



Evaluating the Ability of Met Models to Characterize Daily Cycles in Wind Generation

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ENERGY TECHNOLOGIES AREA
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Temporal profiles of wind needed to integrate wind energy into the power system

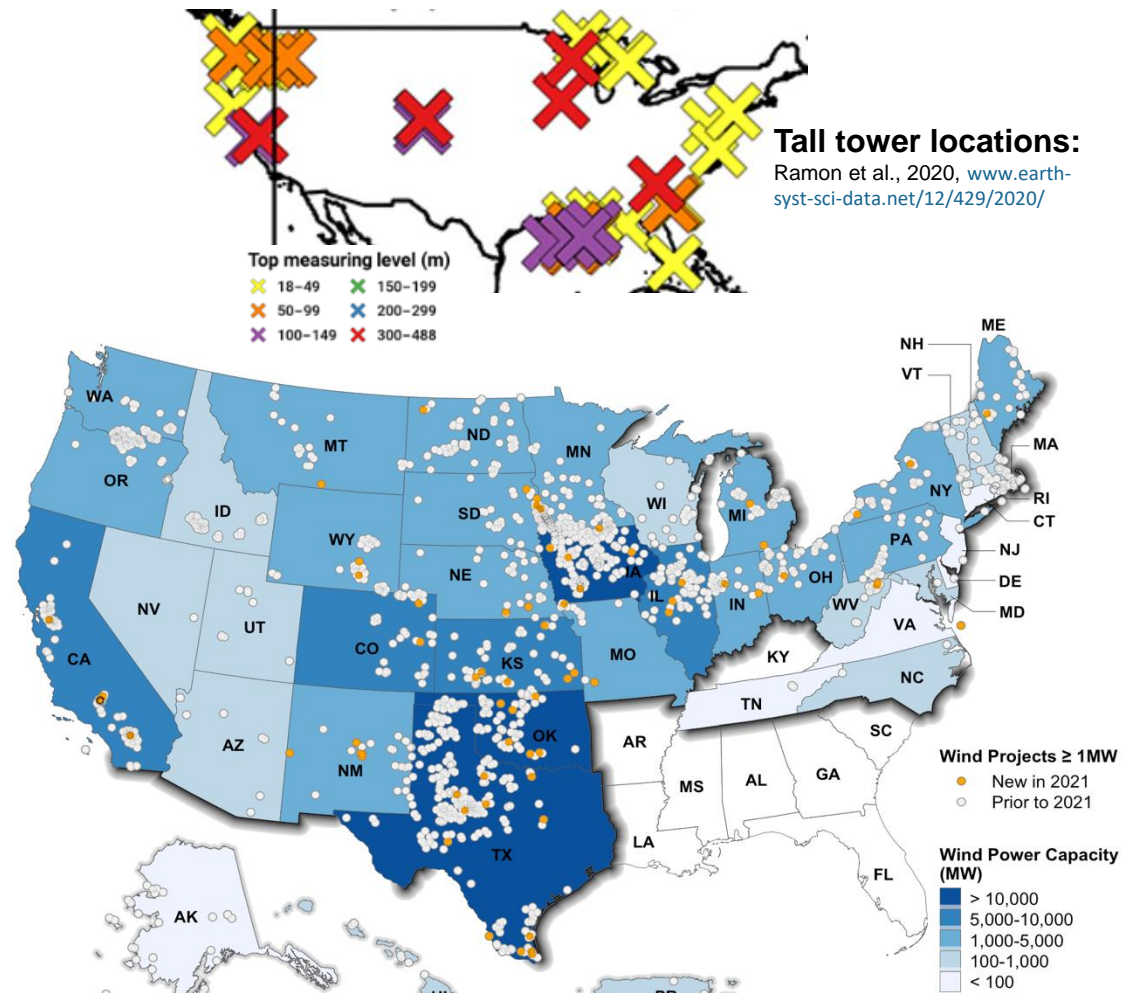
Some example of the needs:

- Understand the value of wind plants
- Help choose sites for wind plants
- Plan for future procurements (from a utility perspective)
- Prepare electricity system resources
- Schedule battery storage charge and discharge
- Even inform research and design of new wind turbines
- Becomes more critical with deeper market penetration

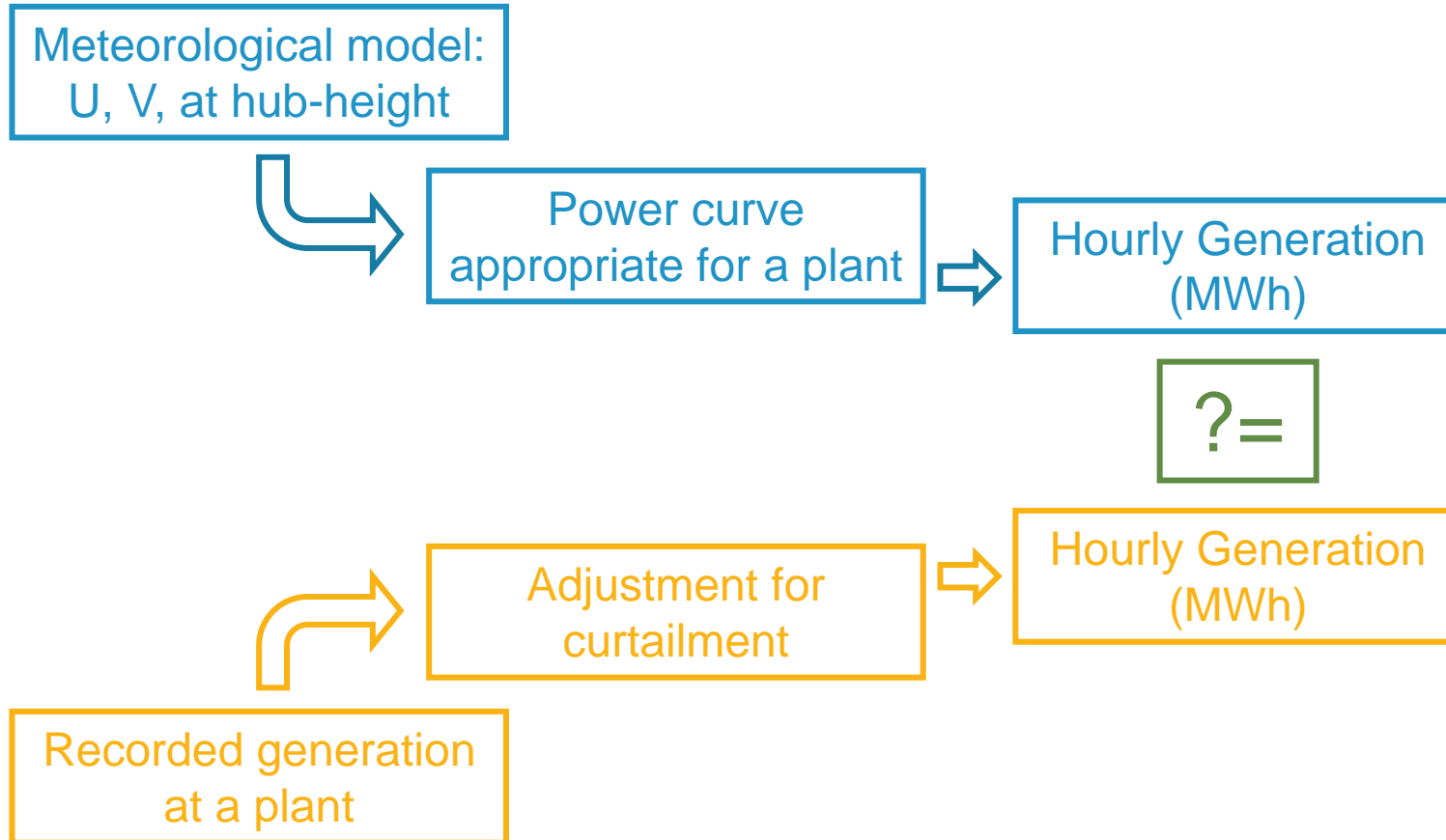
- Both **forecasts of wind profiles** and **retrospective wind profiles** are needed!
- This **presentation focuses on modeled, retrospective profiles** of wind resources, not forecasts
 - ERA5, MERRA2, HRRR
- Biases and errors identified here provide important context for understanding and improving forecasts

