Weather Datasets for Power System Planning
Tutorial Session 1: 8:00 – 10:00

State of the Art in Datasets (20 min)
John Zack, MESO

Problems with Existing Datasets (20 min)
Justin Sharp, Research Leader IV, EPRI

Evaluation and Adjustments to the ERA5 (20 min)
Jim Wilczak, Research Meteorologist, NOAA

Approaches to Historical Datasets – (1 hr)

CONUS404, A High-resolution Hydro-climate Dataset
Sue Haupt, Senior Scientist, NSF National Center for Atmospheric Research

Applying the WIND Toolkit and WTK-LED to Grid Integration
Luke Lavin, Researcher III, NREL

Historical and Forward-Looking Datasets
Cameron Bracken, Earth Scientist, PNNL

10:00 a.m. – 10:20 am
Break
Location: Foyer

Tutorial Session 2: 10:20 - Noon

Approaches to Forward Looking Datasets – (1 hr)

Energy Exascale Earth System Model
Robert Arthur, Staff Scientist, LLNL

Sup3rCC Dataset
Grant Buster, Data Scientist, NREL

Creating Hourly Weather Timeseries for Future Climates
David Larson, Technical Leader, Grid Ops & Planning, EPRI

Using the Data Properly – Example and Facilitated Discussion (40 min)

A Case Study
Josh Novacheck, Transmission Planning Engineer, NextEra Energy Resources;
Chair, ESIG System Planning Working Group

Facilitated Discussion
John Zack, MESO

State of the Art in Datasets

ESIG Tutorial on Weather Datasets for Power System Planning
June 11, 2024
Salt Lake City, Utah

Presenter:

Dr. John W. Zack
Principal
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Troy, NY
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MESO
ATMOSPHERIC RESEARCH
FORECASTING • SIMULATIONS

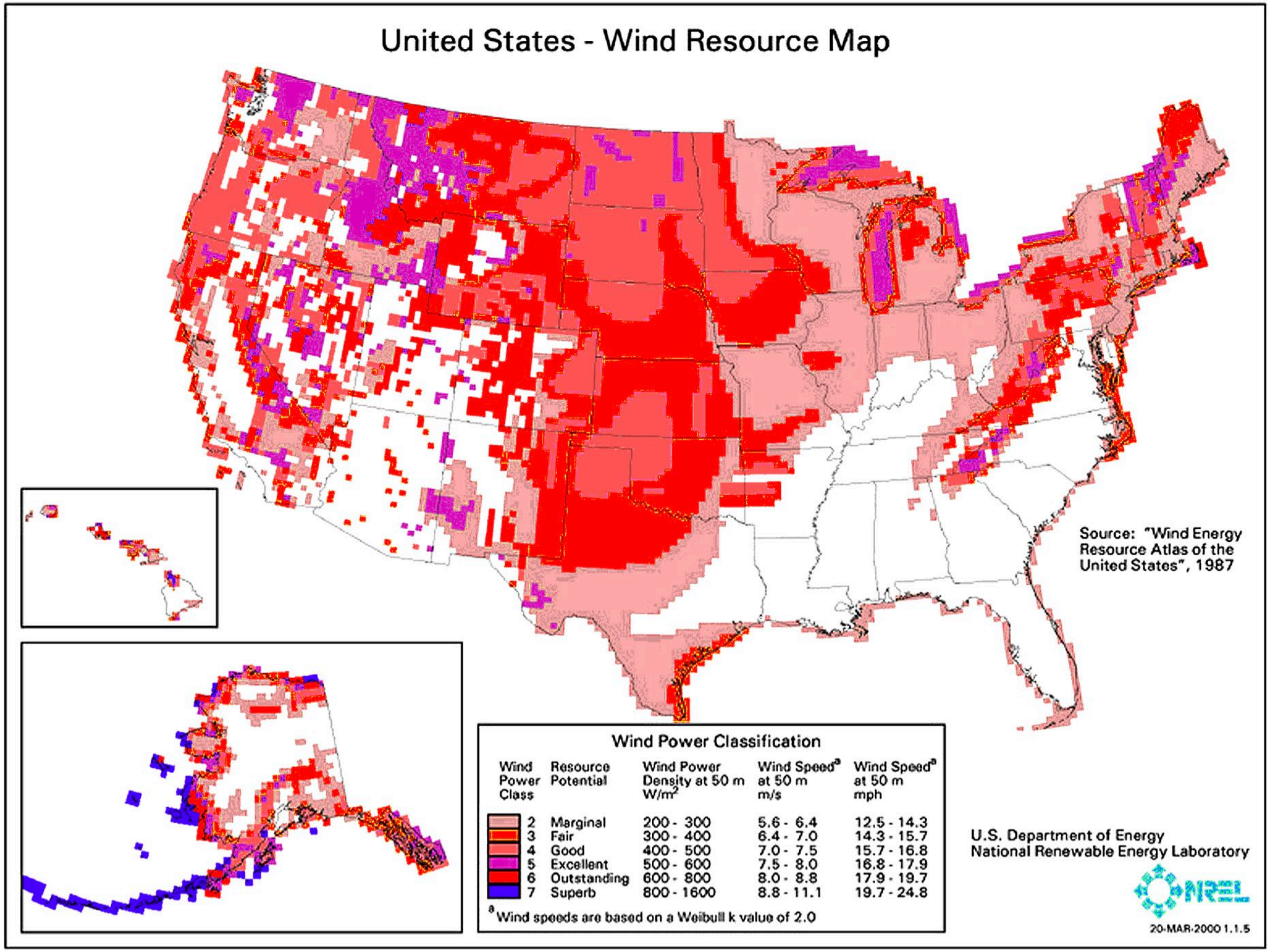
Overview

- Some History: Where have we come from?
- State of the Art in Three Areas
  - Dataset Design/Production with Examples of Issues
  - Dataset Evaluation/Validation
  - Dataset Use

History

The State-of-the-Art: a Historical Perspective

- ❑ 1987 wind resource map
  - o based on wind @ 50m
  - o created by PNNL/NREL
- ❑ Method
  - o surface & rawinsonde wind data
  - o basic elevation (power law profile) & surface roughness wind model
  - o terrain and land use/cover data
  - o and (apparently) some subjective adjustments
- ❑ Technology has noticeably evolved!



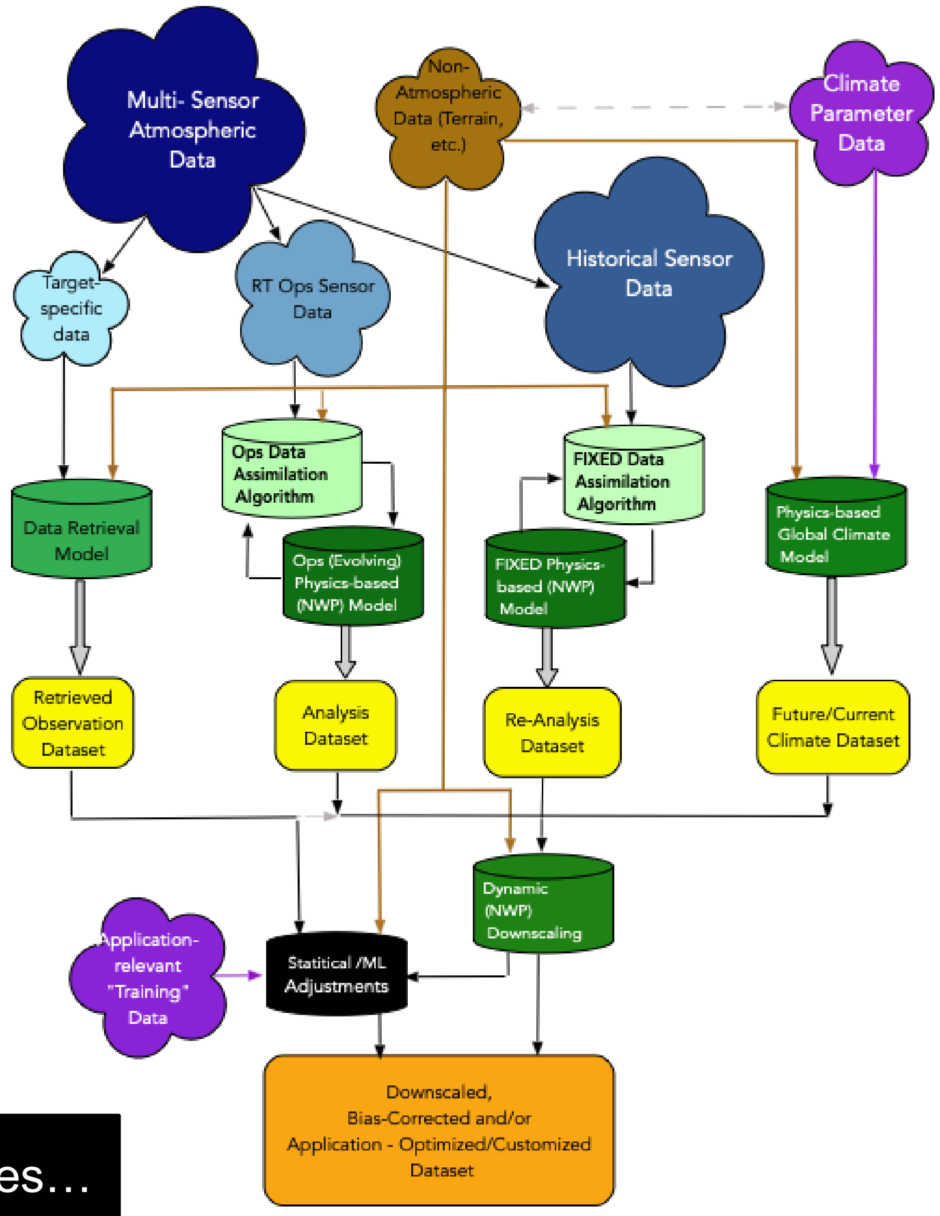
Now back to 2024 …..

State-of-the-Art in Dataset Design & Production

A time series of 3-D states of the past, current and future atmosphere…..

