Super Resolution for Renewable Energy Resource Data With Wind From Reanalysis Data (Sup3rWind) and Application to Ukraine

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Motivation and Objective

SUPPORT IN A TIME OF NEED: In Ukraine, the availability of reliable, long-term resource data is a barrier to accelerating the deployment of renewable energy. Planners are working to find ways to rebuild and decentralize a grid that has been seriously damaged by Russia's full-scale invasion. Public wind resource time series data will support:

- Project feasibility assessments
- Planning to decentralize power generation
- Modeling resiliency and rapid transition to renewables.

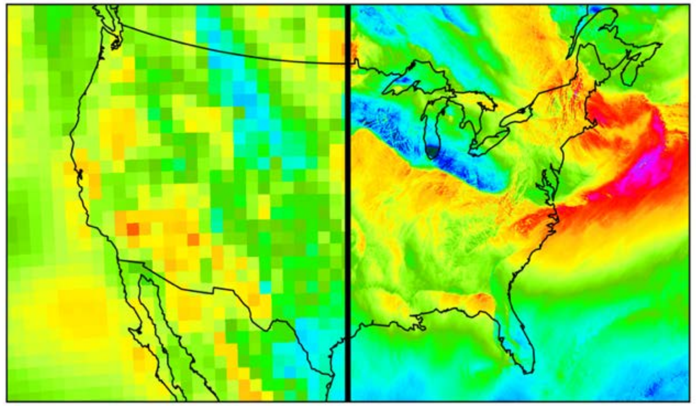
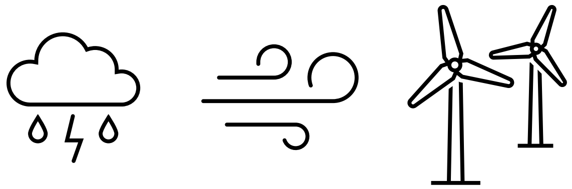


Figure Credit: Ryan King, NREL

OBJECTIVE: Downscale historical meteorological data to finer resolutions for wind energy modeling.



VALUE PROPOSITION: Capture important atmospheric processes for the wind energy community and modeling applications:

- Historically accurate, meso-scale wind flow
- Subhourly to interannual resource variability
- Accurate vertical wind profile (wind shear)
- Ramping rates at fine temporal scales
- Publicly available data that is easy to access.

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Traditional Approach to Wind Resource Assessment

Traditional approaches are based on Numerical Weather Prediction (NWP) using dynamical downscaling, frequently with the Weather Research and Forecasting (WRF) model.

Coarse Global Climate Reanalysis Data + Weather Research and Forecasting (**WRF**) Model = Meso-Scale Wind Resource Time Series Data

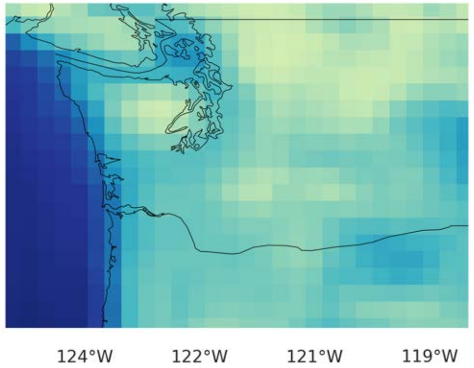


Figure Credit: Brandon Benton, NREL

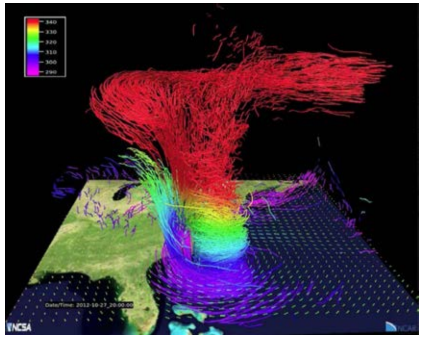


Figure Credit: Mel Shapiro, NCAR

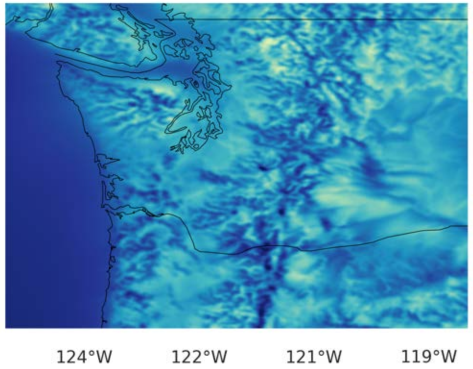


Figure Credit: Brandon Benton, NREL

Highly Accurate but Low Computational Efficiency

A New Paradigm for Wind Resource Assessment

Apply deep machine learning technique[1] to downscale coarse reanalysis data, producing high-resolution wind resource data that is physically consistent with traditional NWP data sets.

Coarse Global Climate Reanalysis Data + Generative Adversarial Networks (**GANs**) = Meso-Scale Wind Resource Time Series Data

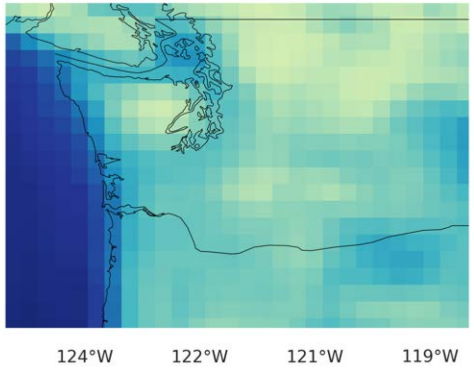
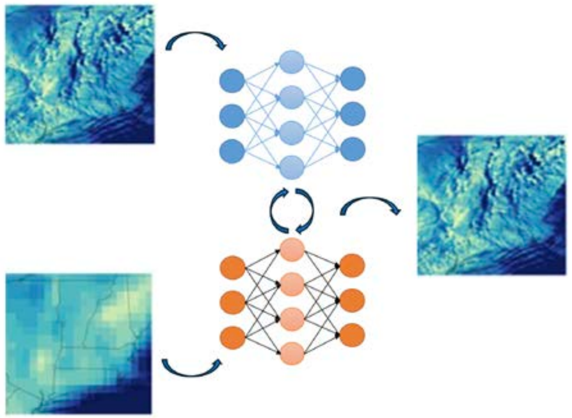
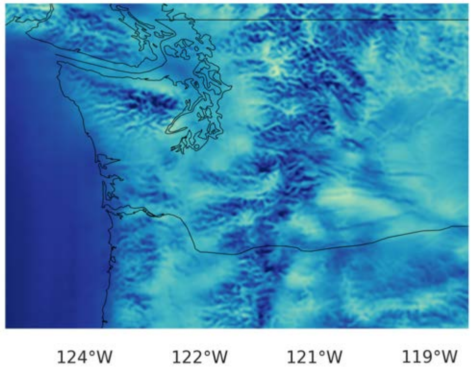


Figure Credit: Brandon Benton, NREL

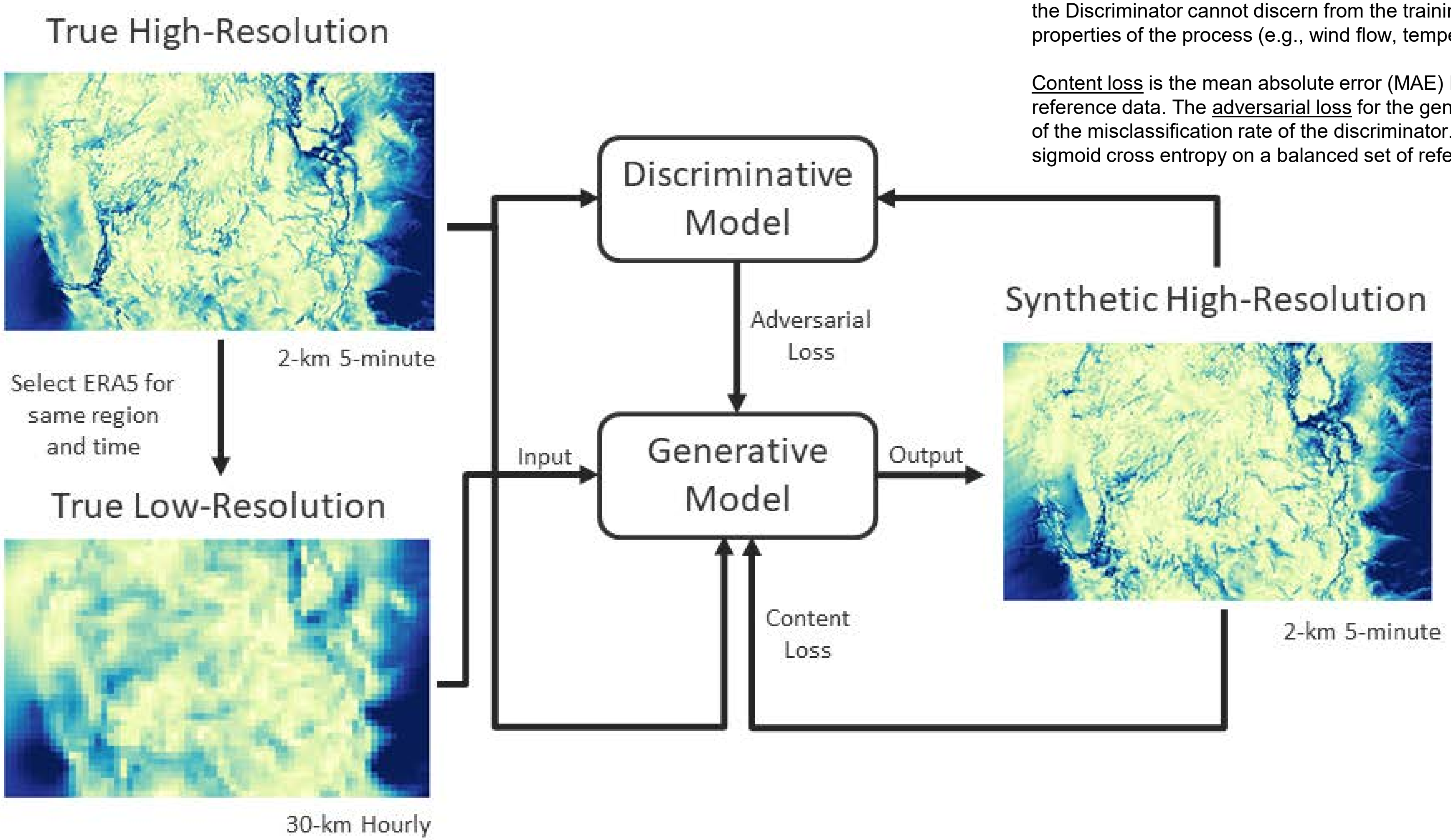




Highly Accurate and High Computational Efficiency

[1] Based on Stengel et al. (2020).

The Model: Super Resolution for Renewable Resource (Sup3r)[2]



Training the Sup3r Model:

A GANs model has two deep learning networks: a Generator and a Discriminator. Training is an iterative process where the Generator learns to produce fields that the Discriminator cannot discern from the training data by replicating the physical properties of the process (e.g., wind flow, temperature, relative humidity).

Content loss is the mean absolute error (MAE) between the simulated data and the reference data. The adversarial loss for the generator is the sigmoid cross entropy[3] of the misclassification rate of the discriminator. The discriminator loss is the sigmoid cross entropy on a balanced set of reference and simulated data.

[2] Benton et al. (2022).
[3] Wang et al. (2022).

Data Overview

- **ERA5**[4]: An atmospheric reanalysis dataset that combines observations from various measurement sources and the output of a numerical model. Consists of hourly atmospheric data from the surface of the earth to roughly 100 km altitude from 1979 to the present day at 30 km nominal horizontal resolution. <u>We train on 2007 – 2013, excluding 2010.</u>

- **WTK**[5]: Wind data produced through dynamical downscaling with WRF version 3.4.1 using ERA-Interim, the predecessor to ERA5, for initialization and boundary conditions. Includes windspeed and wind direction at 10, 40, 80, 100, 120, 160, and 200 meters above ground level. <u>This data serves as the ground truth for our models.</u>

- **MADIS**[6]: A comprehensive collection of meteorological observations covering the entire globe. <u>We use 37 observation locations across Ukraine for performance assessment.</u>

- **Vortex Wind from Global Wind Atlas (GWA)[7]:** Global high-resolution 20-year monthly means of windspeed. <u>This data is used for bias correction prior to inference.</u> We bias correct ERA5 data over Ukraine by matching the corrected ERA5 monthly means over 2000-2020 with the GWA monthly means.

[4] Hersbach et al. (2020).

[5] Draxl et al. (2015).

[6] NOAA (2022).

[7] Davis et al. (2023).

