AI/ML Augmented Hyper-Local Weather Forecast

Outlines/Guiding Principles:

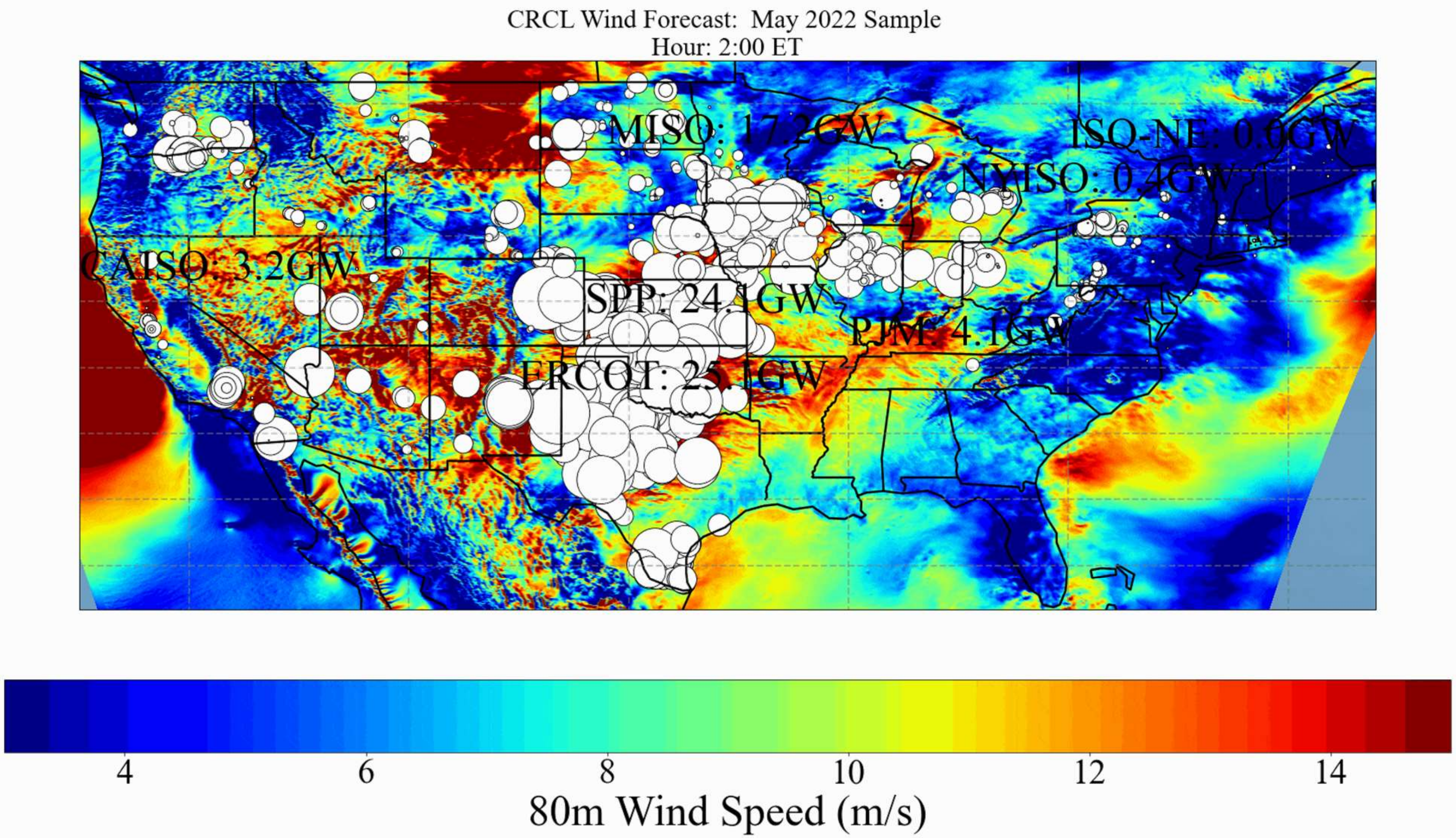
- Building Forecast Enhancement on Top of NWP Analytical Model
- Big-Data (Historical Local Data) Driven
- Optimized Forecast for Specialized/Unique & Localized Renewable Energy Operation

