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Seminar 3 – Acute Climate Driven Severe Weather

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The Multi-Scenario Extreme Weather Simulator

Sandia National Laboratories

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Learning Objectives

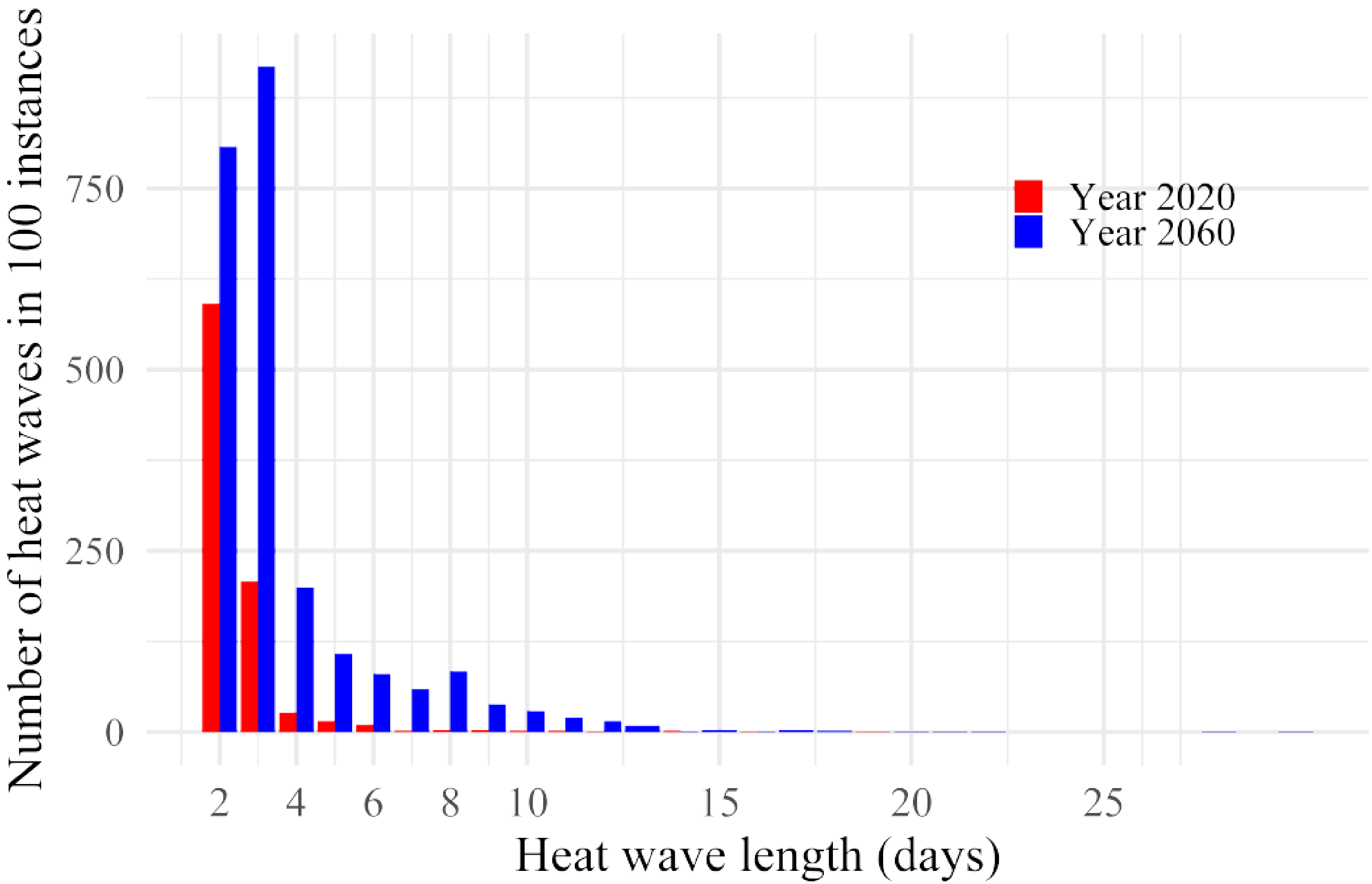
1. **Understand the importance of future weather boundary conditions in climate driven resilience and efficiency analysis.**
2. **Understand why a stochastic framework is needed to assess resilience versus efficiency combined assessments.**
3. Introduction of VCWG modeling paradigm and sub-modules: the rural, rural surface energy-water balance, building energy, surface energy-water balance, soil energy-water balance, vertical diffusion, and urban boundary layer models.
4. Preparation of weather data as boundary and forcing conditions for BEMs: observed weather files, meso-scale models, and downscaling of climate models to produce weather files

Acknowledgements

- The multi-scenario extreme weather simulator (MEWS) is funded by the Department of Energy (DOE) Building Technology Office Future Weather Project
- Funding from the DOE Office of Electricity Energy Resilience for Mission Assurance project was also used to create MEWS

Outline

- Why future weather?
- Why a stochastic approach to resilience analysis?
- Multi-scenario extreme weather simulator (MEWS)
    - Objectives/Overview
    - Algorithm
- Conclusion



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Why future weather?

