



CAMUS
Zero Carbon Grid Orchestration

How NODD Weather Forecasts Are Boosting Grid Operations

David Stuebe, Camus Forecast Team Lead | June 24, 2024

ABOUT CAMUS ENERGY

Grid Orchestration for a 100% Electrified Future

OUR PERSPECTIVE

We leverage deep experience designing & operating **hyperscale, high-reliability software systems** to help utilities build and operate the two-way grid.

Google NREL Uber enel x GE SanDiego National Laboratories amazon WAYMO

Today's speaker

David Stuebe

Forecasting Team Lead



WHAT IS GRID ORCHESTRATION?

Visibility and control for a new era of grid management

CAMUS PLATFORM CAPABILITIES



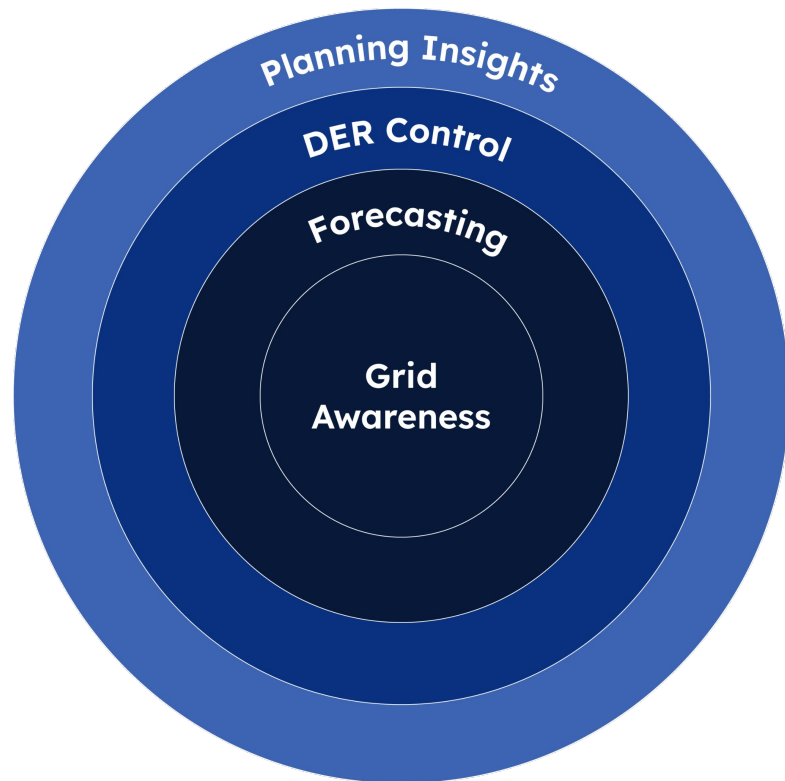
See real-time and forecasted grid conditions using data from AMI, GIS, SCADA, and DERMS



Dispatch DERs with respect for grid constraints, via an ecosystem of DERMS & aggregator partners



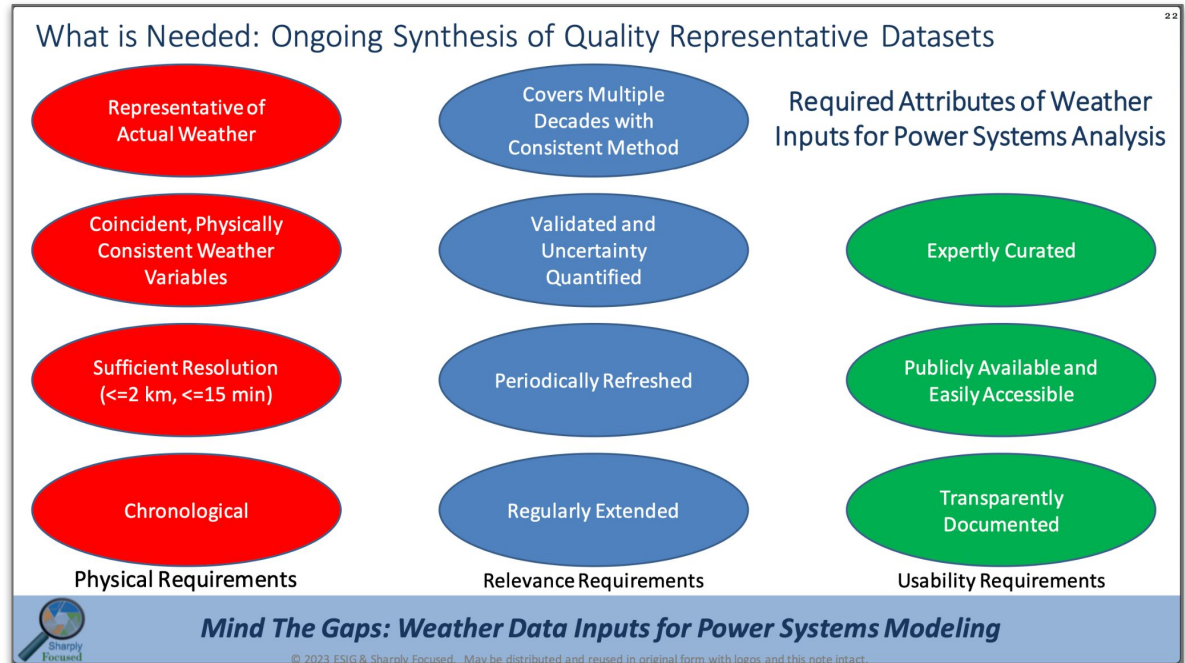
Incorporate DER flexibility into system planning, reducing capital investments and lowering rates