Overview of the Current World of Datasets for Power System Planning

- **Wide Range of Methods to Construct Datasets**
  - **A few fundamental types of approaches**
  - Enormous number of significant variations within types
- **Therefore: Wide Range of Datasets Exist**
  - **Typically have very different attributes depending on how they were constructed**
  - Consistency of data attributes (e.g. spatial/temporal correlations) between datasets should not be assumed
  - **Critical need to evaluate comparative performance on parameters/scales important to specific applications**

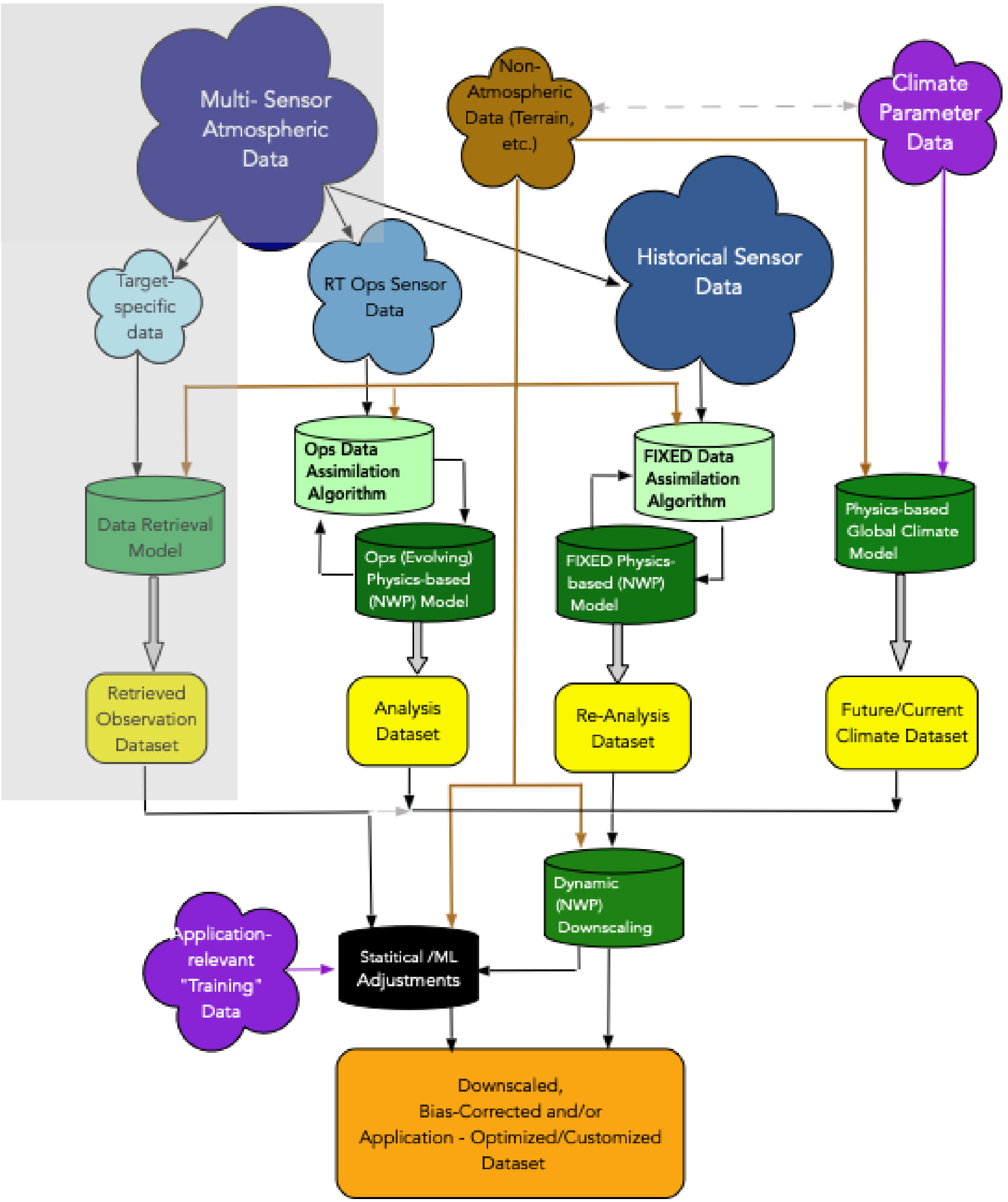


Let's examine the key attributes of the fundamental types of approaches…

"Retrieved" Directly from High Resolution Space-Time Measurements

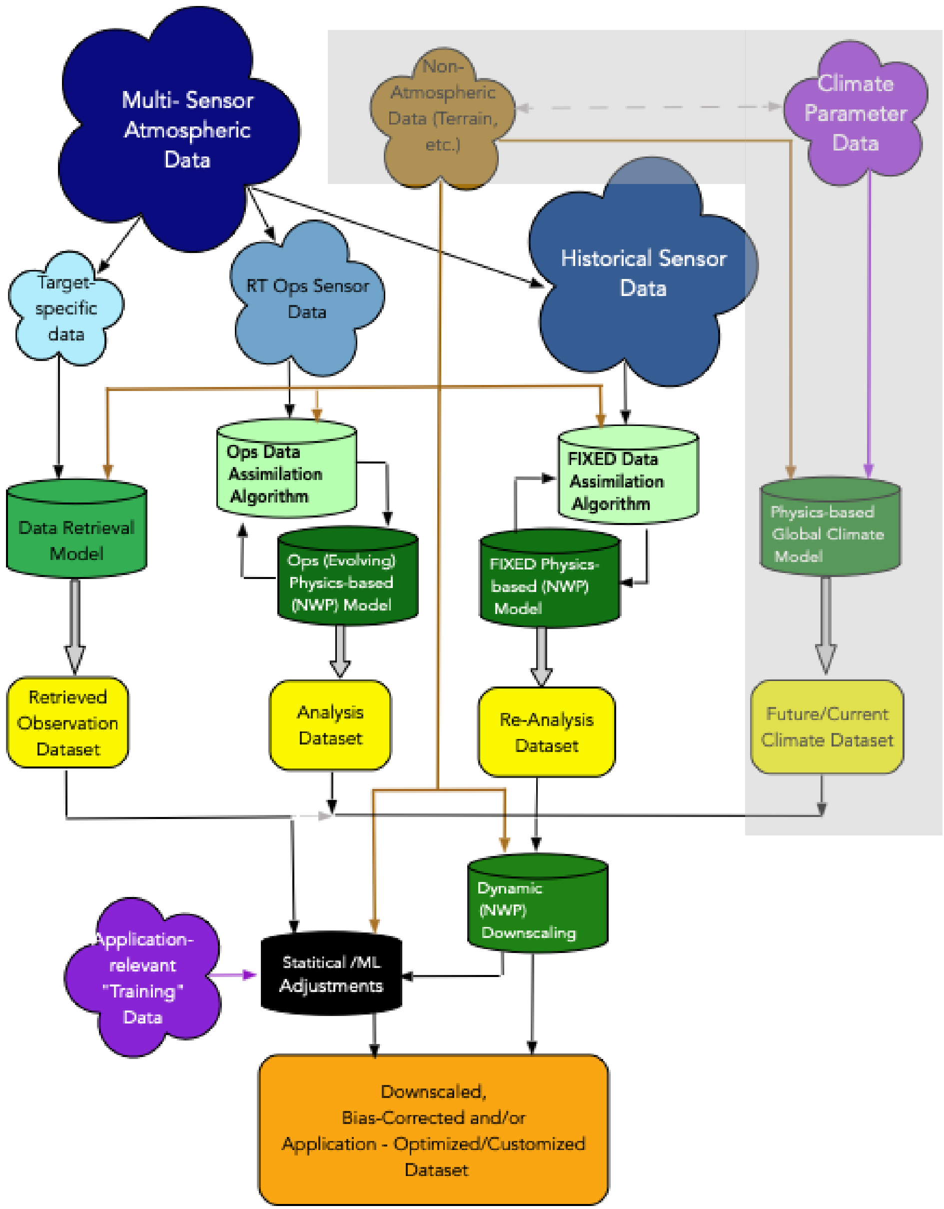
Examples: Satellite-based sensors, radar

- **Pluses**
  - **Closest data to direct measurements**
  - Minimal dependence on "models" & model biases
    - "retrieval" model: measurements → desired variable
    - less assumptions than NWP-based models
- **Minuses**
  - **Only feasible for some variables/areas (e.g. solar)**
  - **Does not assure realistic space-time correlations with other variables from other sensors/models**
  - Limited to Period of Record (PoR) of sensors
  - Limited by sensor space-time resolution
  - No forward-looking data (except Future = Past)
- **Example: NSRDB**