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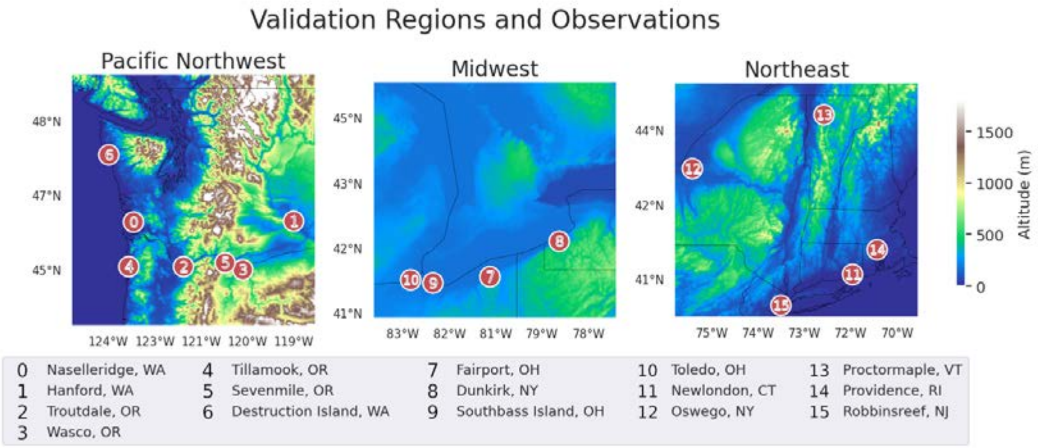
Model Architecture

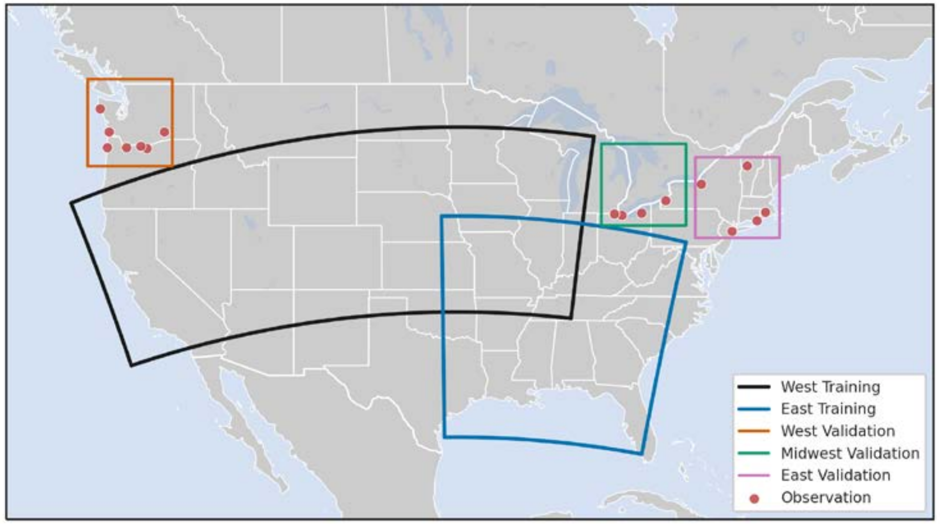
Model Step	Enhancement	Training Features	Input	Output Target	Training Time
1	3x spatial	U/V at 10, 100, 200 meters, cape, k index, surface pressure, instantaneous moisture flux, surface temperature, surface latent heat flux, 2-m dewpoint temperature, friction velocity + 2-km topography	ERA5 (30-km, hourly)	Spatially averaged and temporally subsampled WTK (10-km, hourly)	240 compute node hours, 2,500 epochs
2	5x spatial	U/V at 10, 40, 80, 100, 120, 160, 200 meters + 2-km topography	Coarsened WTK (10-km, hourly)	Temporally subsampled WTK (2-km, hourly)	50 compute node hours, 7,000 epochs
3	12x temporal	U/V at 10, 40, 80, 100, 120, 160, 200 meters + 2-km topography	Subsampled WTK (2-km, hourly)	Original WTK (2-km, 5-minute)	200 compute node hours, 10,000 epochs

- We train three models to perform 15x spatial, 12x temporal enhancement in three separate steps.
- The first model is trained on additional, non-wind, surface variables, to better capture surface-driven dynamics.
- All models are trained on multiple hub heights to encourage an accurate vertical profile.

Training and Validation

- We train on pairs of ERA5 and WTK data to go from ERA5 input to high resolution (2-km, 5-min output).
- Trained on 2007 – 2013, excluding 2010 (held out for validation).
- Final model selection based on performance for 2010, relative to ground truth, across all six validation regions.
- Observational data from Pacific Northwest, Midwest, and Northeast used for final CONUS performance assessment/validation.

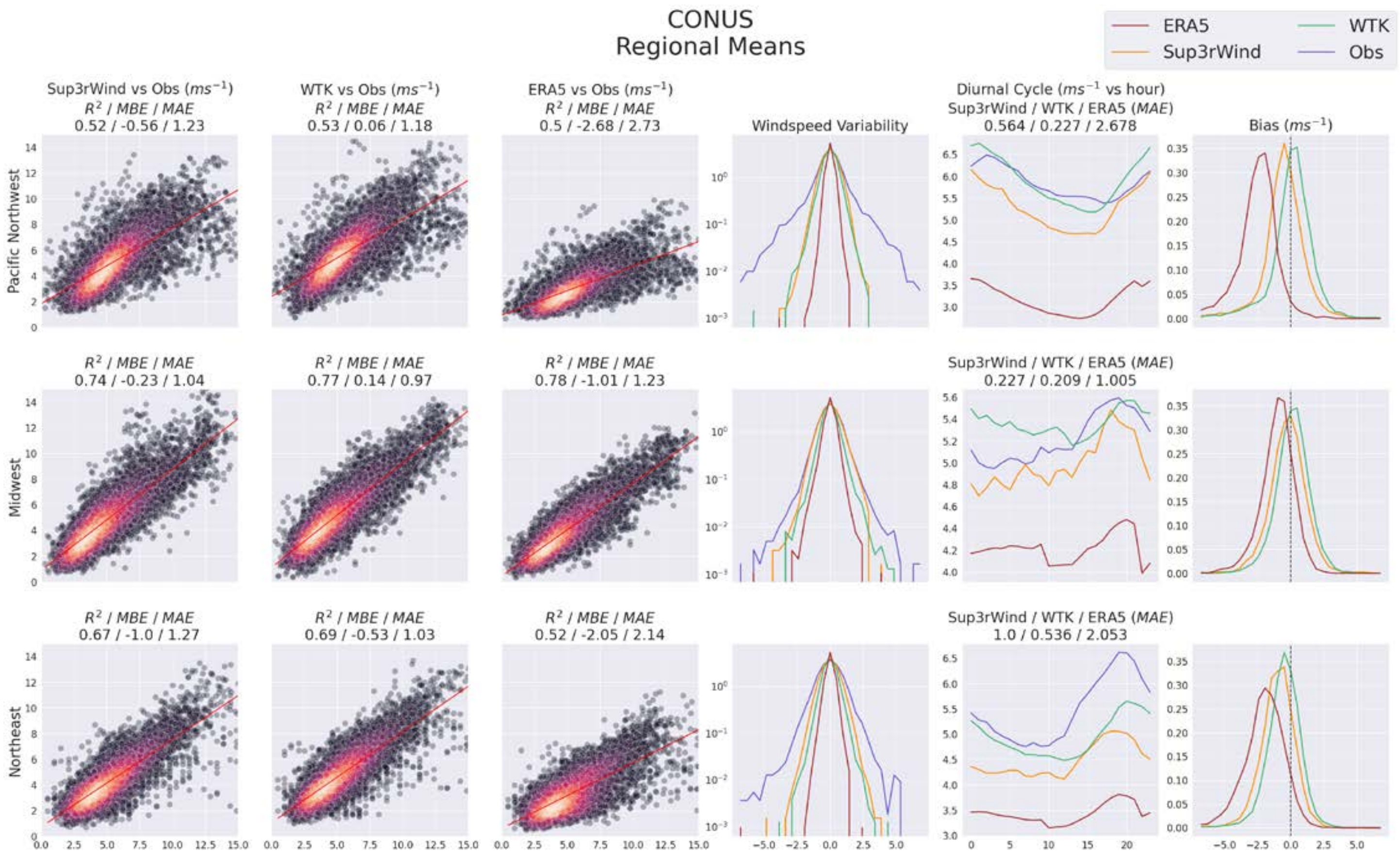




Regional CONUS Validation

Site-wise and physical metrics show excellent agreement with the high-resolution target data (WTK).

Hub heights for observations are all between 20 m and 50 m above ground.



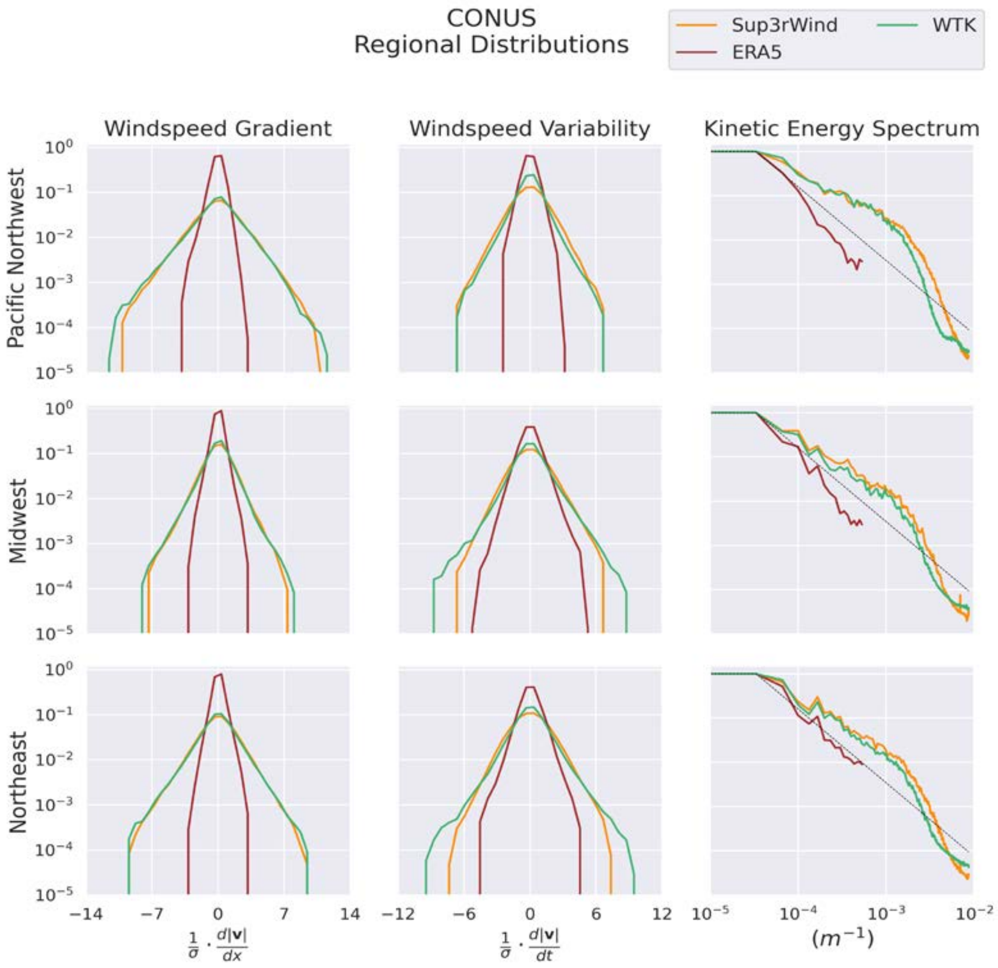
R^2 (coefficient of determination), MBE (mean bias error), and MAE (mean absolute error) shown above scatter plots.

Regional CONUS Validation (cont.)