Why is working with weather forecast data difficult?

Three challenge areas:

1. **Physical** – do we have the right inputs?
2. **Relevance** – do the time scales match what we need?
3. **Usability** – can we, find, access, and use the data?



Source: [Weather Data Inputs for Power System Modeling: Mind the Gaps](#)
December 5, 2023 ESIG Webinar by Justin Sharp

Discretized model of the atmosphere run on a Supercomputer

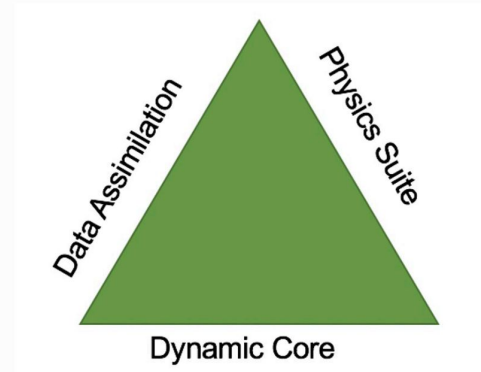
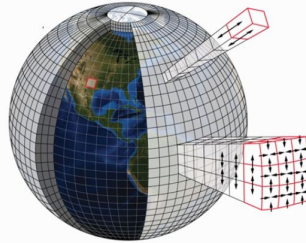
Three components:

- 1. Data assimilation** - initializes model based on current observations
- 2. Dynamic core** - motion & interaction of cell properties, water, heat, etc.)
- 3. Physics suite** - approximates smaller factors (e.g. how raindrops form)

Components of a NWP system



- Dynamic core (to move the air around)
- Data assimilation system (to initialize the model with the current weather conditions)
- Physics package (to represent clouds, precipitation, radiation, turbulence, interactions with the land and ocean, and more)



Observations (of as many variables as possible) are essential for both evaluating (improving) NWP models and initializing them

Source: [NOAA's 3km Rapid Refresh Weather Forecasting Models and Renewable Energy Forecasts](#) January 25, 2024 ESIG Webinar by Dave Turner

What are we (Camus) trying to accomplish with weather forecasts?

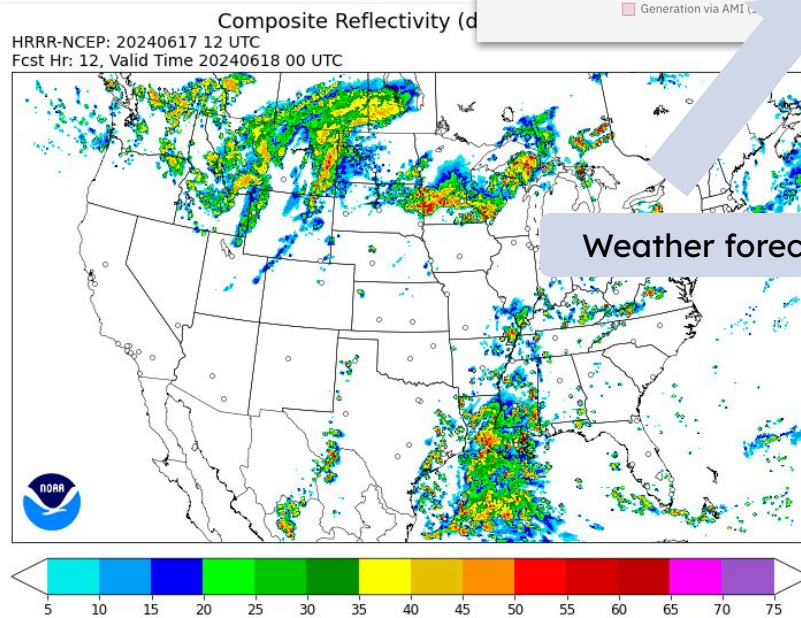
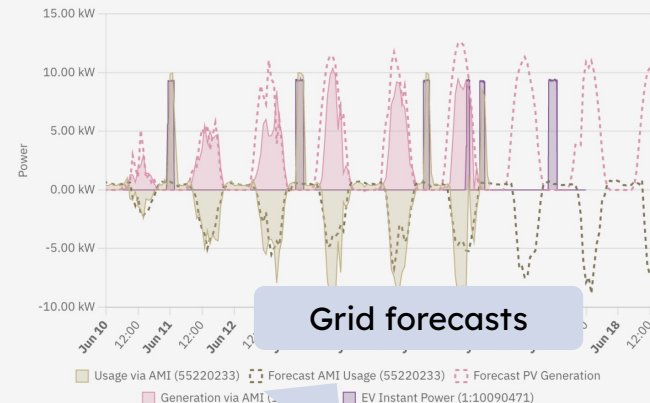
We're using weather data to create operational forecasts for electric utilities.

