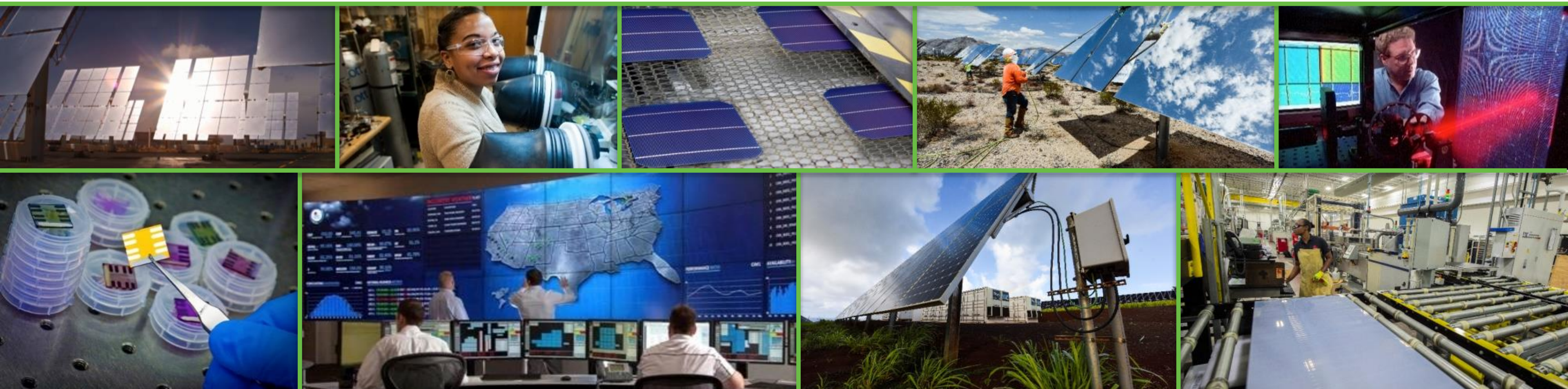
U.S. DEPARTMENT OF ENERGY

Office of ENERGY EFFICIENCY & RENEWABLE ENERGY

Solar Forecasting Workshop

Solar Energy Technologies Office

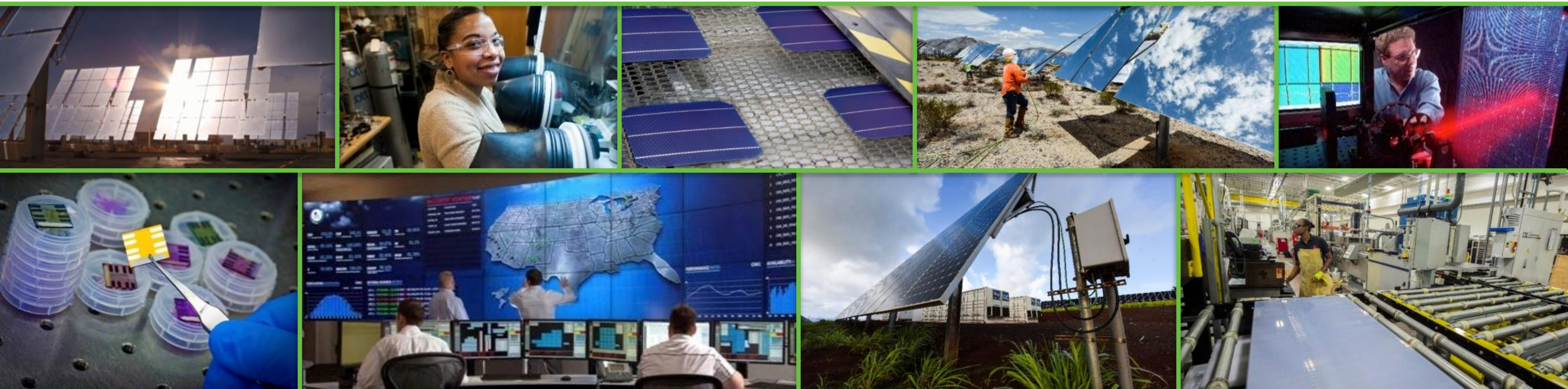


U.S. DEPARTMENT OF ENERGY
Office of ENERGY EFFICIENCY & RENEWABLE ENERGY

SETO Solar Forecasting Workshop

Garrett Nilsen, Deputy Director
Solar Energy Technologies Office, U.S. Department of Energy

July 9, 2024



Solar Energy Technologies Office (SETO) Overview

MISSION

We accelerate the **advancement** and **deployment of solar technology** in support of an **equitable** transition to a **decarbonized economy no later than 2050**, starting with a decarbonized power sector by 2035.

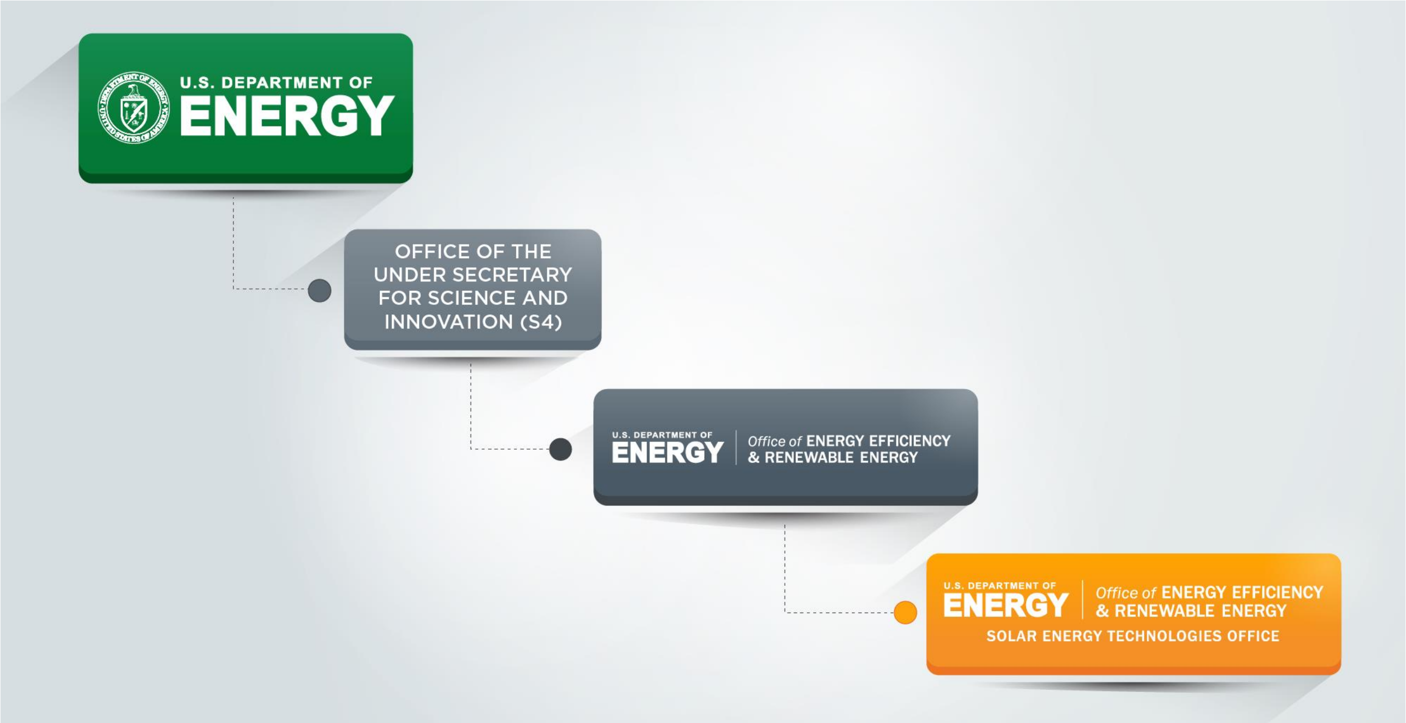
WHAT WE DO

Drive innovation in technology and soft cost reduction to make solar **affordable** and **accessible** for all Americans

Enable solar energy to support the **reliability**, **resilience**, and **security** of the grid

Support **job growth**, **manufacturing**, and the **circular economy** in a wide range of applications

Where Does SETO Fit Within the Energy Department?



Driving Toward Administration Decarbonization Goals

- Reduce hardware and soft costs of solar electricity for all Americans to enable an affordable carbon-free power sector by 2035.
- Enable inverter-based technologies to provide essential grid services and black start capabilities while demonstrating the reliable, resilient and secure operation of a 100% clean energy grid.
- Accelerate solar deployment and associated job growth by opening new markets, reducing regulatory barriers, providing workforce training, and growing U.S. manufacturing.
- Center energy justice by reducing environmental impacts, removing barriers to equitable solar access, and supporting a diverse and inclusive workforce.
- Support a decarbonized industrial sector with advanced concentrating solar-thermal technologies and develop affordable renewable fuels produced by solar energy.

SETO Subprograms

PHOTOVOLTAICS (PV)

CONCENTRATING SOLAR-THERMAL POWER (CSP)

MANUFACTURING AND COMPETITIVENESS

SYSTEMS INTEGRATION

STRATEGIC ANALYSIS AND INSTITUTIONAL SUPPORT *

WORKFORCE AND EQUITABLE ACCESS *

*Funded from the Soft Costs Budget Line

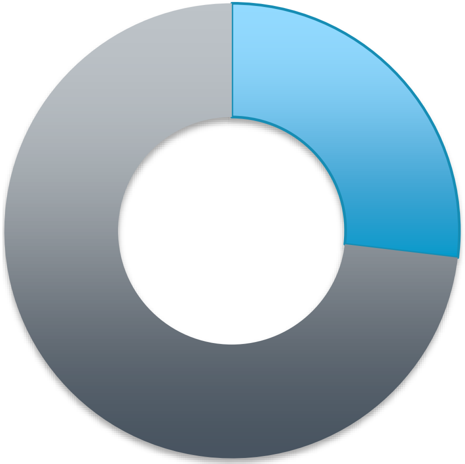
DOE Solar Office Funds 600+ Active Projects

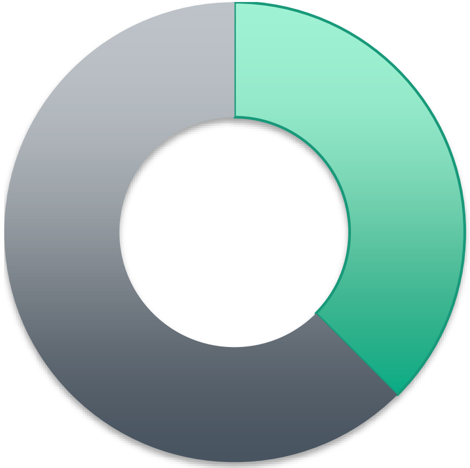
Projects and partners in 43 states plus the District of Columbia

36% of projects led by national labs

25% of projects led by universities

39% of projects led by businesses, non-profits, and state and local government

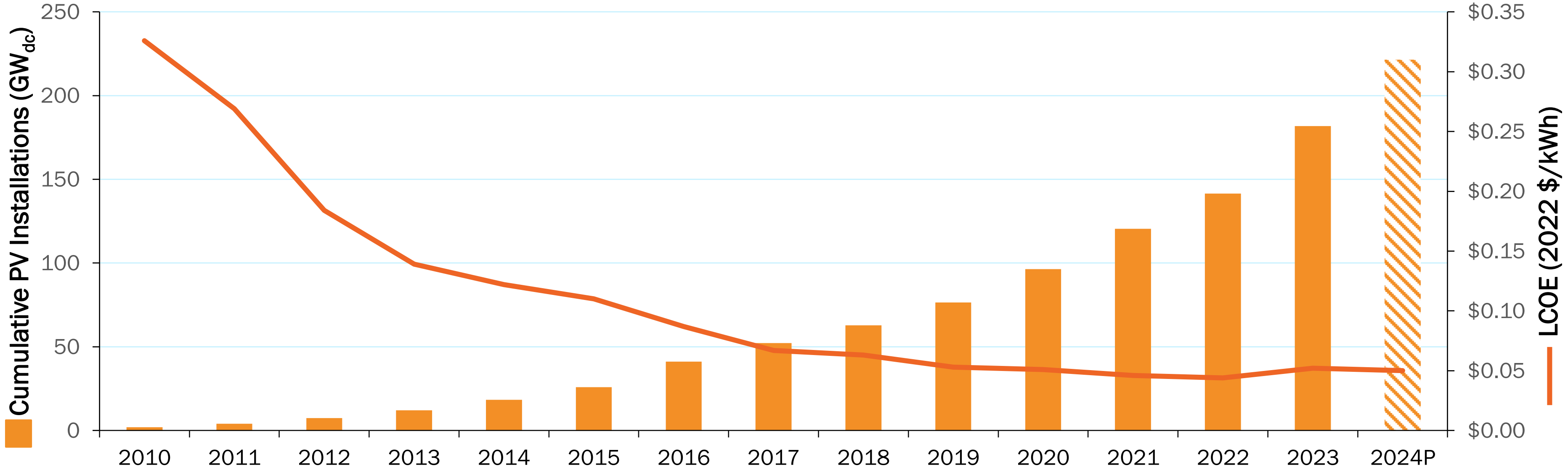




U.S. Solar: Falling Costs, Rising Deployment

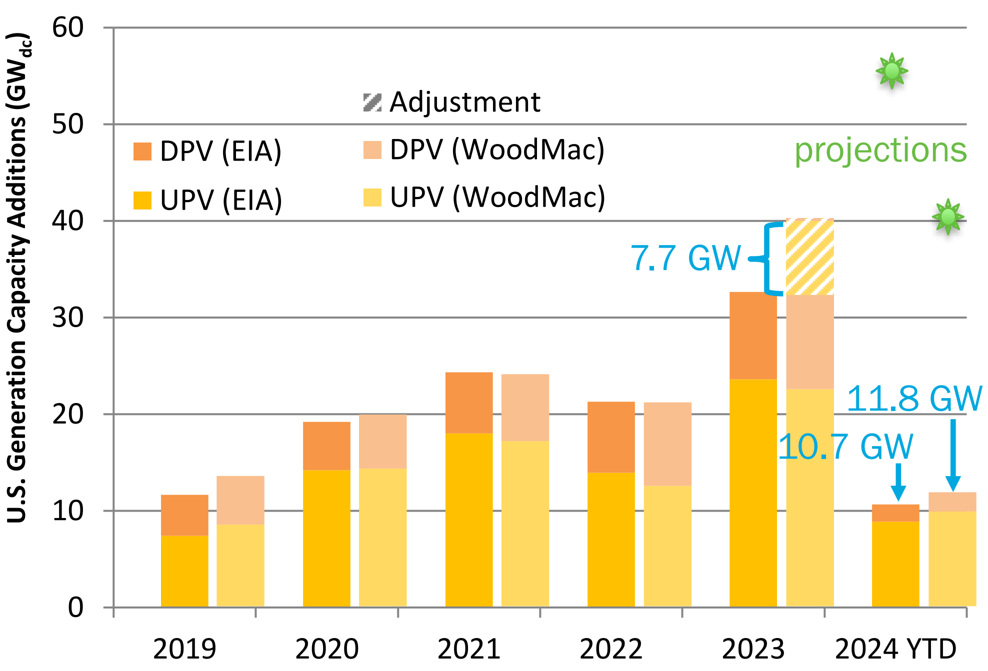
The solar energy industry is one of the fastest growing industries in the nation. Driven by falling costs and state and federal policy, total solar PV installed capacity is now over **180 GW and is projected to grow to about 220 GW by the end of the year.**

PV Deployment and System Price in the U.S. (2010–2023, 2024 Estimate)



Sources: Wood Mackenzie/SEIA: Solar Market Insight Report 2023 Year in Review. National Renewable Energy Lab System Advisor Model was used to depict electricity costs as the levelized cost of energy (LCOE) for a utility-scale system in a mid-America location with average solar resource, without benefit of tax credits

Record-breaking Installation Volumes!



Sources: Energy Information Administration (EIA) Electric Power Monthly, Wood Mackenzie (WoodMac) US Solar Market Insight: Q2 2024. All 2023 and 2024 data is preliminary and different data sources update at different times.

*DPV = distributed photovoltaics, UPV = utility-scale photovoltaics, YTD = year-to-date

**Inverter loading ratio = 1.15 for DPV and 1.3 for UPV

At the beginning of May, WoodMac revised their **2023 annual installations upwards from 32 GW_{dc} to 40 GW_{dc}.** This was the result of a modification to how they determined the installation date for UPV projects in Texas (which represented 29% of installs in 2023 and was 5.2 GW higher in 2023 after the adjustment), plus data from developers that they received after the deadline for their earlier report (including AZ, VA, LA, and NC).

Installation data for **Q1 2024** is *preliminary*, however, estimates range from **10-12 GW_{dc}** of installs. This is nearly double Q1 2023 installations, which is notable because Q1 installations are usually the lowest volume of the year (with Q4 being the highest, often by a substantial margin).

WoodMac's most recent projections (released June 6) for 2024/2025 were revised upwards by a few GW, but they are still projecting nearly flat installation growth for the next several years due to ongoing labor and high voltage equipment constraints plus the trade policy uncertainty.

Research Areas: Systems Integration

The goal for SETO's system integration research is to achieve high-solar grid integration by supporting the reliability of the power system, enhancing resilience and security, and increasing system flexibility to reduce grid integration costs.

Where we are now:

- Inverter-based solar and wind resources pose challenges to system reliability and stability
- Solar generation variability and uncertainties
- System operators have no visibility or control over most distributed solar

Priority R&D Topics:

- Develop long-term planning models and tools for solar integration
- Develop advanced control capabilities for power electronics
- Enhance grid services to operate high-solar grid
- Advance communications and sensing for situation awareness
- Improve solar forecasting
- Integrate storage to add flexibility
- Enhance resilience and security in system design
- Accelerate grid codes and standards development

Find our latest Peer Review feedback here: https://www.energy.gov/eere/solar/2024-seto-peer-review

Thank you for being here today!

Questions?

Solar Forecasting Research through the lens of DOE-SC

July 9, 2024

Gary Geernaert
Earth and Environmental Systems Science Division
Office of Biological and Environmental Research
DOE Office of Science

OUTLINE

- A little about us in Office of Science
- BER portfolios relevant to Solar Forecasting
- Success stories relevant to solar forecasting
- Imagining forecasting capabilities in the next few years

Office of Science Research Portfolio

Advanced Scientific Computing Research	• Delivering world leading computational and networking capabilities to extend the frontiers of science and technology
Basic Energy Sciences	• Understanding, predicting, and ultimately controlling matter and energy flow at the electronic, atomic, and molecular levels
Biological and Environmental Research	• Understanding complex biological, earth, and environmental systems
Fusion Energy Sciences	• Supporting the development of a fusion energy source and supporting research in plasma science
High Energy Physics	• Understanding how the universe works at its most fundamental level
Nuclear Physics	• Discovering, exploring, and understanding all forms of nuclear matter

DOE Office of Science
Harriet Kung, Acting Director

Advanced Scientific Computing Research

Basic Energy Sciences

Fusion Energy

Biological and Environmental Research

Dorothy Koch, Associate Director

High Energy Physics

Nuclear Physics

Biological Systems Science
Todd Anderson, Director

- Genomic Science
  - Bioenergy Research Centers
- Biomolecular Characterization & Imaging Science
- Facilities & Infrastructure
  - Joint Genome Institute

Earth & Environmental Systems Science
Gary Geernaert, Director

- Atmospheric System Research
- Environmental System Science
- Earth and Environmental Systems Modeling
- Facilities & Infrastructure
  - Environmental Molecular Sciences Laboratory (EMSL)
  - Atmospheric Radiation Measurement (ARM)

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DOE EESSD Permanent Staff





ATMOSPHERE TEAM

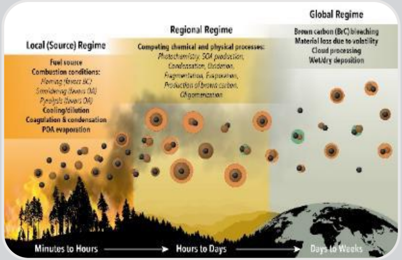
MODELING TEAM

ESS TEAM

Atmospheric Sciences overview relevant to solar forecasting

ASR Priority Research Areas and Working Groups

Convective cloud processes and properties including cloud cover, precipitation, life cycle, dynamics, and microphysics over a range of spatial scales.



Aerosol processes governing the spatial and temporal distribution of atmospheric particles and their chemical, microphysical, and optical properties.

High latitude processes including cloud, aerosol, and surface-interaction processes controlling the surface energy budgets in northern and southern high latitude regions

Warm boundary-layer processes controlling the structural and radiative properties of clouds, aerosols and their interactions with the underlying surface in the lowest few kilometers of the atmosphere.

The Atmospheric Radiation Measurement (ARM) User Facility

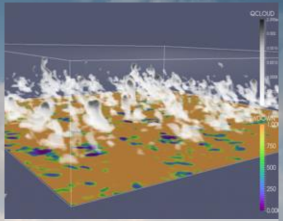
Measurements of clouds, aerosols, precipitation, radiation, surface properties & the atmospheric state since 1992

Support for process studies & model & satellite development

Network of 3 fixed-location & 3 mobile observatories

Piloted & uncrewed aerial measurement platforms

Extensive data management infrastructure. Data freely available

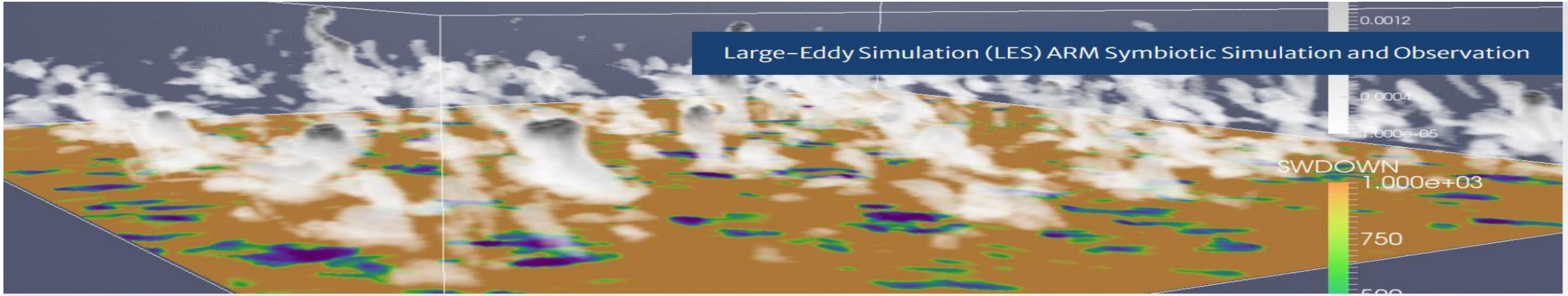


Large-eddy simulation (LES) model simulations & analysis tools

Support for field campaigns ranging from guest instruments to facility deployments

Atmospheric Radiation Measurement (ARM) User Facility

- 3 fixed measurement sites (Oklahoma, Alaska, Azores) in different climate regimes; 1 mobile facility for mid-range (~5 year) deployments (SE US, Oliktok Point)
- 2 mobile facilities available for proposal-driven deployments
  - e.g., the CAPE-k, CoURAGE, EPCAPE, SAIL campaigns
- 24/7 data collection at fixed/mobile facilities with all data freely available at www.archive.arm.gov
- High-performance computing for working with large ARM data sets
- Aerial facility component



ARM Facility data in publications on solar forecasting

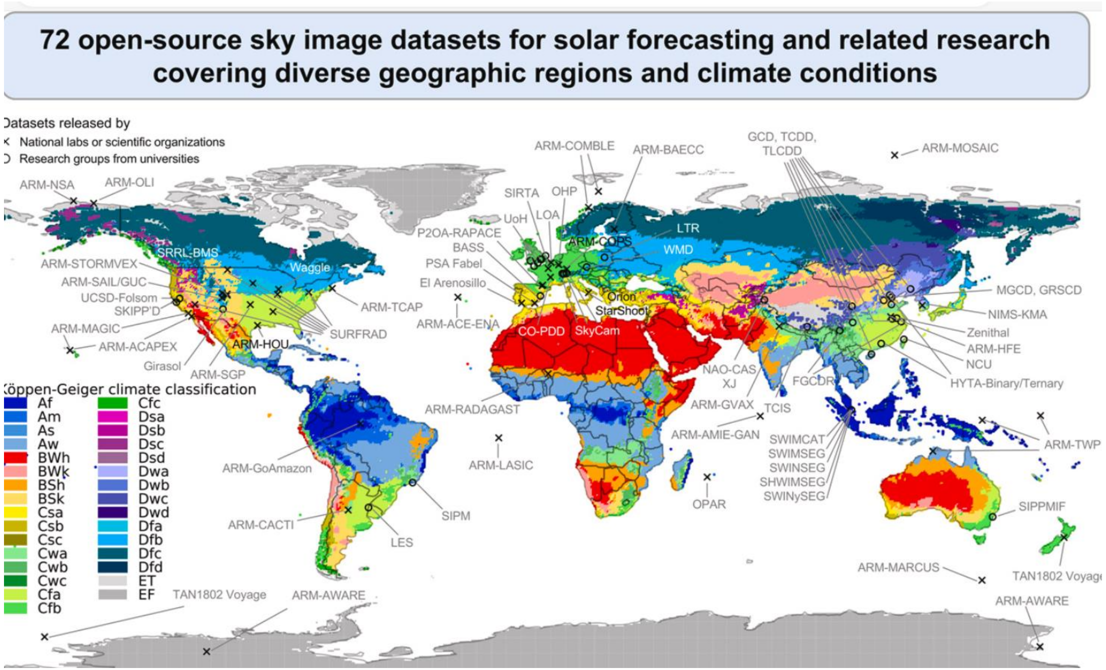
Wang, et al., May 2024: A novel solar irradiance forecasting method based on multi-physical process of atmosphere optics and LSTM-BP model. Renewable Energy.

Liu W, Y Liu, T Zhang, Y Han, X Zhou, Y Xie, and S Yoo. 2022. "Use of physics to improve solar forecast: Part II, machine learning and model interpretability." *Solar Energy*, 244, 10.1016/j.solener.2022.08.040.

Liu W, Y Liu, X Zhou, Y Xie, Y Han, S Yoo, and M Sengupta. 2021. "Use of physics to improve solar forecast: Physics-informed persistence models for simultaneously forecasting GHI, DNI, and DHI." *Solar Energy*, 215, 10.1016/j.solener.2020.12.045.

Manandhar P, M Temimi, and Z Aung. 2023. "Short-term solar radiation forecast using total sky imager via transfer learning." *Energy Reports*, 9(1), 10.1016/j.egyr.2022.11.087.

Open-source sky image datasets for solar forecasting with deep learning: A comprehensive survey: Yuhao Nie, et al., 2024



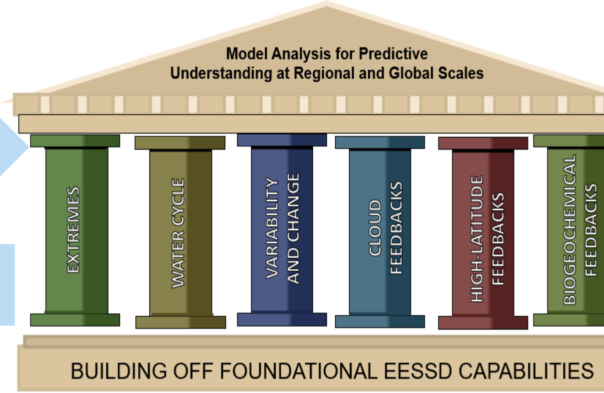
The DOE ARM Facility contributes to the open-source sky imager data base.

Earth and Environmental System Modeling overview relevant to solar forecasting

There are three foci of the Modeling Program, with some interdependence

Earth System Model Development (ESMD)

Regional and Global Model Analysis (RGMA)



Advanced E3SM capabilities for RGMA to enhance understanding

Knowledge from RGMA simulations and analyses to benefit E3SM development

MultiSector Dynamics (MSD)

SMD provides high resolution climate information and extremes, with feedbacks, for use in MSD models

MSD develops and supports GCAM in E3SM

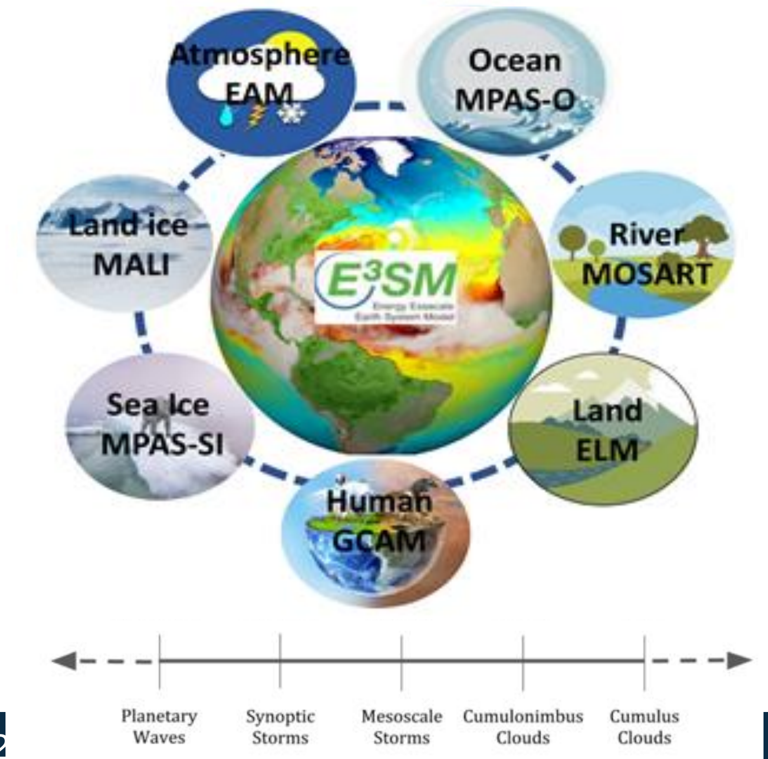
RGMA Metrics and simulations developed inform different sectors

MSD Scenarios needed for projections and uncertainty quantification

The Energy Exacsale Earth System Model (E3SM)

Innovative and computationally advanced ESM capabilities, in support of Energy science and mission

Earth System Across Scales



Goal: *Support the development of E3SM including its subcomponents, to address the grand challenges of actionable predictions of the changing Earth system, emphasizing on the most critical scientific questions facing the nation and DOE*

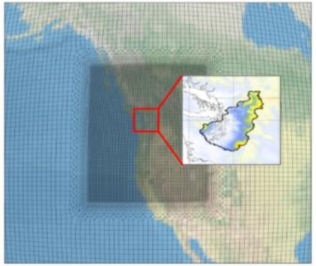
Strategies:

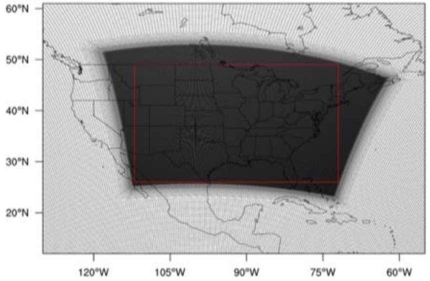
- Science drivers for model development
- Earth system across scales (high-resolution frontier, bridge gaps, quantify uncertainty)
- Prepare for and overcome the disruptive transition to next era of computing, leverage ASCR HPC capabilities
- Innovative mathematical, computational methods, tools, algorithms, technologies (e.g., ML/AI)

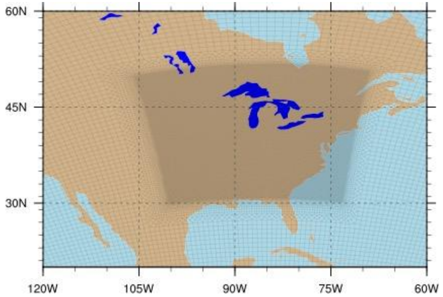
More E3SM Acronyms: https://e3sm.org/resources/help/acronyms/

Key tool for regional scale predictability: DOE's Energy Exascale Earth System Model (E3SM)

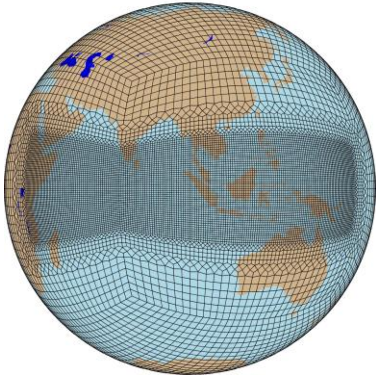
- DOE's flagship climate model
- 7 nat'l labs and NCAR
- Includes the full earth system and many human systems
- Can "zoom in" to regions of interest
- Atmos cloud resolving component at 3 km resolution
- Uses DOE Exascale High Performance Computers