Normalized distributions for:

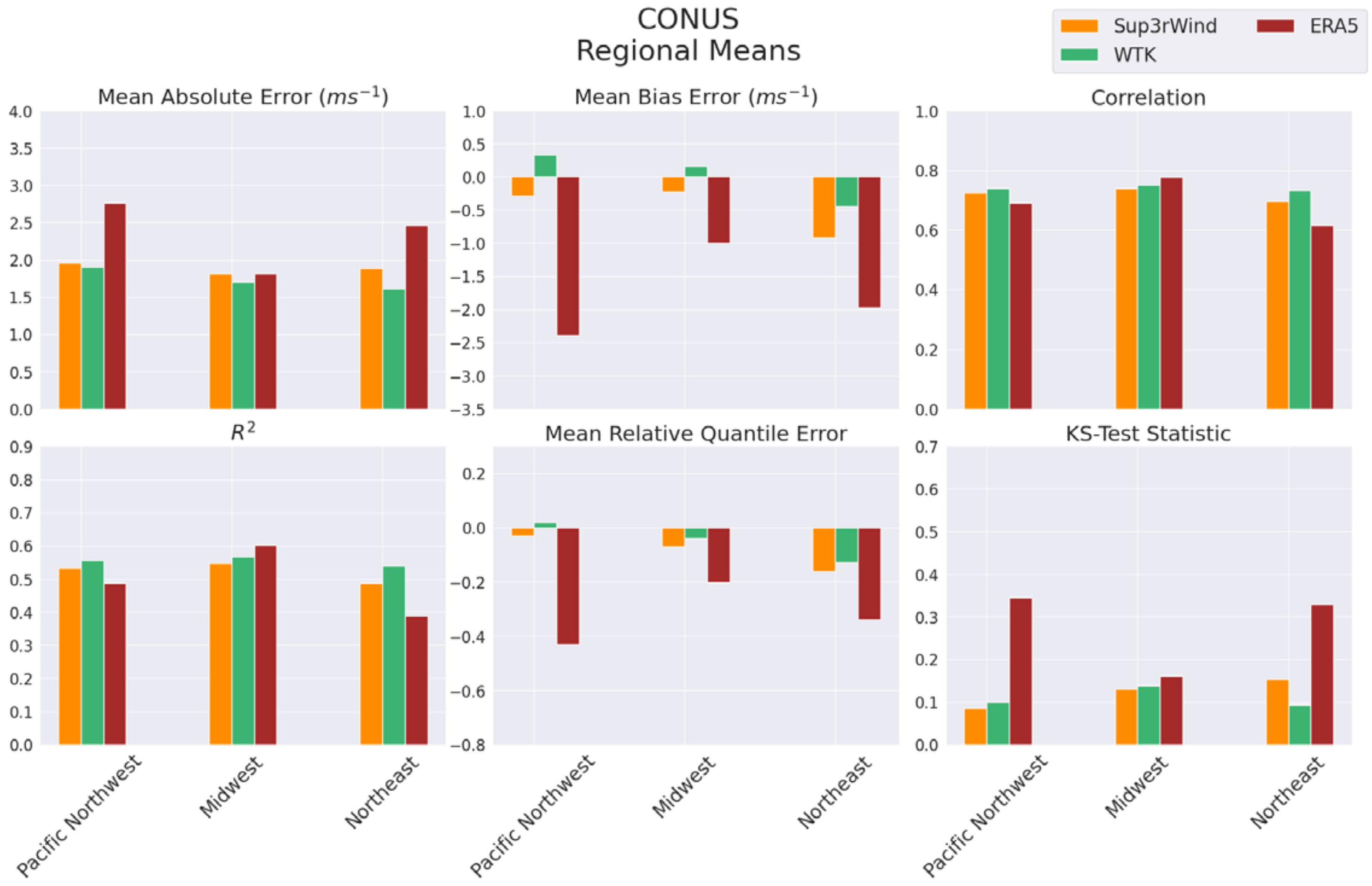
- Longitudinal windspeed gradient
- Windspeed variability
- Kinetic energy spectrum.

Values for windspeed gradient and windspeed variability are shown relative to their standard deviation.



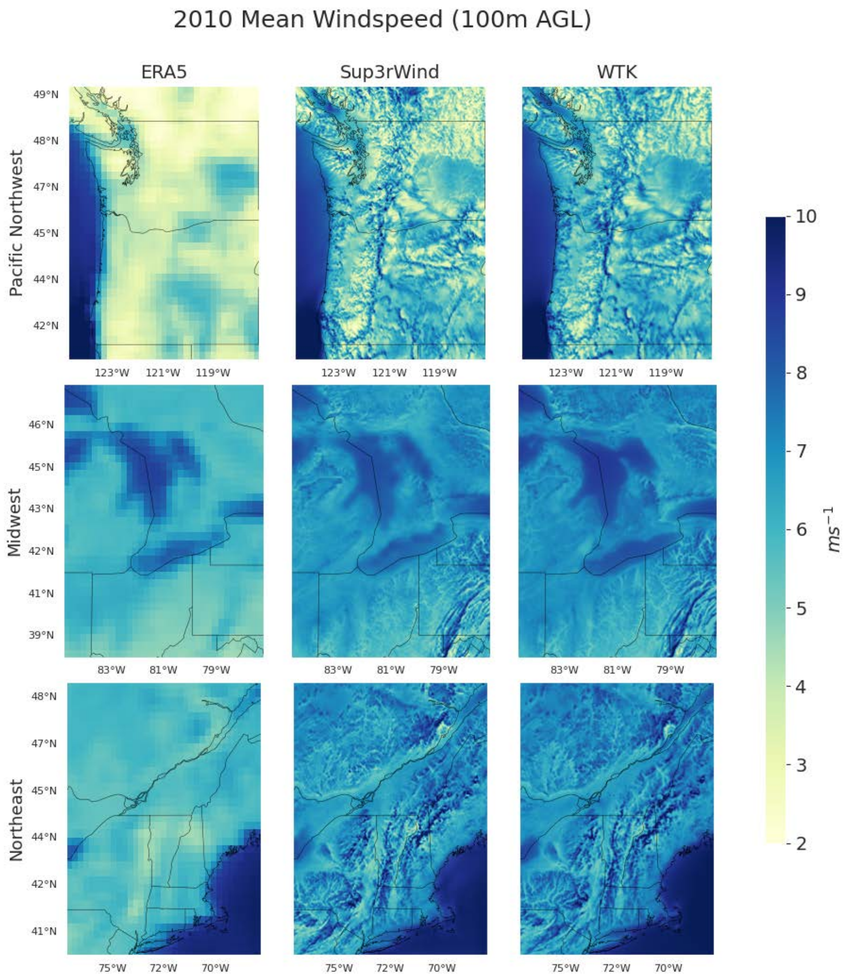
Regional CONUS Validation (cont.)

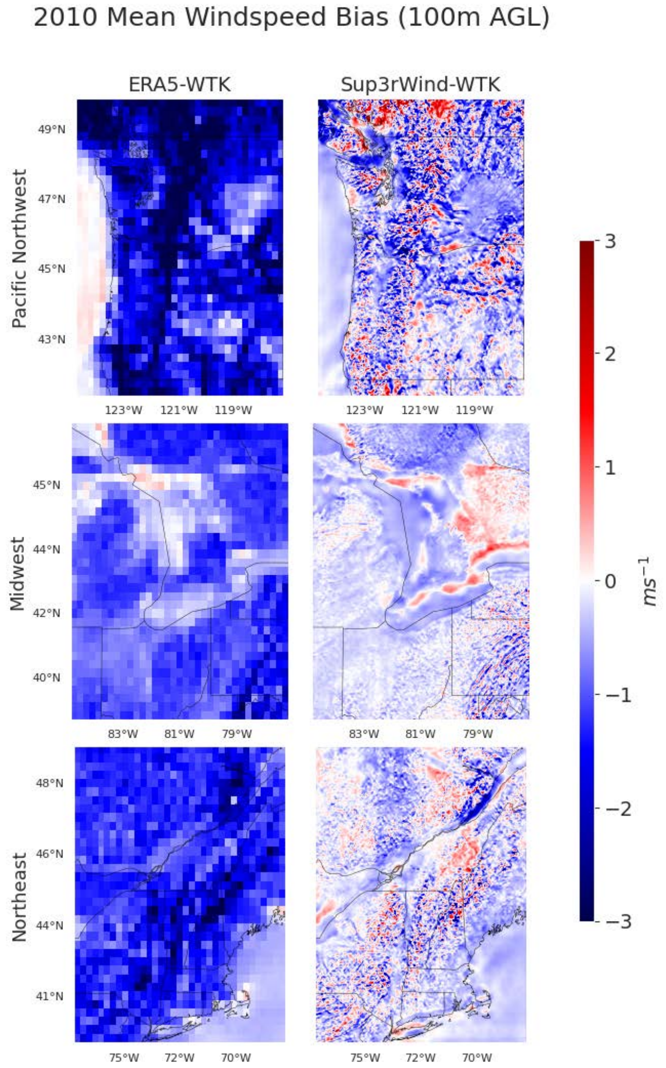
Metric (Mean across all regions)	Sup3rWind	WTK	ERA5
Mean Absolute Error	1.901 m/s	1.769 m/s	2.428 m/s
Mean Bias Error	-0.434 m/s	0.079 m/s	-1.908 m/s
Pearson Correlation Coefficient	0.721	0.741	0.692



Regional CONUS Validation (cont.)

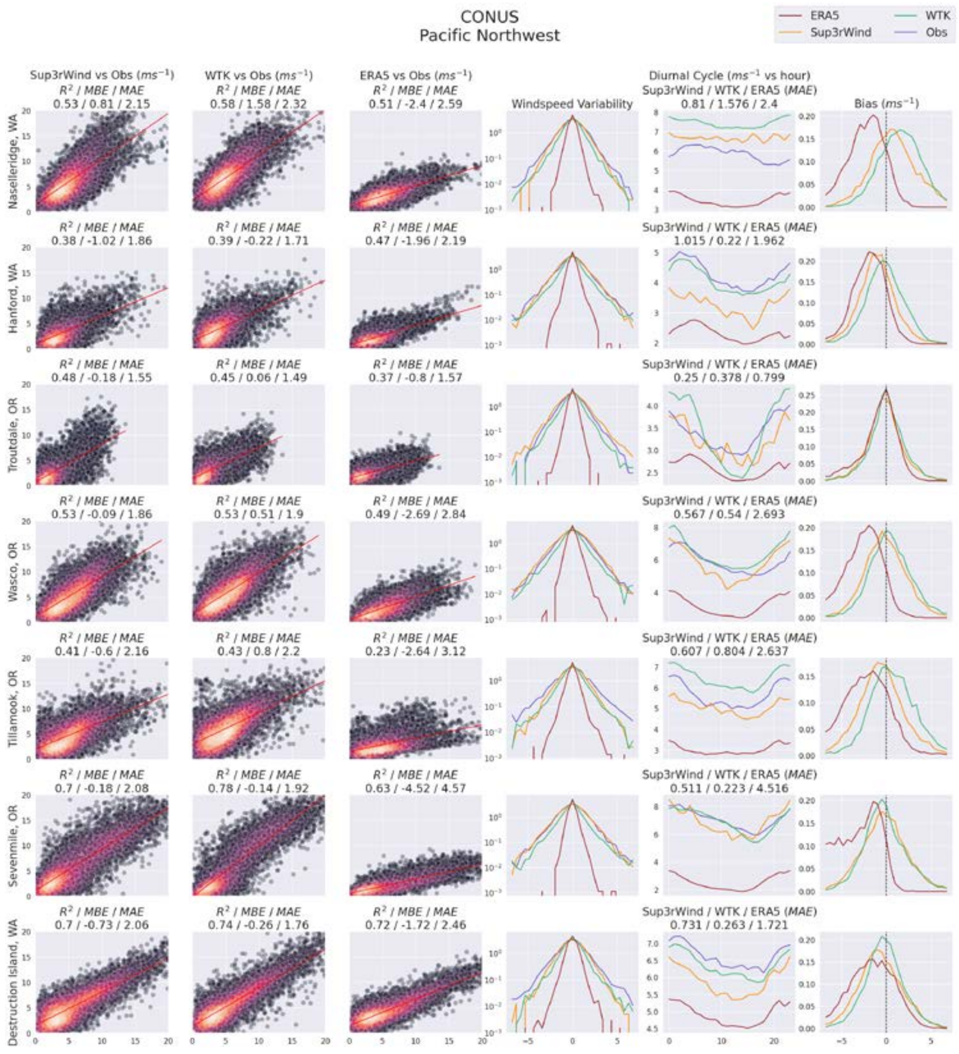
Annual mean windspeed fields from Sup3rWind agree well with WTK across validation regions.





