
Photo by Josh Bauer / Bryan Bechtold, NREL 82067

NREL

Downscaled Earth System Model Data for Resilient Energy System Planning

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ESIG Forecasting and Markets Workshop
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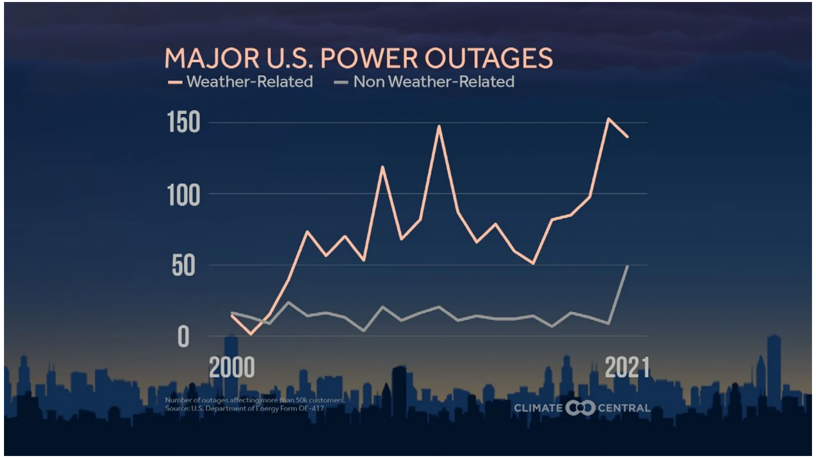
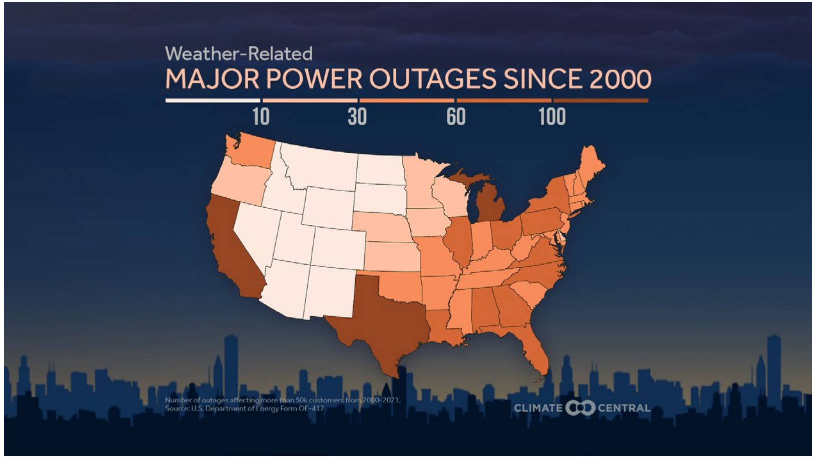
Meteorology and Grid Reliability

- Up to 83% of major reported power-outages in the U.S. from 2000-2021 can be attributed to weather-related events
- Major outages have been increasing over the analysis time period

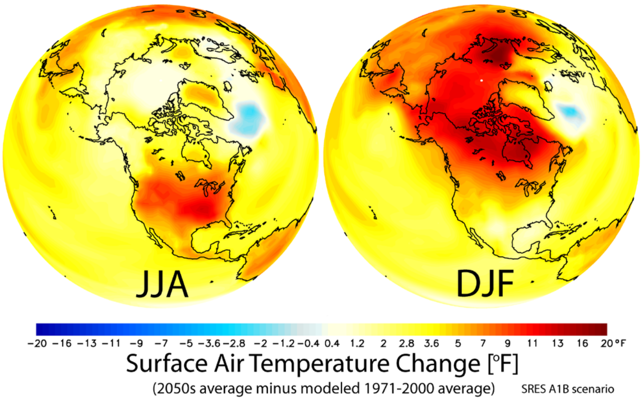




Source: [Climate Central]

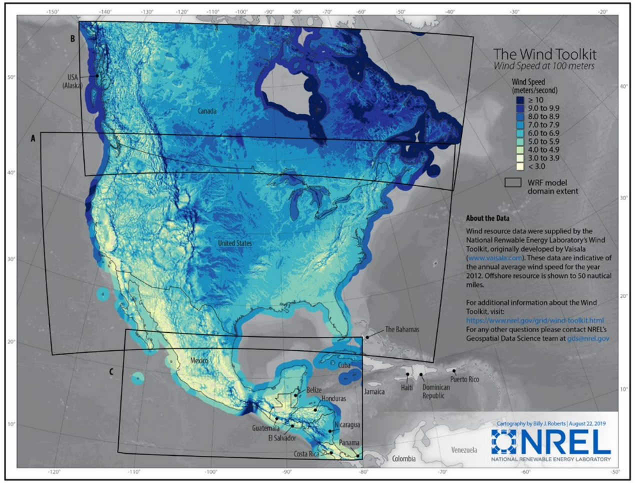
Integration of Earth System Data: Mind the Gap

Earth System Models (ESMs)



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

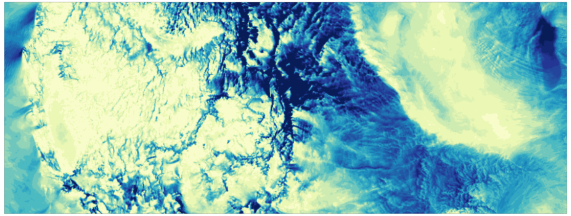
Mesoscale NREL Datasets (WTK, NSRDB)



~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

Generative Adversarial Networks (GANs) for Downscaled Earth System Model (ESM) Data

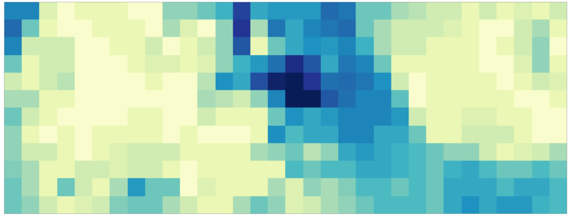
True High Res (WTK or NSRDB)



4km Hourly

Coarsen to create training data

Low Res (WTK, NSRDB, ESM)

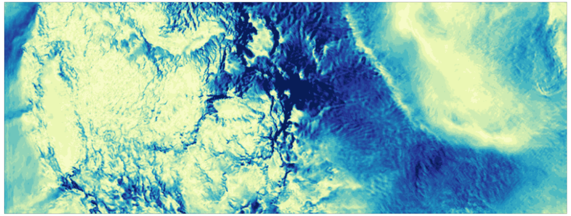


100km Daily

Discriminative Model

Generative Model

Synthetic High-Res Output



4km Hourly

Benefits of Downscaling with ML:

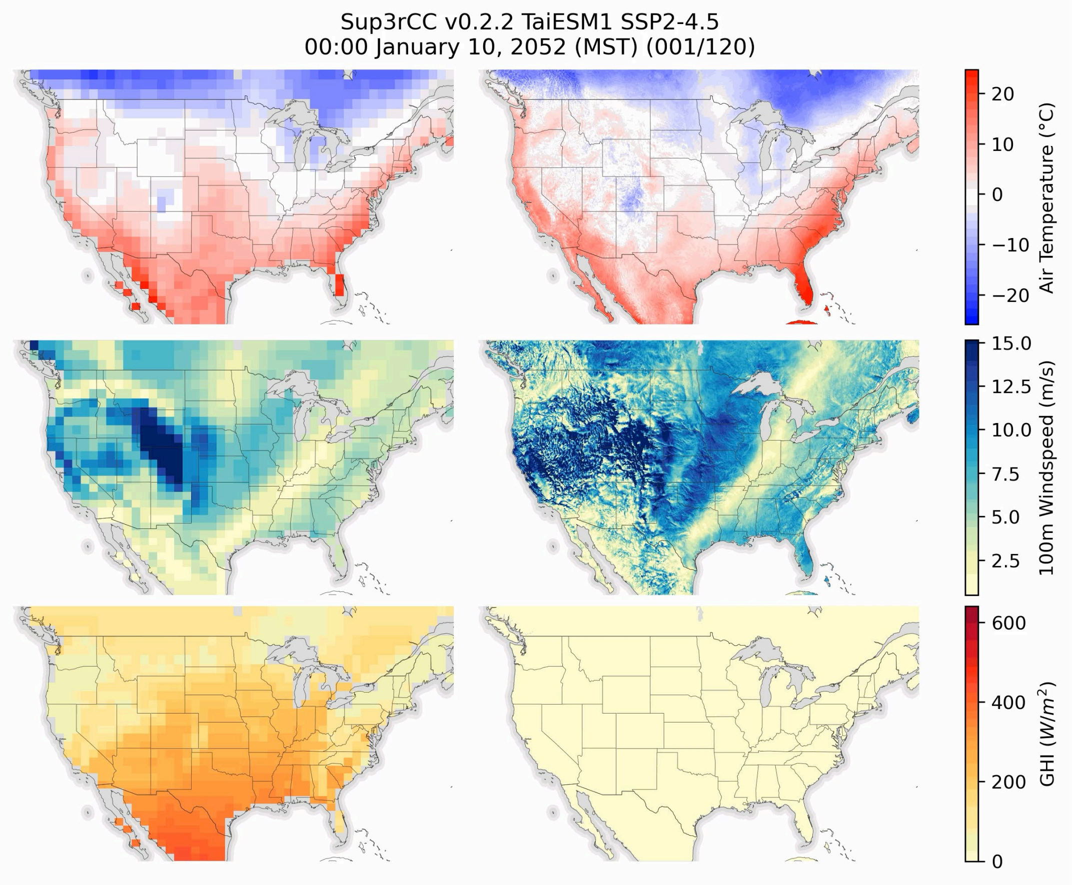
1. Computational efficiency (up to 280x faster than WRF)
2. Designed for renewables (wind, solar, temp, humidity)
3. Fully integrated into energy analysis software
4. Open-source: https://nrel.github.io/sup3r/

