



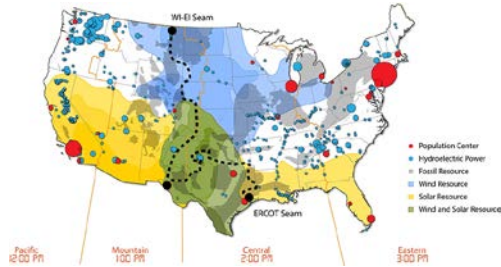
Spatiotemporal Super-Resolution with Generative Machine Learning for Creating Renewable Energy Resource Data Under Climate Change Scenarios

Grant Buster, Brandon Benton,
Paul Pinchuk, Andrew Glaws, Ryan King

Innovations in Climate Resilience
March 29th, 2023

Large Renewable Energy Integration Studies

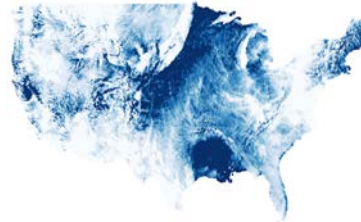
The NREL Seams Study



The North American Renewable Integration Study (NARIS)



The Los Angeles 100% Renewable Energy Study

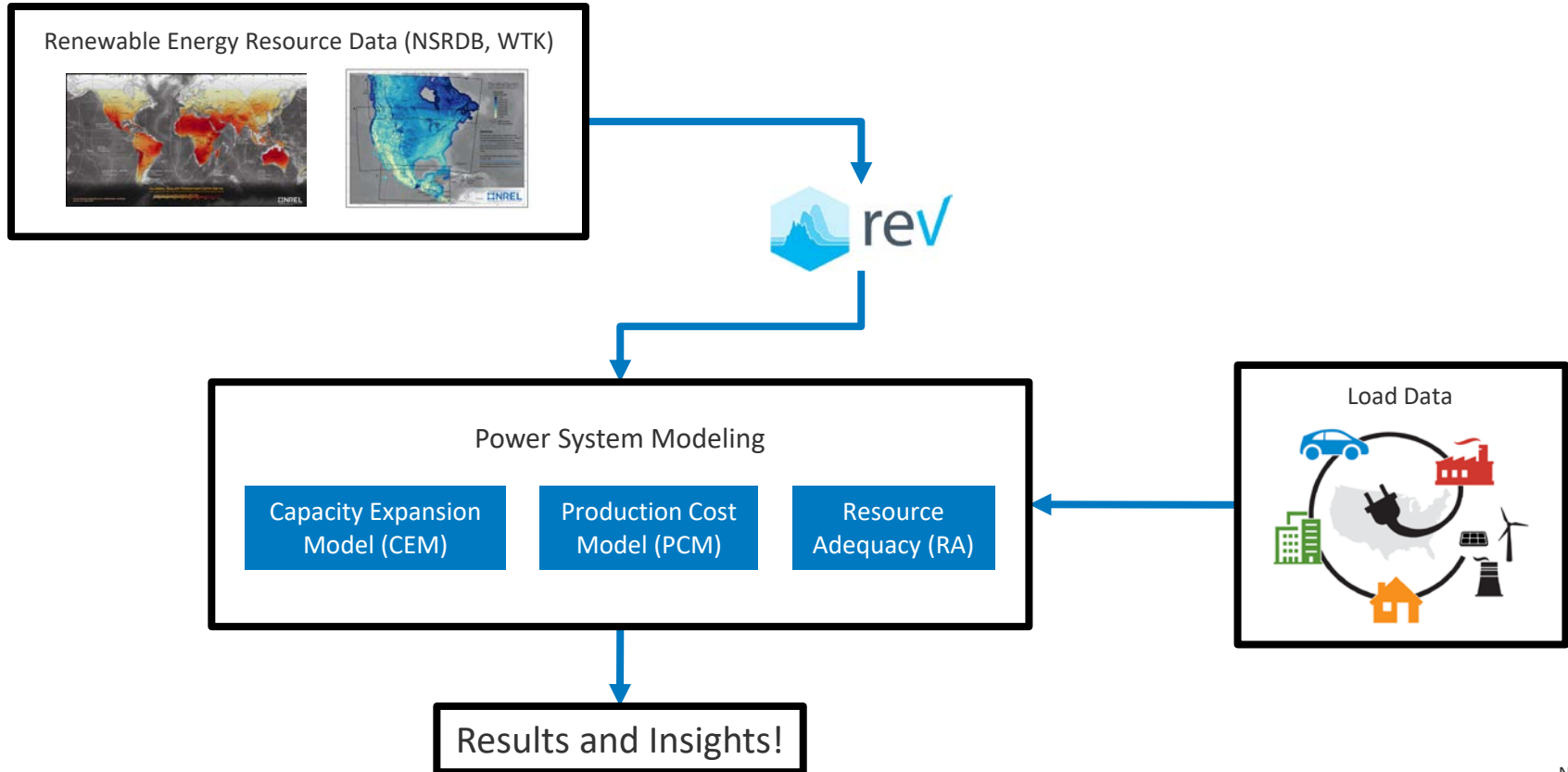


“The Evolving Role of Extreme Weather Events in the U.S. Power System with High Levels of Variable Renewable Energy”