Pacific Northwest Validation

Validation metrics for each site in the Pacific Northwest Validation Region



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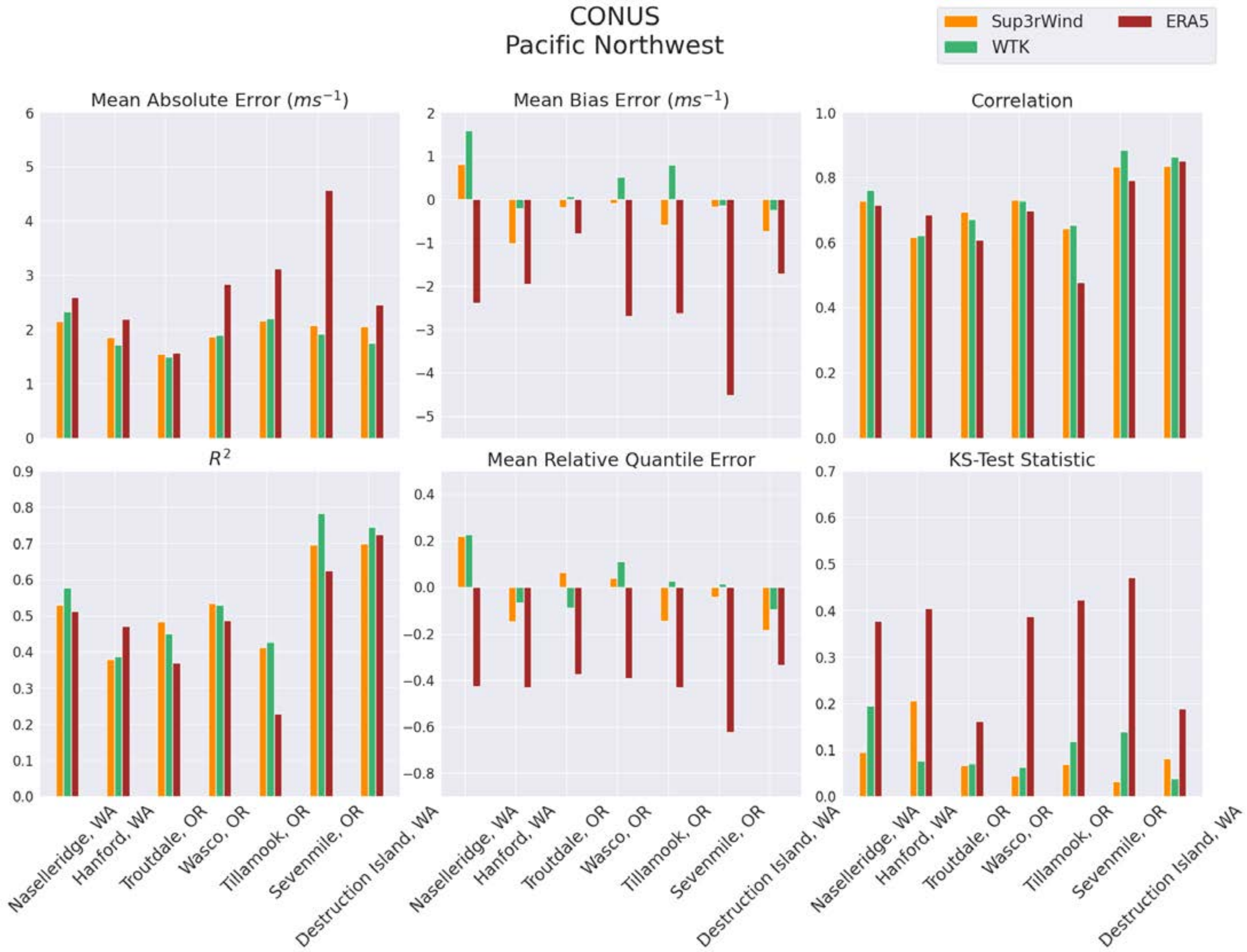
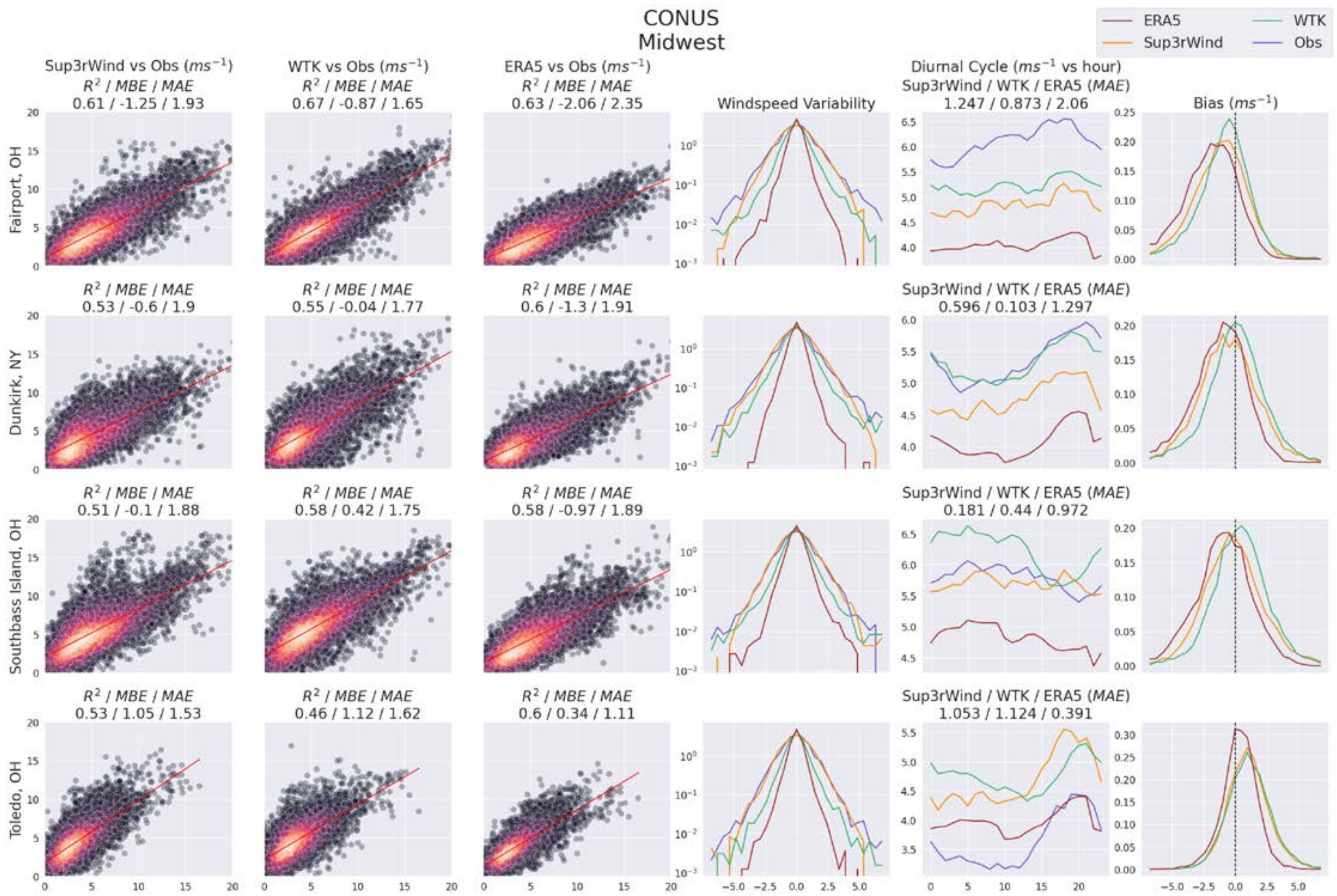
Pacific Northwest Validation (cont.)

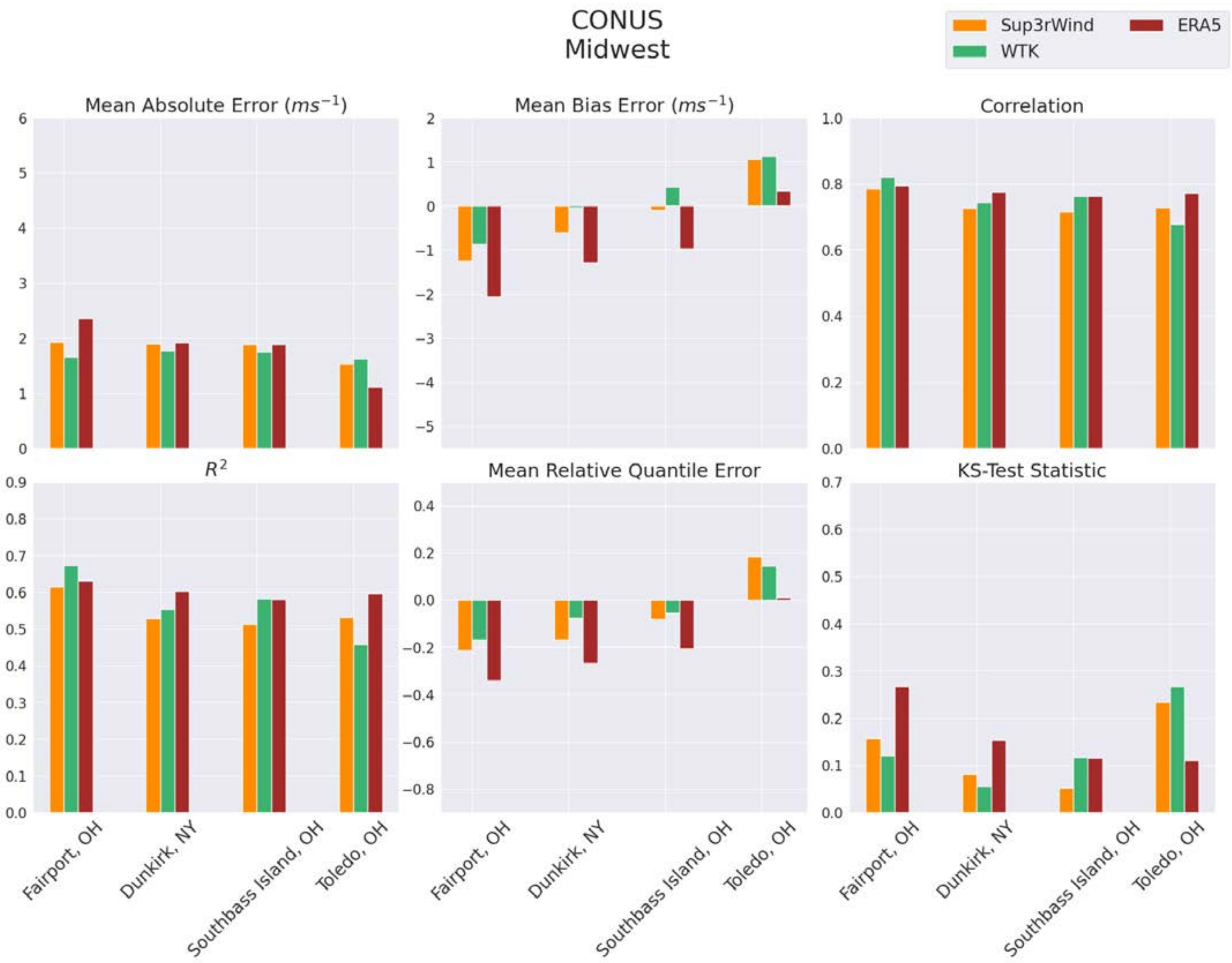


Midwest Validation

Validation metrics for each site in the Midwest Validation Region



Midwest Validation (cont.)



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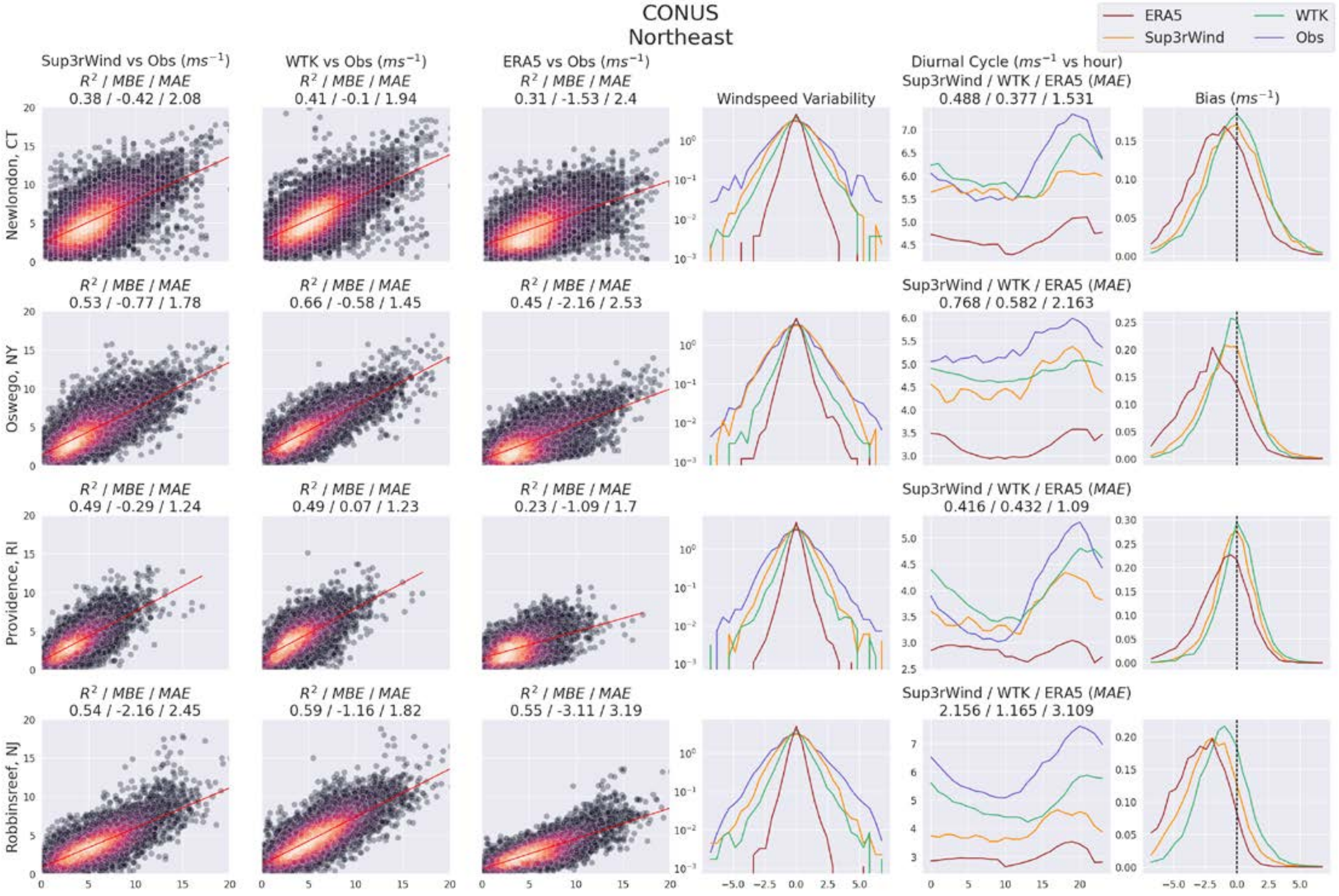
Northeast Validation