Challenges to overcome:

- Weather forecast data is big and complex
 - Terabytes of data per forecast year
 - Grib2 binary data
- Integrating weather data into machine learning models is complex
 - 100's of meteorological variables
 - Geospatial gridded data

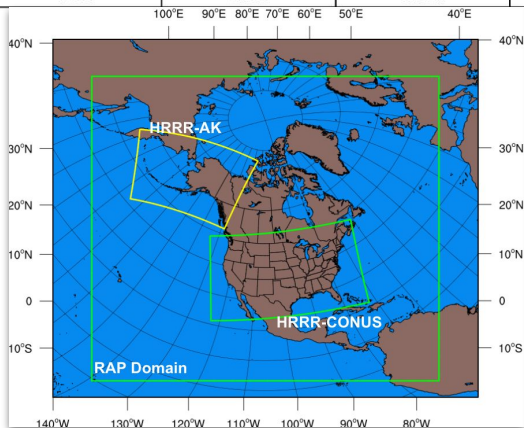
Fortunately, there are many public and private orgs collaborating to help!

Production & Consumption

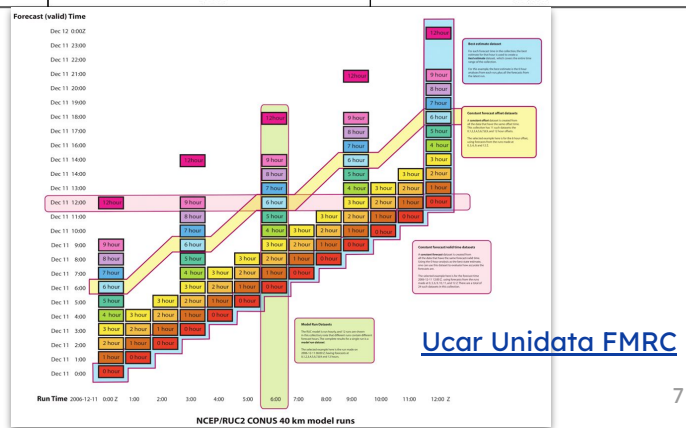


How do we identify the right weather forecast?

Model	HRRR V4 (description)			GEFS (description)			GFS (description)	
Product	surface (sfc)		Subhourly (subh)	pgrb2sp25	pgrb2bp5	pgrb2ap5	pgrb2	
Run Schedule	00, 06, 12, 18 (z)	hourly	hourly	00, 06, 12, 18 (z)	00 (z)	00, 06, 12, 18 (z)	00, 06, 12, 18 (z)	00, 06, 12, 18 (z)
Forecast Horizon	0-48 hours*	0-18 hours	0-18 hours	0 - 240 hours	0 - 840 hours	0 - 384 hours	0-120	120-384
Spatial coverage	3km			0.25°	0.5°	0.5°	0.25°	0.25°
Temporal Resolution	1 hour	1 hour	15 min	3 hour	3 hour	3 hour	1 hour	3 hour
Archive start date	2020-12-03 (v4) 2018-07-03 (V3)			2020-09-25 **			2021-03-22 ***	
Ensemble				Mean, Control, 30 Perterbation Members, Spread				
Status	Till RRFS is operational			Operational			Operational	
GCP Bucket	high-resolution-rapid-refresh			gfs-ensemble-forecast-system			global-forecast-system	
Terabytes/Year	10.0	23.3	29.1	67.3	320.5	77.7	92.2	67.1
Files/Year	70k	157k	157k	3,737k	3,270k	5,980k	42k	93k