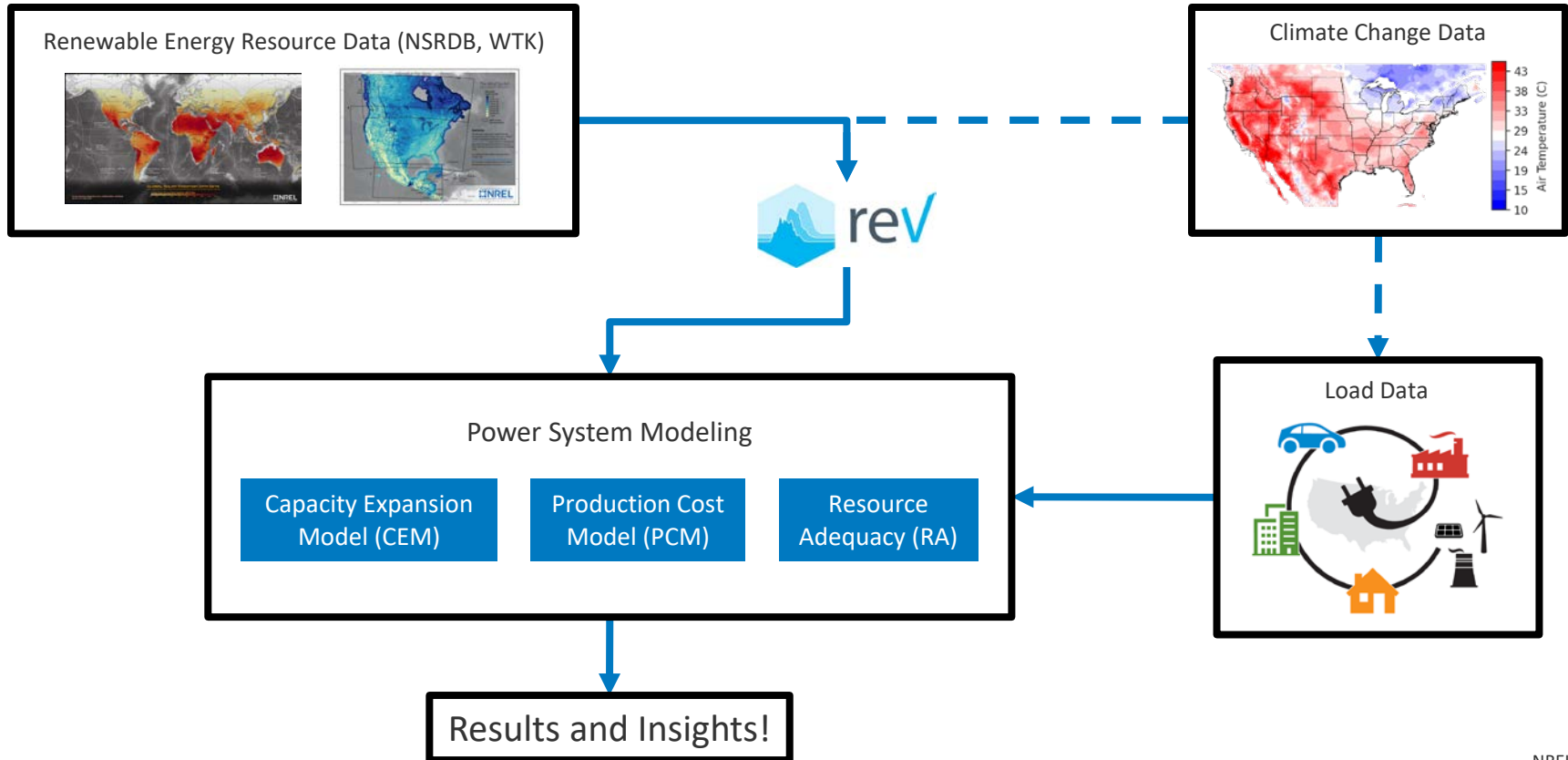


U.S. DEPARTMENT OF ENERGY
Building a Better Grid
National Transmission Planning Study

How does this all fit together?



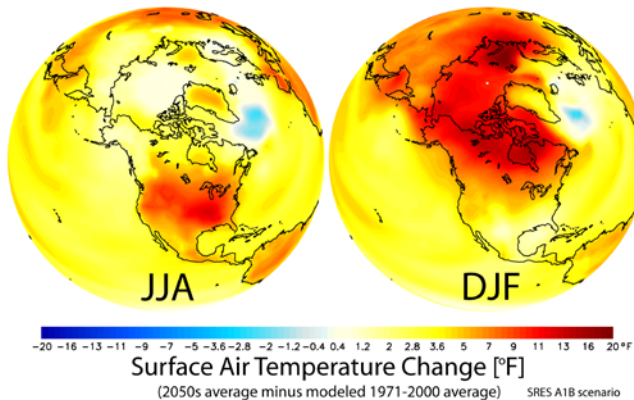
How does this all fit together?



Climate Data Downscaling: Mind the Gap

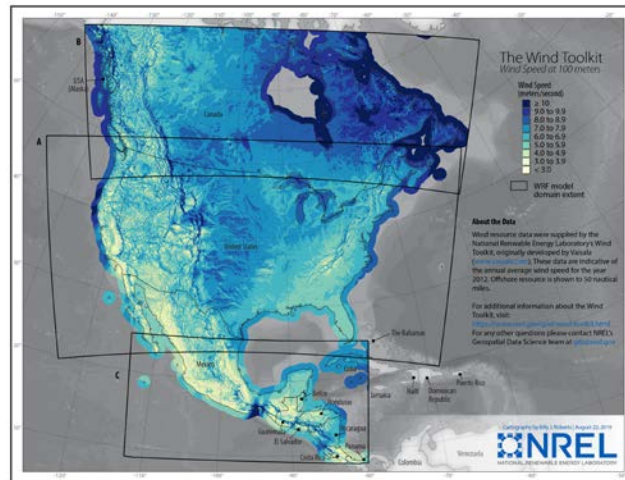
Global Climate Models (GCMs)

NOAA GFDL CM2.1 Climate Model



<https://www.gfdl.noaa.gov/visualizations-climate-prediction/>

Mesoscale NREL Datasets (WTK, NSRDB)



~100 km grid resolution
daily average data
2000-2100

How do we bridge this gap?

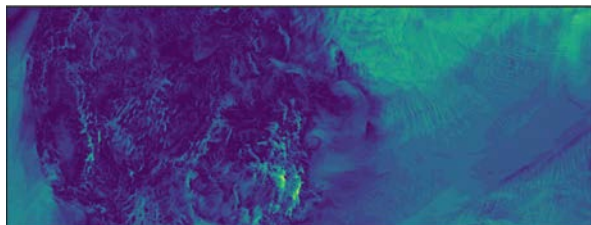


~2-4 km grid resolution
5 min-hourly data
Historical

Our solution needs to be flexible enough to enable researchers to study any climate model or climate change scenario and to stay current with new climate research.