Validation metrics for each site in the Northeast Validation Region



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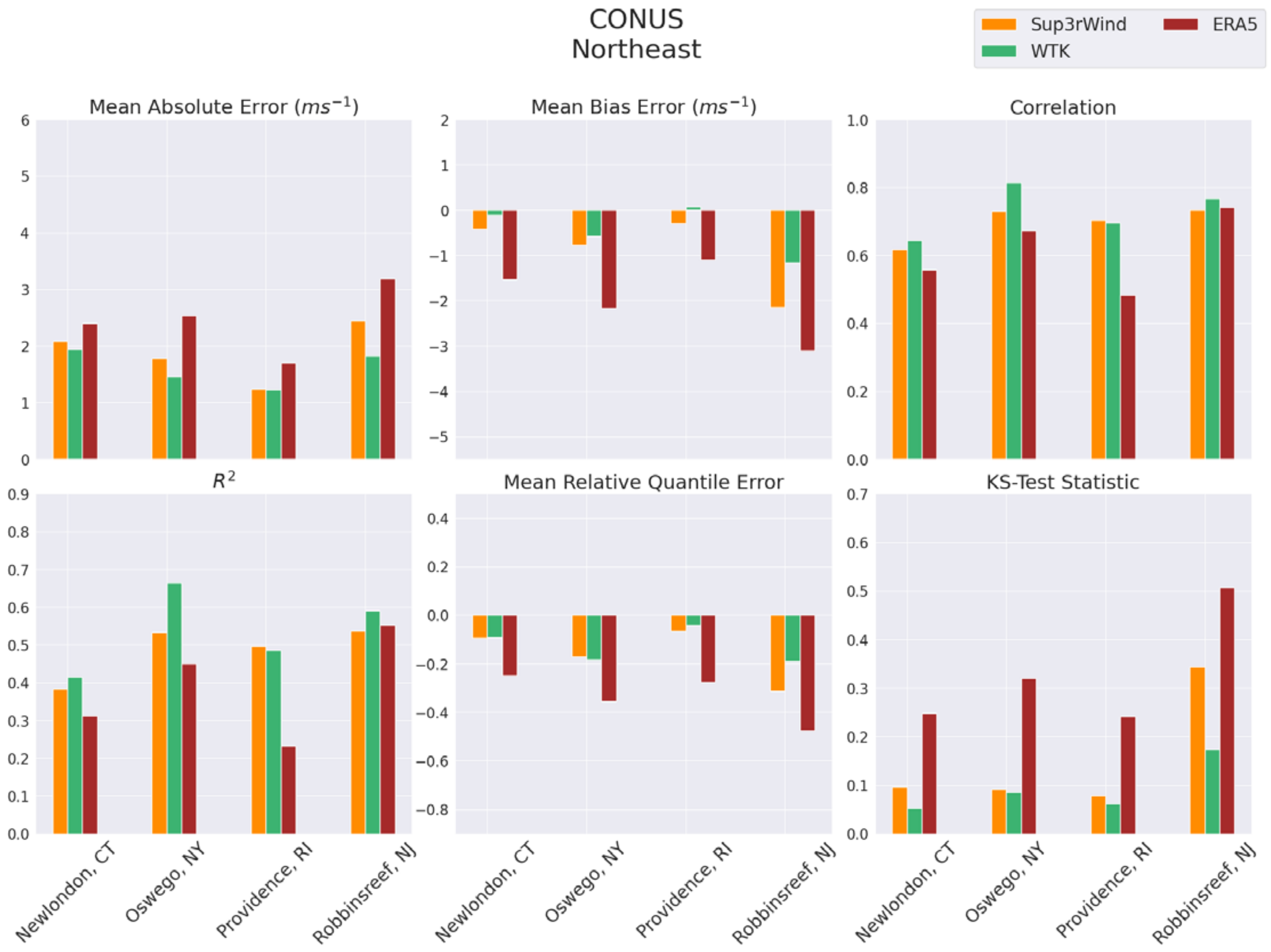
Northeast Validation (cont.)



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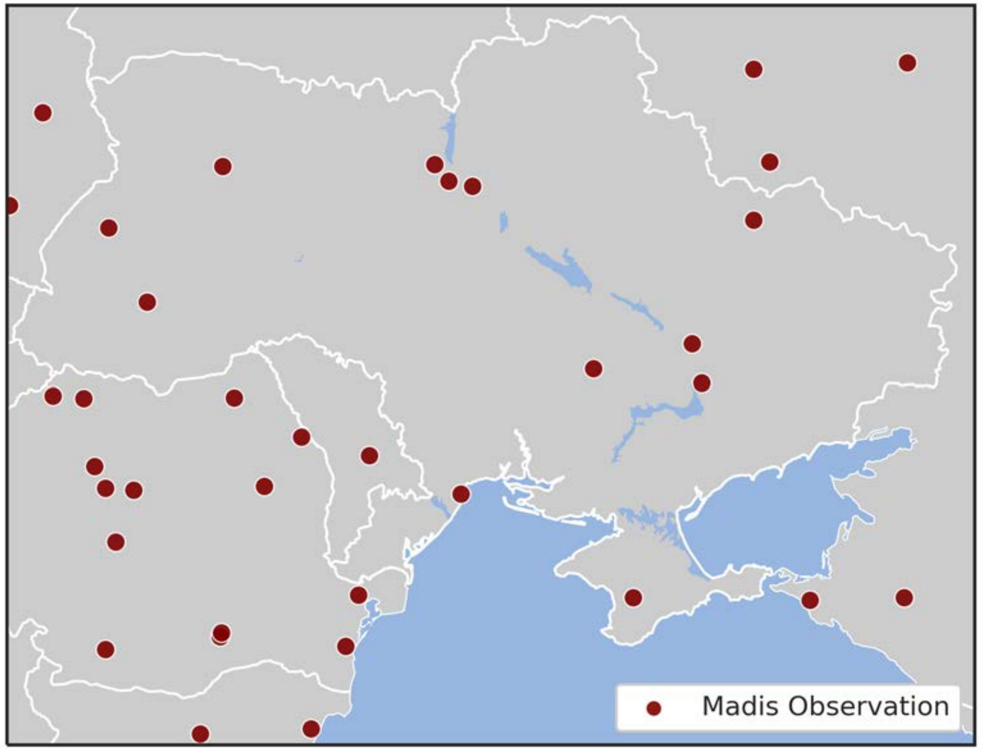
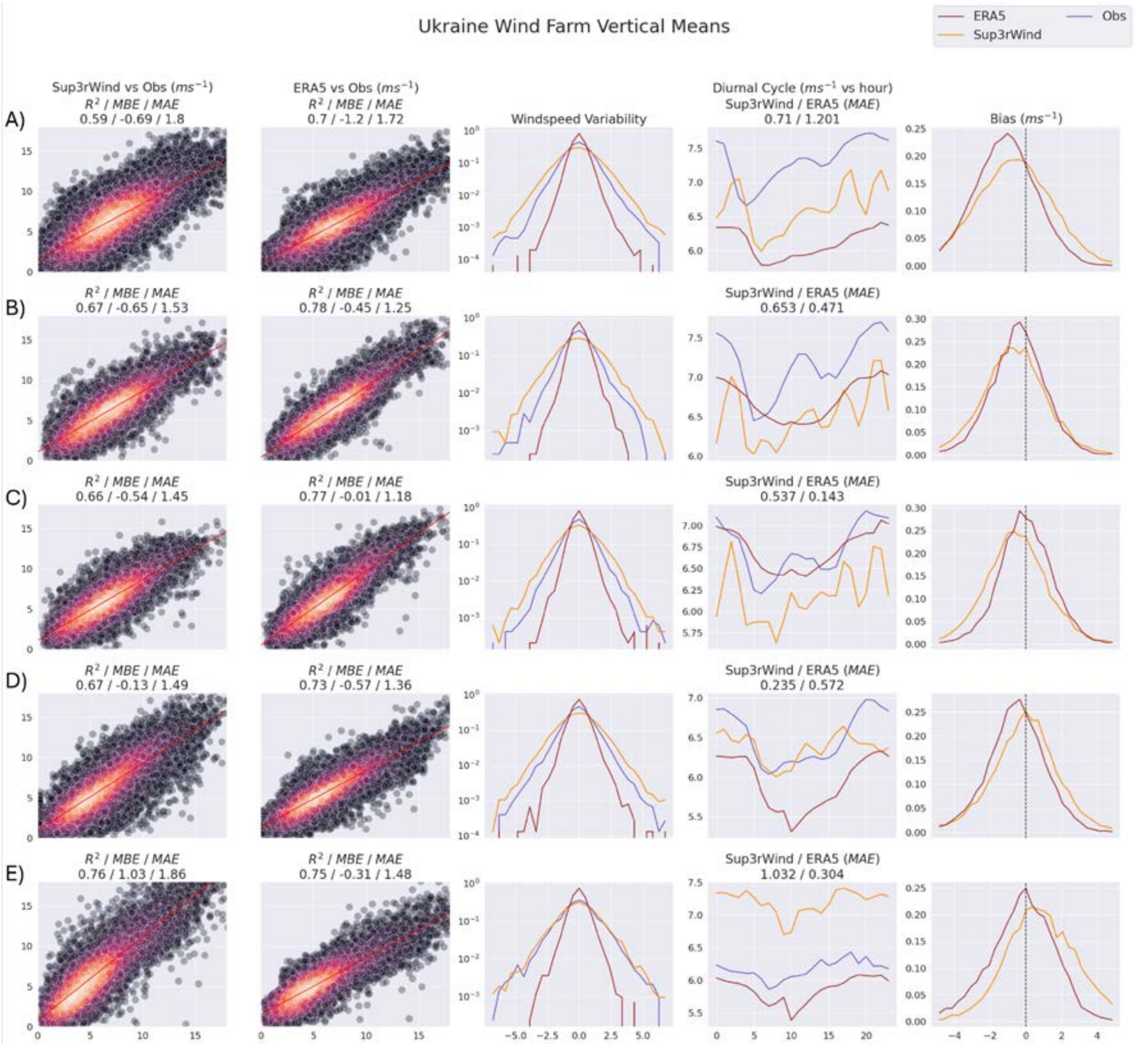
Ukraine Performance Assessment

We compare Sup3rWind with data from 5 wind farm locations, at multiple hub heights, and with 30+ MADIS locations (10 m) in Ukraine and neighboring countries. *Wind farm locations are not shown due to security concerns.*



Ukraine Wind Farm Comparisons

- Performance metrics for each wind farm location. Sites with data from multiple heights are vertically averaged.
- We refer to wind farm locations as Wind Farm A-E, due to security concerns