Buster et al. 2024

Sup3rCC

- The Sup3rCC 4km hourly outputs (right) add **high-resolution spatial features and temporal dynamics** conditioned on the low-res ESM input (left)
- Data availability:
  - v0.1.0 EC-Earth3 (SSP5-8.5, 2015-2059)*
  - v0.1.0 MRI-ESM-2.0 (SSP5-8.5 , 2015-2059)*
  - v0.2.2 MRI-ESM-2.0 (SSP5-8.5, 2000-2059)
  - v0.2.2 TaiESM1 (SSP2-4.5, 2000-2099)
  - v0.2.2 GFDL-CM4 (SSP2-4.5, 2000-2059)
  - v0.2.2 MPI-ESM1.2-HR (SSP2-4.5, 2000-2059)
  - v0.2.2 EC-Earth3-CC (SSP2-4.5, 2000-2059)
  - v0.2.2 EC-Earth3-Veg (SSP2-4.5, 2000-2059)
- Data available on NREL-HPC and OEDI:
  - /datasets/sup3rcc/
  - [DOI 10.25984/1970814](DOI 10.25984/1970814)

*v0.2.2 data is strongly recommended over v0.1.0

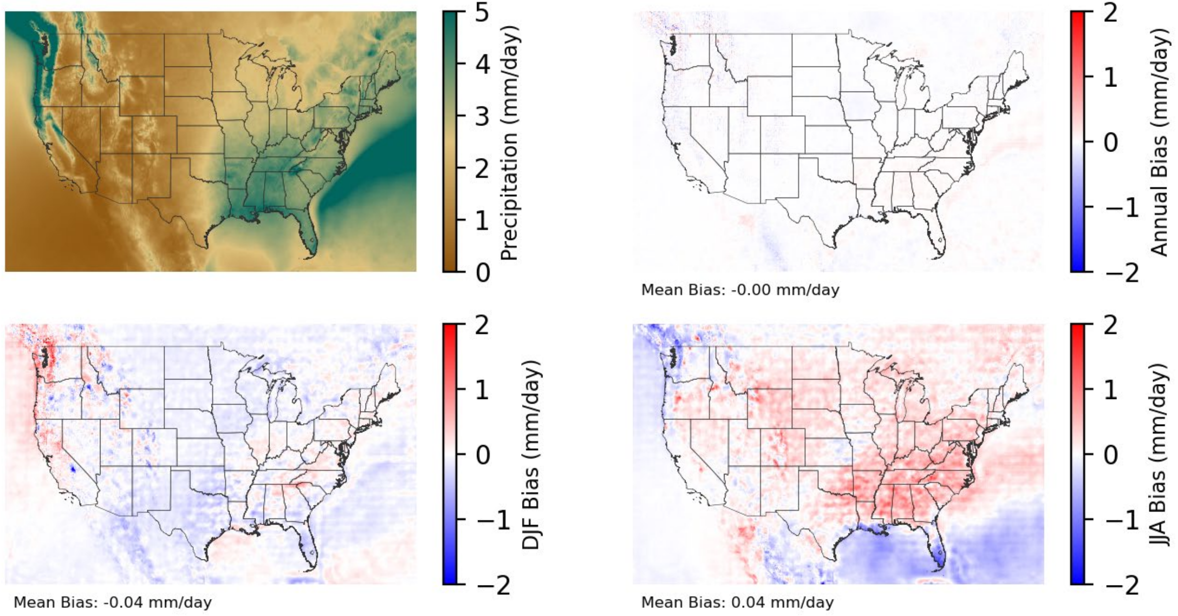


Buster et al., "High-resolution meteorology with climate change impacts from global climate model data using generative machine learning", *Nature Energy* (2024). https://doi.org/10.1038/s41560-024-01507-9

What’s new in v0.2.2?

Sup3rCC v0.2.2 Improvements

1. **Precipitation**
   - New 4km daily precipitation data
   - Based on Daymet 4km precipitation data
   - Being validated in ORNL hydrological models
2. Double Bias Correction
3. Generative Model Improvements

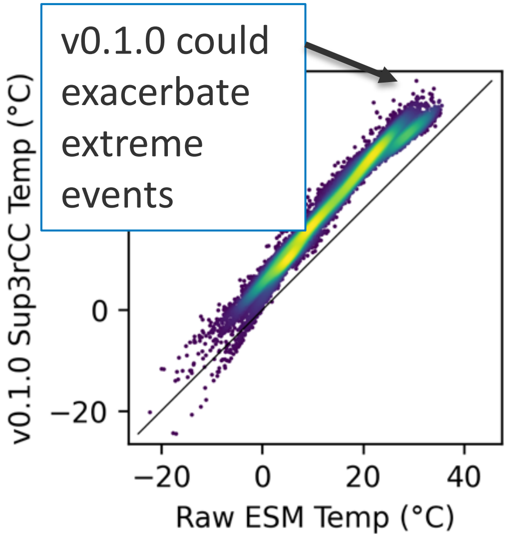


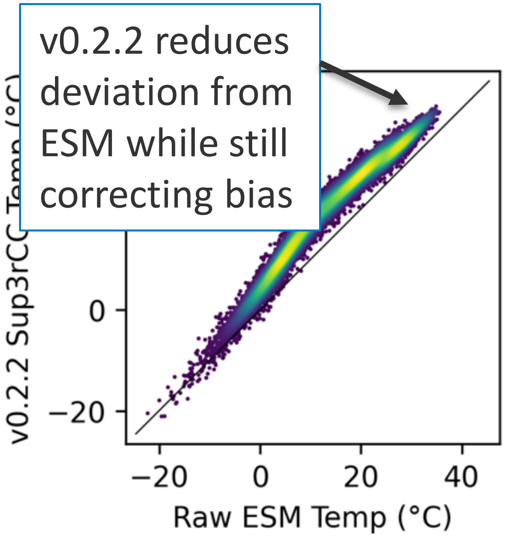
Multiyear mean and bias maps for precipitation for v0.2.2 Sup3rCC-TaiESM1 over the overlapping historical years 1980–2019. Bias is calculated as Sup3rCC minus data from Daymet. Top left panel is Sup3rCC mean values; top right is mean annual bias vs. Daymet; bottom left is mean bias for December, January, and February (DJF); bottom right is mean bias for June, July, and August (JJA).

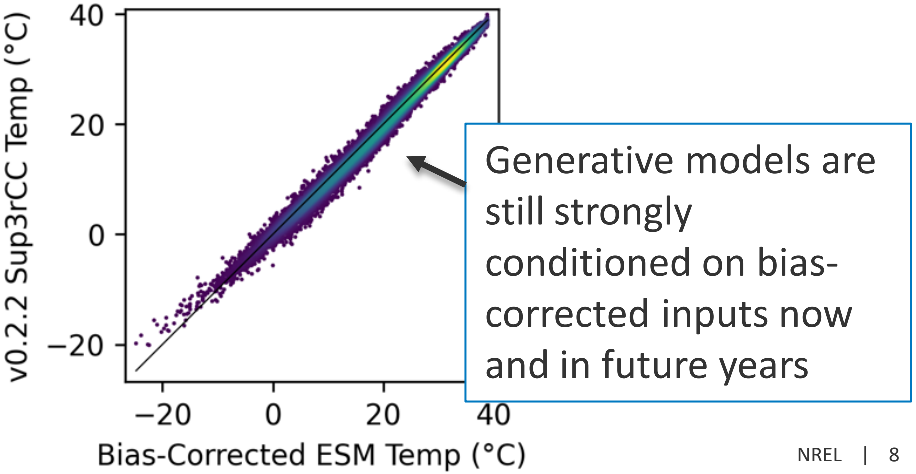
Buster et al. 2025

Sup3rCC v0.2.2 Improvements

1. Precipitation
2. **Double Bias Correction**
   - Previous bias correction was not trend-preserving
   - New method (Quantile Delta Mapping) is trend-preserving and handles each quantile explicitly
   - Minimal bias in new data vs. historical datasets over 1980-2019
3. Generative Model Improvements