SSEC

Allen Huang
allenh@ssec.wisc.edu

Busan, S. Korea
AOMSUC-13
8 November 2023

CRCL Solutions

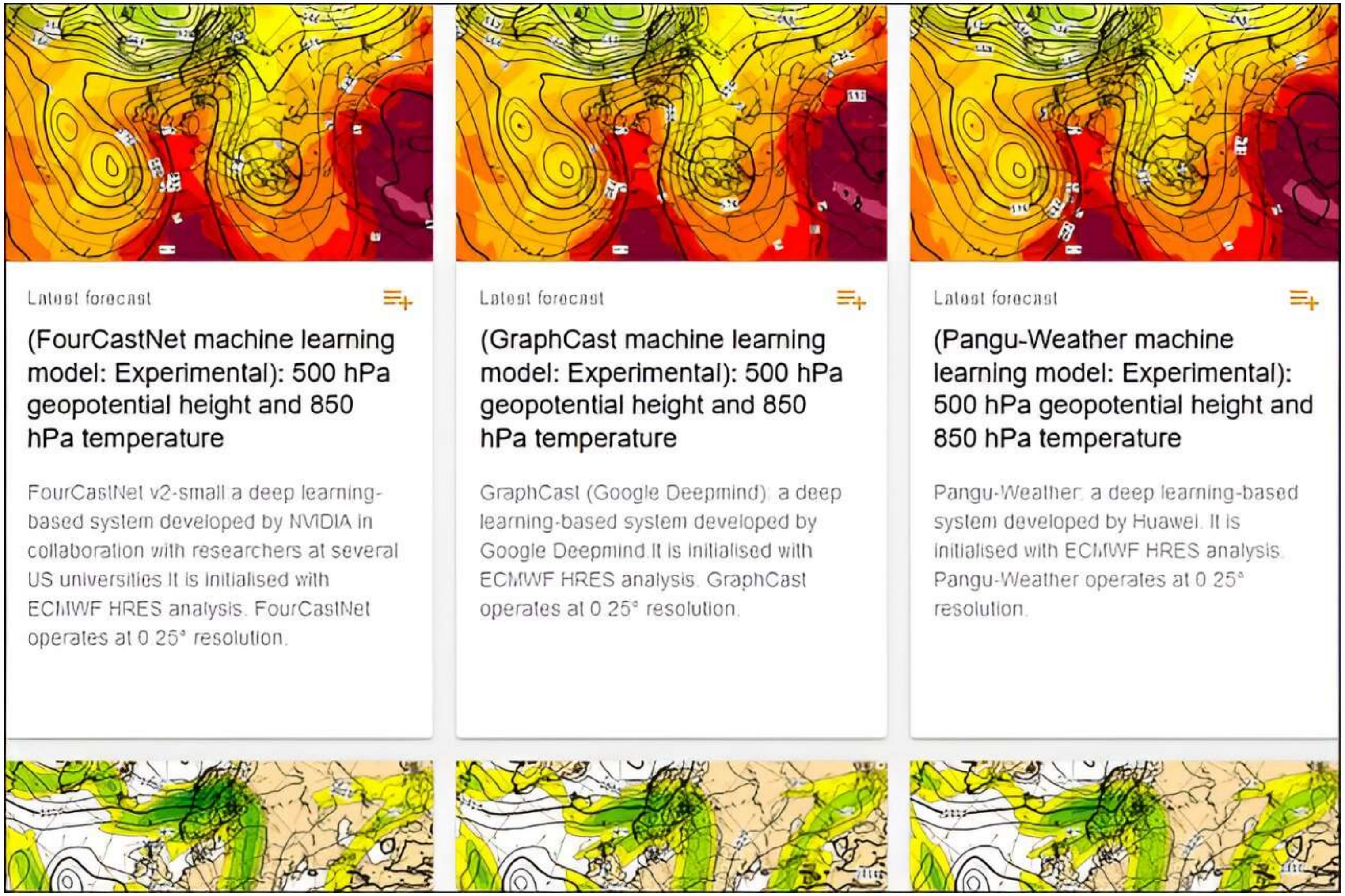


Routinely to provide much-improved wind and solar production forecast data to the energy industry

How AI models are transforming weather forecasting: A showcase of data-driven systems

https://phys.org/news/2023-09-ai-weather-showcase-data-driven.html

Phys.org/news (Sep. 6, 2023)



https://phys.org/news/2023-09-ai-weather-showcase-data-driven.html#google_vignette

Daily forecasts starting from ECMWF initial conditions and using **NVIDIA's FourCastNet**, **Huawei's Pangu-Weather** and **Google DeepMind's GraphCast** are now freely available to view on ECMWF's public charts pages.

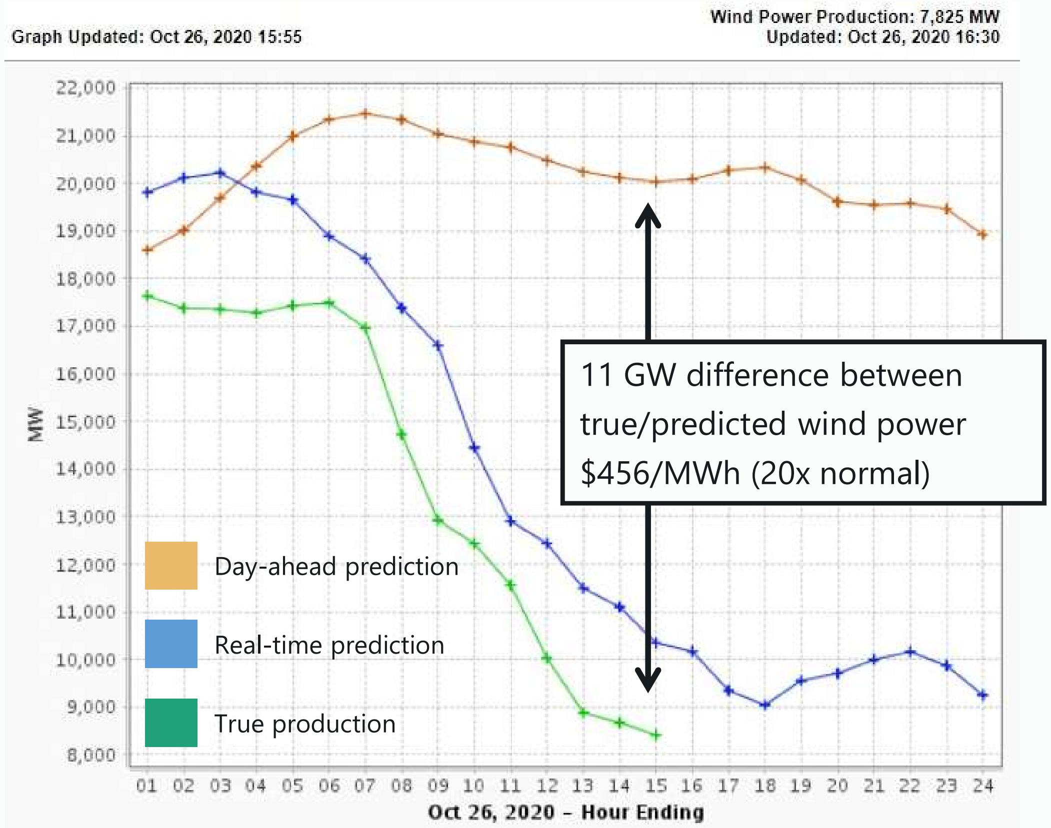
At this early stage in the technology, some results are already displaying comparable skill to ECMWF's Integrated Forecasting System (IFS)

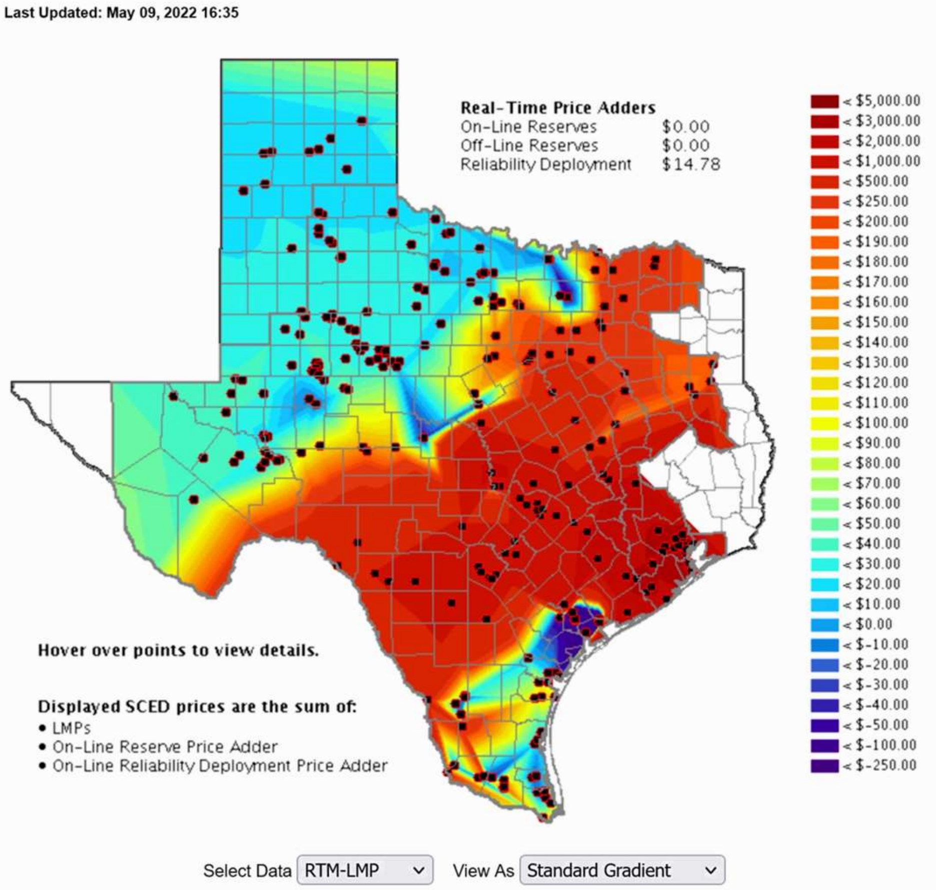
Through a plug-in system, we make the different models installable and accessible to anyone. This is freely released as ai-models, with public plugins for FourCastNet, Pangu-Weather and GraphCast.