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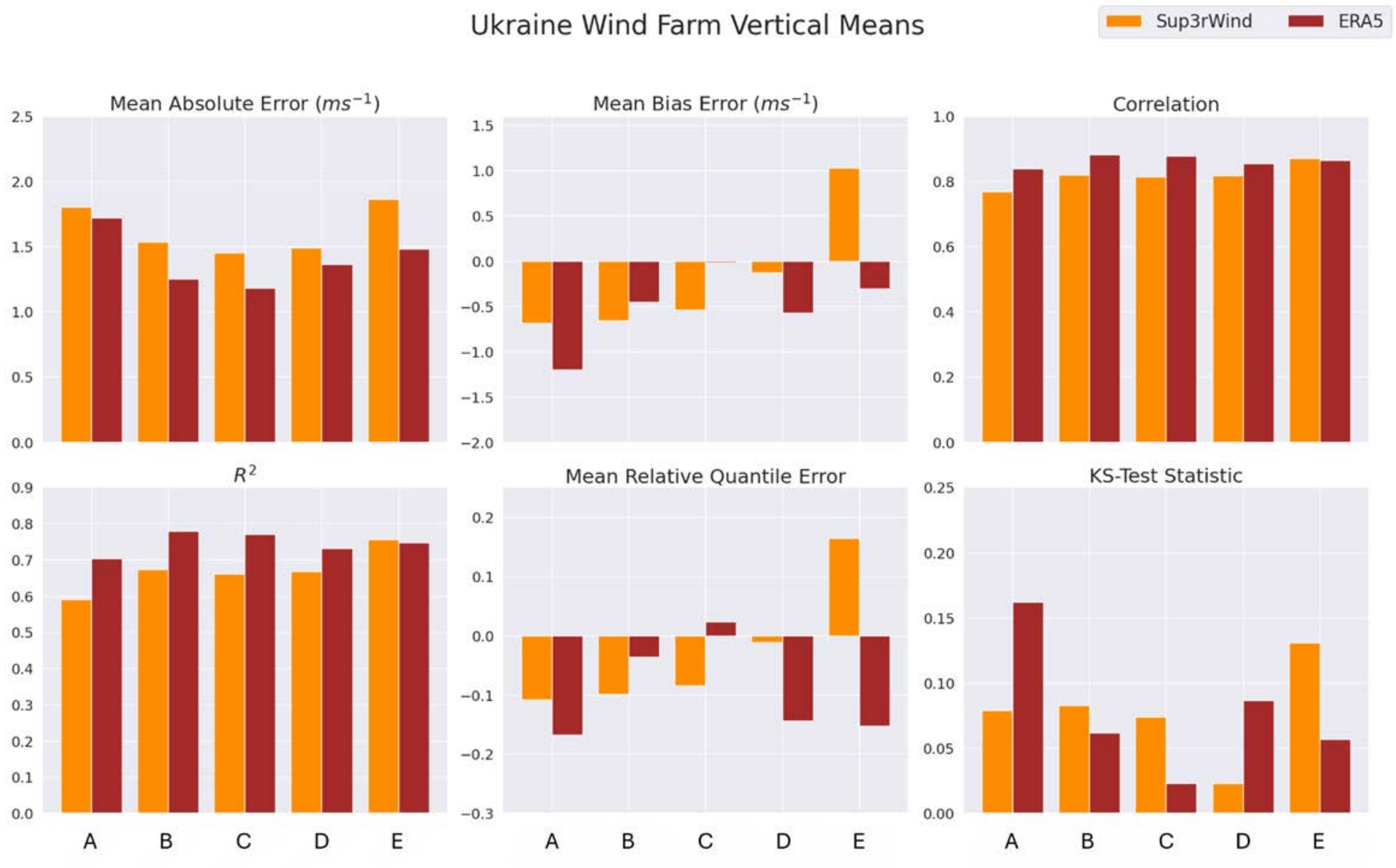
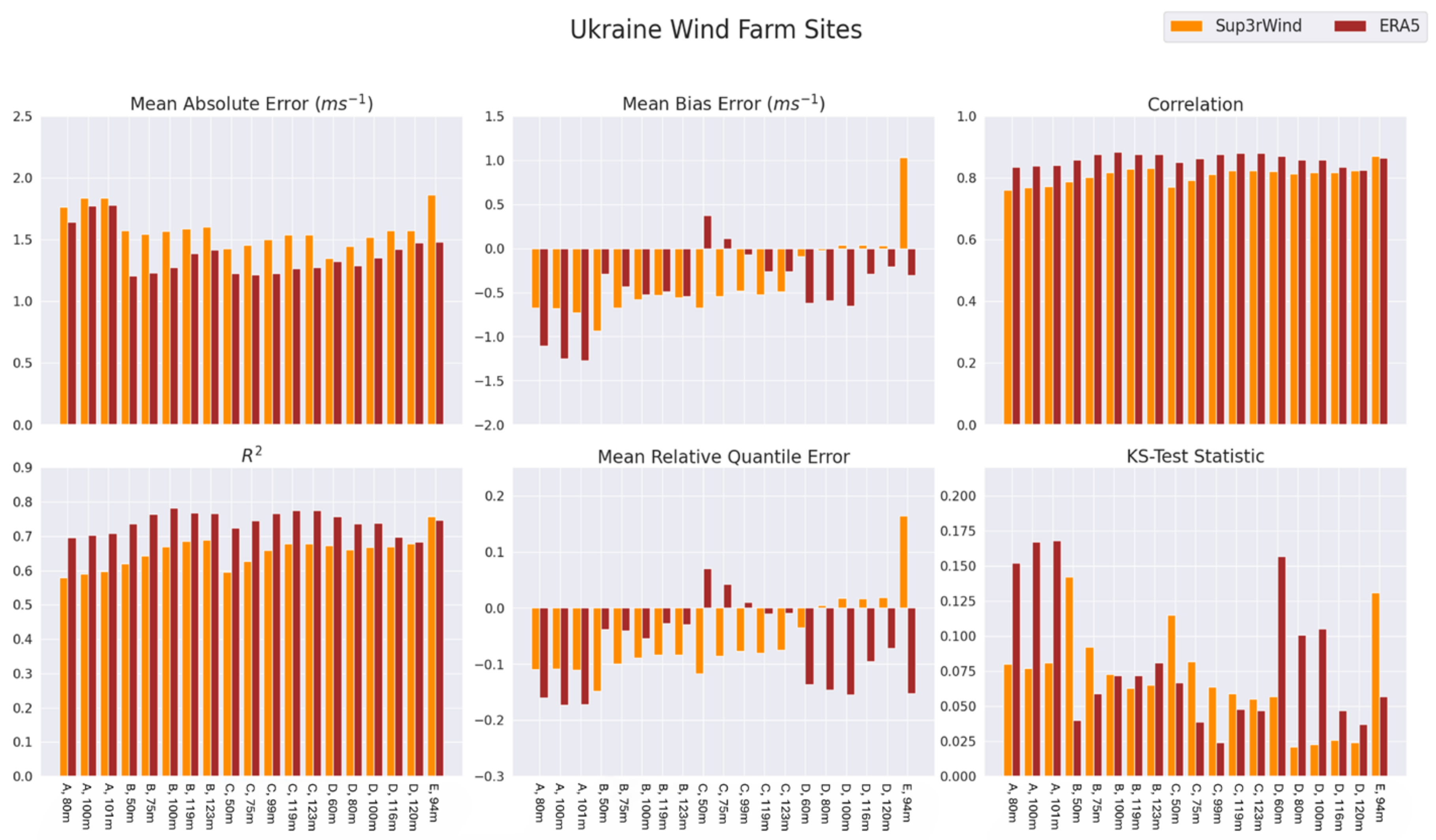
Ukraine Wind Farm Comparisons (cont.)

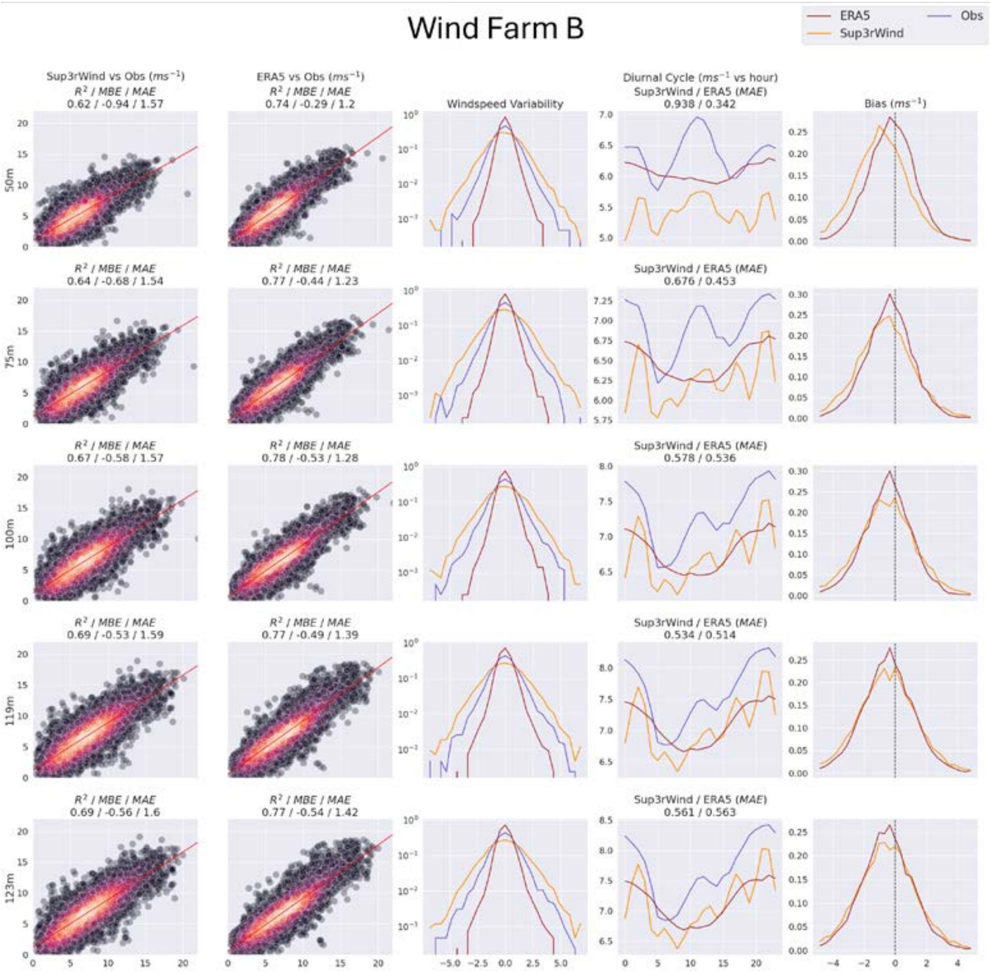


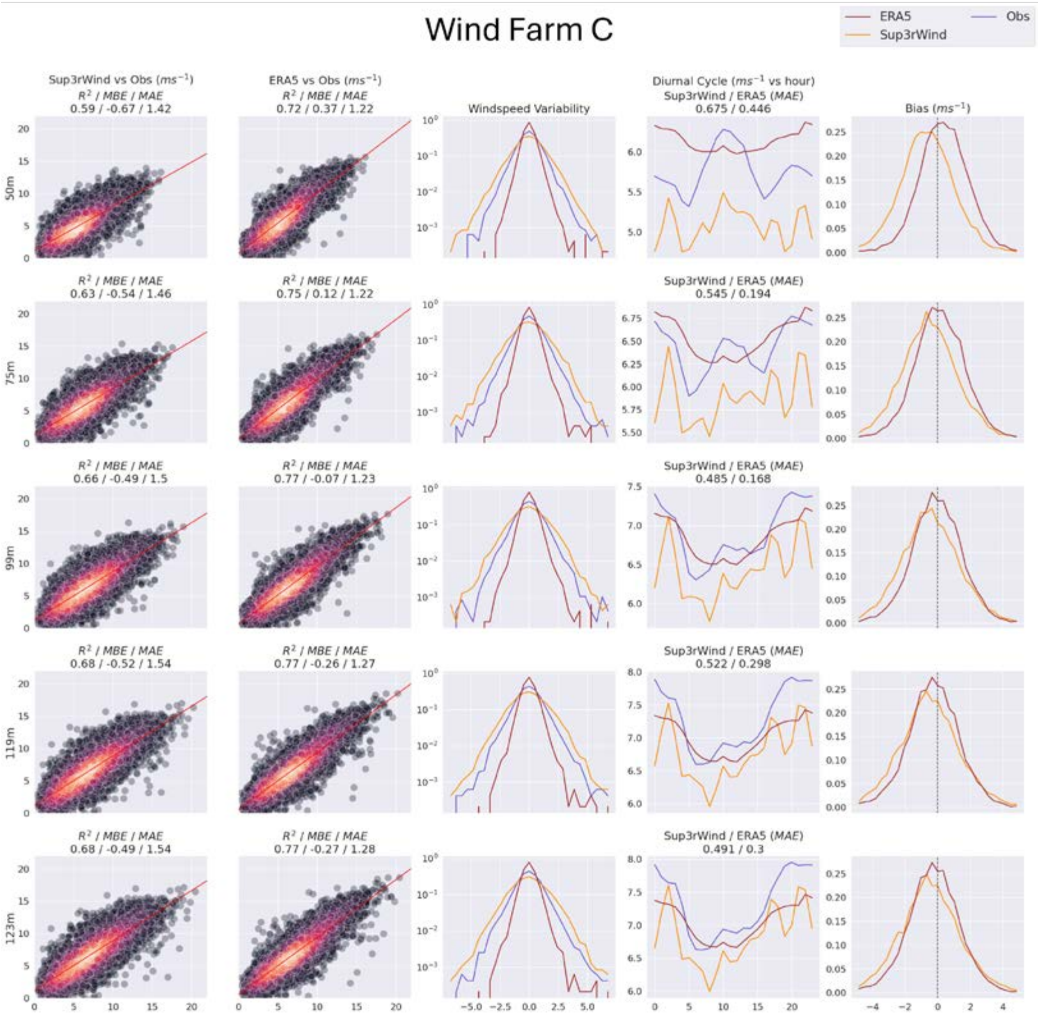
Metric (Mean across all observations)	Sup3rWind	ERA5
Mean Bias Error	-0.4879 m/s	-0.7407 m/s
Mean Absolute Error	1.7186 m/s	1.6202 m/s
Pearson Correlation Coefficient	0.7598	0.8016

Ukraine Wind Farm Comparisons (cont.)



