AIRU-WRF: An AI-Powered Offshore Wind Forecasting Model for the U.S. Mid/North Atlantic Offshore Wind Energy Regions

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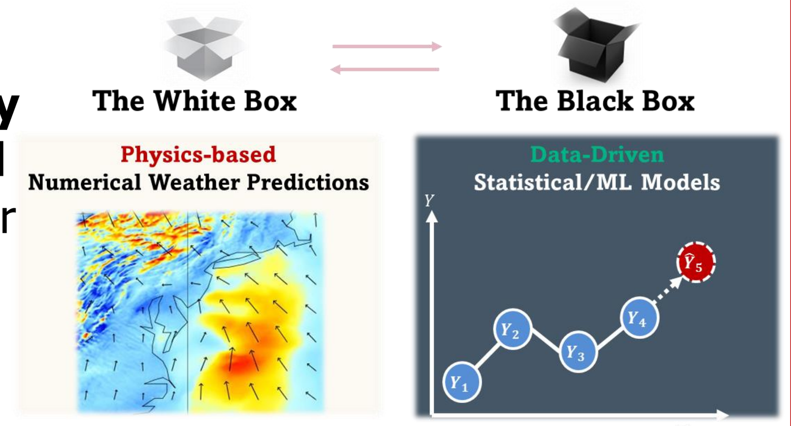
Introduction

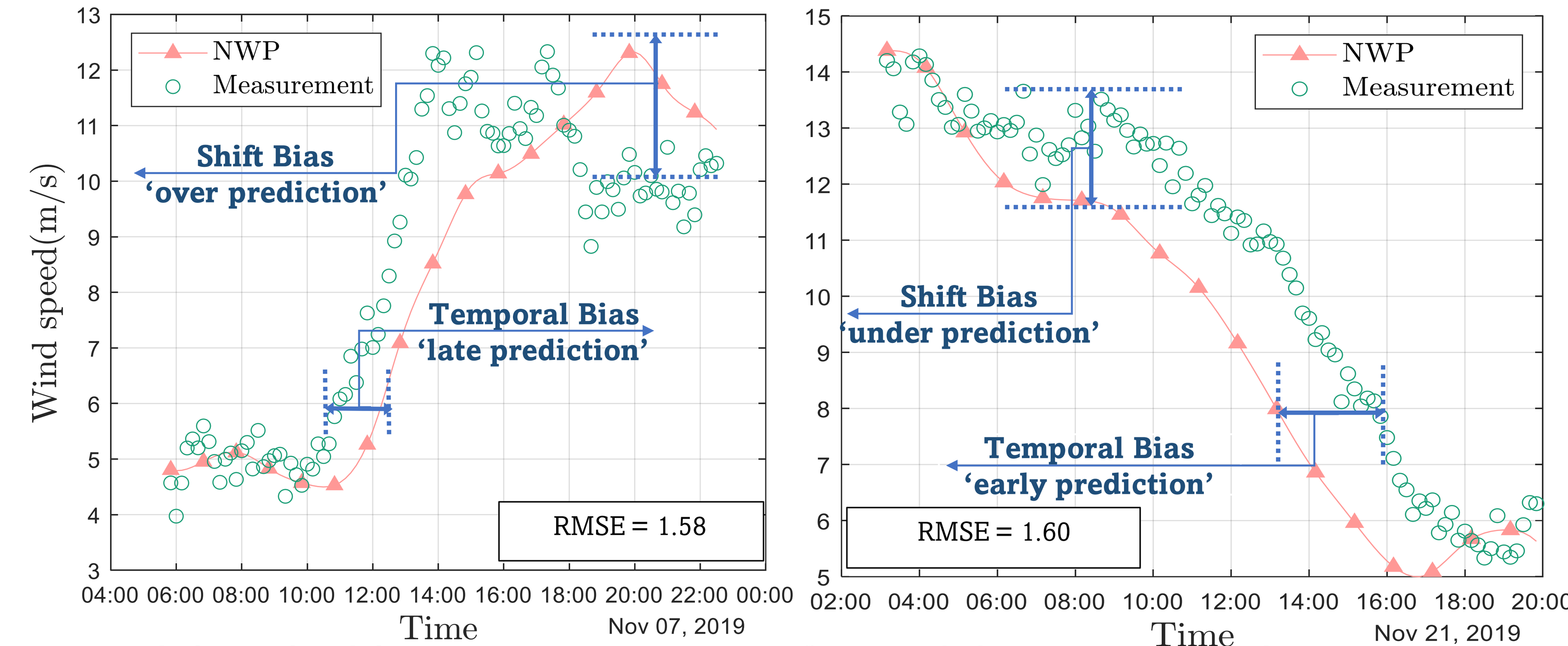
- **Background:** United States (US) plans to install 30 Gigawatts (GW) of offshore wind (OSW) capacity by 2030. The US Mid/North Atlantic will be a major contributor to the rising US OSW energy sector.
- **Motivation:** Accurate OSW wind speed and power forecasts are pivotal to several wind energy operations, 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.