The challenge: Publicly available observations at >50 m rare

- Tall tower locations – order TENS
- Wind plant locations – order THOUSANDS
- Surface wind speed observations provide limited insight into wind patterns at hub and tip height
- How do we assess how well meteorological models represent wind profiles if very few observational locations are available?
- Common approaches include:
 - Analysis of existing tall tower data
 - Intensive measurement campaigns
- Approach described here:
 - Use generation records themselves to evaluate meteorological models

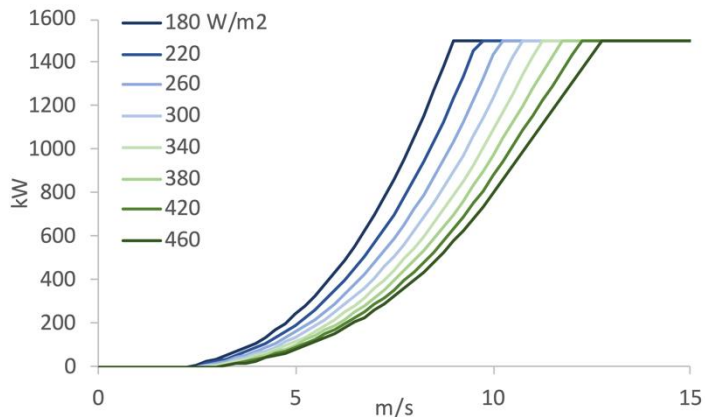


Compare generation records to generation estimates



Details and limitations

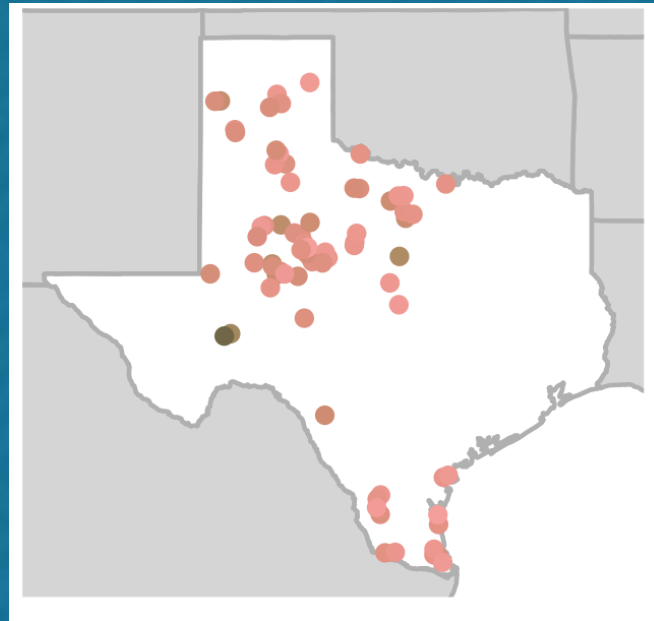
- Wind speed to generation transformation a function of a simple power curve
 - Matches specific power for each plant
 - Will not account for wake losses, intra-plant variation, turbulence, wind shear, etc.
- Hourly data
- Plant-level generation and curtailment records available in ERCOT (Texas), but not elsewhere
- Regional generation and curtailment records available in all ISO/RTOs
- Generation records can contain errors
- Generation records do not differentiate between maintenance needs and wind variation



Example power curves and how they vary with specific power

ERCOT – Comparison across >100 wind plants

Davidson and Millstein, 2022, *Wind Energy*, DOI: 10.1002/we.2759
“Limitations of reanalysis data for wind power applications”



Error between modeled generation and recorded generation

- Errors = $(CF_{\text{Model}} - CF_{\text{Actual}})$

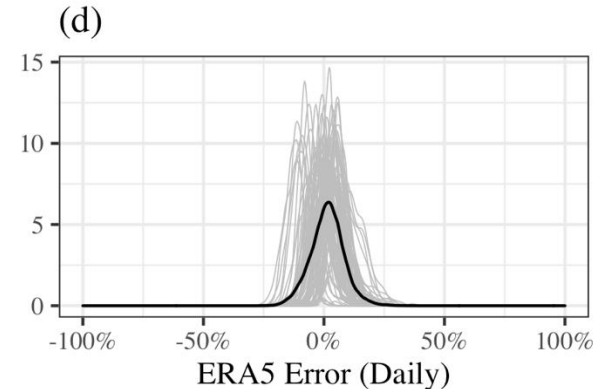
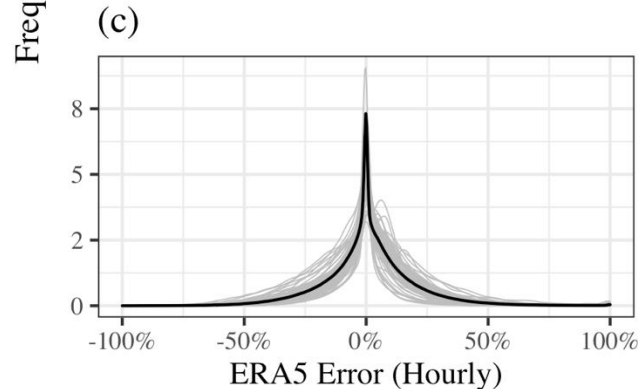
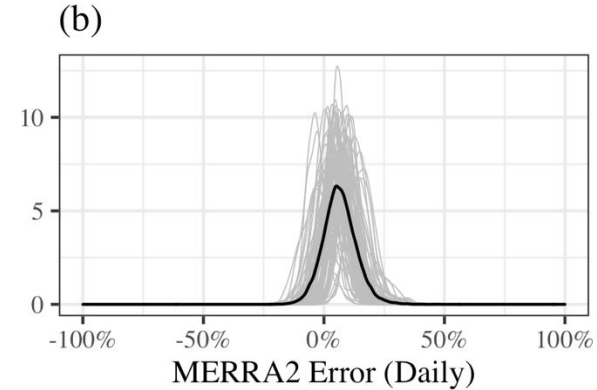
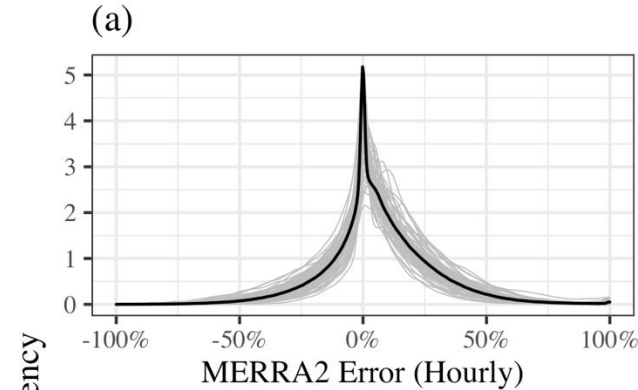
- Example:

- Model CF = 50%
- Actual CF = 30%
- Error = 20%

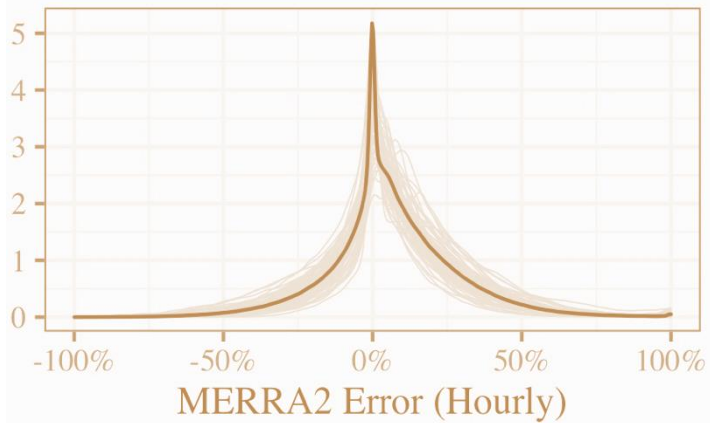
- Mean errors across the set of plants shown in each panel