1. **Global Climate Change**

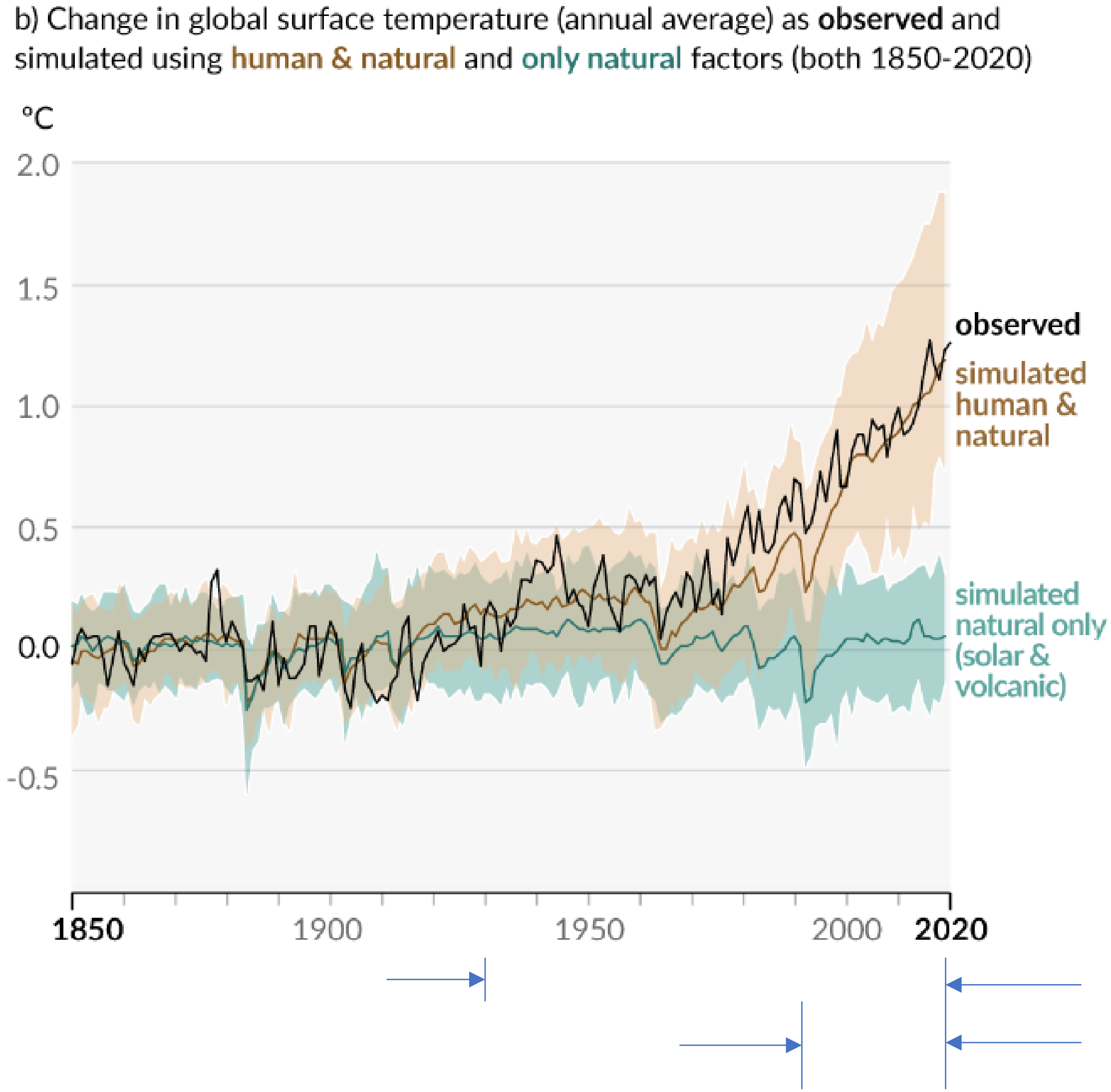


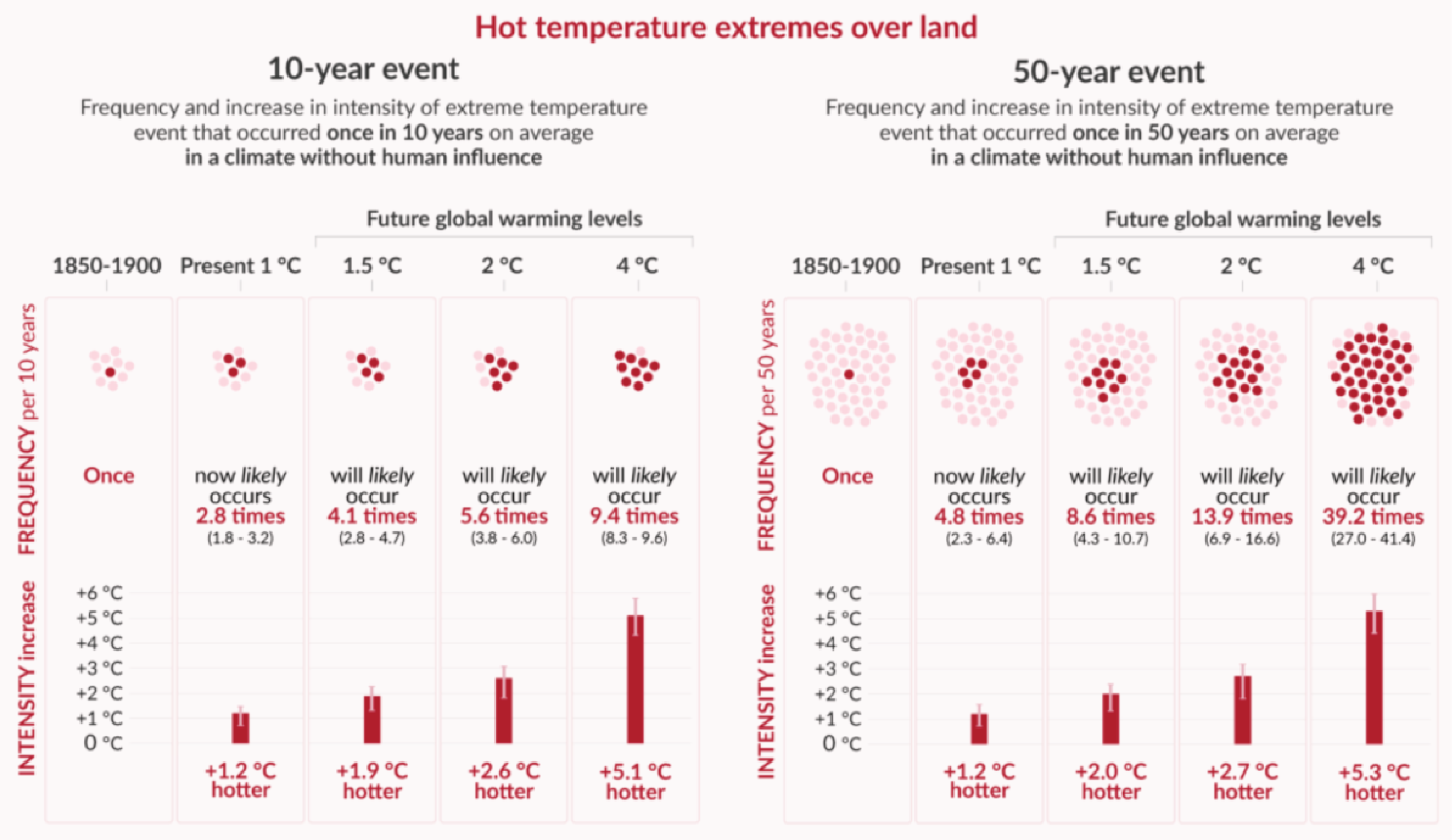
Figure SPM.1 Intergovernmental Panel on Climate Change (IPCC) Working Group I – The Physical Science Basis Sixth Assessment Report (AR6) (approved for release for education on climate change issues to society)

Approximate building & HVAC timescales

See ASHRAE fundamentals chapter 36 on climate change

Why future weather? (2)

2. Increased frequency, and intensity of extreme weather



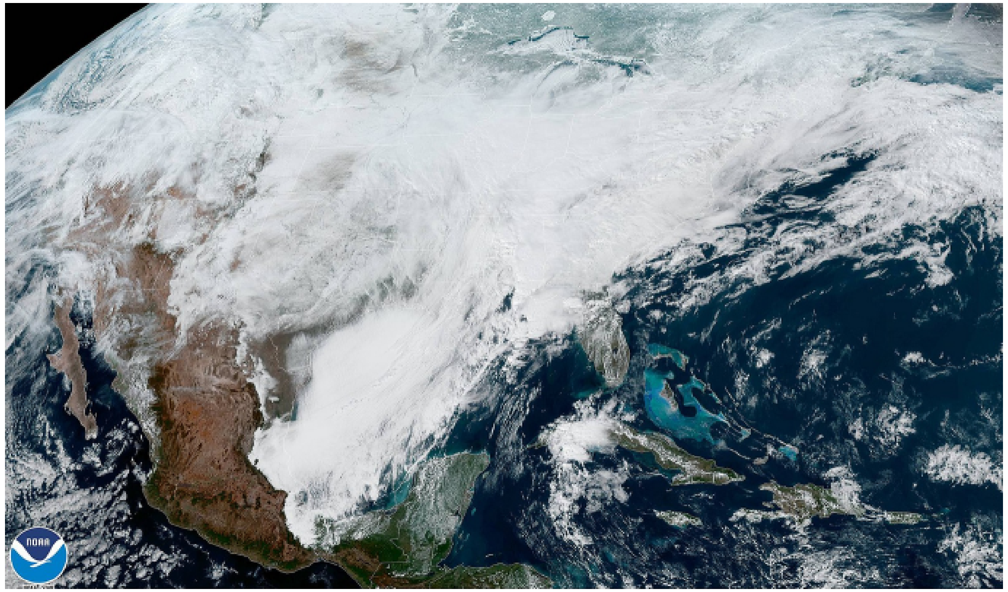
IPCC’s AR6 Working Group I: The physical basis Figure SPM.6

Why future weather? (3)

3. Increased demand for resilience to future design basis threats (DBR)

- Resilience analysis requires simulation of a system's failure and recovery due to **DBR's**

Extreme Weather DBR's



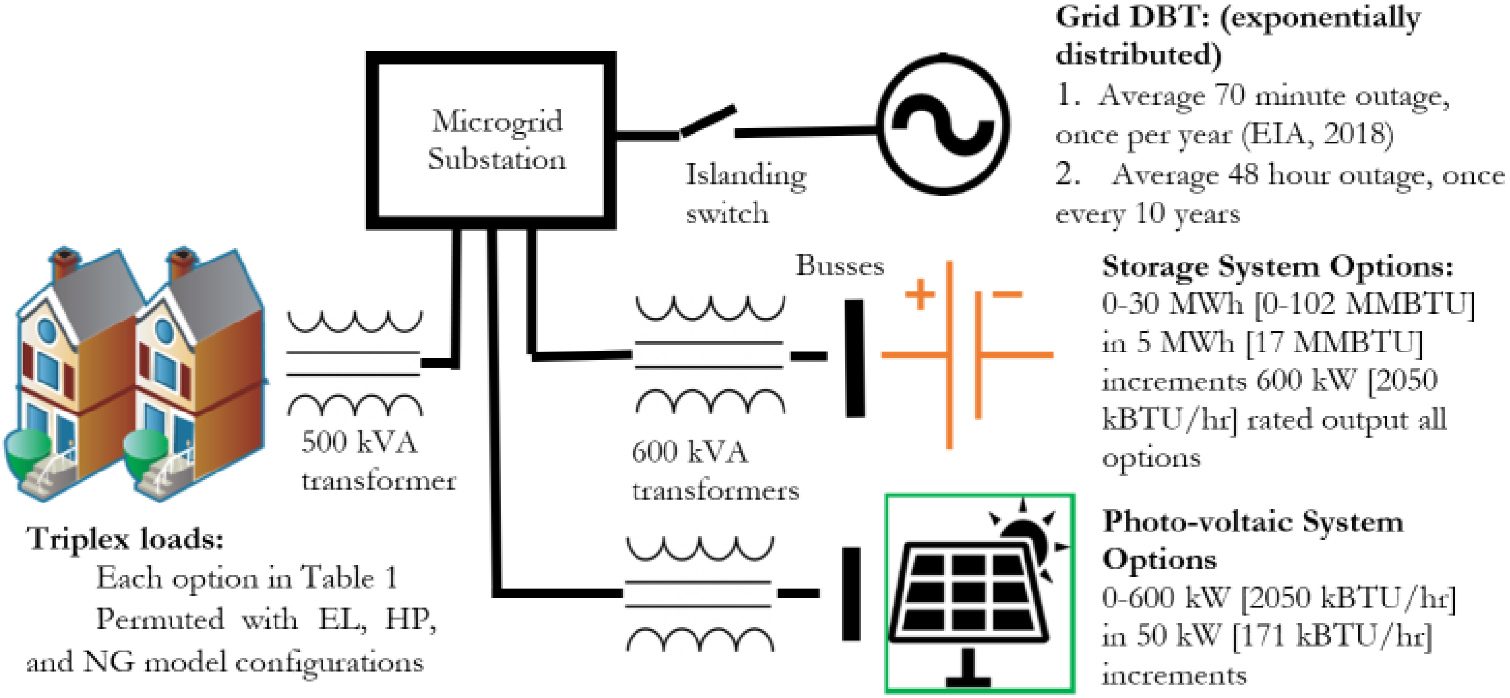
Creative commons Wikimedia – Winter Storm URI over the U.S. February 15th, 2021