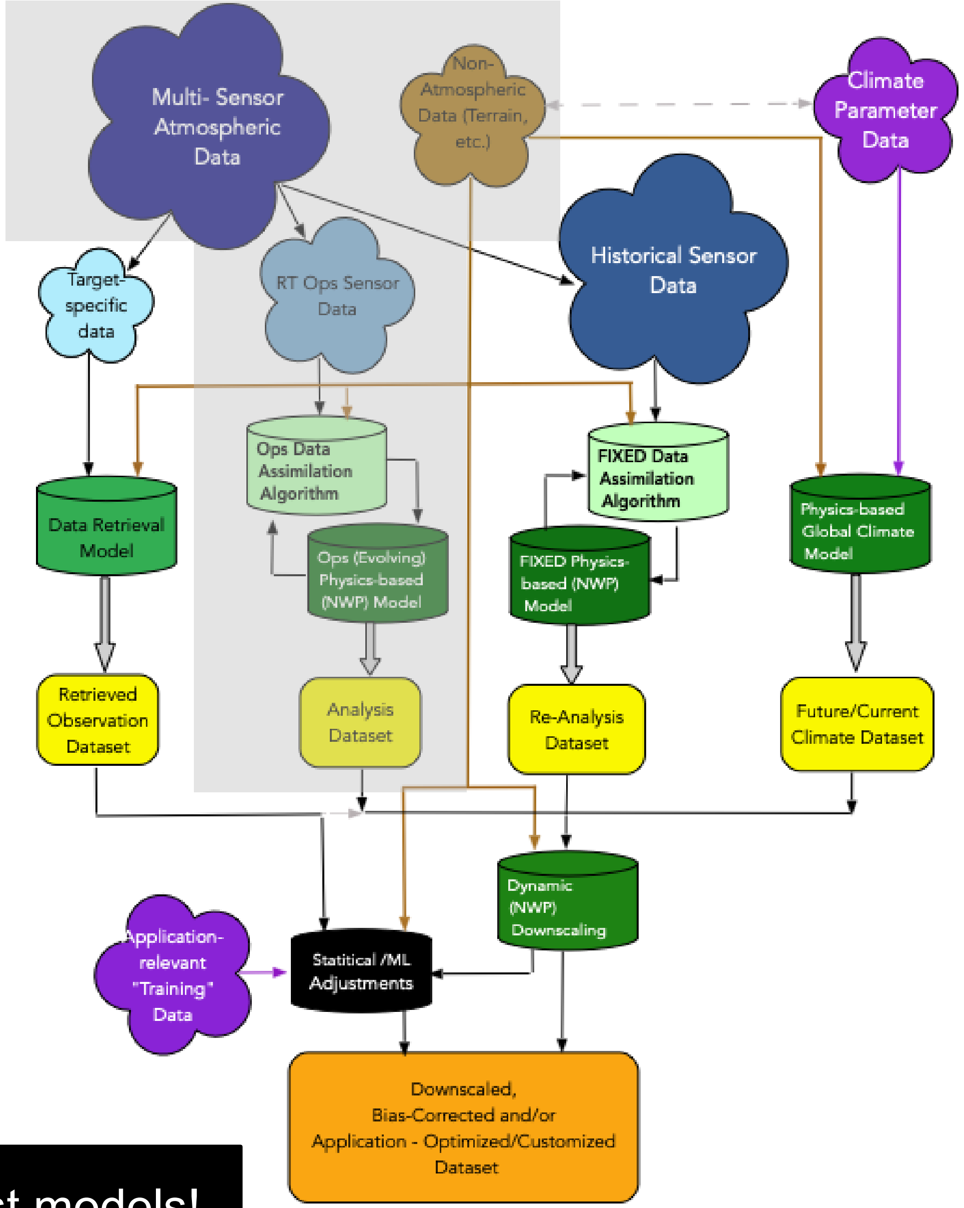
Physics-Based Models with Little/No Sensor Data Input

- **Pluses**
  - Can simulate the past, current or **future**
  - No intrinsic PoR limitations (computational cost a factor for resolution/PoR length trade-offs)
  - Physically consistent space-time relationships among variables for past, present and future
- **Minuses**
  - Requires coupling with other components of earth-atmosphere system (oceans, biosphere etc.)
  - Model biases not constrained by observations
  - Model physics-formulation play a more critical role
  - Assumptions needed for future values of key parameters (greenhouse gases, land use changes)
- **Example: the CMIP6 set of datasets**



Blend of Physics-based Model and Sensor Data: Operational Analysis

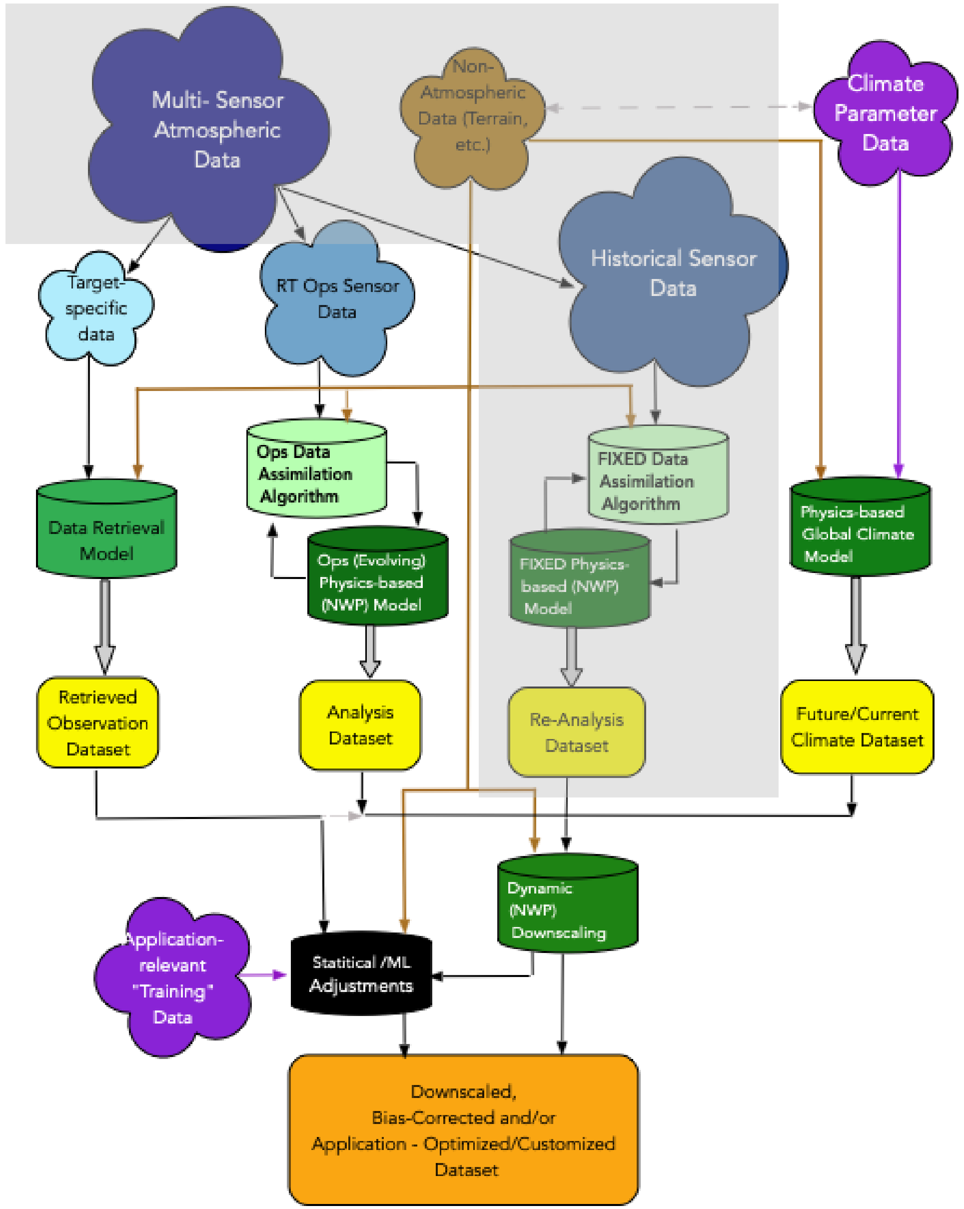
- **Pluses**
  - Ongoing upgrades to the latest technology in model physics, data assimilation and computing power
  - Real-time updates to the dataset (i.e. each day)
  - Physically consistent space-time structures among all variables to the limit of the resolution
- **Minuses**
  - Ongoing upgrades: **system formulation changes over time**
    - Performance (e.g. biases) can change over time
  - **Assimilated data is limited to what is available and can be processed in the operational window** (i.e. not all ultimately available data can be used)
  - Period of record limited by life span of the modelling system
  - No forward-looking data (except Future = Past / Trends)
- **Example: HRRR analysis (a popular one!)**



Designed to create 3-D initialization datasets for operational forecast models!

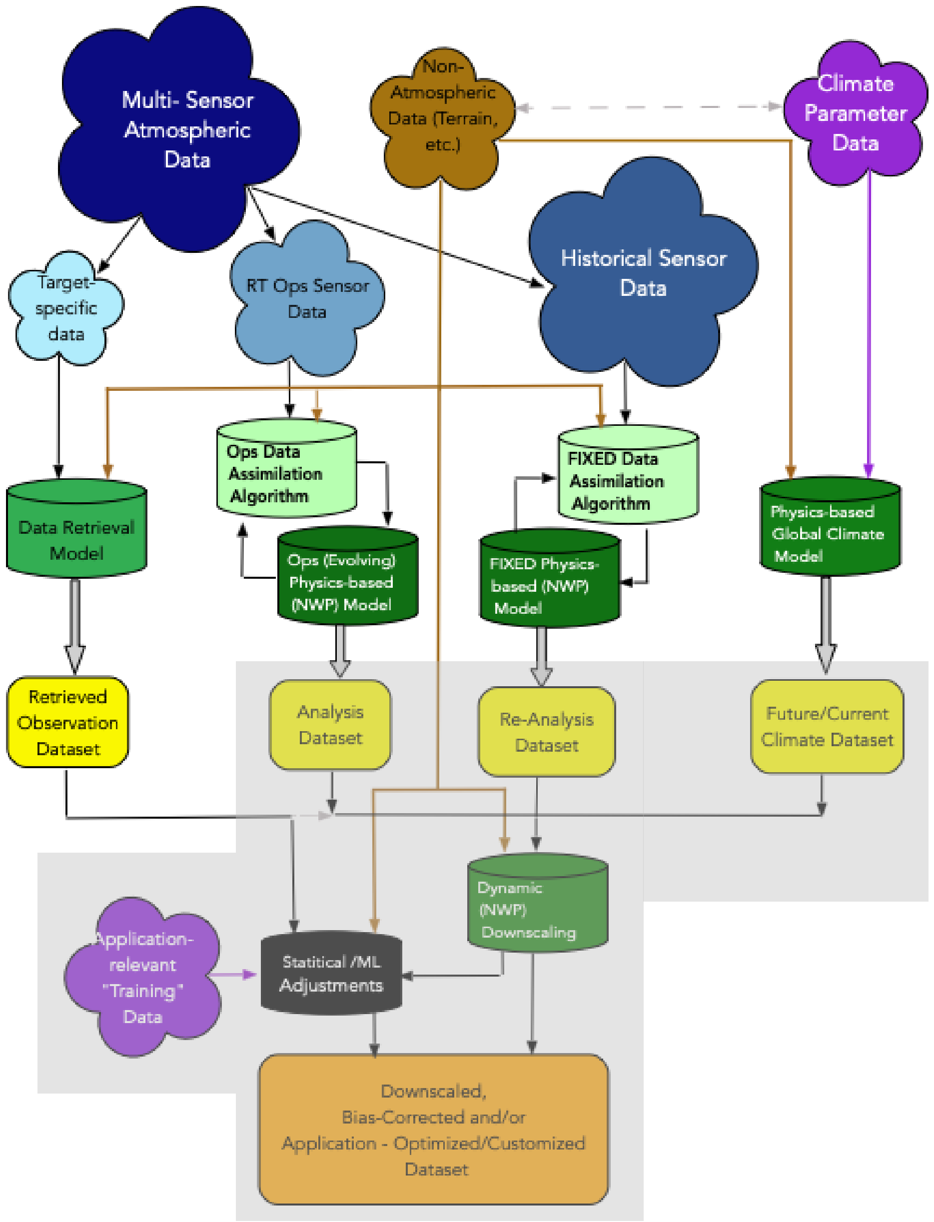
Blend of Physics-based Model and Sensor Data: Reanalysis

- **Pluses**
  - **Unchanging physics-based model and data assimilation system for full PoR**
    - More consistent biases?
  - Longer PoR than operational datasets
  - Physically consistent space-time structures among all variables to the limit of resolution
- **Minuses**
  - **Data assimilation inputs change over time even though model/DA system does not**
  - System not updated to latest technology until an entirely new dataset is created
  - Resolution often limited to make it feasible to have long PoR and global coverage
  - No forward-looking data (except Future = Past / Trends)
- **Examples: ERA5, MERRA-2**



Secondary Modeling: Downscaling, Bias Correction, etc.

