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Seminar 50: Future Heat Wave Effects in Cold Versus Hot Climate Zones

Future Heat Wave Effects in Cold Versus Hot Climate Zones

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Sandia National Laboratories

Learning Objectives

1. To understand the impacts of climate change in different communities.
2. To understand the risk analysis method at a community scale using building energy simulations.
3. To understand how extreme heat wave events have different effects in different climate zones.
4. To understand how heat waves affect heat emission and energy consumption from buildings, and the heterogeneity of heat emission across different building types and local climates.

Acknowledgements

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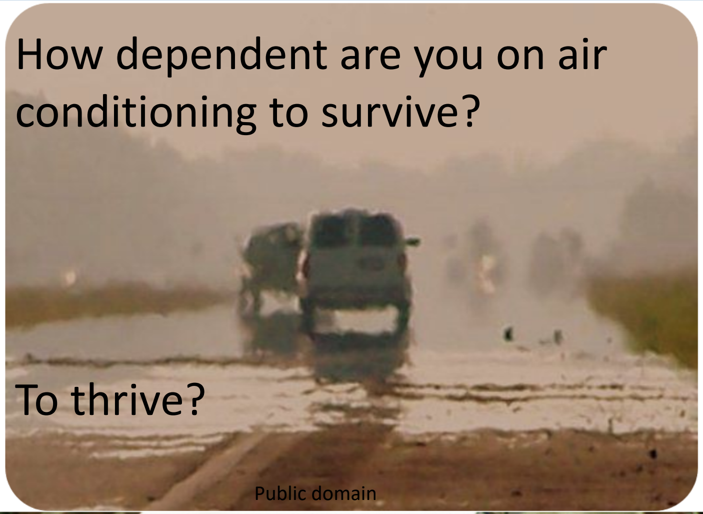
- Bias disclosure:
  - Villa - Sandia National Laboratories (SNL); National Technology and Engineering Solutions of Sandia (NTESS); Honeywell
  - Schostek – Purdue University
  - Goversten – Northeastern University
  - MacMillan – National Renewable Energy Laboratory; Colorado School of Mines

Outline

- Background
  - Why future weather?
  - Global warming impacts
  - History of future weather approaches
- Multi-scenario Extreme Weather Simulator
  - Objectives/Overview
  - Algorithm/Working hypotheses
- Worcester-Houston Study Results
  - Climate Scenarios
  - Heat wave distributions
  - Building Energy
  - Thermal Comfort
- Conclusions



A member of a civil engineering squadron suffers from heat exhaustion during Exercise READINESS CHALLENGE 87

