AIRU-WRF: A Physics-Guided AI-Powered Model for Wind Forecasting in the U.S. Mid-Atlantic Offshore Wind Energy Areas

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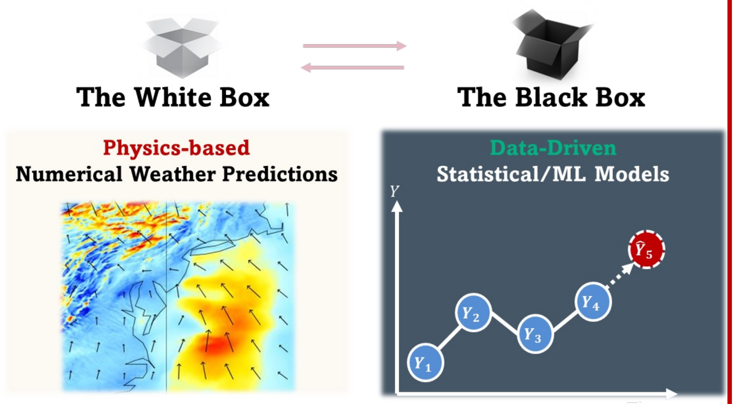
Introduction

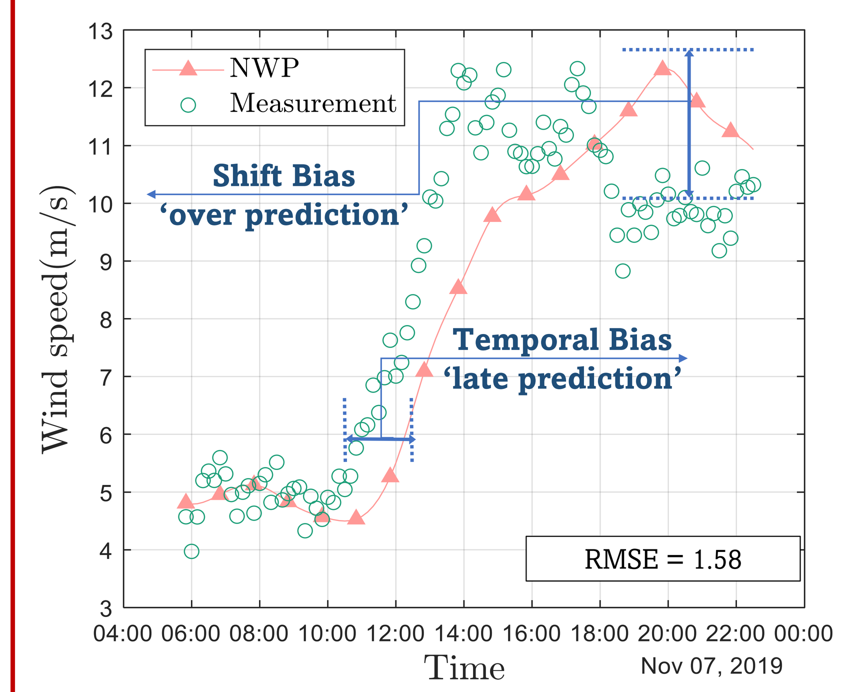
➢**Background:** United States (US) plans to install 30 Gigawatts (GW) of offshore wind (OSW) capacity by 2030. The US Mid/North Atlantic will be a major contributor to the rising US OSW energy sector.

