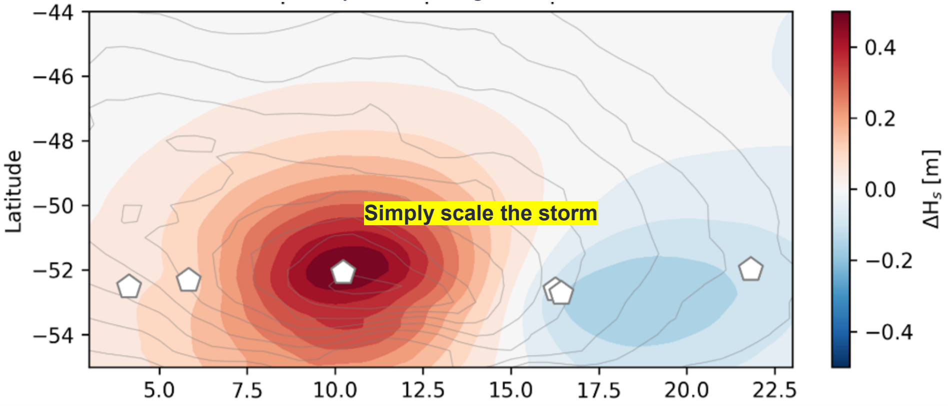
Ensemble-based DA Update

Ensemble provides a more physically realistic update to the wave field and an understanding of the uncertainty.



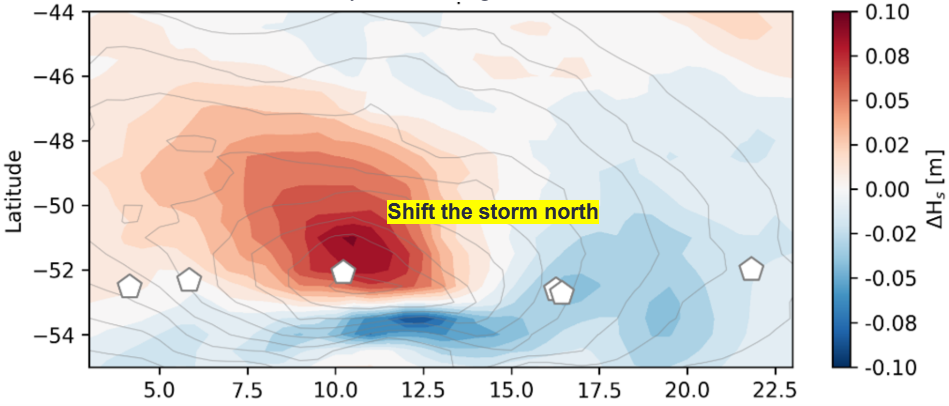
Optimal Interpolation Update

Analysis - Background Field



LETKF Update

Analysis - Background Field

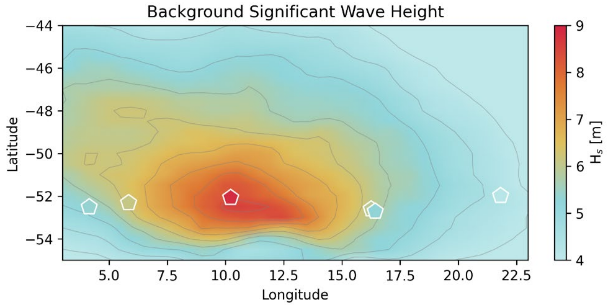


Houghton, et al. (2023). Ensemble-Based Data Assimilation of Significant Wave Height from Sofar Spotters and Satellite Altimeters with a Global Operational Wave Model, *Ocean Modelling*.

What's next

Ensemble-based DA Update

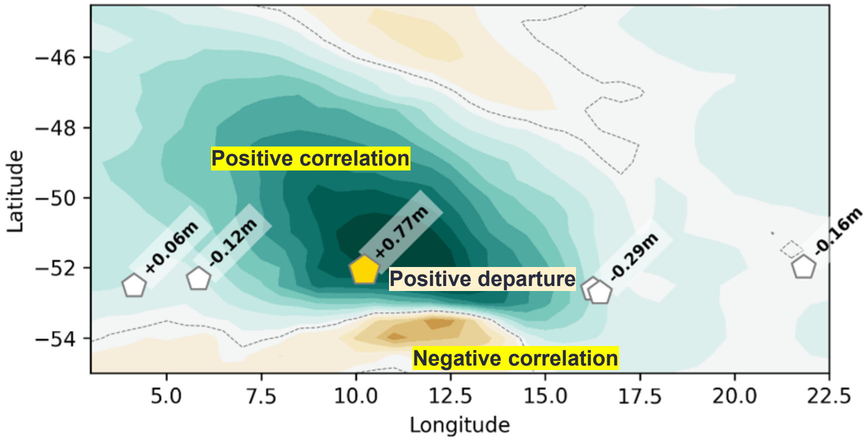
Wave model ensemble provides estimate of error covariances between all locations.



Model Error Covariances

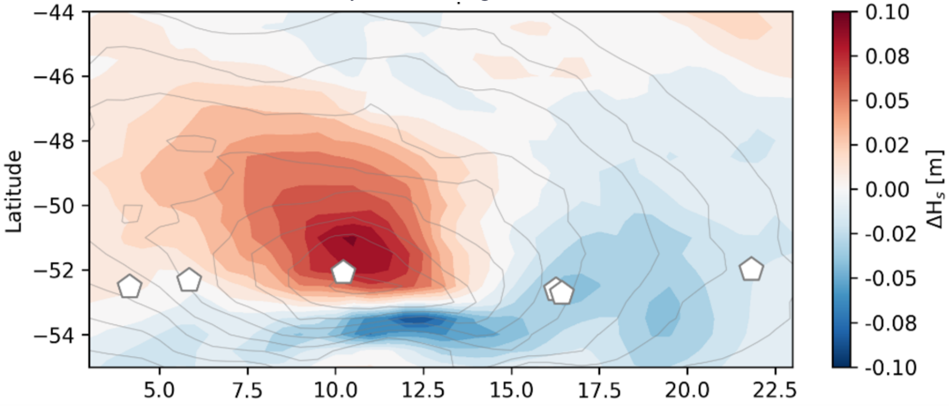
Derived from wave ensemble

$$\mathrm{cov}(X, Y) = \sum_{i=1}^{N} \frac{(x_i - \bar{x})(y_i - \bar{y})}{N}.$$



LETKF Update

Analysis - Background Field



Houghton, et al. (2023). Ensemble-Based Data Assimilation of Significant Wave Height from Sofar Spotters and Satellite Altimeters with a Global Operational Wave Model, *Ocean Modelling*.

Coupled forecast system

The picture can't be displayed.

Atmosphere Winds

Ocean Waves

We want to take advantage of the strong correlations between winds, waves, and currents to better leverage Sofar observations

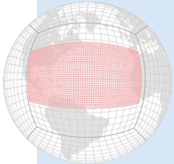
In production - Sofar Wave Modeling

Wave

We leverage the exceptional performance of Sofar’s operational wave forecast system (WaveWatch3 assimilating Spotters and altimeter measurements) *Houghton et al. (2022)*

In development - Sofar Coupled Modeling

SHiELD



Atmosphere

We use the System for High-resolution modeling for Earth-to-Local Domains (SHiELD) with Finite Volume Cube Sphere dynamical core (FV3), developed at GFDL *(Harris et al., 2020)*.

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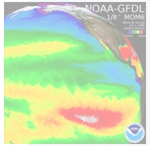
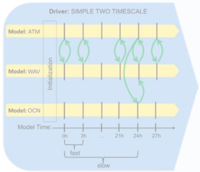


Ocean

We use the Modular Ocean Model (MOM6) developed at GFDL.

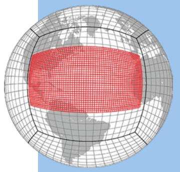


Coupler

We use the Earth System Modeling Framework (ESMF)
National Unified Operational Prediction Capability (NUOPC)
(supported by: NASA, NOAA, DoD, NSF).