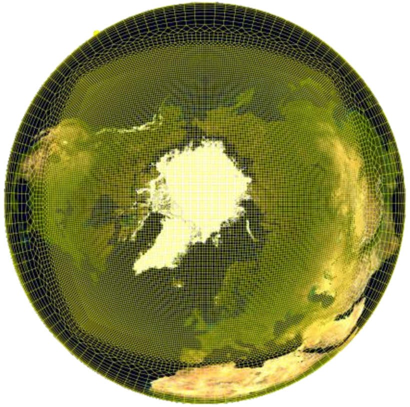




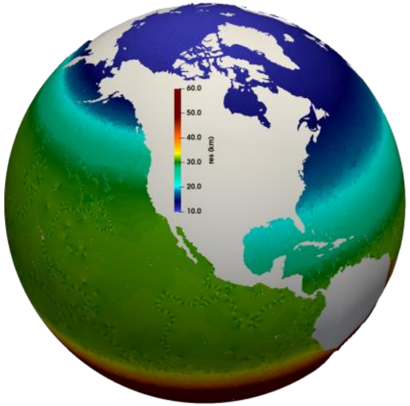


Indian Ocean/Maritime Continent (IOMC)





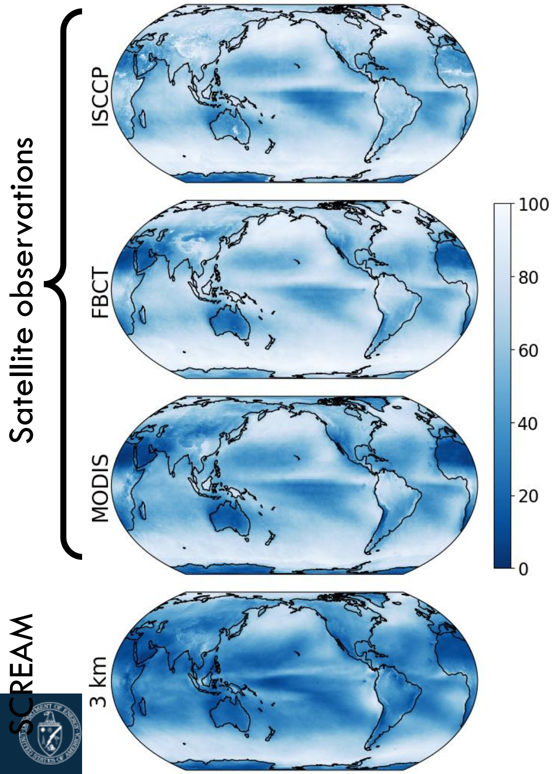
E3SM-Arctic atmosphere grid



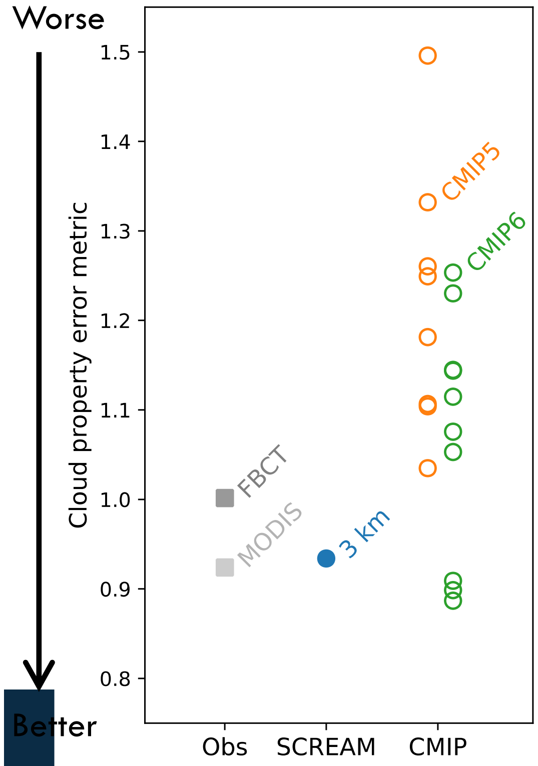
E3SM-Arctic ocean grid

E3SM SCREAM is skillful in simulating present-day clouds and predicts more surface solar with warming

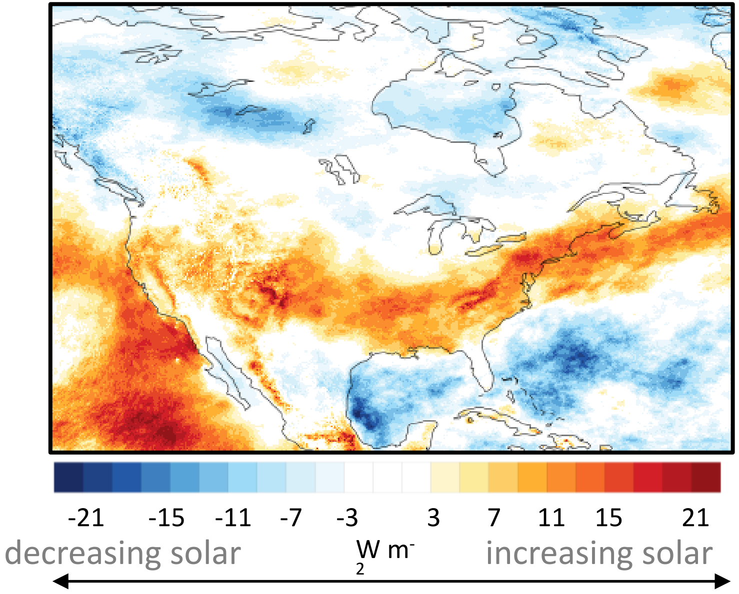
Present-day total cloud cover



Skill in reproducing ISCCP's present-day cloud properties

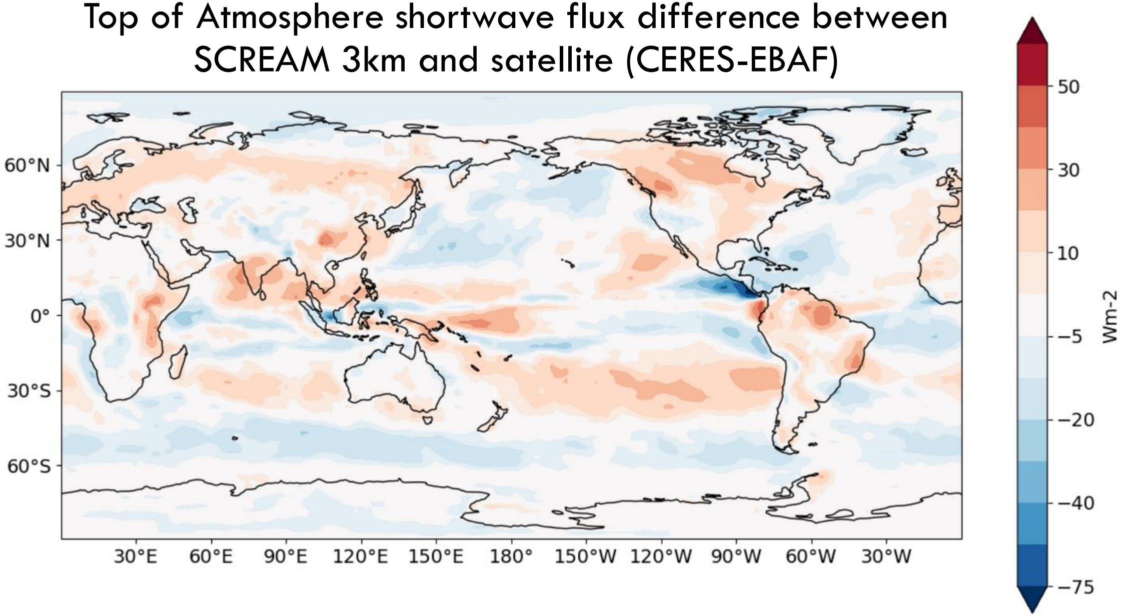


Predicted change in downward surface solar flux with +4K warming*

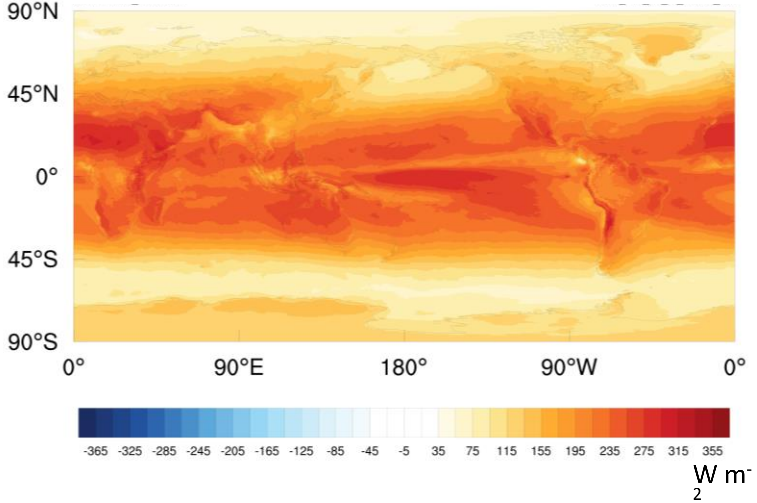


*Longer, non-idealized simulations needed t establish robustness of response.

Top of Atmosphere shortwave flux difference between SCREAM 3km and satellite (CERES-EBAF)

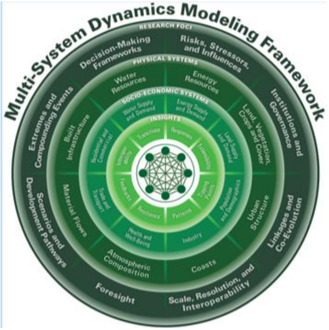


Baseline surface downward solar radiation flux in SCREAM 3km



AI/ML techniques is a new priority to more rapidly advance science and prediction

Multi-system, multi-sector modeling framework to explore stressors, risks and responses, tipping points, of interconnected physical and socioeconomic systems

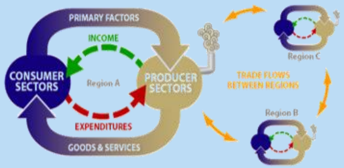


Multi-Scale Interactions

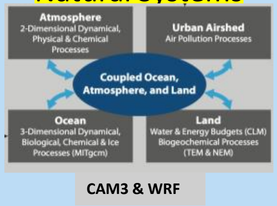
Global Drivers » Teleconnections » Local Systems » Decision-Making

Toolbox for Multi-Sector Modeling

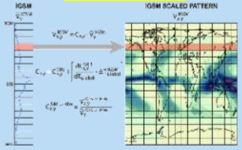
Human Systems



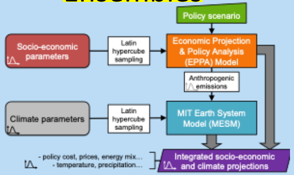
Natural Systems



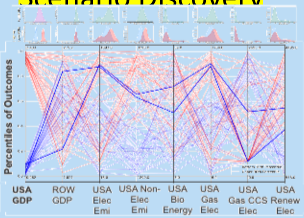
Pattern Scaling Extremes



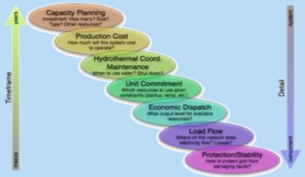
Probabilistic Ensembles



Scenario Discovery

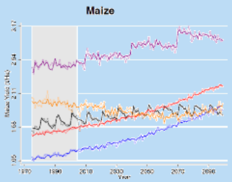


Electricity Models

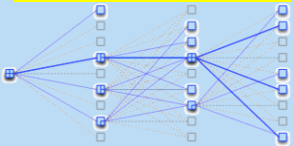


Water Resources

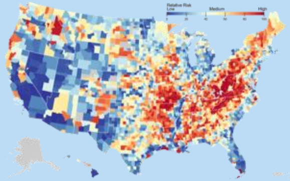
Emulators



Decision Frameworks



Risk Triage



Major Tasks:

- Human-Natural System Interactions
- Transportation Infrastructure
- Stress-Testing Paired Systems

https://globalchange.mit.edu/research/research-projects/integrated-framework-modeling-multi-system-dynamics

U.S. DEPARTMENT OF ENERGY | Office of Science

Opportunities to improve solar forecasting based on research in BER

- The E3SM prediction capability will be further developed with a flexible grid to extend atmospheric modeling below 3 km
- ARM data coupled with AI will yield an improved stochastic representation of high resolution patterns of solar irradiance over specific regions of interest.
- Projections of future changes in solar radiance patterns, associated with climate change, will be included in the E3SM simulations.


THANK YOU!

Climate modeling and grid planning

NREL
Transforming ENERGY

Creating High-Resolution Climate Data for Solar Energy Applications

Jaemo Yang (NREL)

DOE Solar Forecasting Workshop

July 9-10 | Washington, D.C.

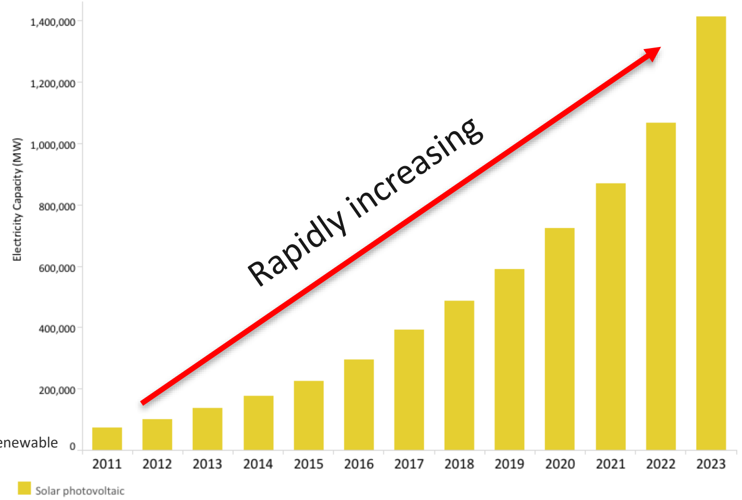
Photo by Dennis Schroeder, NREL 55200

Contents

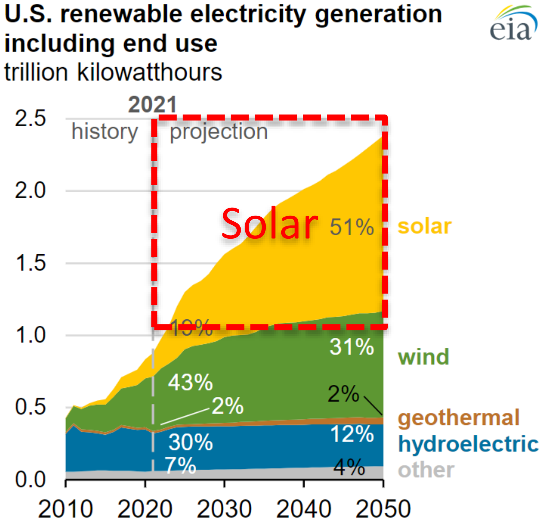
Introduction

Why are climate data needed ?

Installation capacity of solar energy worldwide



Graphic from International Renewable Energy Agency

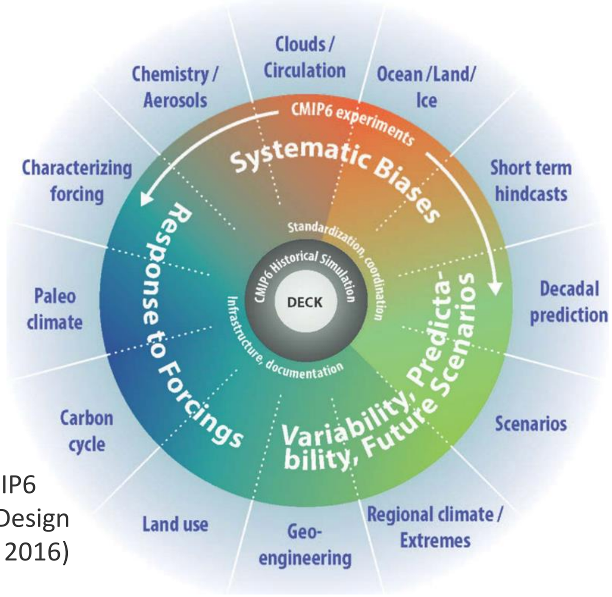


Graphic from U.S. Energy Information Administration

- PV technology has rapidly advanced in the last decades, and its global deployment has significantly grown.
- Solar irradiance is greatly influenced by the Earth's atmosphere and weather.
- Climate change likely leads to changes in future weather (e.g., increases in heat waves).
- Climate change is increasingly causing extreme weather events to become more frequent and intense.
- Thus, it is essential to assess and understand the potential impacts of future climate change on solar generation and the power sector.

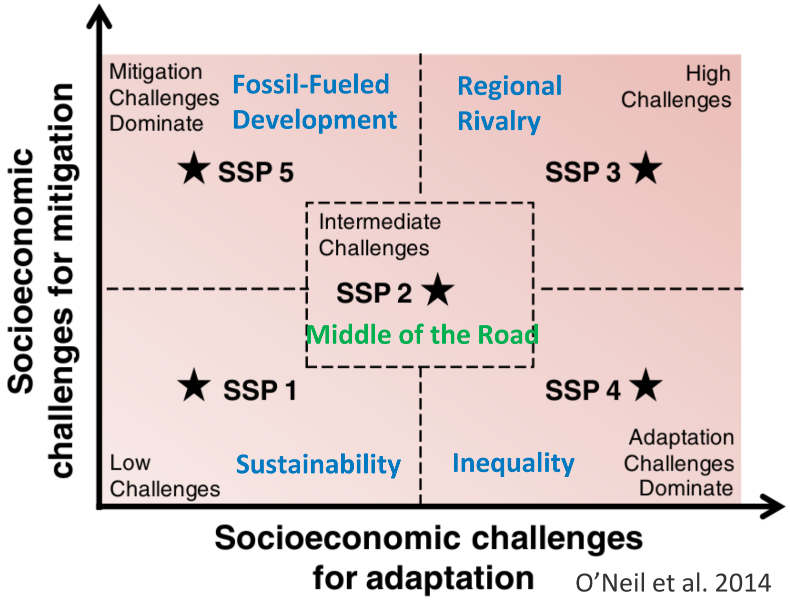
CMIP and Climate Scenarios

- **CMIP (Coupled Model Intercomparison Project):**
  - Managed by World Climate Research Programme (WCRP)
  - Climate scenarios resulted from multi global-scale models contribute to IPCC report



CMIP/CMIP6 Experiment Design (Eyring et al. 2016)

- **CMIP6:**
  - Consider different socio-economic developments as well as different pathways of greenhouse gas concentrations.
  - Provide climate simulations under Shared Socioeconomic Pathways (SSPs)



O'Neil et al. 2014

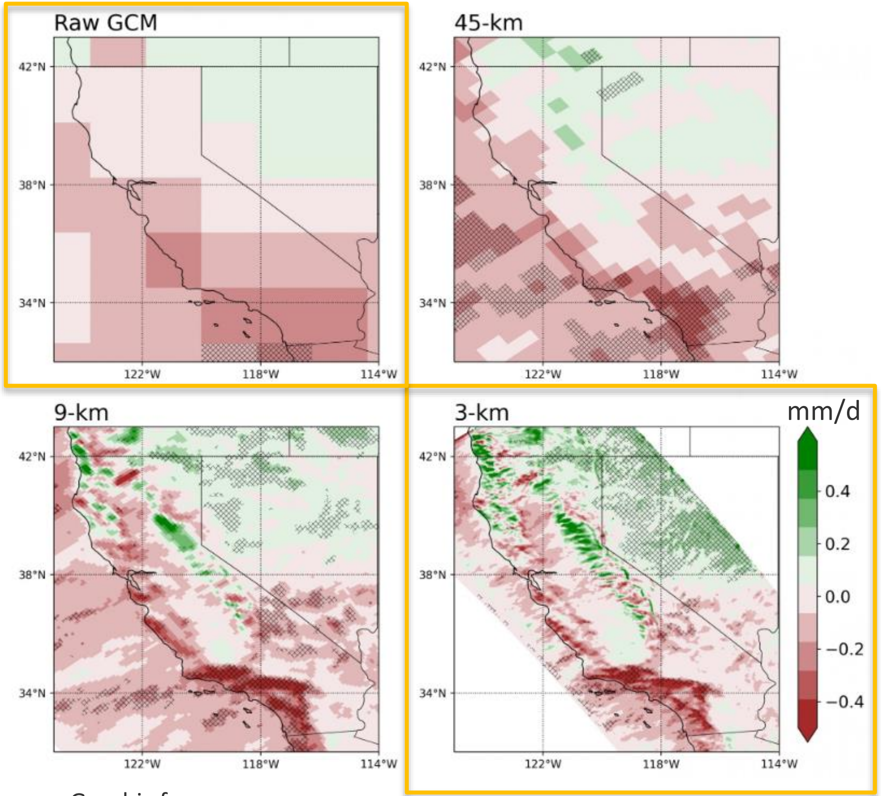
Why high resolution?

- **General circulation model (GCM) limitations:**
  - Very low resolution (> 100 km and daily)
  - Systematic errors or biases
  - High deviations from observational data

- **Needs:**
  - Provide high resolution data
  - Provide un-biased climate projections

- **Options:**
  - Dynamical downscaling methods
  - Statistical/machine-learning based downscaling approaches
  - Bias correction

Example: simulated precipitation anomalies



Graphic from: https://dept.atmos.ucla.edu/alexhall/downscaling-cmip6

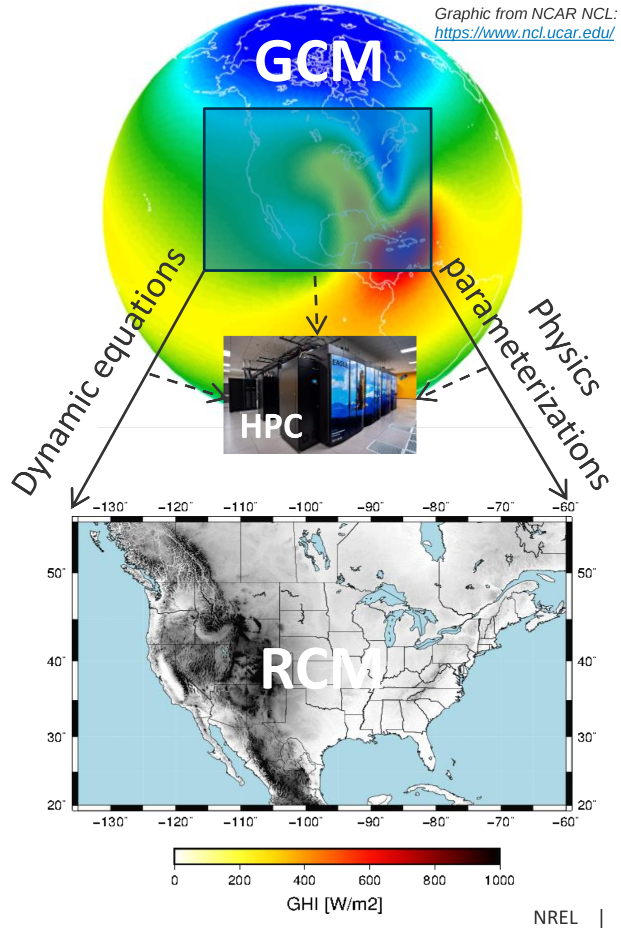
Resolution relevant for climate impact studies!

Methods for Downscaling of Climate Data

Dynamical Downscaling

- Use GCM's outputs as inputs for regional climate models (RCMs) (e.g., WRF, RegCM)
- Use governing physical laws to integrate dynamic solution

Graphic from NCAR NCL: https://www.ncl.ucar.edu/



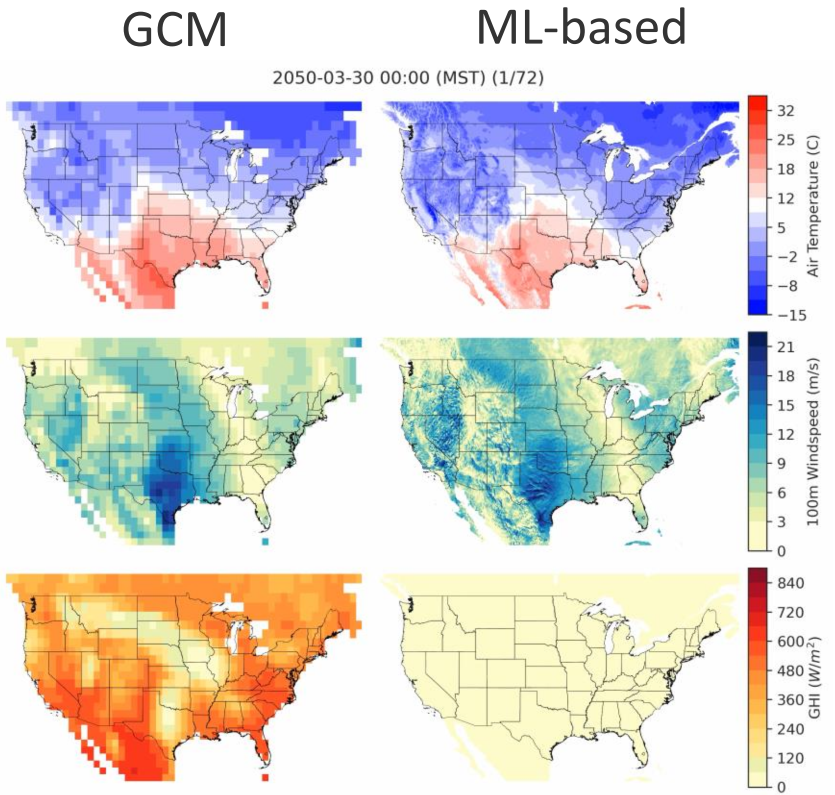
PROS & CONS	
PROS	▪ Downscaling approach that is based on consistent and physical mechanism. ▪ Capable of resolving atmospheric and surface processes occurring at sub-GCM grid scale. ▪ Not constrained by historical record. ▪ Capable of producing various atmospheric variables as outputs.
CONS	▪ Computationally intensive. ▪ Affected by bias of driving GCM. ▪ Uncertainties in modeling when selecting different parameterizations. ▪ May require further bias correction of RCM outputs.

Trzaska, S, Schnarr, E (2014) A review of downscaling methods for climate change projections. United States Agency Int Dev by Tetra Tech ARD 1–42, http://www.ciesin.org/documents/Downscaling_CLEARED_000.pdf

Statistical/ML-based Downscaling

- Use statistical relationships between large-scale predictor fields and high-resolution predictands
- Train the model on observational datasets

PROS & CONS	
PROS	▪ Computationally inexpensive and efficient. ▪ Methods range from simple to elaborate and are flexible enough to tailor for specific purposes. ▪ Relies on the observed climate as a basis for driving future projections.
CONS	▪ Very difficult to capture convective-scale atmospheric phenomenon (i.e., dx < 10 km) because of no representation of physics such as convection/turbulence. ▪ High quality observed data may be unavailable for many areas or variables. ▪ Over-fitting problem. ▪ Machine-learning approach is sometimes defined as "black-box" model – i.e., not interpretable model.



Buster et al., "High-resolution meteorology with climate change impacts from global climate model data using generative machine learning", *Nature Energy* (2024). https://doi.org/10.1038/s41560-024-01507-9

On-going Project 1: PACES

PACES: Power Planning for Alignment of Climate and Energy Systems

GRID MODERNIZATION INITIATIVE
U.S. Department of Energy

Project Overview:

- **Climate change is already posing significant chronic and acute risks** to power system planning targets and operations.
- The energy sector **lacks cohesive frameworks and datasets** to answer national-scale planning questions related to climate risks.
- This project aims to **establish best practices and open-access datasets** to bridge these capability gaps.

Key Innovations:

- Application of two different climate downscaling methods- **machine learning-based** and **dynamical** techniques.
- Best practices in **equitable power system planning** for climate change impacts.
- Analysis of **extreme events**- heat and cold waves, wind/solar/water droughts, wildfires, and floods.
- **A roadmap for utility implementation** demonstrated with Tennessee Valley Authority and Southern Company.

Partners

NREL Transforming ENERGY
Oak Ridge National Laboratory
Los Alamos National Laboratory
TVA Tennessee Valley Authority
Southern Company
Evolved Energy Research
EPRI Electric Power Research Institute
Colorado State University
CUNY The City University of New York
UCONN School of Engineering

Impact: We will enable the energy industry to plan systems that are robust to the impacts of climate change

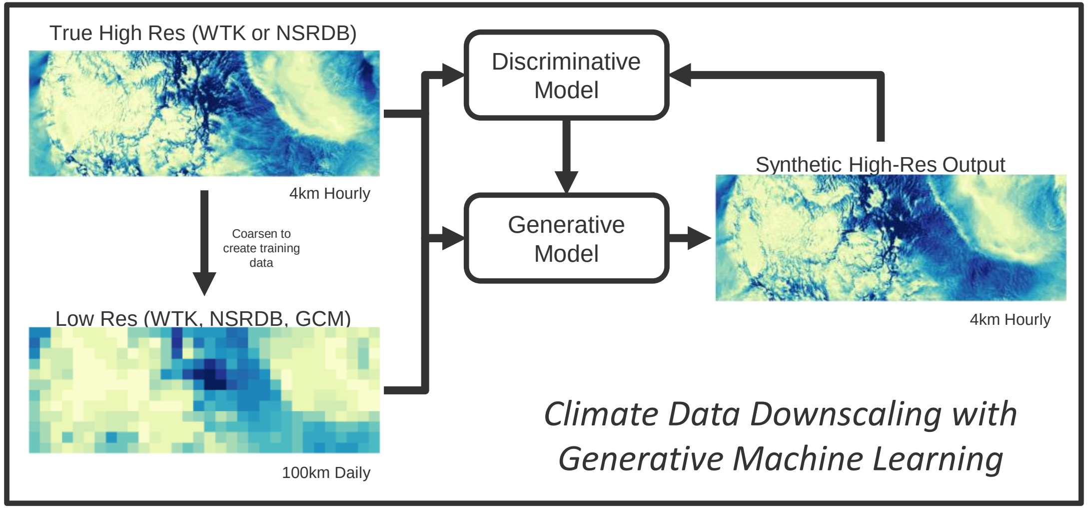
Sup3rCC (ML-based)

- Super-Resolution for Renewable Energy Resource Data with Climate Change Impacts (Sup3rCC)
- **Computationally efficient:**

  Downscale 1 year of CONUS data to 4km hourly resolution in 30 minutes wall-clock time
- Designed for renewables:

  wind, solar, temp, humidity, precipitation
- **Fully integrated into NREL energy analysis software** (reV, ReEDS, etc…)
- Open-source

  https://nrel.github.io/sup3r/

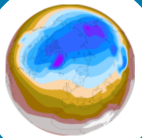


Buster et al., "High-resolution meteorology with climate change impacts from global climate model data using generative machine learning", *Nature Energy* (2024). https://doi.org/10.1038/s41560-024-01507-9

WRF Dynamical Downscaling (Physics-based)

- Dynamical downscaling approach can generate a full set of **physically consistent** high-resolution climate data.
- Use the **widely used Weather Research and Forecasting (WRF) model** to downscale 100 years of GCM data for SSP2-4.5 and SSP5-8.5.
- The **best WRF configurations** will be developed to accurately represent modeled atmospheric variables related to renewable energy applications.

Objective: Develop unbiased, physically consistent, high-resolution **(4 km and hourly)** downscaled future projections for entire CONUS



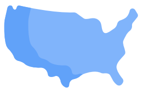
GCM Data:
- High-quality input (~100 km resolution) for RCM
- Consider bias-corrected fields in GCM data: air temperature, pressure, humidity, wind, etc.

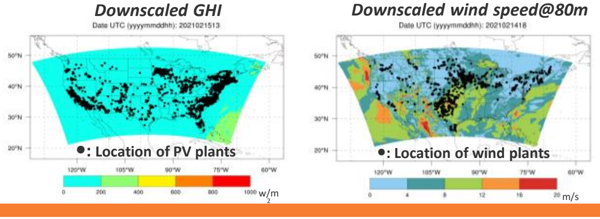
Graphic from NCAR NCL: https://www.ncl.ucar.edu/

WRF model (RCM)

WRF physics modules
- Radiative transfer
- Planetary boundary layer
- Microphysics
- Land surface model, etc.