- Interest in this case is in the spread of the errors not average bias

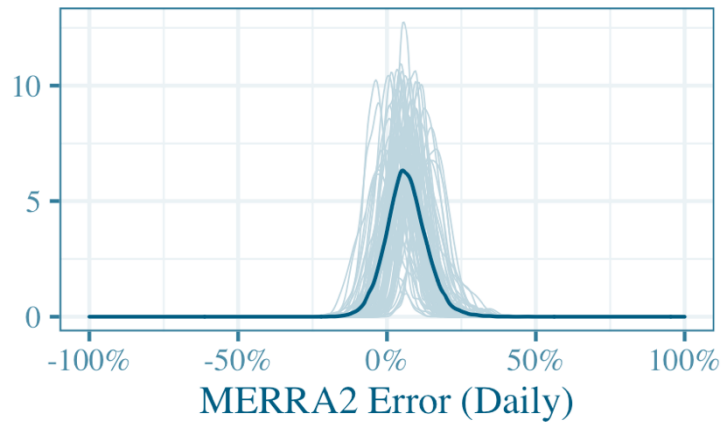
- Small overall biases shown here are likely to be swamped by losses
- Bias analysis will be discussed in later slides



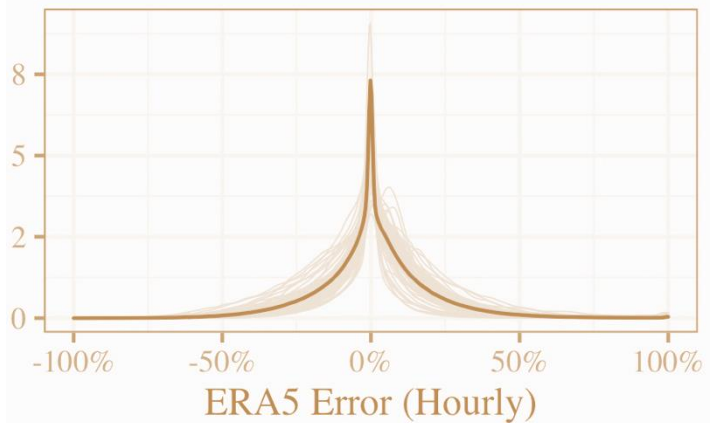
(a)



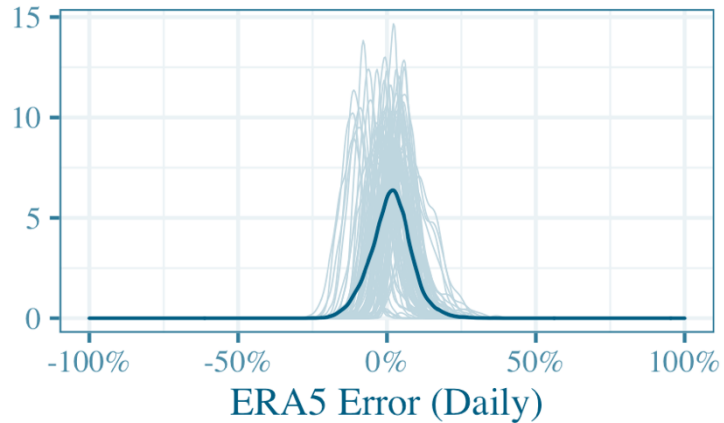
(b)

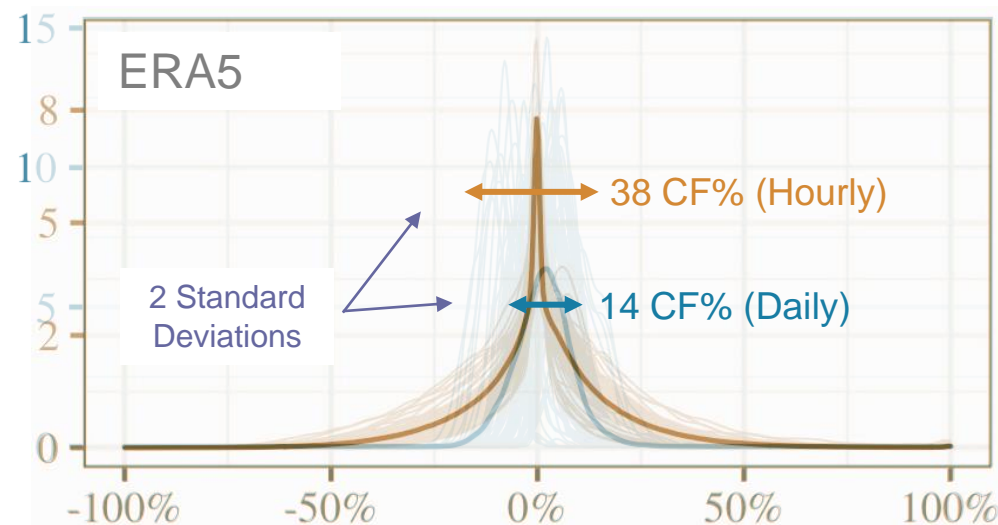
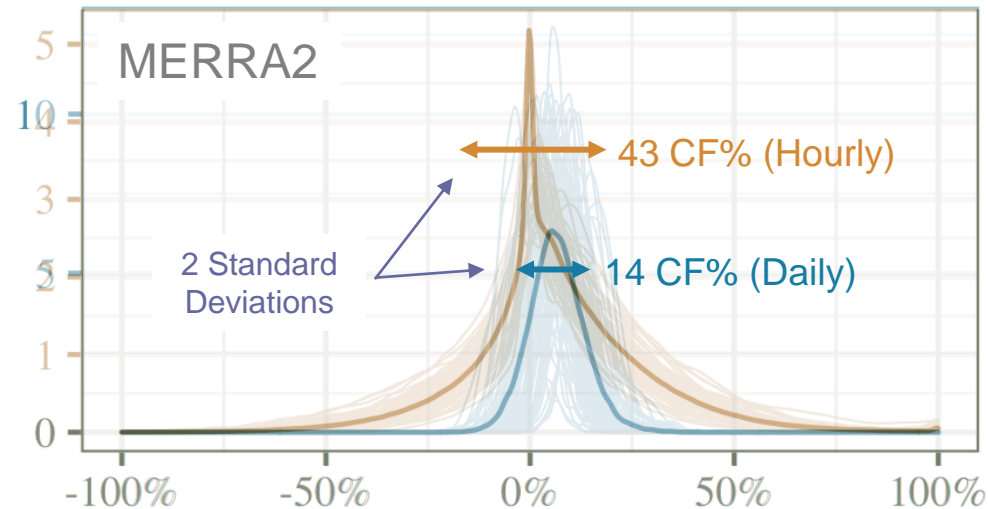


(c)



(d)





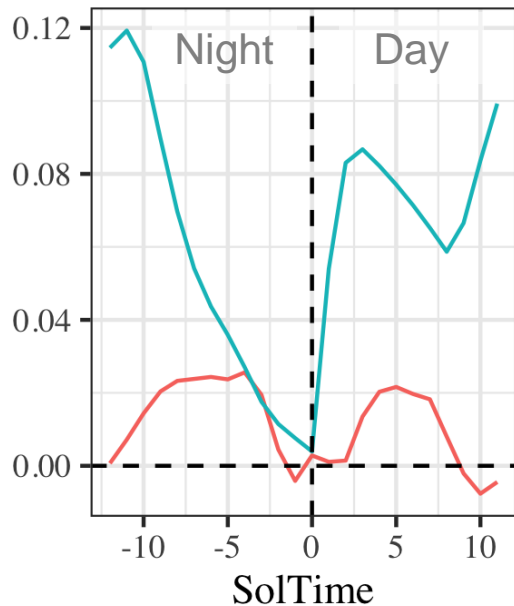
- **Averaging over time dampens differences between modeled and recorded capacity factors**
- Probability of CF within $\pm 20\%$ CF of actual:
 - ERA5 Daily: 99.1%
 - ERA5 Hourly: 78.0%
 - MERRA2 Daily: 97.0%
 - MERRA2 Hourly: 70.3%