Contributions of this work

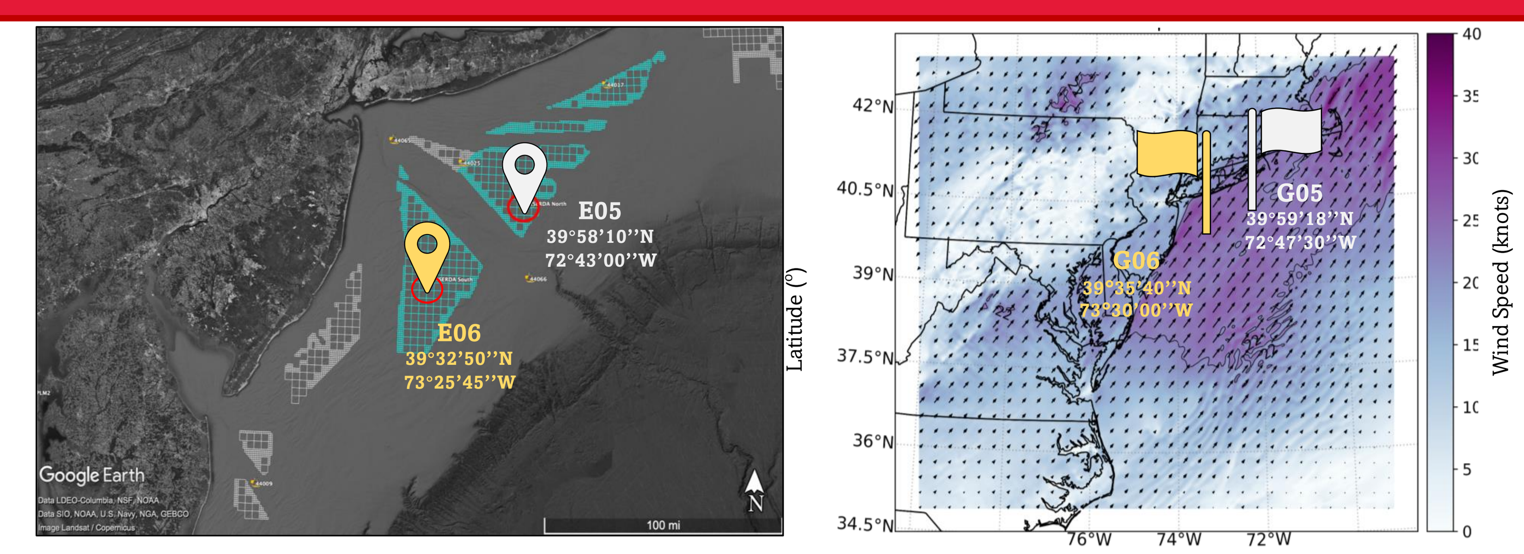
- **AIRU-WRF:** AI-powered Rutgers University Weather Research & Forecasting. A physics-guided ML model for OSW forecasting.
- AIRU-WRF integrates exogenous predictors that are both **meteorologically** relevant and **statistically** significant.
- AIRU-WRF constructs physically meaningful kernels that 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/North Atlantic, and is shown to outperform various benchmarks in terms of both point and probabilistic forecasting.

NWP biases



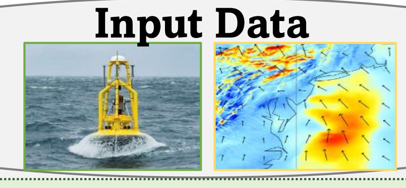
While valuable on its own, NWP often exhibit noticeable biases when downscaled at higher spatial-temporal resolutions.