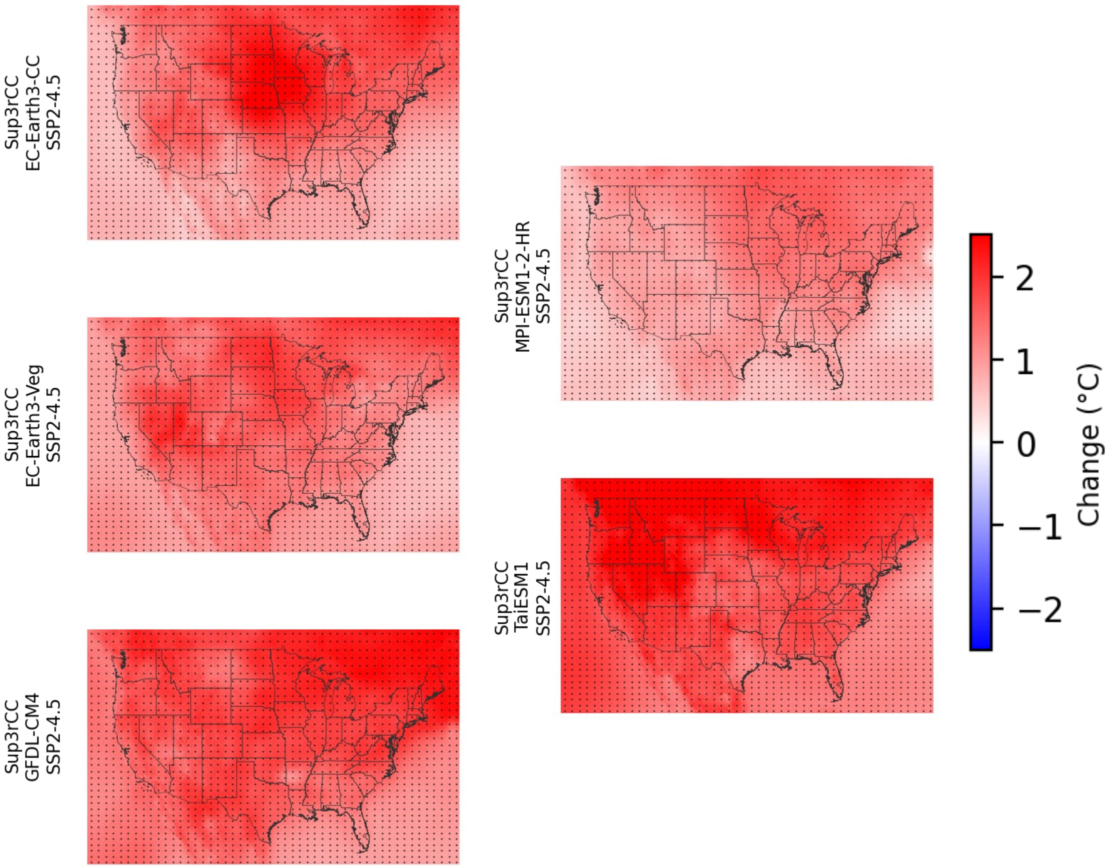




Buster et al. 2025

Sup3rCC v0.2.2 Improvements

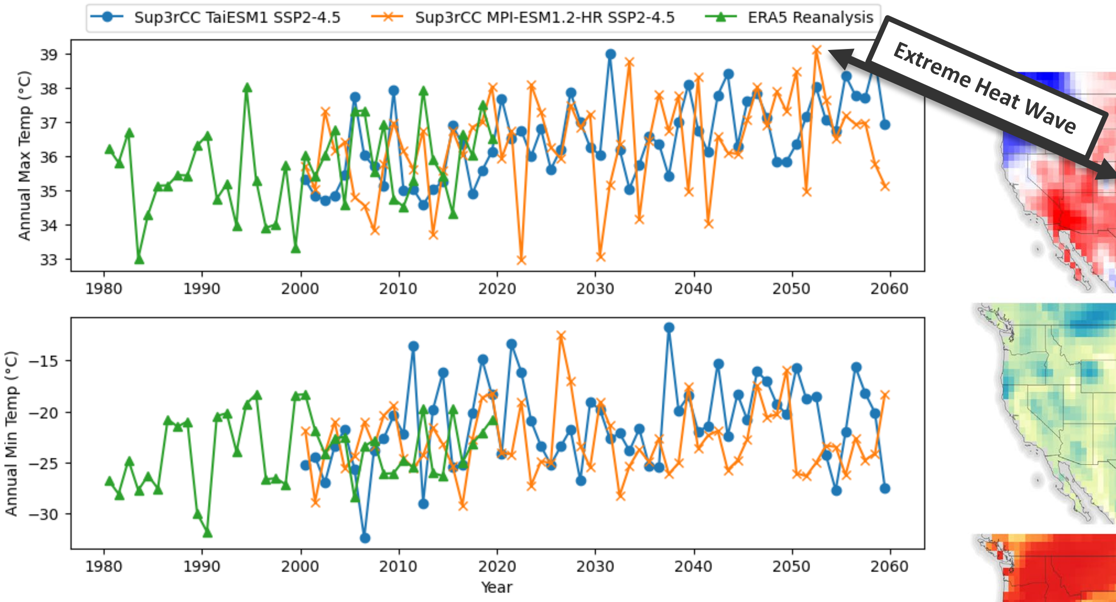
1. Precipitation
2. Double Bias Correction
3. **Generative Model Improvements**
   - Improved computational efficiency: 7x faster than the original work and 283x faster than the original WRF estimate
   - Annual hourly timeseries for 1e6 grid cells in 24 node hours on NREL HPC
   - Enabled us to downscale more ESMs to better quantify uncertainty

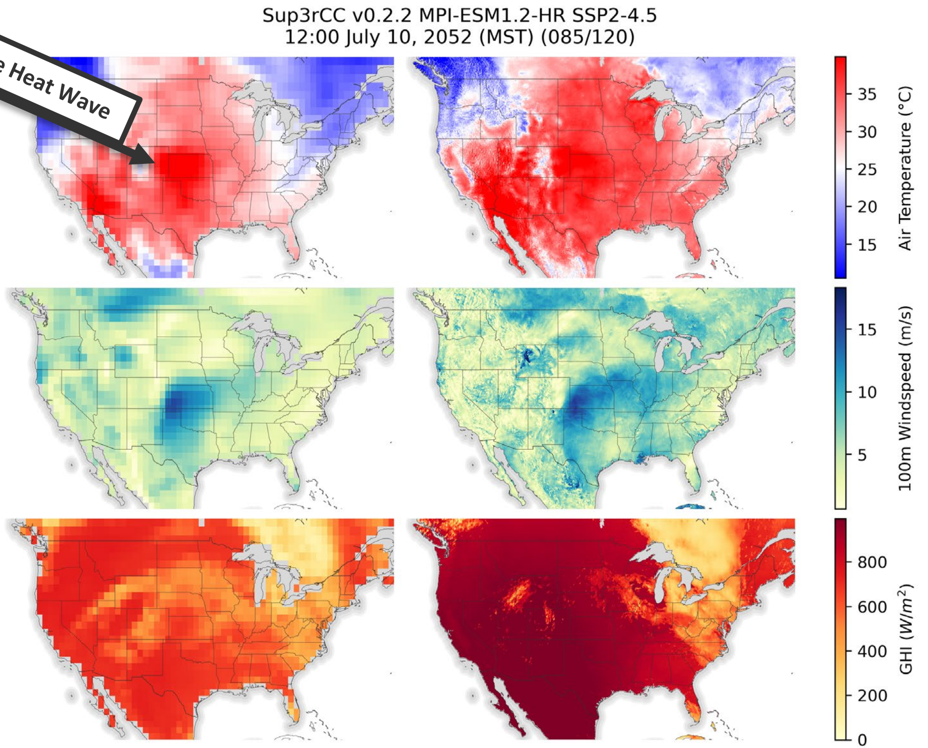


Maps of dry-bulb temperature changes in temperature through midcentury (2040–2059 minus 2000–2019) for v0.2.2 Sup3rCC SSP2-4.5 scenarios. The change maps include stippling where four or more of the downscaled data products are in agreement on the sign of change.

Buster et al. 2025

Extreme Events in Denver, CO



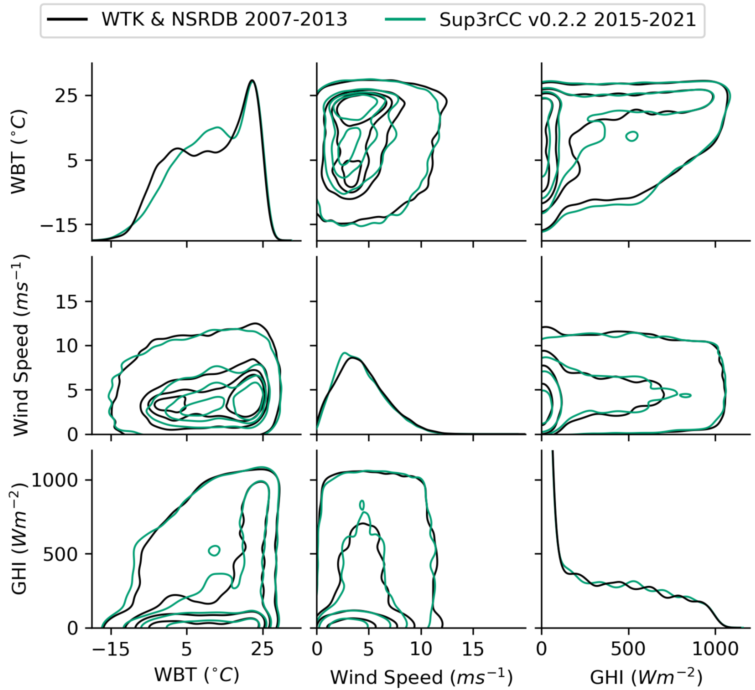


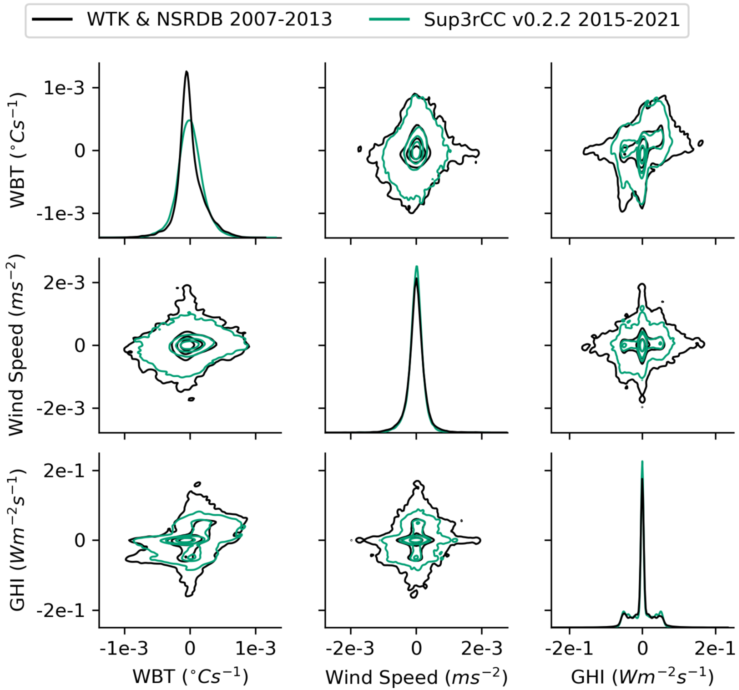
Sup3rCC can be used to study the impact of unprecedented heat waves and cold snaps but **cannot be used to study historical events**

Validation?