In dev - Sofar Coupled Atmosphere-Wave Modeling

SHiELD



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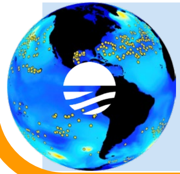

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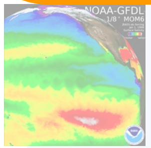

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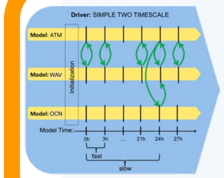
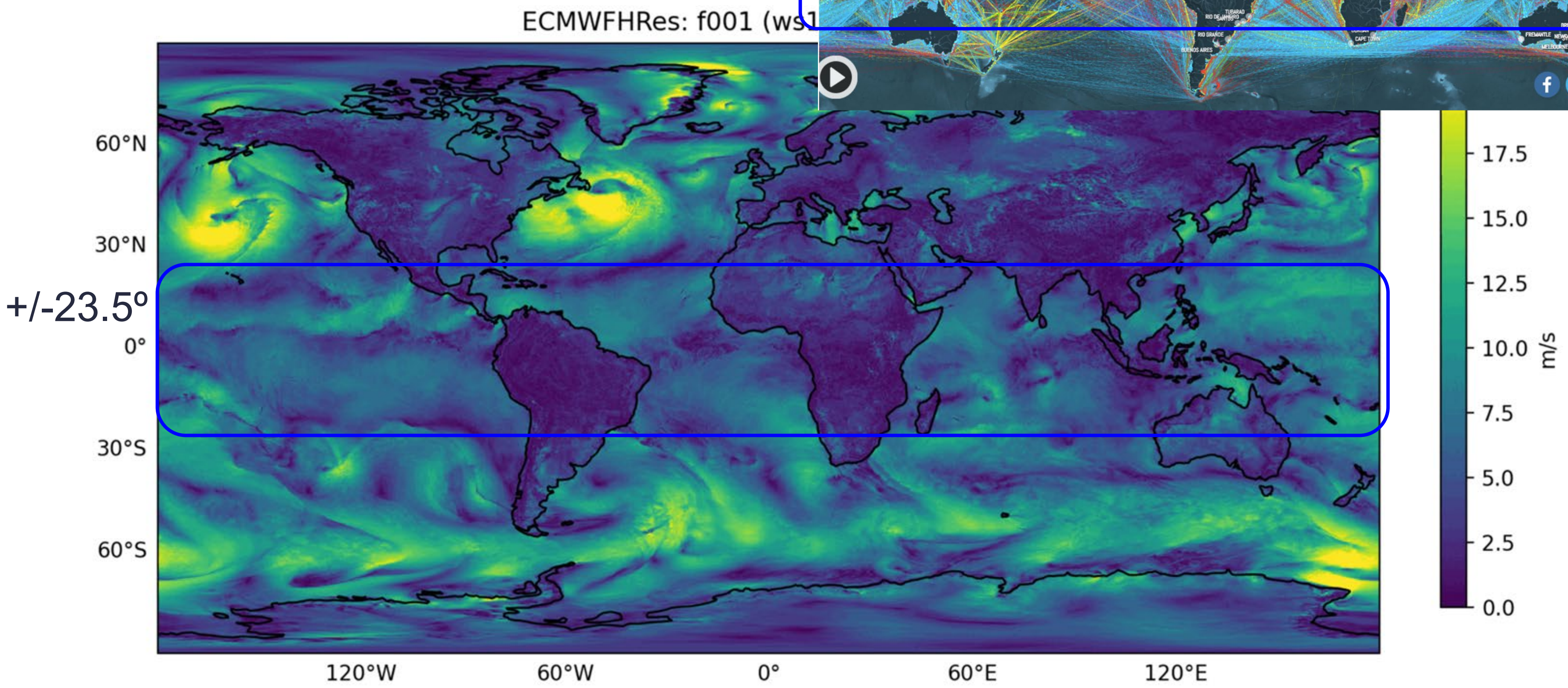
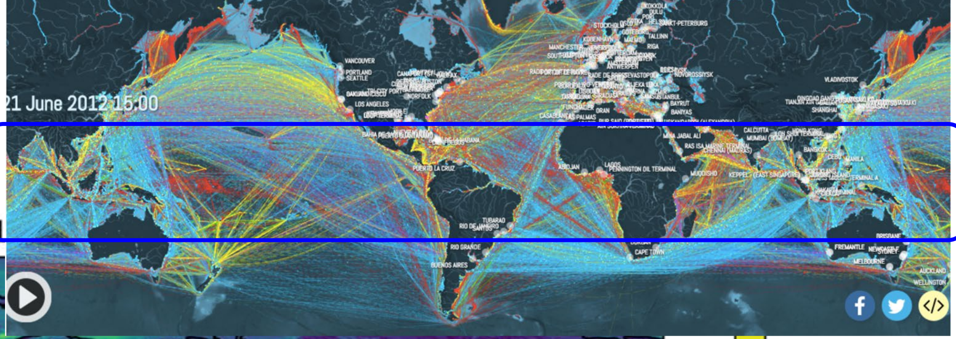


Coupler

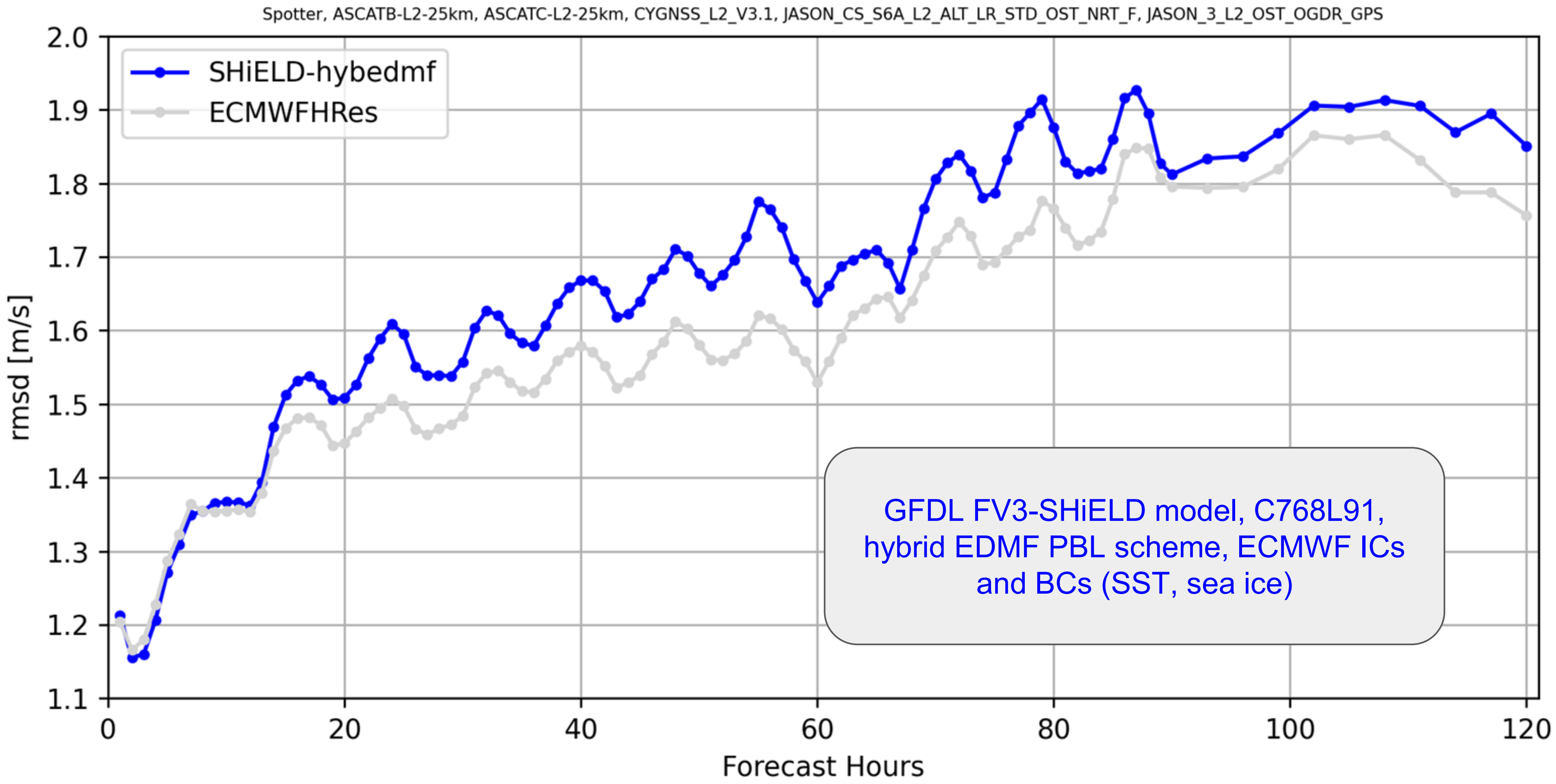
We use the Earth System Modeling Framework (ESMF)
National Unified Operational Prediction Capability (NUOPC)
(supported by: NASA, NOAA, DoD, NSF).