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
$Y_g(s,t) = \sqrt{u_g^2 + v_g^2}$,
$u_g = -\frac{g}{2\Omega \sin\rho}\frac{\partial H}{dy_c}$, $v_g = \frac{g}{2\Omega \sin\rho}\frac{\partial H}{dx_c}$,

FORM THE FOLLOWING SETS
$\mathcal{X} = \{\mathcal{W}, \Delta, Y_g \mid |\mathcal{X}| = p\}$,
$\mathcal{Y}^{\ell} = \{\mathcal{Y}(s,t), \dots, \mathcal{Y}(s, t-\ell) \mid \ell \in \mathbb{Z}^+\}$

INTERPOLATE $\mathcal{X}, \mathcal{Y}, \mathcal{Y}^{\ell}$ USING CUBIC SPLINES (CS) TO MATCH THE RESOLUTION
$\tilde{\mathcal{X}}, \tilde{\mathcal{Y}}, \tilde{\mathcal{Y}}^{\ell} \leftarrow u_{cs}(\mathcal{X}, \mathcal{Y}, \mathcal{Y}^{\ell})$

FEATURE SELECTION

PLOT PARTIAL AUTO CORRELATION FUNCTION (PACF) TO DETERMINE A SUITABLE VALUE FOR ℓ OF $\tilde{\mathcal{Y}}^{\ell}$

SET VARIABLE INDEX
$i = 1 \mid i \in \{1, \dots, p\}$

FIND THE LAGGED VERSION OF $\tilde{\mathcal{X}}_i$ WITH THE HIGHEST CORRELATION TO WIND SPEED
$\mathcal{M}_x = \max_d corr\left(Y(s,t), \tilde{\mathcal{X}}_i(s, t+d)\right)$,
$d \in [-3, 3], d \in \mathbb{Z}$

$\mathcal{M}_x \geq \mathcal{M}_{max}$? 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

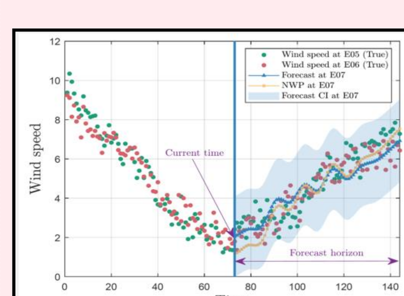
PROBABILISTIC WIND SPEED FORECASTING

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
$\eta(s,t) = Y(s,t) - \hat{\mu}(s, t \mid \hat{a}, \hat{b}, \hat{c})$,

TRAIN A SPATIO-TEMPORAL GAUSSIAN PROCESS (GP) VIA MAXIMUM LIKELIHOOD
$\boldsymbol{\eta} \sim \mathcal{GP}(\beta_0, K^{\eta})$
$K^{\eta} = \alpha\{\lambda K_{SEP} + (1-\lambda) K_{asym}\} + \mathbb{I}_{\{|\boldsymbol{u}|=|w|=0\}}\delta$,
$K_{SEP} = K_s(\boldsymbol{u}) \times K_t(w)$
$K_{asym}(\boldsymbol{u}, w) = \frac{1}{\sqrt{|\boldsymbol{1}_{2\times 2} + \boldsymbol{\Sigma}_{\boldsymbol{\theta}} w^2|}} \exp(-D)$
$D = (\boldsymbol{u} - \boldsymbol{m}_{\boldsymbol{\theta}} w)^T (\boldsymbol{1}_{2\times 2} + \boldsymbol{\Sigma}_{\boldsymbol{\theta}} w^2)^{-1} (\boldsymbol{u} - \boldsymbol{m}_{\boldsymbol{\theta}} w)$
$\boldsymbol{m}_{\boldsymbol{\theta}}, \boldsymbol{\Sigma}_{\boldsymbol{\theta}} \leftarrow$ 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:
$\hat{F} \sim \mathcal{N}(\hat{\mu} + \hat{\eta}, \hat{\Sigma}_{\eta})$