Phys.org/news (Sep. 6, 2023)

Background

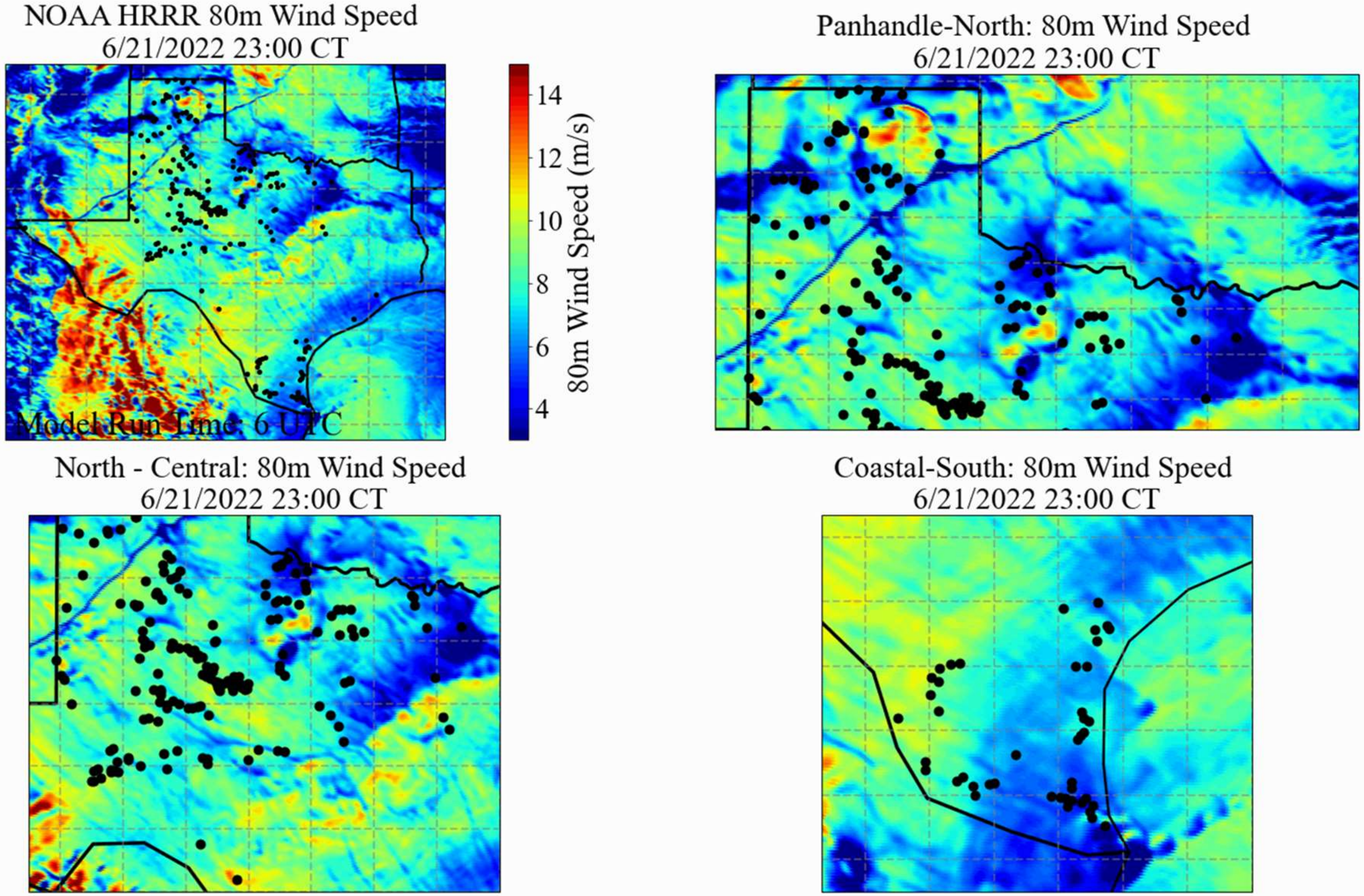
e.g., Poor Texas Wind Power Forecasting





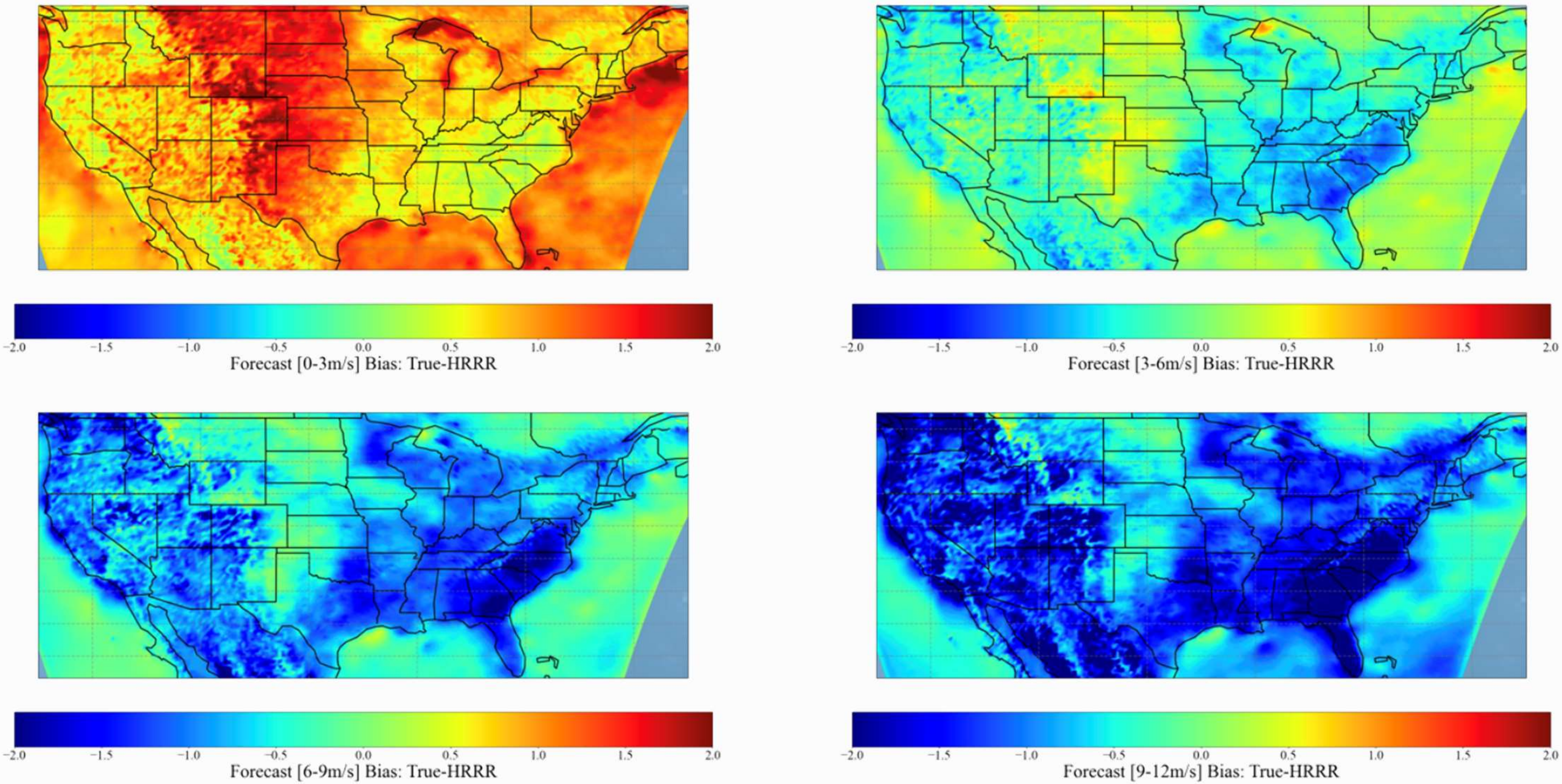
Poor weather forecasting leads to poor renewable energy forecasts and volatile markets

Weather Models



NWPs output space-time evolution of weather variables