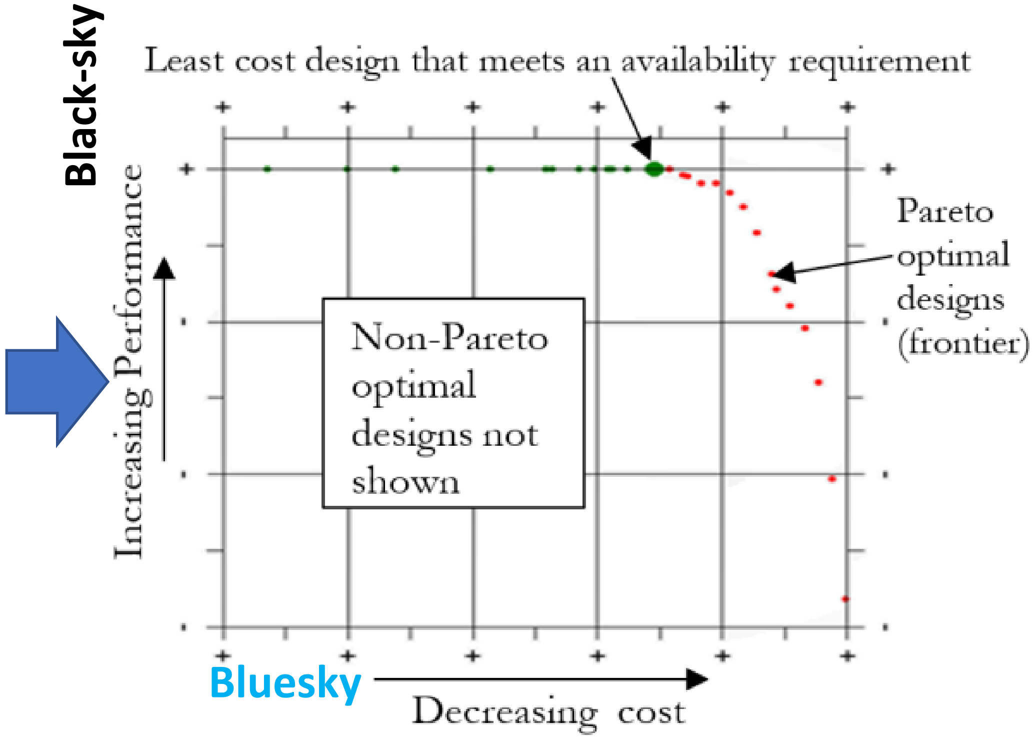
Other DBR's Earthquake

Collapsed apartment buildings in the Niigata area of Japan. *DOC/NOAA/NESDIS/NCEI (1964) Public Domain*

Why a stochastic approach?

How much money should be invested in resilience?



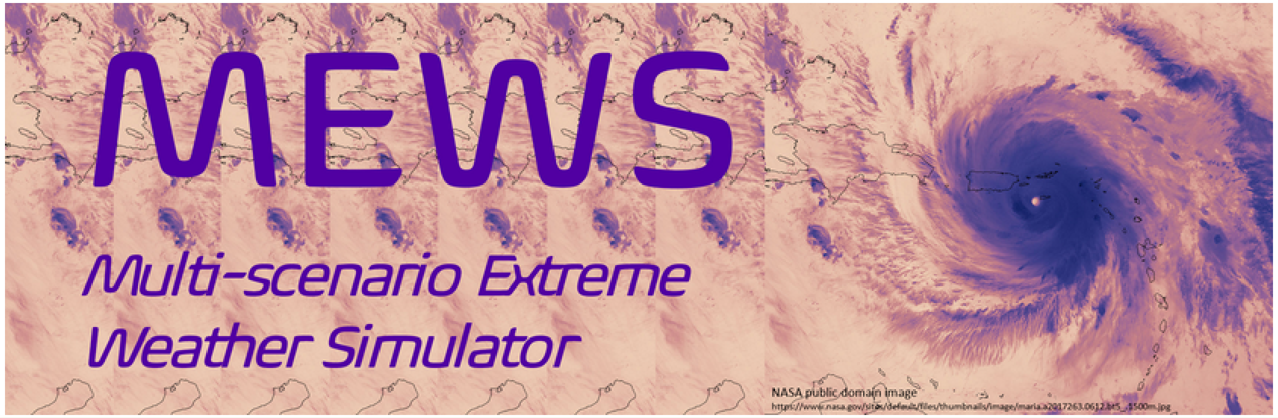


A Stochastic weather and model approach allows simultaneous assessment of ordinary (blue-sky) and resilience (black-sky) outcomes

Figures adapted from Villa et. al, 2022. "Low Cost Community Microgrids by Efficiency and Reduced Availability" *ASHRAE Summer meeting 2022 (separate presentation).*

Multi-scenario Extreme Weather Simulator (MEWS)

1. Stochastic weather file generation for building energy modeling (BEM) resilience analysis
   - Outputs weather files for major BEM tools
2. Used for a site-wide energy assessment for SNL NM
3. Open-source python (https://github.com/sandialabs/MEWS)



MEWS Objectives

1. Provide extreme weather files that contain statistically realistic increases in severity and frequency based on climate model predictions and historical data

- Extreme temperature (heat waves and extreme cold)

- Future:

  Extreme Precipitation, Drought, Hurricanes, …

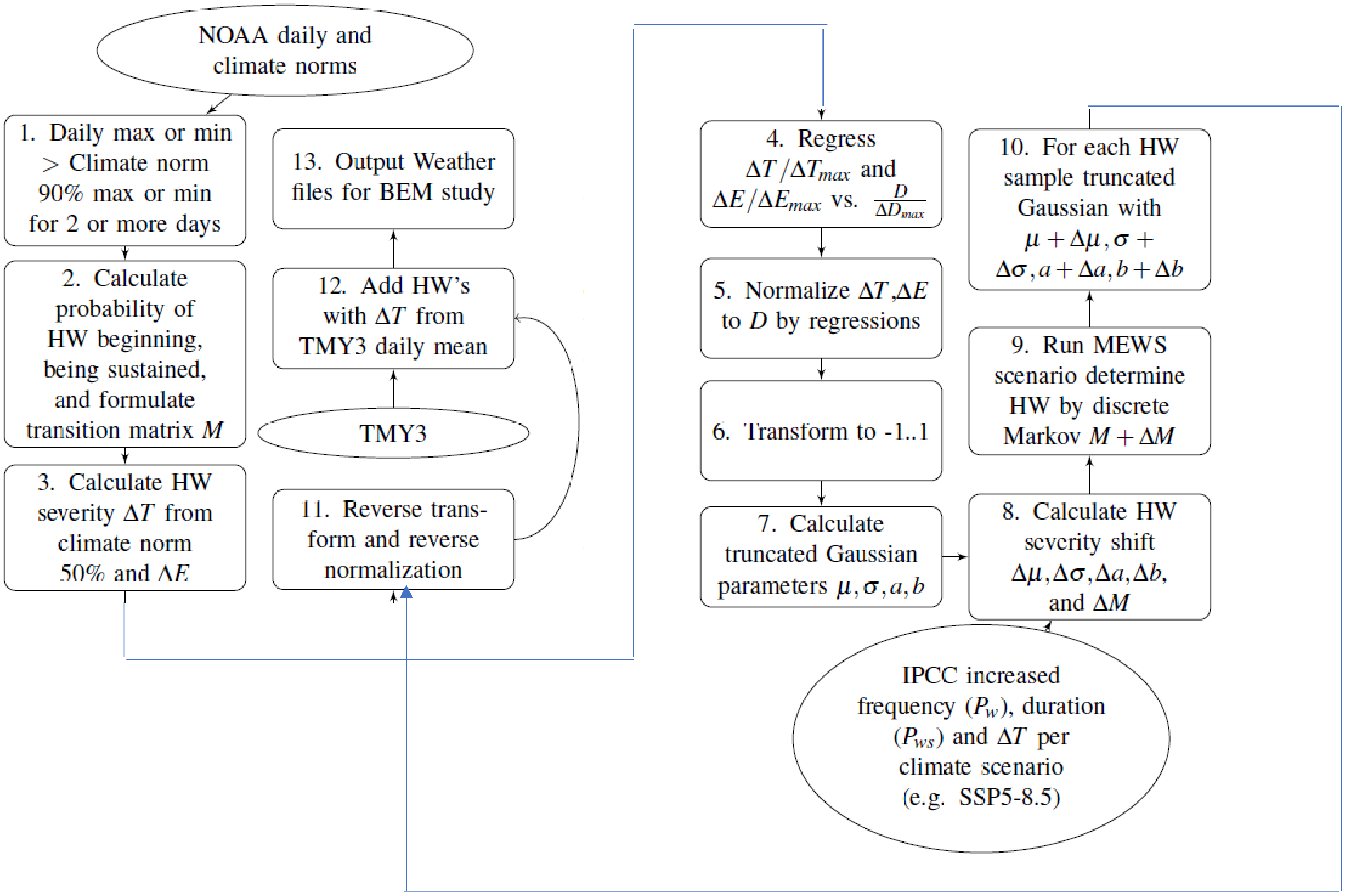
2. Quickly generate files with reasonable output with a data-driven approach