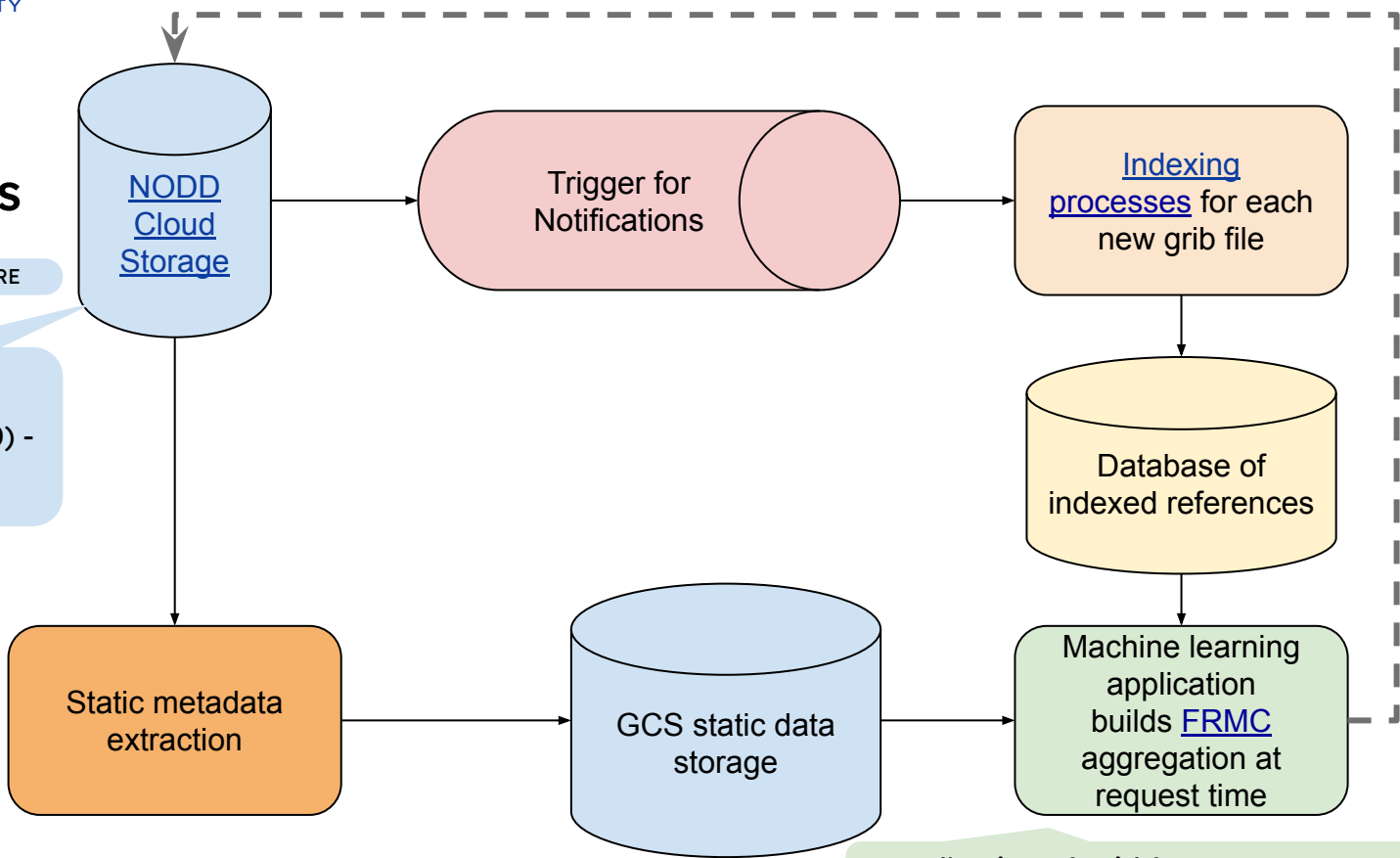
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Translating weather to grid forecasts

WE START HERE

Weather forecast archives (since 2020) - zero cost to read!



Specific improvements for accessibility

Big picture: Grid forecasting is now fast and efficient (\$0.02 per meter per year)

100X (!) performance improvement on index ingestion and ML operation!

- We use Xarray DataTree to express grib2 “group” data model for all layers
- Fast & efficient indexing of NODD grib archives using “idx” metadata
- Operational NODD archive index data is stored in a database
- Xarray dataset “kerchunks” are created from index queries for variables and time ranges
- Zarr patch allows fault tolerant & parallel reads for fast & efficient IO

To forecast each individual electric meter for a large investor-owned utility (>1 million meters), it costs \$0.02 per meter-year forecast.

Why is it so economical? There is a lot we have done in our machine learning too, but an important one = we don’t pay for storing or serving weather data. NODD’s partnership with the cloud providers does this for us.

Technical details and source code: [Optimizations for Kerchunk aggregation and Zarr I/O at scale for Machine Learning](#)

INCREASING ACCESSIBILITY

Super fast!

Sustained read rates of 1 to 2 Gb/second while training over multiple years.