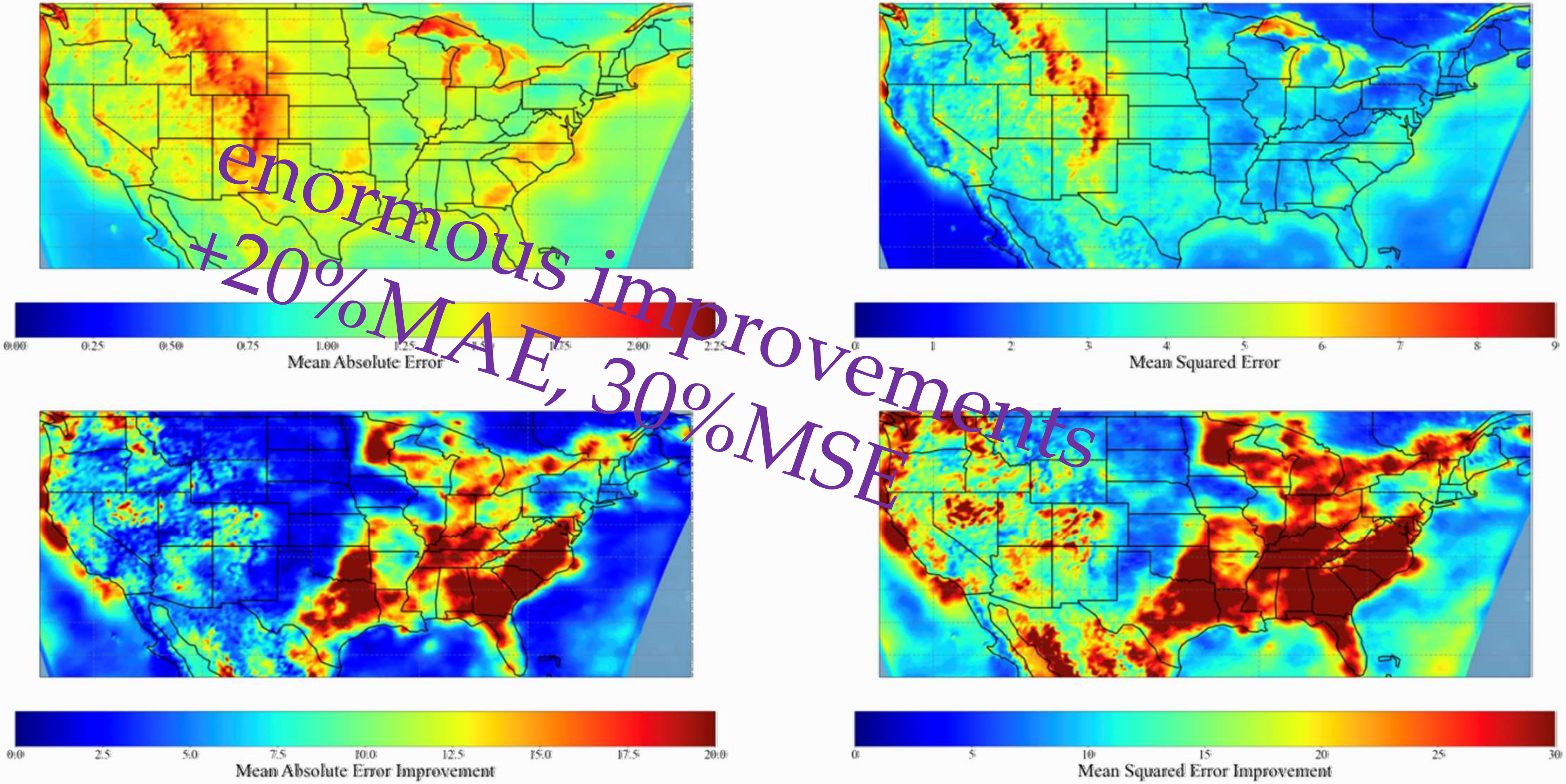
Weather Models: Accuracy



Performance depends on atmospheric regimes and location

Weather Models: Accuracy

enormous improvements
+20%MAE, 30%MSE



NOAA’s HRRR forecast data is corrected with AI/ML
Great forecast data is made better