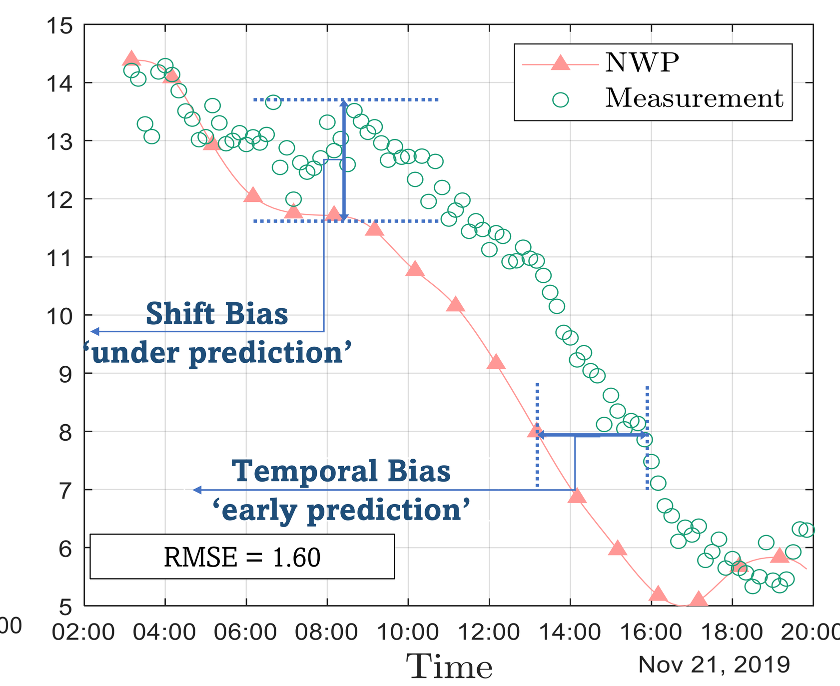
➢**Motivation:** Accurate OSW wind speed and power forecasts are pivotal to several wind energy operations, e.g., electricity markets, asset management, operations & maintenance scheduling, etc.

➢ **Aim: The Quest for the "Grey Box":** Develop a physics-guided machine learning (ML) model for OSW forecasting that borrows strength across physics-based and data-driven models.



NWP biases





While valuable on its own, NWP often exhibit noticeable biases when downscaled at higher spatial-temporal resolutions.

Contributions of this work

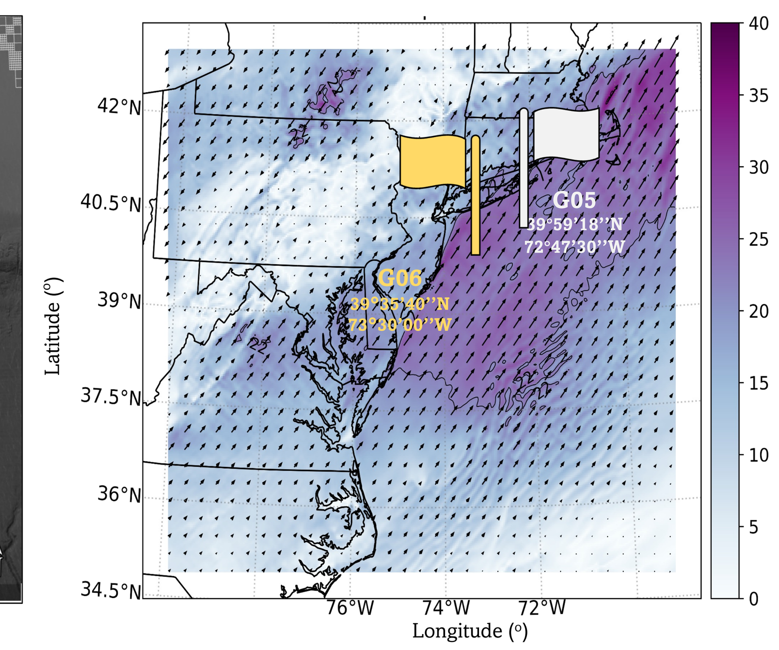
➢**AIRU-WRF:** AI-powered Rutgers University Weather Research & Forecasting. A physics-guided ML model for OSW forecasting.

➢AIRU-WRF integrates exogenous predictors that are both **meteorologically** relevant and **statistically** significant.

➢AIRU-WRF constructs physically meaningful kernels that can align with the physical principles of **wind advection and diffusion**.