The parallel processing overhead is much higher for the short prediction tasks. Observed read rates are typically 50-100 Mb/second.



View data using off the shelf community tools

XPublish is a web services layer for the PyData ecosystem.

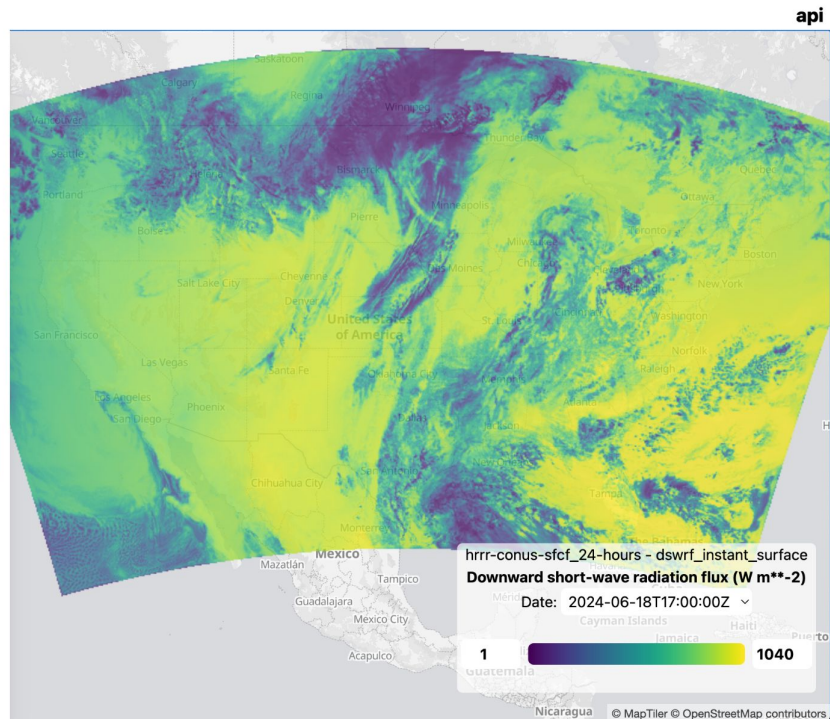
XReds is a configuration based webmap service gui frontend.

Accessibility beyond the ML models - visual exploration using standard webmap services.

× xreds viewer

Datasets Layer Tiling

- ⊕ hrrr-conus-sfcf_6-hours
- ⊖ hrrr-conus-sfcf_24-hours
- t2m_instant_heightAboveGround (2 metre temperature)
- d2m_instant_heightAboveGround (2 metre dewpoint temperature)
- r2_instant_heightAboveGround (2 metre relative humidity)
- u10_instant_heightAboveGround (10 metre U wind component)
- v10_instant_heightAboveGround (10 metre V wind component)
- si10_max_heightAboveGround (10 metre wind speed)
- dswrf_instant_surface (Downward short-wave radiation flux)**
- vdsf_instant_surface (Visible Diffuse Downward Solar Flux)
- vbdsf_instant_surface (Visible Beam Downward Solar Flux)
- prate_instant_surface (Precipitation rate)
- ⊕ hrrr-conus-sfcf_48-hours
- ⊕ hrrr-conus-subhf_6-hours
- ⊕ hrrr-conus-subhf_12-hours
- ⊕ hrrr-conus-subhf_18-hours



INCREASING TRANSPARENCY & ACCESSIBILITY

An open-source stack for weather data



Machine Learning Forecasts for Grid Operators

Fsspec & Kerchunk



Open Source Python Data Science Tools



CFGrib



Zarr

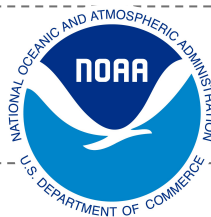
XPublish



xarray



NumPy



NOAA Open Data Dissemination



Microsoft Azure



Google Cloud



Cloud Services

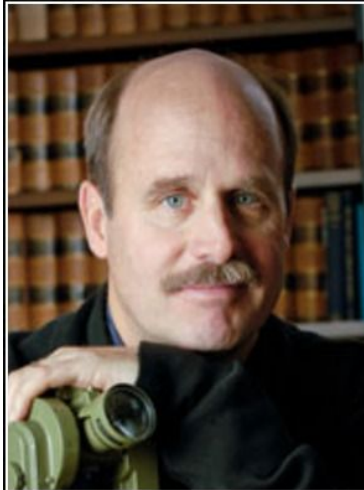
Who helps us make the available data operational for utilities?



SO WHAT?

How utilities use forecasts

Distribution system operators need foresight to operate their grid - the urgency only increases with more DERs making prediction more complex.