MERRA2 bias shows strong diurnal cycle

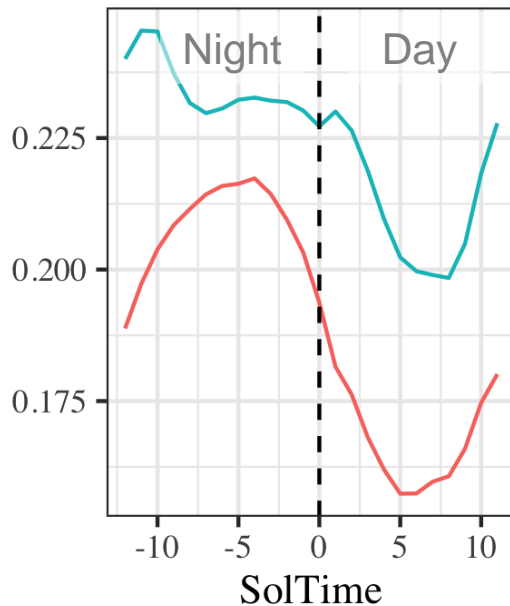
Model RMSE lower during daytime

Model correlation improved during daytime

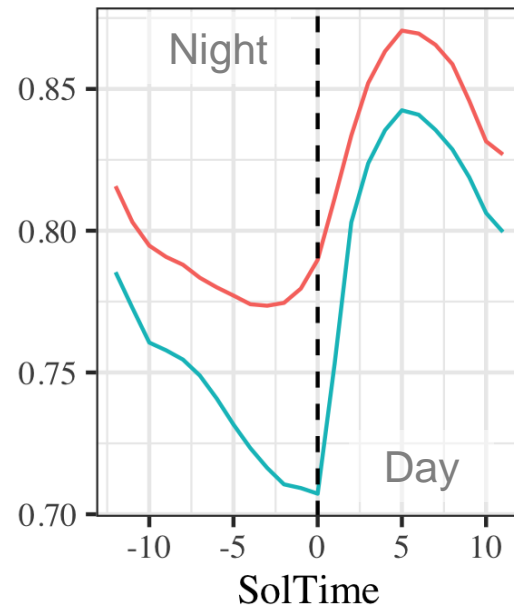
(a) Mean Error



(b) RMSE

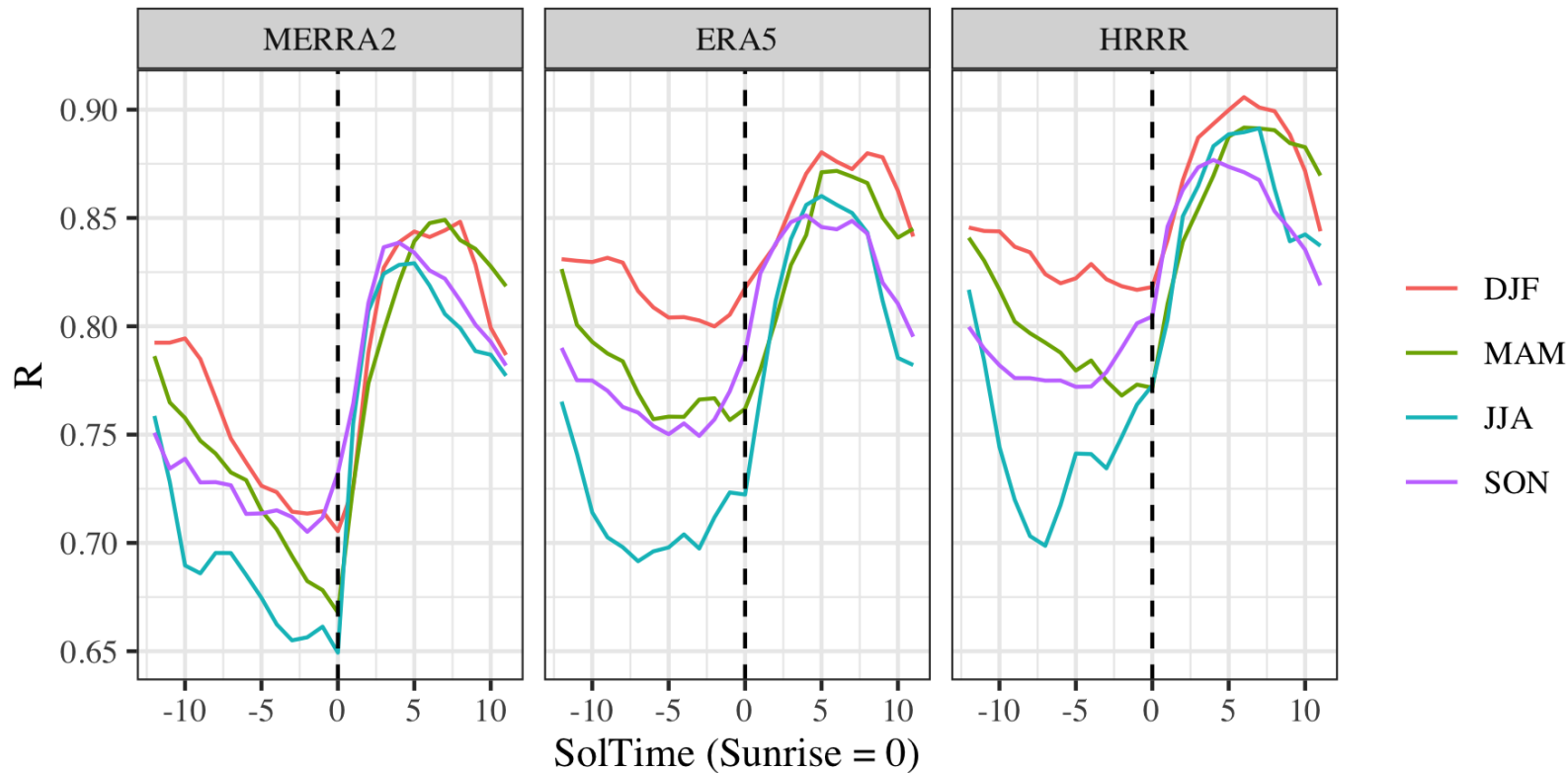


(c) R



Sunrise = SolTime 0

— ERA5 — MERRA2



- Model correlation best during daytime in all seasons
- Winter nighttime the worst
- HRRR has the highest correlation
 - HRRR's high resolution does not solve winter nighttime woes

3 Take away points from ERCOT plant-level comparisons

1. Hourly correlation and RMSE worse during nighttime than daytime

- Several causes possible: We suspect model errors in boundary layer representation drive declining model performance during nighttime
 - Error metrics have a strong connection to sunrise
 - Boundary layer height lower at night than day

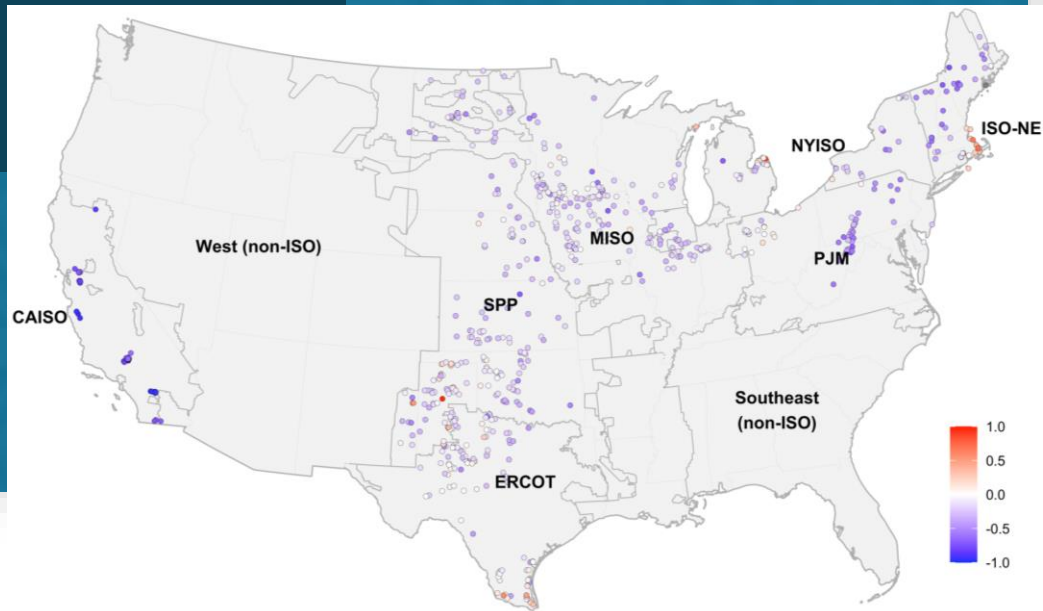
2. Correlation improves with model resolution (50 km > 30 km > 3 km)