ECMWFHRes surface wind-speed (2024-02-15)





10m Wind Speed RMSD on 2/15/24 (Tropics)



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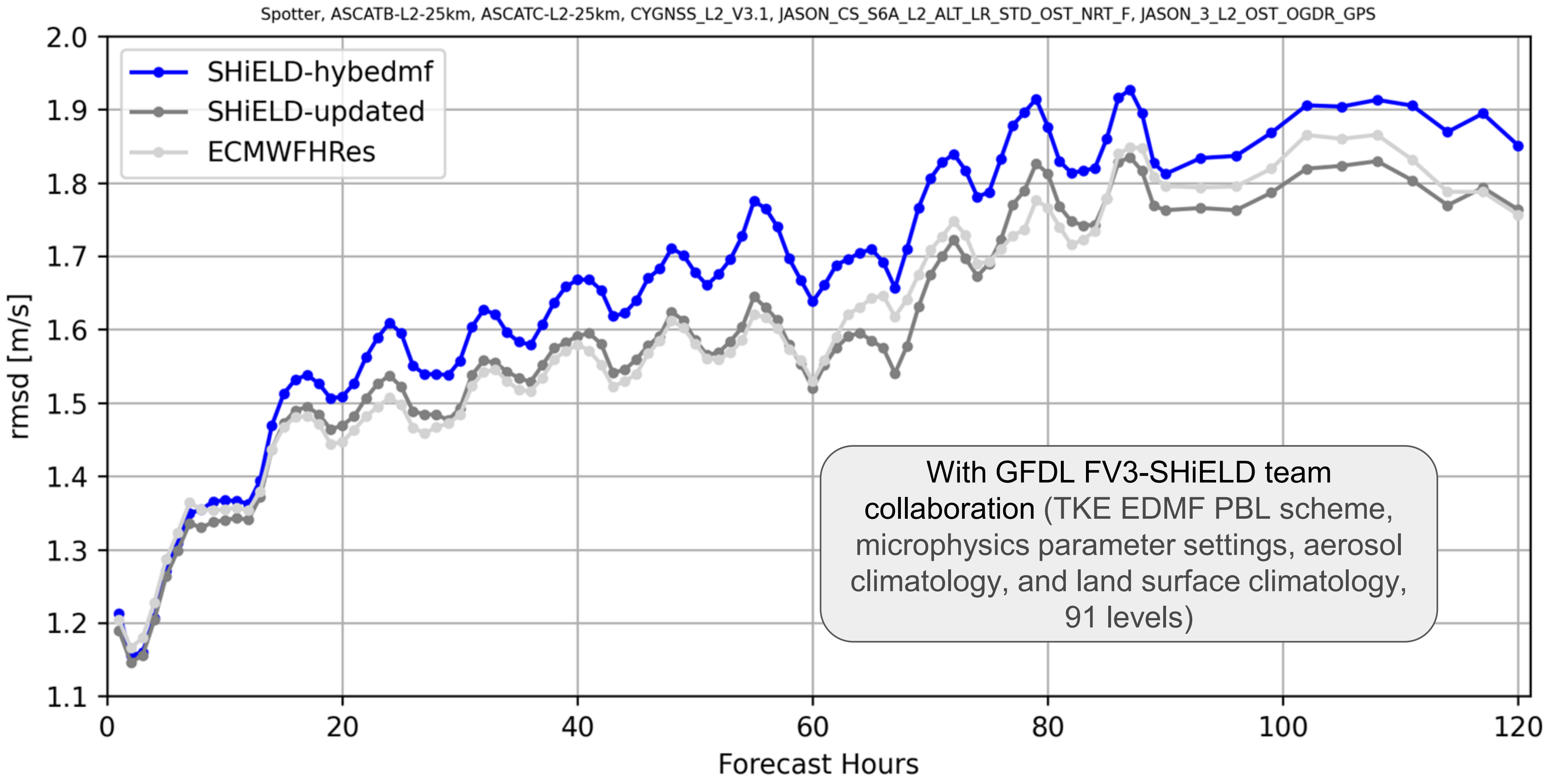