- **Pluses**
  - Could be physics-base (NWP) or statistical or both
  - **Can serve many purposes**
    - Bias correction with measurement data
    - Downscaling using higher resolution local data (terrain, surface attributes etc.)
    - Optimization for specific application variables
    - Assimilate local data (e.g. mesonet data)
- **Minuses**
  - **Can result in a swap of one set of biases for another**
  - **Could introduce dataset inconsistencies (such as using different model configurations in different areas)**
  - Can require a lot of computation power depending on what is done and that could limit PoR and/or resolution
  - Constrained by PoR of parent dataset(s)
- **Example: NREL Wind Tool Kit**



Emerging Technology:

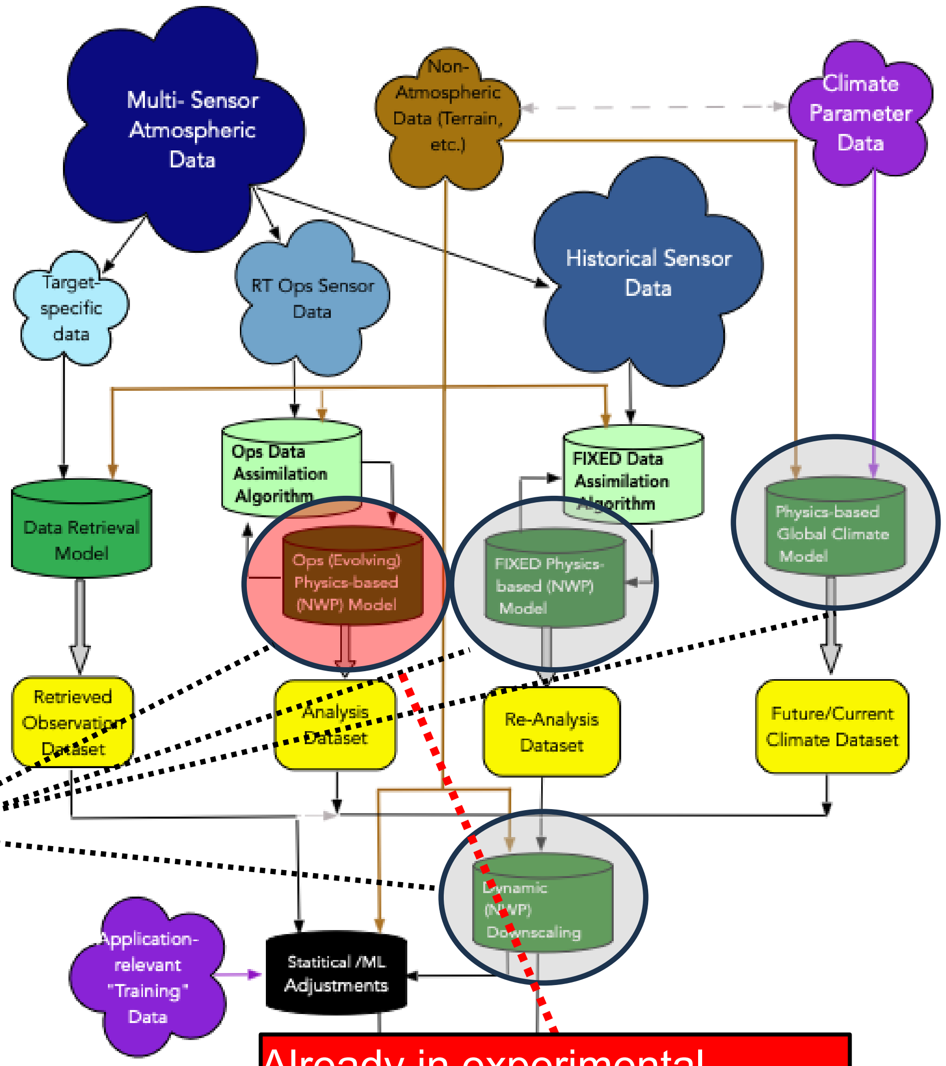
Machine Learning-based Weather Prediction (ML-WP) Models

❑ What is it?

- A machine learning model (usually a deep neural network) that is trained to emulate a numerical weather prediction modeling system (essentially it learns the physics!)
- Currently trained mostly on analysis/reanalysis datasets
- Training process is computationally intensive but forecast production is much faster than traditional NWP models
- Not addressing data assimilation YET

❑ Potential Benefits

- Could replace the traditional NWP components of the database creation systems with a much more computationally efficient alternative
- **Potential to make production of much higher space-time resolution long-term datasets computationally feasible**
- Could implicitly minimize many physics-based model biases since trained on analysis/reanalysis or (maybe in the future) pure observational datasets



Already in experimental operational forecast production at some forecast centers (e.g. ECMWF)

Some Examples of Not-so-obvious Dataset Issues

- ERA5 used as an example since it is widely used and regarded as one of the best datasets
- But all datasets have issues related to how they are constructed
- Some comparisons of ERA5 to HRRR

ELSEVIER

Renewable Energy

Volume 126, October 2018, Pages 322-331

ERA5: The new champion of wind power modelling?

Jon Olauson [a b]

First impression of strengths and weaknesses of the ERA5 dataset

Strengths

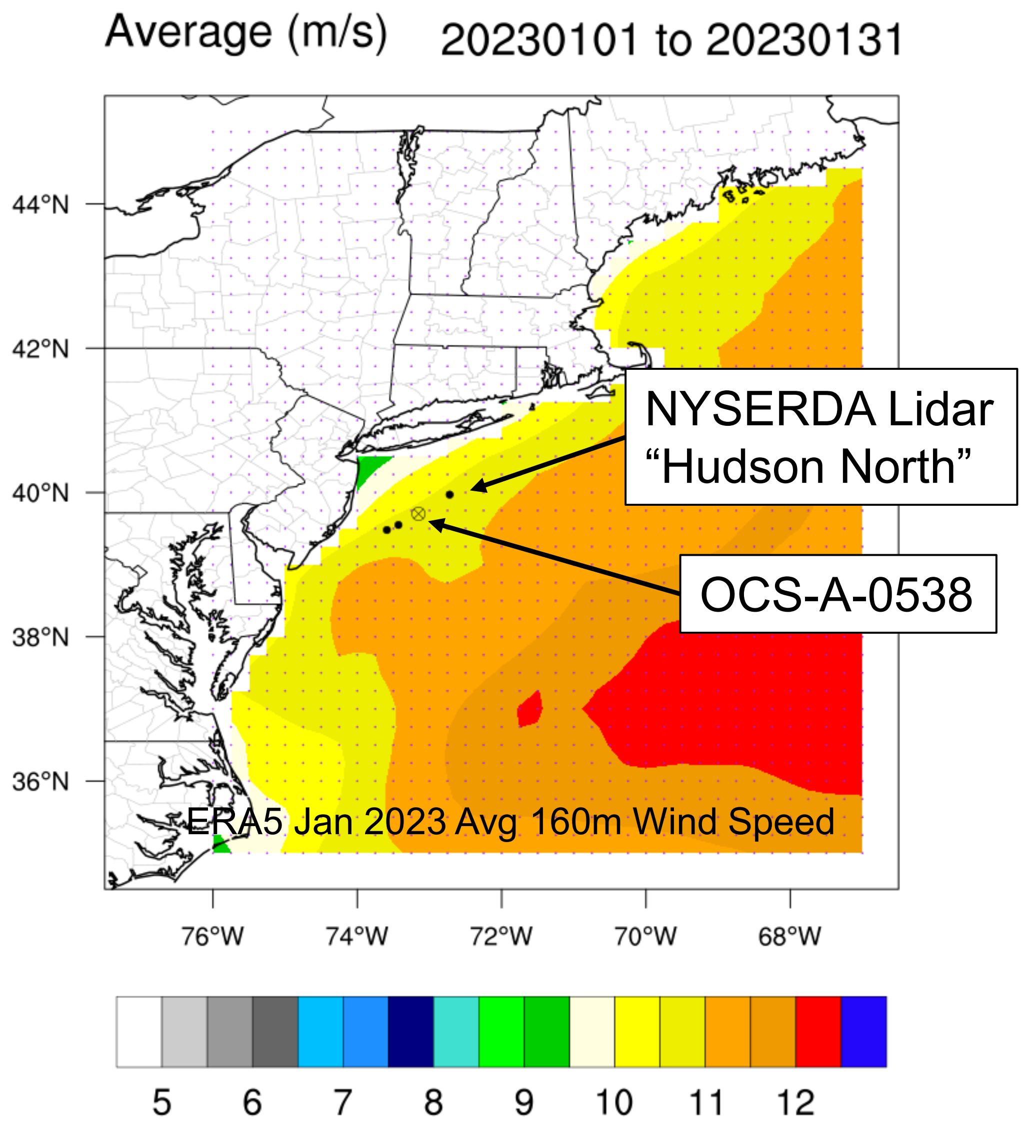
- Based on a well-known operational data-assimilation and forecast system (ECMWF) with demonstrated very high-quality (best in the world?) forecast performance
- High vertical resolution: 137 levels for sfc to 80 km; (20m to 40m vertical resolution below 300 m)
- Long period of record and routinely extended: In its 85th year – 1940 to present
- Assimilates large archive of historical atmospheric sensor data