Q: Why future weather? A: The Global Climate Crisis

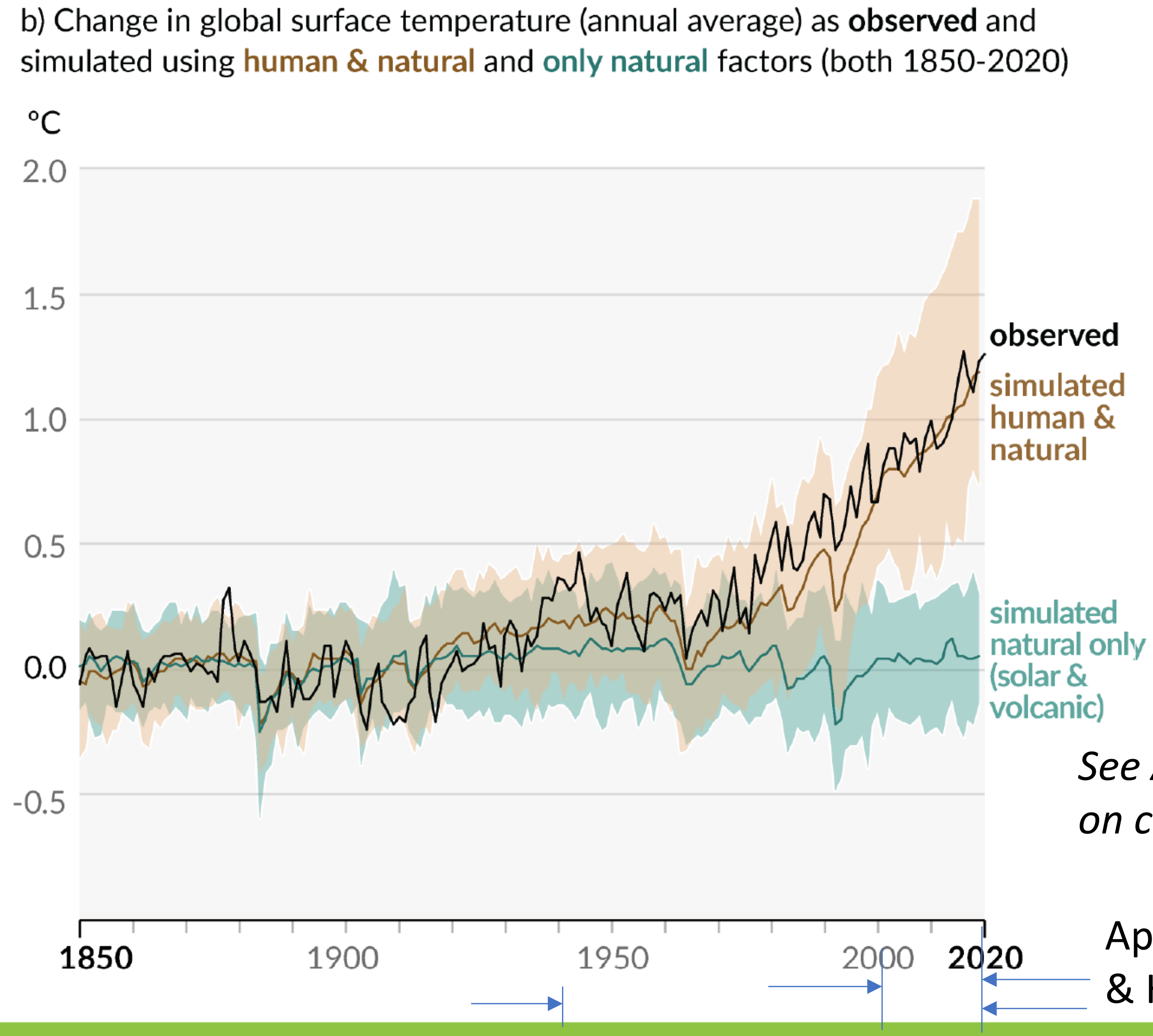


Figure SPM.1 Intergovernmental Panel on Climate Change (IPCC) Working Group I – The Physical Science Basis Sixth Assessment Report (AR6) (approved for release for education on climate change issues to society)

See ASHRAE fundamentals chapter 36 on climate change

Approximate building & HVAC timescales

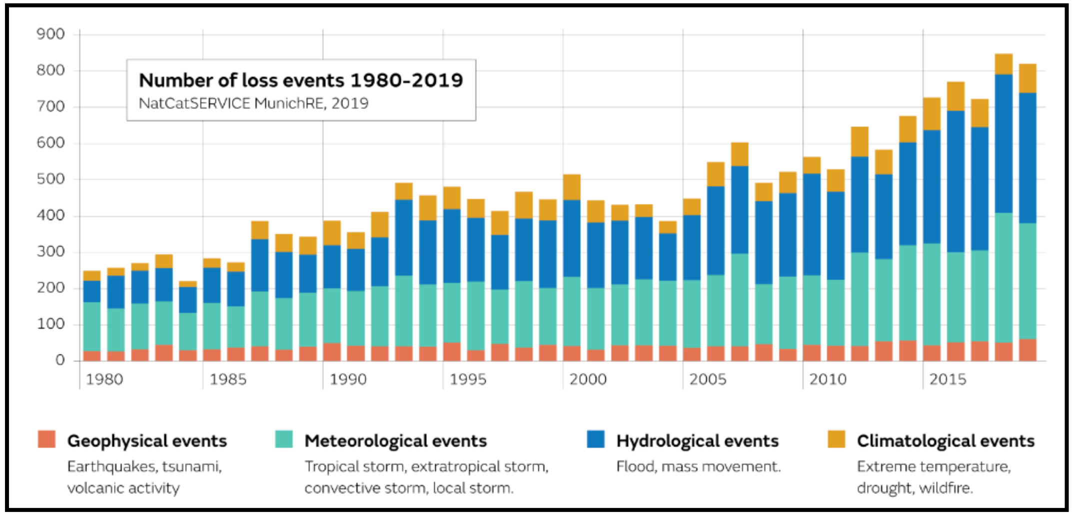
Impacts of Global Warming

<u>IPCC (Intergovernmental Panel on Climate Change) Sixth Assessment Report 2021:</u>

"…human influence has warmed the atmosphere, ocean and land. Widespread and rapid changes in the atmosphere, ocean, cryosphere and biosphere have occurred… Evidence of observed changes in extremes such as heatwaves, heavy precipitation, droughts, and tropical cyclones…"

<u>Research Goal:</u>

Quantify effects of global warming on extreme weather for energy and resilience modeling