WRF: https://www.mmm.ucar.edu/models/wrf





Graphic by NREL. Meta and atmospheric data from EIA and HRRR: https://www.eia.gov/, https://rapidrefresh.noaa.gov/hrrr/

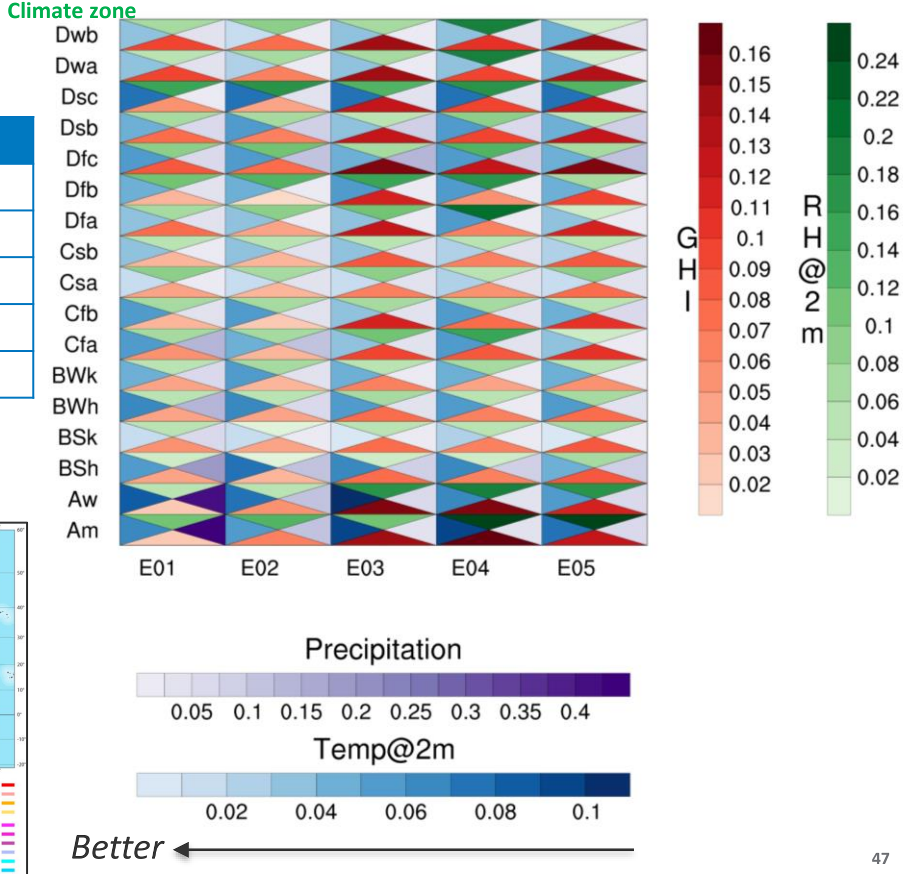
Numerical Experiments (Dynamical Downscaling)

- Designed numerical experiments with five different WRF configurations to find a right combination of physics modules.

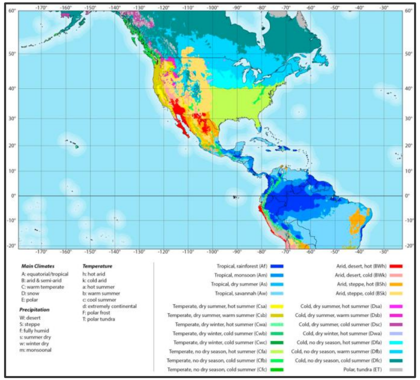
Experiment	Based on WRF configuration used in (applications to entire CONUS)
E01	WRF-Solar (NWP specialized for solar energy applications)
E02	WRF-Solar EPS (ensemble prediction system tailored for solar energy)
E03	PR100 + Wind Toolkit (high-resolution wind resource data)
E04	IM3/HyperFACETS TWG simulations (downscaled climate data, 12 km)
E05	CONUS404 (downscaled reanalysis data, 4 km)

- Implemented an evaluation of key atmospheric variables against observational data for 17 climate zones on CONUS domain.

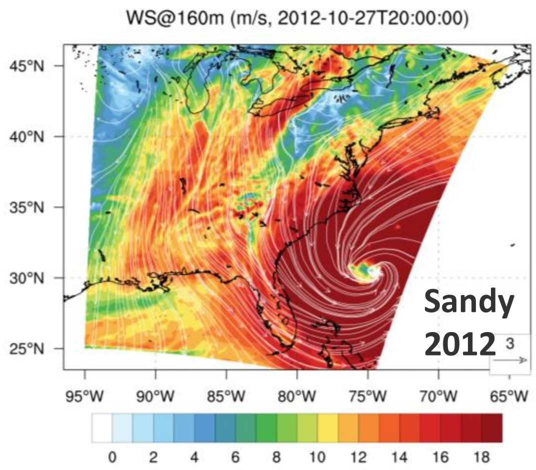
KS-Test for WRF Simulations (15 years)

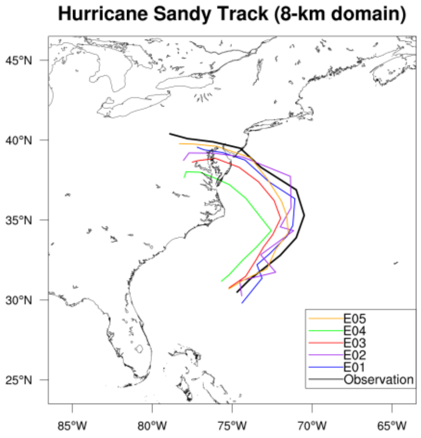


Köppen-Geiger (KG) climate classification (Habte et al. 2020)

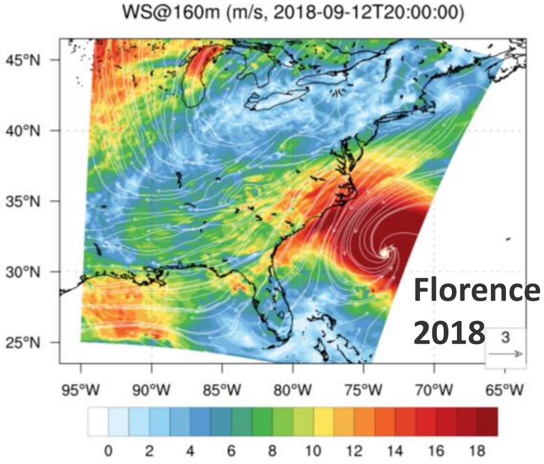


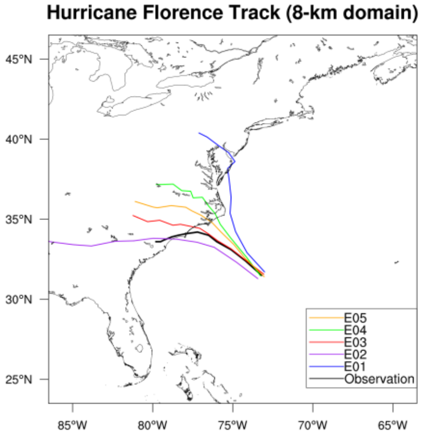
Modeling Extreme Events





- Capability of representing extreme events (e.g., tropical cyclones)





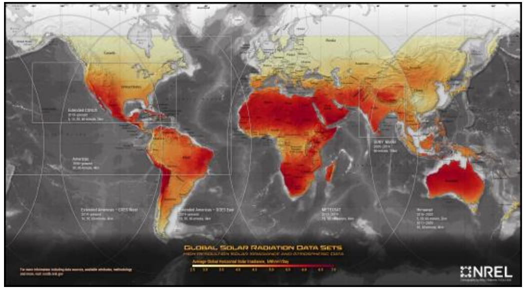
On-going Project 2: NCDB

Downscaling Future Solar Projections

- This work aims to 1) **develop statistical methods** within an efficient framework and 2) **downscale future climate data sets** tailored for solar energy applications.
- The NSRDB is used to build and calibrate the statistical downscaling models.
- Technical approach:

RCM-based climate projections obtained from the North American Coordinated Regional Climate Downscaling Experiment (**NA-CORDEX**; https://na-cordex.org/) are used as inputs to the proposed statistical methods.

NSRDB: https://nsrdb.nrel.gov/



Calibrate RCM parameters using solar, temperature, and wind observations

Climate Data Downscaling with Statistical methods

Statistical model

Large scale RCM daily data in future years

Statistical model

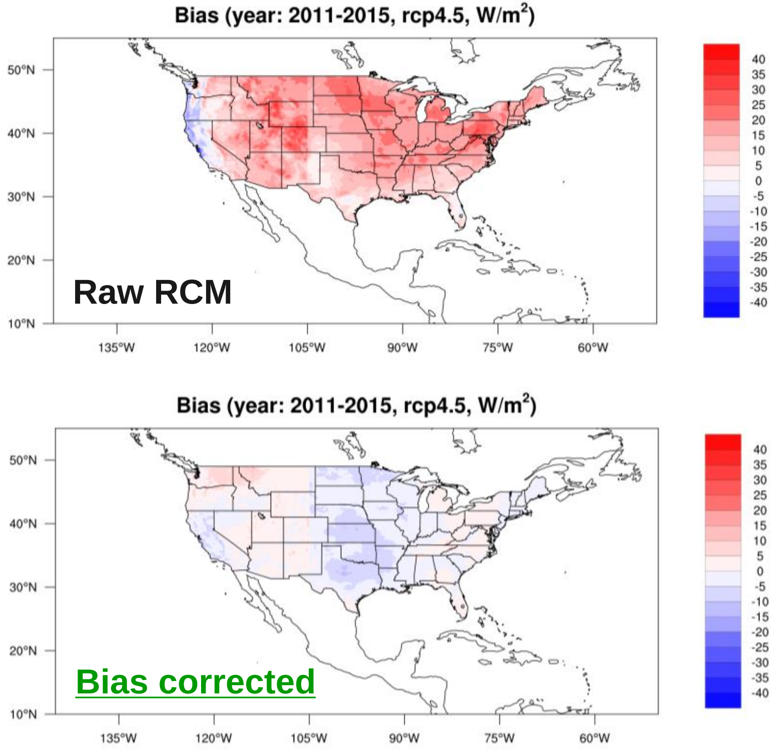
Small scale projected hourly solar, wind, and temperature in future years

❶Regridding → ❷Bias-correction → ❸Temporal downscaling → ❹Spatial downscaling

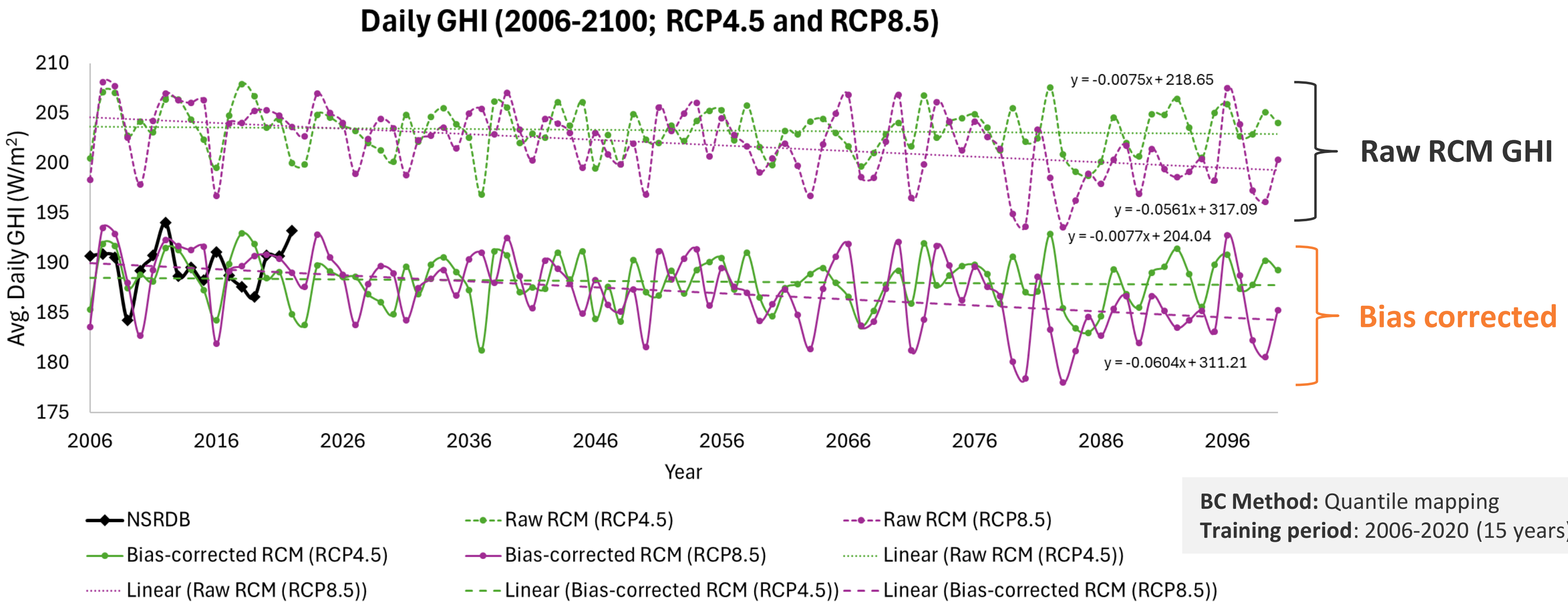
Bias-correction of RCM GHI

- GCM's horizontal grid spacing (> 100 km) is too coarse to represent local processes and terrain heterogeneity and the RCM's also have inherent systematic and random modeling errors stemming from various model components.
- Therefore, bias-correction of RCM output should be considered before any application of climate data
- We employed a bias correction technique based on quantile mapping to reduce bias of RCM GHI.

On average across all pixels, the bias of bias-corrected GHI is **<u>less than 10%</u>** compared to the NSRDB.



95-years Bias-corrected GHI Projections

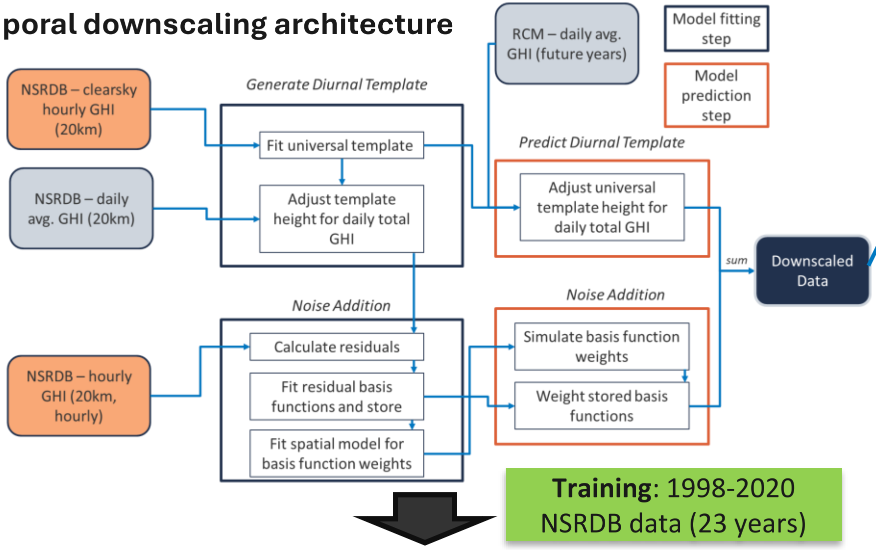


BC Method: Quantile mapping
Training period: 2006-2020 (15 years)

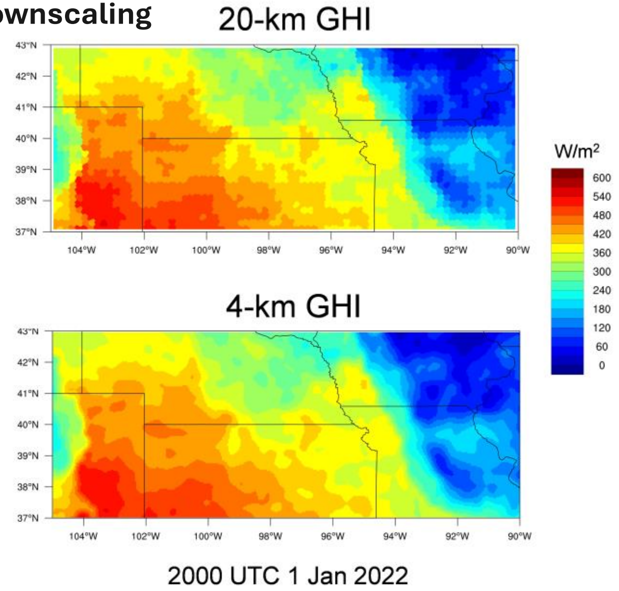
- The bias-correction method applied to the raw RCM conserves both the trend and pattern of the raw RCM GHI.
- This indicates that the quantile mapping reduces the bias of RCM GHI without adversely impacting the RCM's ability to represent future projections of solar irradiance trend and variability.

Temporal and Spatial Downscaling of RCM GHI

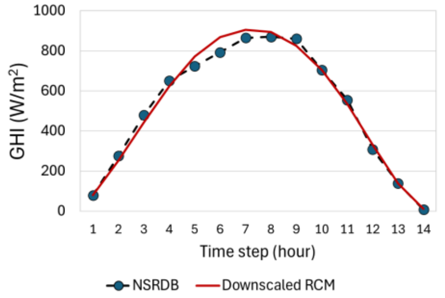
Temporal downscaling architecture

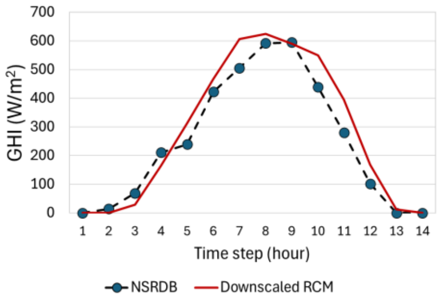


Spatial downscaling



Simulated timeseries (out-of-sample application)

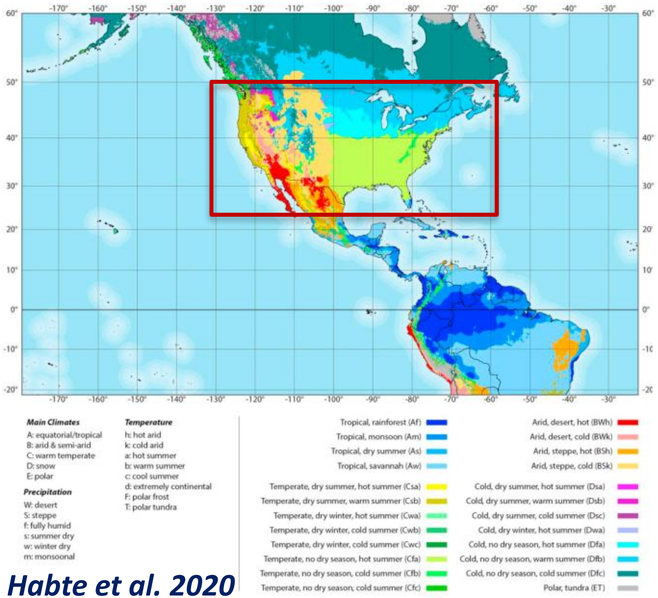




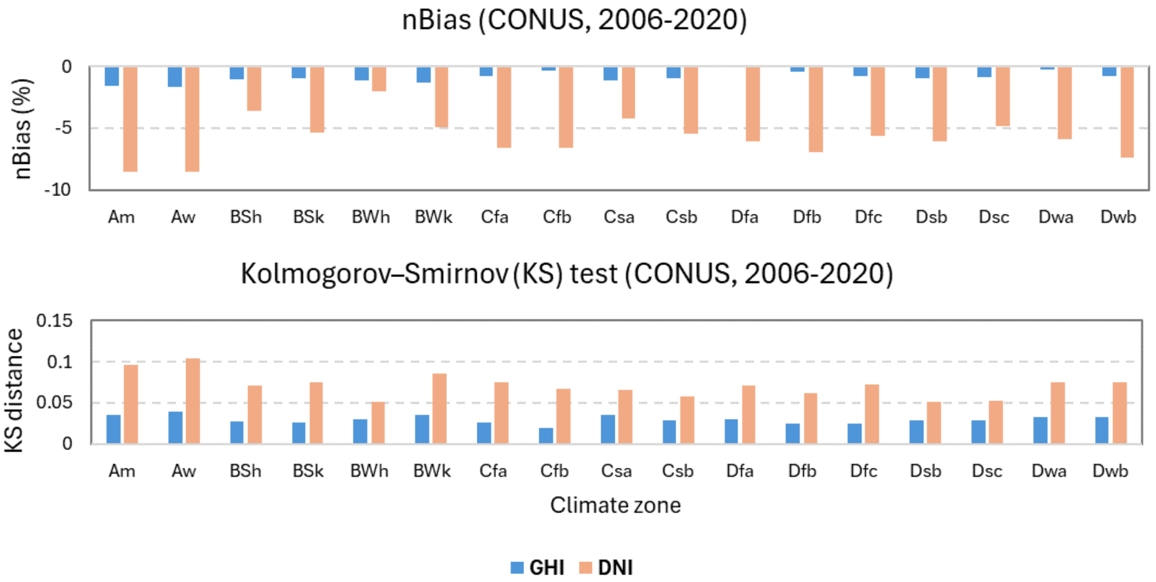
- Temporal downscaling is the key to accurate generation of hourly-scale GHI using statistical methods.
- The thin plate splines (TPS) is used as a method to spatially downscale the 20-km RCM GHI to 4-km resolution.

Evaluation of Downscaled GHI and DNI (daily total, 2006-2020)

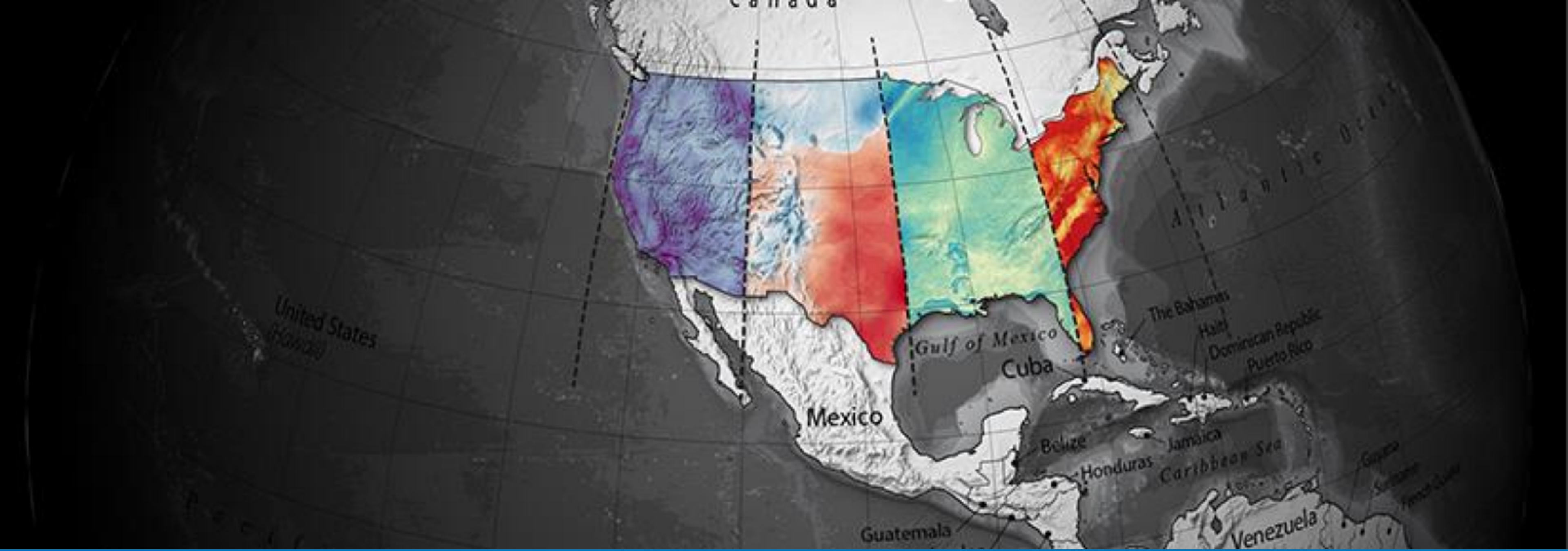
Köppen-Geiger (KG) climate classification



Habte et al. 2020



- Downscaled climate projections show nBIAS less than 2% and 10% for GHI and DNI, respectively across all climate zones.
- KS-test shows the similar distance between two distributions (NSRDB and downscaled climate data).



National Climate Database (NCDB)

- The ***climate.nrel.gov*** data application will be a public facing web interface to allow users to explore, visualize, and download climate resource data sets.
- This platform will compliment the NSRDB
- Become the go to platform for meteorological climate data

Concluding Remarks

- Climate change and its impacts on renewables cannot be ignored anymore in energy fields.
- To help mitigate climate effects on energy systems, DOE is now seeking to understand the short-term and long-term impacts of climate and extremes and develop future climate data to be included in a range of risk management tools for the energy sector (e.g., PACES project).
- Downscaled climate datasets specialized for solar and other renewable energy applications are currently being developed using different approaches.
- It is expected that the high-resolution data will be leveraged for various energy applications.

Thank you

www.nrel.gov

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Manajit.Sengupta@nrel.gov

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NREL Transforming ENERGY

Q&A and Discussions

Current state-of-the-art of solar forecasting technologies: from physics-based model to AI/ML-based models

NREL
Transforming ENERGY

Current State of the Art in Solar Forecasting Techniques: From Physics Based Models to AI/ML Based Models

Dr. Manajit Sengupta, Dr. Cong Feng and Dr. Jaemo Yang
NREL
SETO Solar Forecasting Workshop: July 9-10, 2024

Photo by Dennis Schroeder, NREL 55200

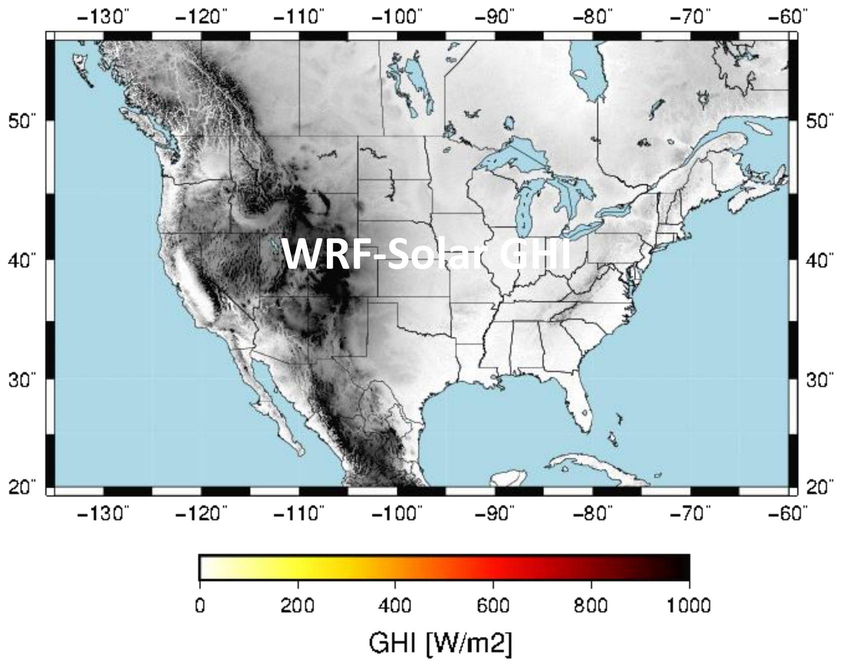
Contents

Physics Based Models: WRF-Solar Ensemble Prediction System

WRF-Solar

Ensemble prediction system based on WRF-Solar that-

- Provides probabilistic forecasts for the grid with ensemble members tailored for solar forecasts.
- Delivers calibrated forecasts that -
  - Produce unbiased estimation of irradiance.
  - Improves previous state-of-art solar forecasts and reduces uncertainty by over **50%**.
- The model is publicly downloadable.



Approach

- Identify variables that significantly influence the formation and dissipation of clouds and solar radiation through a **tangent linear analysis** of WRF-Solar modules that influence cloud processes.

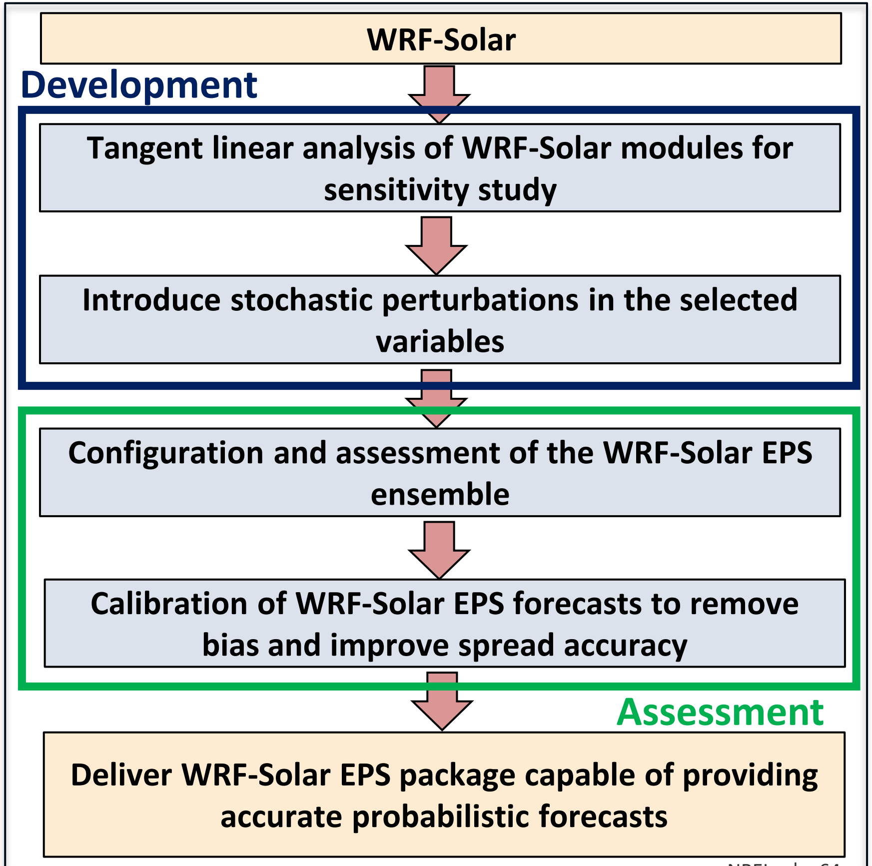
- Introduce stochastic perturbations in the variables identified in previous step to develop **WRF-Solar ensemble prediction system (WRF-Solar EPS).**

- **Calibrate WRF-Solar EPS** using observations to ensure that the forecasts' trajectories are unbiased and provide accurate estimates of forecast uncertainties under a wide range of meteorological regimes.

- **Demonstrate the improvements of WRF-Solar EPS.**

- Incorporate WRF-Solar EPS in the WRF-Solar community model as an open-source probabilistic framework: https://ral.ucar.edu/solutions/products/wrf-solar-eps

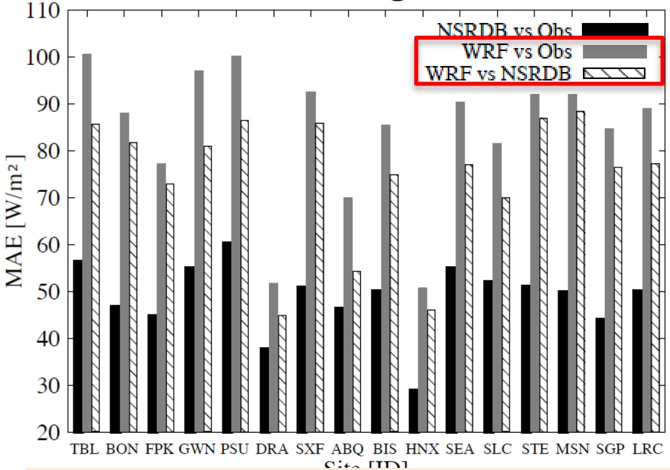
WRF-Solar EPS is the first NWP ensemble model specifically designed to provide probabilistic irradiance forecast.



Satellite-derived Datasets for Validation

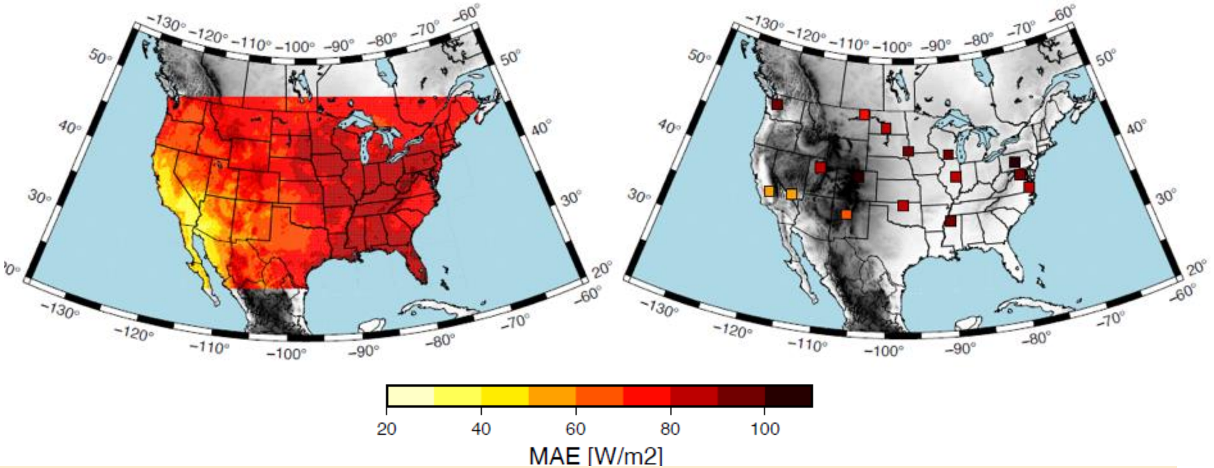
NSRDB compared with surface observations and deterministic WRF-Solar day ahead forecasts (2018).