Validation: Statistical

- Sup3rCC reproduces joint distributions between correlated weather variables (left) including their time derivatives (right)





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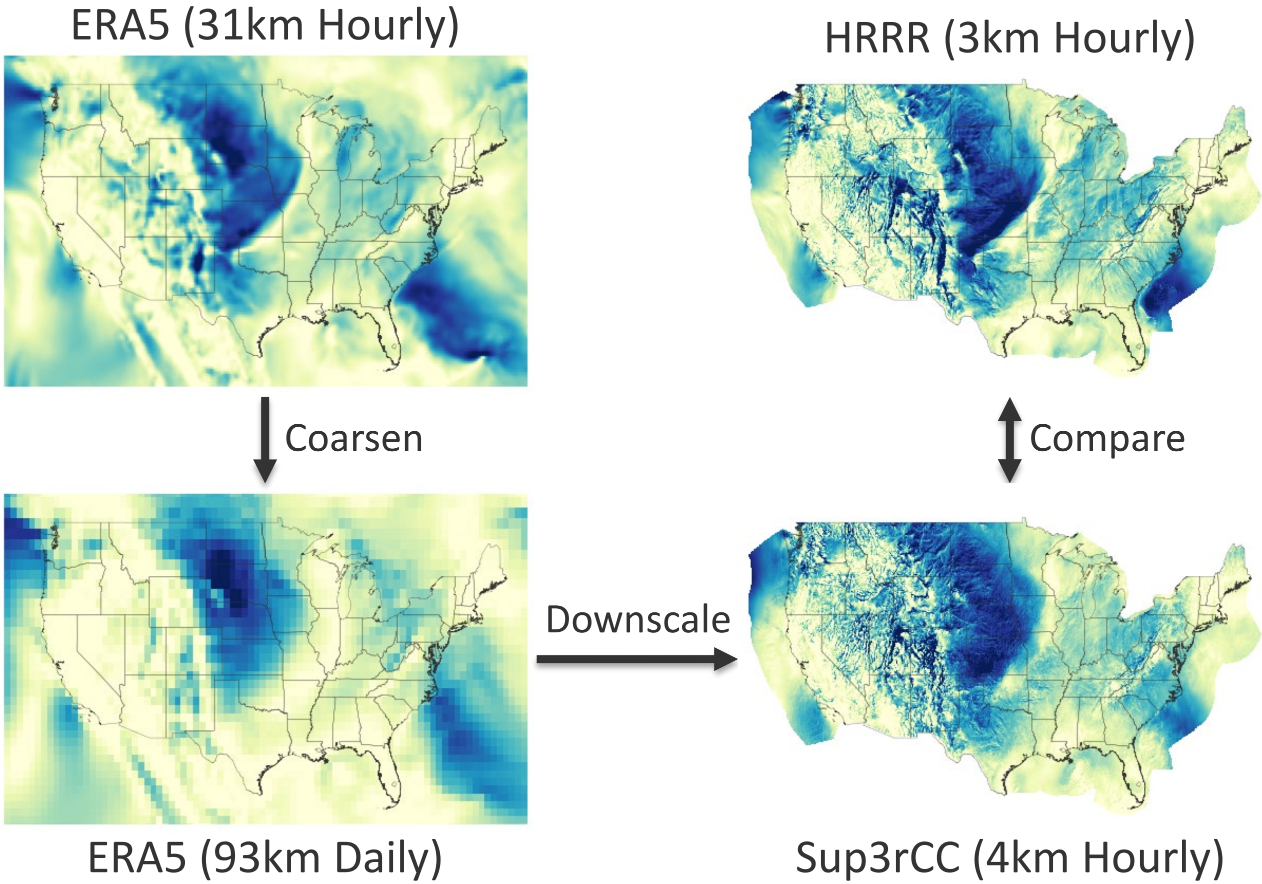
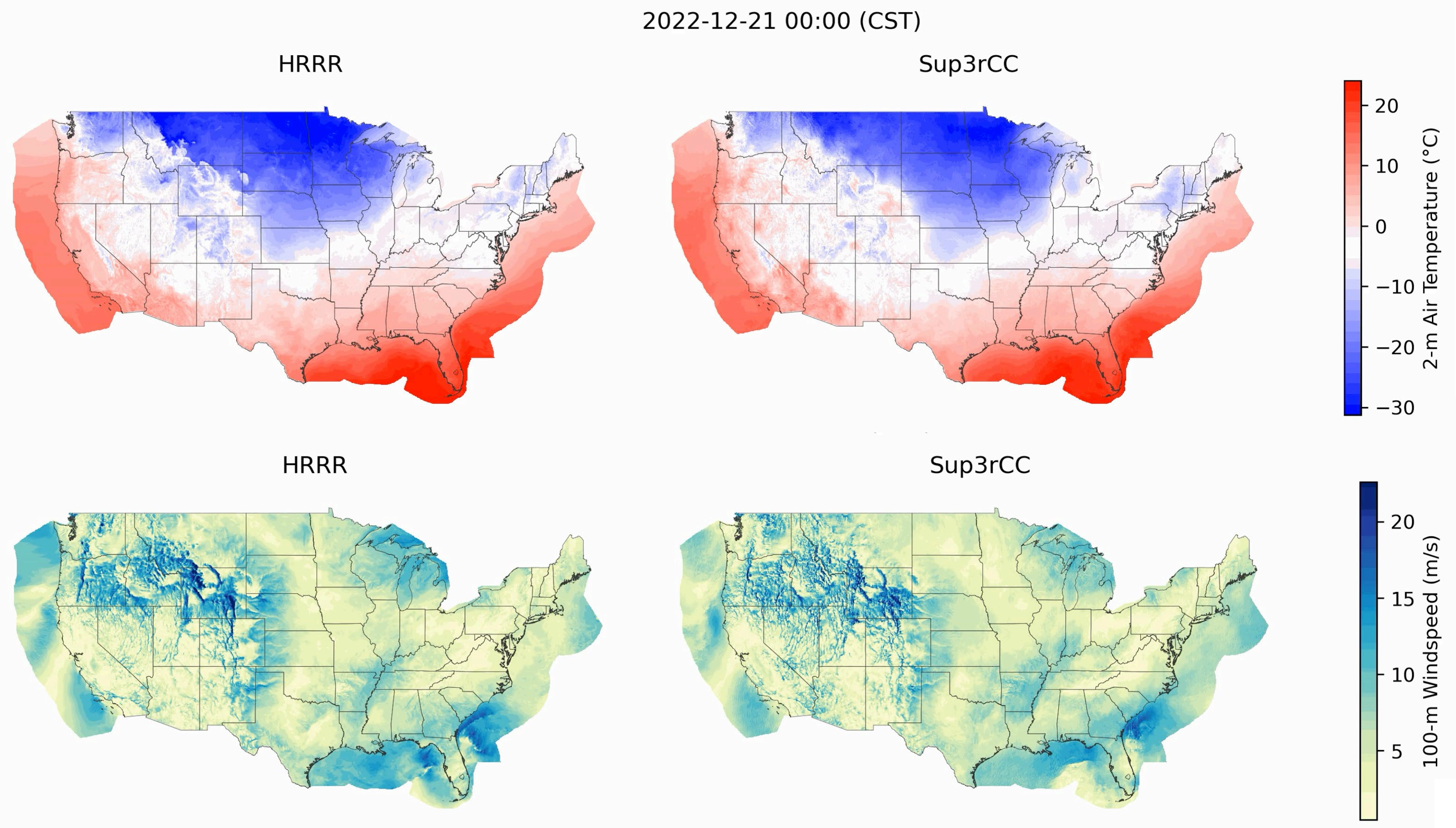
Validation: Perfect Model

- Coarsened 93km ERA5 is treated as surrogate for ESM
- 93km ERA5 data is bias corrected and downscaled with pretrained Sup3rCC v0.2.2 models
- 4km Sup3rCC outputs compared against “ground truth” HRRR data



Validation: Perfect Model (2022 Winter Storm)