➢AIRU-WRF is tested on **real data and state-of-the-art forecasts** from the U.S. Mid Atlantic, and is shown to outperform various benchmarks in terms of both point and probabilistic forecasting.

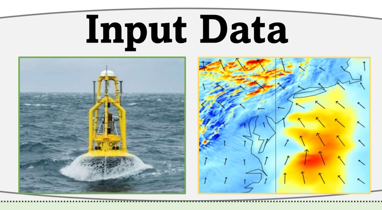
Real Data & Forecasts



Data: NYSERDA's Lidar buoys (E05 and E06) **NWP forecasts:** RU-WRF 4.1.

High-level Workflow of AIRU-WRF

Input Data



1. Historical Weather Data, Y
Time series of wind speed measurements (Y)

2. Numerical Weather Predictions from RU-WRF, $\mathcal{Y}$, $\mathcal{W}$
Times series forecasts, including wind speed ($\mathcal{Y}$) and other meteorological variables ($\mathcal{W}$)

FEATURE ENGINEERING

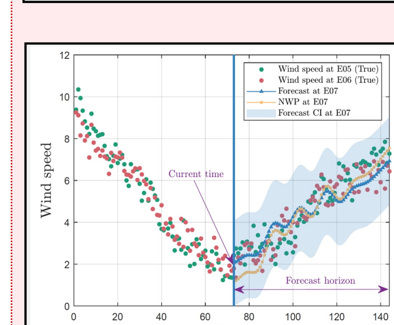
- COMPUTE SPATIO-TEMPORAL PRESSURE DIFFERENTIAL
  $\Delta(s_i, s_j, d) = p(s_i, t) - p(s_j, t + d)$
- ESTIMATE GEOSTOPHIC WIND
  $Y_g(s,t) = \sqrt{u_g^2 + v_g^2}$,
  $u_g = -\frac{g}{2\Omega \sin\rho}\frac{\partial H}{d y_c}$, $v_g = \frac{g}{2\Omega \sin\rho}\frac{\partial H}{d x_c}$,
- FORM THE FOLLOWING SETS
  $\mathcal{X} = \{\mathcal{W}, \Delta, Y_g \mid |\mathcal{X}| = p\}$,
  $\mathcal{Y}^\ell = \{\mathcal{Y}(s,t), \ldots, \mathcal{Y}(s, t-\ell) \mid \ell \in \mathbb{Z}^+\}$
- INTERPOLATE $\mathcal{X}, \mathcal{Y}, \mathcal{Y}^\ell$ USING CUBIC SPLINES (CS) TO MATCH THE RESOLUTION
  $\tilde{\mathcal{X}}, \tilde{\mathcal{Y}}, \tilde{\mathcal{Y}}^\ell \leftarrow \mathcal{U}_{cs}(\mathcal{X}, \mathcal{Y}, \mathcal{Y}^\ell)$

FEATURE SELECTION

- PLOT PARTIAL AUTO CORRELATION FUNCTION (PACF) TO DETERMINE A SUITABLE VALUE FOR ℓ OF $\tilde{\mathcal{Y}}^\ell$
- SET VARIABLE INDEX
  $i = 1 \mid i \in \{1, \ldots, p\}$
- FIND THE LAGGED VERSION OF $\tilde{\mathcal{X}}_i$ WITH THE HIGHEST CORRELATION TO WIND SPEED
  $M_x = \max_d corr\left(Y(s,t), \tilde{\mathcal{X}}_i(s, t+d)\right)$,
  $d \in [-3, 3], d \in \mathbb{Z}$
- $M_x \geq M_{max}$? — NO / YES
- INCLUDE $\tilde{\mathcal{X}}_i(s, t+d)$ IN THE FINAL FEATURE SET $\tilde{\mathcal{G}}$
- UPDATE VARIABLE INDEX
  $i = i + 1$
- $i > p$? — NO / YES