Super-Resolution for Renewable Energy Resource Data with Climate Change Impacts (Sup3rCC)

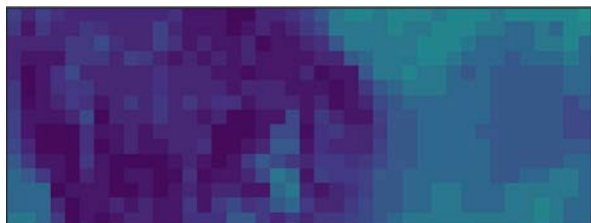
True High Res (WTK or NSRDB)



4km hourly

Coarsen high res to create training data

True Low Res (WTK or NSRDB)

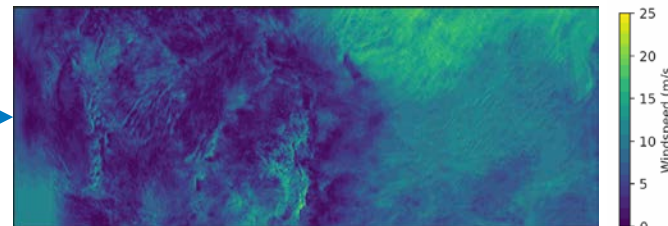


100km Daily

Discriminative Model

Generative Model

Synthetic High-Res Output



4km hourly

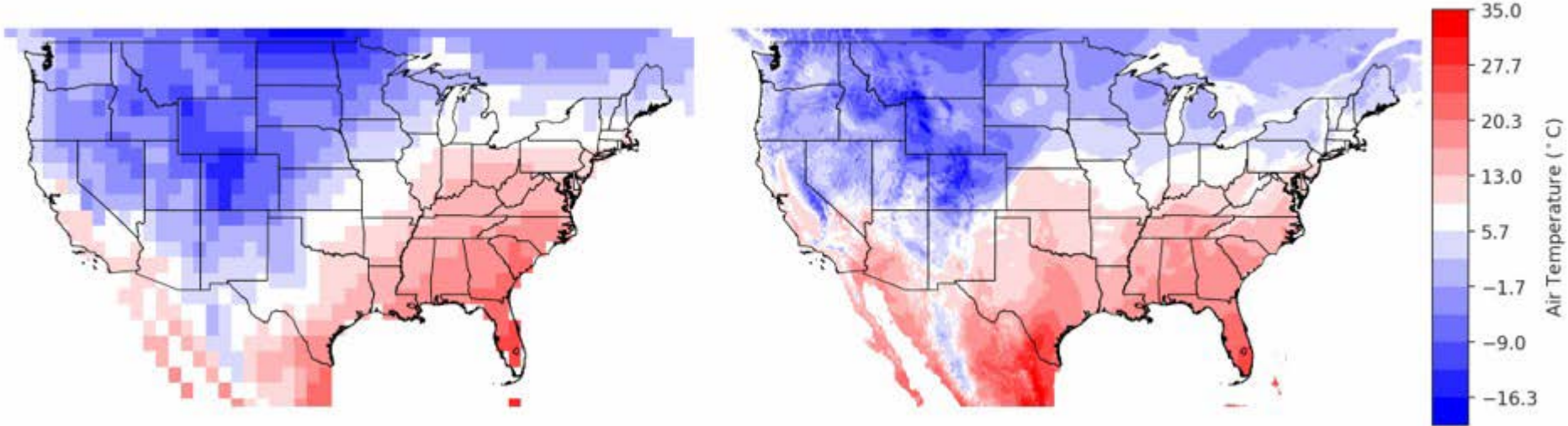
Benefits of Downscaling with ML:

1. Computational efficiency (10-100x faster than WRF)
2. Designed for renewables
3. Fully integrated into energy analysis software