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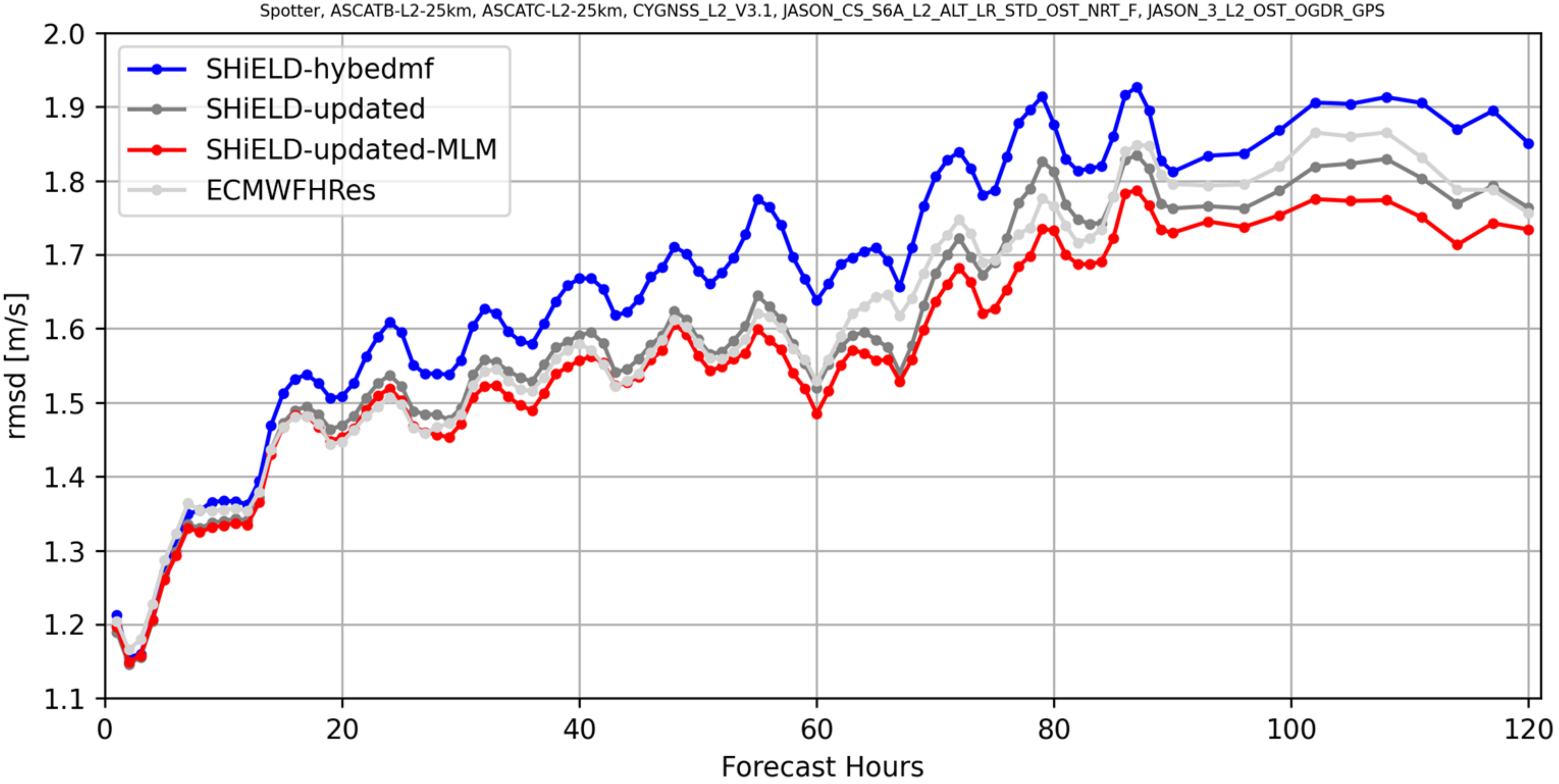
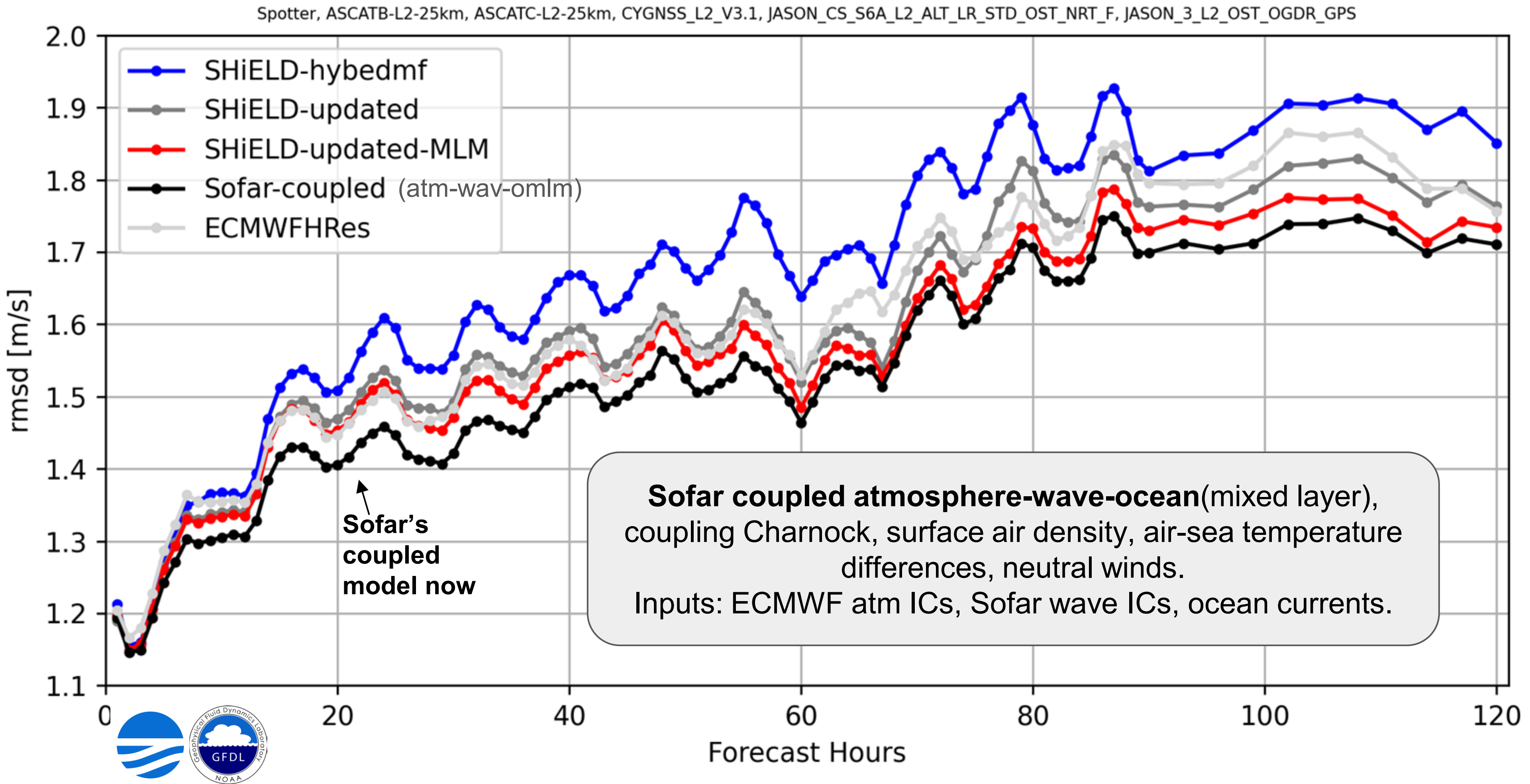
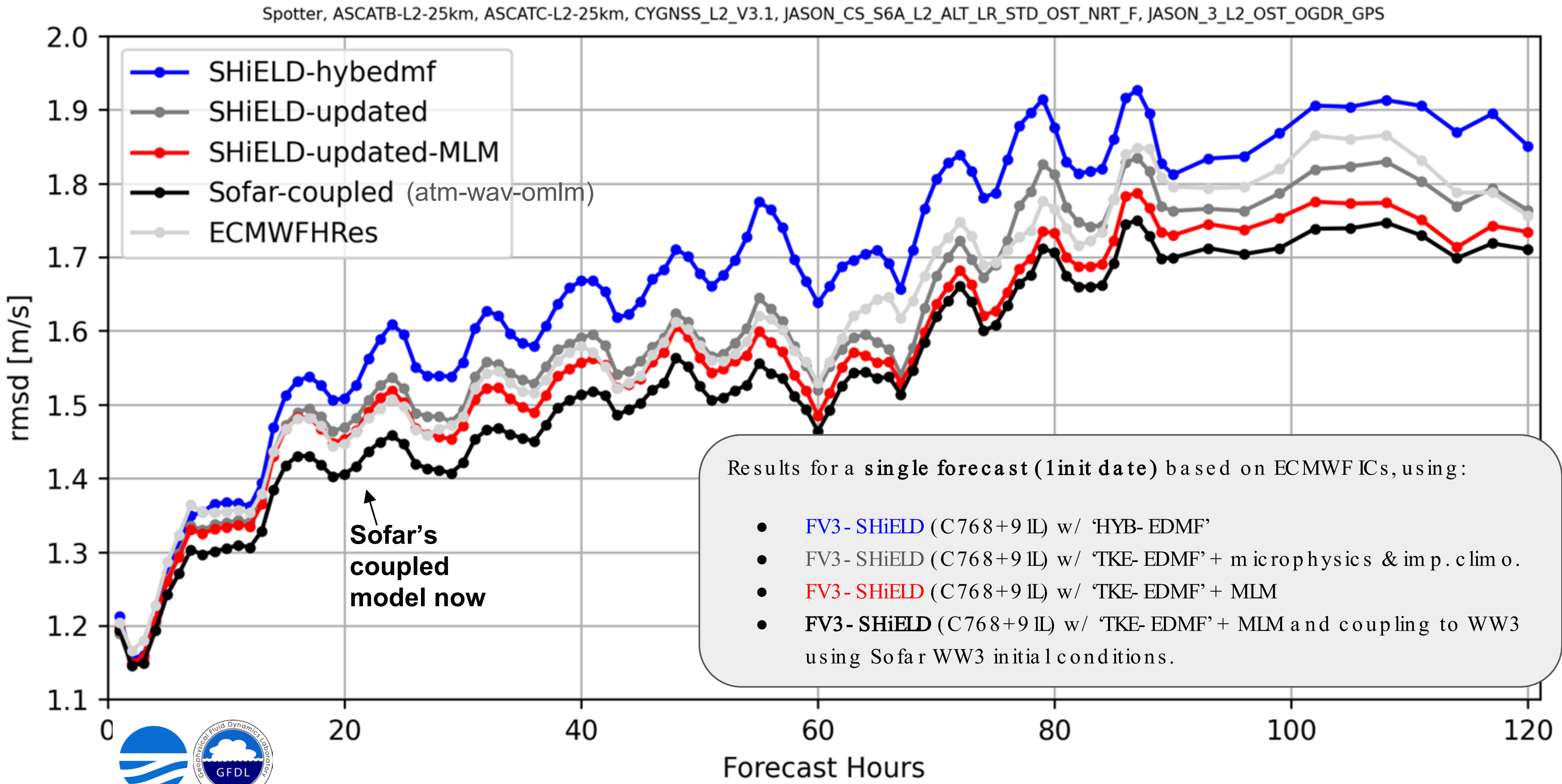


10m Wind Speed RMSD on 2/15/24 (Tropics)



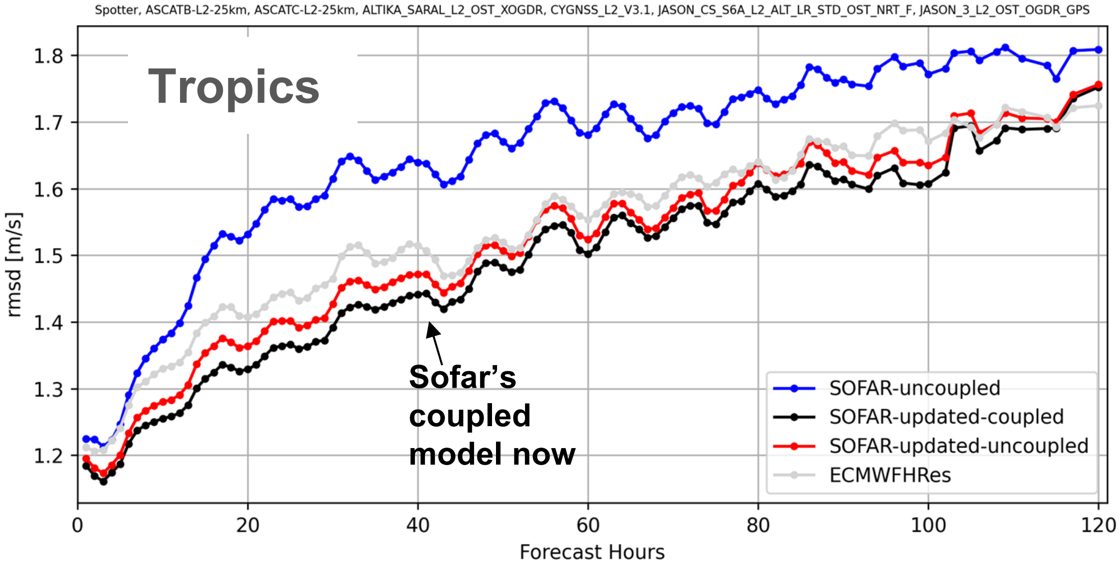
10m Wind Speed RMSD on 2/15/24 (Tropics)