PROBABILISTIC WIND SPEED FORECASTING

- TRAIN THE FOLLOWING BIAS CALIBRATION MODEL USING ORDINARY LEAST SQUARES
  $\mu(s,t) = a^T \tilde{\mathcal{Y}}^\ell + b^T \tilde{\mathcal{G}} + (c^T \tilde{\mathcal{G}})\tilde{\mathcal{Y}}$
  OUTPUT: parameter sets $\{\hat{a}, \hat{b}, \hat{c}\}$
- GET SPATIO-TEMPORAL BIAS CALIBRATION MODEL RESIDUALS
  $\eta(s,t) = Y(s,t) - \hat{\mu}(s, t|\hat{a}, \hat{b}, \hat{c})$,
- TRAIN A SPATIO-TEMPORAL GAUSSIAN PROCESS (GP) VIA MAXIMUM LIKELIHOOD
  $\eta \sim \mathcal{GP}(\beta_0, K^\eta)$
  $K^\eta = \alpha\{\lambda K_{SEP} + (1-\lambda)K_{asym}\} + \mathbb{I}_{\{\|u\|=|w|=0\}}\delta$,
  $K_{SEP} = K_s(u) \times K_t(w)$
  $K_{asym}(u, w) = \frac{1}{\sqrt{|1_{2\times 2} + \Sigma_\theta w^2|}}\exp(-D)$
  $D = (u - m_\theta w)^T (1_{2\times 2} + \Sigma_\theta w^2)^{-1}(u - m_\theta w)$
  $m_\theta, \Sigma_\theta \leftarrow$ training sample mean & covariance of $\tilde{\mathcal{Y}}$
  OUTPUT: parameter sets $\{\hat{\beta}_0, \hat{\alpha}, \hat{\lambda}, \hat{\delta}, \hat{r}^s, \hat{r}^t\}$
- MAKE PROBABILISTIC WIND SPEED FORECASTS VIA THE MULTIVARIATE JOINT PROBABILITY DISTRIBUTION:
  $\hat{F} \sim \mathcal{N}(\hat{\mu} + \hat{\eta}, \hat{\Sigma}_\eta)$