Ukraine Wind Farm Comparisons (cont.)





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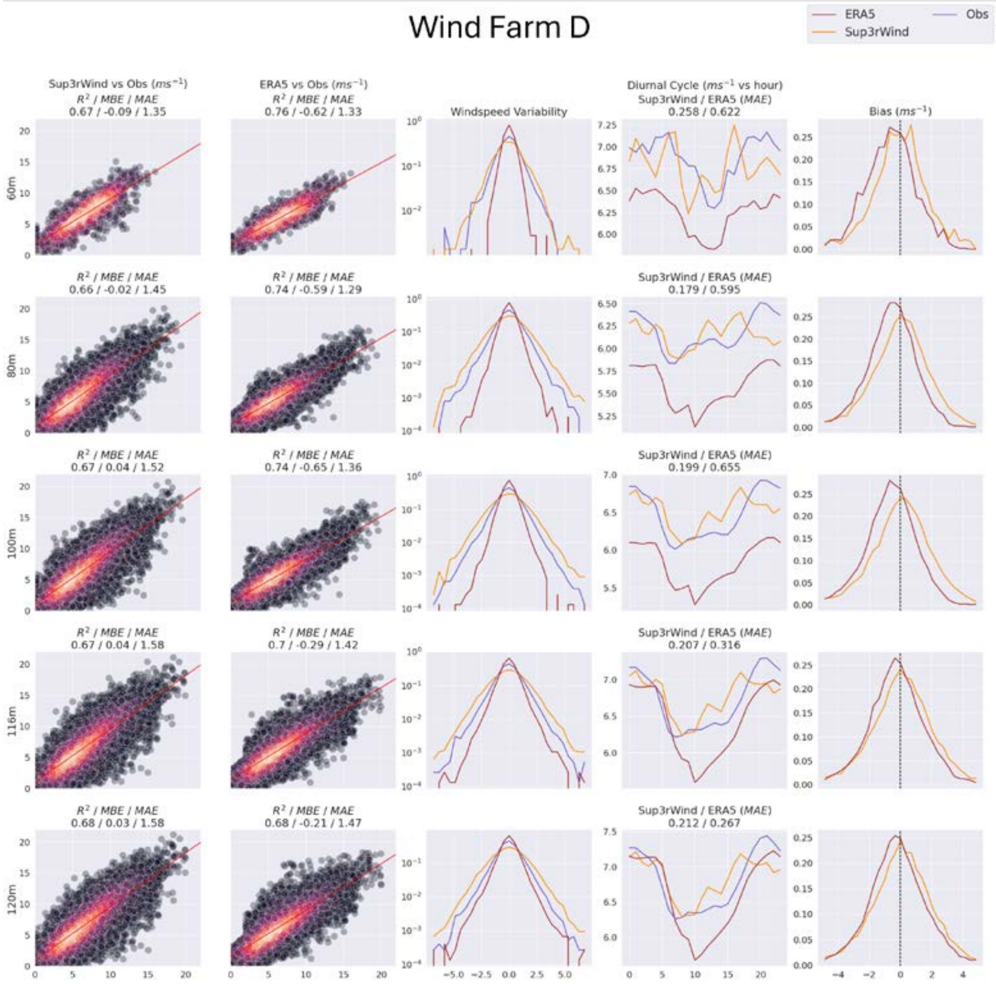
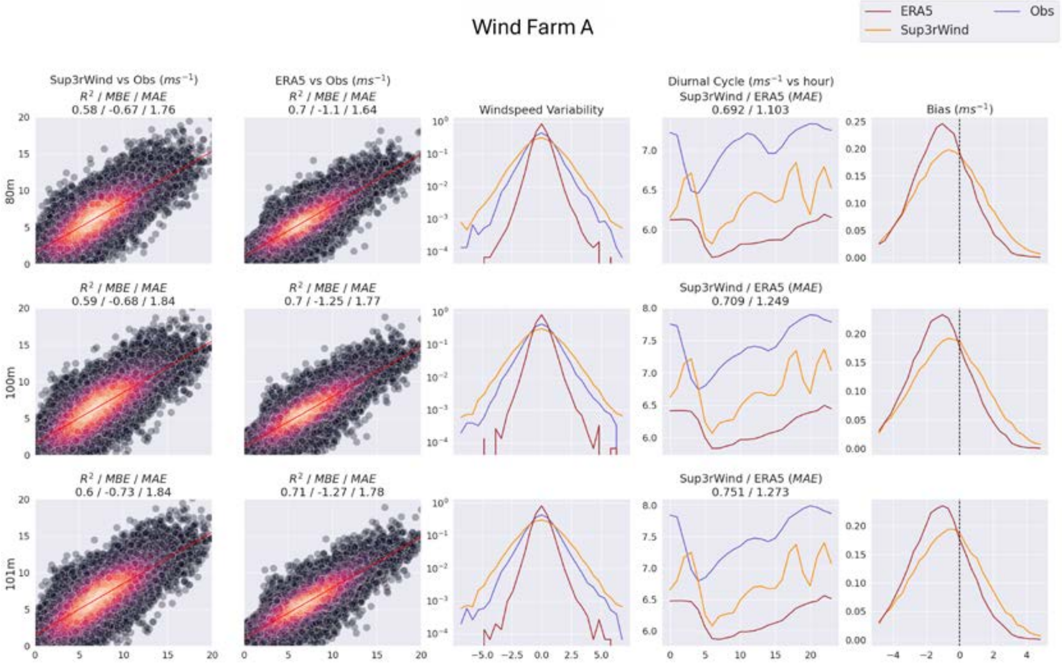
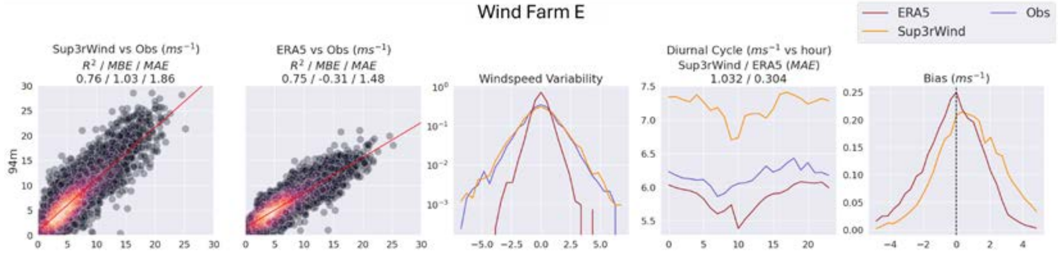
Ukraine Wind Farm Comparisons (cont.)

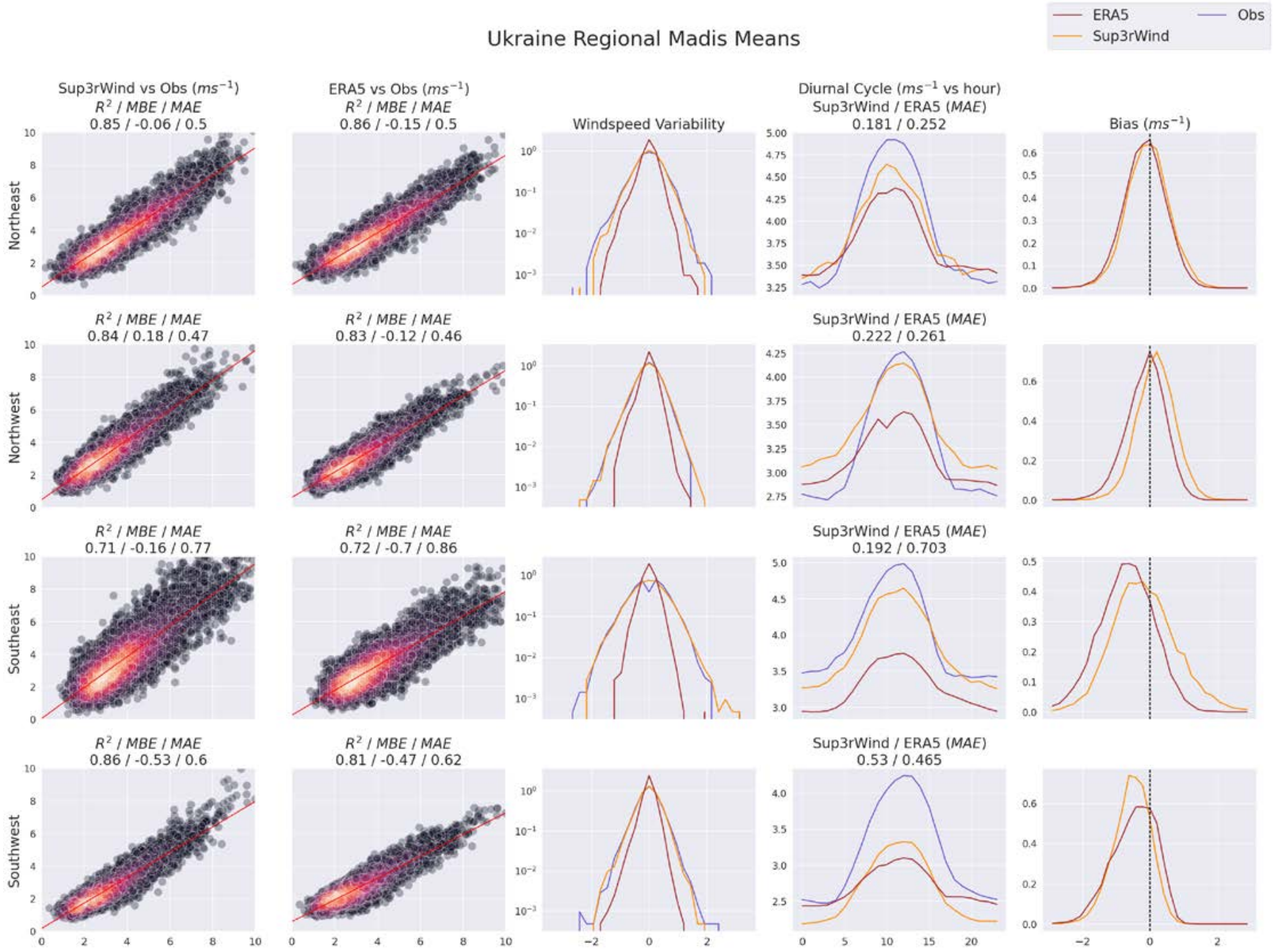






Ukraine MADIS Comparisons

MADIS sites averaged over NE/SE/NW/SW quadrants of full domain



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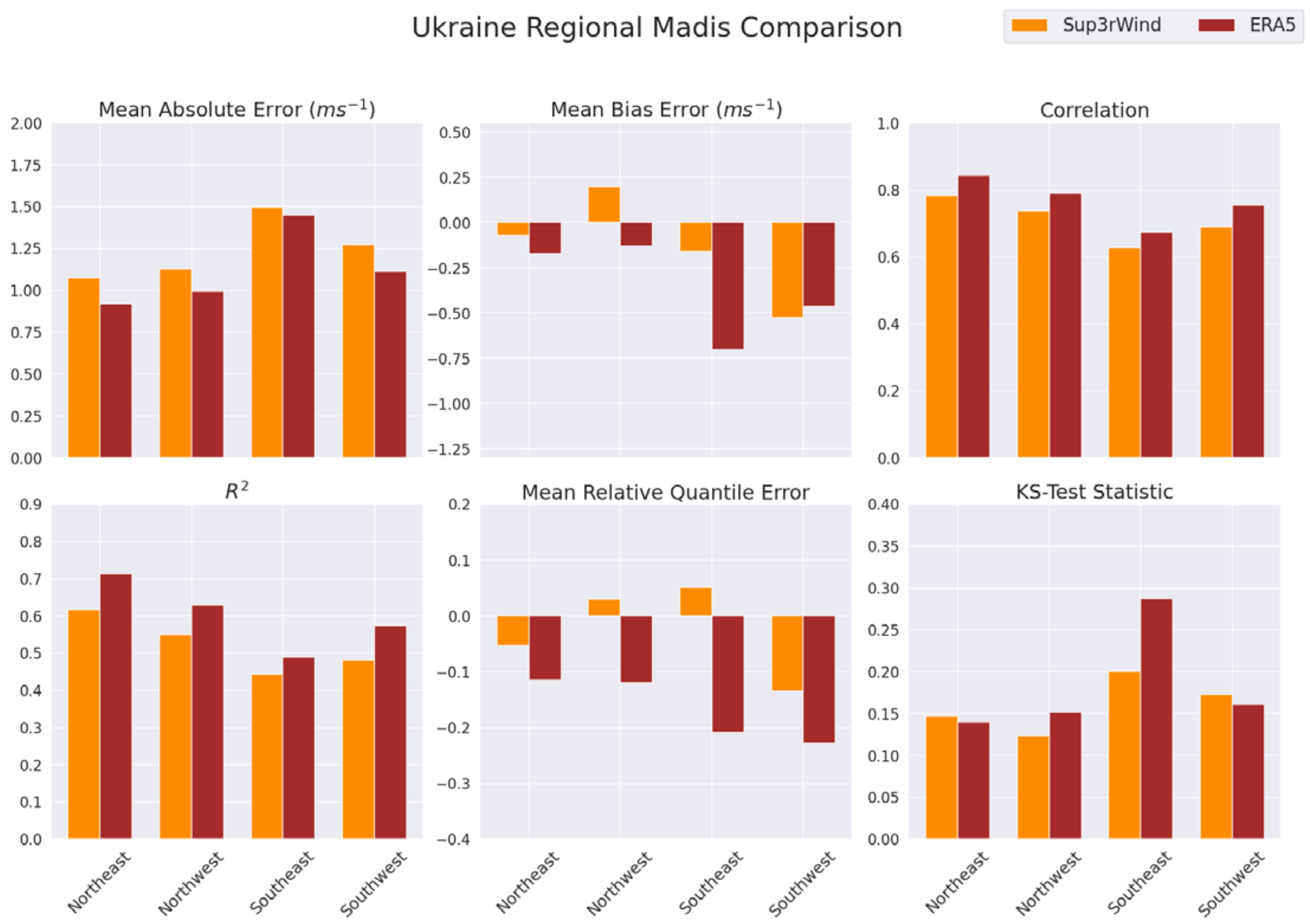
Ukraine MADIS Comparisons (cont.)