MAE comparison of WRF-Solar, NSRDB, and ground Obs.



MAE of WRF-Solar GHI calculated with NSRDB.

MAE of WRF-Solar GHI calculated with ground Obs.

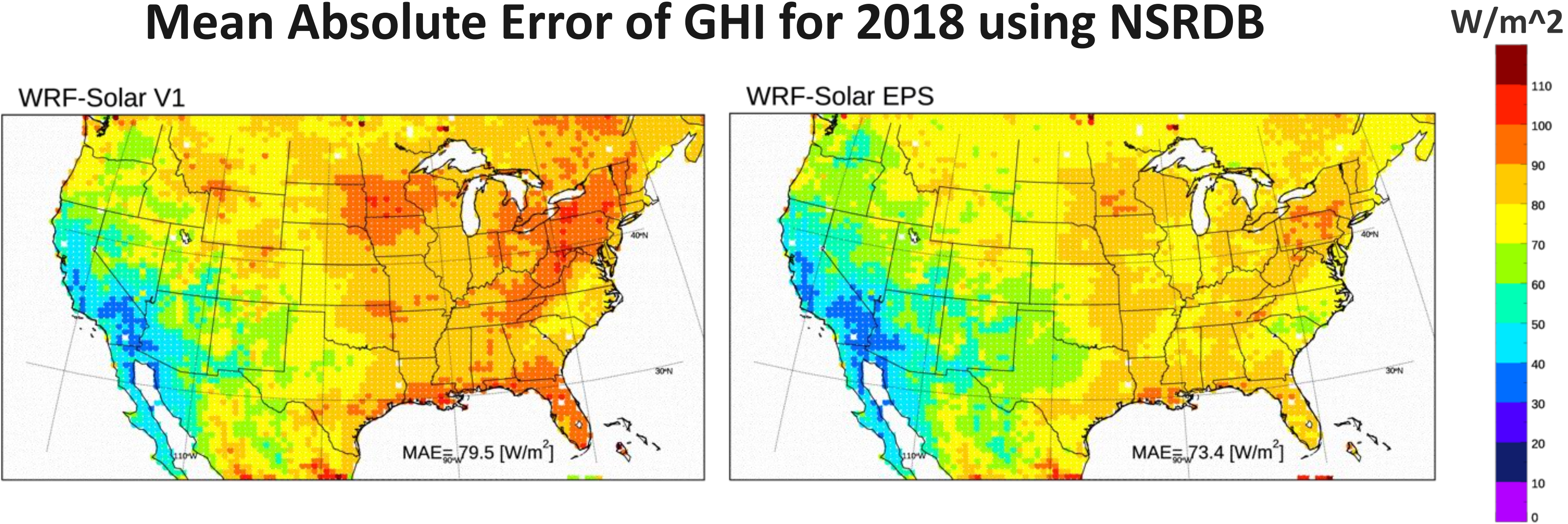


The MAE calculated with NSRDB is within ~5% of high-quality ground observations and reproduces the spatial variability of the error (r = 0.96).

Accuracy of NSRDB is sufficient for WRF-EPS validation.

WRF-Solar v1 vs WRF-Solar EPS

Mean Absolute Error of GHI for 2018 using NSRDB

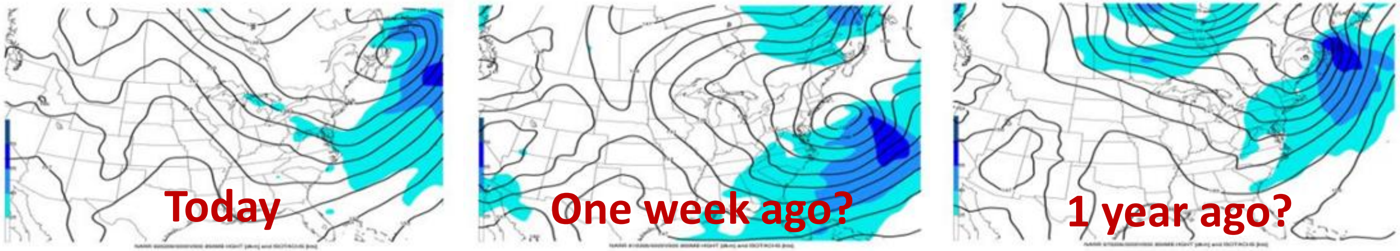


MAE of GHI was reduced by 8% when using WRF-Solar EPS and comparing the day-ahead forecast to baseline WRF-Solar V1.

Ensemble Calibration: Methodology

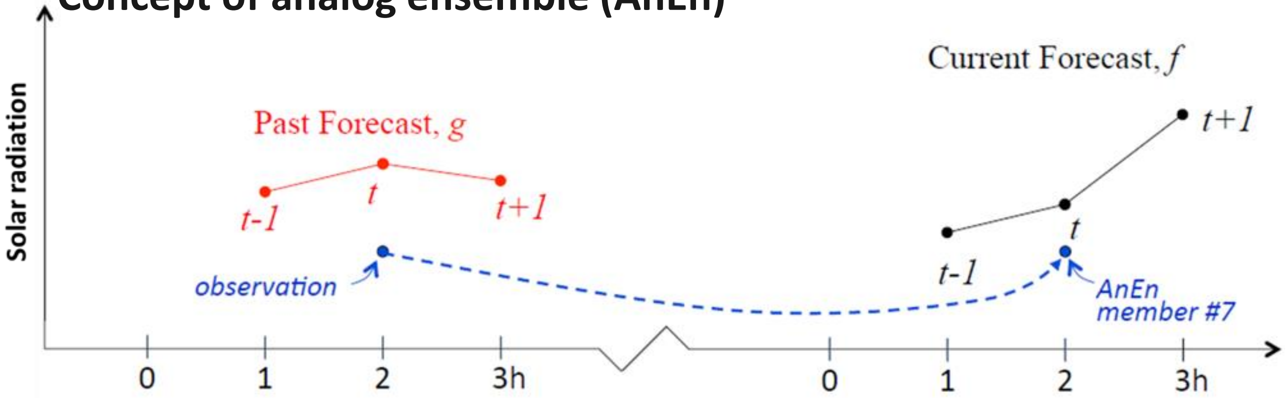
We implemented an analog technique as an ensemble post-processing method to improve the performance of WRF-Solar EPS. High-quality observations are essential to improve solar forecasts.

Basic idea of weather analogs



Can we use this information to improve NWP forecast?

Concept of analog ensemble (AnEn)

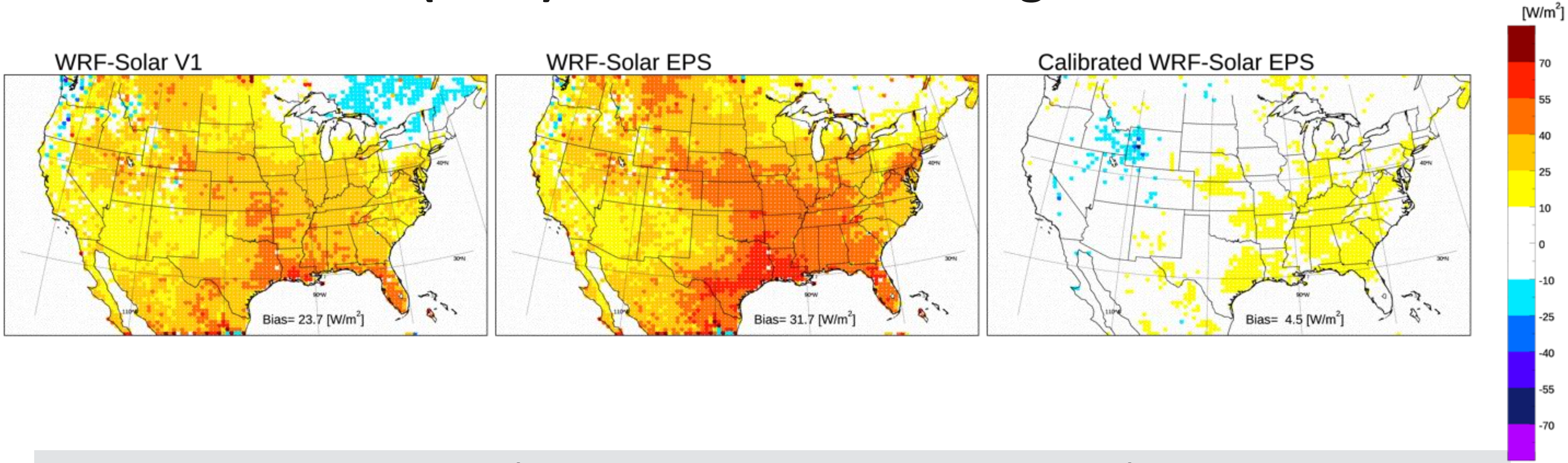


We used **the NSRDB** to calibrate the ensemble forecasts.

Delle Monache et al. 2013

Ensemble Calibration: Results

Mean Bias Error (MBE) of GHI for 2018 using NSRDB



- GHI bias was reduced by 81% (calibrated WRF-Solar EPS vs. WRF-Solar V1).
- GHI bias is approximately 1% compared to NSRDB.
- Forecast bias was reduced for all regions.

Cloud Detection Metrics

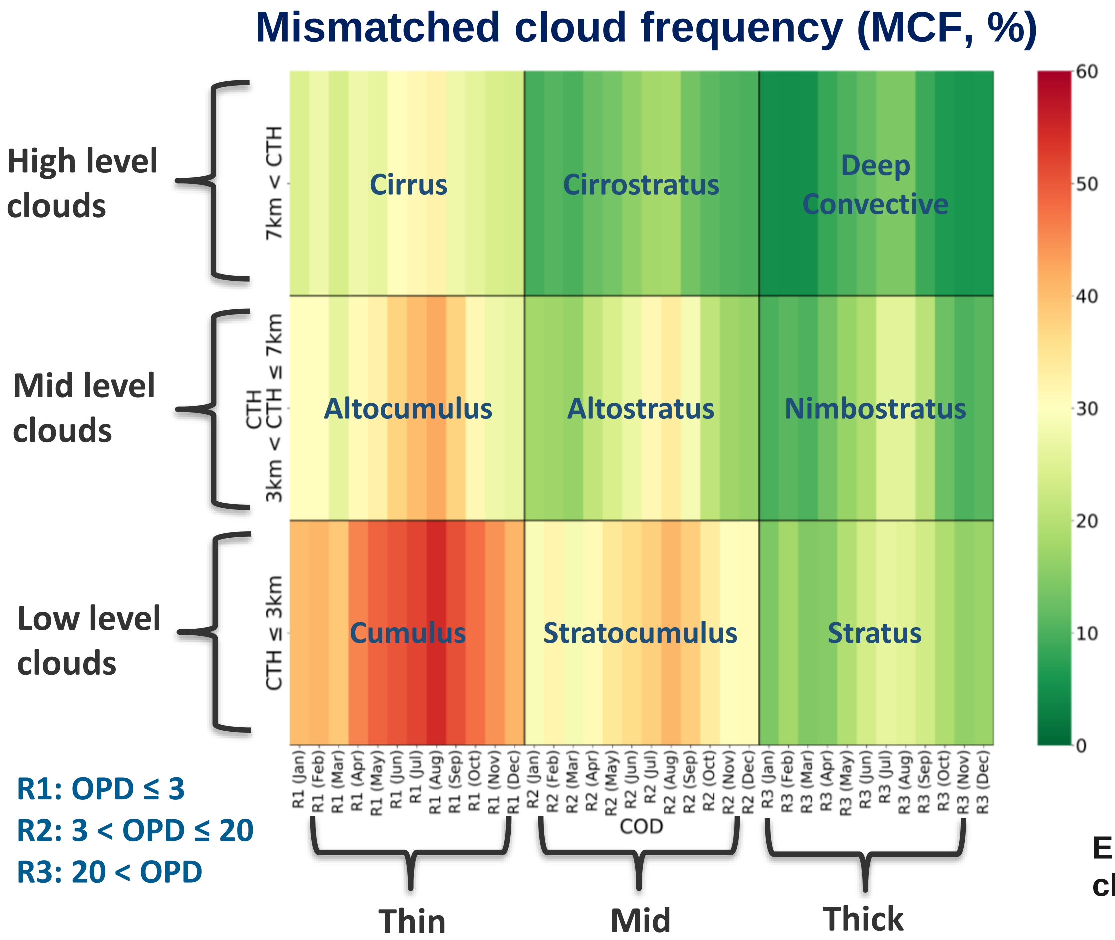
Contingency matrix for the WRF-Solar EPS and NSRDB:

	WRF-Solar EPS (prediction)		
	Scenario	Clear	Cloudy
NSRDB_{9km} (observation)	Clear	a	b
	Cloudy	c	d

Mismatched cloud frequency (MCF)

$$MCF = \frac{c}{c+d} \times 100\%$$

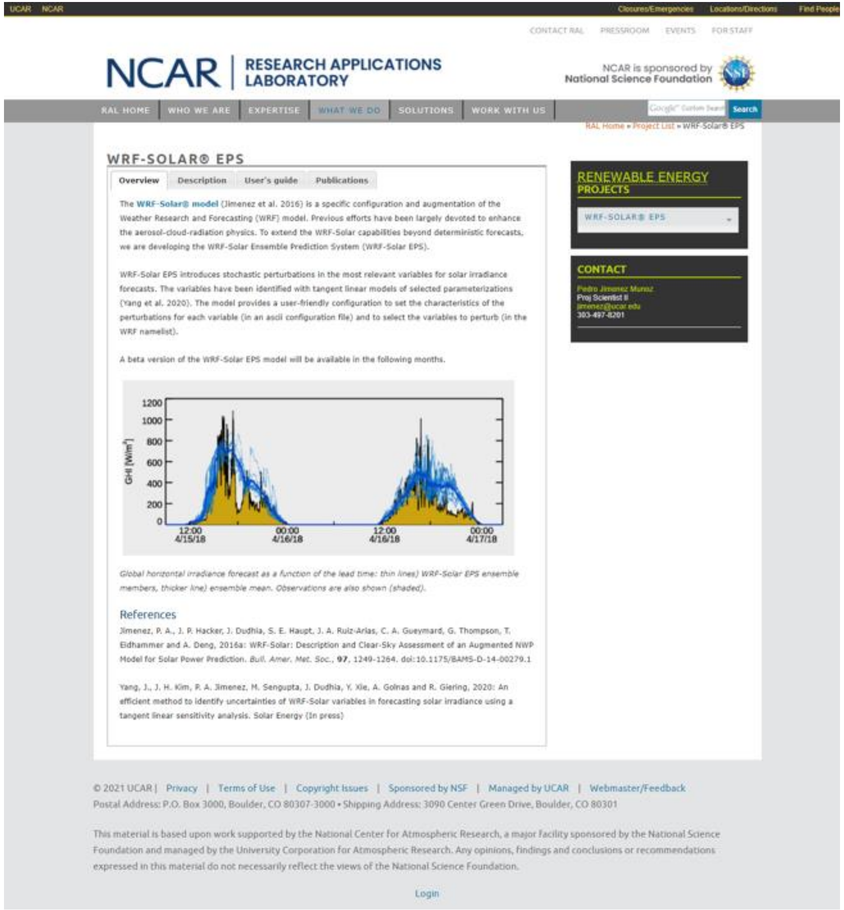
Evaluation of Monthly Cloud Mask Forecast for Different Cloud Types



- We used **EM_{P50}** and analyzed MCF classified in different cloud optical depth (COD) and cloud top height (CTH).
- Given the MCF, WRF-Solar EPS provides accurate forecasts for high-level and thick clouds, whereas low-level and thin clouds cause difficulties in predicting cloud masks from the WRF-Solar EPS.
- There are notable low MCF values for 'Cumulus' category in summer.
- This might be a result of the representation of shallow cumulus clouds using the Deng parameterization in WRF-Solar EPS.
- But note that there are also difficulties in detecting thin and low-level clouds from satellite.

EM_{P50} : Observations are cloudy when cloud fraction from NSRDB is > 50%

WRF-Solar EPS Website



- **WRF-Solar has been incorporated into the official version from WRF v4.4**
- **We have created the website for WRF-Solar EPS (https://ral.ucar.edu/projects/wrf-solar-eps).**

- **This website includes a preliminary overview of WRF-Solar EPS:**

✓ **Description of WRF-Solar EPS**
✓ **User's guide**
✓ **Publications**

Machine Learning-based Solar Forecasting

Era of Large Foundation Models

History of Hybrid NWP AI Models

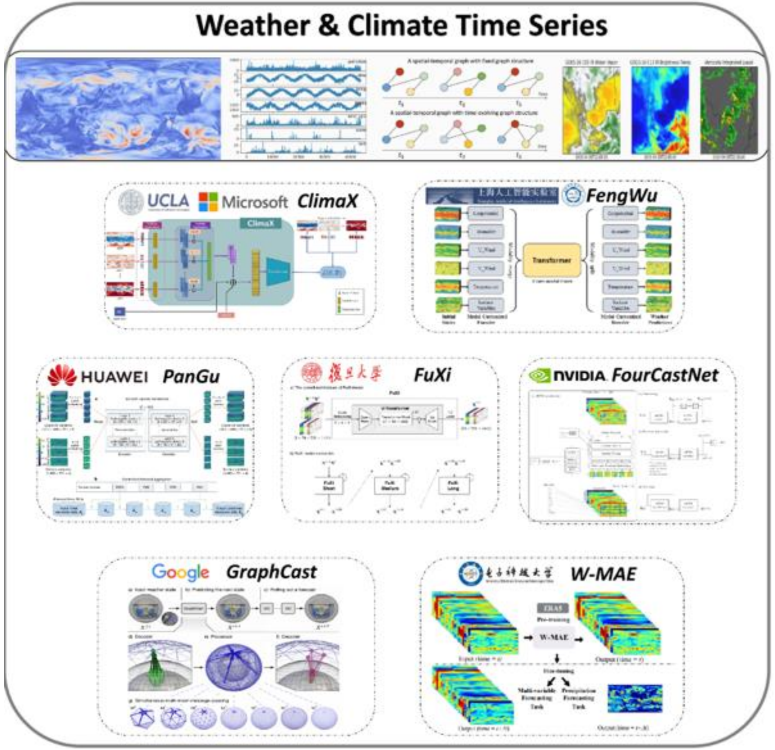
	Current NWP Workflow	Hybrid NWP-ML Workflow	Future End-to-End DL Workflow
	Input: meteorological observation (weather stations, radiosondes, satellites, etc.)		
Pre-processing	Physical feature calculation	Physical feature calculation Machine learning feature engineering	Data preparation
		Pre-processed data	
	3D-/4D- Var + ensemble Kalman filter + Nudging	Machine learning	
	Initial conditions		
Prediction	Dynamical core; Parameterization of non-resolved process	Machine learning	End-to-end Foundational Deep Learning
	Gridded forecasts		
Post-processing	Statistical downscaling	Machine learning downscaling	
		End-user forecasts	

Adapted from Schultz, M.G., Betancourt, C., Gong, B., Kleinert, F., Langguth, M., Leufen, L.H., Mozaffari, A. and Stadtler, S., 2021. Can deep learning beat numerical weather prediction?. *Philosophical Transactions of the Royal Society A*, *379*(2194), p.20200097.

Can deep learning beat NWP – Wave of Foundation Models

Steady progress in NWP development vs. more **disruptive advances** in machine learning

Discussion of the possibility of **completely replacing** current NWP with deep learning?

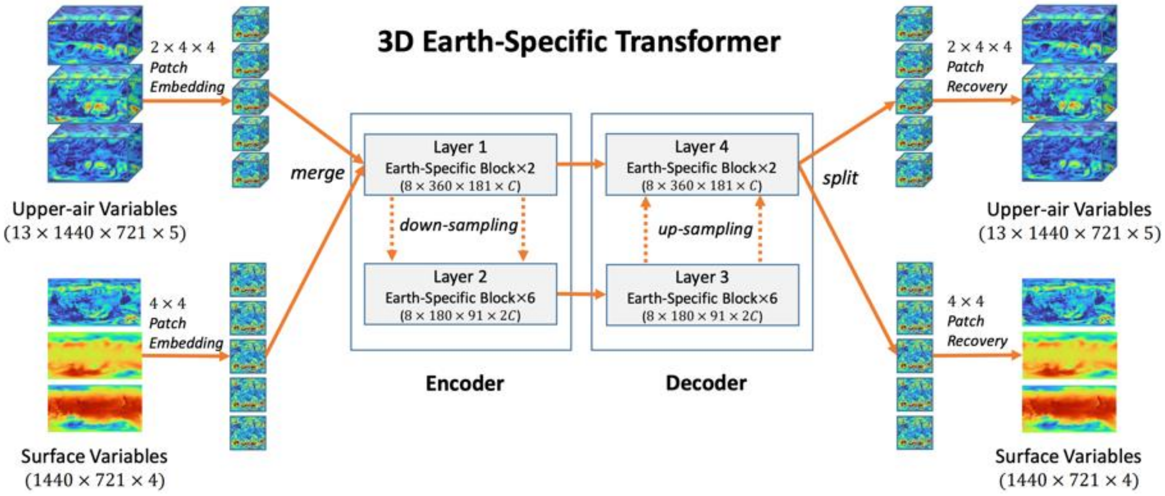


1. Schultz, M.G., Betancourt, C., Gong, B., Kleinert, F., Langguth, M., Leufen, L.H., Mozaffari, A. and Stadtler, S., 2021. Can deep learning beat numerical weather prediction?. *Philosophical Transactions of the Royal Society A*, *379*(2194), p.20200097.
2. Chen, S., Long, G., Jiang, J., Liu, D. and Zhang, C., 2023. Foundation models for weather and climate data understanding: A comprehensive survey. *arXiv preprint arXiv:2312.03014*.

PanGu-Weather: A Case Study

Weather forecasting breakthrough featured in *Nature*[1] and *Science*[2]

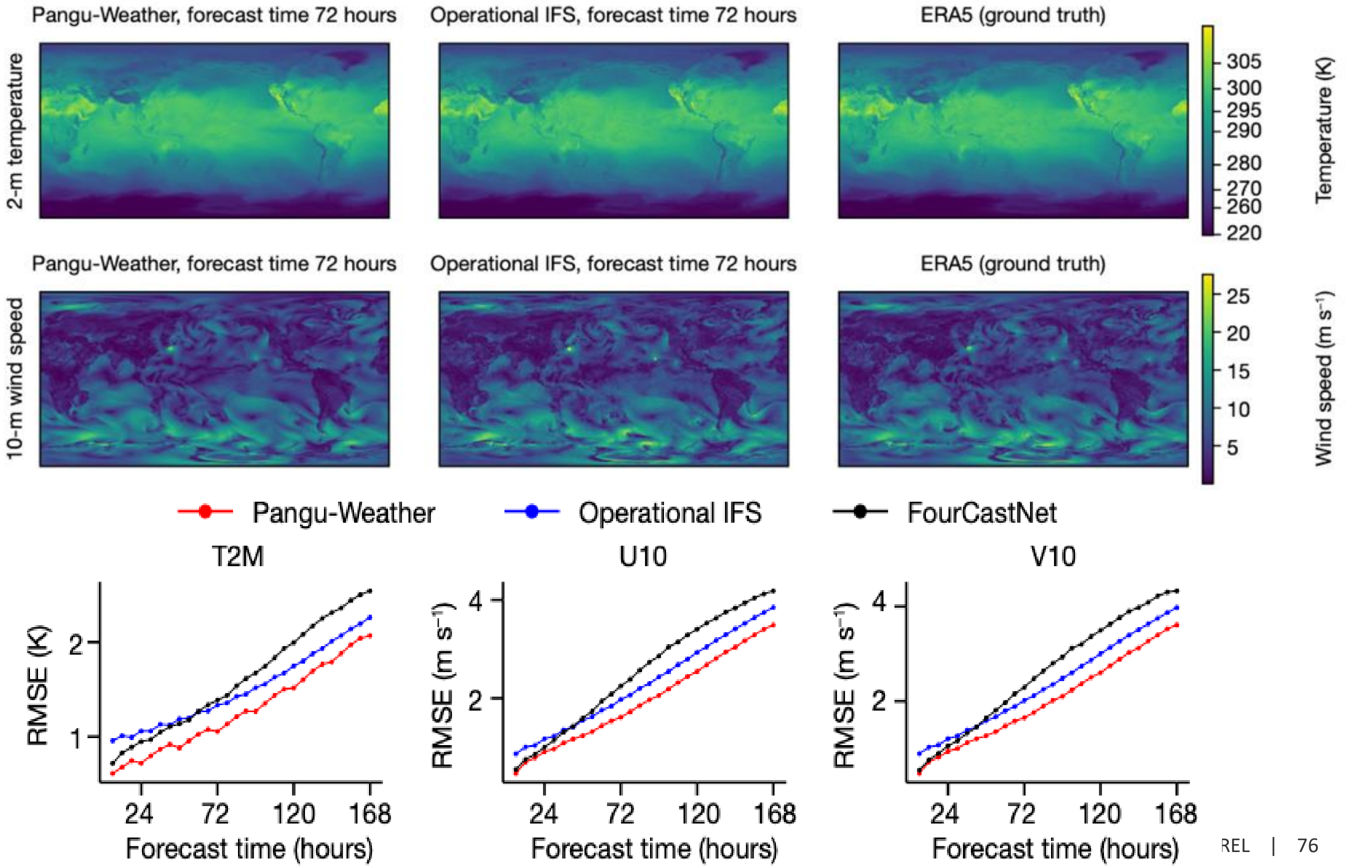
- Global scale
- Medium-range (up to 7-days-ahead)
- Multi-variate output (temperature, wind, but no solar)
- 60 TB ERA5 training data



1. Bi, K., Xie, L., Zhang, H., Chen, X., Gu, X. and Tian, Q., 2023. Accurate medium-range global weather forecasting with 3D neural networks. *Nature*, *619*(7970), pp.533-538.
2. Lam, R., Sanchez-Gonzalez, A., Willson, M., Wirnsberger, P., Fortunato, M., Alet, F., Ravuri, S., Ewalds, T., Eaton-Rosen, Z., Hu, W. and Merose, A., 2023. Learning skillful medium-range global weather forecasting. Science, 382(6677), pp.1416-1421.

Pathway

- **10,000x** faster than NWP in prediction
- **Better accuracy**
  - Normal
  - Extreme



Bi, K., Xie, L., Zhang, H., Chen, X., Gu, X. and Tian, Q., 2023. Accurate medium-range global weather forecasting with 3D neural networks. *Nature*, *619*(7970), pp.533-538.

Limitation and Roadmap

Limitation 1. Data: reanalysis data ≠ solar observation data

Reason 1.1 Lack of high-quality and quantity solar data

Reason 1.2 Lack of easily-accessible solar data

Solution: Create NSRDB-based SolarBench to standardize the AI-based solar forecasting development

Limitation 2. Model: weather forecasting ≠ solar forecasting

Reason 2.1 Out of interests for AI mainstream

Reason 2.2 Challenging due to cloud dynamics

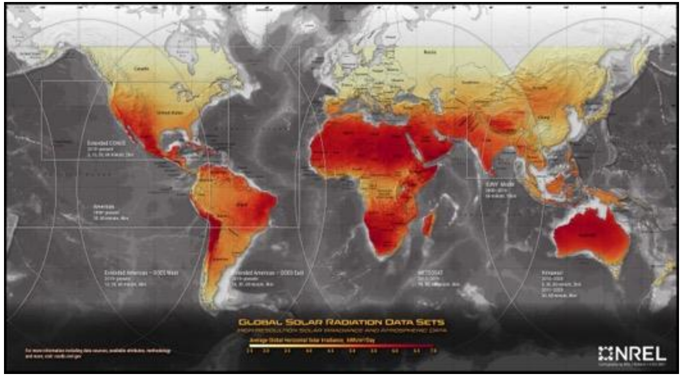
Solution: Lead the effort in developing solar forecasting foundation model

Limitation 3. Evaluation: better accuracy ≠ physic consistency

Reason 3.1 No physics embedded in AI models

Reason 3.2 Lack of physics-based evaluation metrics

Solution: Develop physics-constrained AI for better solar forecasting



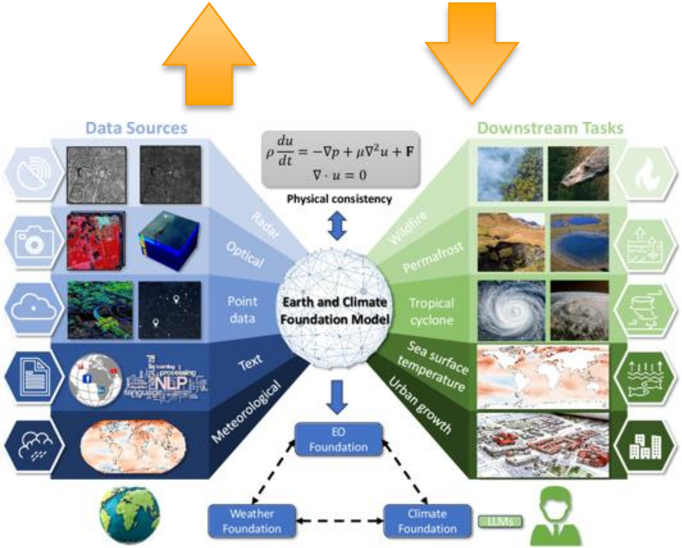


Figure adapted from Zhu, X.X., Xiong, Z., Wang, Y., Stewart, A.J., Heidler, K., Wang, Y., Yuan, Z., Dujardin, T., Xu, Q. and Shi, Y., 2024. On the Foundations of Earth and Climate Foundation Models. *arXiv preprint arXiv:2405.04285*.