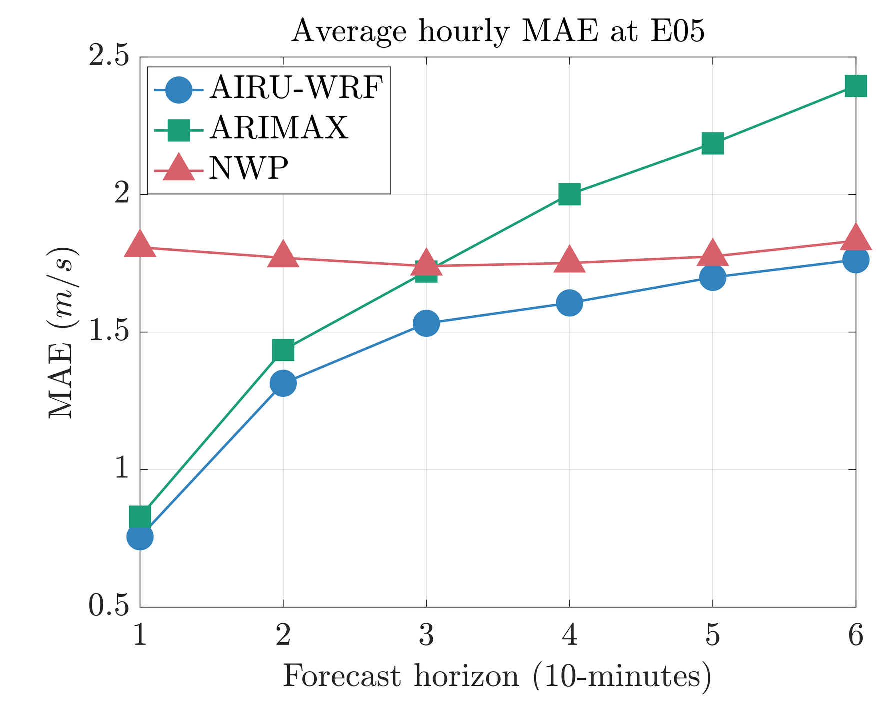


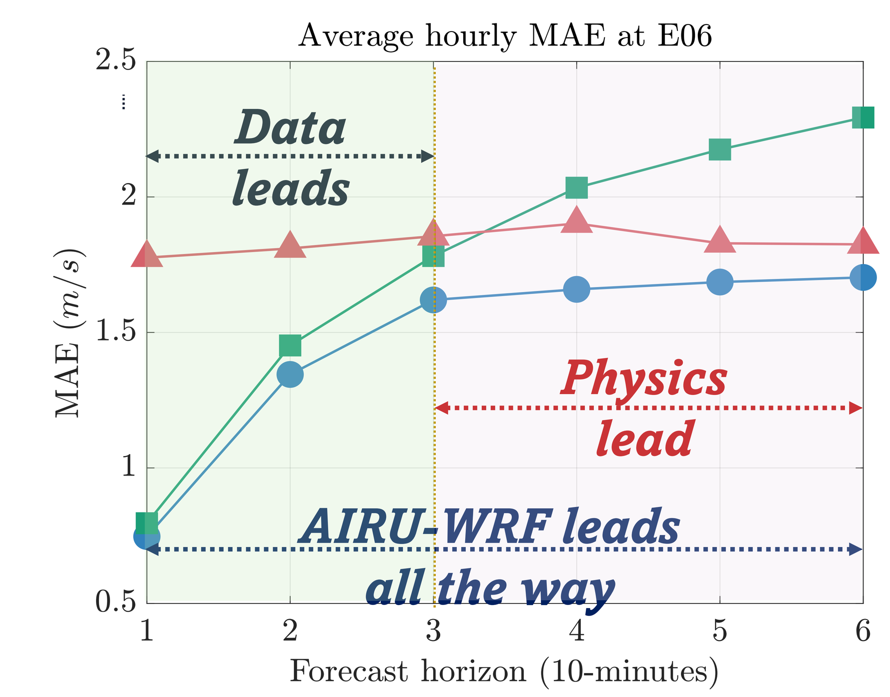
FINAL OUTPUT:
MAKE POINT FORECASTS & PREDICTION INTERVALS AT TARGET LOCATIONS & FORECAST HORIZONS