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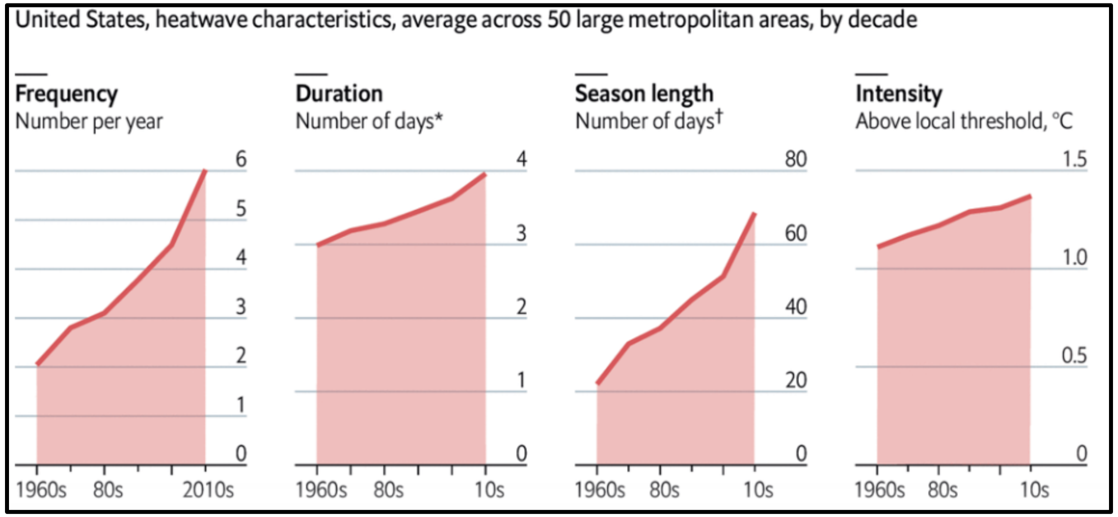


NOAA – public domain image

Extreme Weather Events

Extreme Event	Effect
Heat Waves	Temperature Rise
Cold Snaps	Temperature Drop
Winter Storms	High Winds
Tornados	Flooding
Heavy Rainfall	Multiple Effects
Hurricanes	
Droughts	
Floods	

Example US Extreme Weather Since 2000:

Hurricane Katrina	Aug. 2005	1,800 deaths
Winter Storm Uri	Feb. 2021	250+ deaths
Oregon Heat Wave	June 2021	100 deaths