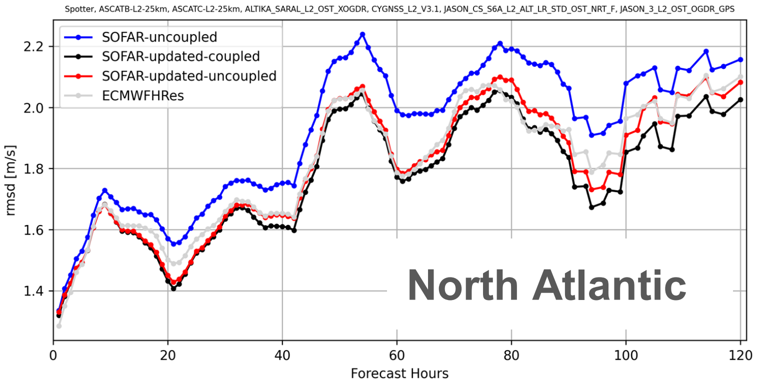


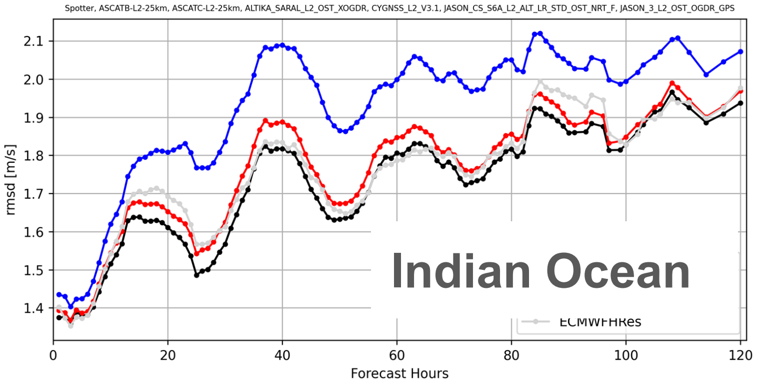
Results for a **single forecast (1 init date)** based on ECMWF ICs, using:

- FV3-SHiELD (C768+91L) w/ 'HYB-EDMF'
- FV3-SHiELD (C768+91L) w/ 'TKE-EDMF' + microphysics & imp. climo.
- FV3-SHiELD (C768+91L) w/ 'TKE-EDMF' + MLM
- **FV3-SHiELD** (C768+91L) w/ 'TKE-EDMF' + MLM and coupling to WW3 using Sofar WW3 initial conditions.

10m Wind Speed, all seasons (4 sampled dates 2023-2024)



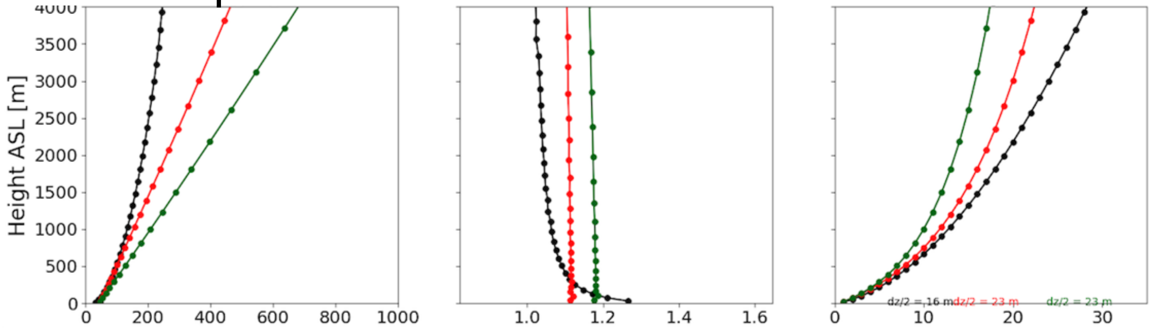


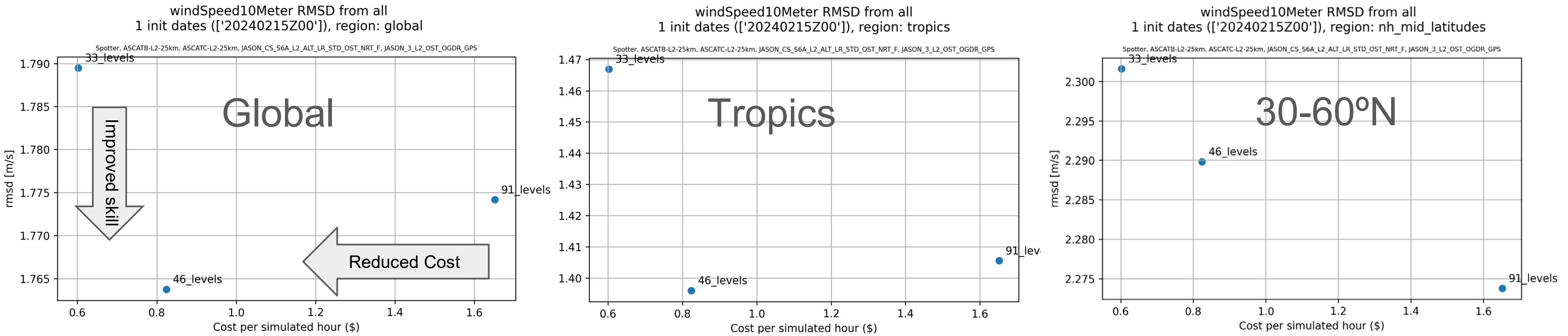


Coupled atmosphere-wave model development

Improving costs

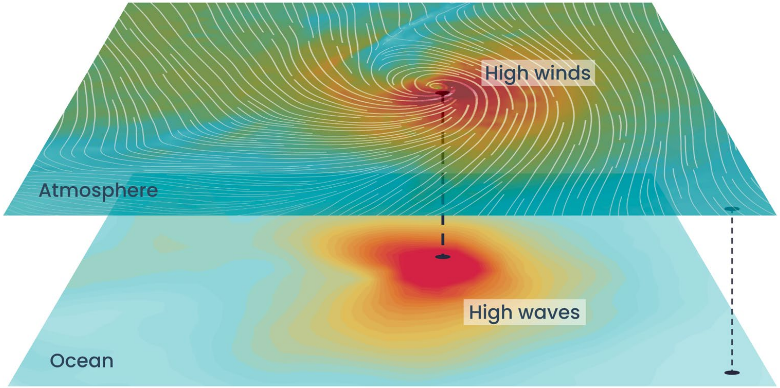
atmosphere vertical levels: 91 46 33



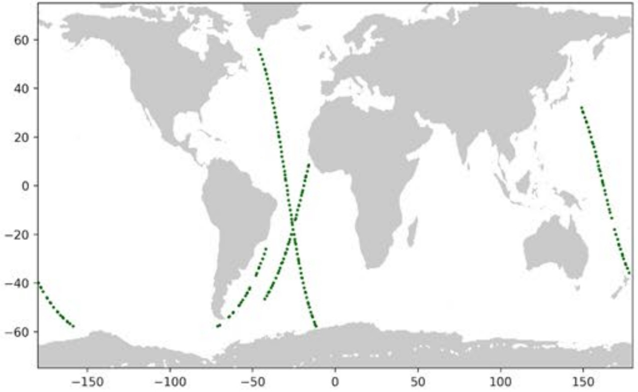


Coupled Data Assimilation

- Apply information from observations across domains (atmosphere, wave)
- Bring in more observations