Open-source: <https://nrel.github.io/sup3r/>

High-Resolution Spatial Features and Dynamics

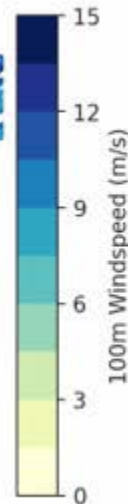
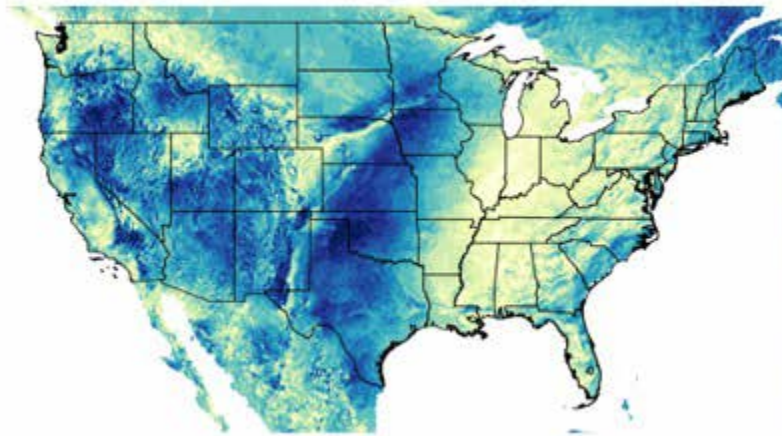
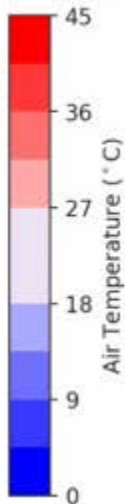
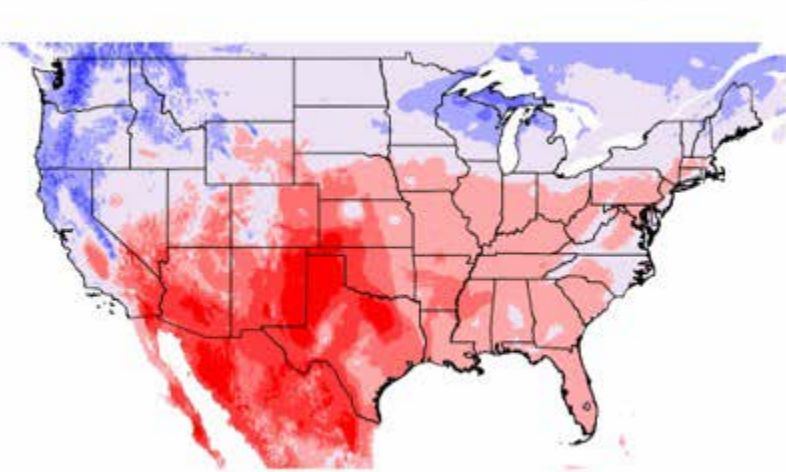
Sup3rCC Data 2050-2-19 17:00 (MST) (1/96)



- The Sup3rCC generative models (right) add high-resolution spatial features and temporal dynamics conditioned on the low-resolution GCM input (left)

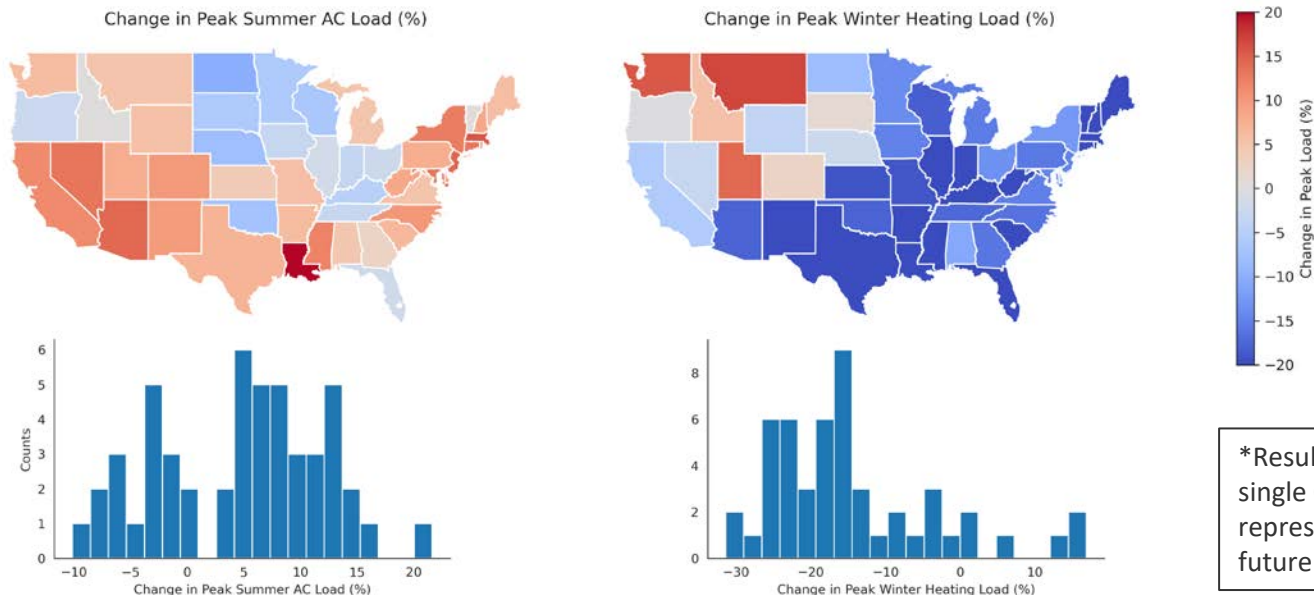
Variables are Spatiotemporally Coincident