NASA – public domain image

Hurricanes

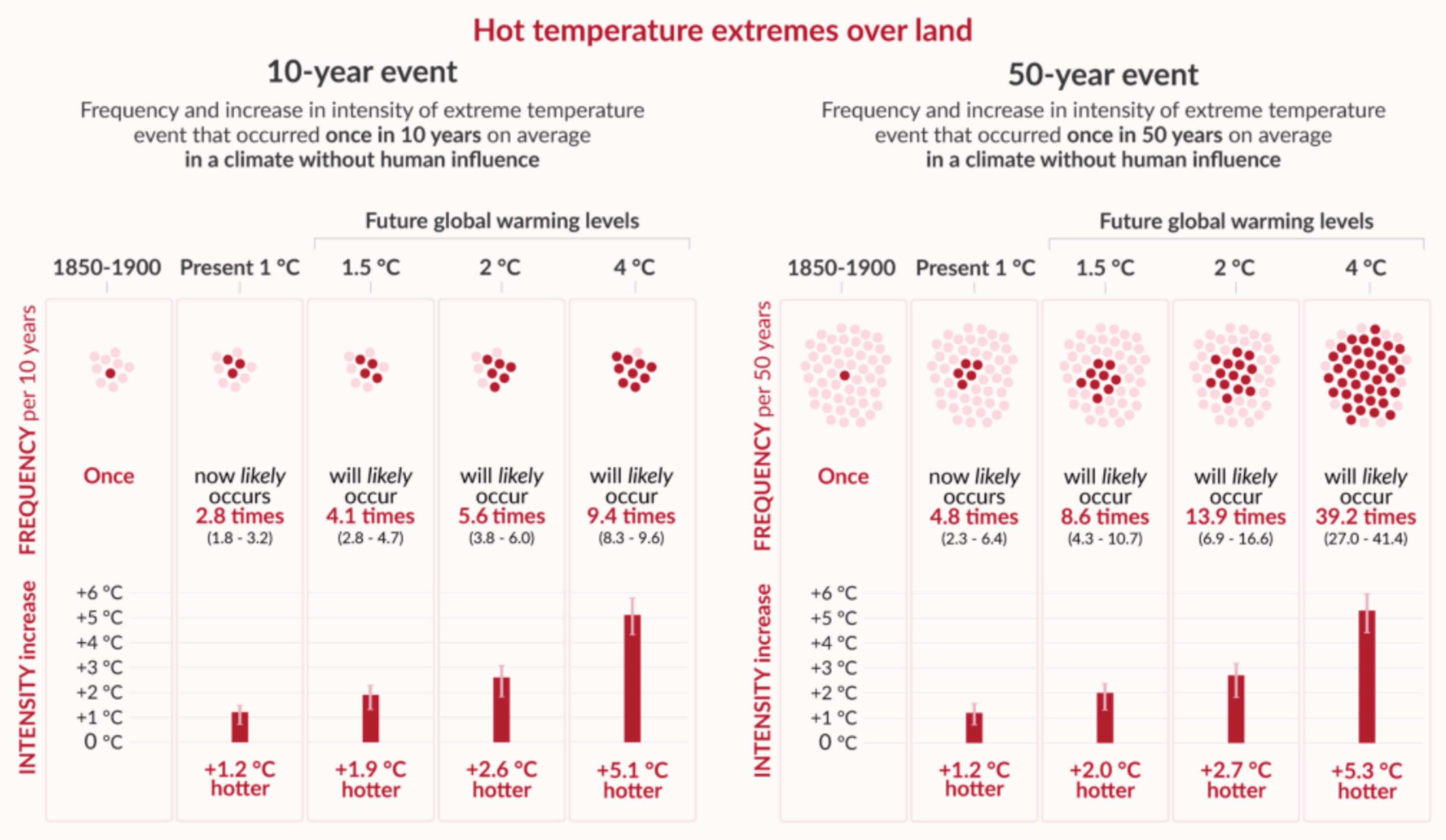
NOAA – public domain image

Tornadoes

NOAA – public domain image

Floods

Why future weather? A: Increased frequency, and intensity of extreme weather



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

Future Weather in Buildings Infrastructure

"Although the potential changes in weather conditions associated with changes in both global climate change and the surrounding context could have a significant effect on the operating energy over the next 50-100 years, **they remain extremely difficult to both predict and account for in the analysis."**

Raymond J. Cole and Paul C. Kernan
"Life Cycle Energy Use in Office Buildings" *Building and Environment* 1996

Future Weather History

1st Regional Climate model dynamic downscaling (Dickinson et. al, 1989; Giorgi & Bates, 1989)

Recognition that weather variations matter for BEM (Crawley and Huang, 1997; Williams et. al., 1996)

"Morphing" statistical downscaling for building energy simulation (Belcher, 2002)

Uncertainty in morphing technique via running variation of climate models (Jones et. al., 2009)

Stochastic weather generation (Williams et. al., 2011)

Stochastic variations of normal weather (Rastogi, 2016)

Dynamic downscaling characterizes extreme heat frequency/ intensity increases (Zobel, 2017)

Extreme Meteorological years and Extreme Reference years (Crawley and Lawrie , 2019; Pernigotto et. al. 2020)

Population inclusive earth systems models Giorgi, 2022

Stochastic variations on extreme weather events

Multi-scenario extreme weather simulator (Villa et. al., 2022)