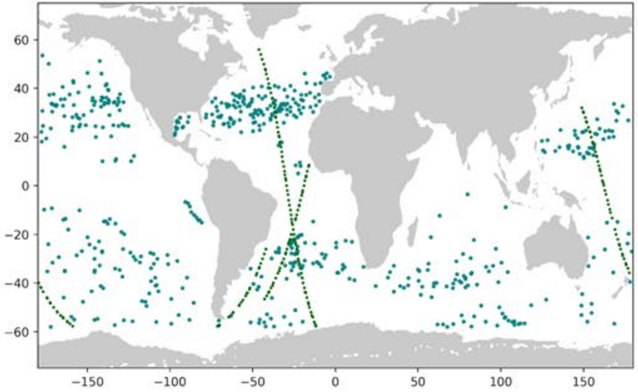


Altimeters

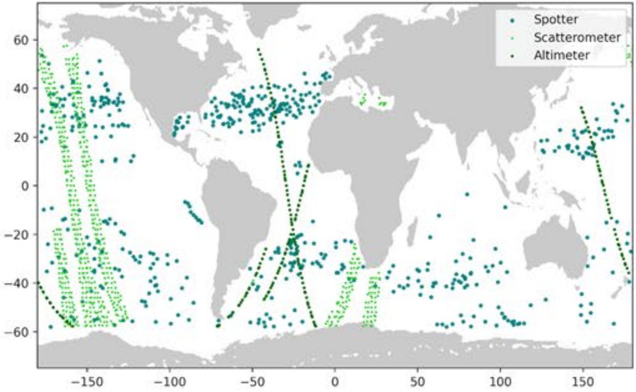


Jason-3, SARAL, Sentinel 6A

Altimeters + Spotters



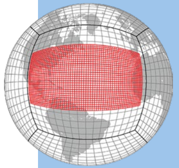
Altimeters + Spotters + Scatterometers



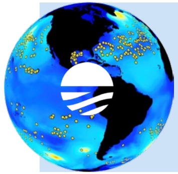
ASCAT on METOP-A, METOP-B

Coupled Data Assimilation Framework

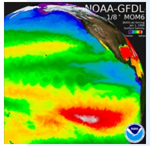
SHiELD



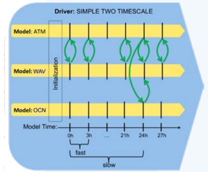
Atmosphere



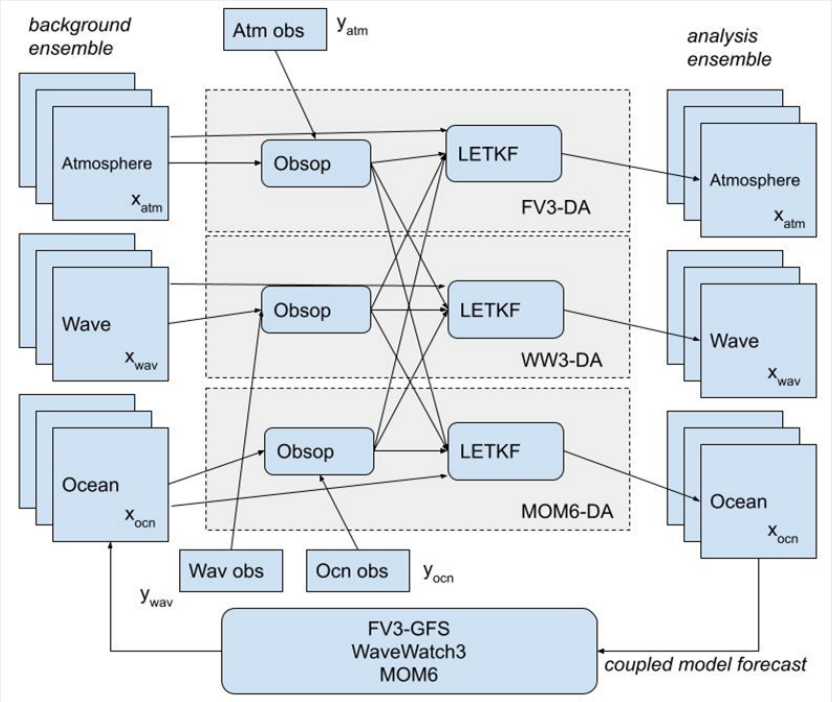
Wave



Ocean



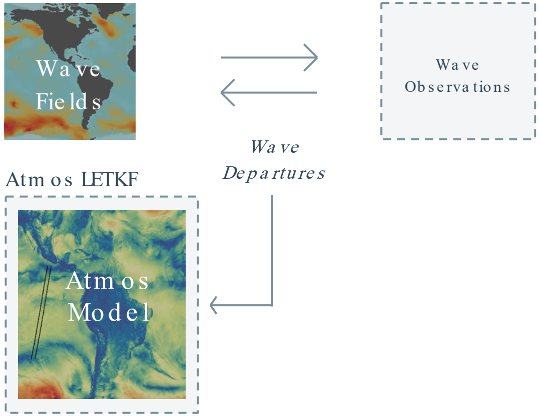
Coupler

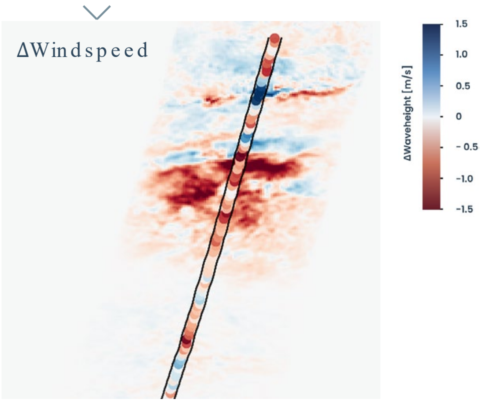


EXPERIMENT 01

Wind Update

from Wave Observations



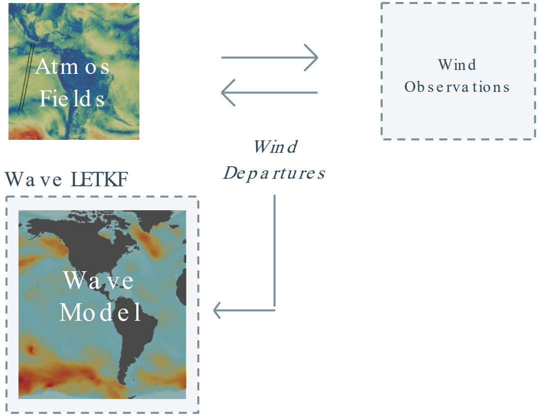


Streak indicates independent (unused) data to validate update. Matching colors indicates update agrees.

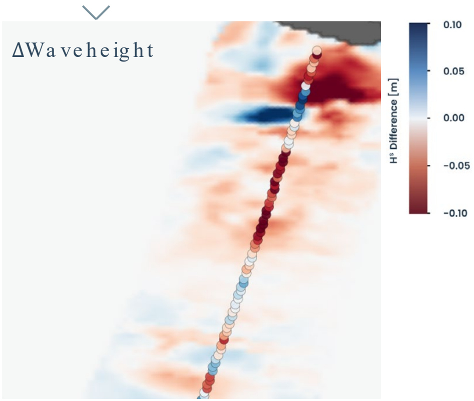
EXPERIMENT 02

Wave Update

from Wind Observations



Using the LETKF CDA framework of Sluka et al. (2016)



Streak indicates independent (unused) data to validate update. Matching colors indicates update agrees.

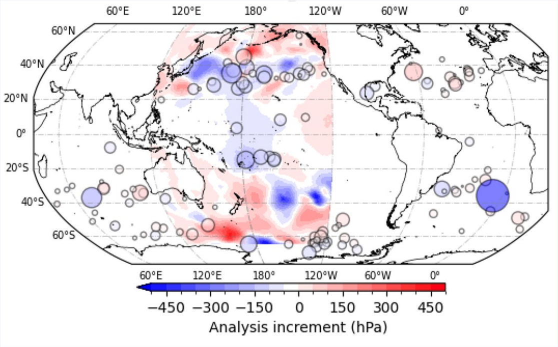
Sofar Coupled DA

We are setting up an ensemble coupled forecast system using FV3-GFS(SHiELD) coupled to WaveWatchIII and MOM6.