Data here includes climate model outputs

- Fuse historical data and climate projections into “best-guess” sampling distributions and Markov processes

3. Keep the algorithm simple (as possible!)

MEWS Algorithm



Step 1: Data and extreme temperature definition

National Oceanic and Atmospheric Association (NOAA)

- Climate norms (1991-2020)
- Daily summaries

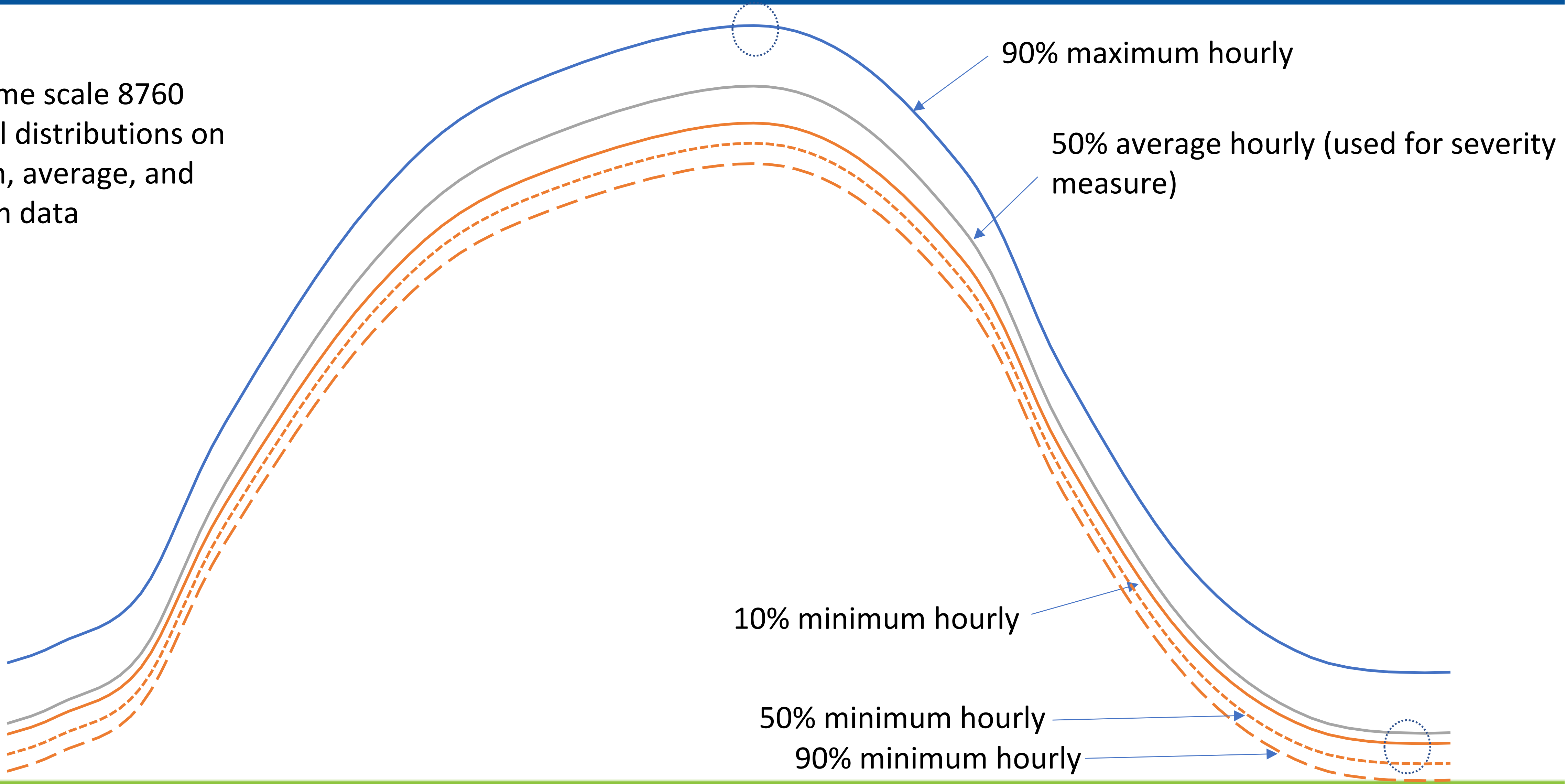
Definition

Heat wave: 2 days of either daily maximum temperature greater than 90% climate norm maximum temperature or daily minimum temperature greater than climate norm daily 10 % minimum temperature

Cold snap: 2 days of either daily minimum temperature less than 10% climate norm minimum temperature or daily maximum temperature less than climate norm 10% daily maximum

Climate norms data

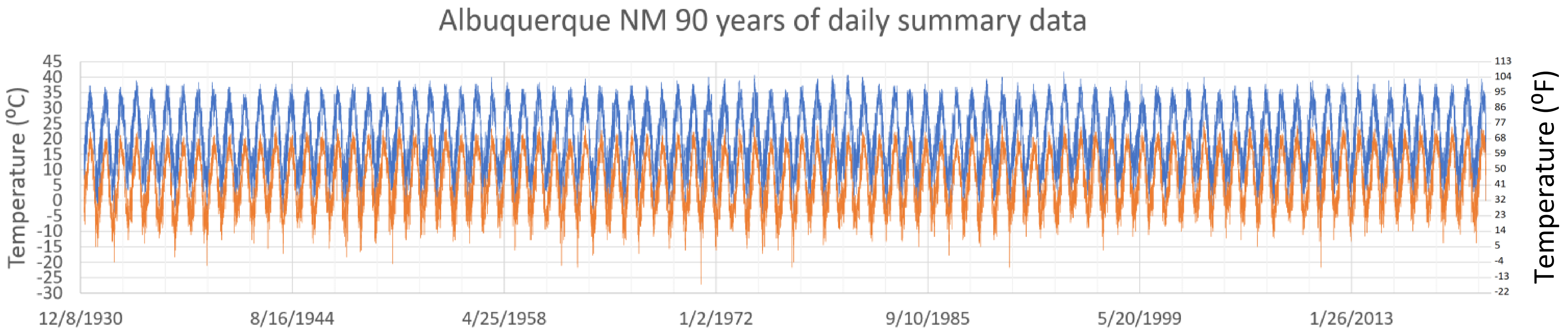
- Hourly time scale 8760
- Statistical distributions on minimum, average, and maximum data