Results

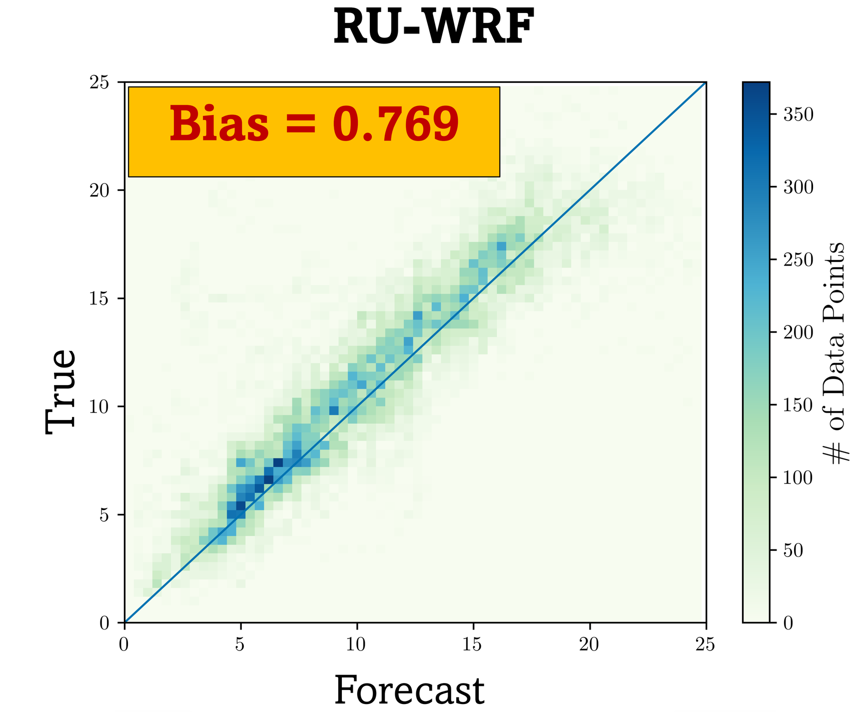
E05 (39°58'10"N and 72°43'00"W)									
	MAE						CRPS			
Horizon (hrs)	AIRU-WRF	GOP	NWP	ARIMAX	LSTM	PER	AIRU-WRF	GOP	ARIMAX
1	0.753	0.922	1.657	0.794	0.791	**0.743**	**0.575**	0.742	0.643
2	**1.267**	1.628	1.601	1.333	1.300	1.287	**0.957**	1.205	1.039
3	**1.451**	1.750	1.592	1.587	1.716	1.708	**1.094**	1.282	1.212
4	**1.478**	1.798	1.586	1.860	2.150	2.164	**1.133**	1.319	1.407
5	**1.561**	1.859	1.591	2.055	2.499	2.495	**1.186**	1.358	1.536
6	**1.651**	2.052	1.741	2.287	2.782	2.801	**1.274**	1.490	1.656
Average	**1.360**	1.668	1.631	1.653	1.873	1.866	**1.037**	1.233	1.249
% Improvement	-	18.5%	16.6%	17.7%	27.4%	27.1%	-	15.9%	17.0%

E06 (39°32'50"N and 73°25'45"W)									
	MAE						CRPS		
Horizon (hrs)	AIRU-WRF	GOP	NWP	ARIMAX	LSTM	PER	AIRU-WRF	GOP	ARIMAX
1	**0.727**	0.975	1.621	0.767	0.805	0.729	**0.556**	0.753	0.614
2	**1.271**	1.702	1.691	1.347	1.372	1.277	**0.969**	1.291	1.018
3	**1.530**	1.902	1.730	1.663	1.855	1.753	**1.193**	1.447	1.256
4	**1.558**	1.978	1.801	1.942	2.235	2.156	**1.216**	1.470	1.463
5	**1.592**	1.973	1.706	2.077	2.566	2.504	**1.235**	1.440	1.515
6	**1.584**	1.988	1.659	2.137	2.827	2.779	**1.252**	1.441	1.557
Average	**1.377**	1.753	1.701	1.656	1.943	1.866	**1.070**	1.307	1.237
% Improvement	-	21.4%	19.1%	16.8%	29.1%	26.2%	-	18.1%	13.5%