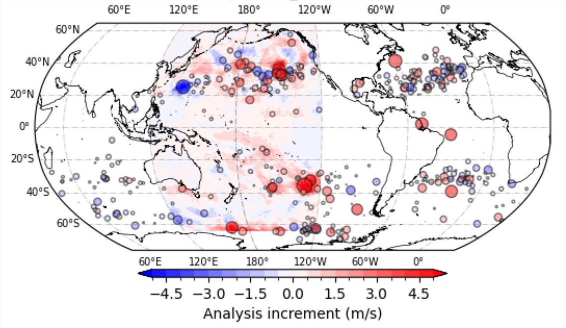
- Cycled coupled data assimilation:
  We have an R&D cycled coupled forecast system, and have set up the capability to cycle the coupled model with the Local Ensemble Transform Kalman Filter (LETKF) (strongly coupled) Data Assimilation applied with each component.
- Compare forecast against observations:
  We have developed an observation oriented assessment package to tune our coupled forecast model. This is applied to the ML-calibrated forecast system as a component of our “loss function” to quantify forecast skill.

Right: circles (size and color) indicate the size of the departure between observation and forecast. Shaded areas represent the analysis increment calculated by coupled DA based on those departures.

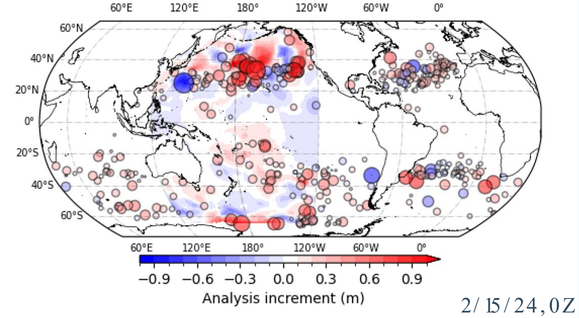
Assimilating Spotter data in the Pacific w/ LETKF



Surface Pressure



Surface Winds



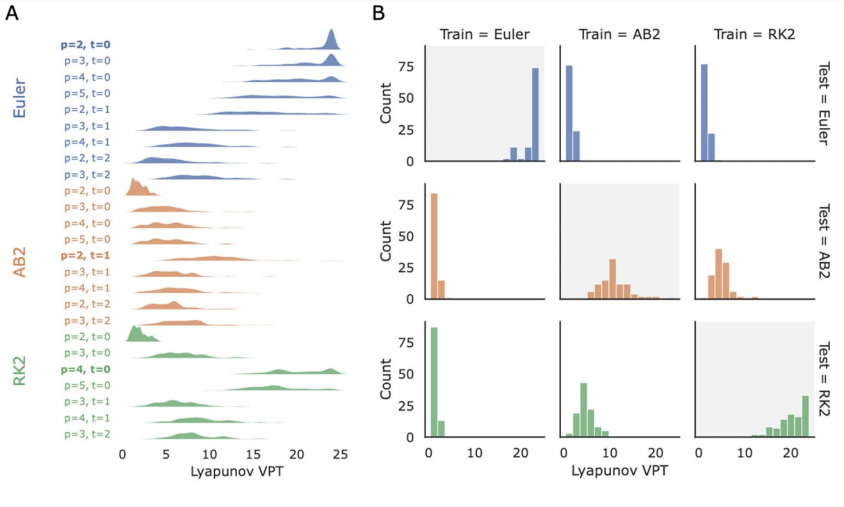
Significant wave height

2/15/24, 0Z

Machine Learning caution - what is it learning?

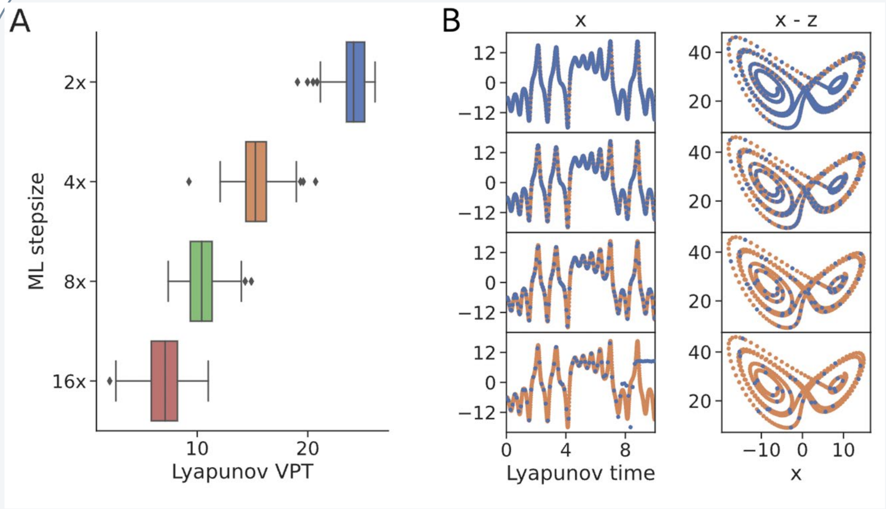
Chen, **Penny**, Smith, Platt (2025) https://journals.ametsoc.org/view/journals/aies/aop/AIES-D-23-0088.1/AIES-D-23-0088.1.xml

Lorenz-96



- The best models trained on datasets generated by different numerical integrations methods cross validated
- Prediction skill is *significantly worse* when predicting across methods
- Highlights dangers in using reanalysis datasets as "truth" for ML training

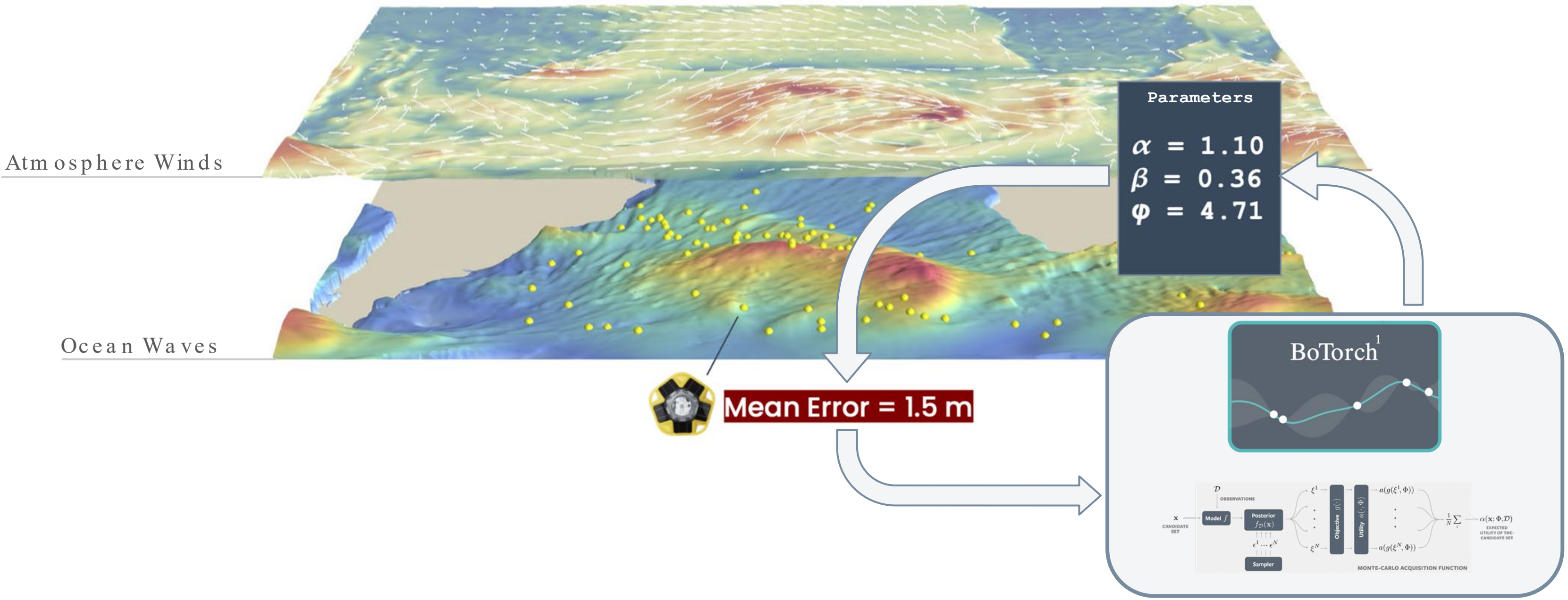
Lorenz-63



- A 16x subsampling of training data *significantly reduces* forecast skill
- E.g. ERA5 6-hour timestep versus IFS with a 720s timestep is 30x subsampled, or versus FV3 nonhydrostatic 150s timestep is 144x.
- Highlights dangers in temporal subsampling in reanalysis datasets for ML training

The Sofar-Earth System Model becomes a "hybrid physics/ML" model

We use machine learning to optimize our physics-based model parameters to fit Spotter data - ensuring the high fidelity from precise physics equations while leveraging advances in machine learning to reduce uncertainties.