Weaknesses

- Relatively spatial course horizontal resolution (~ 0.28 degree lat/lon or ~31 km)
- 1-hr data intervals

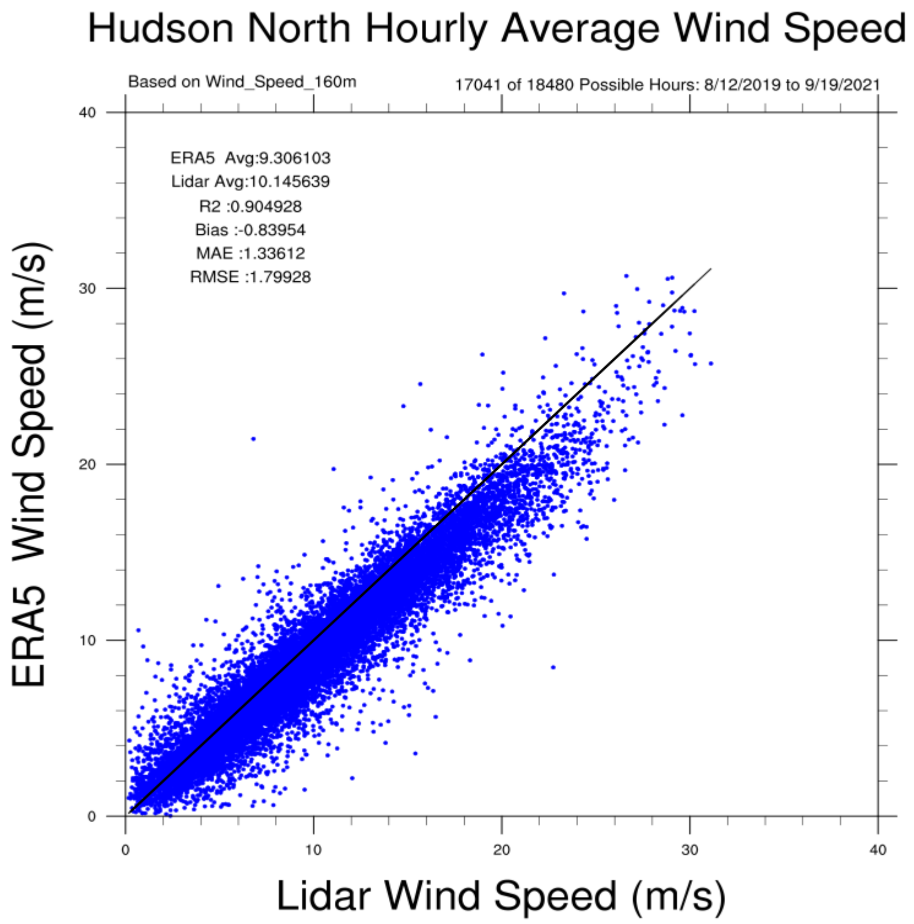
The Example Venue: Offshore Mid-Atlantic

- ❑ Example is focused on a US DOE offshore development area (OCS-A-0538) off the coast of New Jersey
- ❑ A State of NY agency (NYSERDA) operated 3 lidar sites near this location over parts of several years (2019-2023)
- ❑ Off-shore area …so complex terrain and other land surface attributes not expected to be an issue



Typical dataset evaluation…

- ❑ Typical analysis looks at standard metrics such as Bias, MAE, RMSE, and correlation between measured and simulated data
- ❑ ERA5 160 m wind speed data evaluated with hourly average (+/- 30 mins) "Hudson North" Lidar measurements over a ~ 2-yr period
- ❑ Analysis indicates fairly good performance
  - ○ R^2 of about 0.90
  - ○ Bias (ERA5 too low): -0.83 m/s
  - ○ MAE: 1.34 m/s
  - ○ Similar performance results at other nearby measurement sites

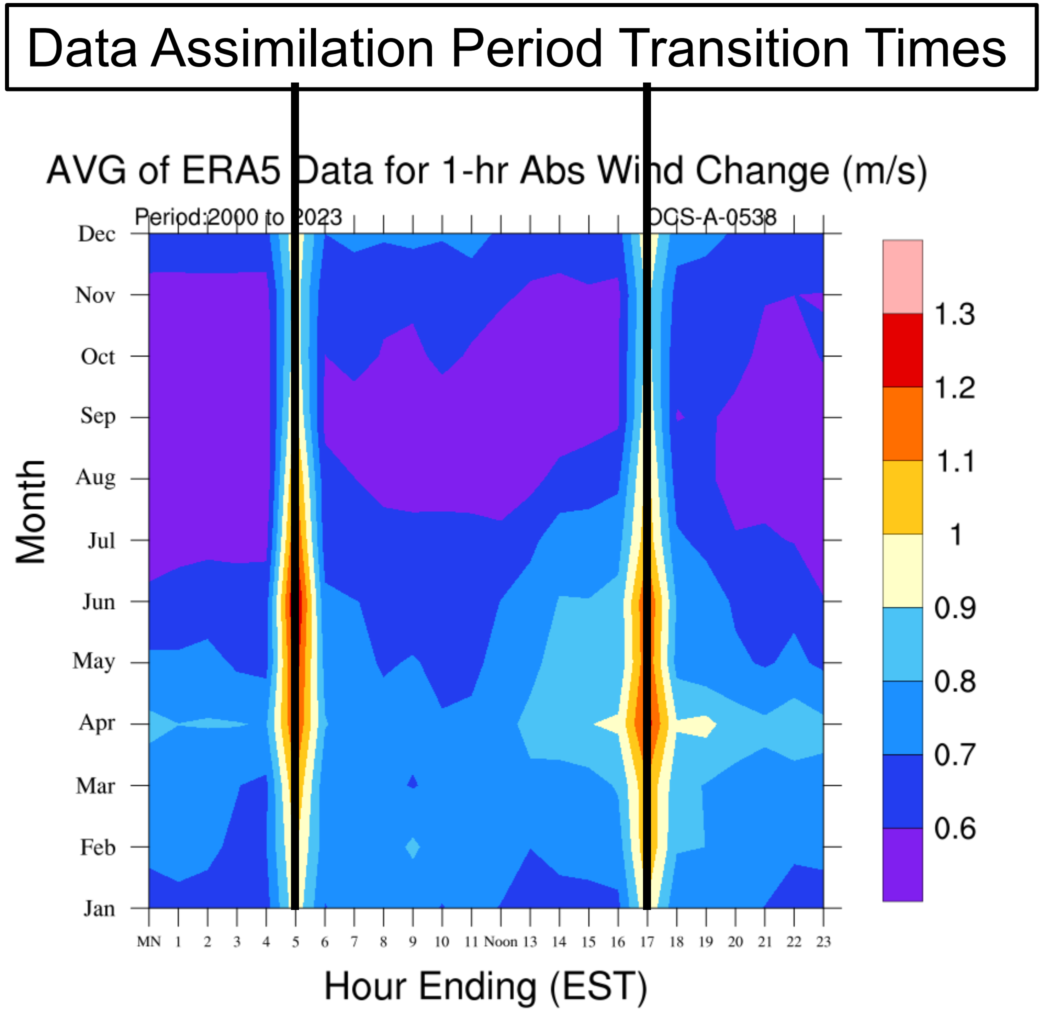


But among the list of known problems listed on the ERA5 web page….

8. ERA5 diurnal cycle for near surface winds: the hourly data reveals a mismatch in the analysed near surface wind speed between the end of one assimilation cycle and the beginning of the next (which occurs at 9:00 - 10:00 and 21:00 - 22:00 UTC). This problem mostly occurs in low latitude oceanic regions, though it can also be seen over Europe and the USA. We cannot rectify this problem in the analyses. The forecast near surface winds show much better agreement between the assimilation cycles, at

Example Issue: Impact of data assimilation

- The ERA5 data was created with a 4-D-Var DA scheme using two 12-hr data assimilation cycles per day
- To see impact examine the average absolute value of the 1-hr wind speed change by month and time of day
- Larger average changes occur at the transition time between data assimilation periods (0500 EST and 1700 EST)
- Impact varies substantially by time of year
- Therefore, ramp event analysis with the raw ERA5 data is suspect (at least in some locations at some times of the year)



24-year (2000-2023) ERA5 Average 1-h Absolute Wind Speed Change by Month and Hour of the Day