The goal of forecasting is not to predict the future but to tell you what you need to know to take meaningful action in the present

— Paul Saffo —

AZ QUOTES

Let's briefly highlight **two utility use cases** for operational weather forecasts:

1. **Peak demand reduction** (e.g. demand response)
2. **Flexible interconnection** (generation) / **flexible service connection** (loads)

Managing peaks can save millions of \$

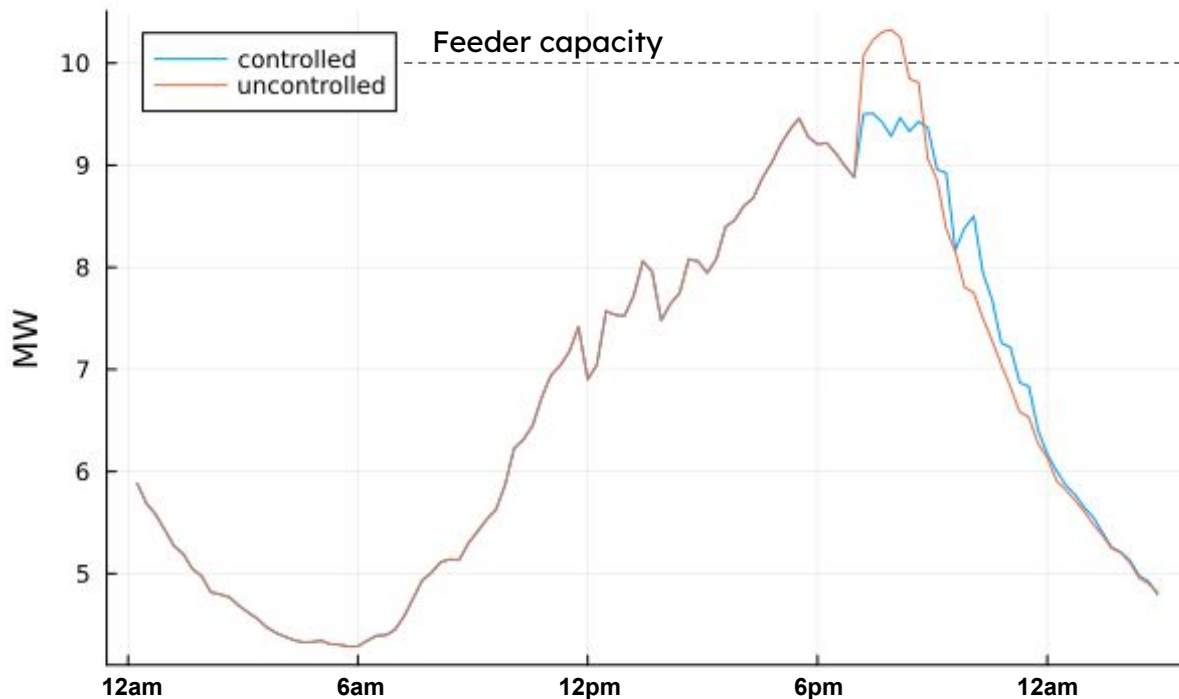
The grid **must be ready** to serve maximum demand at any time.

By reducing peak demand, costs are lowered via:

- Less peak-cost generation purchased
- Avoided transmission and distribution upgrades

Accurate forecasting is required to reduce peaks.

Example of Peak Reduction via DER Control

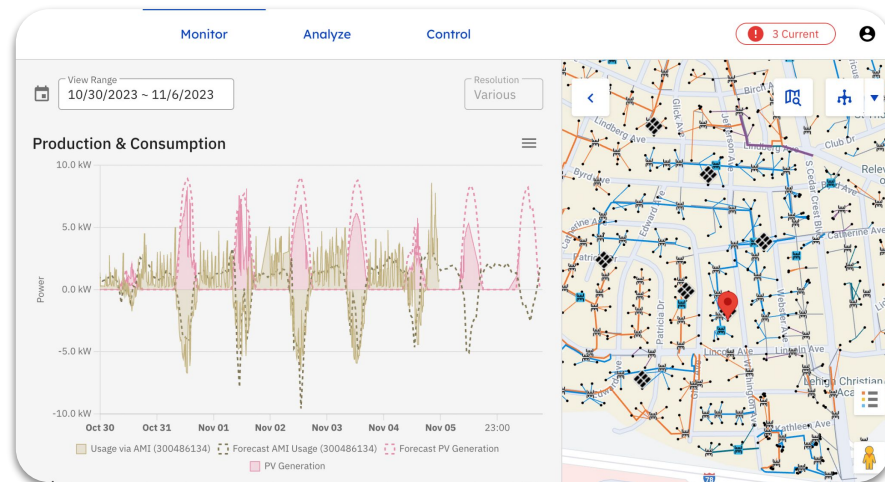
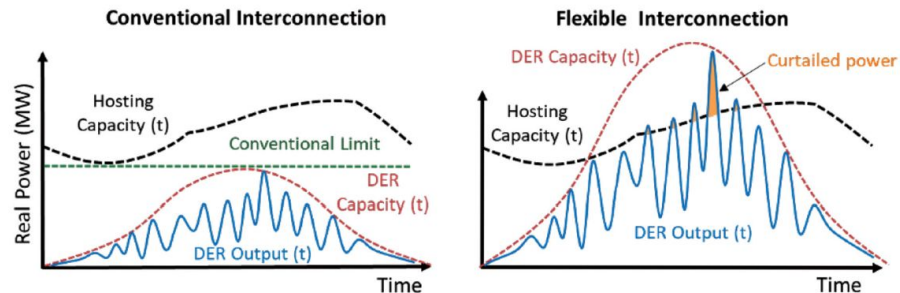