AI/ML Framework- Correcting the Time Series

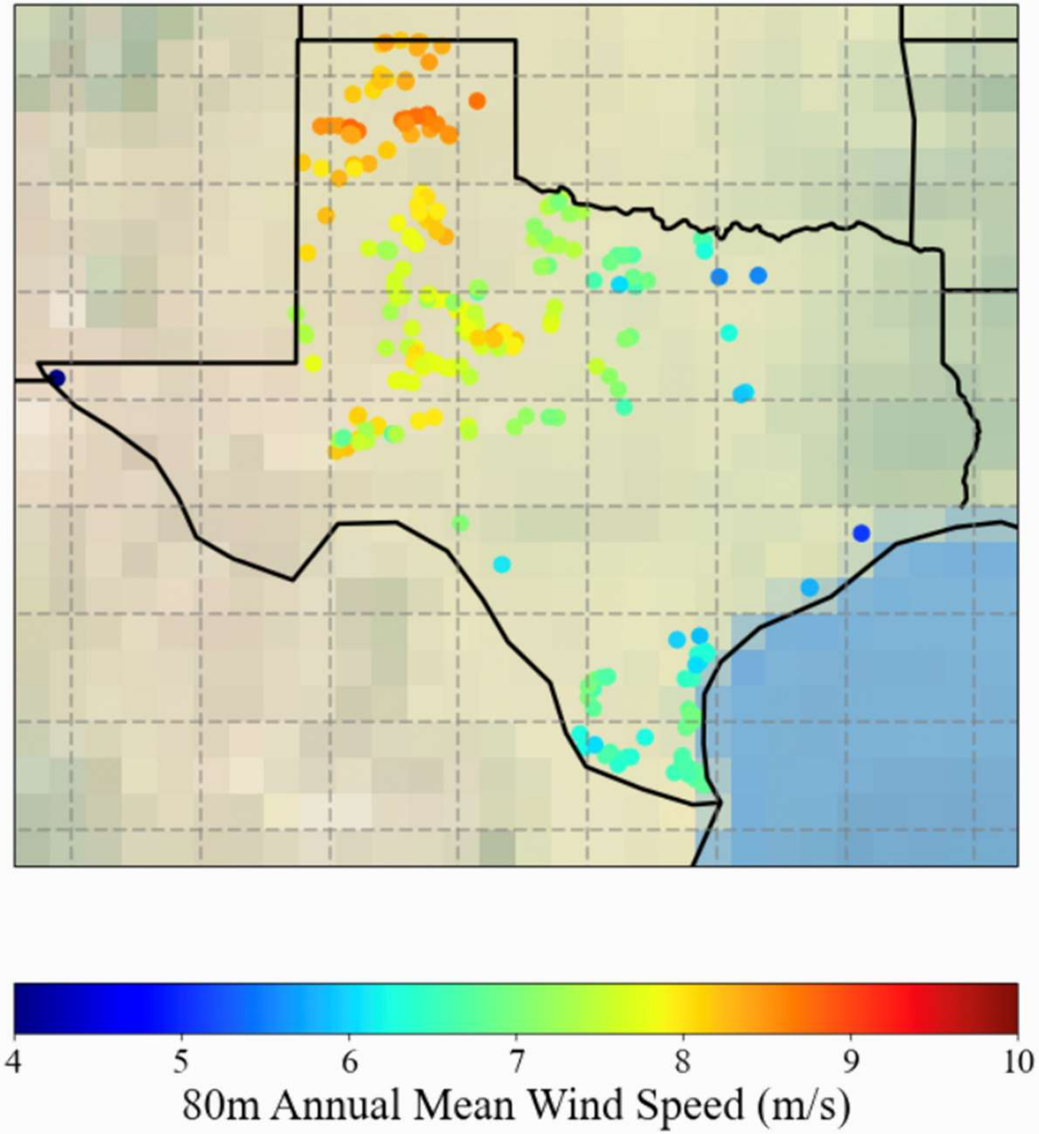
AI/ML Problem Framework Overview

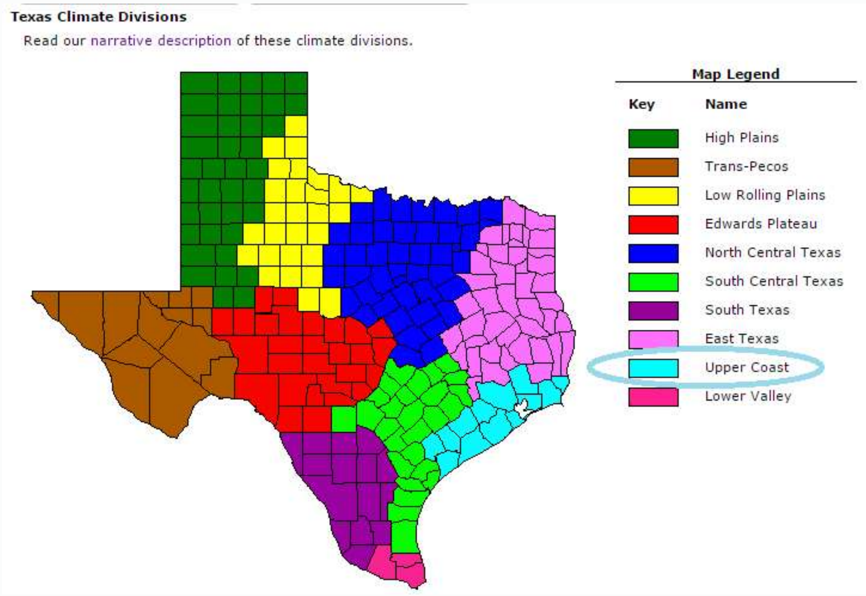
1) Historical NOAA HRRR Forecast Data - +100 billion points
   - HRRR Model Error $= f(wind\ speed, time, lead\ time, geography)$
   - HRRR Model Error $= HRRR$ analysis $- HRRR$ forecast

2) Train models to learn HRRR errors
   - Train models on 2019 data
   - Test models on 2020 data
   - Inputs: {HRRR wind forecast, direction, expected change in wind speed, time of day, wind variability across region}
   - Outputs: Corrected wind speed