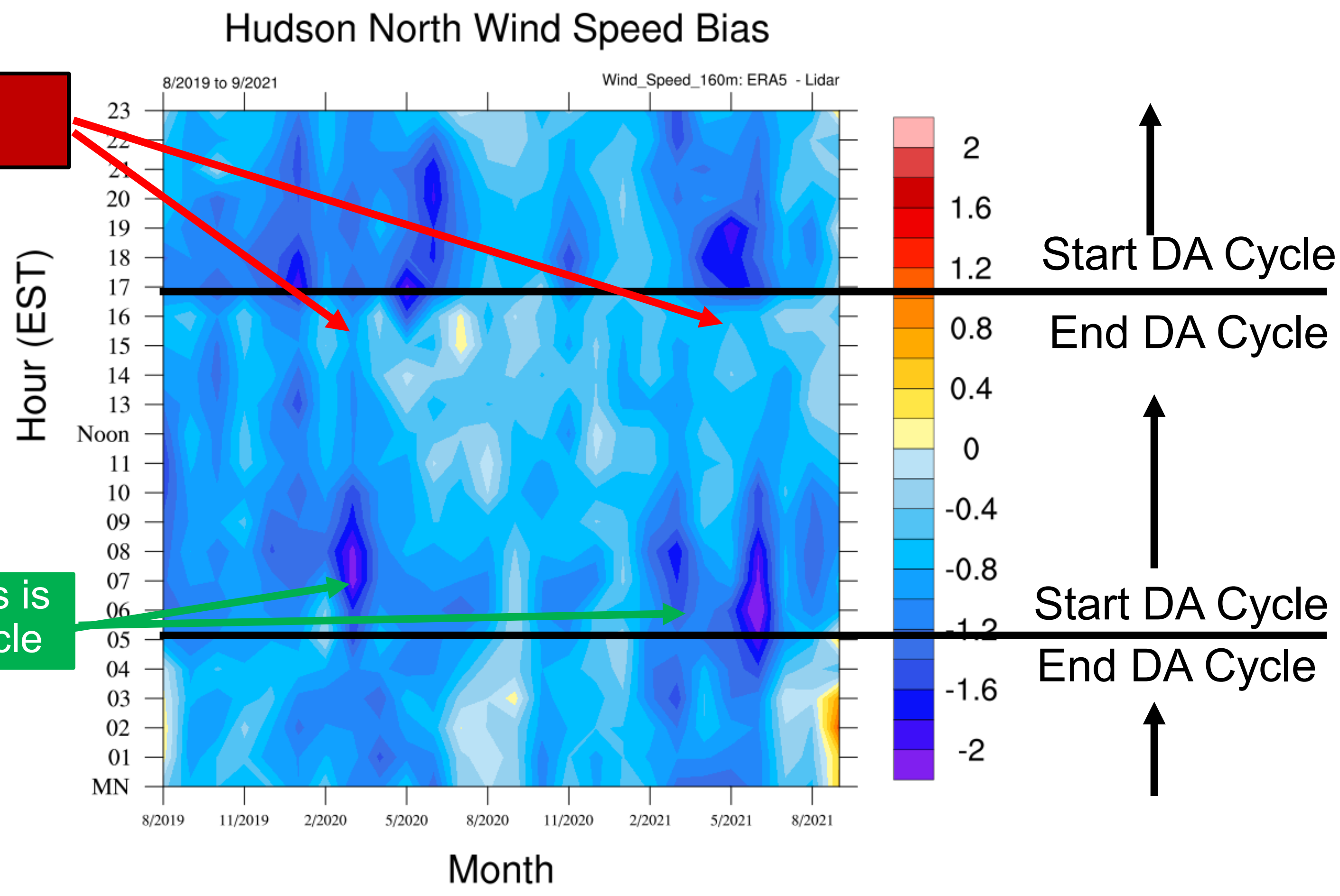
A Closer Look at the ERA5 Data Assimilation (DA) Issues

- 160m ERA5 Wind Speed Bias (m/s) for period of Hudson North Lidar data (8/12/19 - 9/19/21)

- Data Assimilation reduces bias by end of each cycle

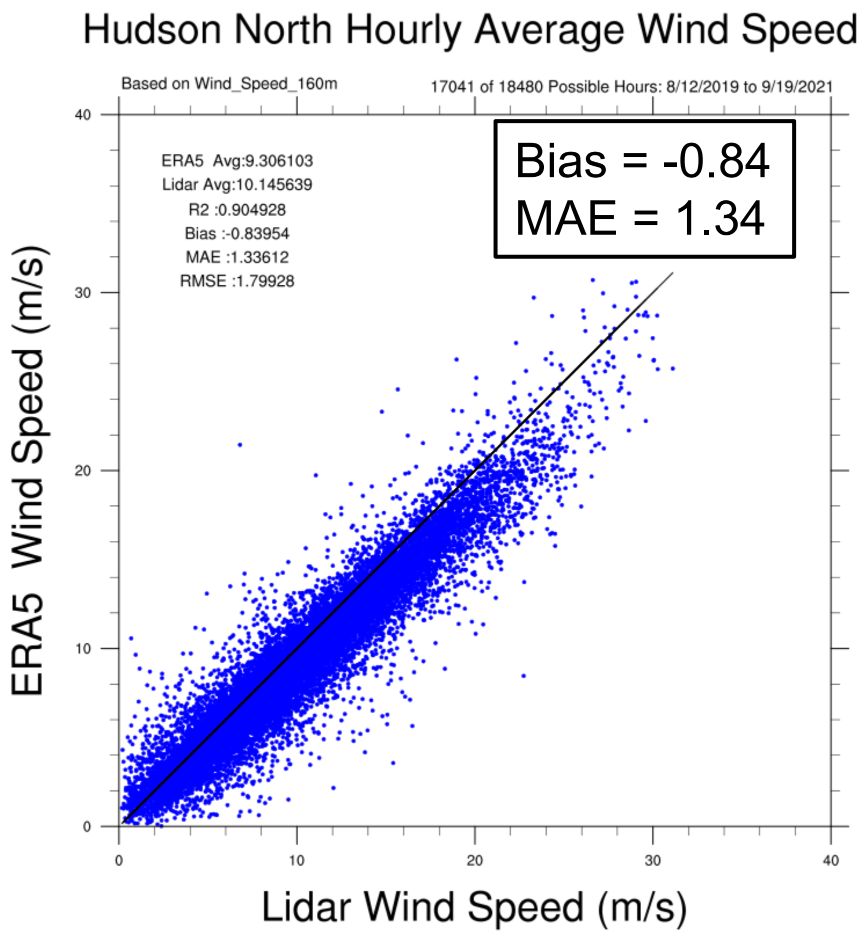
Overall period bias = -0.83 m/s

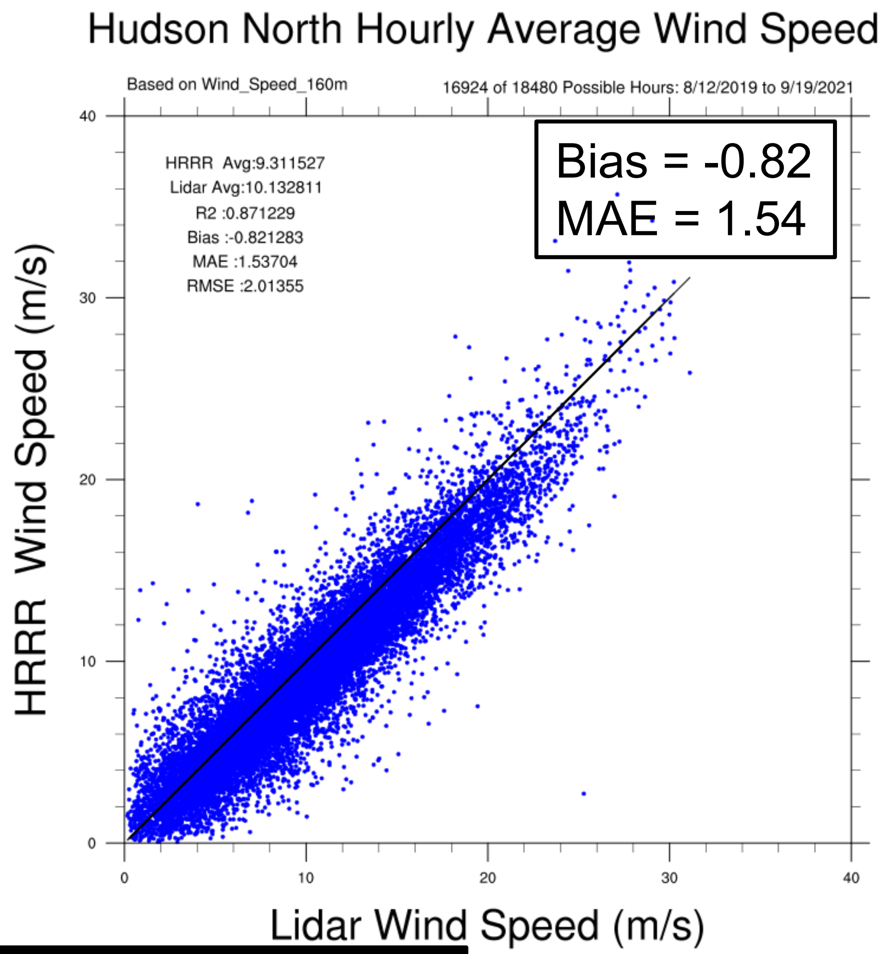
- Physics-based (NWP)-model bias is most evident at the start of the cycle



ERA5 Reanalysis vs HRRR Analysis

Standard Metrics for 160 m @ Hudson North 8/12/19 – 9/19/21

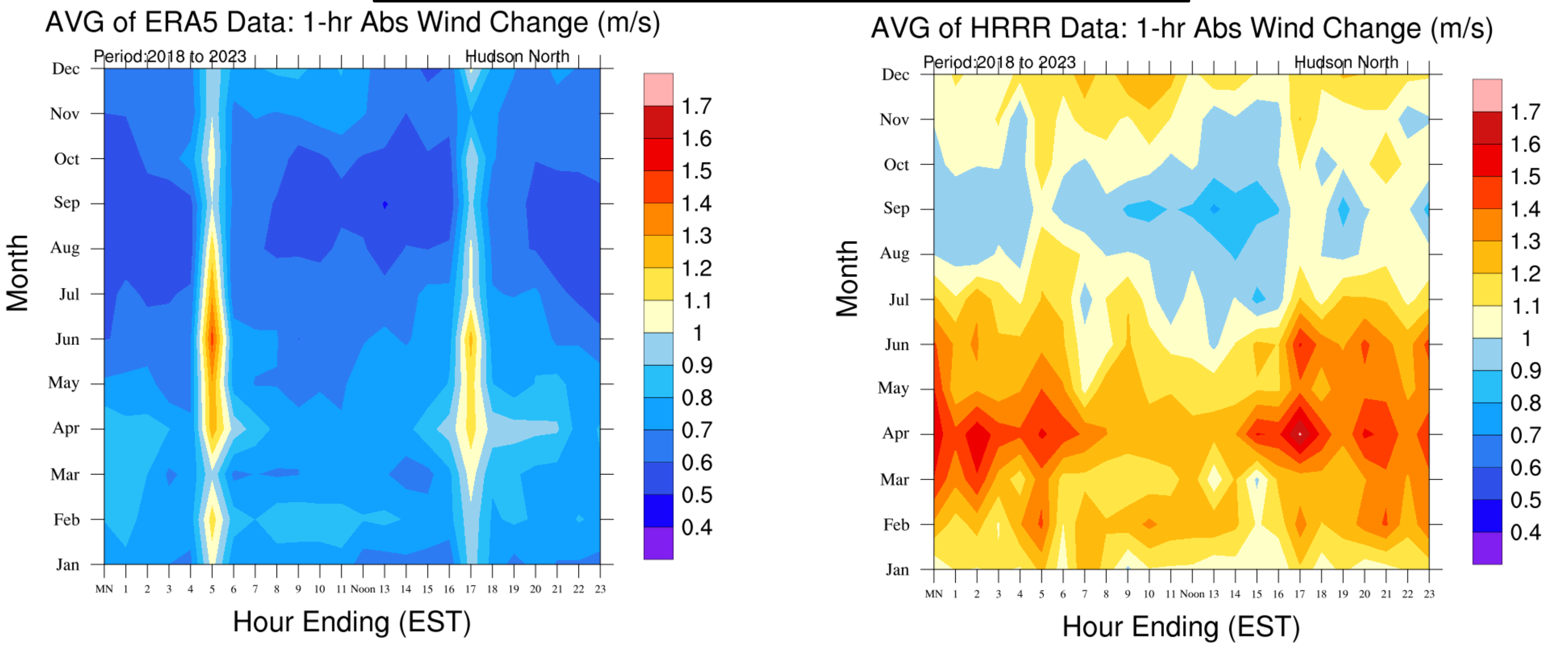




Fairly similar… maybe ERA5 appears to be slightly better

1-hr 160 m Wind Speed Variability: ERA5 vs HRRR: 2018 – 2023 (6 years)