1990 — 2000 — 2010 — 2020

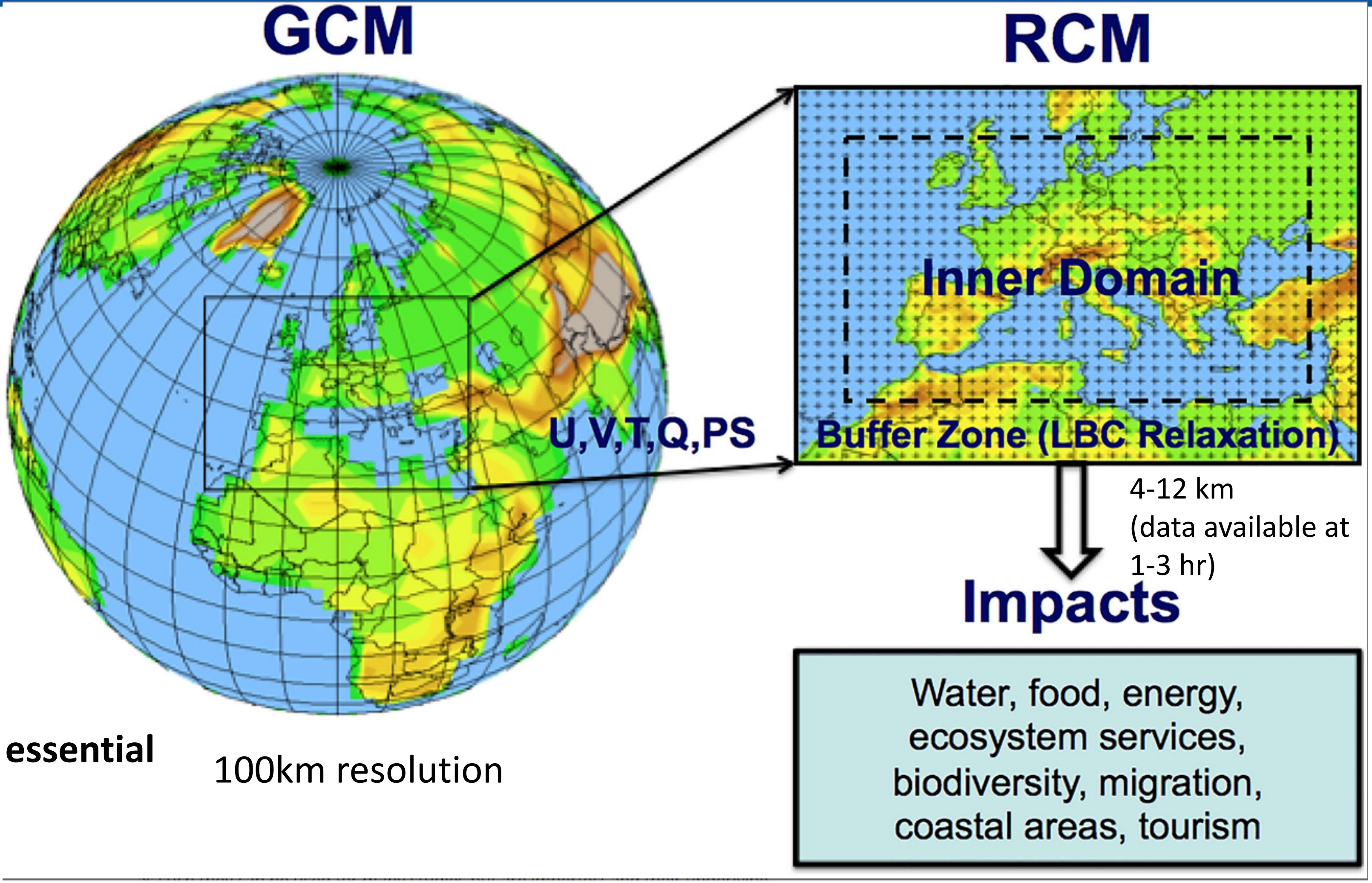
Approaches – Dynamic Downscaling

High resolution regional climate models provide dynamically downscaled results that are high enough resolution to provide reasonable meso-scale extreme events such as heat waves and hurricanes, precipitation, and strong winds

Disadvantages for resilience analysis

More transient extreme events such as tornadoes, localized extreme precipitation/hail are unlikely to be captured with a regional approach

Probability distributions via ensembles of runs intractable for supercomputers



4-12 km (data available at 1-3 hr)

100km resolution

Reanalysis of RCM for historic conditions is essential to extreme weather pattern statistical characterization

Used with permission Giorgi, 2019. "Thirty years of regional climate modeling: where are we and where are we going next? *JGR Atmospheres* https://doi.org/10.1029/2018JD030094

Typical Meteorological Year (TMY) and Extreme Meteorological Year (XMY)

TMY timeseries are derived from a procedure for selecting historical months based on statistical criteria of an ensemble of years (Wilcox, 2008)

New procedure from Oak Ridge samples across both climate models and years to select typical months in the future (New and Bass, 2022)

New procedures for eXtreme Meteorological Years (XMY - Crawley and Lawrie , 2019) and Extreme Reference Years (ERY - Pernigotto et. al. 2020)

-- Have competing objectives for different applications

<u>Disadvantages for resilience analysis</u>

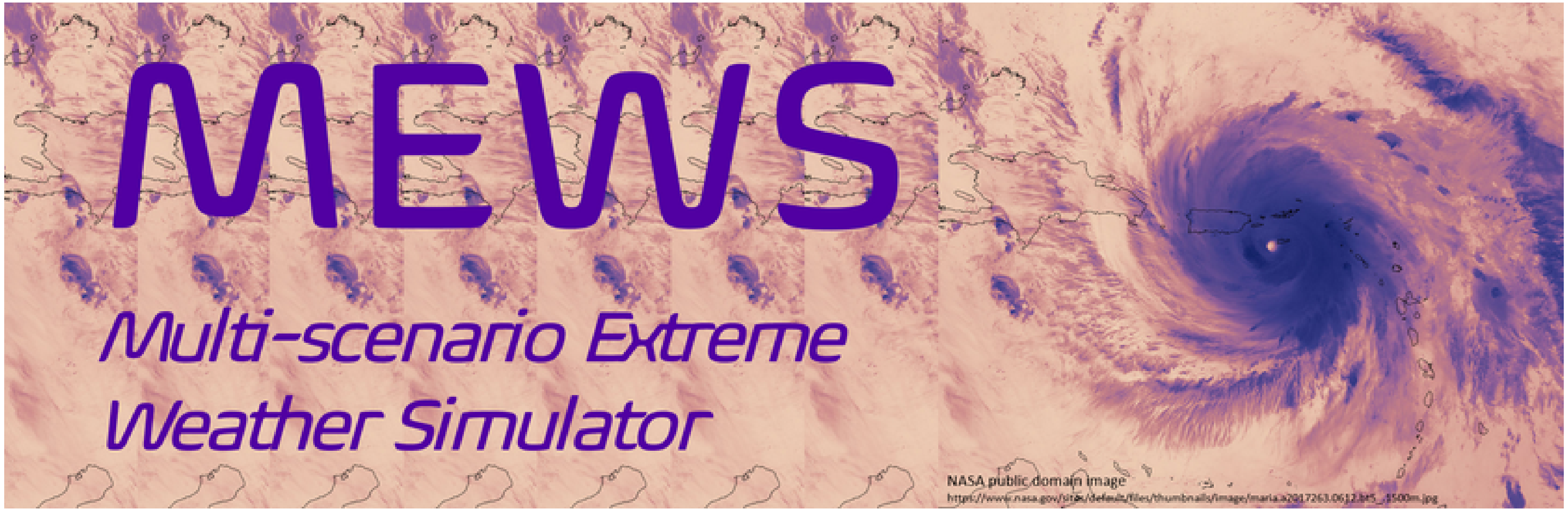
Cannot quantify probability of outcomes (i.e. gives min/avg/max range with a specific statistical priority)