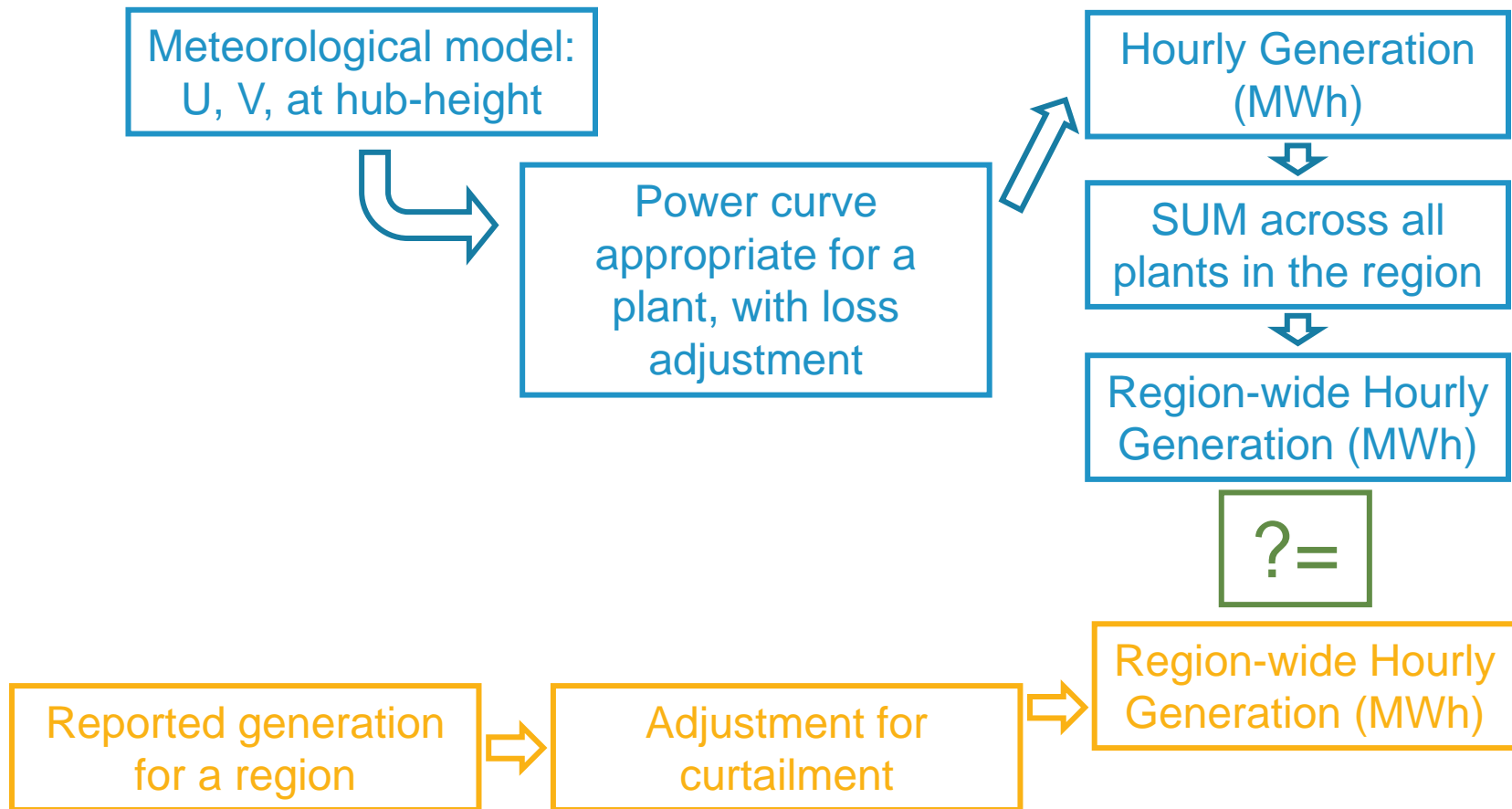
- Hourly correlation: MERRA2 < ERA5 < HRRR
 - But note that improved model resolution does not solve nighttime representation identified above, especially during the summer

3. Daily errors much smaller than hourly errors

- Daily modeled CF almost always within 20% of recorded value
- So many interesting questions for future research: What drives seasonal variation? How much do low-level jets influence model performance? Do turbulence and atmospheric stability meaningfully influence model performance? What about offshore? ...