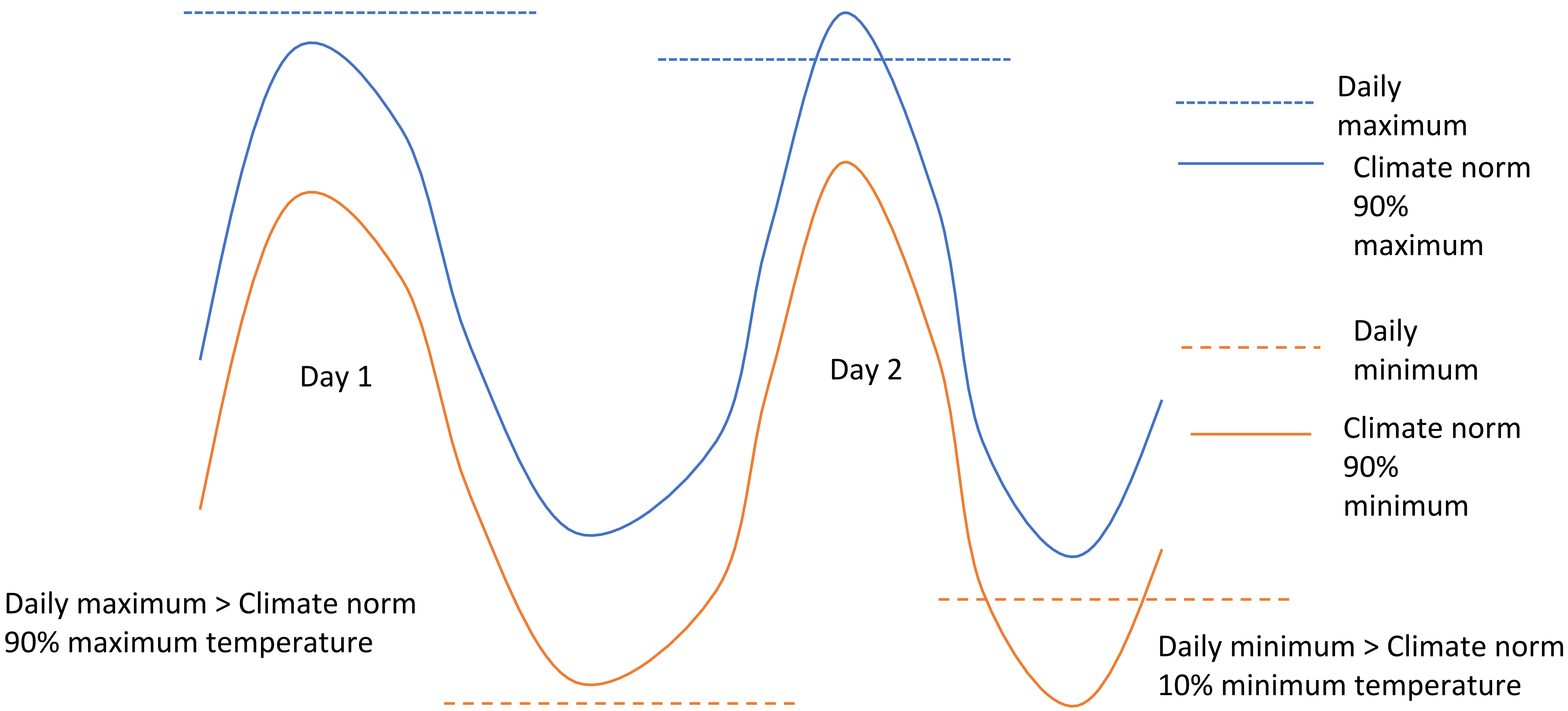
Daily summaries

Chosen because longest historical records available

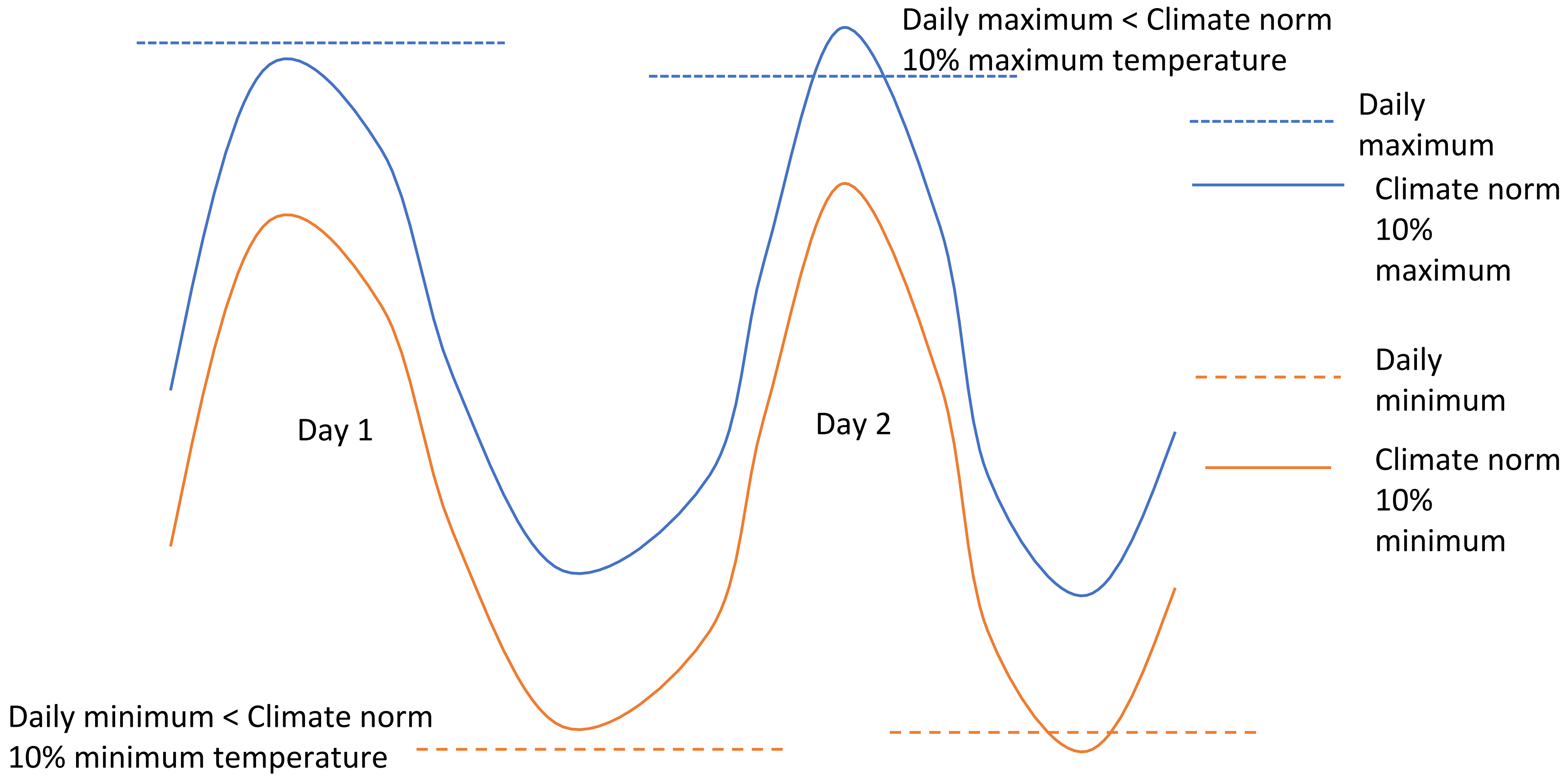
Daily maximum, minimum, and average temperatures



2 Day heat wave example



2 Day cold snap example



Step 2: Calculate the Markov probabilities for heat waves and cold snaps (Frequency and Duration)

1. Probability of heat wave P_{hw_m} ~ number of heat waves in historic record for month m / total hours in historic record for month m
2. Probability of sustaining a heat wave when in a heat wave P_{hws_m} find via regression of $P_{hws_m}^{D_{HW}}$ probability a heat wave is of a given duration divided by the sum of all heat wave's duration
3. Similar reasoning for cold snaps

$$M_m = \begin{bmatrix} 1 - P_{hw_m} - P_{cs_m} & P_{cs_m} & P_{hw_m} \\ 1 - P_{css_m} & P_{css_m} & 0 \\ 1 - P_{hws_m} & 0 & P_{hws_m} \end{bmatrix}$$

Steps 3-7: Characterize extreme temperature event severity

Heat wave severity is magnitude measured above daily average of climate norms. Each heat wave has a ΔT_{hw} peak.

Forms a set $\{\Delta T_{hw_m}\}$ for each month of the year.

The difference between the heat wave daily maximum temperature and daily average of climate norms is also integrated to form the total energy ΔE_{hw} in °C $\cdot$ day added by each heat waves.

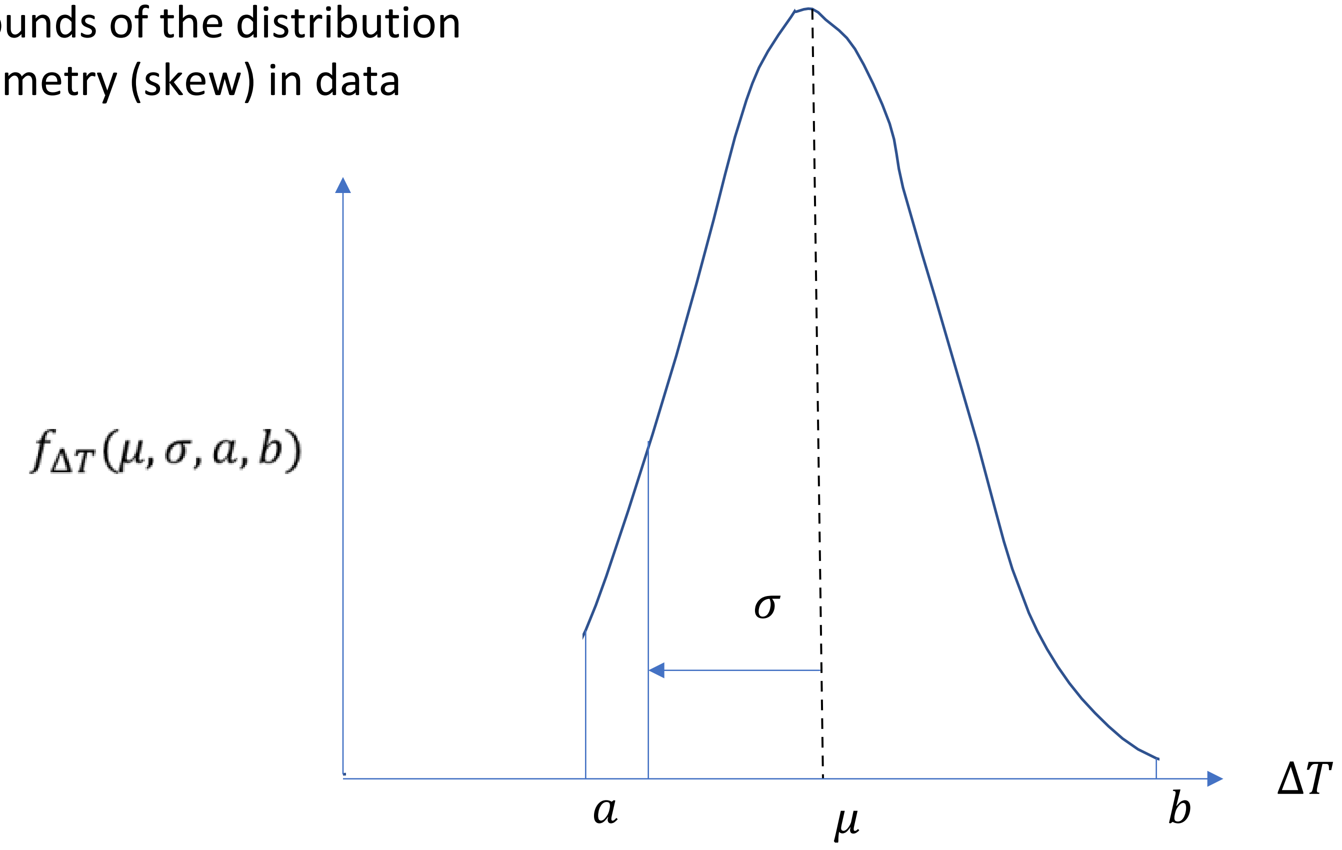
Form a second set $\{\Delta E_{hw_m}\}$ for each month of the year.