Sup3rCC Data 2050-6-18 17:00 (MST) (1/96)



- The Sup3rCC data includes temperature, humidity, wind, and solar irradiance variables, all spatiotemporally coincident
- Sup3rCC enables research of future energy systems with high levels of both wind and solar capacity using a single synchronous dataset

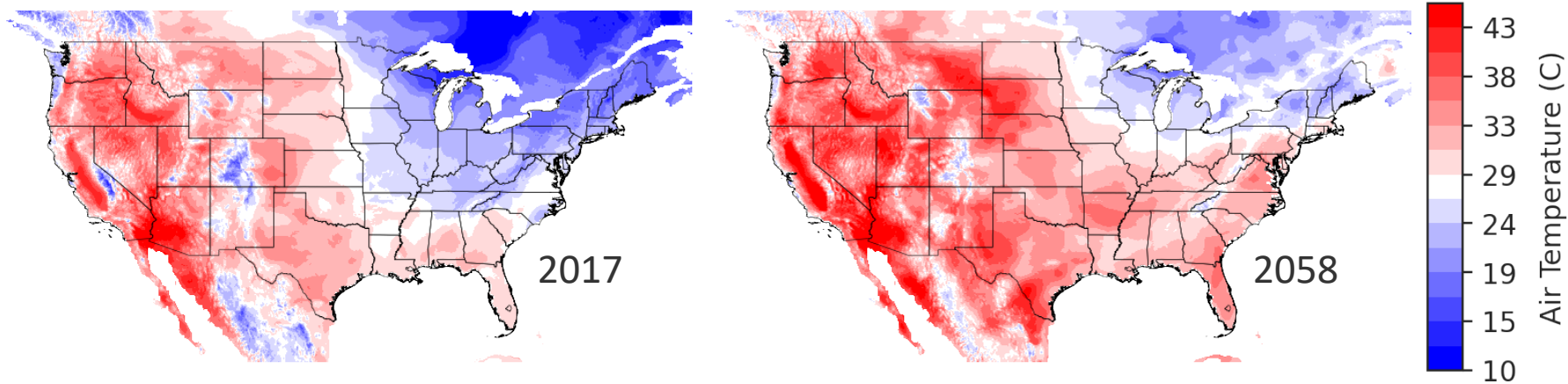
Impacts on Energy Demand



*Results are from a single GCM and only represent one possible future climate

- The high-resolution Sup3rCC temperature and humidity data can be used to estimate the impacts of climate change on future energy demand
- The load data above is based on bottom-up electrical load modeling from [Evolved Energy Research](#) for a hypothetical net-zero 2050 electrified infrastructure