When multiple objectives in an analysis exist (i.e. resilience and energy efficiency) this approach does not provide conservative bounds for each objective (Gasparella et. al., 2021)

Statistical Downscaling

- Use a combination of historical data, climate model output and data-driven methods to provide detailed weather for a local site.

- Uncertainty via variations of GCM/RCM runs accomplished (Jones et. al., 2009)
- Stochastic weather generators that do not cover extreme events in current forms (Rastogi, 2016; Williams et. al., 2011))
- **New direction:**
- New methods that emphasize statistical accuracy of weather extremes in a stochastic way are needed
- **Disadvantages**
- Such methods may not fit normal conditions as well since they prioritize fitting extreme conditions
- High computational burden when using a stochastic method


MEWS
Multi-scenario Extreme
Weather Simulator
NASA public domain image

(MEWS = Tool 1)

Tool 1

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 New Mexico site

3. Open-source python ~28,000 lines of code (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 using 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!)

New algorithm theory

Goal: A low-order stochastic model that:

1) Has enough parameters that can fit arbitrary shifts in event characteristics

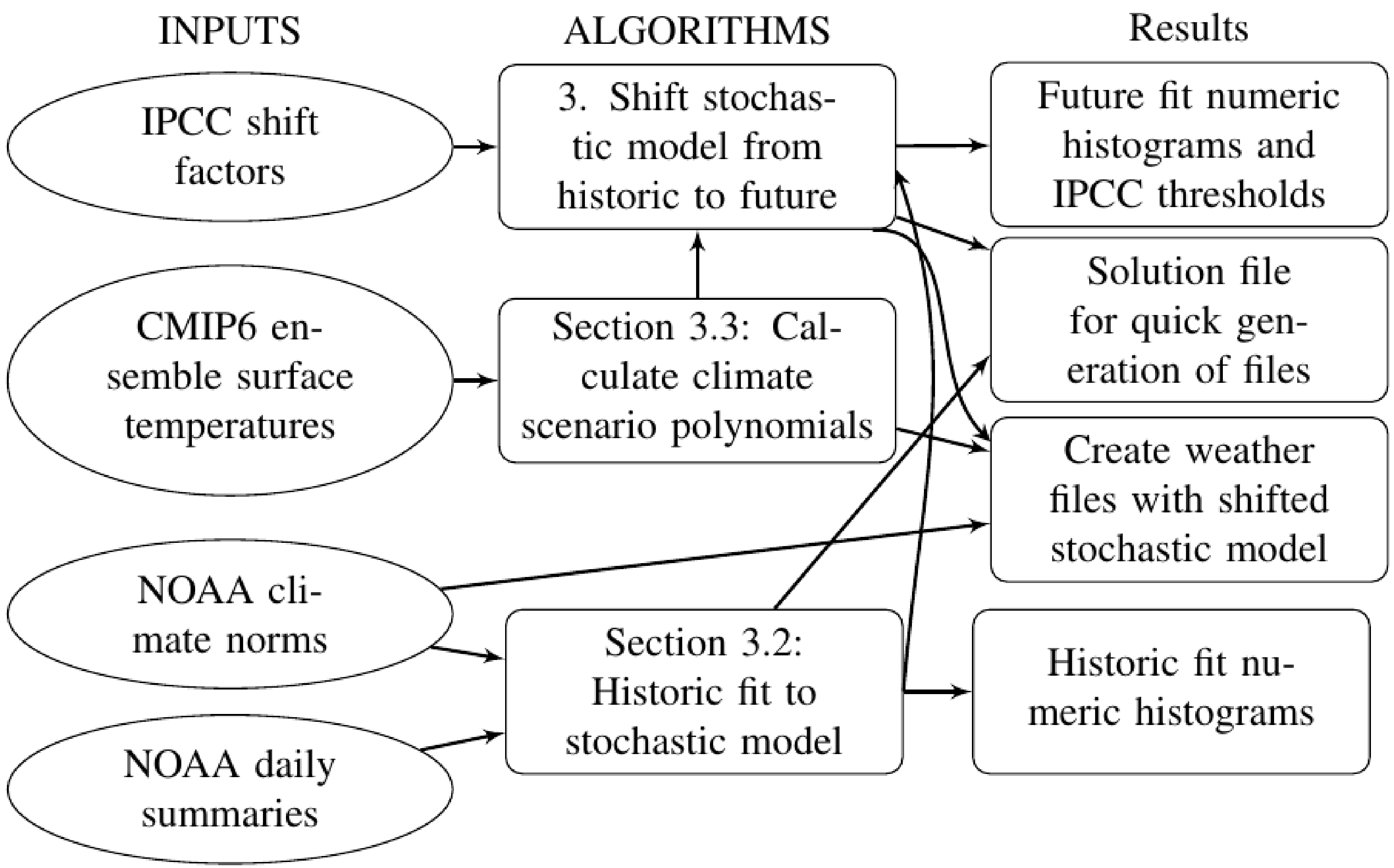
2) Has enough parameters to fit historical data (or climate model reanalysis output)