Thank you

www.nrel.gov

Contact:

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Cong.Feng@nrel.gov

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NREL Transforming ENERGY

Prediction of Solar Variability by Cloud Type and Cloud Cover at ARM and SURFRAD Sites

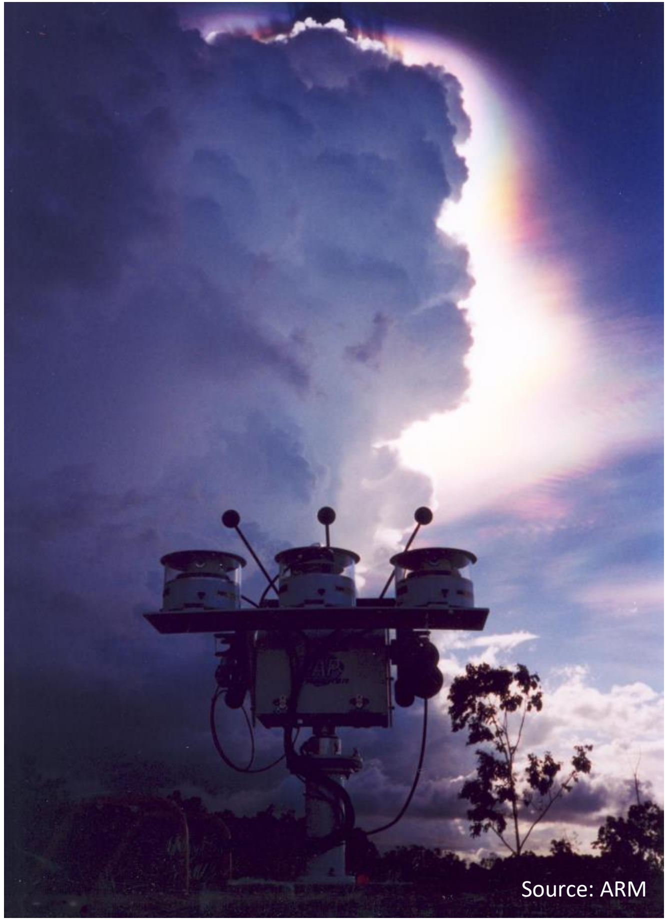
Kelly A. Balmes[1, 2], Laura D. Riihimaki[1, 2], Joseph Sedlar[1, 2],

Kathleen O. Lantz[2], David D. Turner[3]

[1]CIRES/University of Colorado Boulder

[2]NOAA Global Monitoring Laboratory

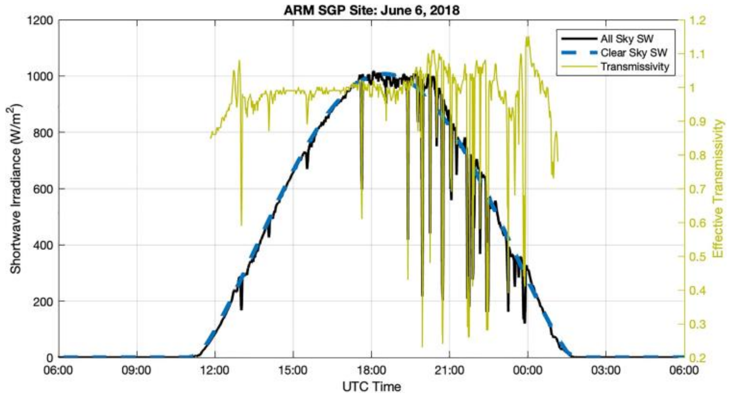
[3]NOAA Global Systems Laboratory



GRAD GML RADIATION, AEROSOL, AND CLOUD DIVISION   CIRES   University of Colorado **Boulder**   NOAA

Introduction

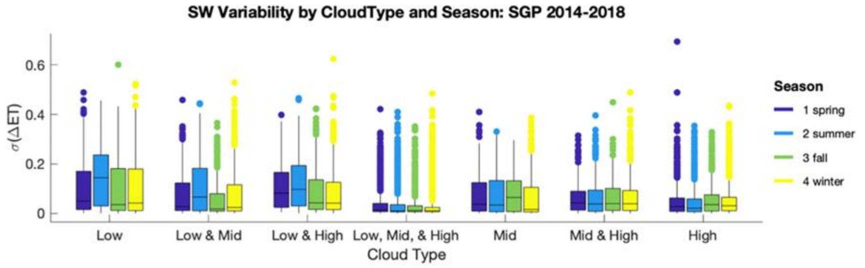
- Riihimaki et al. (2021) built relationship from observations that can be used to diagnose surface shortwave (SW) irradiance variability from model output
  - Variability depends strongly on cloud type and cloud cover
  - Observations from DOE Atmospheric Radiation Measurement Program (ARM) Southern Great Plains (SGP) site in Oklahoma

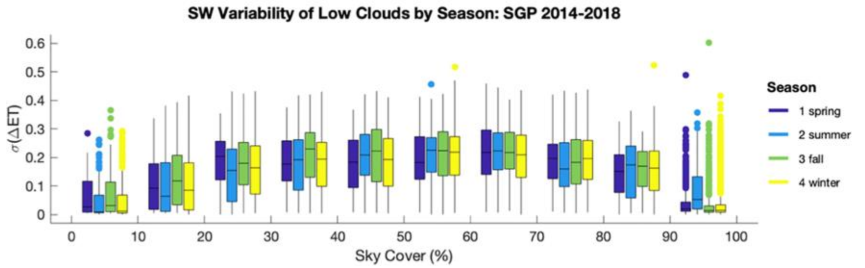


$$Effective\ transmissivity = \frac{All - sky\ SW\ flux}{Clear - sky\ SW\ flux}$$

Introduction

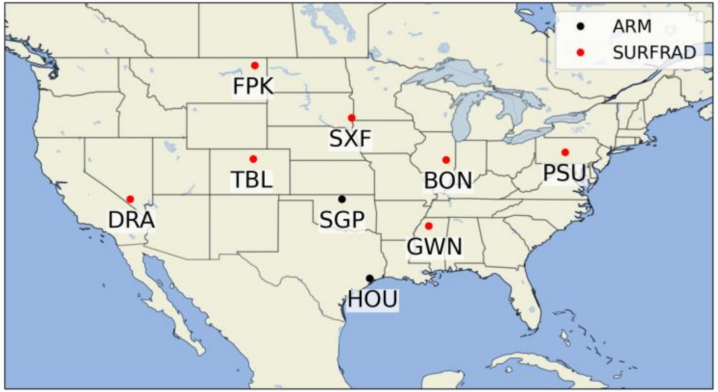
- Riihimaki et al. (2021) built machine learning (ML) model to predict solar variability
- Seasonal analysis suggests the relationship is relatively weather regime and location independent
  - Need to further test at additional sites





Evaluation of Riihimaki et al. (2021)

- The evaluation of the ML model in Riihimaki et al. (2021) is extended to 25 years at ARM SGP and to other ARM sites globally
- Evaluation is also tested at NOAA's Surface Radiation Network (SURFRAD)

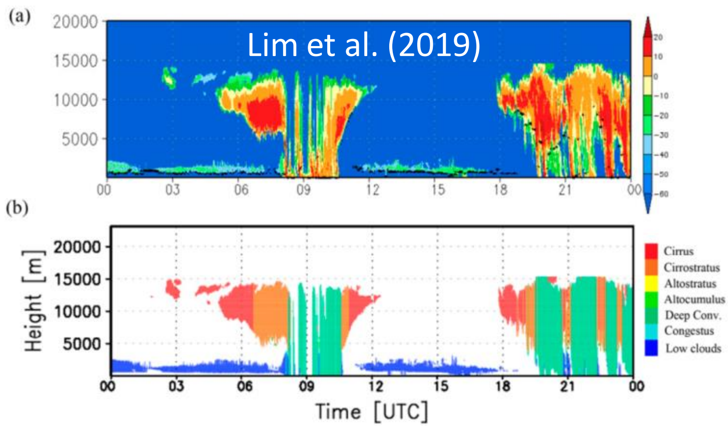


University of Colorado **Boulder**

NOAA

Data - ARM observations

- Solar variability: all-sky and clear-sky SW fluxes from RADFLUX
- Cloud cover: cloud fraction from RADFLUX
- Cloud type: CLDTYPE data product (Lim et al., 2019)
  - Cloud types include low cloud, congestus, deep convection, altocumulus, altostratus, cirrostratus/anvil, and cirrus
  - Cloud types simplified into low, mid, high clouds



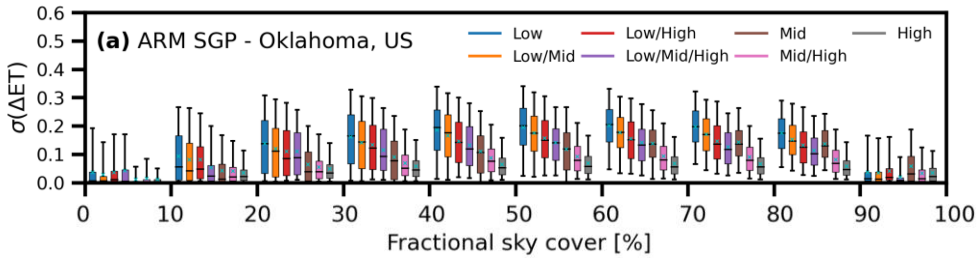
Data - SURFRAD observations

- Solar variability: all-sky and clear-sky SW fluxes from RADFLUX
- Cloud cover: cloud fraction from RADFLUX
- Cloud type: identified by random forest model based on observational inputs (Sedlar et al., 2021)
  - Cloud types include low stratiform, low cumulus, congestus/deep convection, high cirrostratus/anvil, high cirrus, and multi-level (low-high, low-mid, and mid-high)
  - Cloud types simplified into low, mid, high clouds

University of Colorado Boulder

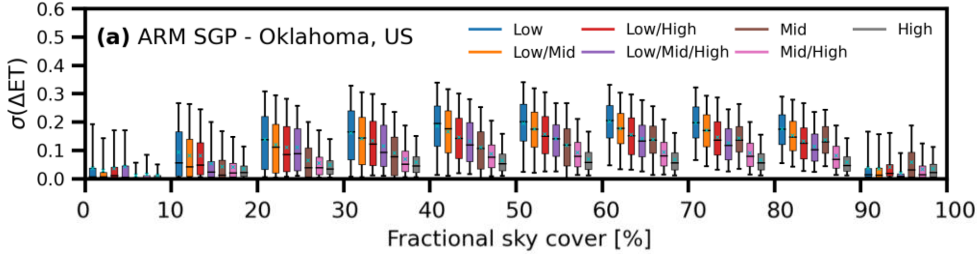
ARM, SURFRAD solar variability observations

- Solar variability metric: $\sigma(\Delta ET)$
  - standard deviation of the minute to minute change in ET over 15 min



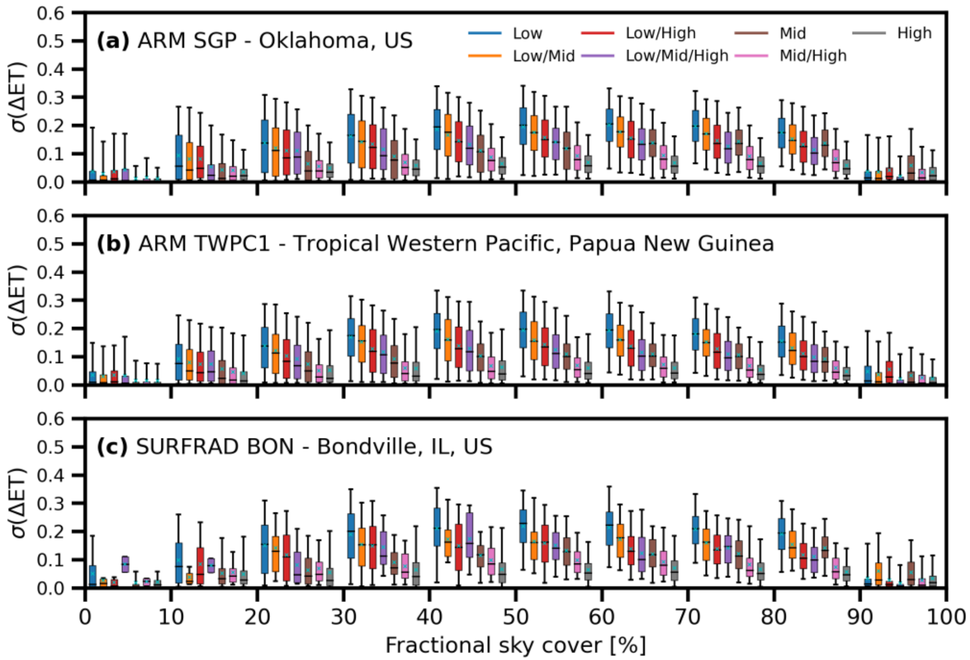
ARM, SURFRAD solar variability observations

- Solar variability metric: $\sigma(\Delta ET)$
  - standard deviation of the minute to minute change in ET over 15 min
- $\sigma(\Delta ET)$ is larger for low cloud and smallest for high cloud
- $\sigma(\Delta ET)$ is largest for partial cloudy skies



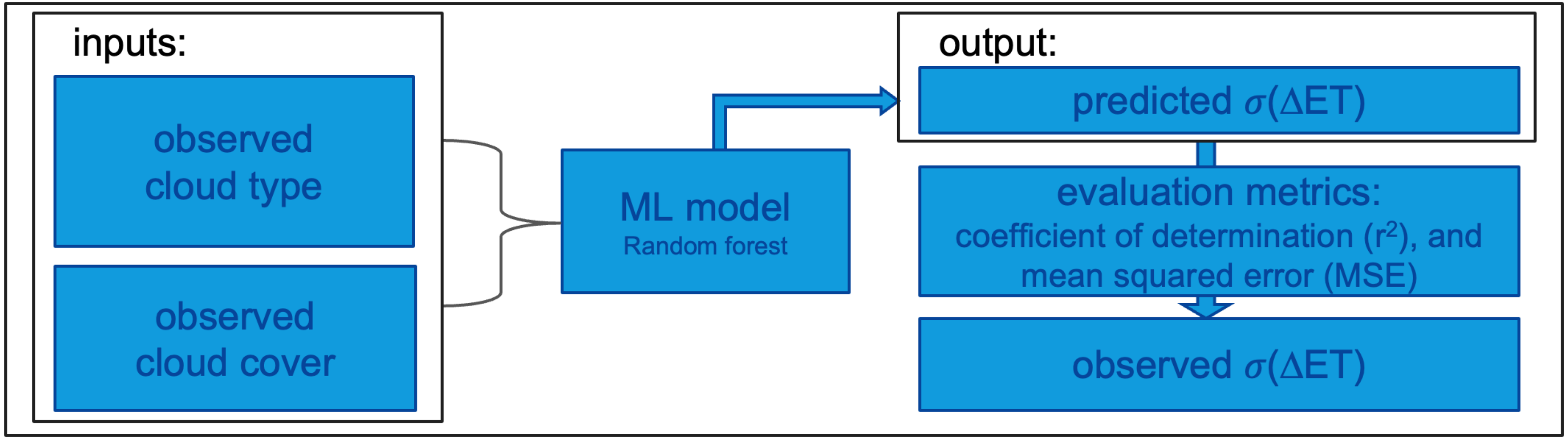
ARM, SURFRAD solar variability observations

- Solar variability metric: $\sigma(\Delta ET)$
  - standard deviation of the minute to minute change in ET over 15 min
- $\sigma(\Delta ET)$ is larger for low cloud and smallest for high cloud
- $\sigma(\Delta ET)$ is largest for partial cloudy skies
- Similar features noted across ARM and SURFRAD sites



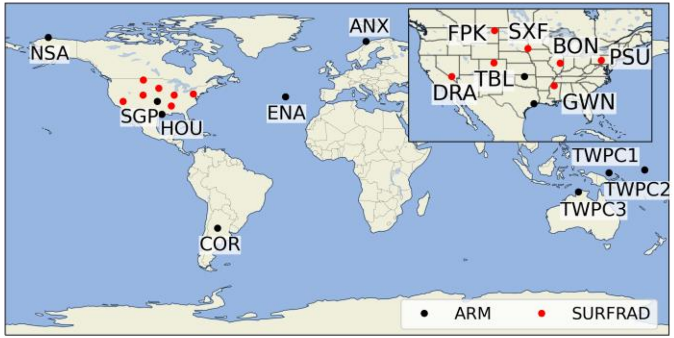
Methods

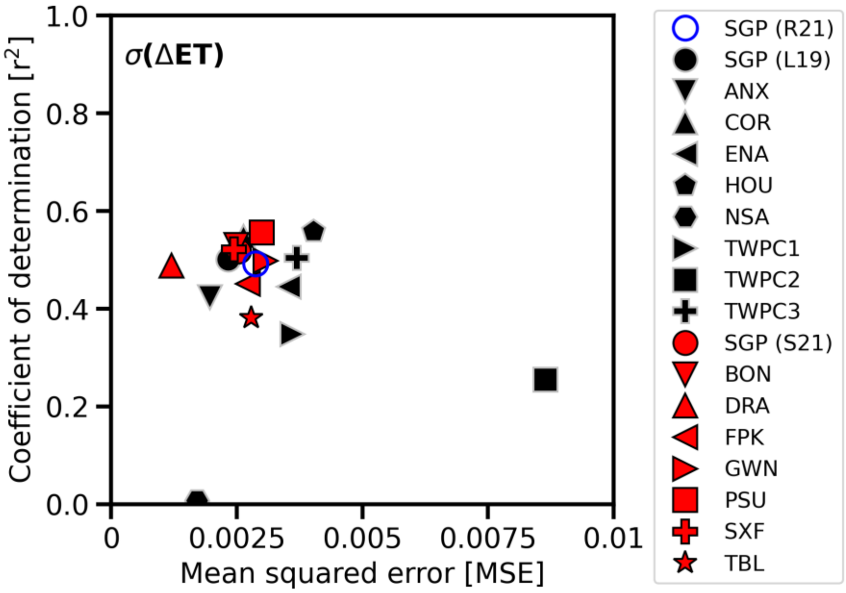
- Observed cloud type and cloud cover are inputted into the ML model to predict $\sigma(\Delta ET)$ and then evaluated against observations of $\sigma(\Delta ET)$



Results

- Solar variability predictability is largely generalizable





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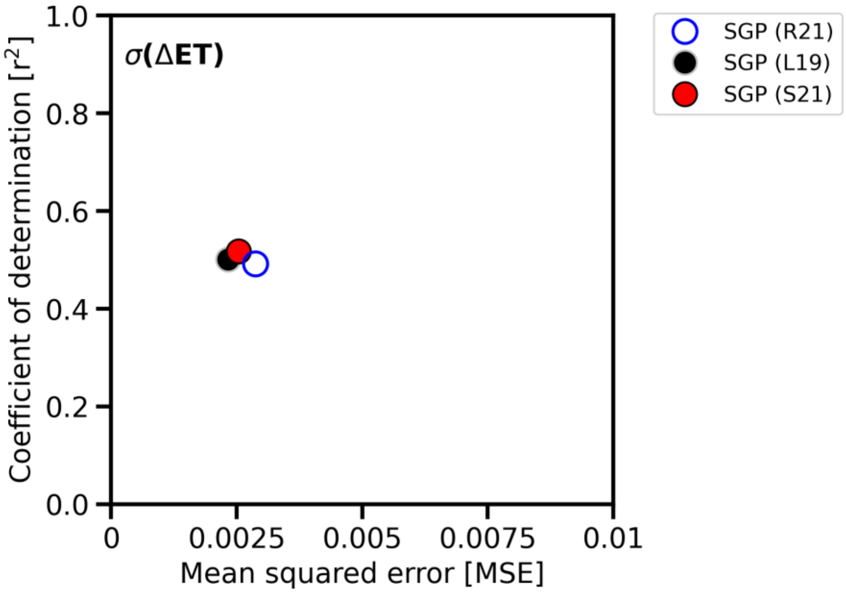
Results at SGP

- Similar r^2 and lower MSE found for SGP compared to those in Riihimaki et al (2021), which indicates that the results are:
  - independent of cloud cover product
  - not due to overfit data
- Similar results are found when using the ARM or SURFRAD cloud types



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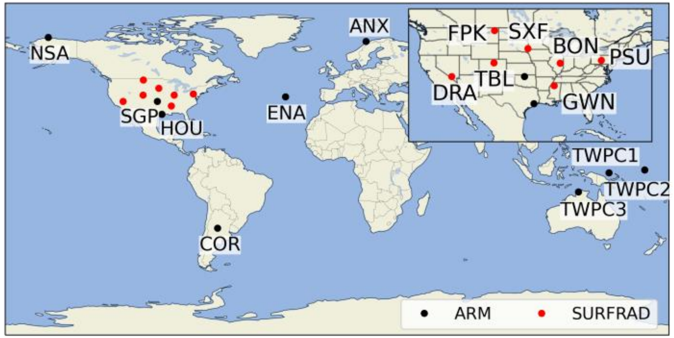
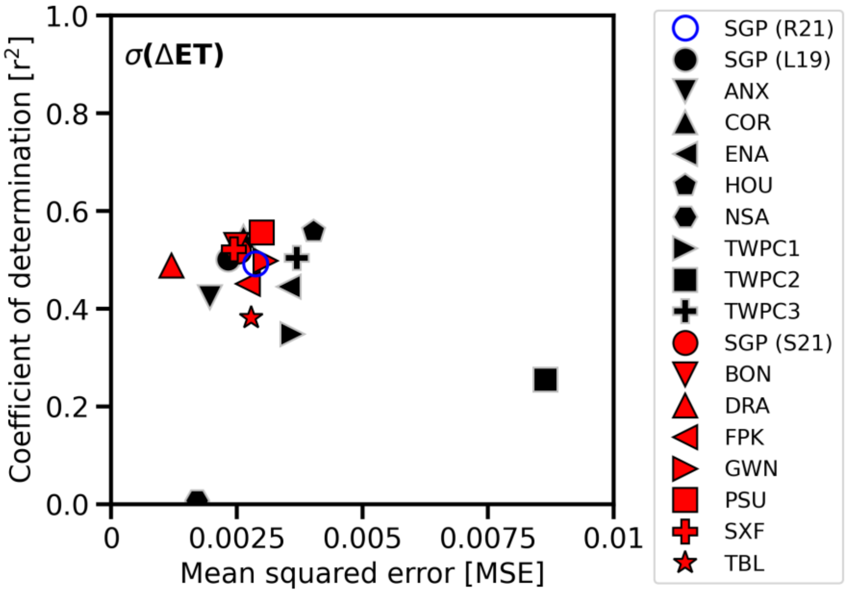
Results at SURFRAD sites

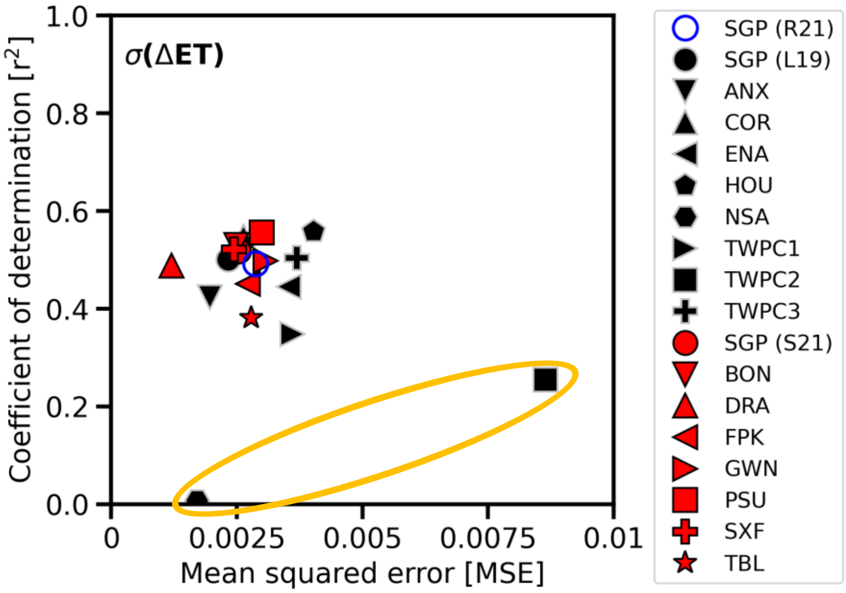
- SURFRAD performance is similar to ARM performance



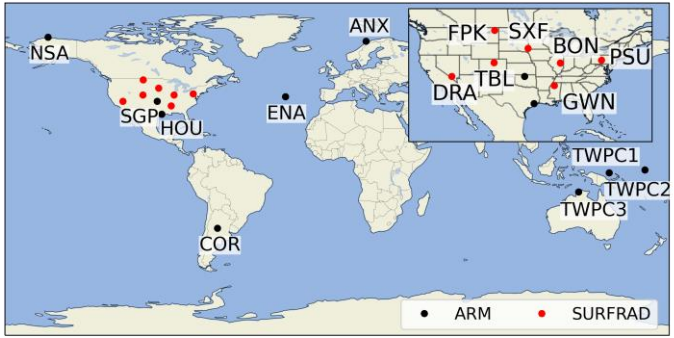


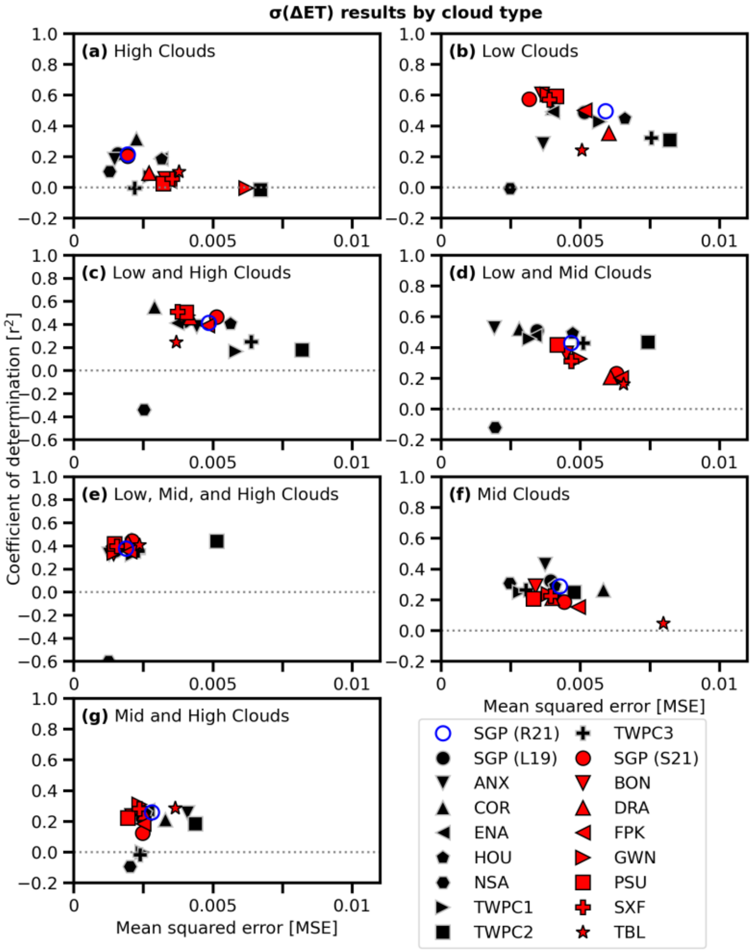
Predictability is less for some locations

- Nauru Island (TWPC2) has largest MSE
- North Slope of Alaska (NSA) has the lowest r^2



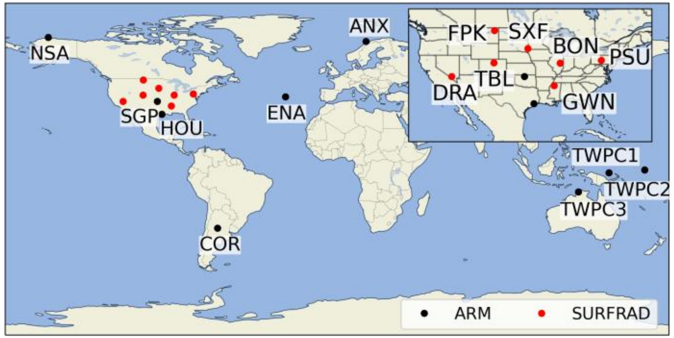
Results by cloud types

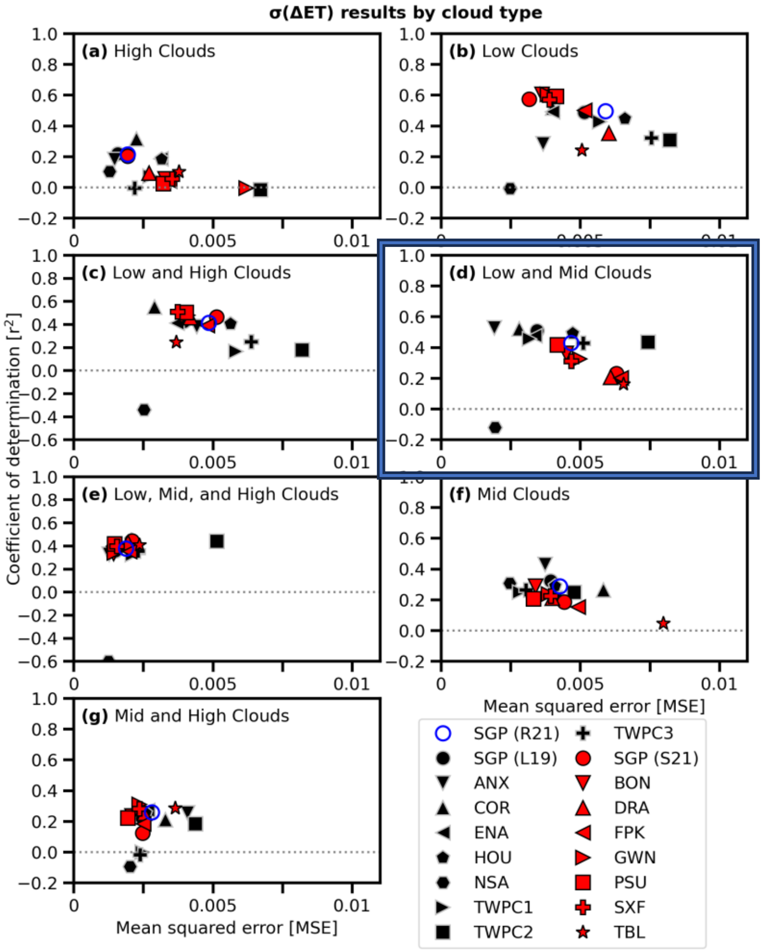




Results by cloud types

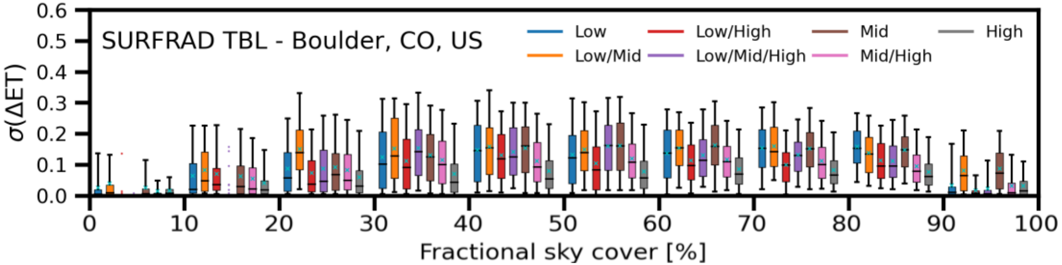
- SURFRAD performance is worse for low and mid clouds

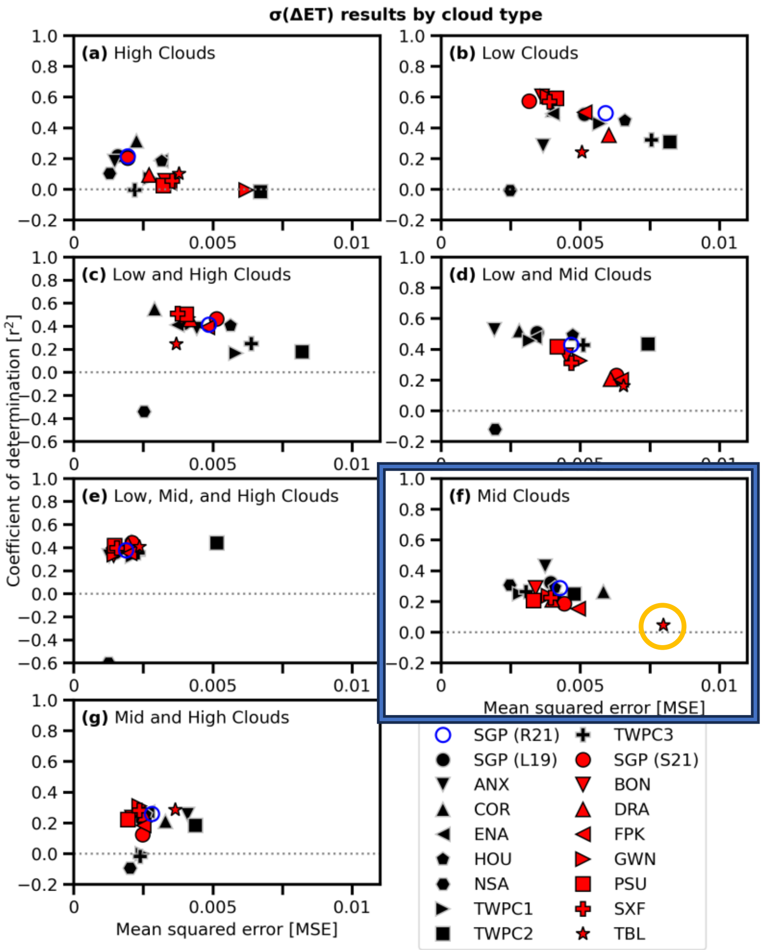




Results by cloud types

- SURFRAD performance is worse for low and mid clouds
- Mid cloud variability is higher relative to low clouds at NSA and Boulder (TBL) for partial cloudy skies, which impacts predictability





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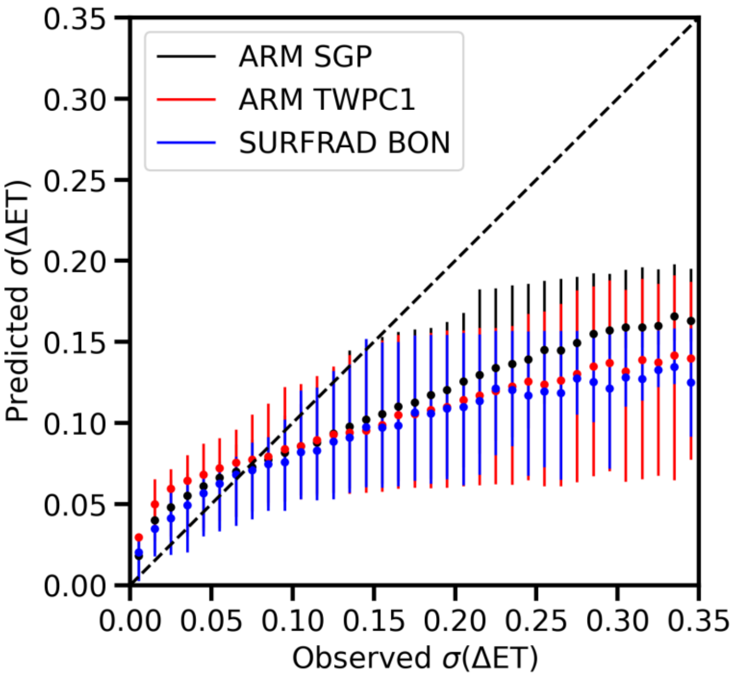
Results by observed variability

- Predicted $\sigma(\Delta ET)$ slightly overestimates for low observed $\sigma(\Delta ET)$ but underestimates for high observed $\sigma(\Delta ET)$



Summary

- Solar variability predictability from Riihimaki et al. (2021) are generalizable to other locations
- Solar variability predictability is robust to different cloud type and cloud cover observations
- Predictability is lower for certain locations and cloud types