Other regions – Region-wide diurnal profiles

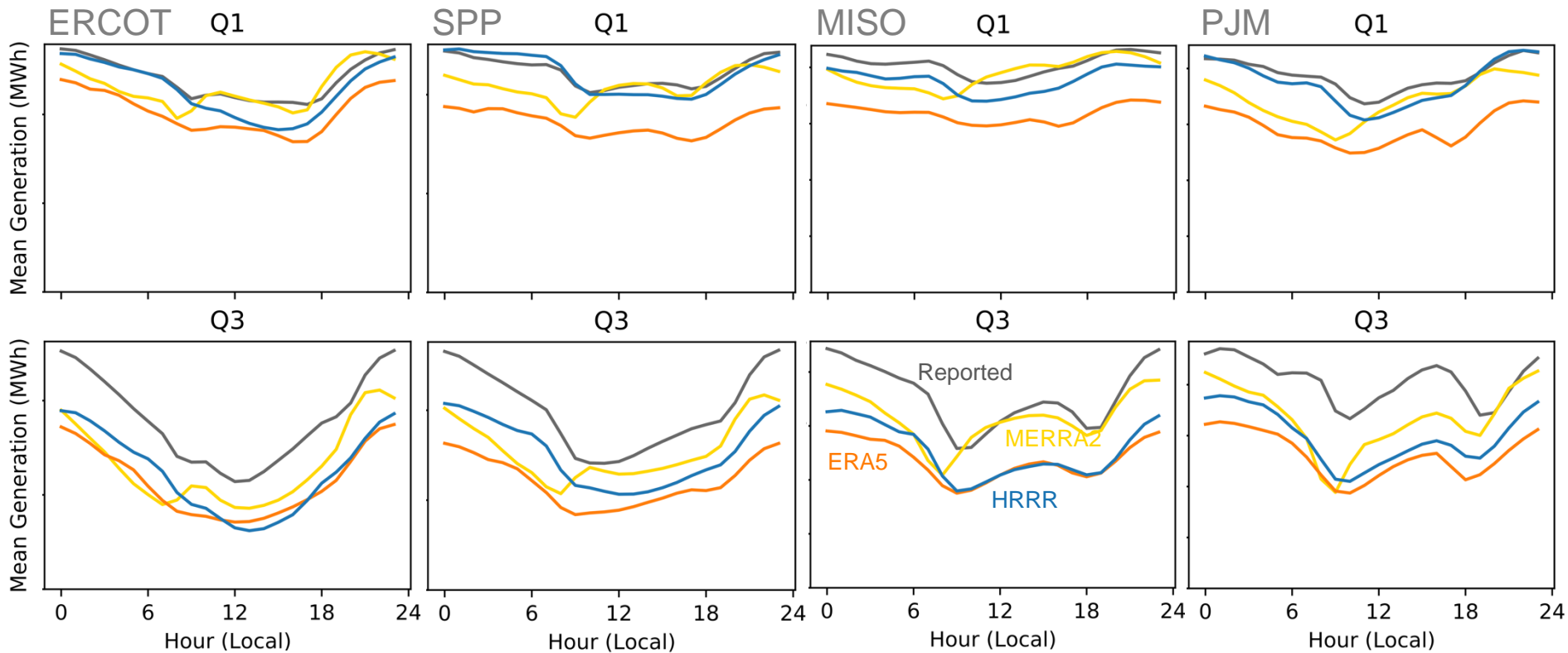




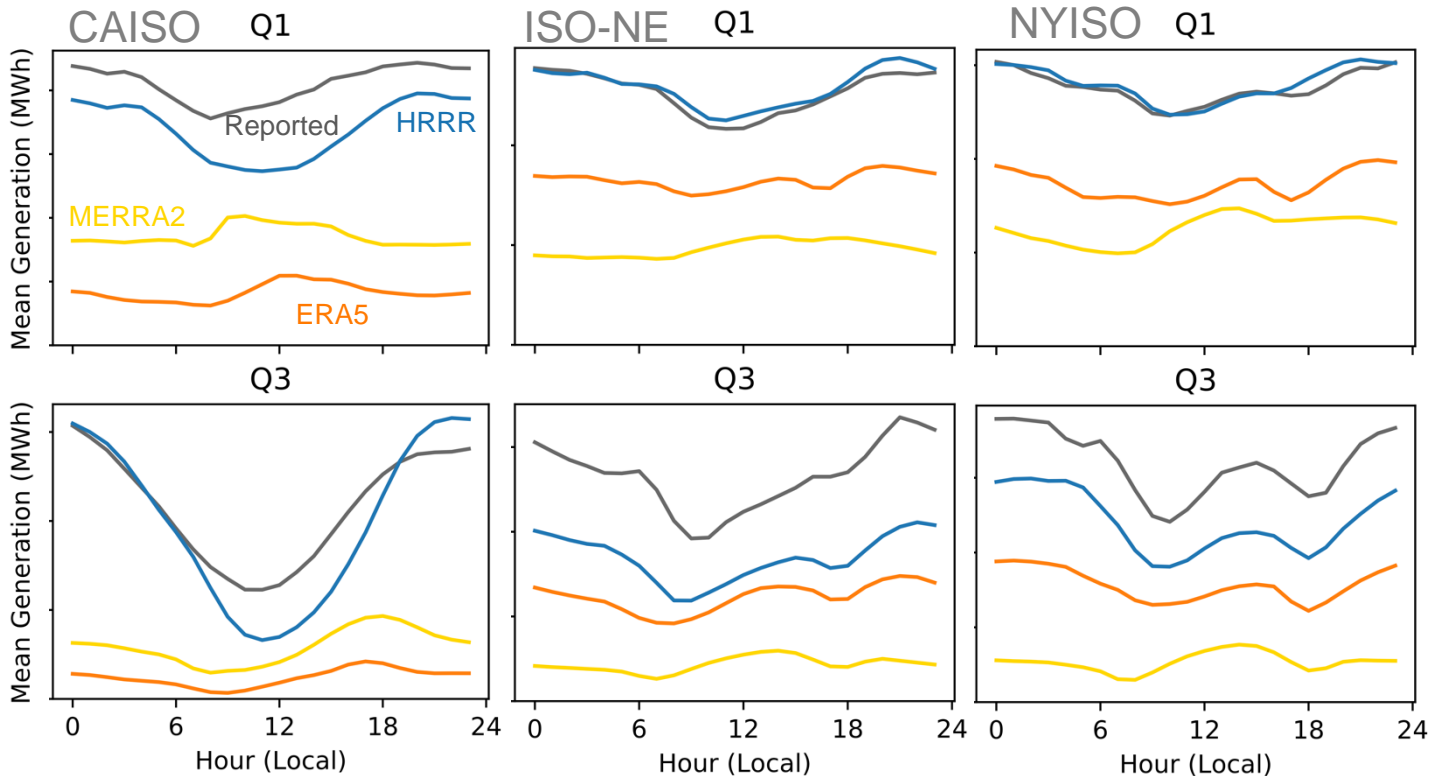
Diurnal plots notes

- Sum of generation for all plants in a region
 - May not match exact set of plants used by region for their reporting
 - Overall bias may differ from appendix
 - Relative bias (HRRR v. ERA5 v. MERRA2) still interesting
- Main purpose: provide a sense for how well the models represent diurnal cycles in regional wind generation

ERA5 and HRRR more faithfully represent diurnal profiles in the center of the country than MERRA2



HRRR more faithfully represent diurnal profiles in challenging regions than ERA5 or MERRA2



PLUSWIND Data Repository!

- Available to all at DOE's Wind Data Hub

- <https://a2e.energy.gov/project/pluswind>

- Wind speed profiles and generation estimates

- Hourly, 2018 – 2021
 - ~1200 U.S. plants
 - HRRR, ERA5, MERRA2
 - Generation based on power curve matching plant average specific power
 - Reported as hourly capacity factor by plant
 - Simple loss assumptions as an option
 - Simple air density adjustment as an option
 - All data stored in simple csv files

The Plant-Level US multi-model WIND and generation (PLUSWIND) data

PROJECT DATASETS (1)

Description

Overview

The Plant-Level US multi-model WIND and generation (PLUSWIND) data provides hub-height wind speed and generation (i.e., capacity factor) information for 1,175 wind plants across the continental United States (CONUS). Three sets of hourly wind speed and generation estimates for each wind plant were derived from three state-of-the-art meteorological models: ERA5 (ECMWF Reanalysis v5), MERRA2 (Modern-Era Retrospective Analysis for Research and Applications, Version 2), and HRRR (High-Resolution Rapid Refresh).

Objective

PLUSWIND aims to provide users with multi-source wind speed (raw and density corrected) and generation data for 2018 – 2021 that can be used in projects (e.g., energy value analysis) involving United States wind plants. Accurately simulating wind speed is key to reducing uncertainty in predicting wind energy generation patterns and trends. However, a substantial upfront effort is required to download and process the meteorological and plant characteristic data necessary to compare wind speed and generation estimates based on different meteorological models. The

610 Views

12 Requests

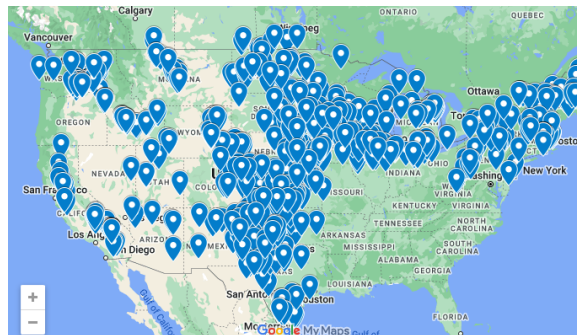
38,775 Files Requested

96.31 GB Requested

1 Datasets

11.68 GB Stored

4,700 Files Stored



Conclusions

Plant-level comparisons in ERCOT

- Models performed worse during nighttime, especially summer nighttime
- More finely resolved models performed better overall, but high resolution did not solve summer nighttime issues
- Daily errors much smaller than hourly errors

Regional diurnal cycles

- Across almost all cases, HRRR contained the most faithful representation of average regional diurnal cycles in wind generation – California and northeast – poor performance from MERRA2 and ERA5

PLUSWIND publicly available!

Contact and acknowledgements

Contact: Dev Millstein (dmillstein@lbl.gov)

Thanks to my coauthors!