3) General enough to handle multiple types of events

Solution:

- 12 models for each month of the year to capture seasonal variations
- Duration normalized intensity and total energy fit to truncated Gaussian distributions
- Stochastic time stepping process with time dependence of probability within an event
- Specialized shape functions that smoothly add new weather events

Algorithm Overview



IPCC = Intergovernmental Panel on Climate Change

CMIP6 = Sixth Coupled Model Intercomparison Project

NOAA = National Oceanic and Atmospheric Association

Hypotheses

1. Heat wave peak temperature and total energy have positive correlation to heat wave duration
2. Duration normalized heat wave peak temperature and energy distributions are represented well by truncated Gaussian distributions
3. A stochastic process with a time transient matrix of the specific form on the next slide can characterize heat wave and cold snap frequencies and durations
4. IPCC shift in frequency and intensity factors can scale for frequency and shift for temperature factors
5. Linear extrapolation beyond 4^{o}C to 6^{o}C does not produce a significant error
6. The difference between baseline surface temperature for climate norms and daily summary data is negligible (2 slides down)
7. A single 3 parameter shape function represents all future extreme waves in a stochastic context without significantly changing analysis outcomes (3 slides down)

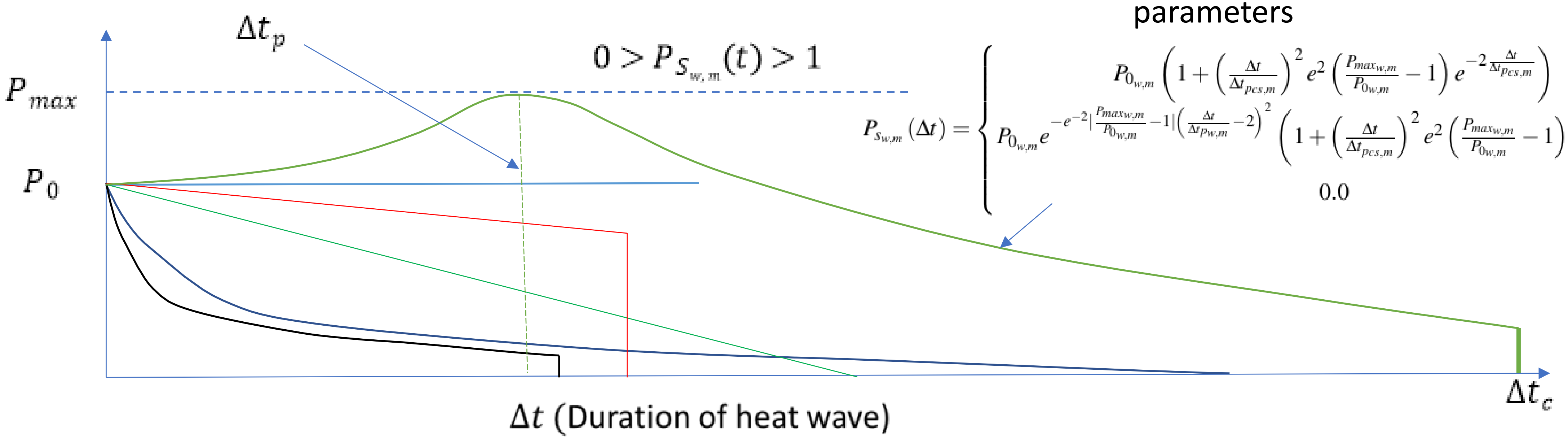
Stochastic process

$$M_m = \begin{bmatrix} 1 - P_{hw,\,m} - P_{cs,\,m} & P_{cs,\,m} & P_{hw,\,m} \\ 1 - P_{S_{cs,\,m}}(t) & P_{S_{cs,\,m}}(t) & 0 \\ 1 - P_{S_{hw,\,m}}(t) & 0 & P_{S_{hw,\,m}}(t) \end{bmatrix}$$