Customers and regulators want faster interconnections

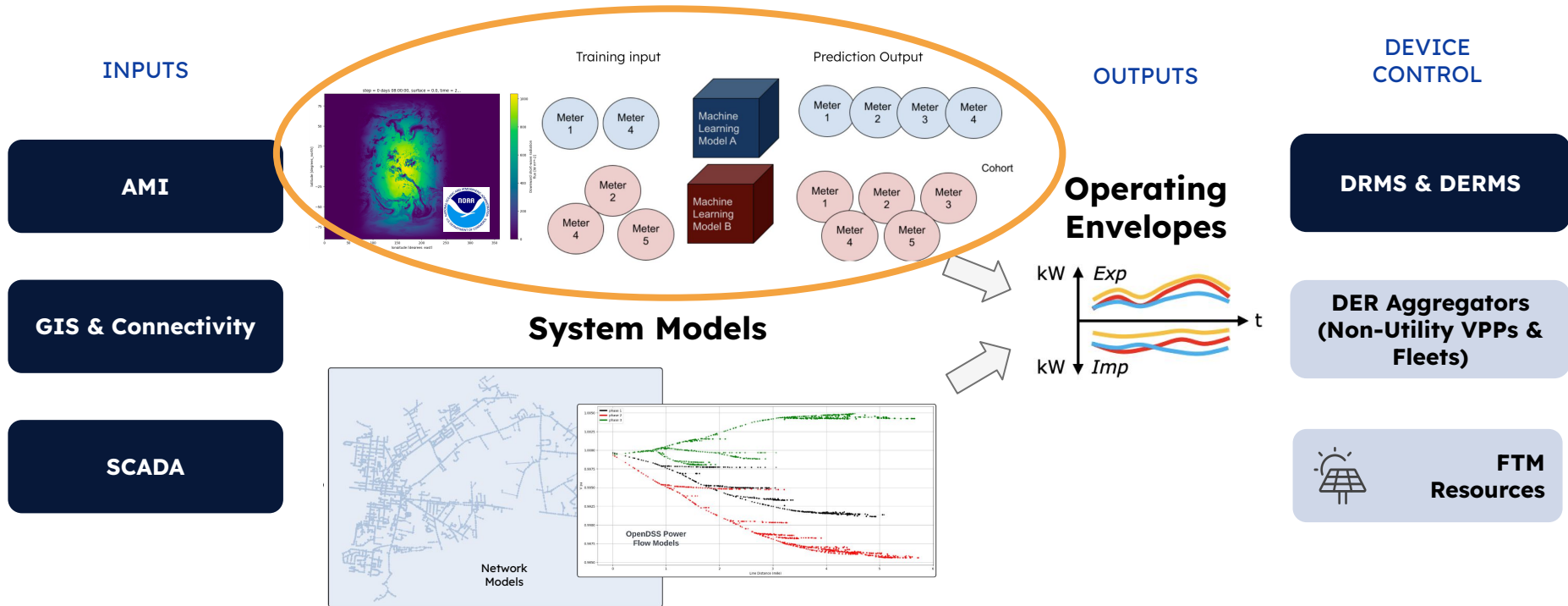
Goal: Enable increased utilization of existing infrastructure and **accelerate interconnection** of more DERs

How it works:

1. Use GIS/connectivity, conductor attributes, & asset ratings to establish system models
2. Train machine learning models to **predict outputs at the meter-level**, then aggregate
3. Evaluate network at min/max DER dispatch
4. Generate “operating envelopes” and manage devices to avoid voltage/loading violations



Forecasting is an essential enabler for flexible interconnections



There's much more to do; here are ideas for how to get involved!