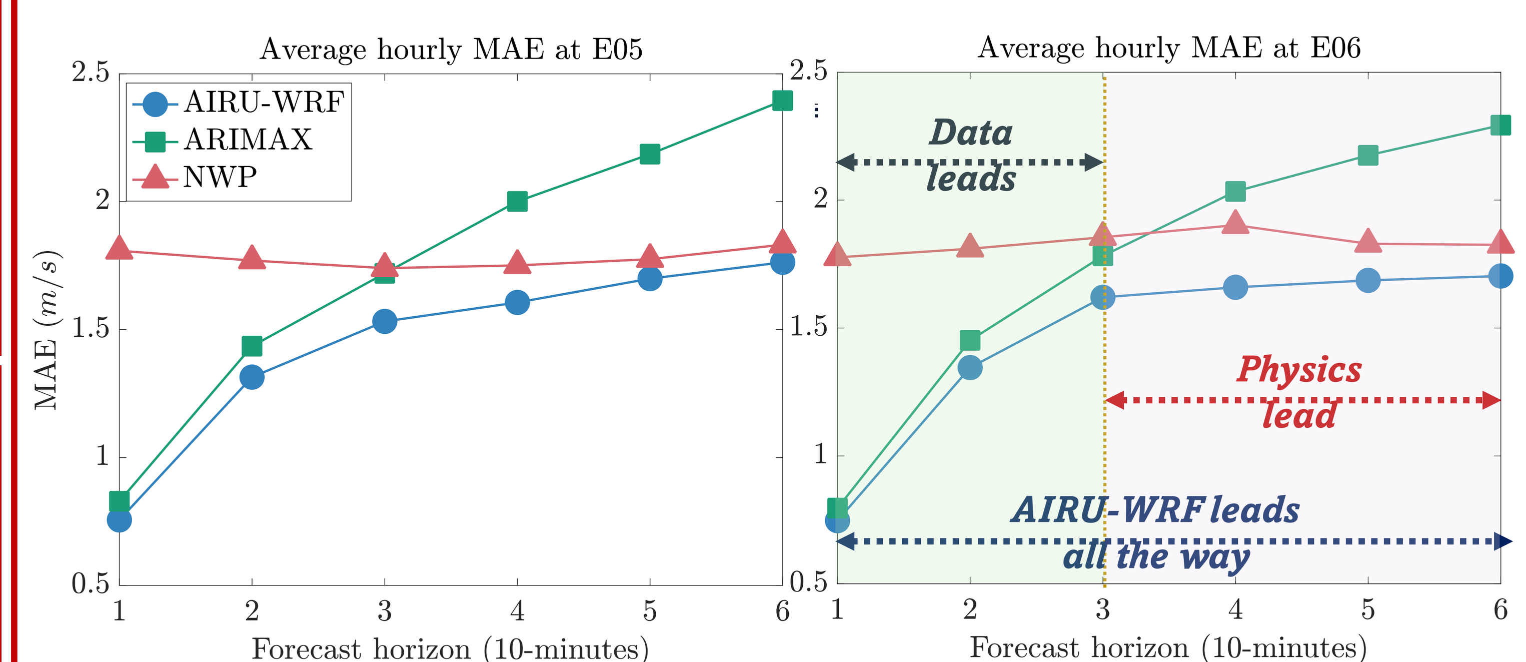


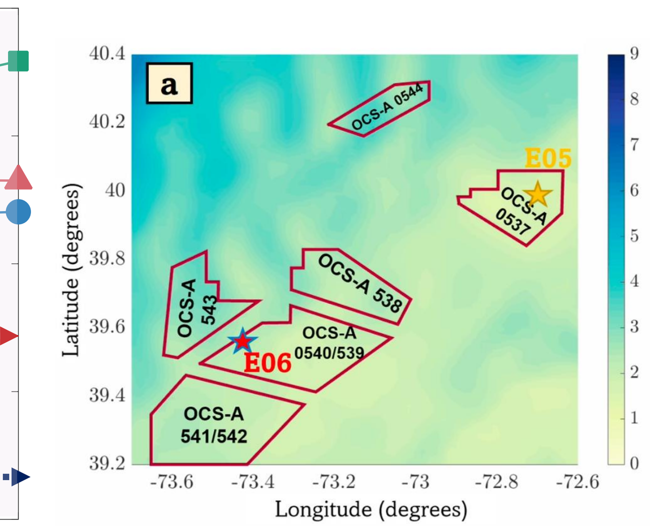
FINAL OUTPUT: MAKE POINT FORECASTS & PREDICTION INTERVALS AT TARGET LOCATIONS & FORECAST HORIZONS