[1] Balandat, Maximilian, et al. "BoTorch: A framework for efficient Monte-Carlo Bayesian optimization." Advances in neural information processing systems 33 (2020): 21524-21538.

Solvik, Penny, and Hoyer (2025) https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2024MS004608

4D-Var using Backpropagation and Hessian approximation

Leveraging (A) automatic differentiation and (B) ML software tools to minimize the data assimilation cost function

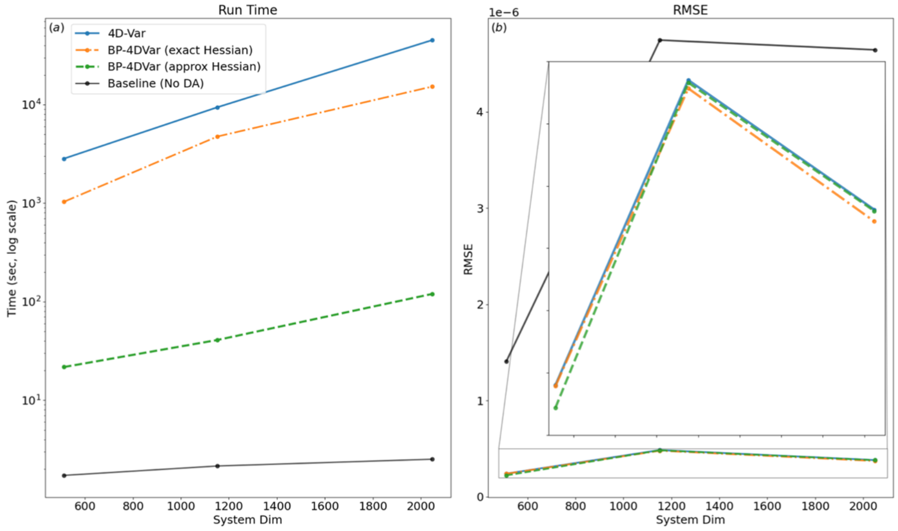
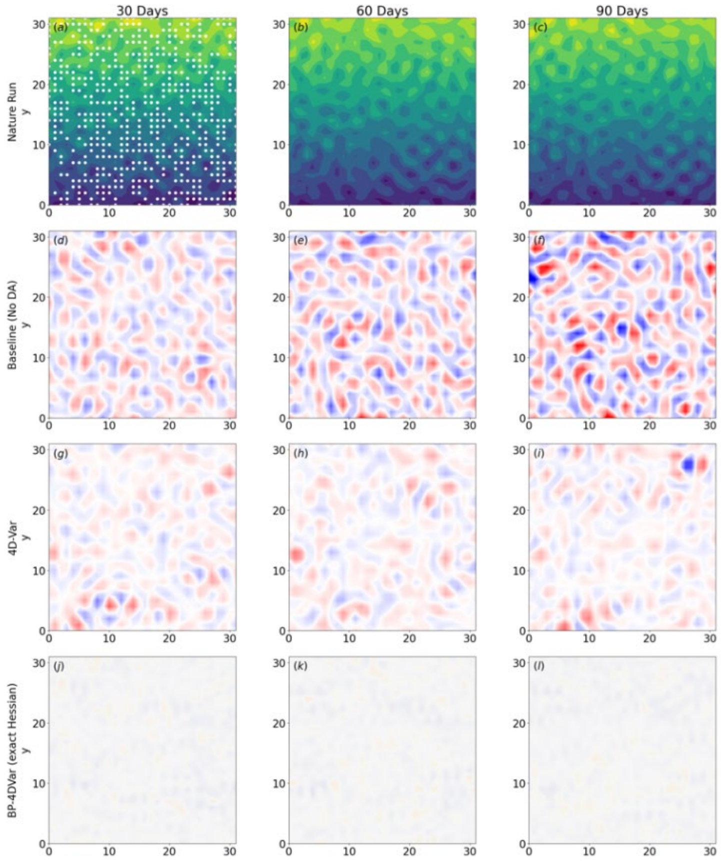


Figure 5. (a) Run times (log scale) and (b) RMSE for the QG dynamics using the PyQG-JAX forecast model, for 4D-Var and Backprop-4DVar. An unconstrained free run without data assimilation is provided as a baseline for comparison. While all three DA methods show similar performance in terms of RMSE, Backprop-4DVar using the approximate Hessian (green) is an order of magnitude faster than the reference methods.



Solvik, Penny, and Hoyer (2025) <submitted>

DataAssimBench

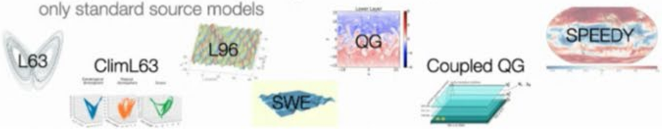
Benchmarking and "workbench", inspired by WeatherBench but focused on data assimilation with AI/ML

https://github.com/StevePny/DataAssimBench
https://github.com/StevePny/DataAssimBench-Examples

DataAssimBench: Google-funded development of a benchmarking repo for integrating AI/ML with Data Assimilation (with Jax support)

Where are the benchmark training sets?

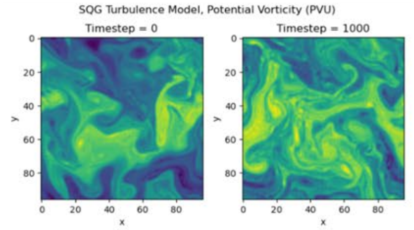
- We generate them from known dynamical systems, there is no standard set, only standard source models



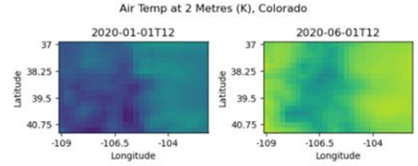
- This is a stepping stone toward the use of more realistic models, real real-world observational data

FV3-GFS
IFS
COAMPS
Wavewatch3
NOAA UFS
MOM6
Hycom
NEMO
Navgen

```
In [1]: from dabench.data import sqgturb
        import matplotlib.pyplot as plt

In [2]: model_obj = sqgturb.DataSQGturb()
        model_obj.generate(n_steps = 1000)
        gridded_vals = model_obj.to_original_dim()

In [3]: fig, ax = plt.subplots(1, 2)
        fig.suptitle('SQG Turbulence Model, Potential Vorticity (PVU)')
        ax[0].imshow(gridded_vals[0, 1])
        ax[0].set_title('Timestep = 0')
        ax[0].set_xlabel('x'); ax[0].set_ylabel('y')
        ax[1].imshow(gridded_vals[-1, 1])
        ax[1].set_title('Timestep = 1000')
        ax[1].set_xlabel('x'); ax[1].set_ylabel('y')
        fig.tight_layout()
        fig.subplots_adjust(top=1.2)
        plt.show()
```




```
In [1]: from dabench.data import aws
        import matplotlib.pyplot as plt
        import numpy as np

In [2]: data_obj = aws.DataAWS(variables = ['air_temperature_at_2_metres'],
                               years = [2020, 2021],
                               min_lat = 36.992426, max_lat = 41.003444,
                               min_lon = -109.060253, max_lon = -102.041524
                              )
        data_obj.load()
        gridded_values = data_obj.to_original_dim()

In [3]: fig, ax = plt.subplots(1, 2)
        fig.suptitle('Air Temp at 2 Metres (K), Colorado')
        ax[0].imshow(gridded_values[12], vmin=250, vmax=300)
        ax[0].set_title(np.datetime_as_string(data_obj.times[12], unit='h')); ax[0].set_xl
        ax[0].set_yticks(ticks=[0, 5, 10, 15], labels=[37, 38.25, 39.5, 40.75]); ax[0].set
        ax[1].imshow(gridded_values[3660], vmin=250, vmax=300)
        ax[1].set_title(np.datetime_as_string(data_obj.times[3660], unit='h')); ax[1].set_
        ax[1].set_yticks(ticks=[0, 5, 10, 15], labels=[37, 38.25, 39.5, 40.75]); ax[1].set
        fig.tight_layout()
        fig.subplots_adjust(top=1.4)
        plt.show()
```



Contact:
steve.penny@sofarocean.com

Steve Penny, Kylen Solvik (CU),
Stephan Hoyer (Google),
Tim Smith (CIRES/NOAA),
Tse-Chun Chen (PNNL)

Fin

Stephen G. Penny
Head of Weather

+1.415.230.2299
steve.penny@sofarocean.com
www.sofarocean.com

Access our global Spotter sensor weather network:

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