- 1** Support NOAA to improve data and data accessibility
 - [NOAA Open Data Dissemination](#)
 - [NOAA Center for Environmental Prediction](#)
 - [US Integrated Ocean Observing System](#)
- 2** Engage with existing solution providers for off the shelf solutions
 - [Camus Energy](#)
 - [RPS](#)
 - [EarthMover](#)
 - [OpenMeteo](#)
 - [Anaconda](#)
- 3** Engage with organizations to support further development of these tools
 - [Energy Systems Integration Group](#)
 - [Pangeo Discourse](#)
 - [Earth Science Information Partners](#)
 - [OpenClimateFix](#)
 - [Numfocus](#)
- 4** Get your hands dirty by developing new features to advance the capabilities
 - [zarr-python](#)
 - [light-speed-io](#)
 - [Kerchunk](#)
 - [VirtualiZarr](#)
 - [Xpublish](#)
 - [Xreds](#)

Camus source code is available in the RPS/IOOS Nextgen DMAC [Github](#) repo



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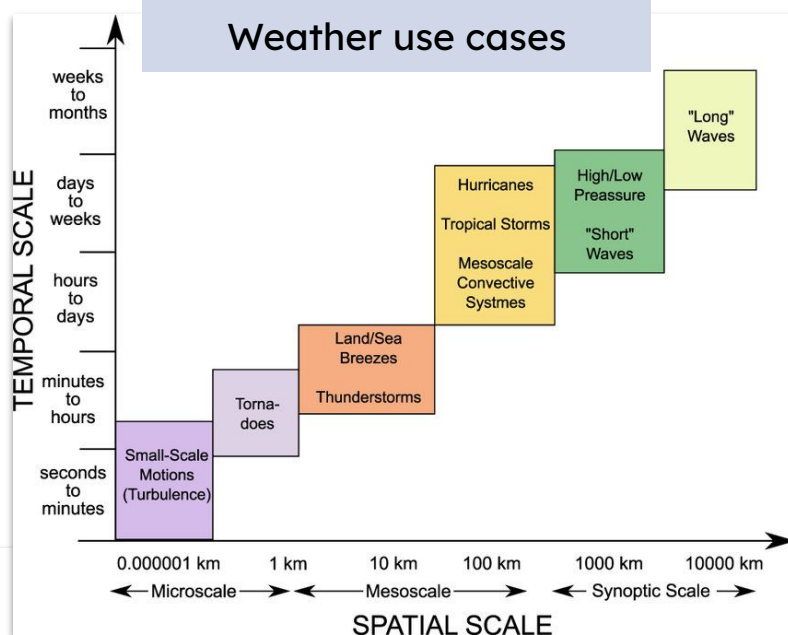
Zero Carbon Grid Orchestration

THANKS!
DAVID@CAMUS.ENERGY

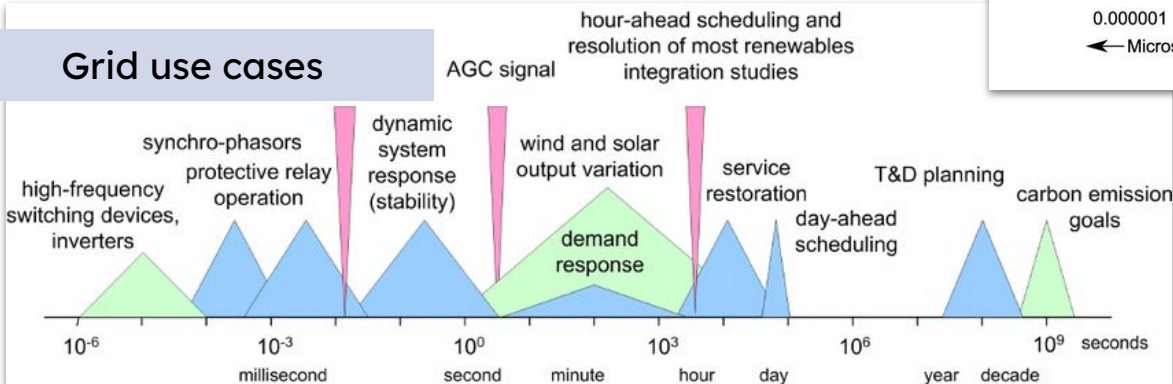
Time scales matter!

Selecting the right data depends on the use case you want to serve. For utility operations, time scales can range from milliseconds to decades across different use cases.

A common tradeoff: **time vs. spatial resolution**



Grid use cases



Meier, Alexandra. (2011). Integration of renewable generation in California: Coordination challenges in time and space. IEEE. 10.1109/EPQU.2011.6128888.

Brisch, Jonathan & Kantz, Holger. (2019). Power law error growth in multi-hierarchical chaotic systems -- a dynamical mechanism for finite prediction horizon. New Journal of Physics. 21. 10.1088/1367-2630/ab3b4c.