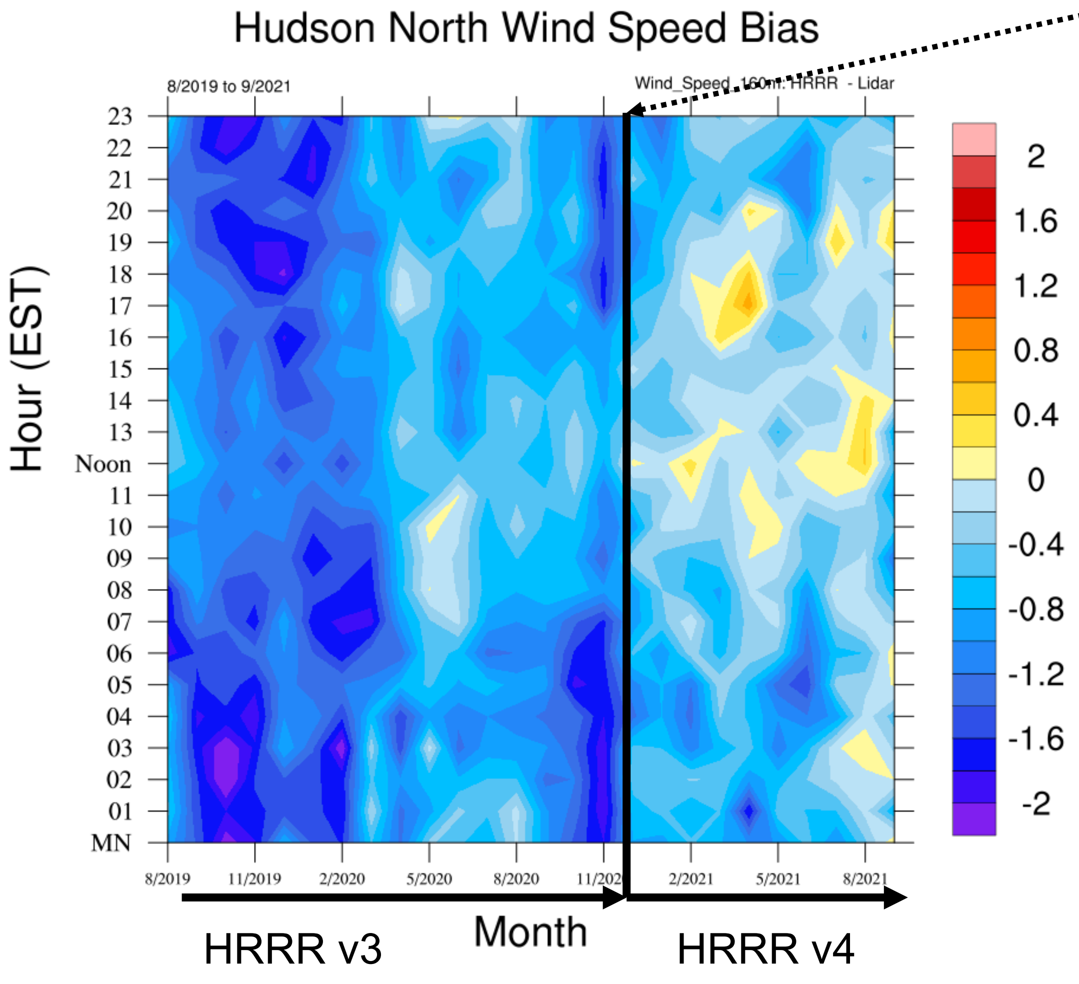
Overall 1-hr scale wind variability is higher in HRRR dataset (~ 3 km grid vs ~ 31 km grid)

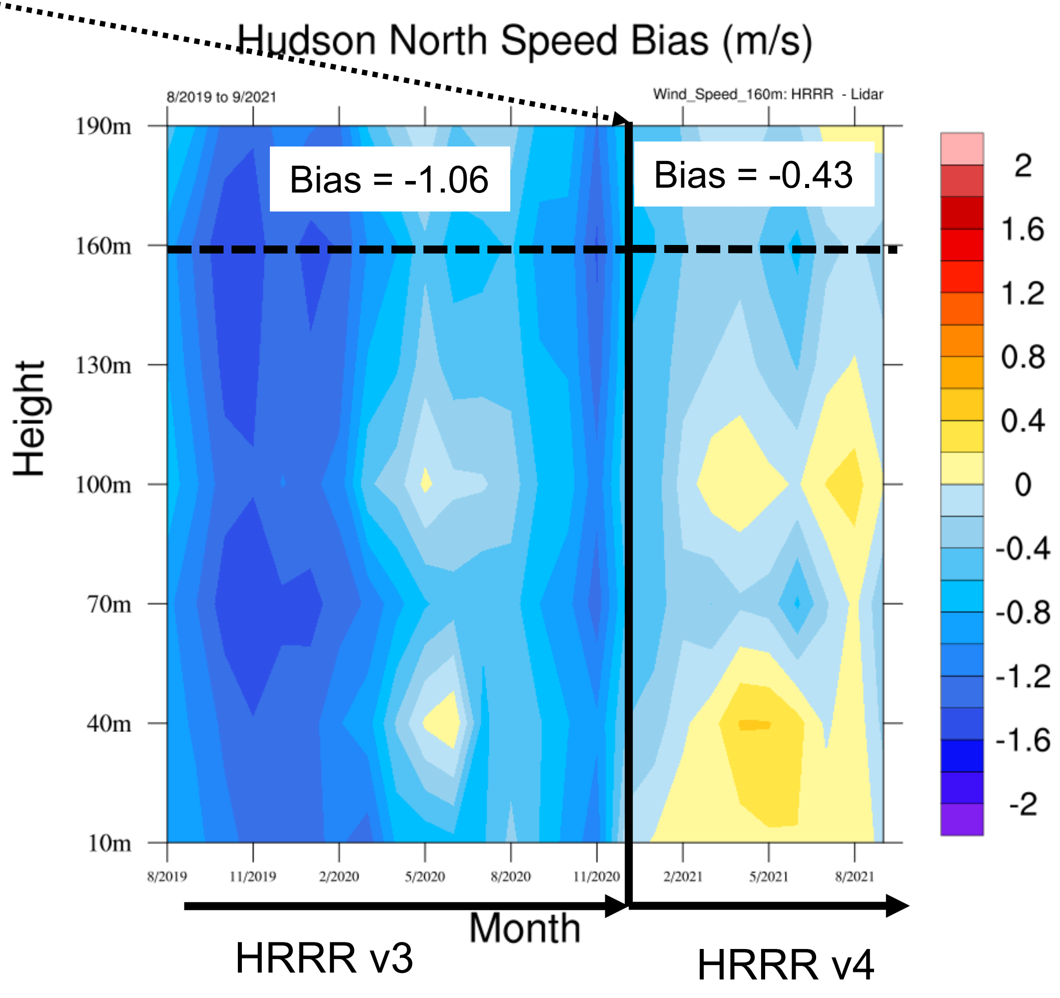


Large DA-driven discontinuity in 1-hr wind speed changes not evident in HRRR dataset

But the HRRR Analysis has Other Issues

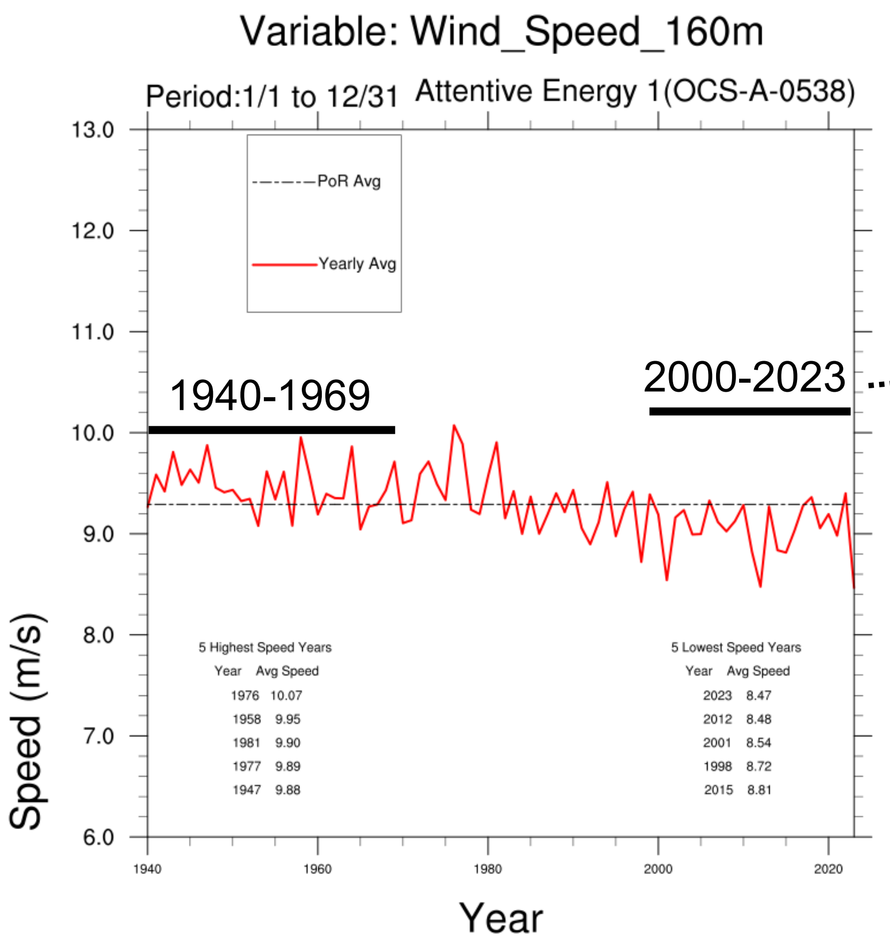
Upgrade from HRRR v3 to HRRR v4 occurred on 12/2/2020