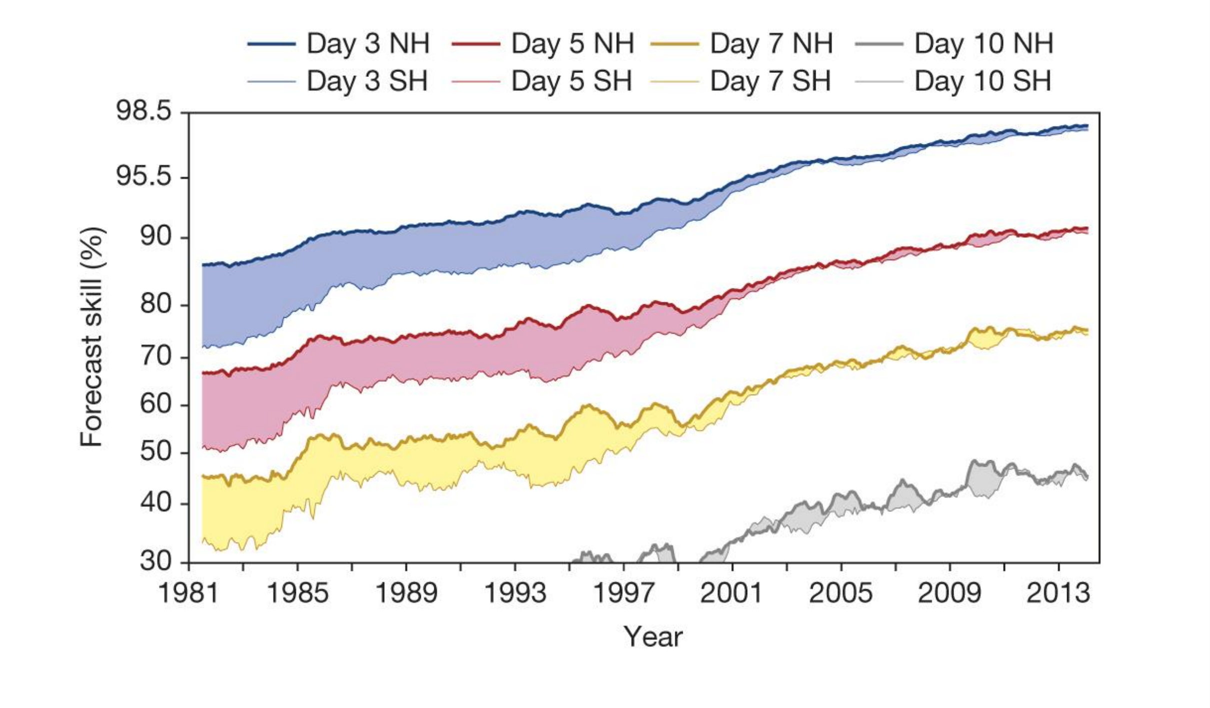
Next steps:

- Improve model to handle very low/high variability cases
- Develop diagnostic from forecasted cloud type and cloud cover to generate day-ahead solar variability estimates

The AI Revolution in Weather Forecasting

Hendrik F. Hamann
Chief Science Officer
IBM Research
hendrikh@us.ibm.com

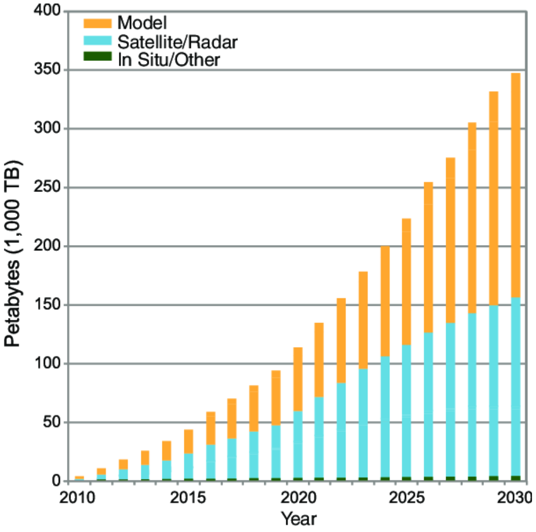
The History of simulation-based weather forecasting is truly impressive



P Bauer *et al. Nature* 525, 47-55 (2015) doi:10.1038/nature14956

Massive observational data and high-performance computing contributed to the success of simulation-based weather predictions

Massive observational data

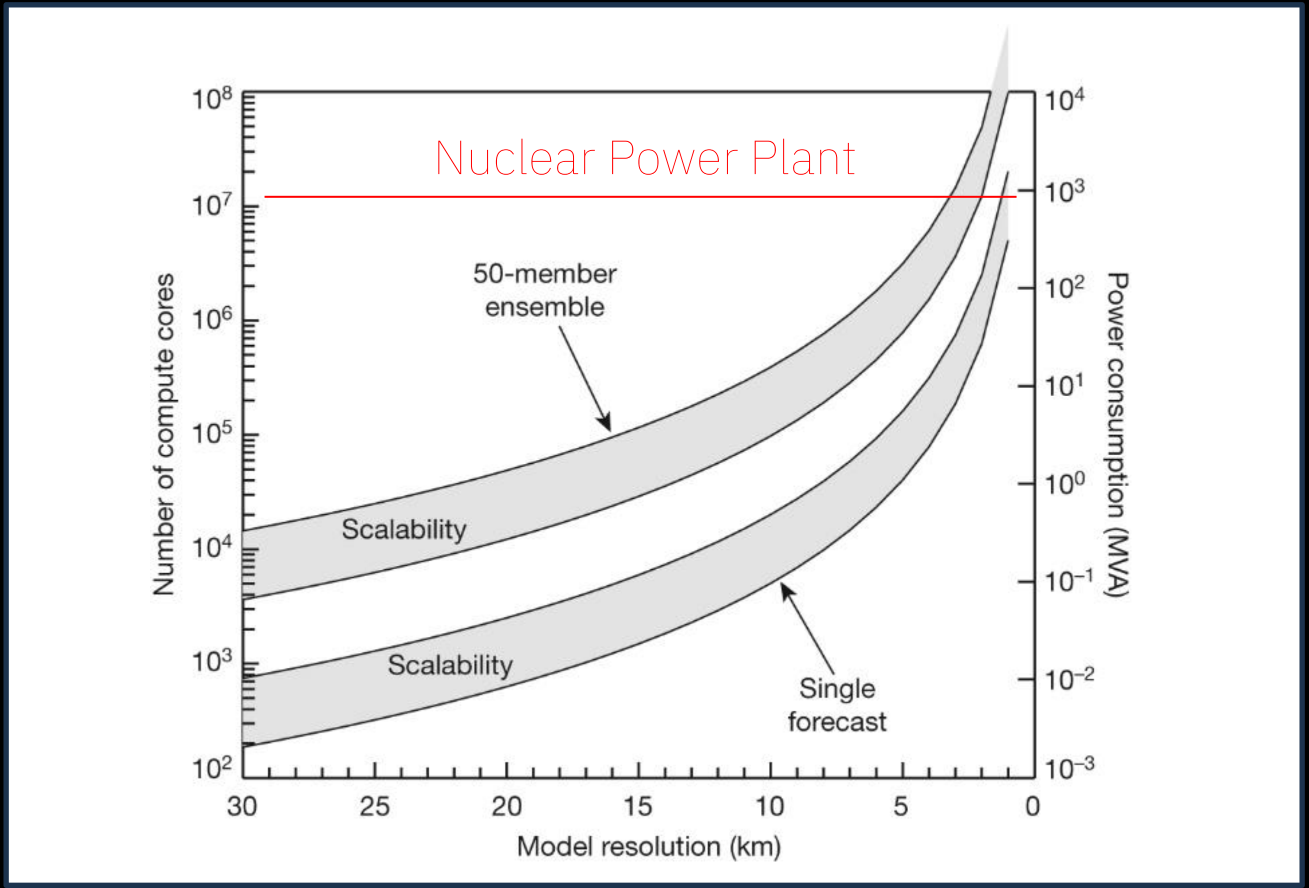


Overpeck, Jonathan & Meehl, Gerald & Bony, Sandrine & Easterling, David. (2011). Climate Data Challenges in the 21st Century. Science (New York, N.Y.). 331. 700-2. 10.1126/science.1197869.

High performance compute

The Atos high-performance computing facility in ECMWF's data centre in Bologna, Italy.

Is this scalable?



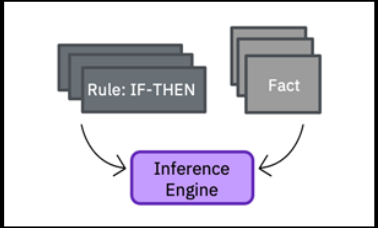
P Bauer *et al.* *Nature* 525, 47-55 (2015) doi:10.1038/nature14956

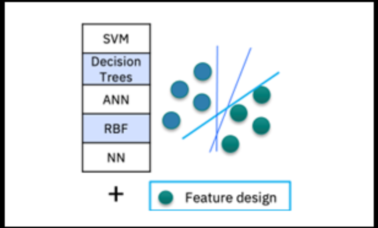
AI/ML is progressing with Foundation Models emerging

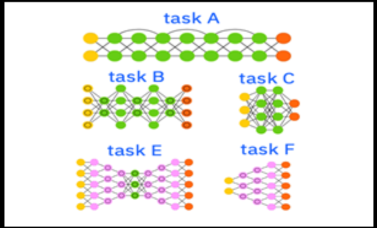
80s | Big data

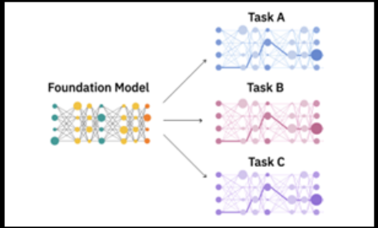
80s to ~2010 | Massive data + Compute

2010 -2017+ | Self-supervision at scale + Massive data + Compute









Expert Systems
Hand-crafted symbolic representations

Machine Learning
Task-specific hand-crafted feature representations

Deep Learning
Task-specific learnt feature representations

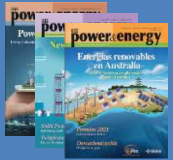
Foundation Models
Generalizable & adaptable learnt representations

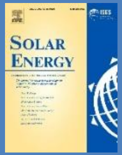
How do Foundation Models work? Three steps are involved

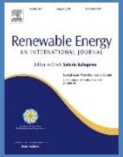
Computational speed

3. Inference and operationalize

2. Finetuning using specific labels/data

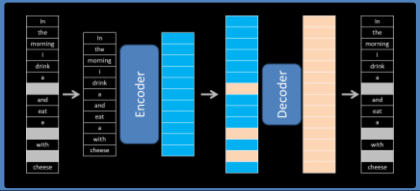






1. Pertaining using self-supervision with attention networks

In the morning, I drink a [redacted] and eat a [redacted] with crème cheese.



In the morning, I drink a coffee and eat a bagel with crème cheese.

AI Foundation models are taking the world by storm

One base model + Less label + Better or similar accuracy + Faster development =

Economy of scale

Bommasani et al. (2021). On the Opportunities and Risks of Foundation Models.

Foundation Models salient features

Salient Features

Excellent “next” token prediction skill

Homogenization and adaptability

Accelerate simulations

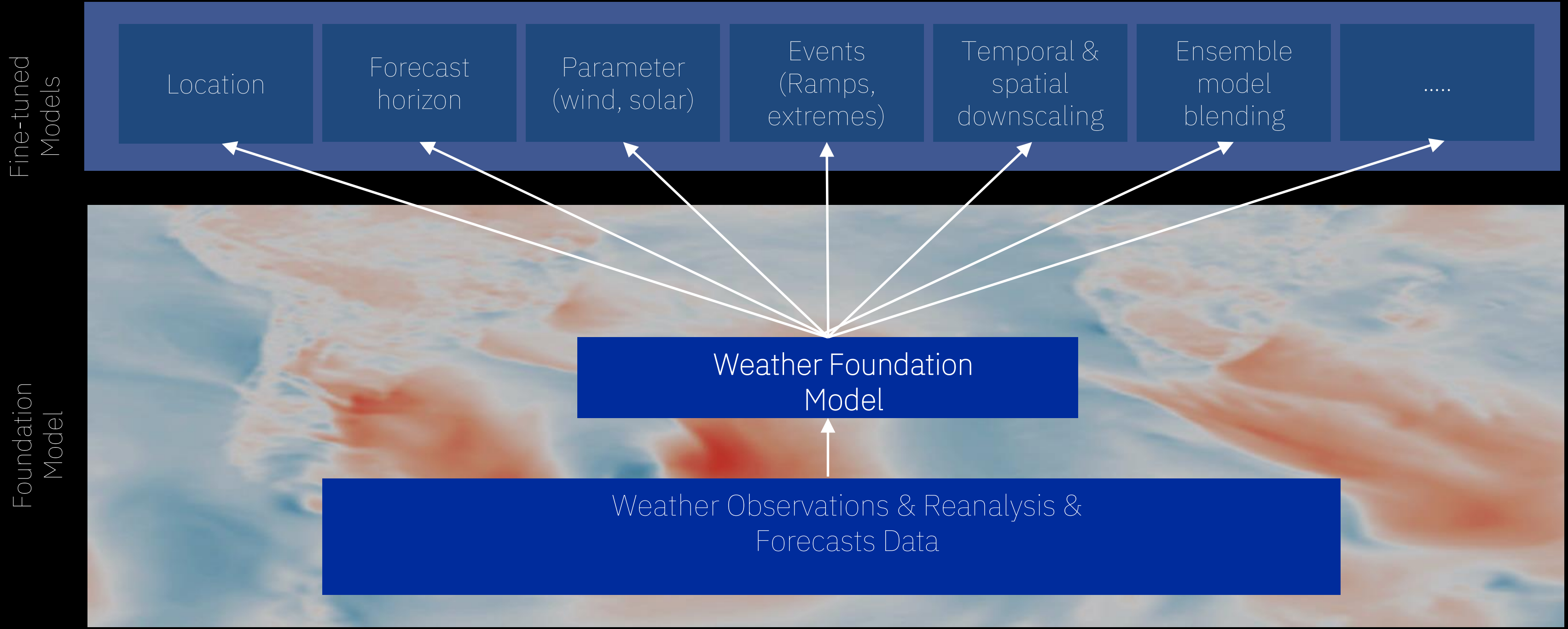
Foundation Models salient features

Salient Features		Enabling technology
Excellent “next” token prediction skill	←	Attention networks & transformers
Homogenization and adaptability	←	Self-supervised learning
Accelerate simulations	←	Deep networks (to directly map inputs to outputs)

Foundation Models salient features

Salient Features		Enabling technology		Benefit
Excellent “next” token prediction skill	←	Attention networks & transformers	→	Excellent forecasting skills
Homogenization and adaptability	←	Self-supervised learning	→	Readily scalable to many applications
Accelerate simulations	←	Deep networks (to directly map inputs to outputs)	→	Higher resolution & richer ensembles

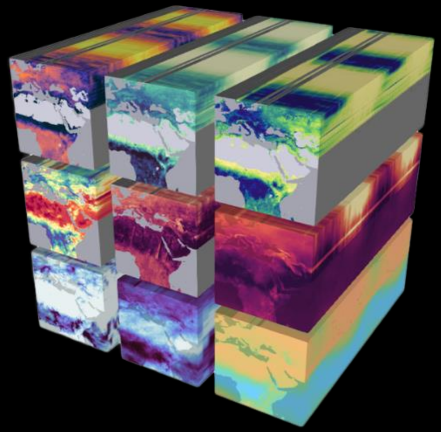
Developing Weather Foundation Models



Development partners

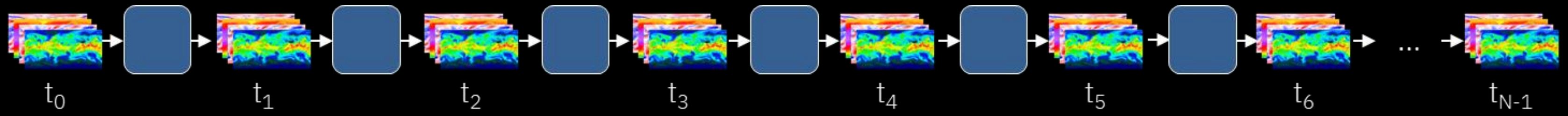
NASA
horizon europe
Environment and Climate Change Canada
Environnement et Changement climatique Canada
OAK RIDGE National Laboratory

Some key technical challenges

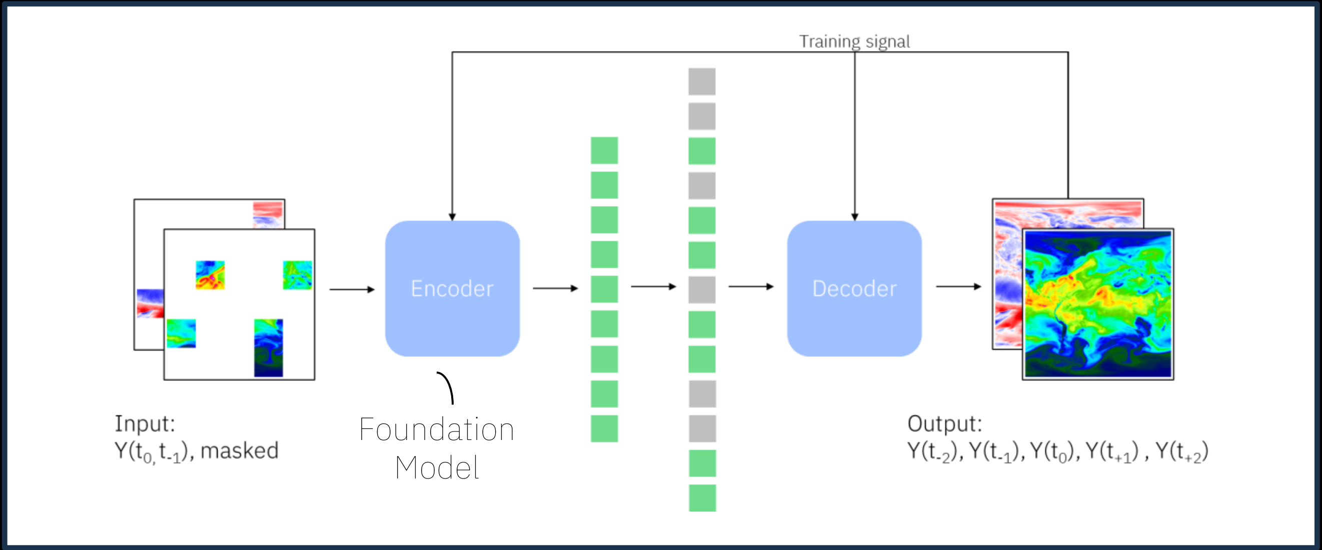


Typical ERA5 subset
0.25 degrees resolution, 37 levels, 6 parameters
721 x 1440 x 37 x 6 x 32 bit = 922 MB / timestamp

- **Data volumes** Sample volumes of 250 MB – 2 GB are common.
- **Token counts** Most models use small tokens (2x2 pixels; 4x4 pixels). Even 2D tokenization schemes push beyond conventional ViT architectures.
- **Stability** Forecasts are typically made via autoregressive rollouts. Numerics need to be stable.
- **Performance** Models compare to HPC simulations.



Pre-training a weather Foundational Model



Input data

- Time-dependent inputs use 2 timestamps. Vertical, temporal and parameter dimensions are all stacked.
- Pretrained on 40-years of MERRA2 data.

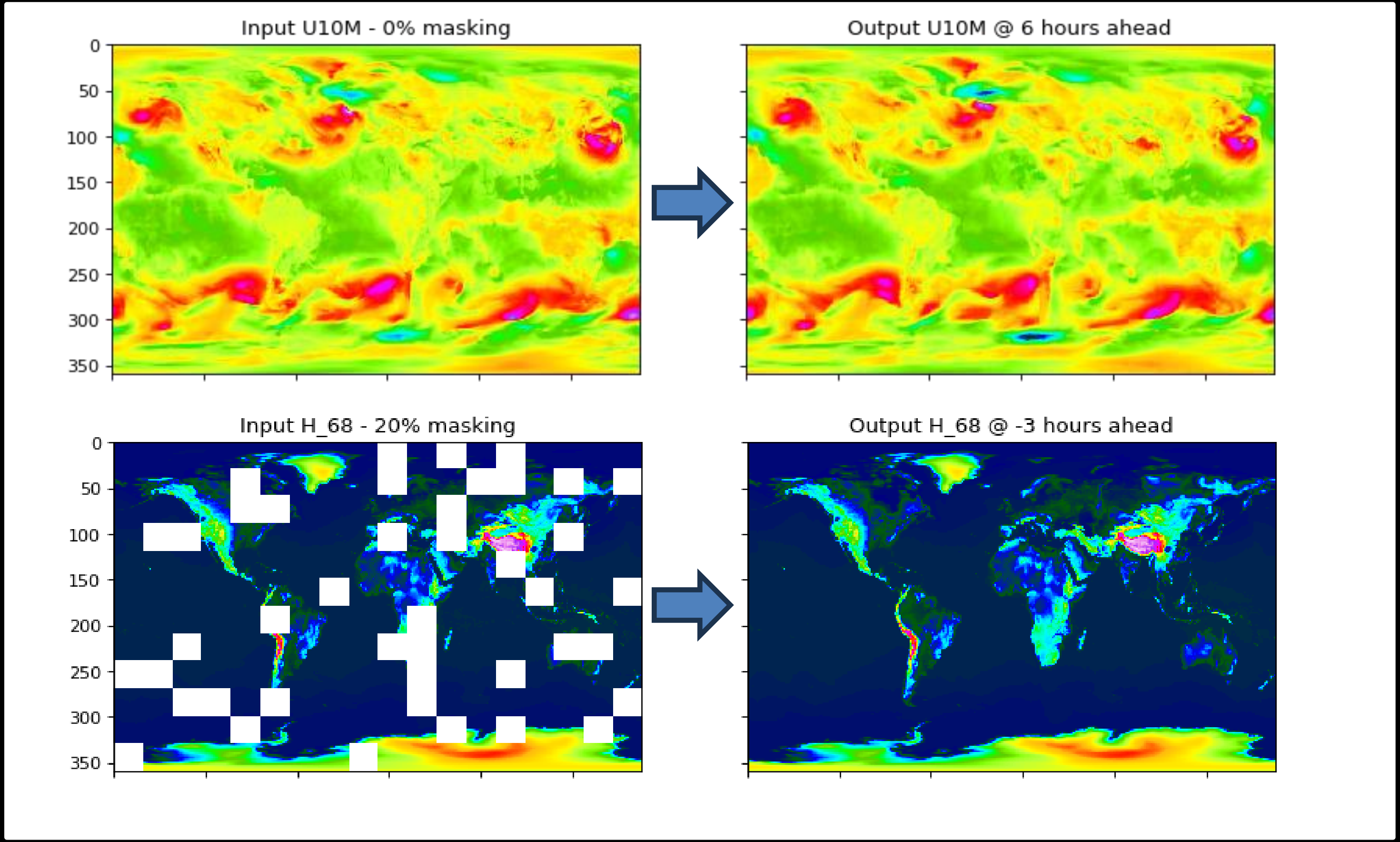
Pre-training task

- Masked pretraining and “forecasting”.

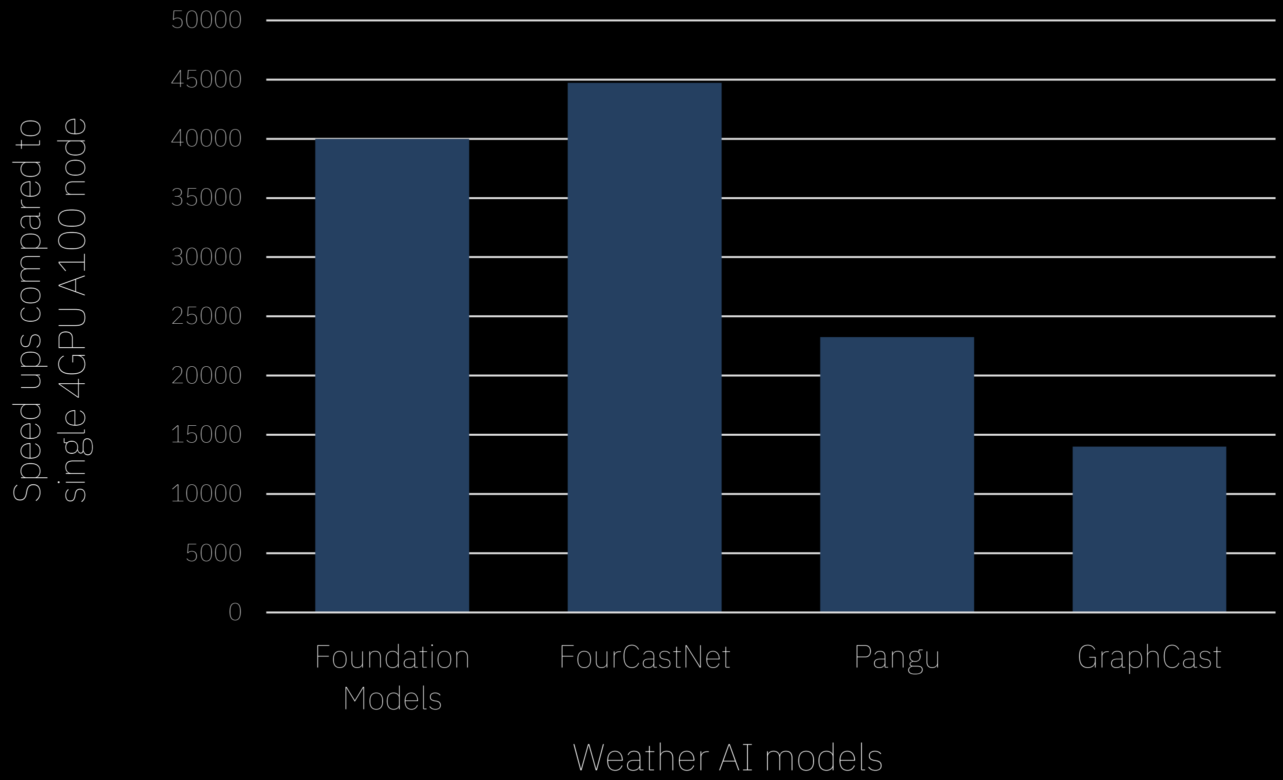
Other key features

- 2D hierarchical vision transformer
- Trained on 51,800 tokens
- Encoder/decoder are fully attention based.
- All auxiliary information (e.g. lead time) injected via context tokens.

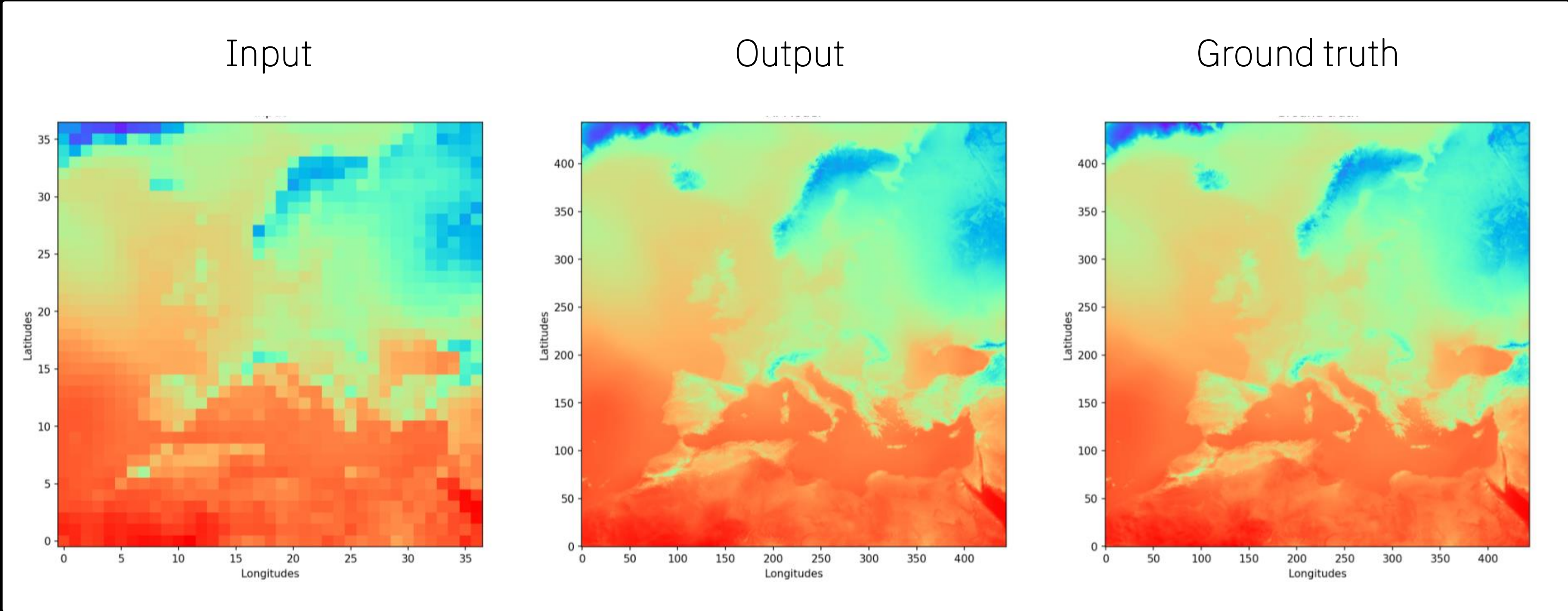
Pre-training / inference



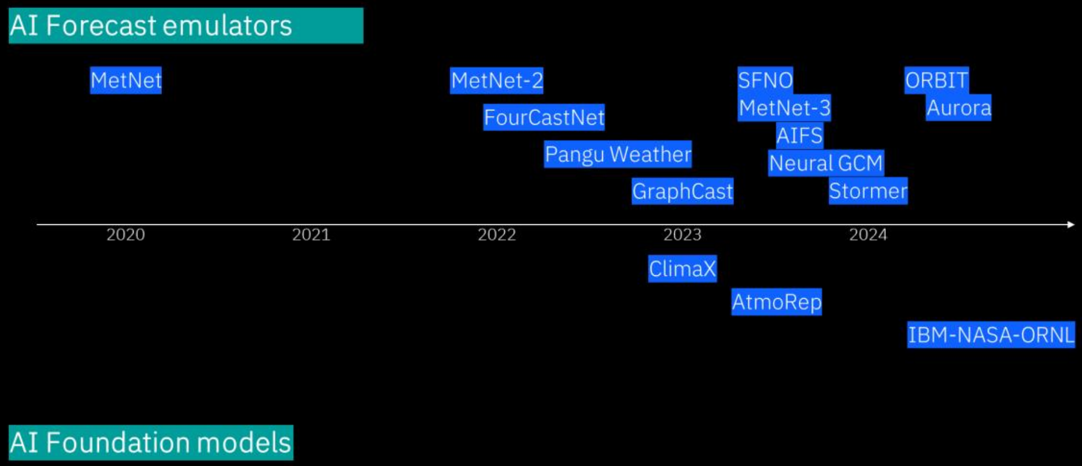
AI provides significant speed-ups compared numerical weather simulations



Finetuning results – Few shot learning



Conclusion



Weather foundation models are emerging

- Computationally much more efficient
- Learn the physics directly from data
- Approaching comparative performances
- Quick adaptability to address the long-tail of applications

Value of Physically Based Models

Hugh Cutcher, Lead Data Scientist

Solcast, a DNV company

Founded in
2016

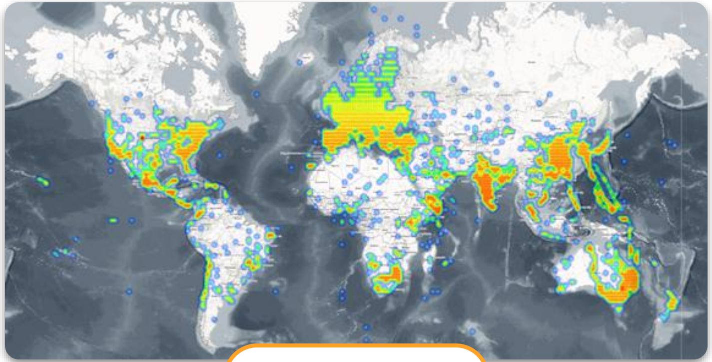
Acquired by DNV in
2022

Headquartered in
Sydney

Sales & Support in
USA & EU

Serving
300+ Customers

200+
Validation Sites



Recent API Usage

Providing services for
200+ GW

130+
Countries

2TB
Data every day

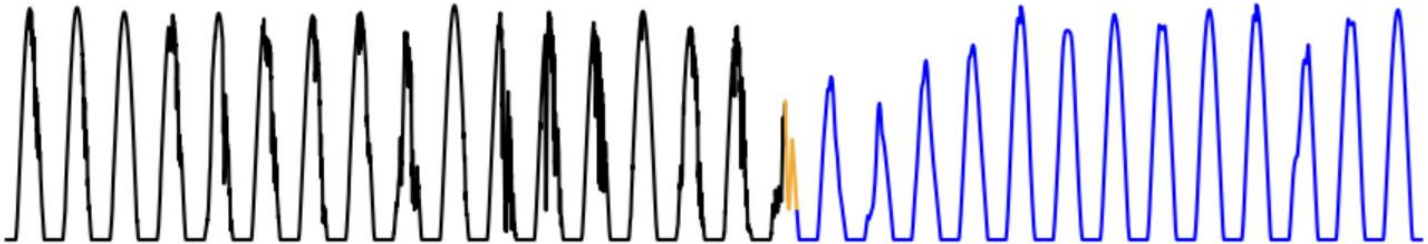
30+
Publications

26 million
API calls daily

99.99%
API uptime

SOLCAST
a DNV company

Solcast data overview



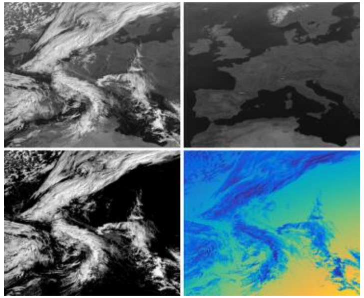
2007 to -7 Days

-7 days to present

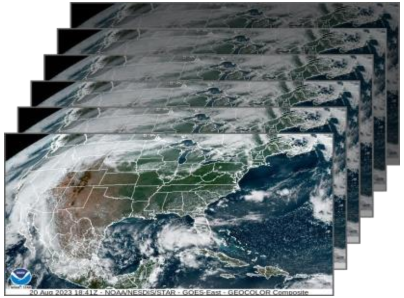
Present to +2 hours
Nowcast

+2 hours to +4 hours
Blend

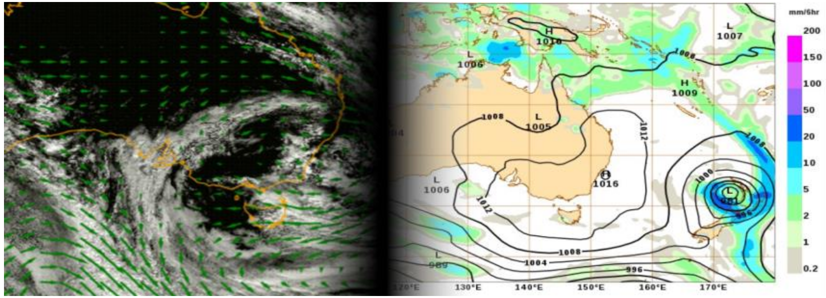
+4 hours to +14 days
NWP



GMS Satellite Archive



Live GMS Satellite Data



Nowcast
(GMS Satellite Extrapolation)