3) Modeling Frameworks
   - Artificial Neural Networks, Support Vector Regression, Gradient Boosting Regression, Ridge Regression, Lasso Regression, Elastic Net, K-nearest neighbors, and **Random Forest**

Case Study: ERCOT Wind Farms



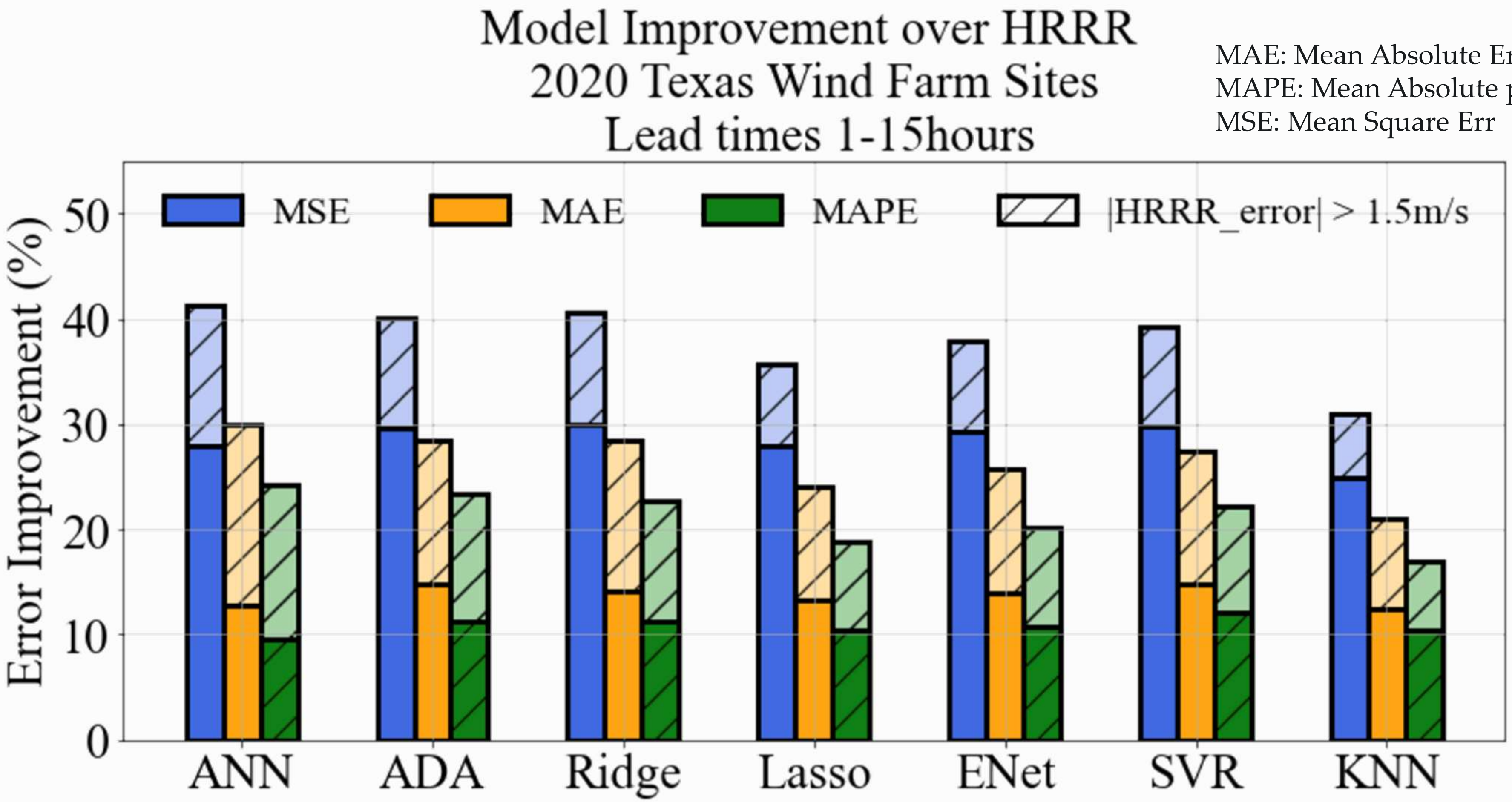


We consider 80m wind speeds for 253 sites in Texas corresponding to wind farm locations

Operational Demonstration of an AI-Optimized Hyper-Local Weather Forecast for Wind and Solar Energy Trading Management

	Input Features
Model 1	Current HRRR Wind Speed, Wind Direction, Variability in wind speed forecasts, Forecasted Temporal Wind Speed Change, Wind variability across the region, Time of Day
Model 2	Bias Corrected Wind Speed, Wind Direction, Variability in wind speed forecasts, Forecasted Temporal Wind Speed Change, Wind variability across the region, Time of Day
Model 3	Bias Corrected Wind Speed, Wind Direction, Variability in wind speed forecasts, Forecasted Temporal Wind Speed Change, Wind variability across the region, Time of Day, Variability of wind speed forecasts for 6 sites in Texas where model error is most correlated with wind speed forecast variability.
Model 4	Bias Corrected Wind Speed, Wind Direction, Variability in wind speed forecasts, Forecasted Temporal Wind Speed Change, Wind variability across the region, Time of Day, Past Wind Speed Forecasts
Model 5	Bias Corrected Wind Speed, Wind Direction, Variability in wind speed forecasts, Forecasted Temporal Wind Speed Change, Wind variability across the region, Time of Day, Past Wind Speed Forecasts, Past Wind Direction Forecasts