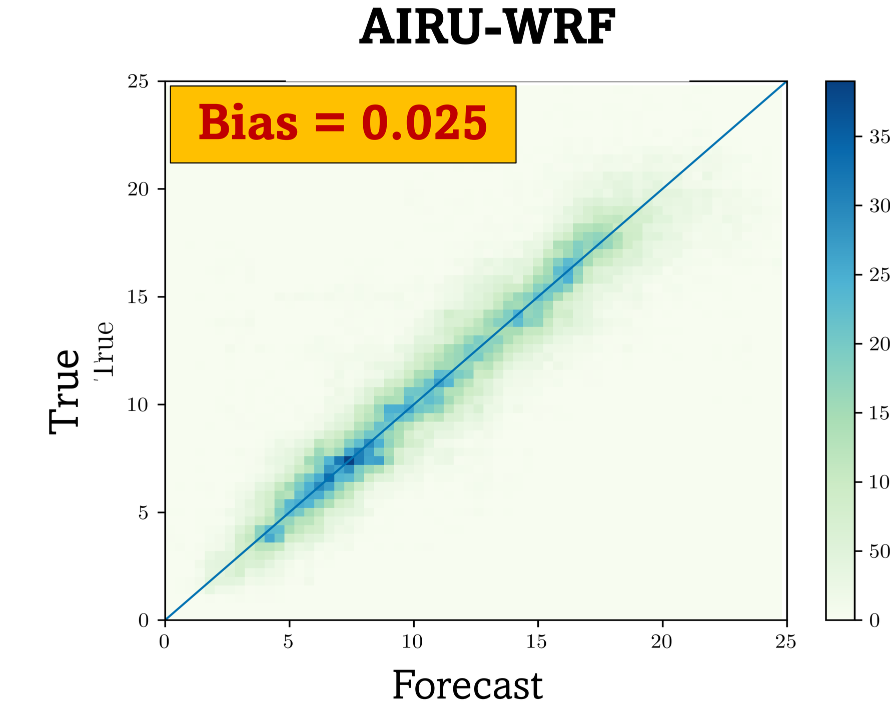


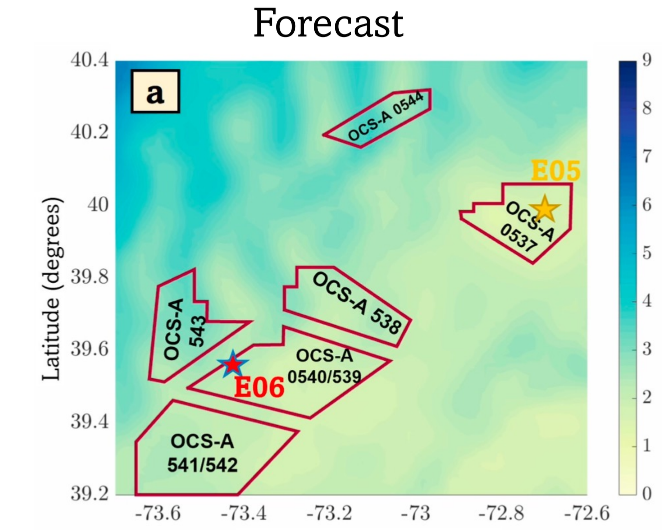


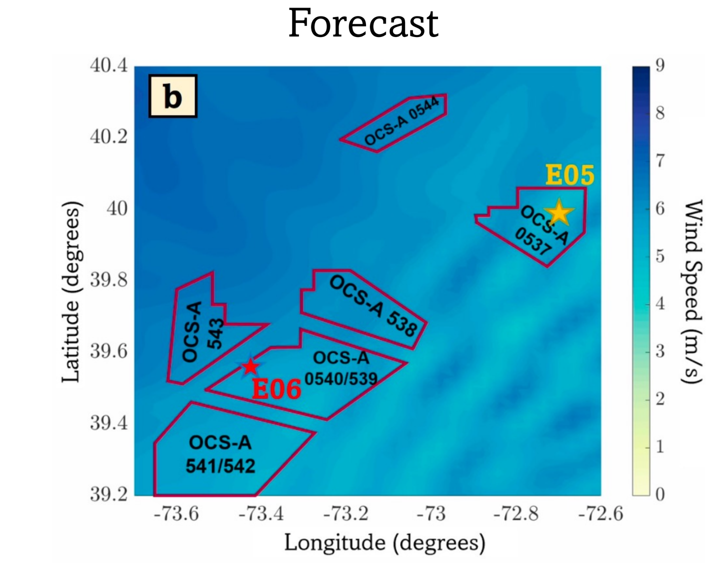
RU-WRF



AIRU-WRF







Conclusions

➢Significant improvements relative to a wide array of forecasting methods. In specific, AIRU-WRF outperforms statistical methods by **29.8-34.8%**, physics-based models by **16.3-18.0%**, hybrid methods by **8.6-9.1%**, and deep learning-based methods by **30.5-36.0%.**

➢Future work includes extensive testing for AIRU-WRF, as well as extending it to produce wind power forecasts, and to inform wind energy operations

Contact Information

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