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Seongeun Jeong, Amos Ancell, Ryan Wiser, LBNL

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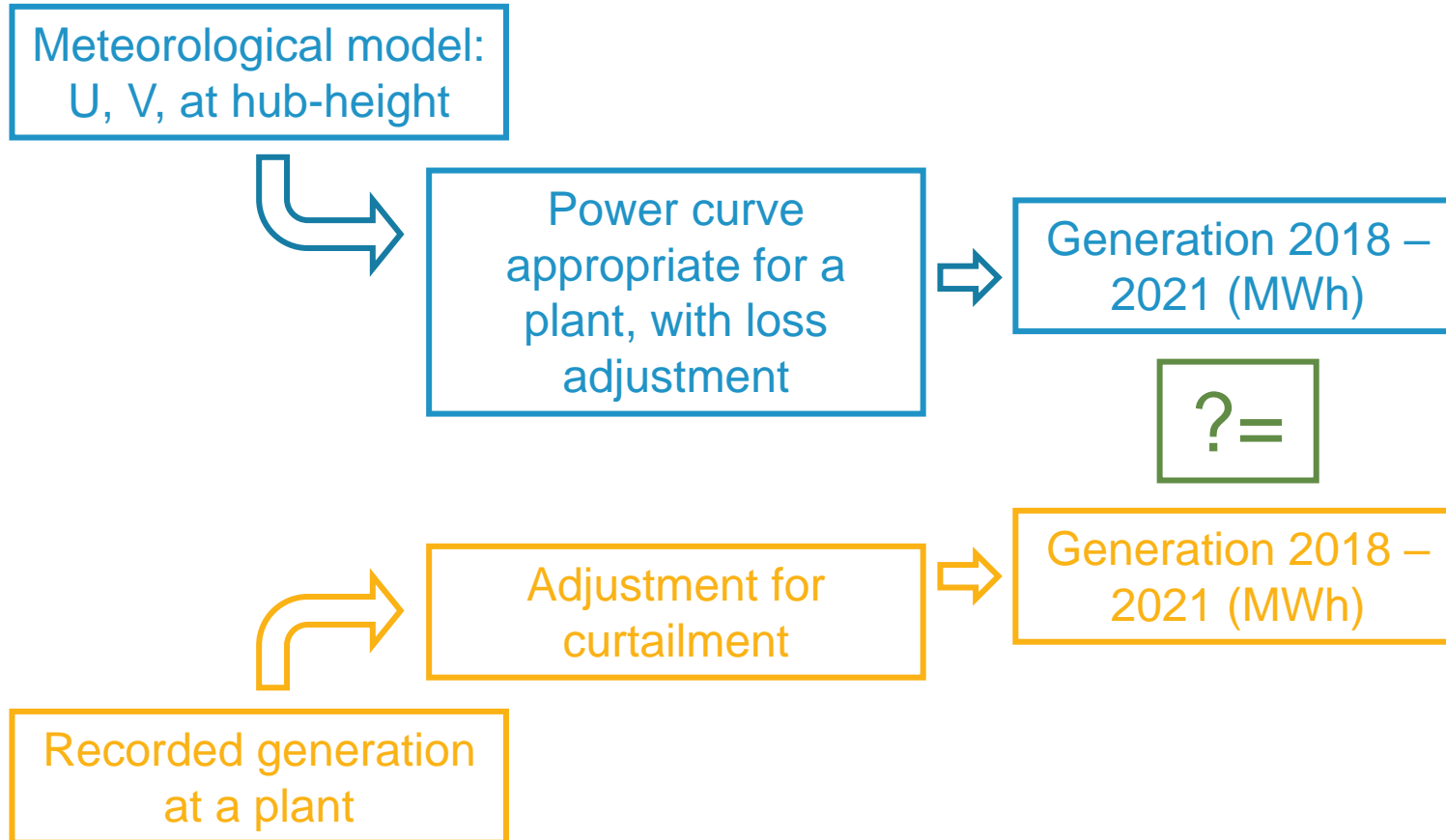
Appendix



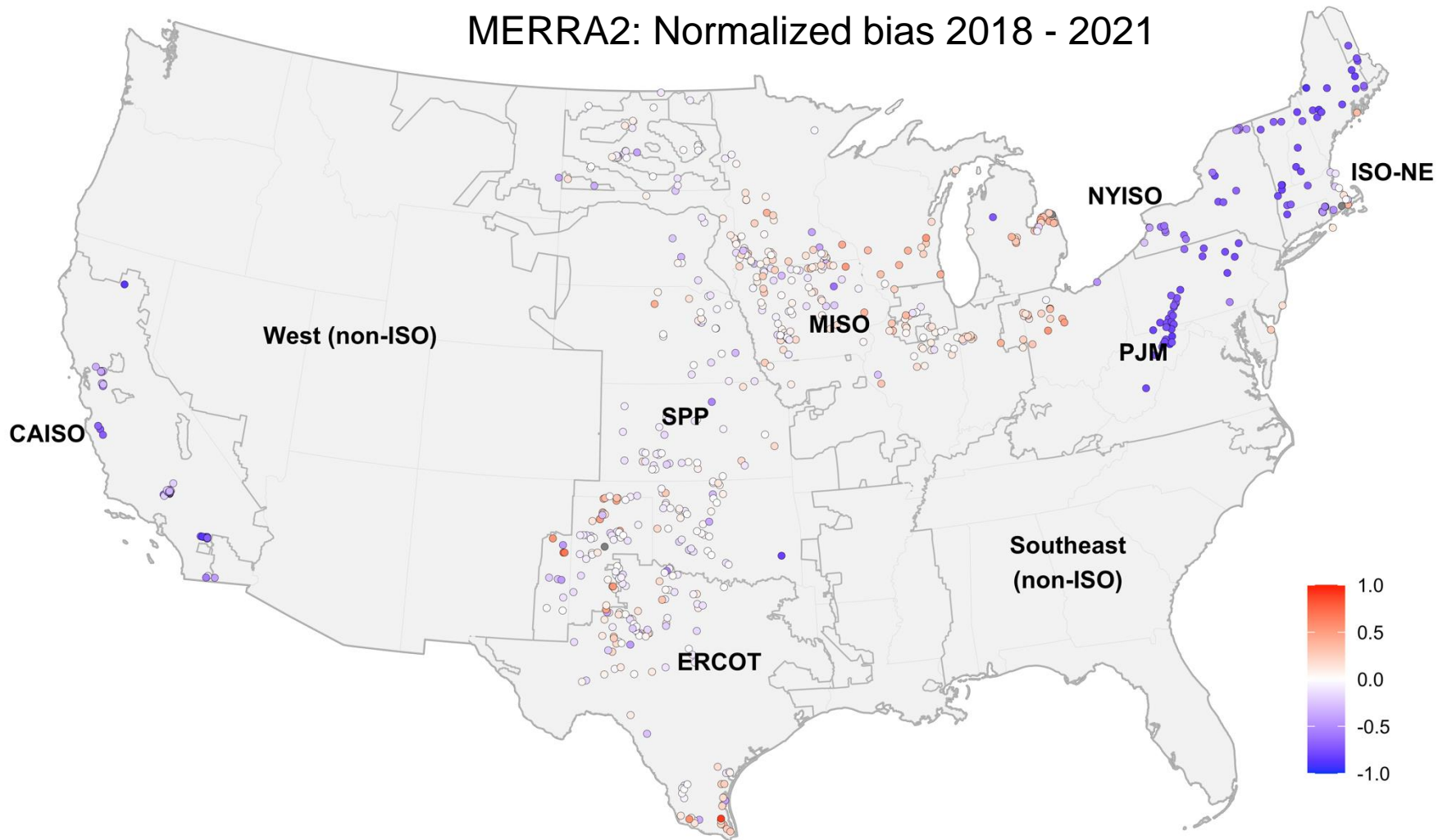
Other regions – Long term bias assessment