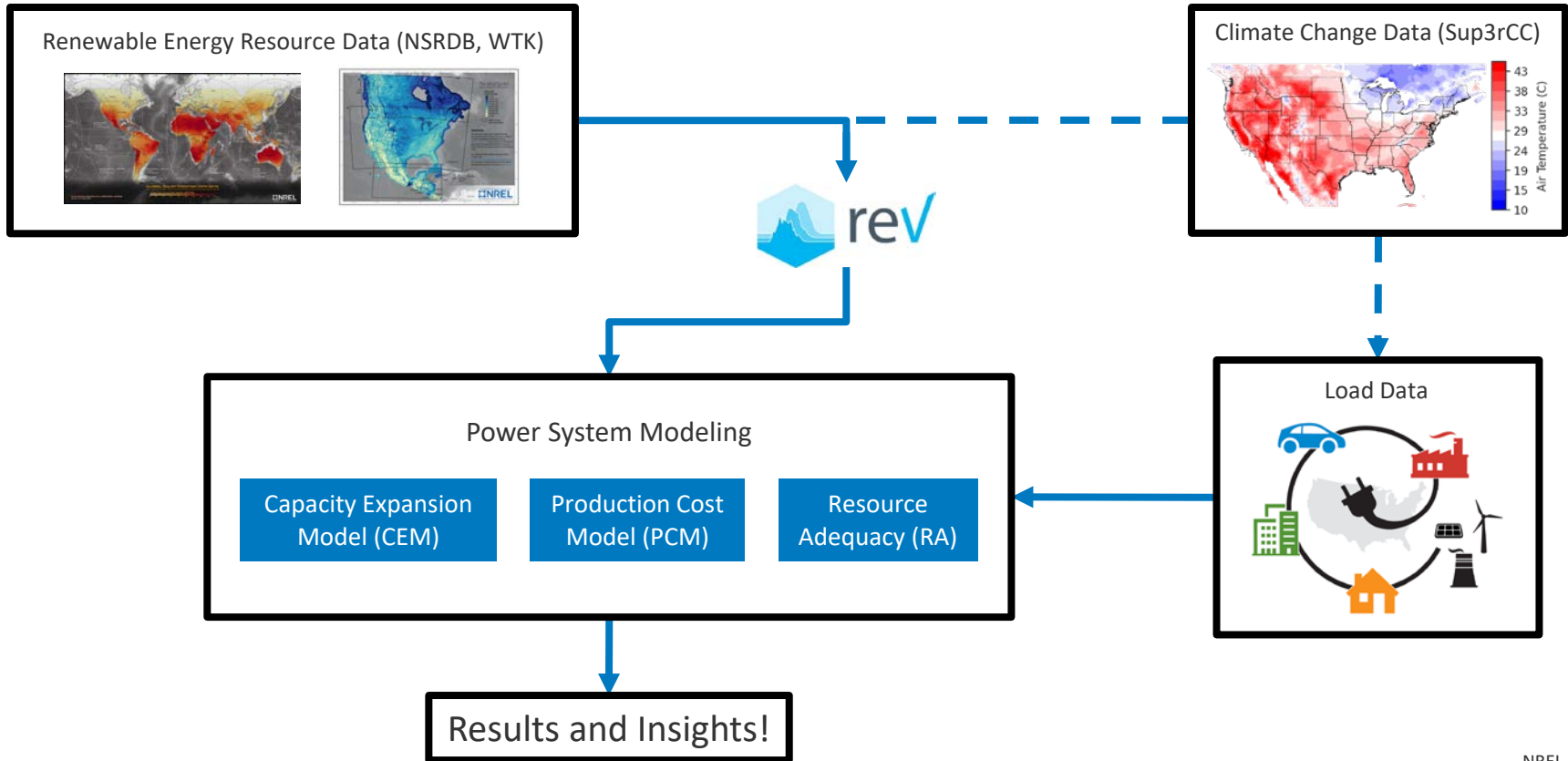
Wind + Solar + Temperature Compound Events



- The maps above show snapshots during the hottest days in the West during unseasonably low wind + solar events (more than 1 stdev from baseline values) from the 2015-2024 and 2050-2059 periods
- Future event is +1.4°C hotter in the West (widespread, population weighted) and up to +3.3°C hotter (localized temperature increase in Los Angeles)
- These generative models and their output data enable a crucial capability to explore how meteorological events that stress the energy system might evolve under climate change.

*Results are from a single GCM and only represent one possible future climate

How does this all fit together?



Future Work

1. Open-source model + data release
2. Documentation + publishing
3. Impacts on the renewable energy supply curve
4. Coupling with buildings and bottom-up load models
5. Integration into capacity expansion, production cost, resource adequacy
6. Uncertainty quantification with large GCM ensembles

Thank you

www.nrel.gov

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