Numerical Weather Prediction

SOLCAST
a DNV company

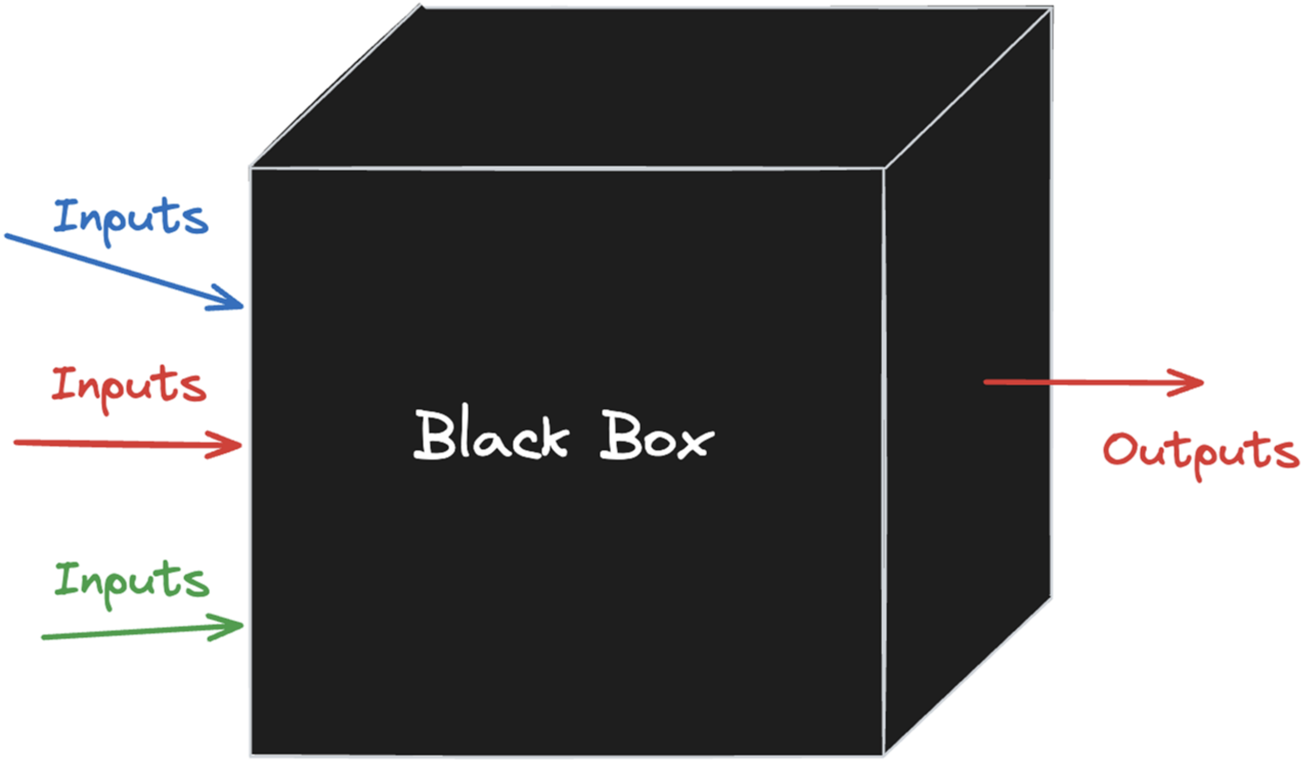
SOLCAST
a DNV company

Diverse Applications

300+ customers across different segments

Monitoring, analytics, and control: Services and products	GE Digital	bazefield (An Envision digital Company)	WÄRTSILÄ	mc	also energy (a stem company)
Asset management	enel	adani	Shell	Iberdrola	NOVASOURCE POWER SERVICES
Solar resource assessment	DNV	RINA	MOTT MACDONALD	aurecon	ENERTIS Applus
Residential PV technology and services	aurora	solaredge	ENPHASE	solo	electronicity
Energy, demand, and price forecasting and trading	ENGIE	Dominion Energy	smartestenergy	TESLA	EnergyAustralia
Distributed energy technologies and microgrids	evergen	EATON	KALUZA	ev.energy	enel x
Grid/market operators (ISOs, TSOs)	KEPCO	AUSTRALIAN ENERGY MARKET OPERATOR	ISO new england	Taipower	HORIZON POWER
Non-solar industries	AccuWeather	GKN HYDROGEN	FIVE RIVERS CATTLE FEEDING	VAISALA	STOCKGUARD

Machine Learning Black Box



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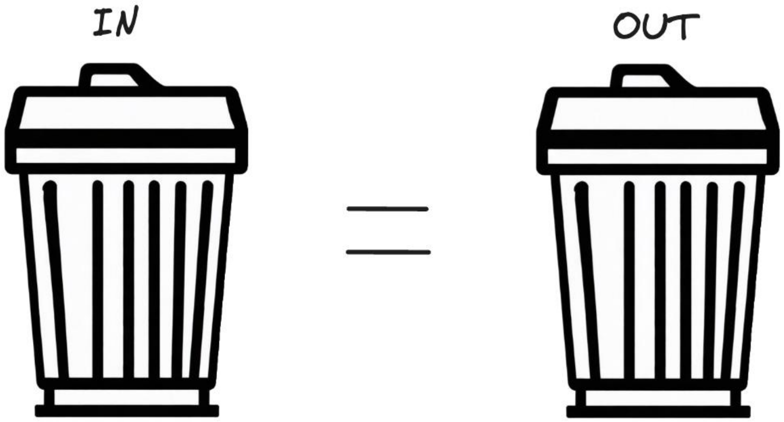
Garbage In, Garbage Out



Once in a Lifetime

SOLCAST
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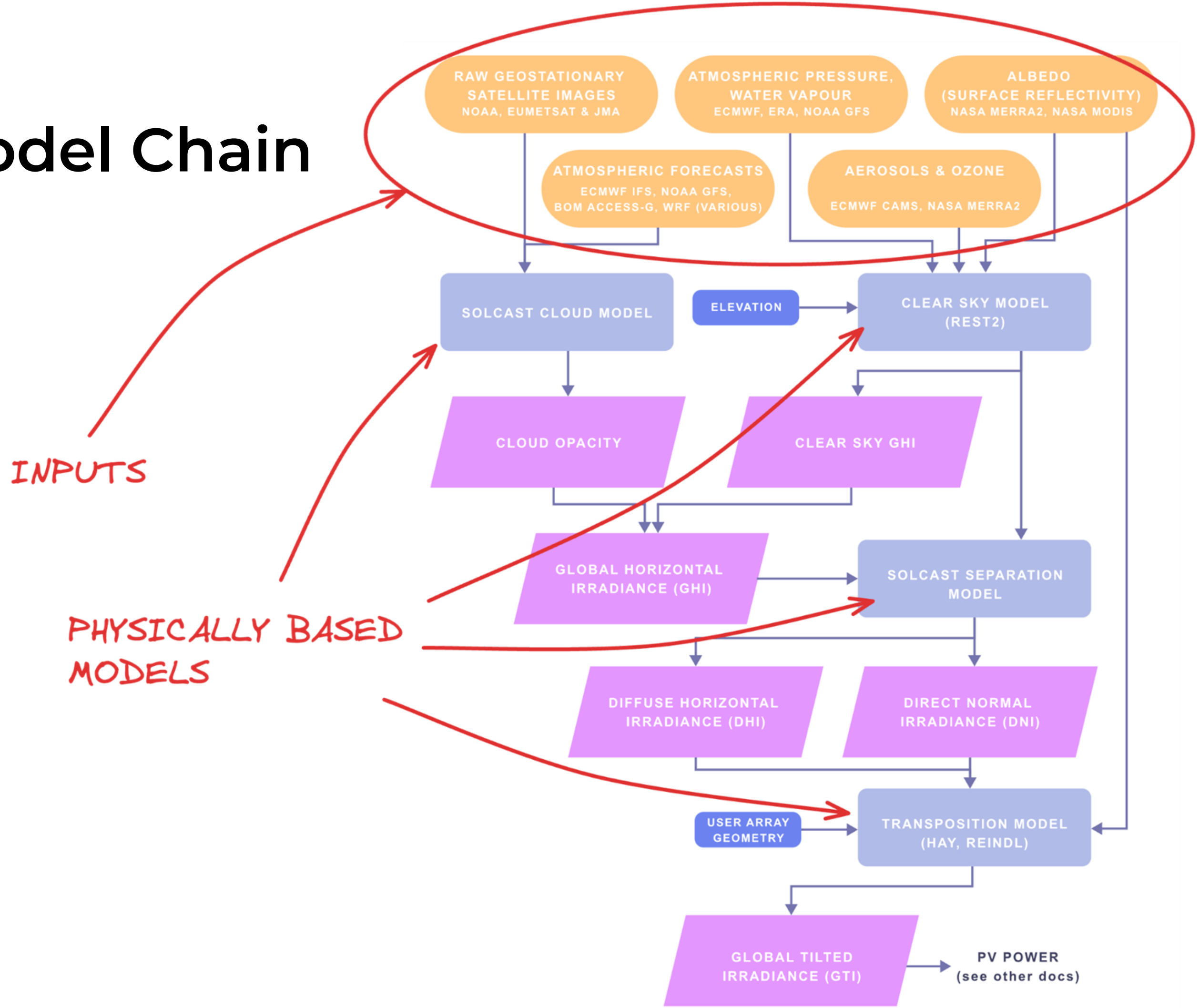
Solcast Model Chain



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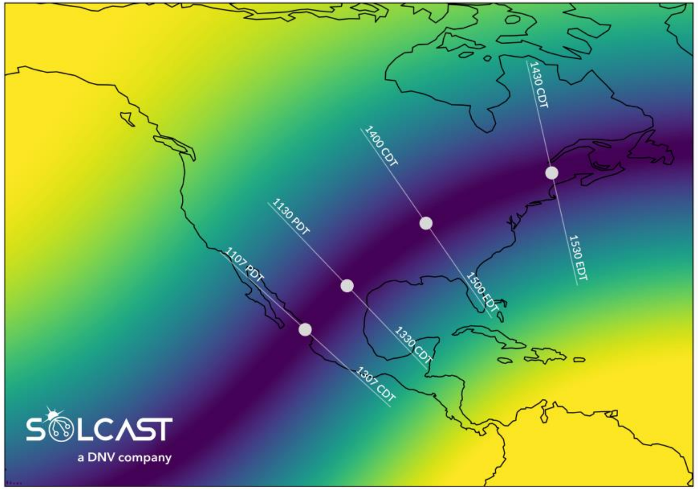
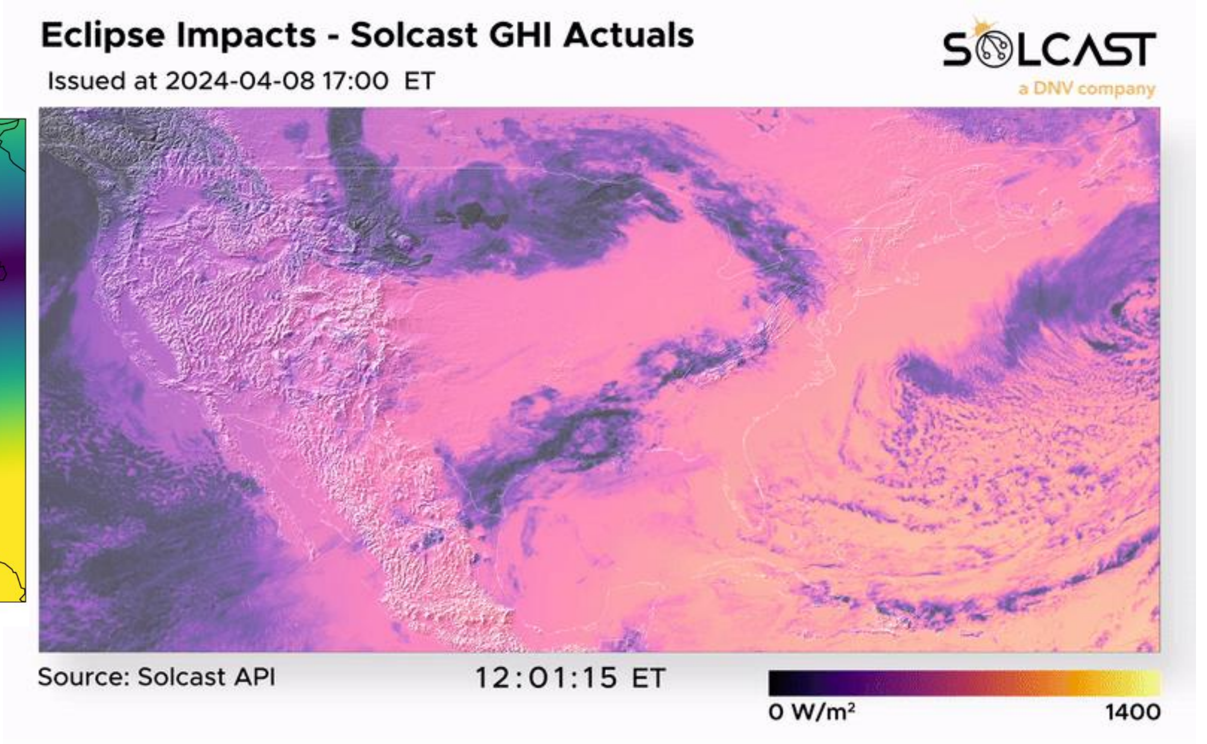
April Eclipse

Astronomical
Phenomena





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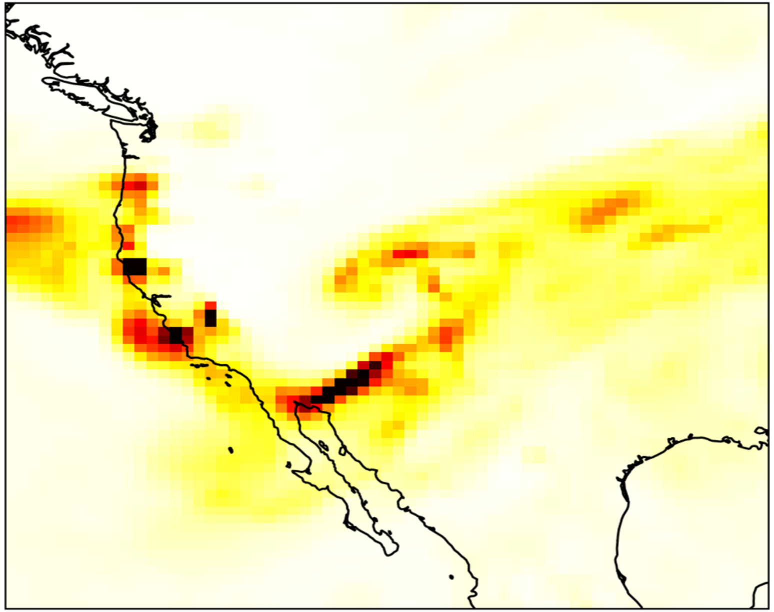
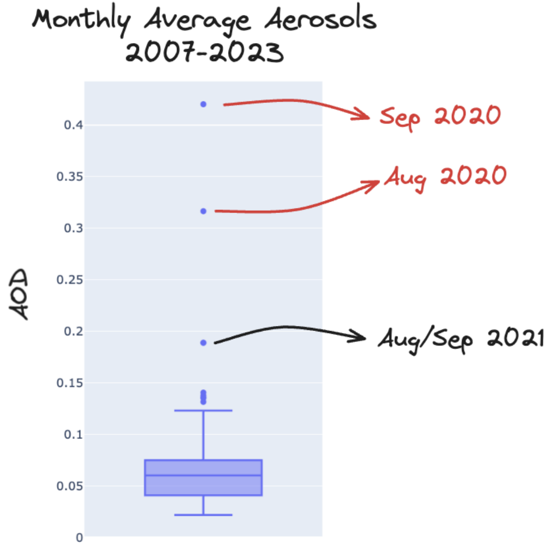
2020 California Wildfires

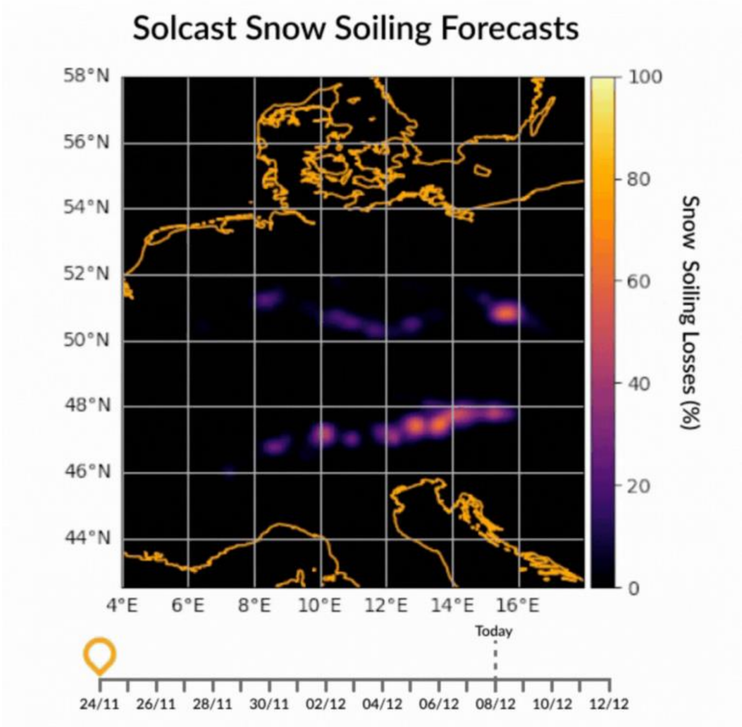
MERRA2 Aerosols: 2020-09-09T01:00Z

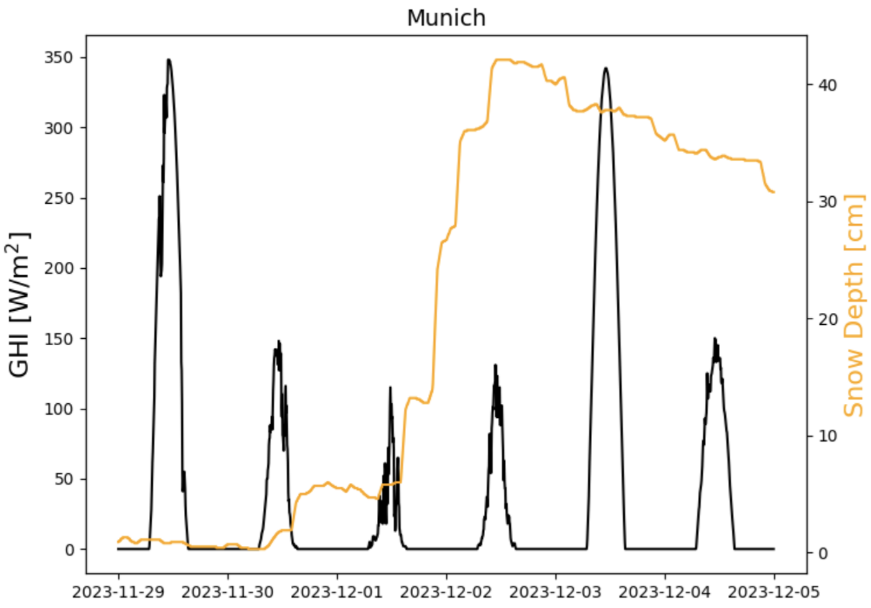




Scale unprecedented in recent history

Snow Soiling





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Terrain Shading

❌Impact on average yields often low as limited in scope

❌Highly localised

✅Consistent

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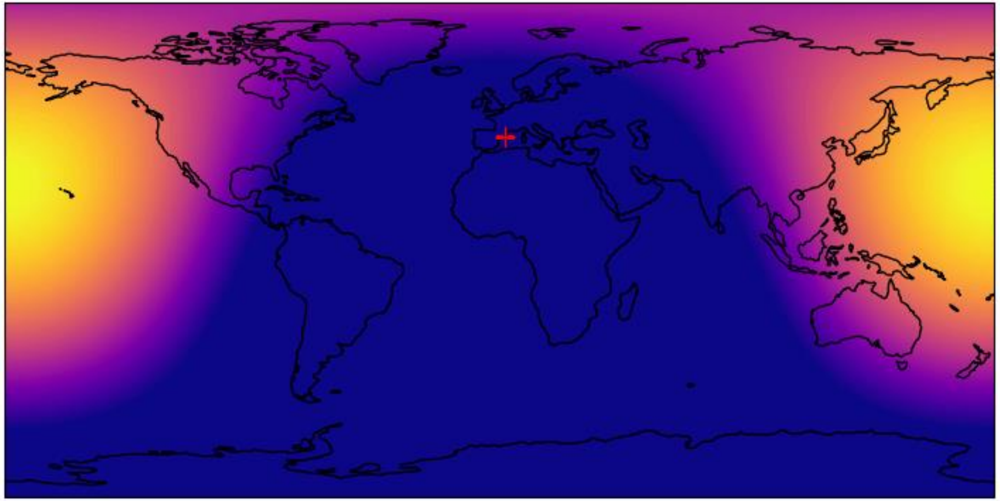
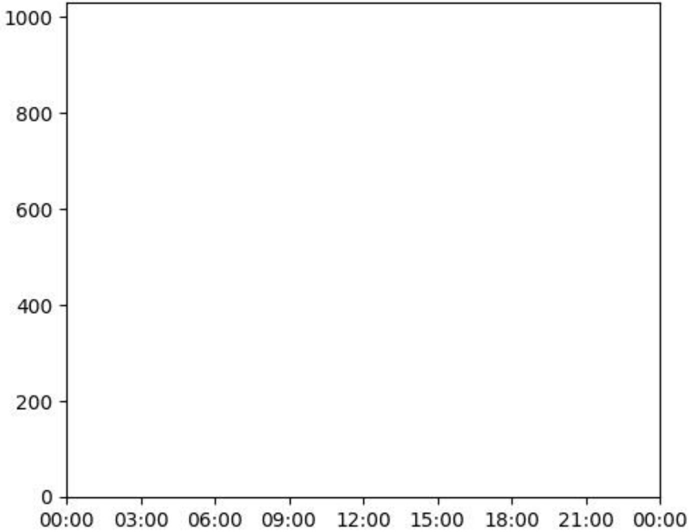
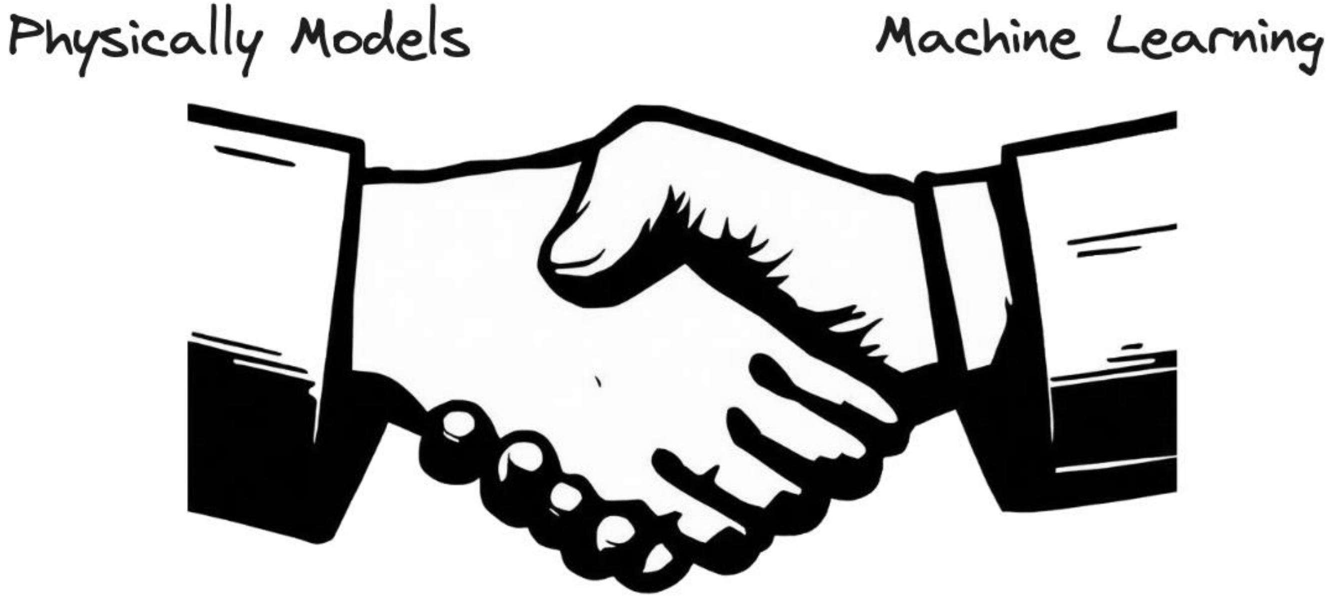
a DNV company

Solar Position






Physically Models
Machine Learning

For any questions...

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Find me on LinkedIn

More info at

solcast.com

go.solcast.com/HiHugh

Q&A and Discussions

Resource and load forecasting for multiple technologies

EPRI

ENERGY DELIVERY AND CUSTOMER SOLUTIONS

Load Forecasting Trends and Challenges

DOE Solar Forecasting Workshop – July 9, 2024

David Larson, PhD
Technical Leader, EPRI
DLarson@epri.com

Load forecasting is key for many grid decisions…

Decarbonization Strategies → Integrated Resource Planning → Resource Adequacy → Delivery System Planning → Real-Time Grid Operations

Improved forecasts will drive more efficient investment decisions and grid performance across timescales

Increased Customer Opportunities

Increased Asset Utilization

Reduced Operating Costs

Reduced Reliability Risks

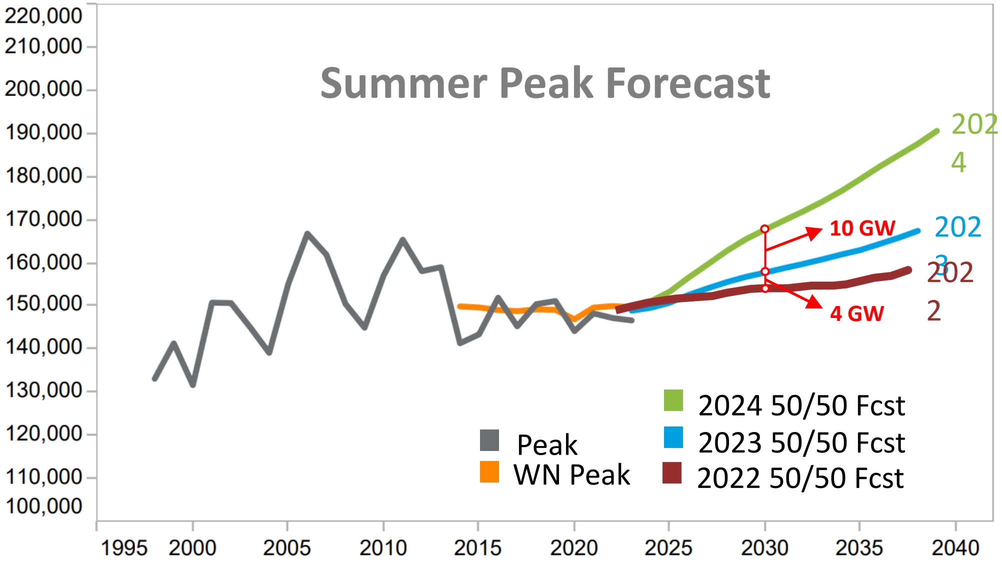
But load forecasting is getting more complicated!

Drivers Complicating Electric Demand Forecasting

- ⬆ Electrification
- ⬆ Decarbonization (H2, heat)
- ⬆ Weather (extreme temps)
- ⬆ Re-industrialization/On-shoring
- ⬆ Digitalization (data centers, crypto)

- ⬇ End-use efficiency
- ⬇ Customer generation/storage
- ⬇ Customer behaviors/rate structures

PJM Peak Load Forecast: 2022 vs. 2023 vs. 2024 Projections



Source: PJM 2024 Load Forecast Report https://www.pjm.com/-/media/library/reports-notices/load-forecast/2024-load-report.ashx

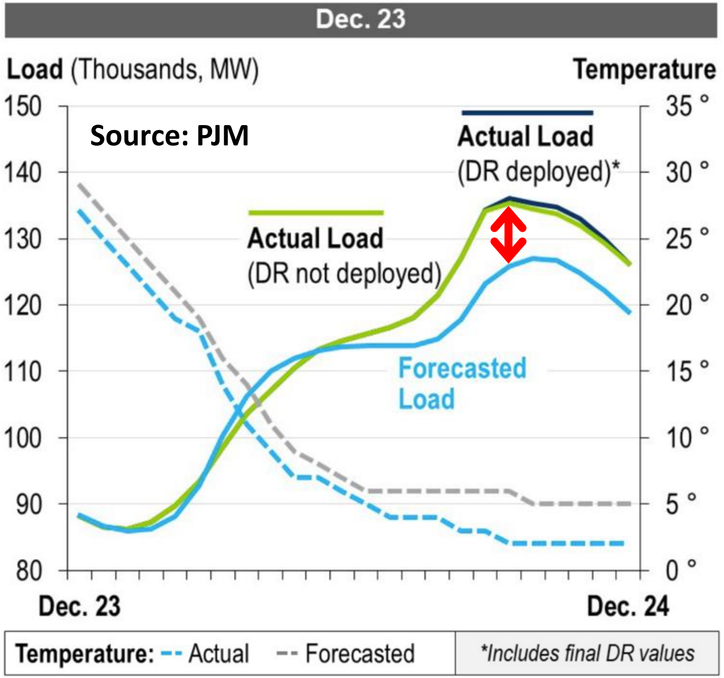
Forecasting in System Operations

Now	Future
Deterministic forecasts	Probabilistic forecasts
Single forecast model	Multiple forecast models
Transmission	Transmission & Distribution
Hourly resolution	Sub-hourly resolution
Load, solar, wind	Load, solar, wind, storage, hybrids, DERs, etc.

?