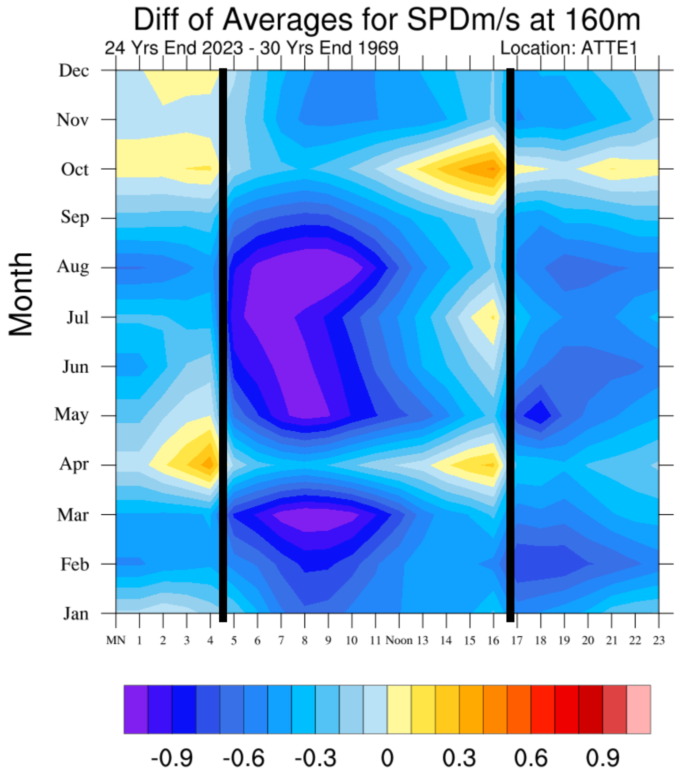


But ERA5 DA issues go beyond the ramp rates….

- An 84-year time series suggests a decrease in wind speed in recent years…



- Looking at **(2000-2023) – (1940-1969) average difference by month and hour of the day suggests** this trend is likely related to DA effects



- Data assimilation impact is stronger after 1980 … much more data to assimilate (satellite, aircraft etc.) .. so an apparent trend appears

- **Take-away**: **Deep dataset evaluation is critical to understanding what issues are (sometimes obscurely) embedded in the dataset one is using**

State-of-the-Art in Dataset Evaluation

Some Points on the Current Status of Dataset Evaluation

- **Users always say they want more accurate data**
  - But what does that mean?
  - More accurate representation of dataset attributes that impact their applications/decisions?
  - Or lower bias/MAE/RMSE? Other?
- Evaluations typically done with standard generic metrics at the scale of whatever measurement ("actuals") data is available
- **Importance of different dataset attributes is use-case dependent**
- No standard (protocol, metrics etc.) for intercomparison of datasets exists
- Important current needs
  - define what "users" mean by "more accurate" data
  - a standard reference metric set based on a range of typical use cases
  - obtain use of a larger volume of power system-relevant meteorology-related data

a lot of data is not available to the dataset evaluation process now because of proprietary restrictions

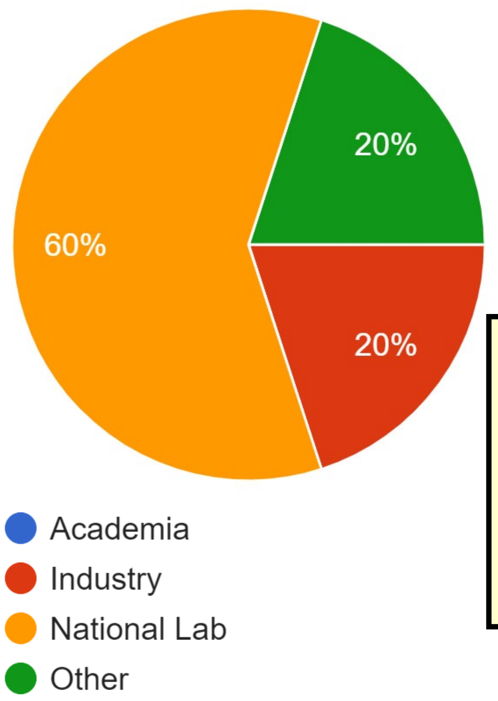
State-of-the-Art in Dataset Use

Status of Dataset Use

- ❑ Knowledge of what the energy system community is using and what they are doing with them is very limited
- ❑ NREL recently conducted a survey of users
  - Results courtesy of Caroline Draxl and Luke Lavin at NREL
  - Heavily weighted to National Lab users
- ❑ Very few (if any) other attempts to gather this type of information have occurred

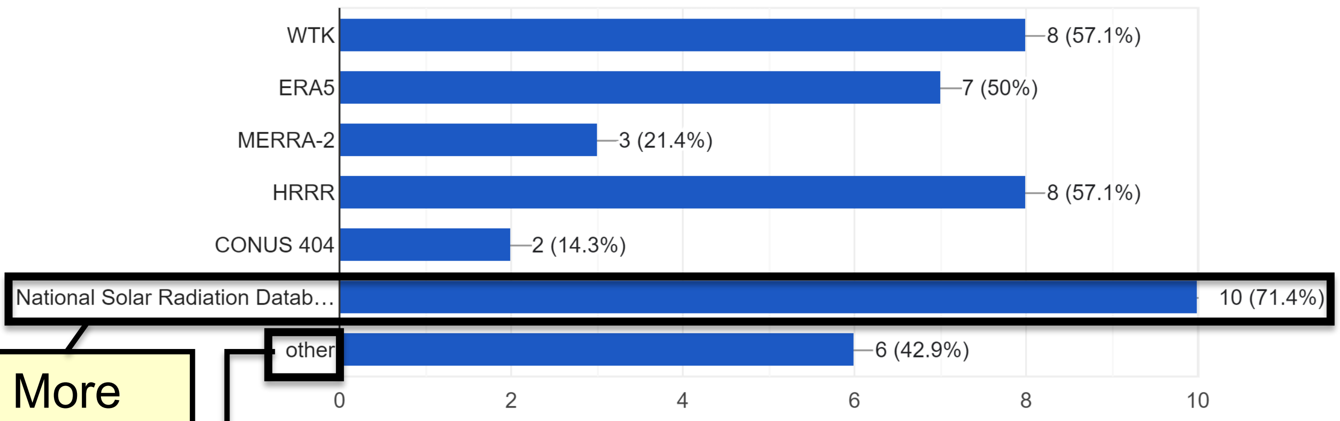
Which sector are you in?

15 responses



What atmospheric data set are you using for your grid integration studies?

14 responses



More common standard for solar than wind

CMIP6 data, Multi-sensor precip data, SPC storm events database, etc.

Daymet, Sup3rCC, various GCM datasets

E3SM

E3SM

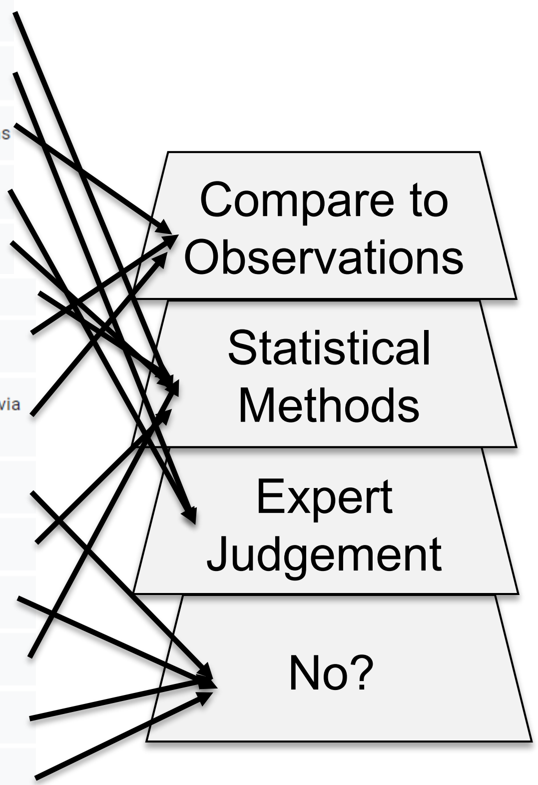
IM3 Thermodynamic Global Warming dataset (dynamically downscaled ERA5 12km)

Re-Explorer

User Validation and Quality Control Approaches

User Responses to NREL Survey

- We use a large ensemble. Usually a bigger ensemble for variables with more uncertainties.
- Scaling the 8760 up/down by a predetermined amount.
- Regular evaluation of model errors with observations, and consistency of time-lagged predictions
- using a spread of different representative days
- Deep uncertainty with climate ensembles
- Using multi-year averages, Calculating seasonal statistics and variability
- Mainly through comparison to observations
- Poorly. But we also try to include historical actual operating data where available and show results via modeled and actual weather data.
- Usually it's not taken into account
- Estimating errors by comparison with observed wind/irradiance, sensitivity tests.
- Not currently modeling
- Monte Carlo approach
- Not accounting for uncertainty
- not directly quantifying this



Implied State of the Art: No explicit or de facto/implicit validation or data use standards exist. User validation for input data for their applications is often minimal, subjective or non-existent

Thank you for your attention

Questions … ?

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