Perform several statistical steps to form truncated Gaussian distributions of $\Delta T \sim \mathcal{N}_{\Delta T}(\mu_{\Delta T}, \sigma_{\Delta T}, a_{\Delta T}, b_{\Delta T})$, normalize the results by D and scale to -1…1

Truncated Gaussian

Enables

1. Maximum and minimum historic cases to be the bounds of the distribution
2. Fitting asymmetry (skew) in data



Step 8: Calculate shift in all parameters based on IPCC data

For each IPCC climate scenario, year, and month each year, calculate shifts $\Delta M, \Delta\mu, \Delta\sigma, \Delta a, \Delta b$

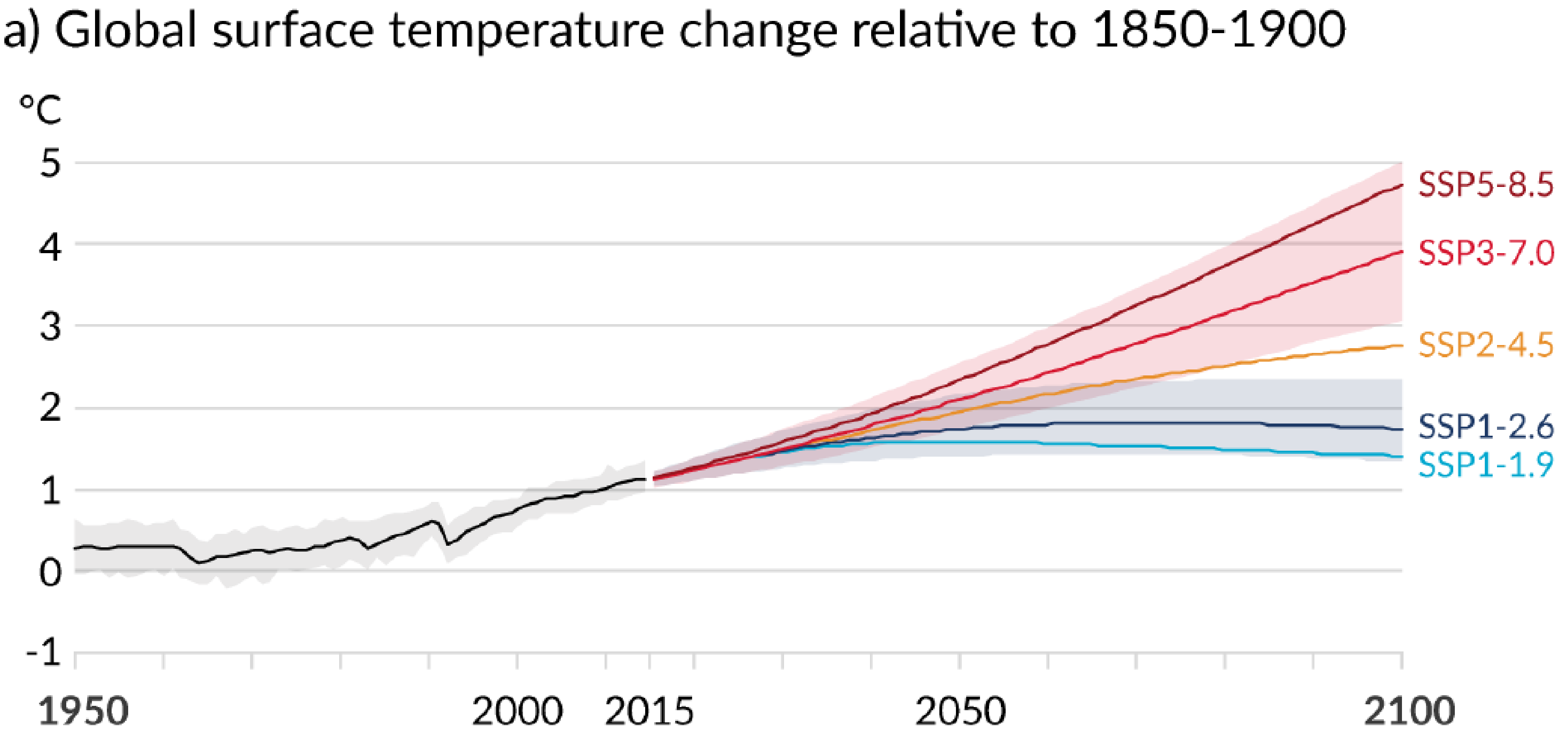
$$\Delta M_m = \begin{bmatrix} P_{hw_m} + P_{cs_m} - P'_{hw_m} - P'_{cs_m} & P'_{cs_m} - P_{cs_m} & P'_{hw_m} - P_{hw_m} \\ P_{css_m} - P'_{css_m} & P'_{css_m} - P_{css_m} & 0 \\ P_{hws_m} - P'_{hws_m} & 0 & P'_{hws_m} - P_{hws_m} \end{bmatrix}$$

Several assumptions needed here so that IPCC data provided for 10 and 50 year extreme temperature events is adequate:

1. Assume increase in ΔT is proportional to ΔE
2. Weighted averages for modified sustained heat wave probabilities (cannot meet 10 and 50 year events exactly with single Markov parameters)

IPCC scenarios (global average here)

IPCC scenarios drive how severe extreme temperature events become in future years



IPCC AR6 Physical Basis Report 2021 Figure SPM.8

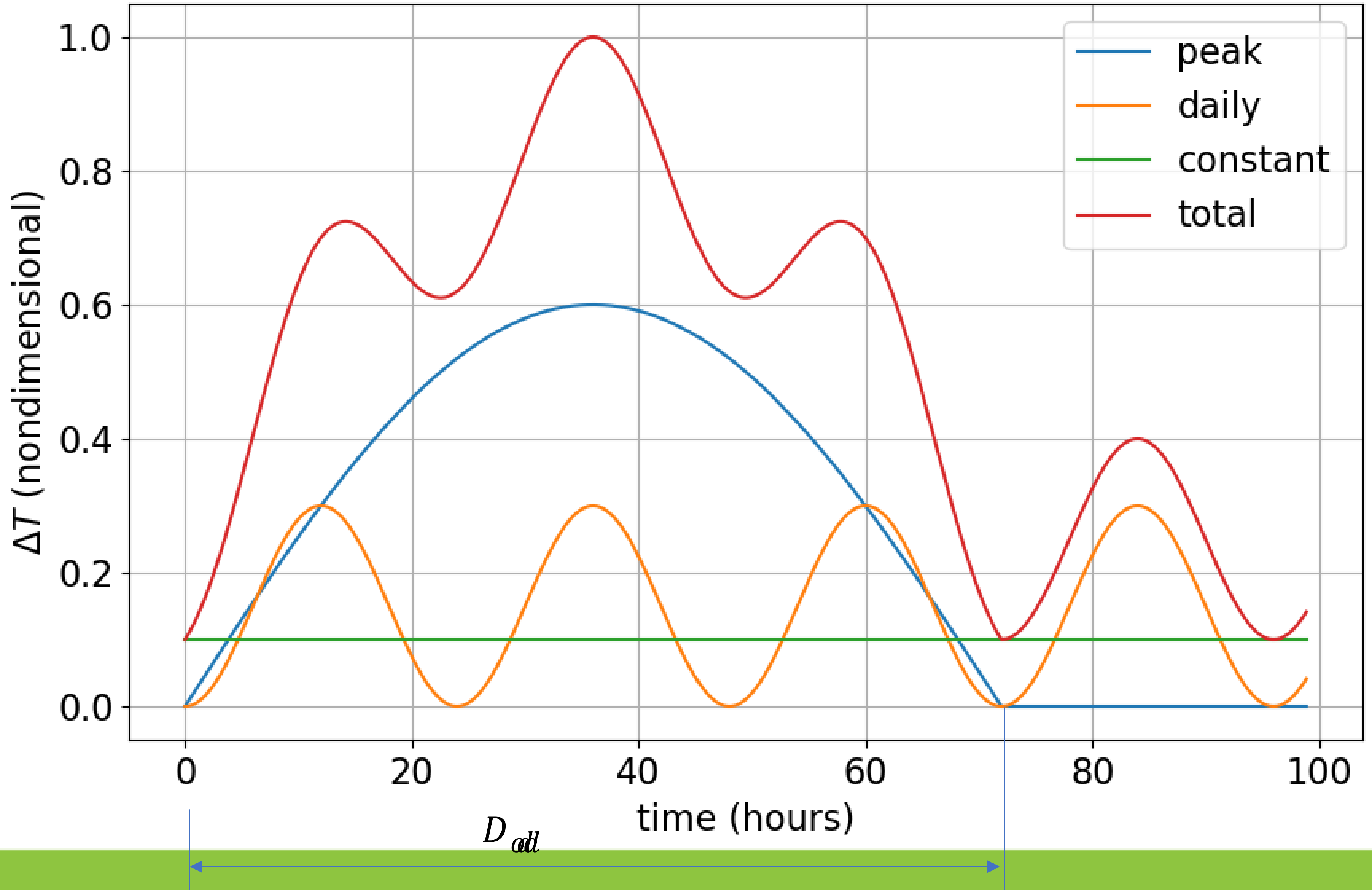
Steps: 9-11 Produce stochastic realizations