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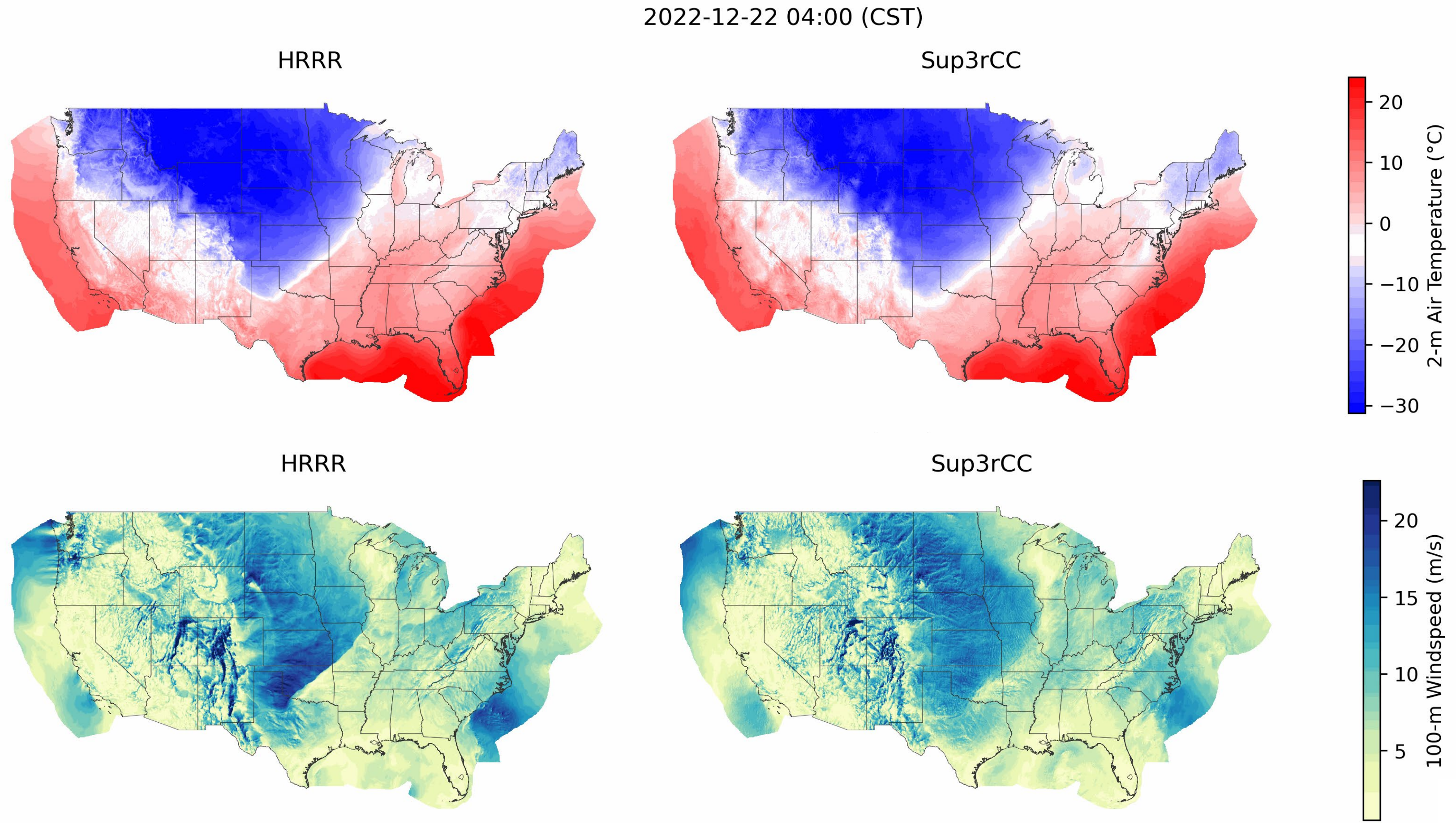

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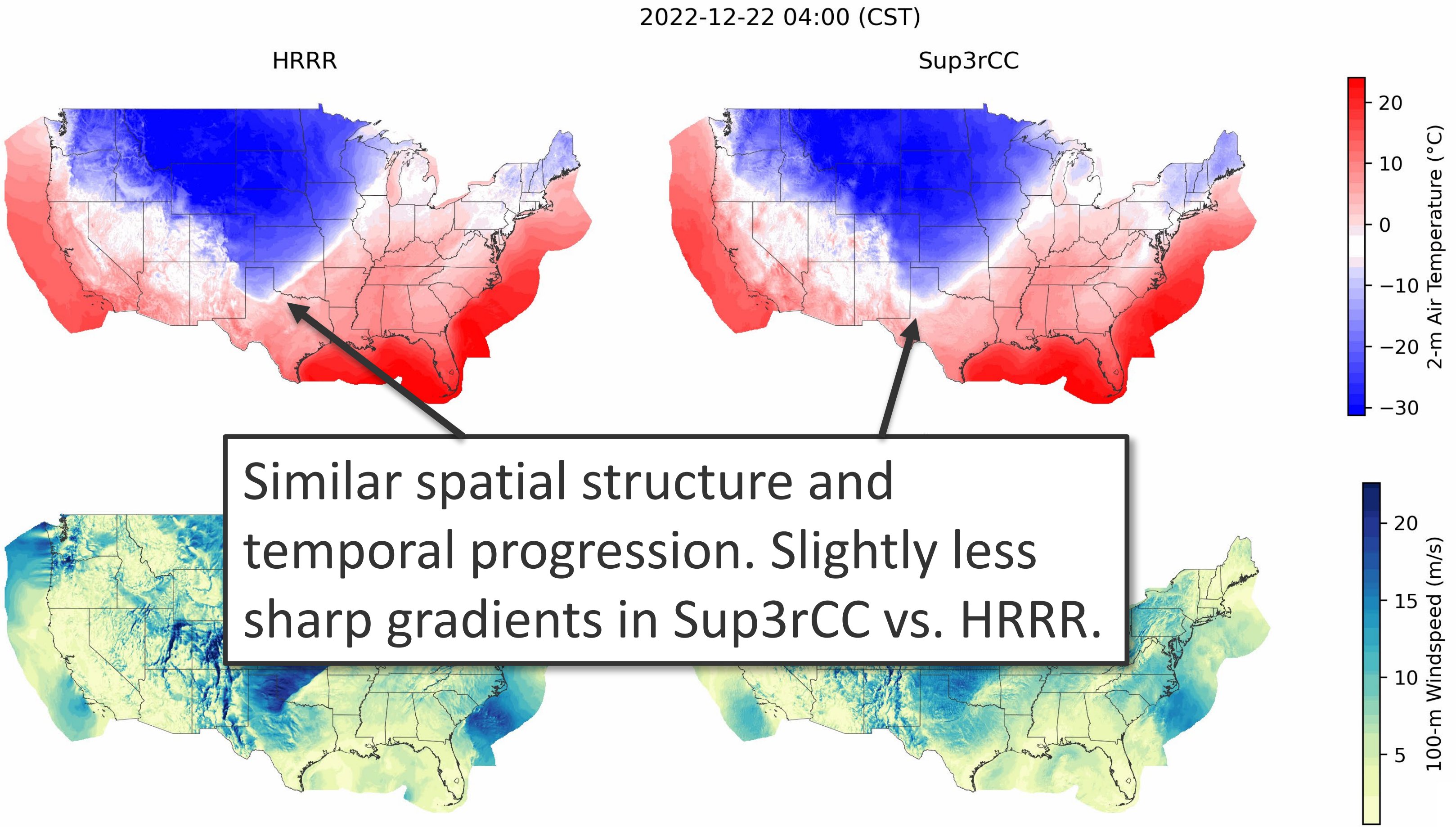