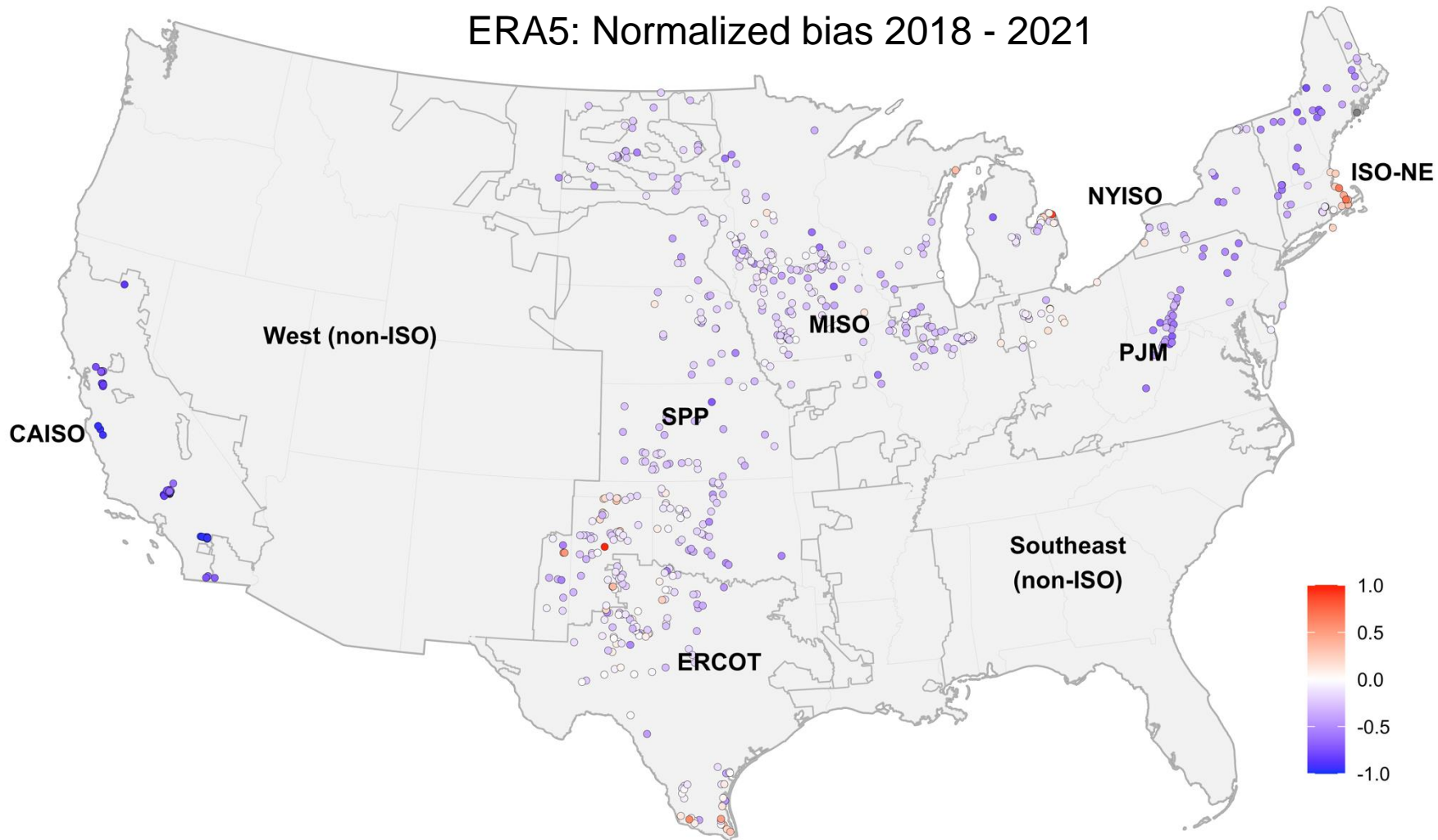
Compare generation records to generation estimates



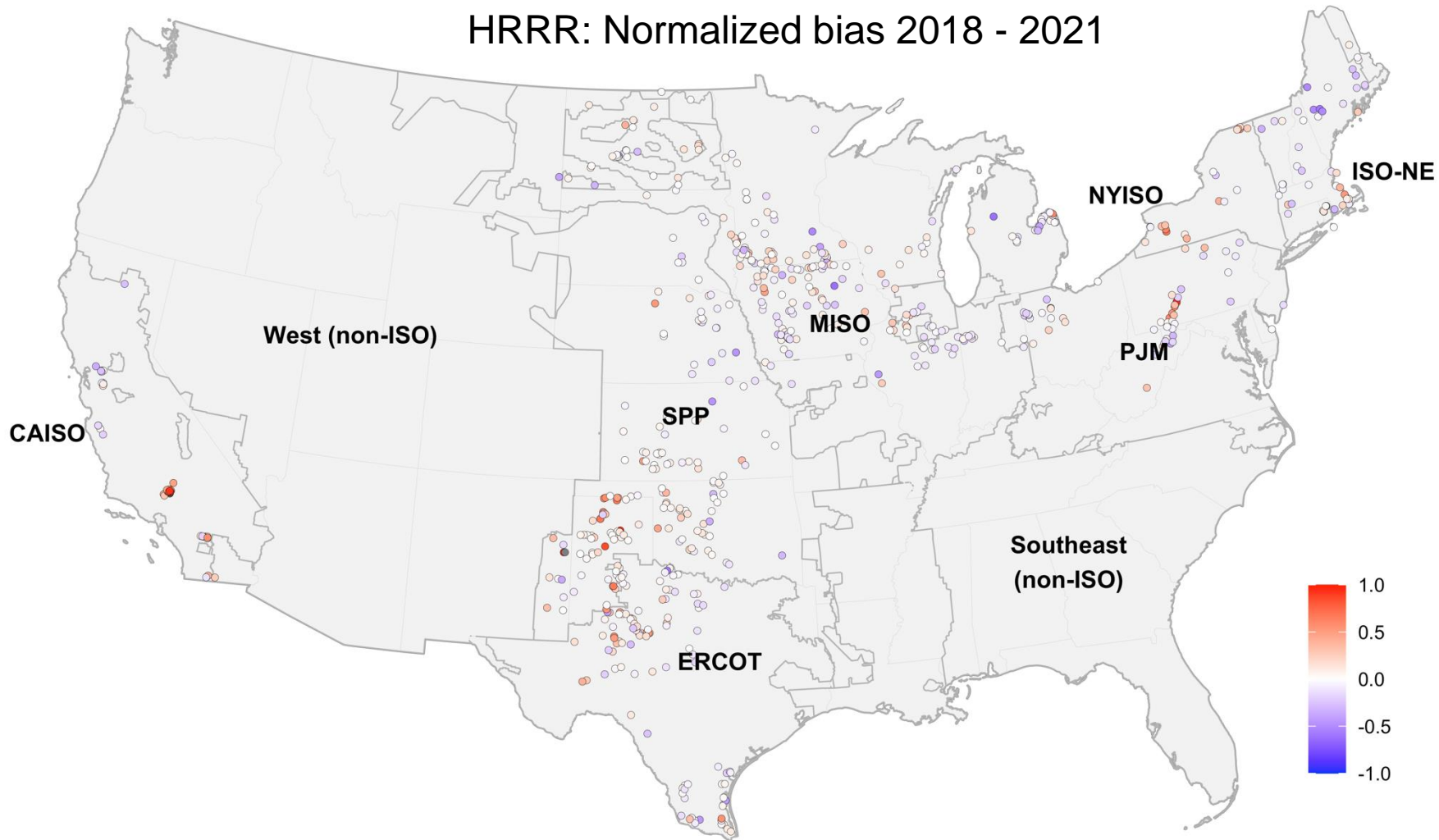
MERRA2: Normalized bias 2018 - 2021



ERA5: Normalized bias 2018 - 2021



HRRR: Normalized bias 2018 - 2021



HRRR has the smallest biases

- **HRRR:**

- ✓ ERCOT, MISO, SPP, PJM, ISO-NE

- ≈ NYISO

- x CAISO

- **ERA5:**

- ✓ ERCOT

- ≈ MISO, SPP, ISONE, PJM, ISO-NE, NYISO

- x CAISO

- **MERRA2:**

- ✓ ERCOT, MISO, SPP

- ≈ NYISO, PJM

- x CAISO, ISO-NE, NYISO

Mean Normalized Annual Bias by Plant:
Density and Loss Adjusted Gen