1. Calculate extreme event initiation and duration for many future years from stochastic sampling of the $M + \Delta M$ Markov process.
2. Sample extreme event duration normalized temperature and energy increases
3. Retrieve durations for each heat wave, reverse transform from -1…1 and denormalize duration to produce physical ΔT and ΔE for each extreme event
4. Solve for heat wave functional form parameters A,B,C

$$\Delta T(t, D, \Delta t_{min}) = \begin{cases} A\sin\left(\frac{\pi t}{D_{odd}}\right) + B\left(1 - \cos\left(\frac{2\pi t}{\Delta t_{min}}\right)\right) + C & t \leq D_{odd} \\ B\left(1 - \cos\left(\frac{2\pi t}{\Delta t_{min}}\right)\right) + C & t > D_{odd} \end{cases}$$

$$\Delta E = \frac{2AD_{odd}}{\pi} + BD - \frac{B\Delta t_{min}}{2\pi}\sin\left(\frac{2\pi D}{\Delta t_{min}}\right) \qquad D_{odd} = \Delta t_{min}\left[\lfloor\frac{D}{\Delta t_{min}}\rfloor - \delta\left(\lfloor\frac{D}{\Delta t_{min}}\rfloor \mod 2\right)\right]$$

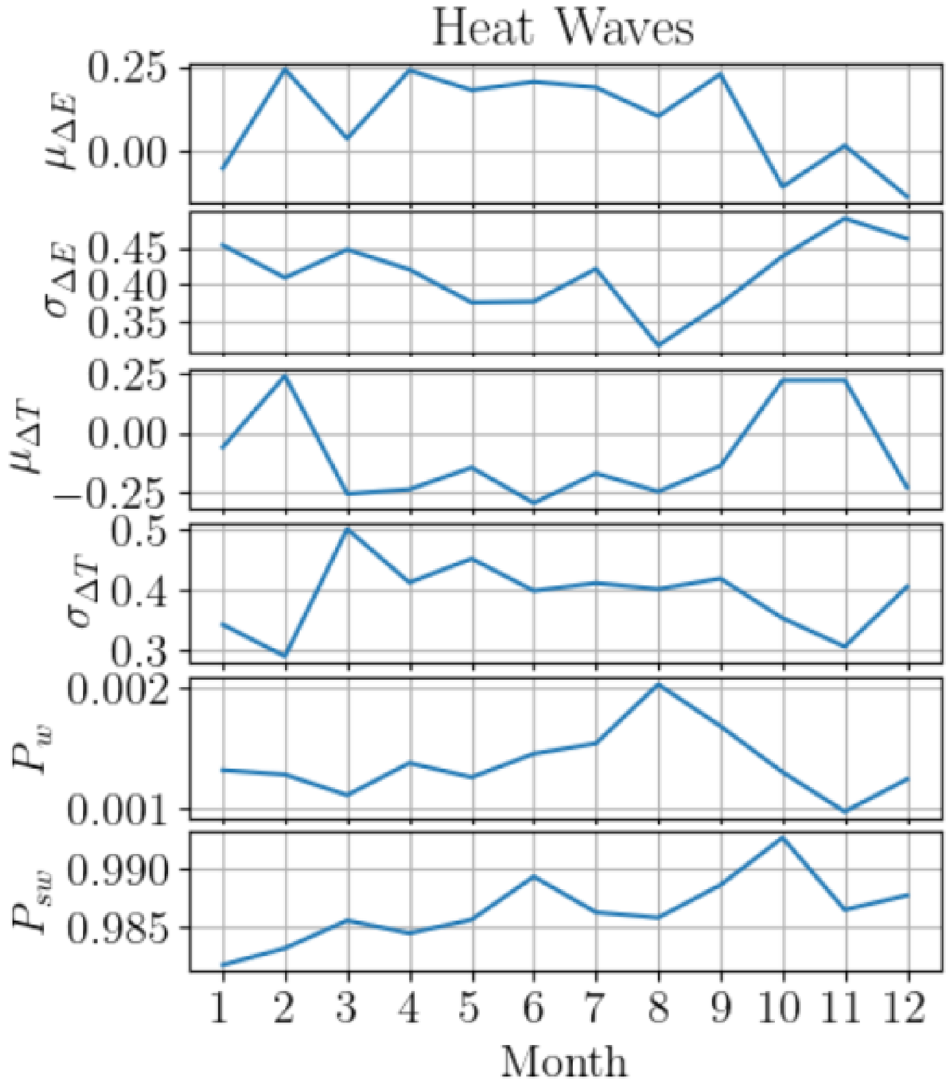
Extreme event functional form

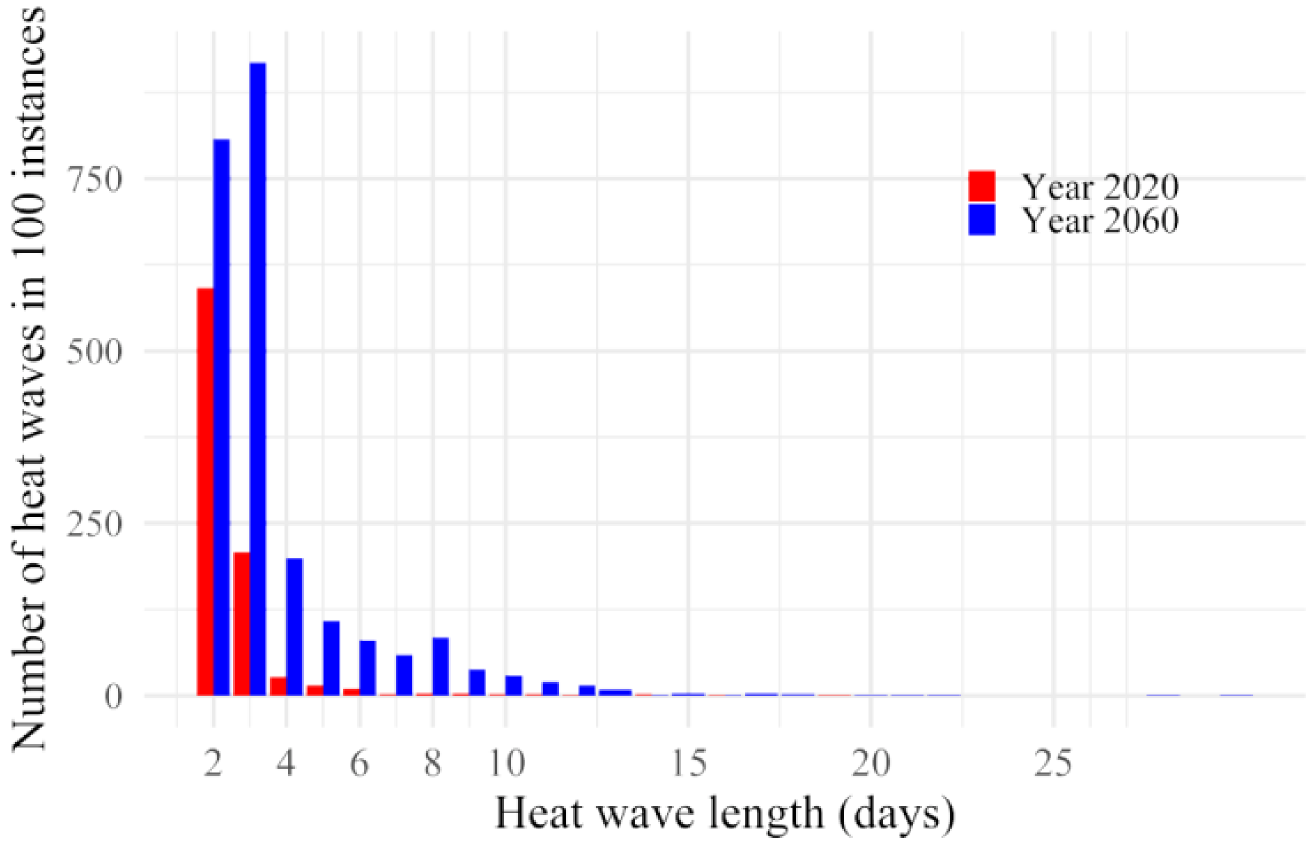


Steps 12-13: Output BEM file

- Start with input from an EnergyPlus *.epw or DOE-2 *.bin weather file
- Outputs *.epw and *.bin weather files with stochastic changes to temperature
- These files can then be used as input to stochastic resilience analysis!