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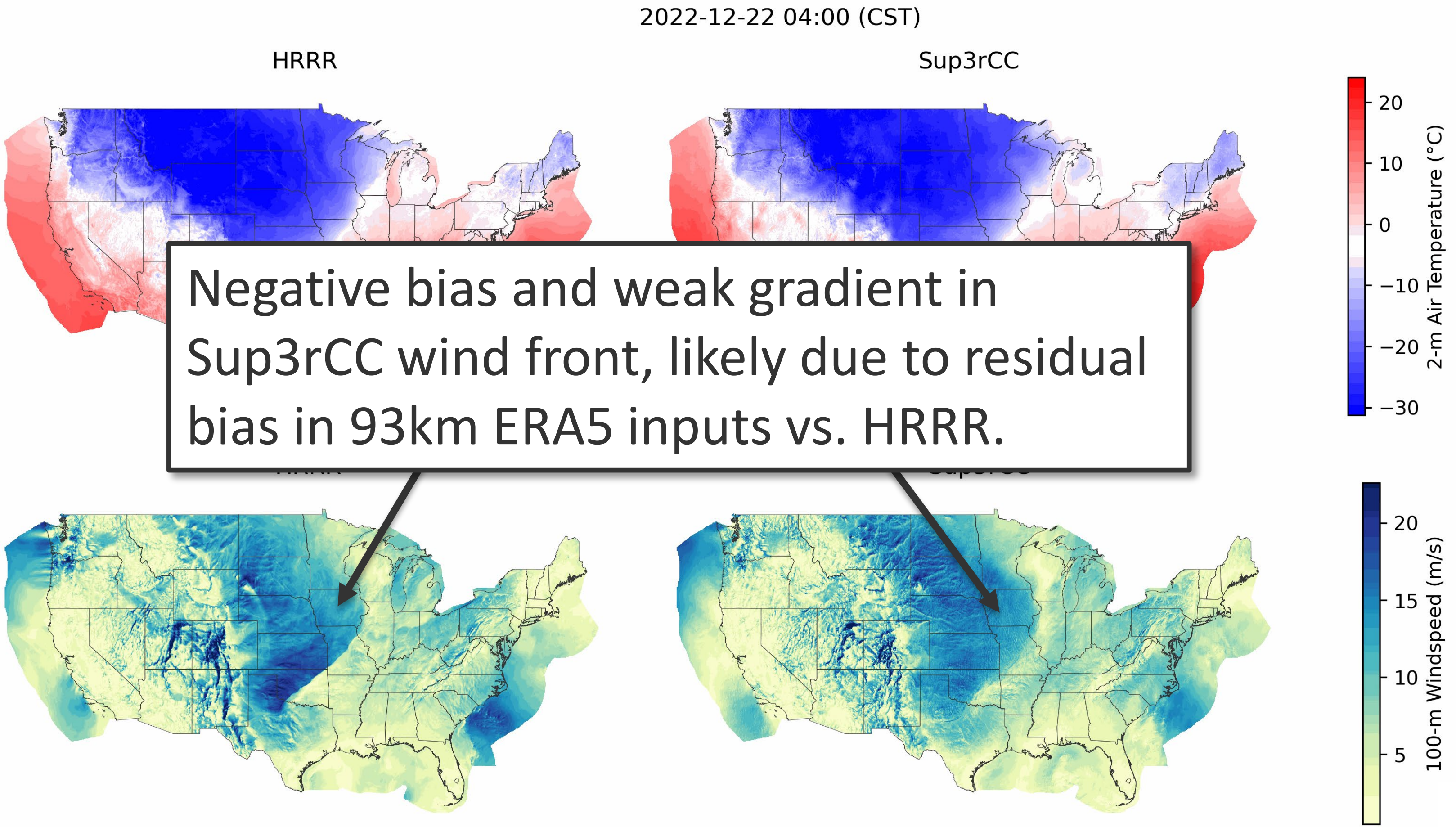
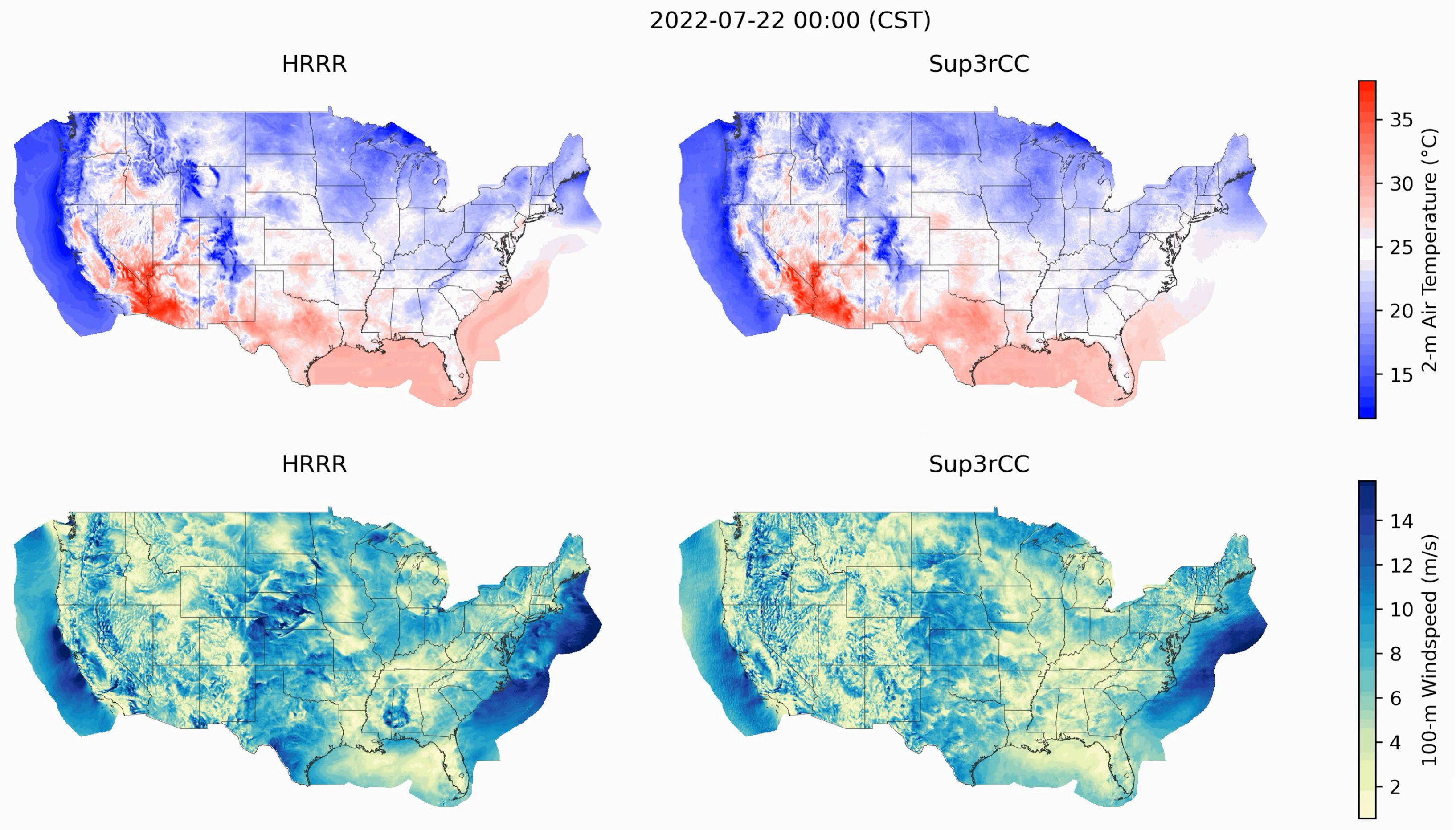
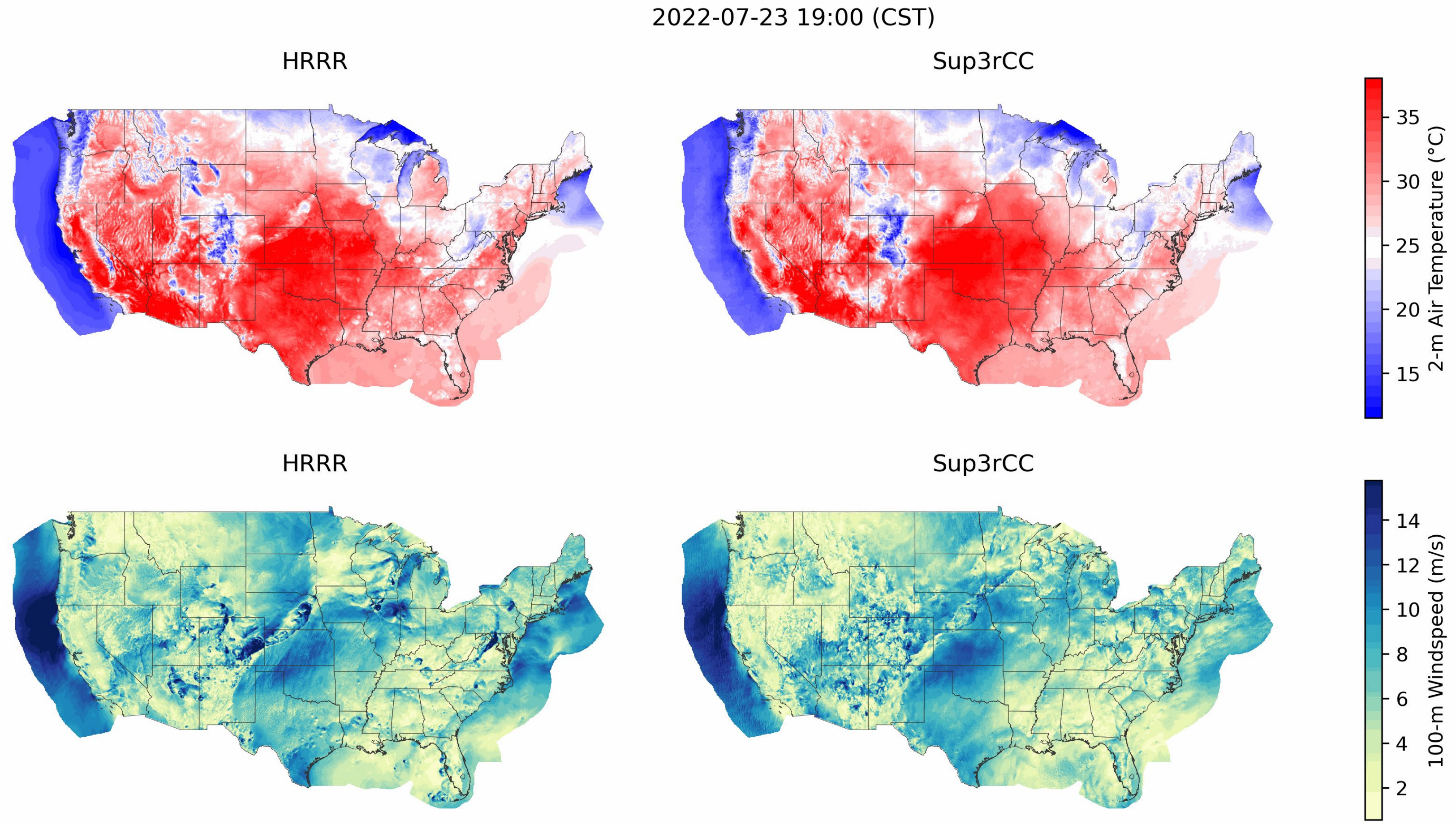


Negative bias and weak gradient in Sup3rCC wind front, likely due to residual bias in 93km ERA5 inputs vs. HRRR.