Winter Storm Elliott: High short-term forecast errors

PJM **under-forecasted** peak load by ~8%[1]



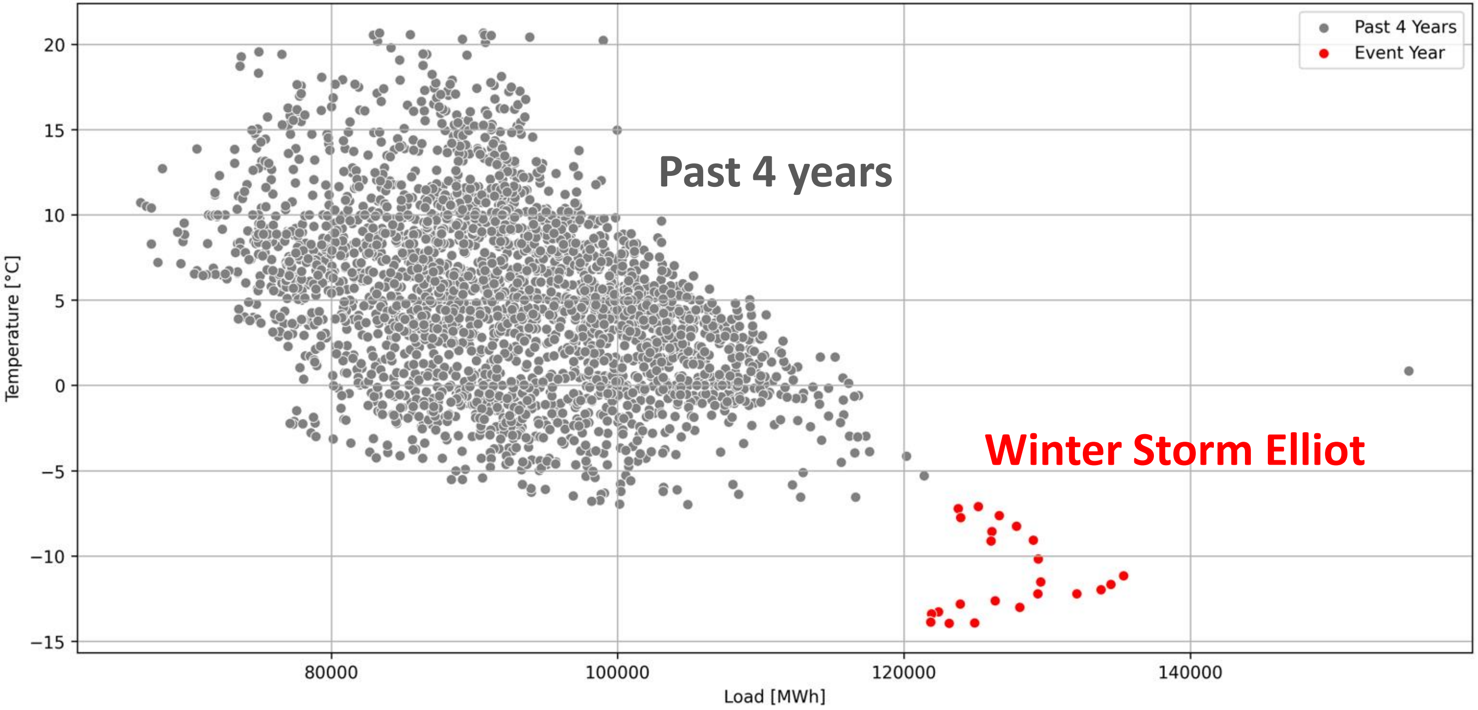
"The load **forecasting tools had never experienced similar weather conditions and load levels to Elliott**, therefore the data history wasn't available to the tools to perform accurate load forecasting" – SPP report[2]

"Abnormally high load forecasting errors occurred due to a **lack of historical data for similar extreme conditions** in December" – MISO report[3]

1: PJM: "Winter Storm Elliot: Event Analysis and Recommendation Report", July 17, 2023
2: SPP: "Review of SPP's Response to the Dec. 2022 Winter Storm", April 17, 2023
3: MISO: "Overview of Winter Storm Elliot December 23, Maximum Generation Event", January 17, 2023

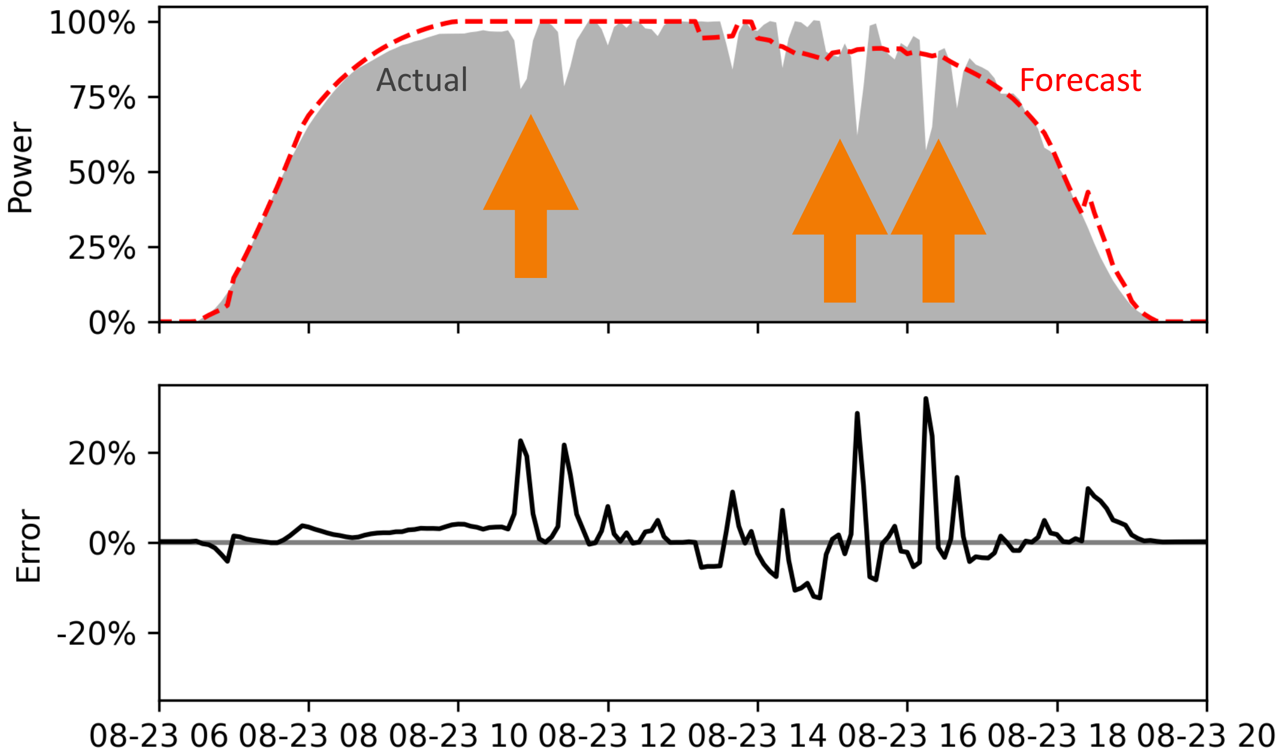
Extreme temperatures with new technologies can fool forecasting algorithms.

More historical data may not be sufficient



Temperature vs load before Winter Storm Elliot

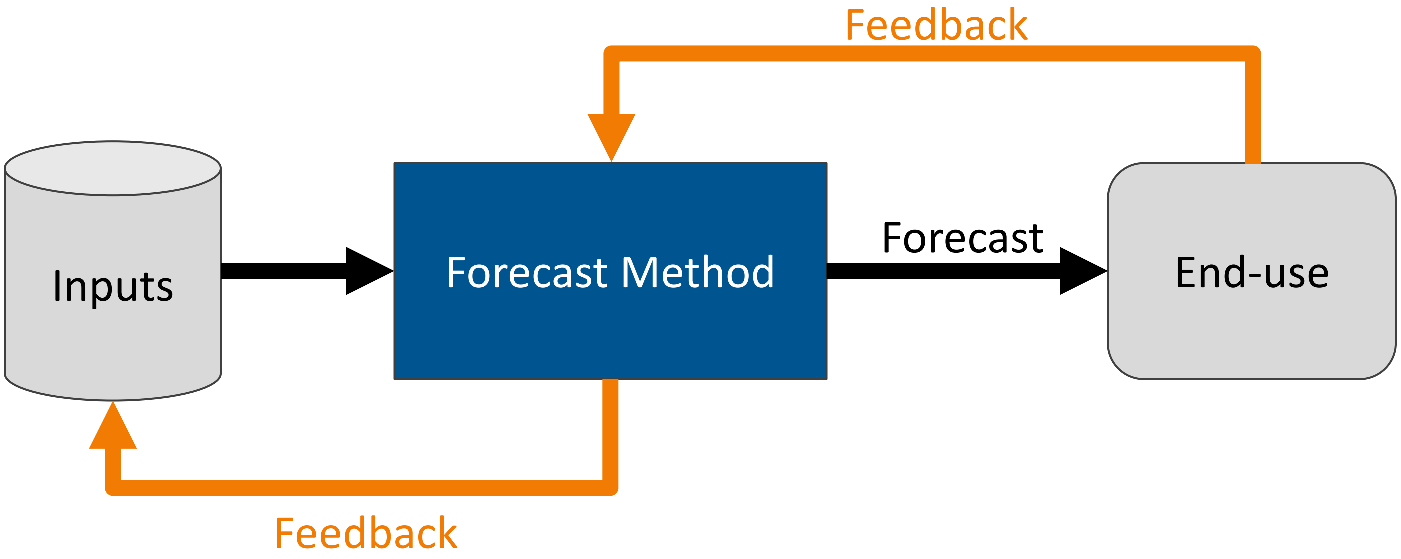
"Best" forecasts still don't capture ramps*



*from a forecast trial with 9 vendors, ran using EPRI's Forecast Arbiter platform and 4 grid-scale PV plants in Southeast US

Where do we go?

Need to consider how forecasts are created *and* used



Focusing only on "reduce average error" no longer enough

What should we prioritize?

(1) Good: Improve Load Forecasts

(2) Better: Improve Net Load Forecasts

(3) Best: Improve Grid Outcomes

EPRI Load Forecasting Initiative

Improved load forecasts at operational and planning timescales* will drive more efficient investment decisions and better grid performance.

EPRI launched a 24-month initiative to address critical needs in load forecasting that will work across three areas:

01	**Industry Coordination** Enable knowledge-sharing and collaboration among utilities, ISOs/RTOs,
02	**Long-Term Forecasting (Planning)** Develop methodologies and guidance to incorporate new load drivers
03	**Short-Term Forecasting (Operations)** Develop methodologies and guidance to mitigate changes in forecast accuracy

msites.epri.com/LFI

*we are defining "planning timescales" as >1-year ahead

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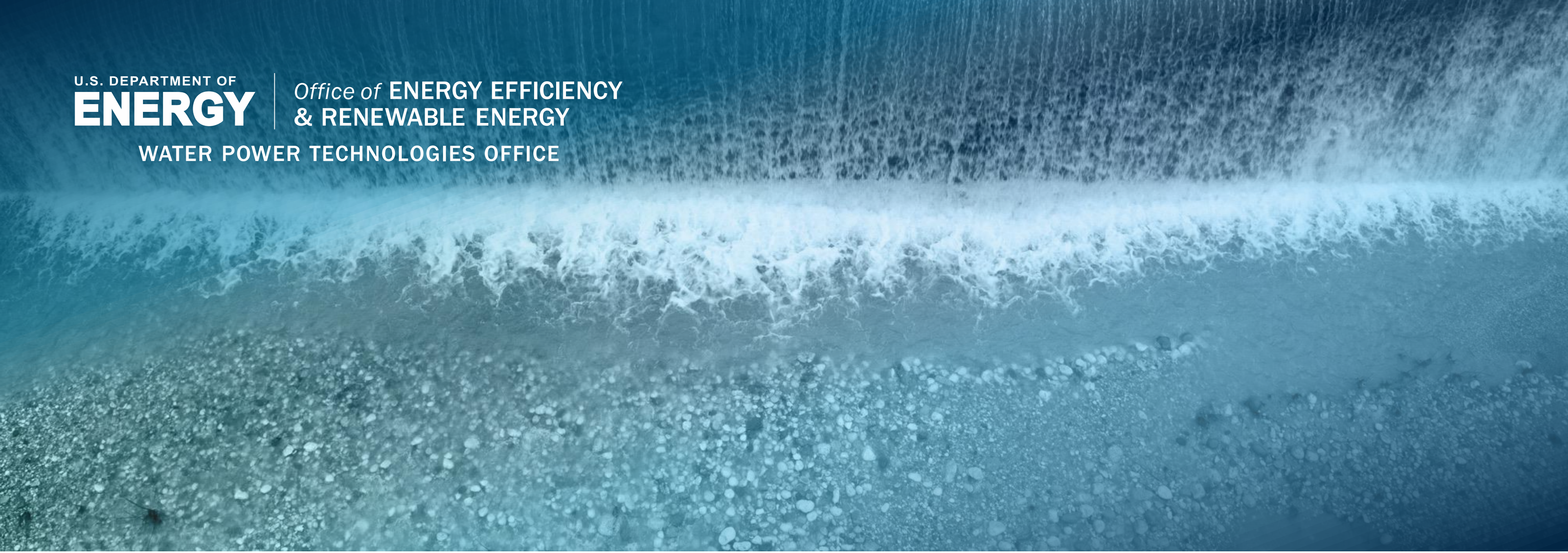
Q&A and Discussions



Forecasting for Hydropower

Water Power Technologies Office, U.S. Department of Energy

Eri Sharifi, Charles Scaife

7/9/2024

WATER POWER TECHNOLOGIES OFFICE

Hydropower Program

Modernizing the Existing Fleet

Pumped Storage Hydropower

New Low-Impact Projects

Marine Energy Program

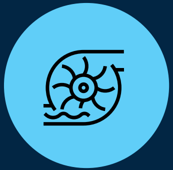
Wave

Tidal, River and Ocean Current

Ocean Thermal

FIVE CORE RESEARCH AREAS

1. Innovations for Low-Impact Hydropower Growth
2. Grid Reliability, Resilience, & Integration (HydroWIRES)
3. Fleet Modernization, Maintenance, & Cybersecurity
4. Environmental & Hydrologic Systems Science
5. Data Access, Analytics, and Workforce



HydroWIRES

The mission of HydroWIRES *(Water Innovation for a Resilient Electricity System)* is to understand, enable, and improve hydropower's contributions to reliability, resilience, and integration in a rapidly evolving electricity system.

Role in the Hydropower Program

Covering grid related R&D including:

- grid reliability,
- grid resilience, and
- grid integration.

Four Research Areas

Research Area 1

Value Under Evolving Systems Conditions

- Grid Services Taxonomy
- Value drivers
- Valuation Methodologies

Research Area 3

Operations and Planning

- Reliability and Resilience Contribution
- Comparison with Other Resources
- Operations Optimization
- System Effects of Operations

Research Area 2

Capabilities and Constraints

What can the hydropower fleet do?

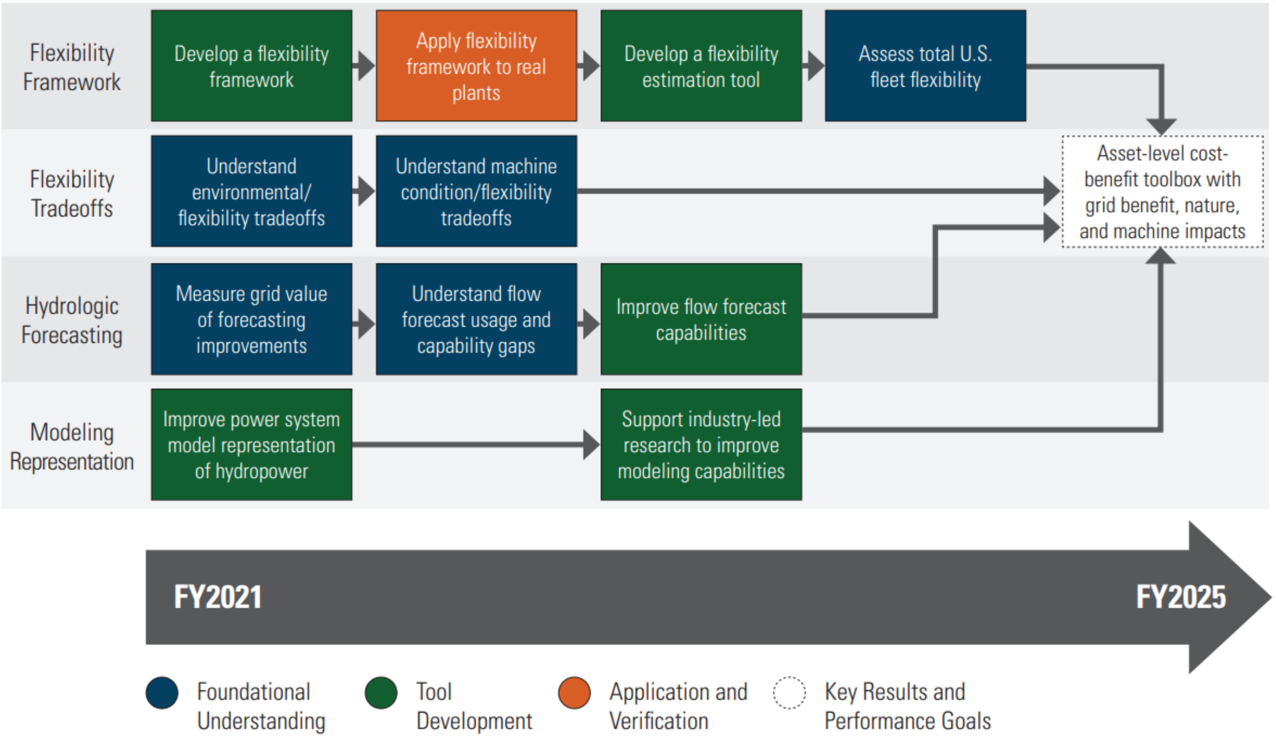
- Flexibility Framework
- Flexibility Tradeoffs
- Hydrologic Forecasting
- Modeling Representation

Research Area 4

Technology Innovation

- Technology Gaps
- Unit Flexibility Enhancement
- Plant Flexibility Enhancement
- New PSH Designs

Hydrologic forecasting is part of the HydroWIRES roadmap



Hydrologic Forecasting

Hydropower operators use inflow forecasting tools to estimate future inflows to hydropower reservoirs.

These tools vary extensively within the hydropower industry in terms of lead time (short, medium, long term), geographic setting, and complexity. Some forecasting tools are proprietary, but can be purchased from vendors; other tools are in-house, developed by the hydropower facility operator to be fit for purpose.

Understanding reservoir inflow is critical to managing multiple water uses and making informed operational decisions. If hydropower plants are required to operate more flexibly, forecasting tools will likely require improvements in accuracy and resolution. For example, there may be some instances where conditions are swiftly shifting, as is the case with low-elevation upper watersheds, snow pack dependent facilities, and lower latitude facilities.

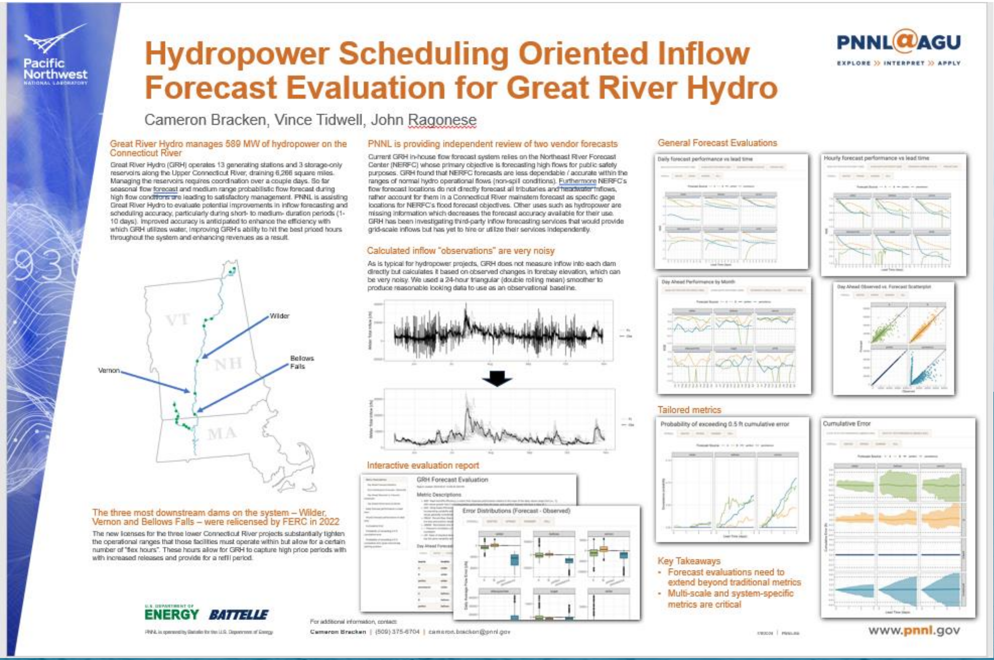
Hydropower flexibility is a function of reservoir capacity; therefore, knowing exactly how much water will be available at a particular time can enable better planning and unlock additional operational capabilities.

Work under this objective will first focus on identifying instances where forecasting tools are currently or prospectively insufficient in the context of increasing operational flexibility, and evaluating the degree to which past and current investments resolve those gaps. Future investments will then be aimed at addressing specific gaps that are highly targeted and impactful.

HydroWIRES B1: Monthly and Weekly Hydropower Constraints Based on Disaggregated EIA-923 Data

This dataset provides both monthly and weekly constraints (maximum and minimum generation) and power targets for hundreds of hydropower plants across the United States. The data is intended for use in Production Cost Models (PCMs) and Capacity Expansion Models (CEMs). The hydropower data is based on disaggregated annual power data which is part of the EIA-923 dataset.

Hydropower Scheduling Oriented Inflow Forecast Evaluation for Great River Hydro TA



Great River Hydro (GRH) operates 13 generating stations and 3 storage-only reservoirs along the Upper Connecticut River, draining 6,266 square miles.

Managing the reservoirs requires coordination over a couple days. So far seasonal flow forecast and medium range probabilistic flow forecast during high flow conditions are leading to satisfactory management. PNNL is assisting Great River Hydro to evaluate potential improvements in inflow forecasting and scheduling accuracy, particularly during short- to medium- duration periods (1-10 days).

Improved accuracy is anticipated to enhance the efficiency with which GRH utilizes water, improving GRH's ability to hit the best priced hours throughout the system and enhancing revenues as a result.

Value of flow forecasts to power system analytics

Hydropower operators use weekly water inflow forecasts to optimize reservoir releases and unit commitment and to meet power grid needs.

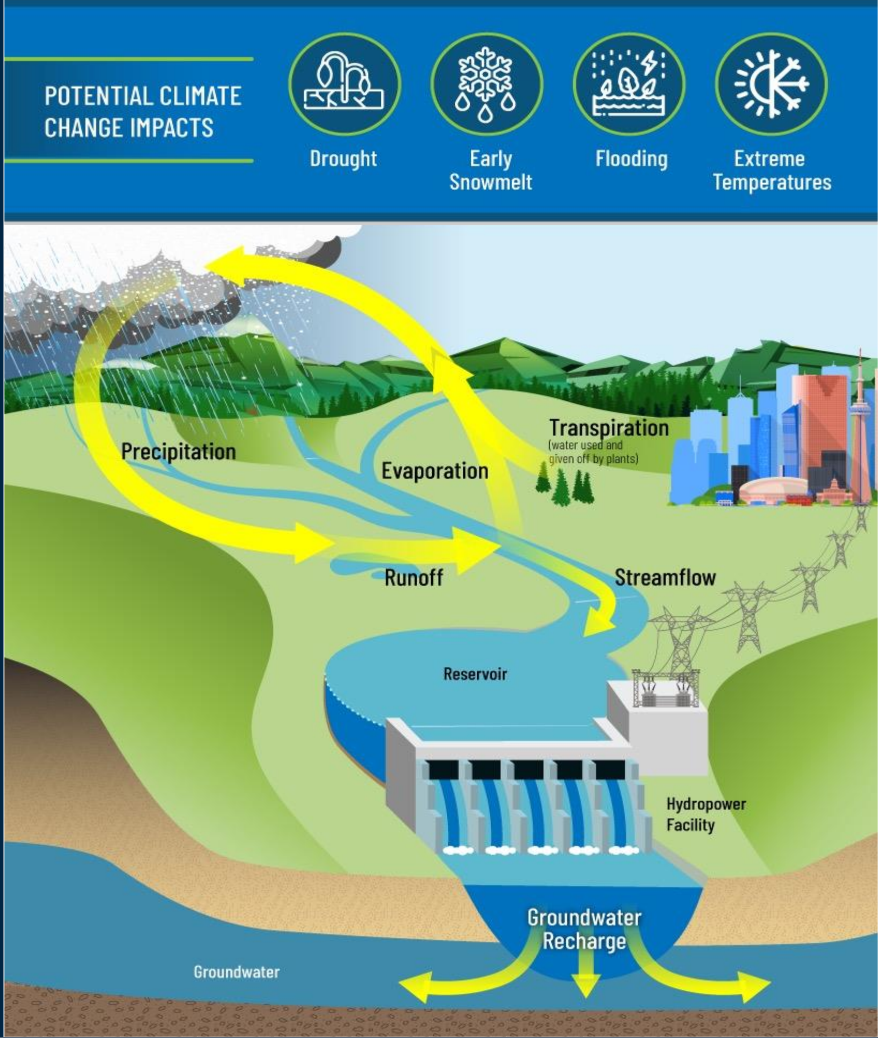
The accuracy of inflow forecasts, combined with related scheduling adjustments, contracts, and market opportunities, are reflected in a utilities' revenue. One of the goals of the HydroWIRES initiative is to quantify the flexibility of hydropower operations and understand its adaptability to changes in water supply, regulation, markets, and power grid needs.

In partnership with North Carolina State University and the National Corporation of Atmospheric Research, researchers from PNNL and INL will use inflow forecasts, reservoir and power system models, and case studies to demonstrate the contribution of flow forecast to provide hydropower services to the grid. Flow forecast accuracy metrics, combined with regional power system analytics (including regional economics and generation portfolios) will help detangle the value of incremental improvement in flow forecasts. This research supports DOE in developing strategic partnerships with other institutions to invest in information products and decision-support practices for meeting power grid needs.

HYDROLOGIC SYSTEMS SCIENCE

MISSION

Advance our understanding of the impacts of climatic and hydrologic changes on hydropower operations and hydropower's effect on the environment to support decision-making of stakeholders across multiple sectors.



HYDROLOGIC SYSTEMS SCIENCE

DATA COLLECTION

Using new and existing sensing technologies that are both accurate and reliable to monitor the natural and built environment

METRICS AND ANALYTICS

The systematic computation of gathered data that leads to meaningful discovery, interpretation, or message that supports decision-making.

MODELING

Understanding and predicting coupled human and natural systems across various spatial and temporal scales through the advancement of earth and power systems models and modeling framework

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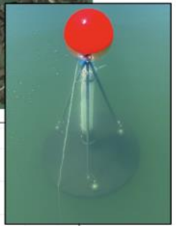

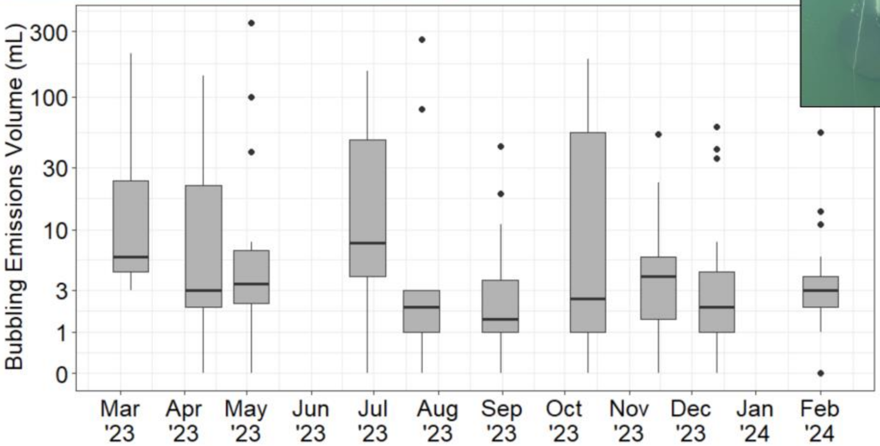

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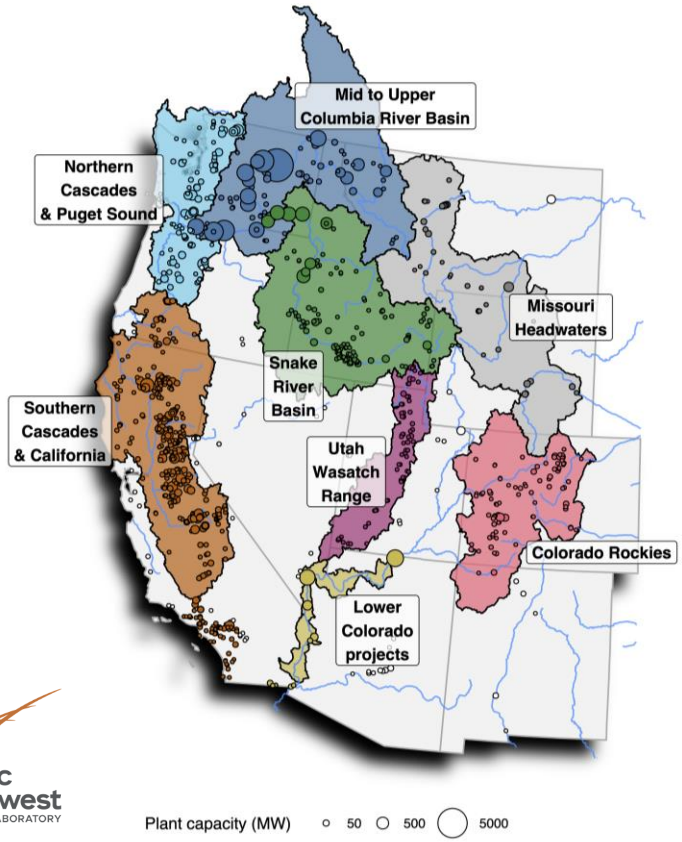

Pacific Northwest
NATIONAL LABORATORY

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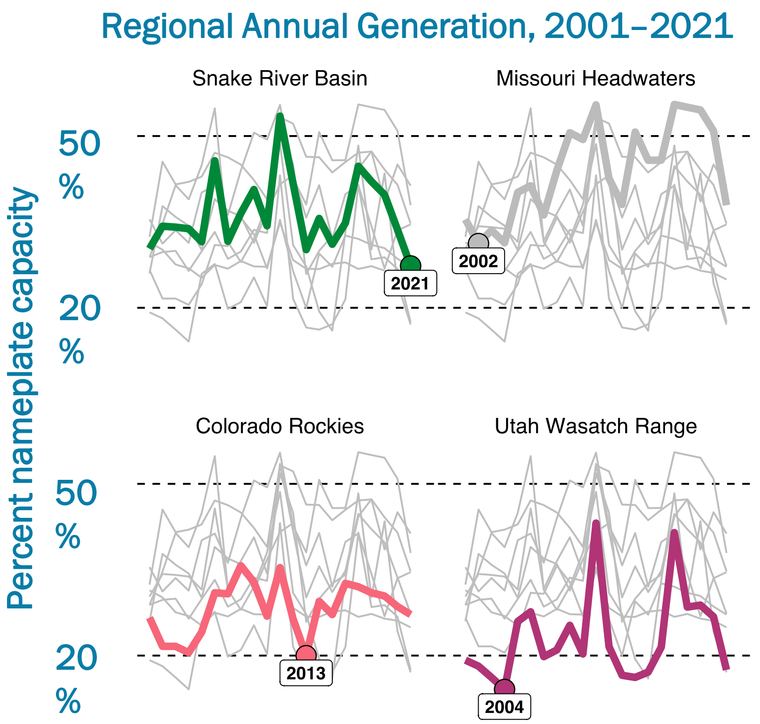

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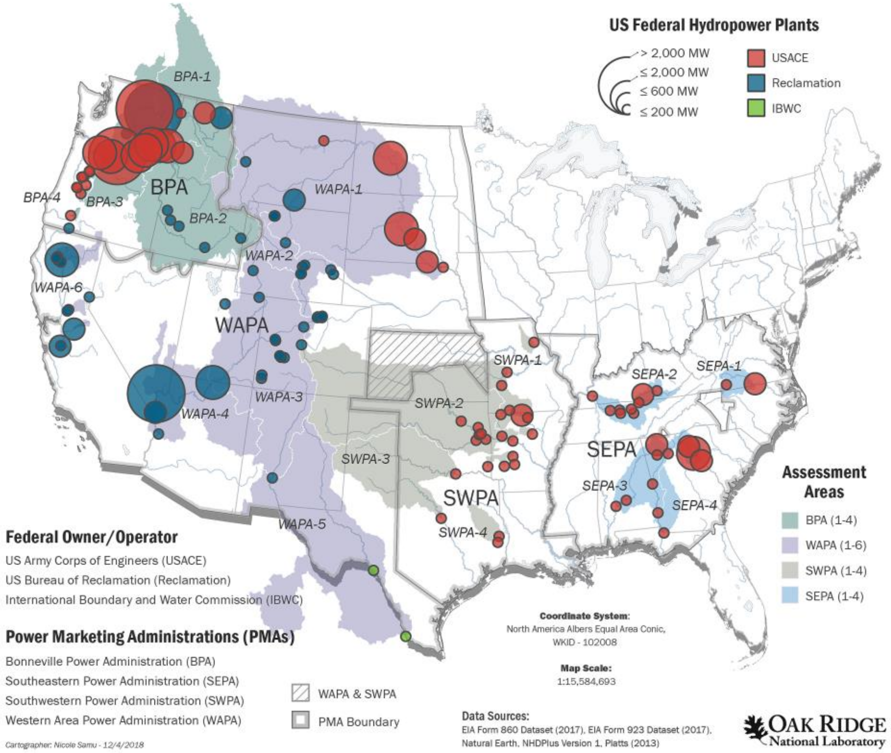

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