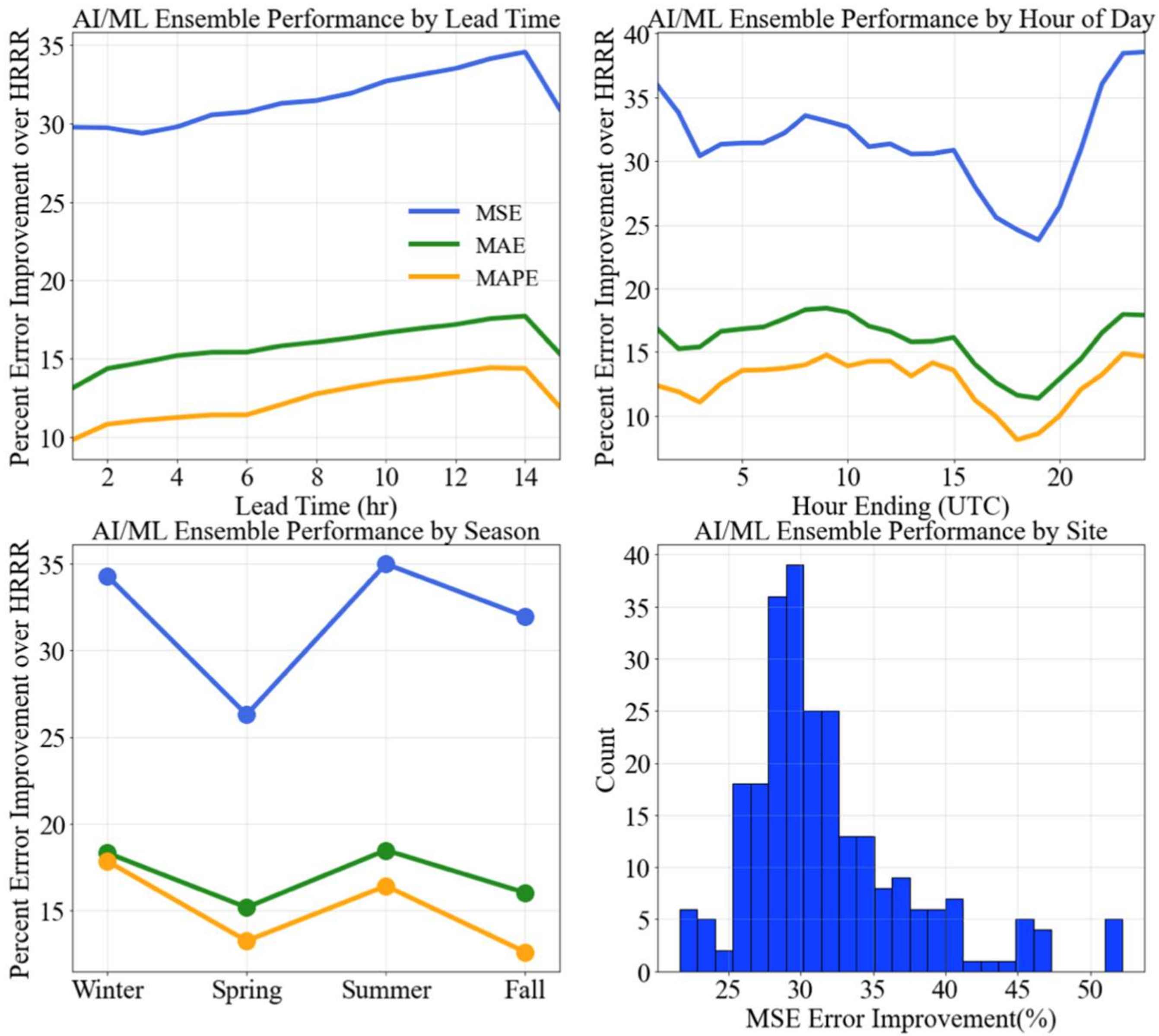
Case Study: Results



MAE: Mean Absolute Err;
MAPE: Mean Absolute percent err;
MSE: Mean Square Err

All ML frameworks provide significant model forecasting improvements over the HRRR