Metric (Mean across all sites)	Sup3rWind	ERA5
Mean Bias Error	-0.1453 m/s	-0.2389 m/s
Mean Absolute Error	0.4209 m/s	0.4743 m/s
Pearson Correlation Coefficient	0.9088	0.8999

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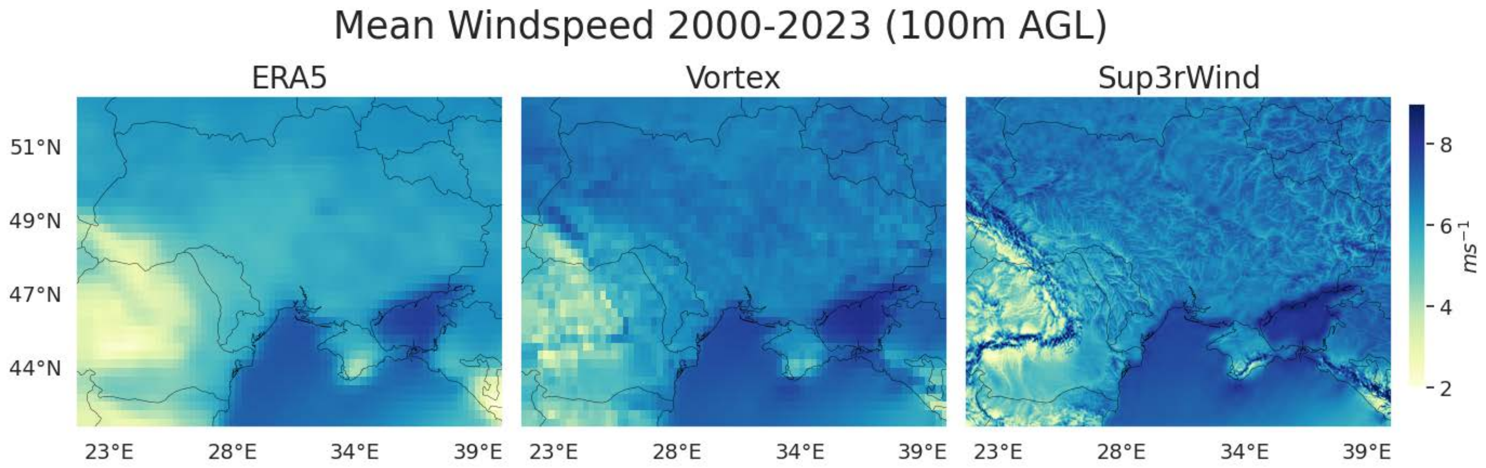
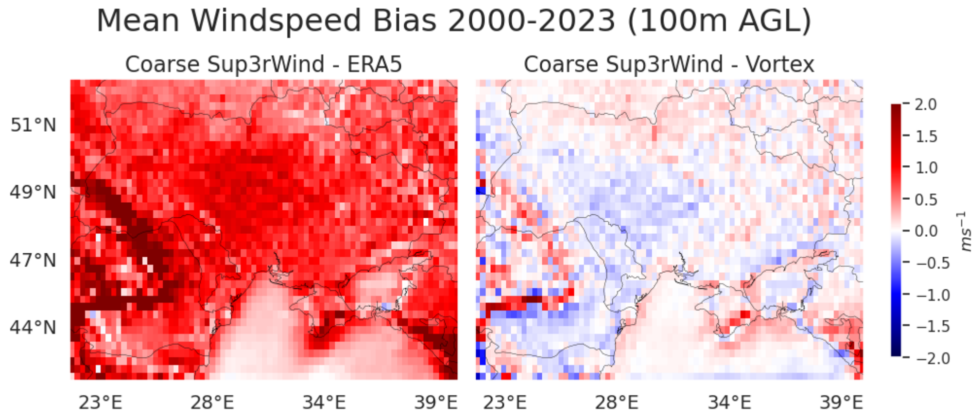
Long-Term Means and Biases Over Ukraine, Moldova, and Romania





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Compute Requirements

All processing was done on NREL's Kestrel HPC system:

- Data throughput for a single year: 4 GB to 1.8 TB
- Generating a single year of 2-km hourly data: ~5 node hours
- Generating a single year of 2-km, 5-min data: ~40 node hours
- All 24 years at 2-km, 5-min data: ~1000 node hours.

This is a speed-up of nearly 85x over dynamical downscaling with WRF.

Final Dataset for Ukraine

Average windspeed at 120 m (m/s), 2000–2022. *Illustration by Billy Roberts, NREL*

Geographic Coverage:
- Ukraine, Moldova, Eastern Romania.

Temporal Coverage and Resolution:
- 2000–2023 at 2-km, 5-minute.

Meteorological Variables:
- Windspeed and direction
- Temperature (hourly)
- Pressure (hourly)
- Relative humidity (hourly).

Heights Above Ground Level:
- 10, 40, 60, 80,100,120, 140, 160, 200 meters.

Data Download Options

NREL provides several data download options:

1. Data for point locations or small areas can be downloaded through the RE Data Explorer:

   www.re-explorer.org

2. Application Programming Interface (API) to access larger quantities of data through automated approaches:

   https://developer.nrel.gov/docs/wind/wind-toolkit/sup3rwind-ukraine-download

3. Access through the Highly Scalable Data Service (HSDS) hosted on Amazon Web Services:

   https://github.com/NREL/sup3r/examples/sup3rwind

4. Directly via OEDI on AWS Public Datasets:

   nrel-pds-wtk/sup3rwind/ukraine/v1.0.0/5min

   nrel-pds-wtk/sup3rwind/ukraine/v1.0.0/60min

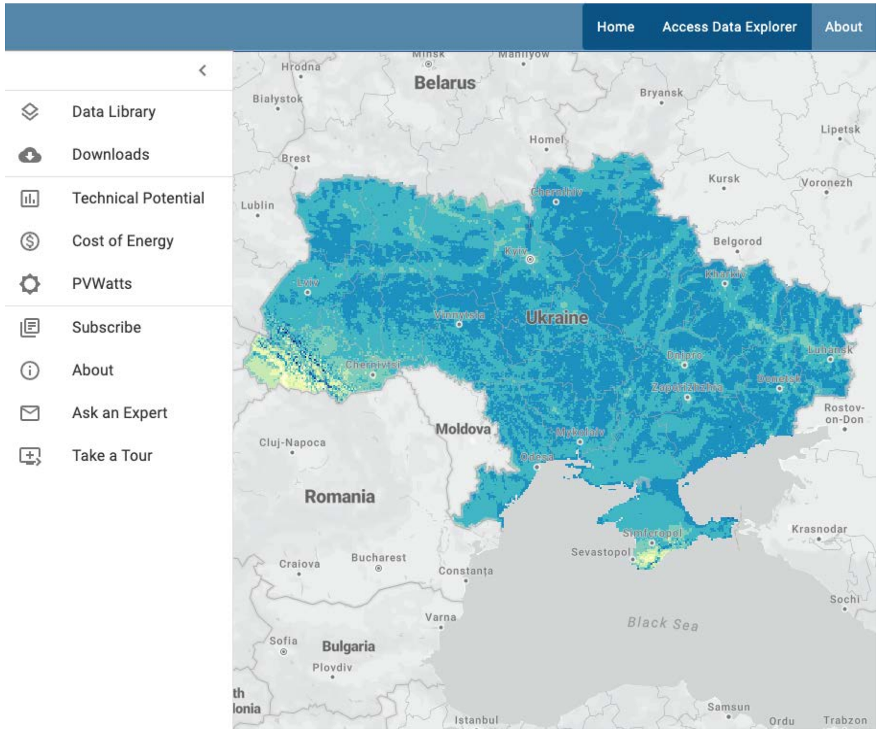

Image from www.re-explorer.org

Summary

- Comparable results to WTK[5] for spatiotemporal cross-validation in multiple out-of-sample regions. Excellent agreement with correlations, mean absolute error, mean relative quantile error, and distributions.
- Similar performance seen across Ukraine, although ERA5 performs significantly better across Ukraine than CONUS. The increased performance of ERA5 could be related to the terrain being less complex than for the CONUS validation regions.
- 85x faster than dynamical downscaling.
- Across MADIS sites, we still see as-good or better correlations, reduced mean bias and absolute error, and significant improvement in extreme quantile accuracy.

- Mean bias does not exceed +/- 1 m/s across all Ukraine wind farm hub heights and correlations are all > 0.75.
- Windspeed variability distributions across wind farm sites show excellent agreement with observations. Diurnal cycles show significant improvement over ERA5.
- Future work could improve bias and near/offshore accuracy.

Metric (Mean across all sites)	CONUS	MADIS	Wind Farms
Mean Bias Error	-0.43 m/s	-0.1453 m/s	-0.4879 m/s
Mean Absolute Error	1.9 m/s	0.4209 m/s	1.7186 m/s
Pearson Correlation Coefficient	0.72	0.9088	0.7598

[5] Draxl et al. (2015).

References

1. Brandon Benton, Grant Buster, Andrew Glaws, Ryan King. Super Resolution for Renewable Resource Data (sup3r). https://github.com/NREL/sup3r (version v0.1.2), 2022. https://doi.org/10.5281/zenodo.10402581.
2. Stengel, K., A. Glaws, D. Hettinger, and R. N. King, 2020: Adversarial super-resolution of climatological wind and solar data. PNAS, 117, 16805–16815, https://doi.org/10.1073/pnas.1918964117.
3. Wang, Q., Y. Ma, K. Zhao, and Y. Tian, 2022: A Comprehensive Survey of Loss Functions in Machine Learning. Ann. Data. Sci., 9, 187–212, https://doi.org/10.1007/s40745-020-00253-5.
4. Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., Thépaut, J. (2020). The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, *146*(730), 1999–2049. https://doi.org/10.1002/qj.3803.
5. Draxl, C., A. Clifton, B.-M. Hodge, and J. McCaa, 2015: The Wind Integration National Dataset (WIND) Toolkit. Applied Energy, 151, 355–366, https://doi.org/10.1016/j.apenergy.2015.03.121.
6. NOAA. (2022, February 27). *Meteorological Assimilation Data Ingest System (Madis)*. Retrieved December 6, 2023, from https://madis.ncep.noaa.gov/index.shtml.
7. Davis, N. N., Badger, J., Hahmann, A. N., Hansen, B. O., Mortensen, N. G., Kelly, M., Larsén, X. G., Olsen, B. T., Floors, R., Lizcano, G., Casso, P., Lacave, O., Bosch, A., Bauwens, I., Knight, O. J., Loon, A. P. van, Fox, R., Parvanyan, T., Hansen, S. B. K., Drummond, R. (2023). The Global Wind Atlas: A High-Resolution Dataset of Climatologies and Associated Web-Based Application. *Bulletin of the American Meteorological Society*, *104*(8), E1507–E1525. https://doi.org/10.1175/BAMS-D-21-0075.1.

Acronyms and Abbreviations

DOE	U.S. Department of Energy
ERA5	European Centre for Medium-Range Weather Forecasts Reanalysis Version 5
MADIS	Meteorological Assimilation Data Ingest System
GAN	Generative Adversarial Network
HPC	High Performance Computing
MAE	Mean Absolute Error
MBE	Mean Bias Error
PCC	Pearson Correlation Coefficient
R^2	Coefficient of Determination (Squared correlation)
RQE	Relative Quantile Error
ML	Machine Learning
Sup3rWind	Super Resolution for Renewable Resource Data with Wind from Reanalysis Data
TKE	Turbulent Kinetic Energy
USAID	United States Agency for International Development
WTK	Wind Integration National Dataset Toolkit
WFIP2	2^{nd} Wind Forecast Improvement Project
CONUS	Continental United States

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Thank you!

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