Validation: Perfect Model (2022 Heat Wave)



Validation: Perfect Model (2022 Heat Wave)



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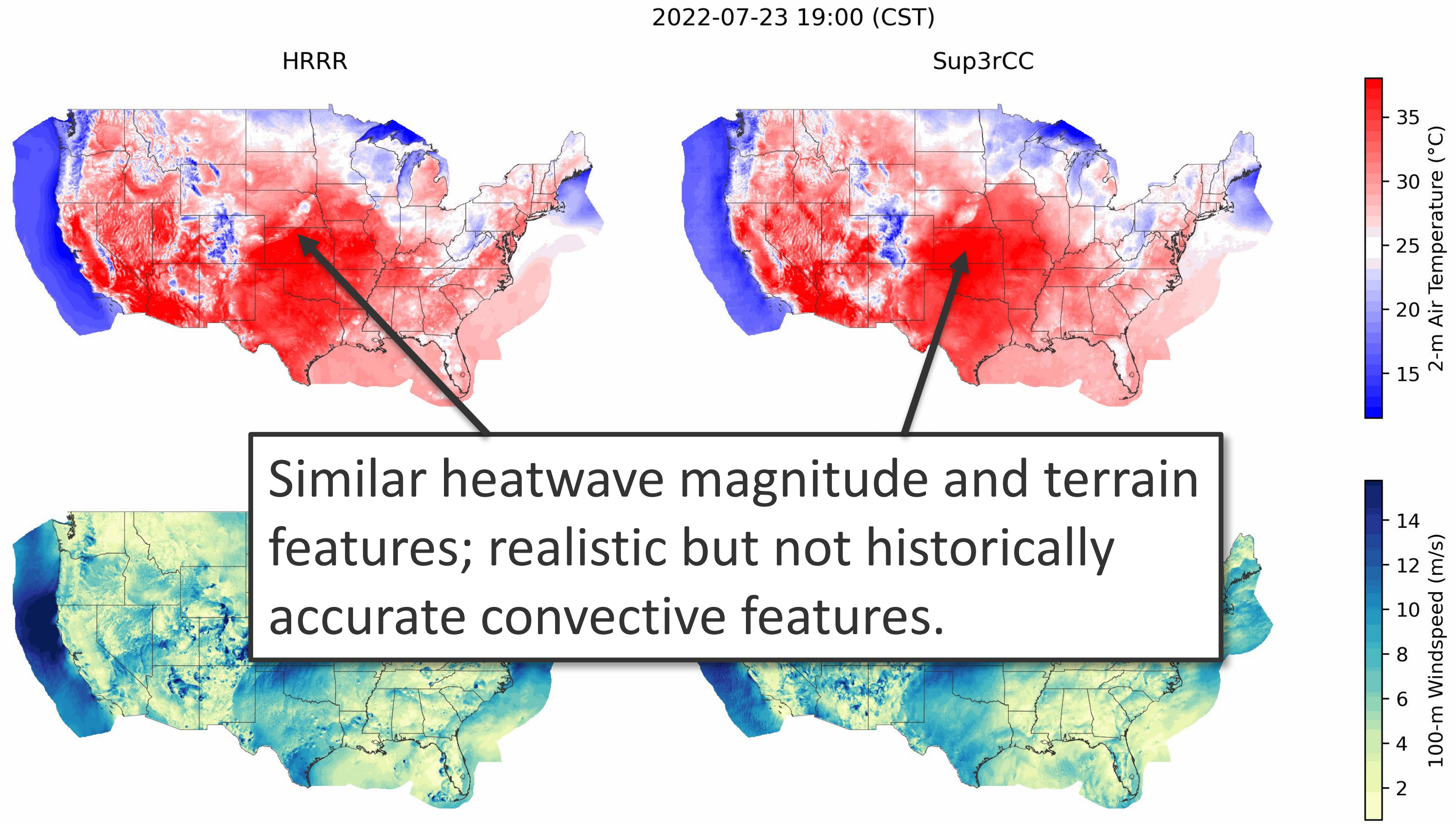
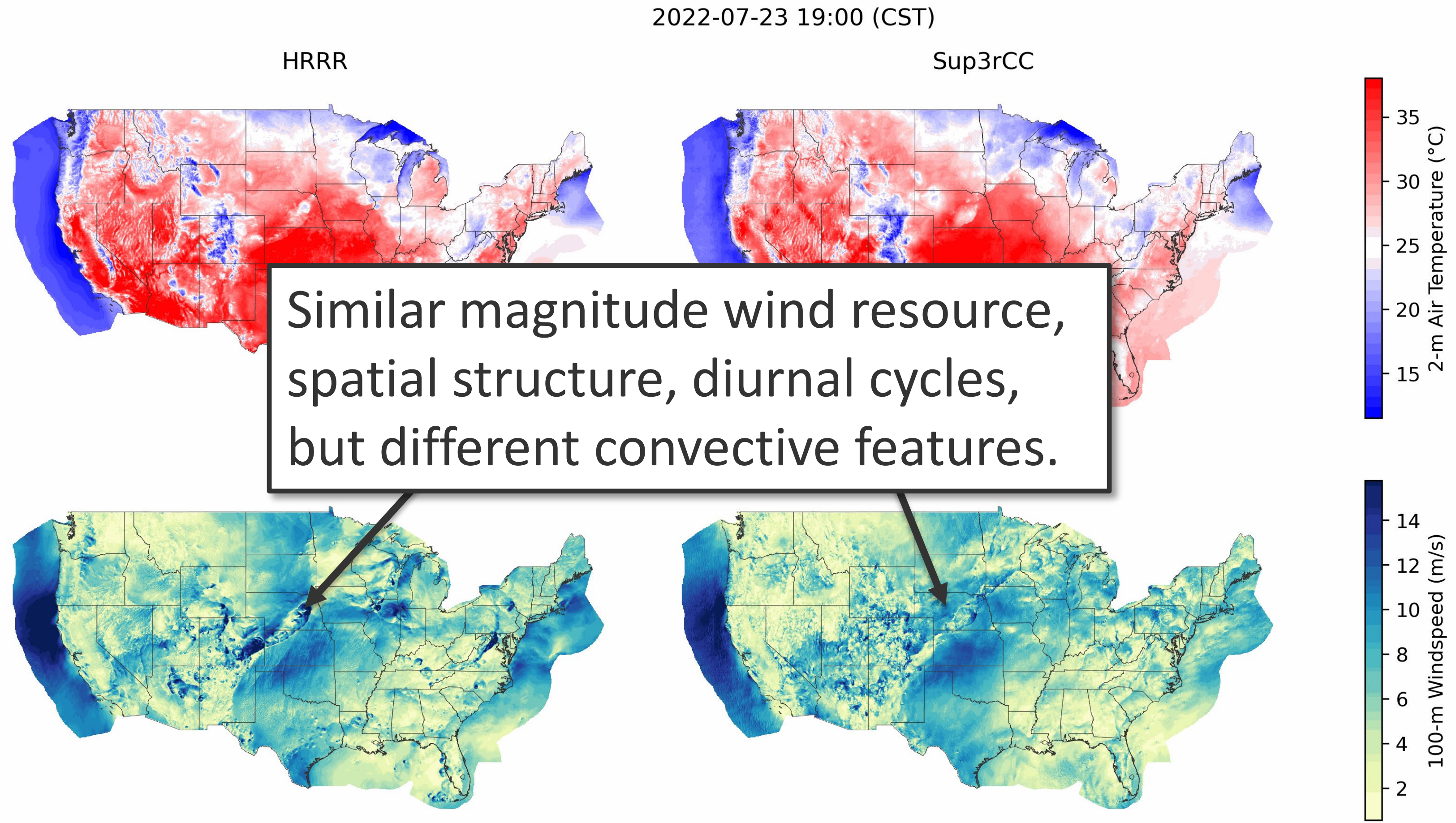


Similar heatwave magnitude and terrain features; realistic but not historically accurate convective features.