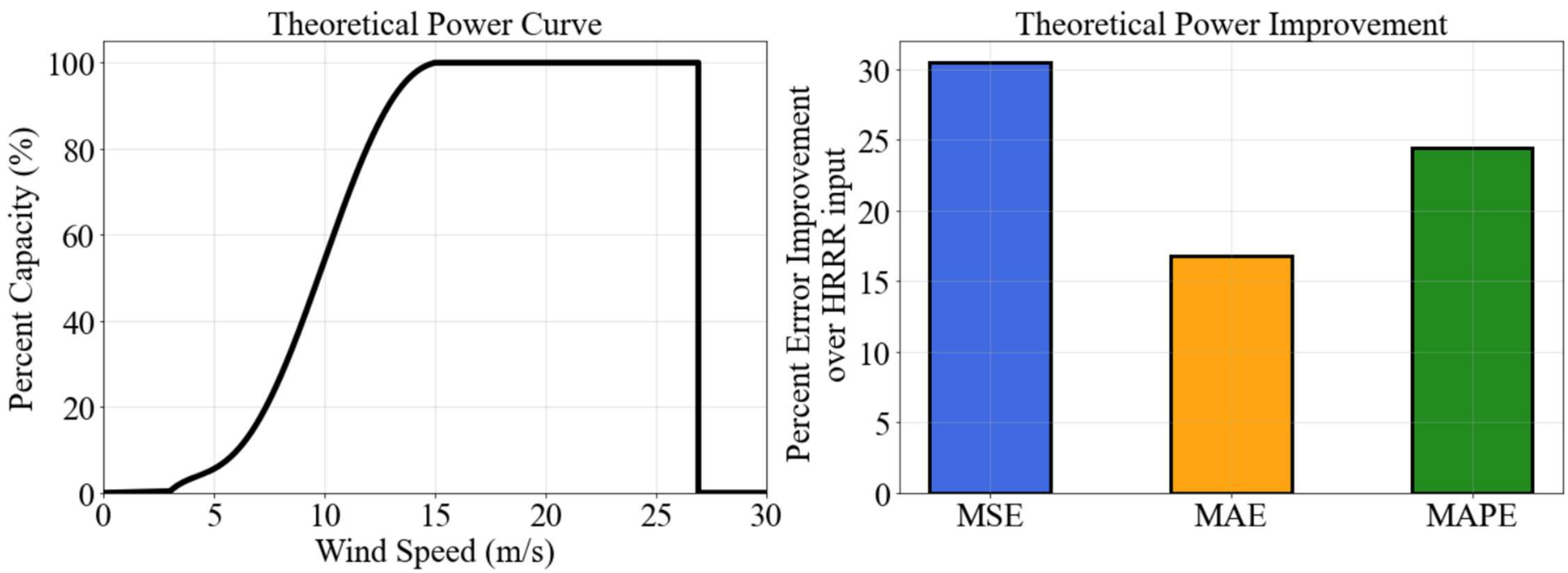
Case Study: Results



MAE: Mean Absolute Err;
MAPE: Mean Absolute percent err;
MSE: Mean Square Err

The ensemble model framework is robust

Energy Applications



Better Weather Forecast = Better Energy Forecast

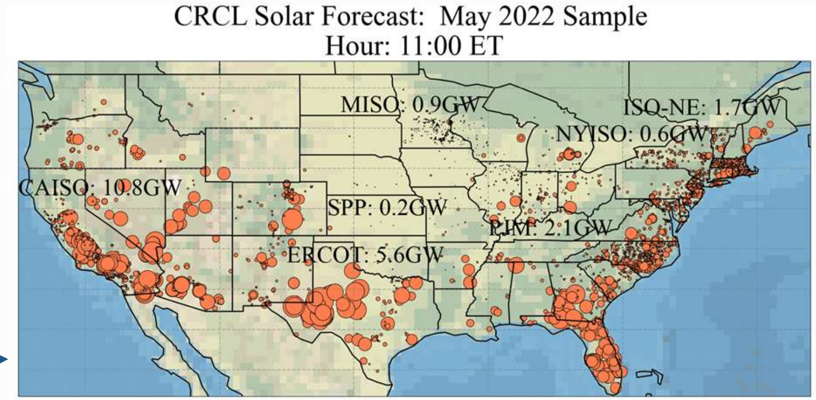
Energy Applications

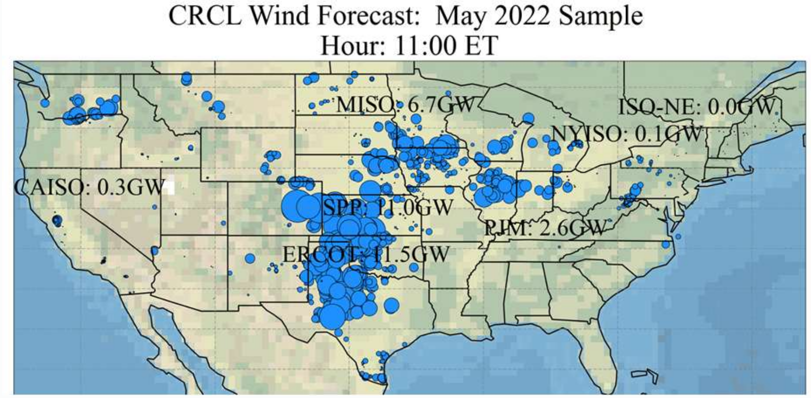
Machine Learning Model

Current Forecast

Power Model

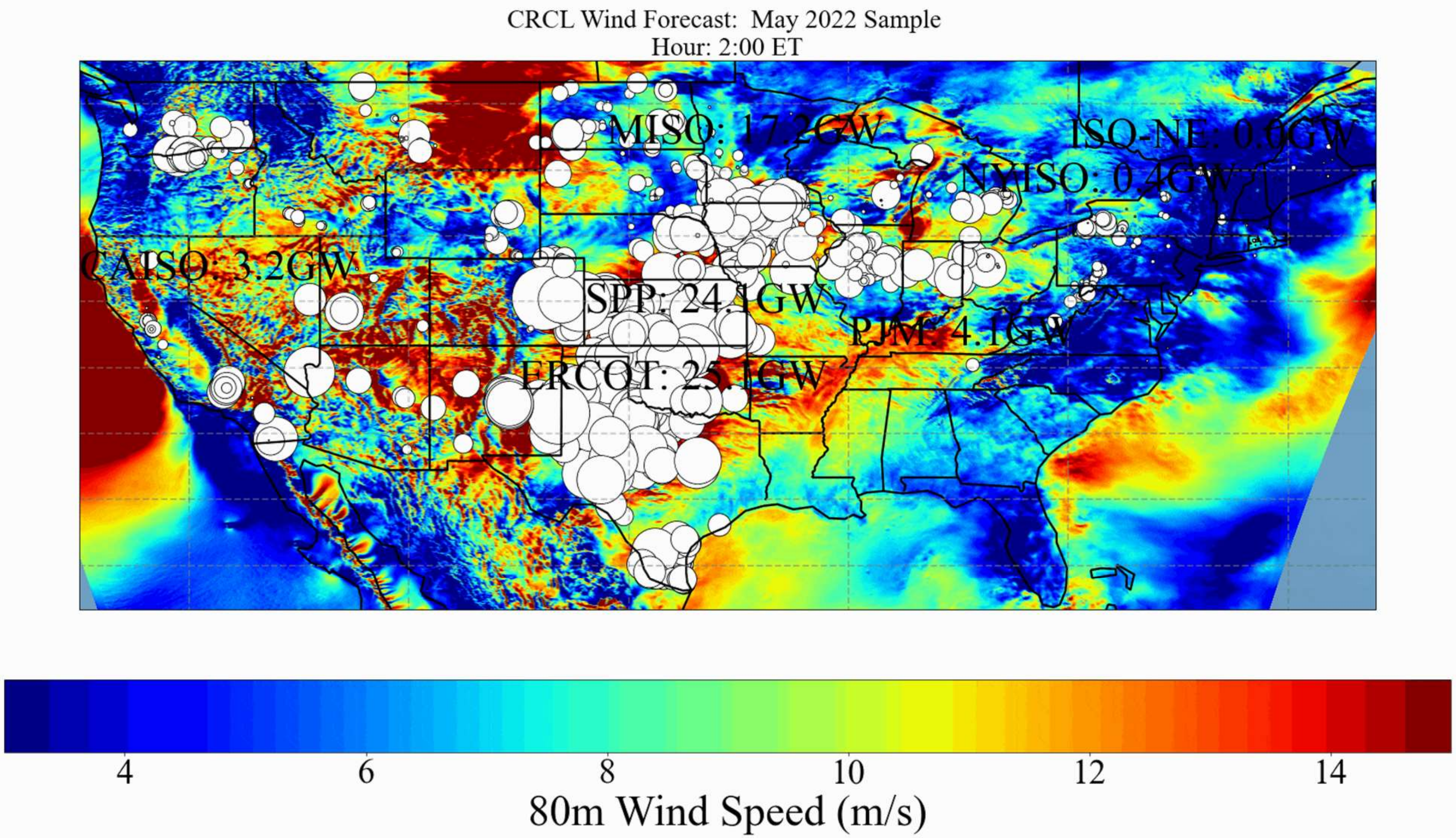
1. Physics-based
2. Site-specific info
3. National coverage





Weather data is converted to farm-level wind/solar power forecasts

AI/ML Solutions



CRCL provides wind and solar production forecast data to the energy industry

AI/ML Augmented Hyper-Local Weather Forecast

Future Prospects/Goals

Put AI/ML on top of the NOAA Regional HRRR model to get the best of hyper-local forecasts: precipitation; temperature, severe weather potential, & other weather variables relevant to the local concerns

- **Forecast enhancement with JPSS LEO Sounder data**
  - ➢ **IR/MW with higher spatial, spectral, and temporal density**
  - ➢ **Optimized to high priority region in CONUS identified by NWS**
  - ➢ **Collaborate with the JPSS program and NWS to shape the priority**
  - ➢ **Demonstration for a handful of selected regions to start and**
  - ➢ **Transition to operational demonstration for routine NWS usage**
  - ➢ **Transition to CSPP distribution for worldwide direct broadcast near-time applications**