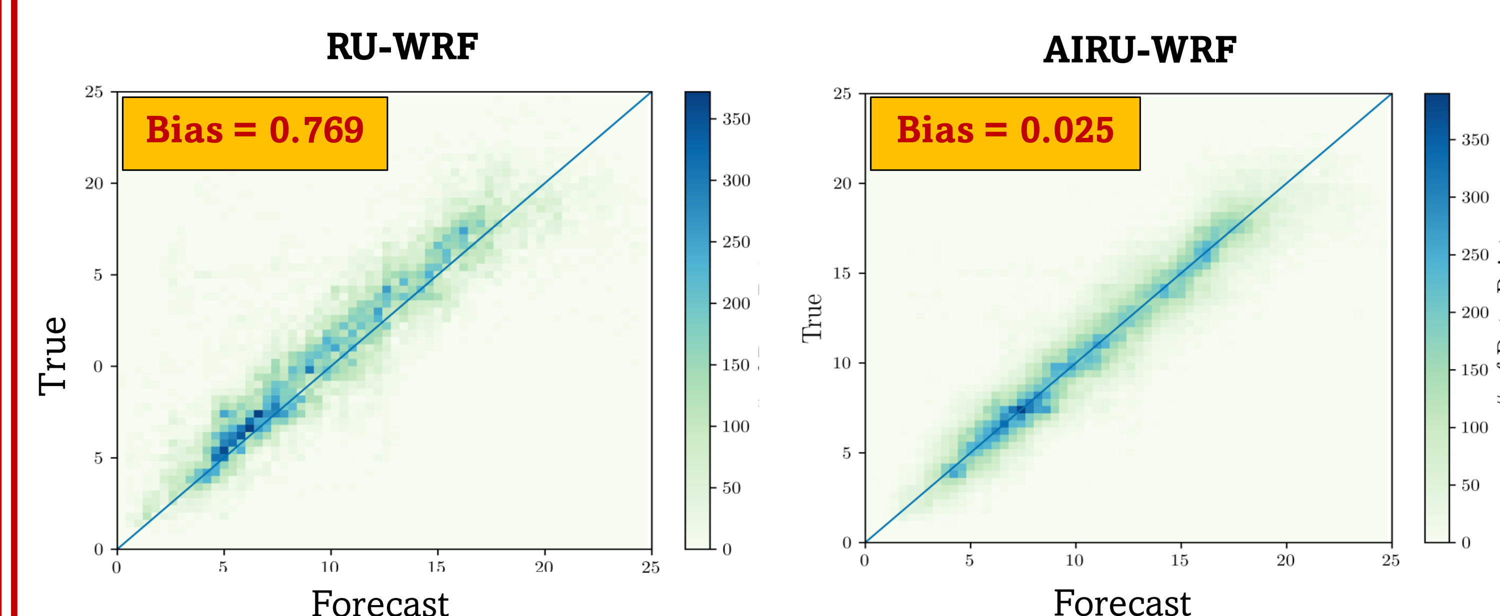
Results

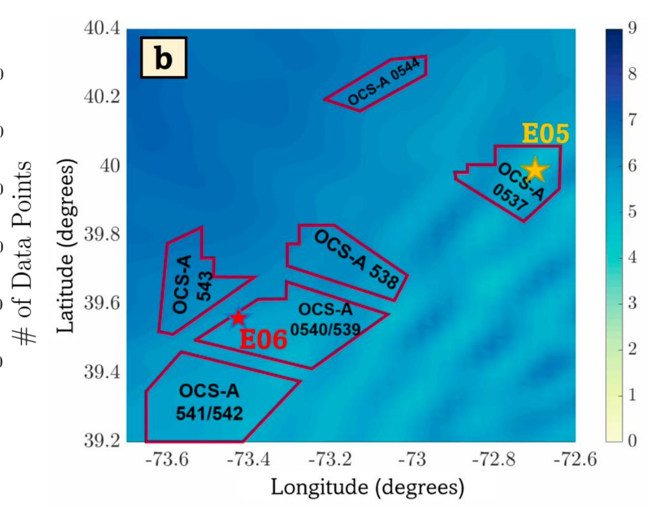
E05 (39°58'10"N and 72°43'00"W)	MAE						CRPS		
Horizon (hrs)	AIRU-WRF	GOP	NWP	ARIMAX	LSTM	PER	AIRU-WRF	GOP	ARIMAX
1	0.753	0.922	1.657	0.794	0.791	**0.743**	**0.575**	0.742	0.643
2	**1.267**	1.628	1.601	1.333	1.300	1.287	**0.957**	1.205	1.039
3	**1.451**	1.750	1.592	1.587	1.716	1.708	**1.094**	1.282	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%









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

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