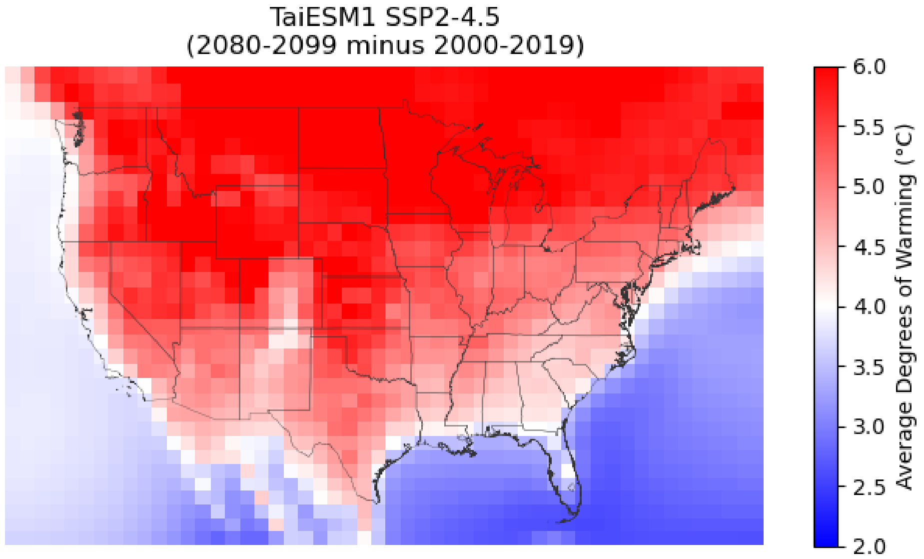
Validation: Perfect Model (2022 Heat Wave)

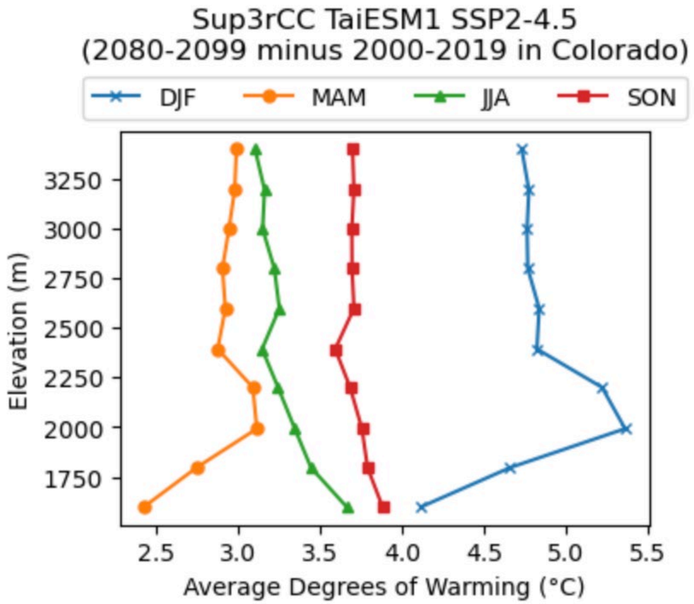


Similar magnitude wind resource, spatial structure, diurnal cycles, but different convective features.

Validation: Elevation-Dependent Warming

- Research by [Minder et al. 2018] has suggested the Rockies will experience elevation-dependent warming due to snow-albedo feedback

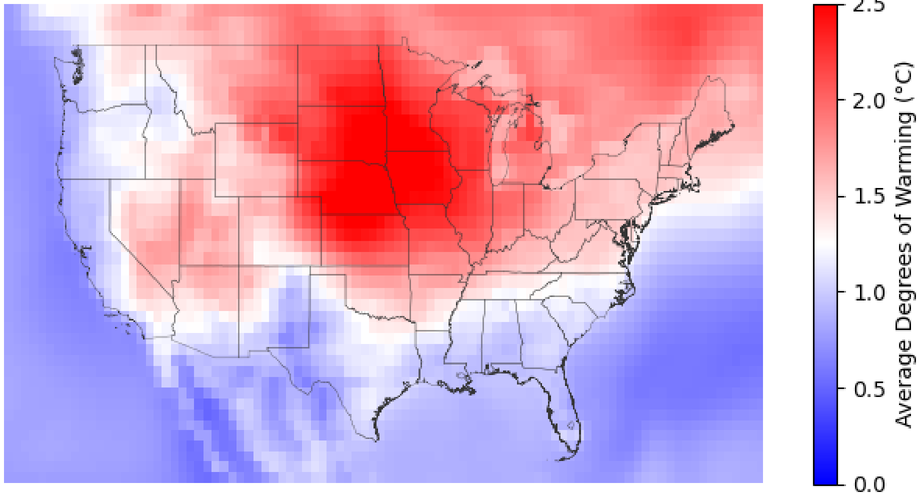


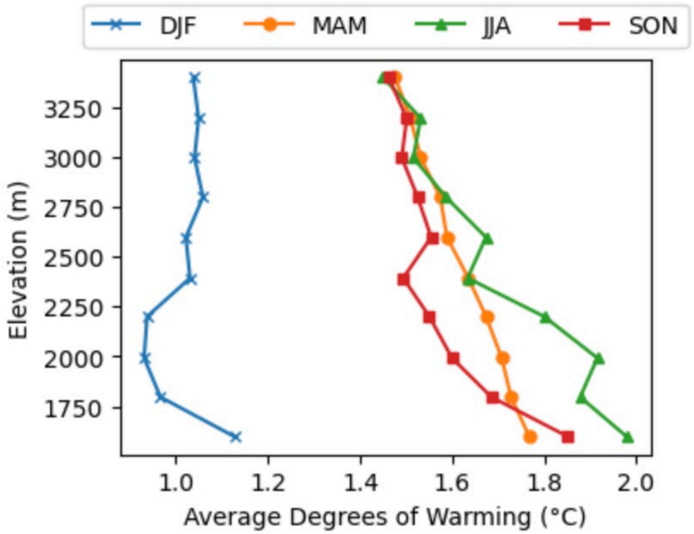


- 100km ESM estimate of warming strongly dictates Sup3rCC outputs
- 4km Sup3rCC *can* reproduce elevation-dependent warming signals in Colorado

Validation: Elevation-Dependent Warming

- Research by Minder et al. 2018 has suggested the Rockies will experience elevation-dependent warming due to snow-albedo feedback





- Sup3rCC strongly preserves spatial trends in ESM warming signals, sometimes in contradiction of the trends found by Minder et al.

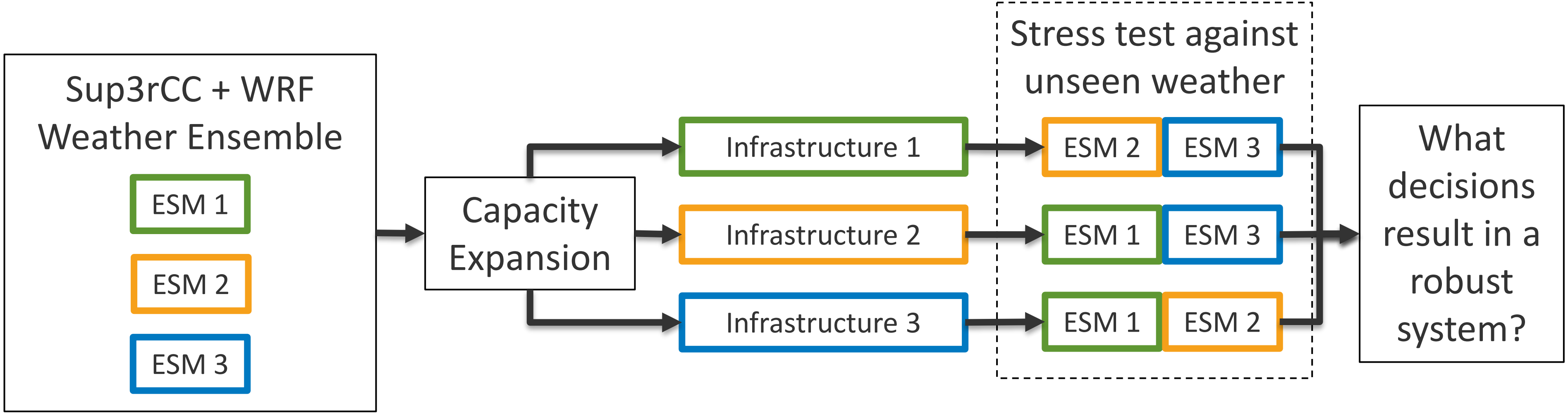
So how are we using this data in power system analysis?

Energy System Planning for Resilience during Severe Weather (ESPRS)

- Downscaling future weather projections for power system analysis with multiple methods
  - Generative Machine Learning (Sup3rCC)
  - Numerical Weather Prediction (WRF)
- Exploration of planning strategies under meteorological uncertainty
  - Decision making with deep uncertainty (DMDU)
  - Stochastic capacity expansion
- Application to utilities
  - Tennessee Valley Authority
  - Southern Company

Decision Making Under Deep Uncertainty (DMDU) for Power System Planning

- Deep uncertainty occurs when there are multiple plausible futures, where we **cannot assign a probability distribution or characterize their likelihood**, and we **lack confidence in modelling the system** outcomes under these plausible futures
- Robust decision making (RDM) is one DMDU method used to evaluate **which decisions are robust to multiple possible futures** by stress testing these options against the possible futures



Each ESM has many weather years; each infrastructure plan results from a set of decisions and one ESM

Adapted from [Sundar et. al 2024](), Earth's Future

We Are Exploring Meteorological, Economic, and Policy Uncertainties on Long Term Power System Planning

We answer the question:

Which pathways are robust and resilient amidst future uncertainties?

Uncertainties Considered

Climate

- Different ESMs – meteorology trajectory
- Unseen weather years

Economic and Policy

- RE siting scenarios
- Fuel prices
- Technology costs
- Transmission scenarios

Outcome metrics

- Resource adequacy (LOLE)
- Generation cost
- Stranded asset cost
- Unserved energy
- Emissions

PRAS

Zonal PCM or **Simple dispatch**

DMDU Analysis Plan

We plan to execute the DMDU activity in the following stages:

1. Capacity Expansion modeling for all CONUS regions
   - *Multiple infrastructure portfolios based on different weather scenarios*

2. Resource adequacy stress tests for all CONUS regions
   - *Explore meteorological sensitivities and robust infrastructure plans*

3. Zonal PCM or simple dispatch for a specific ISO/RTO
   - *Explore uncertainties with coarse zonal resolution*

4. Nodal PCM for a utility partner footprint
   - *Explore uncertainties at higher spatial resolution*

Sup3rCC and DMDU Contributors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Thank you!

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https://data.openei.org/submissions/5839
https://nrel.github.io/sup3r/

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