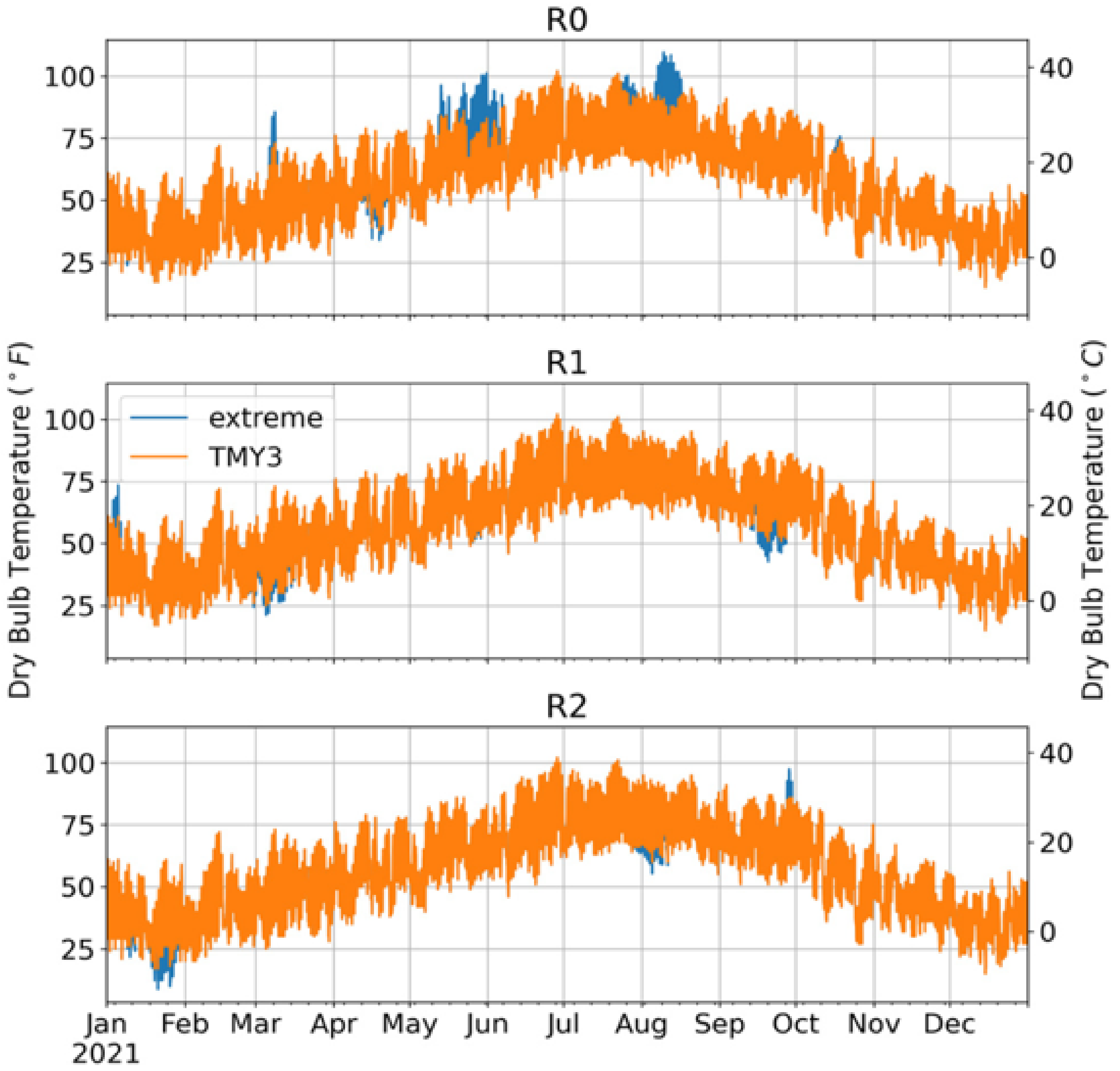
Albuquerque results





Hot/Cold extreme example

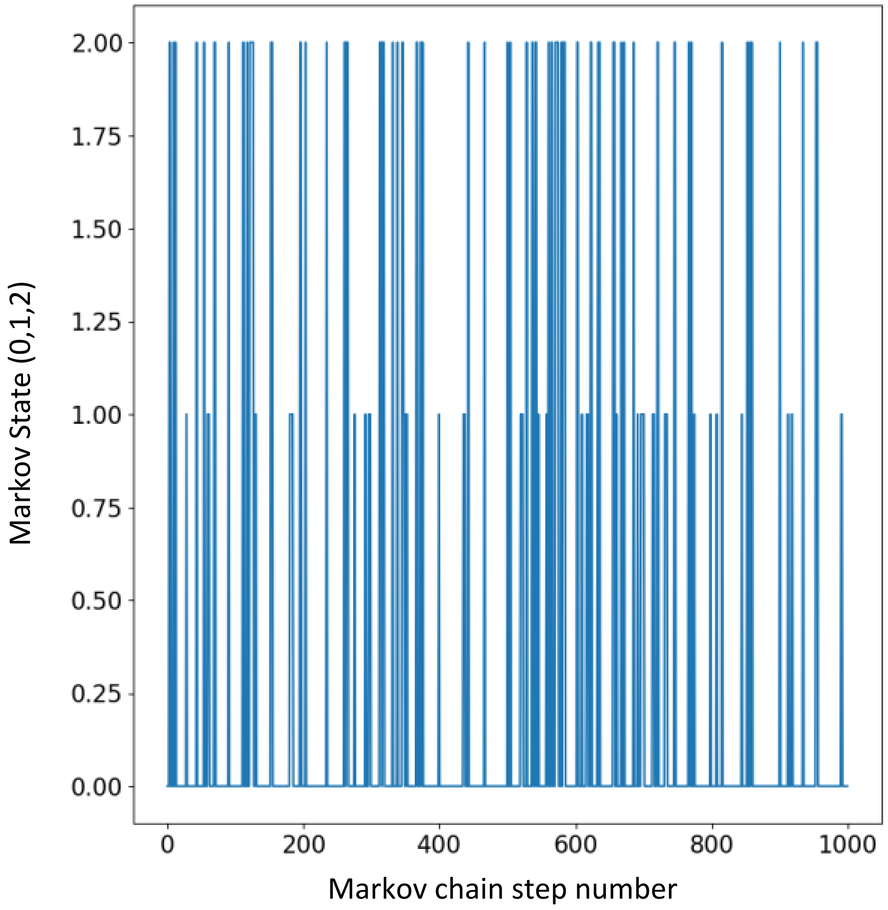
- MEWS produces a user specified number of realizations based on historical data and IPCC projections for extreme heat and cold

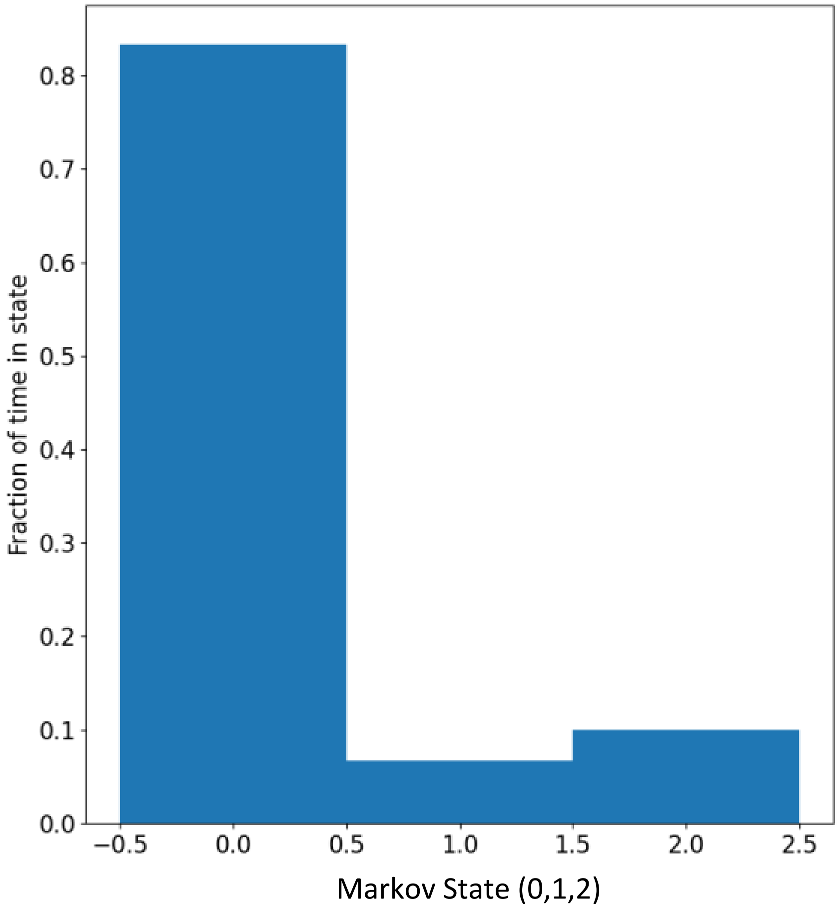


3 demo realizations for possible future heat wave conditions in Albuquerque

Multi-state Markov chains

- MEWS has an efficient tested multi-state Markov chain algorithm





Conclusions

- Stochastic weather generation for future files can be an important part of resilience analysis
- The MEWS algorithm has been developed and has been briefly reviewed. It is available as open-source code: https://github.com/sandialabs/MEWS
- Practical application of MEWS using BEM is currently underway
- Significant enhancements are envisioned:

1. Validate MEWS against climate model future weather for several cases
2. Show convergence of multi-parameter stochastic resilience analysis
3. Generalize heat wave definition and functional form and show that it mimic weather
4. Extend heat waves to include humidity, pressure, wind, cloud, and other effects

Questions?

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