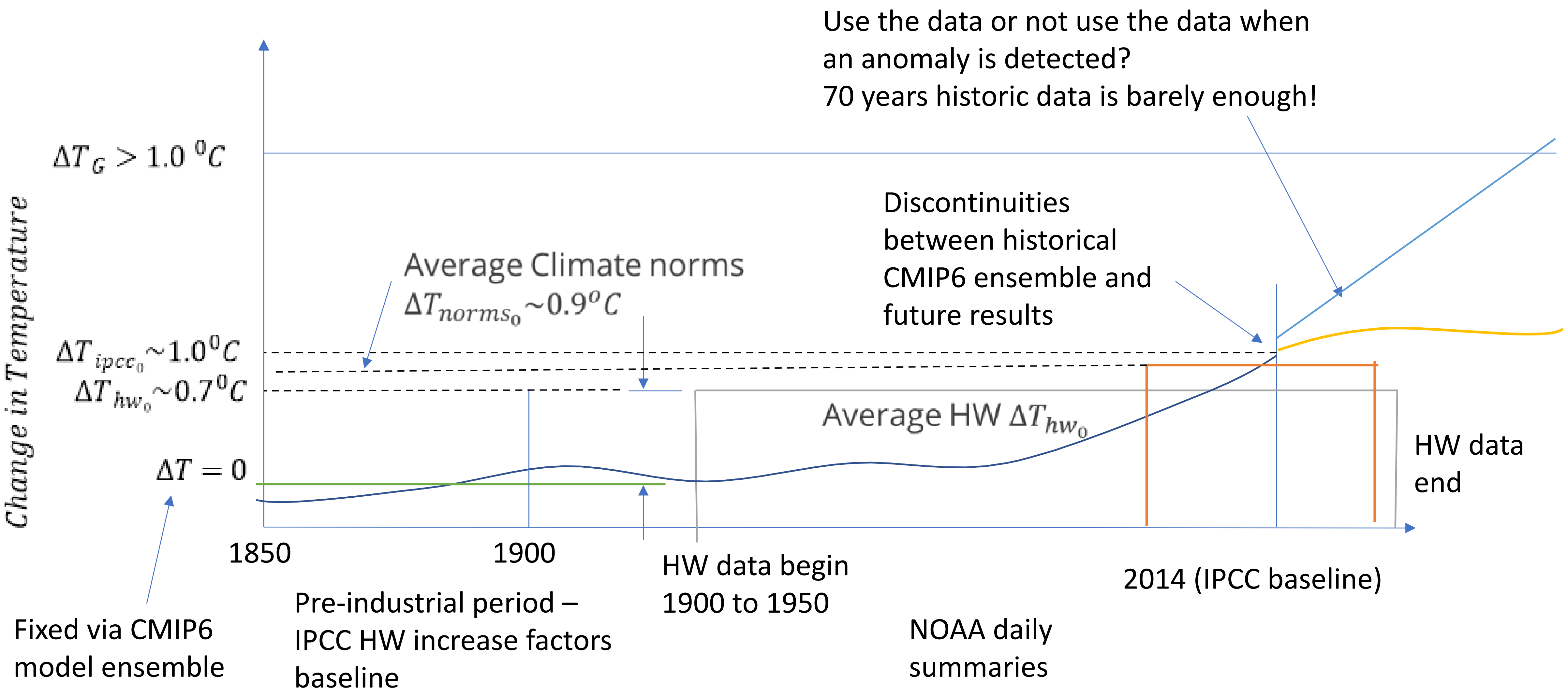
Decay function form

1 – 4 parameters x 2 x 12 = 24-96 additional parameters

$$P_{s_{w,m}}(\Delta t) = \begin{cases} P_{0_{w,m}} \left(1 + \left(\frac{\Delta t}{\Delta t_{pcs,m}}\right)^2 e^2 \left(\frac{P_{max_{w,m}}}{P_{0_{w,m}}} - 1\right) e^{-2\frac{\Delta t}{\Delta t_{pcs,m}}}\right) & \Delta t \leq 2\Delta t_{p_{w,m}} \\ P_{0_{w,m}} e^{-e^{-2}\left|\frac{P_{max_{w,m}}}{P_{0_{w,m}}} - 1\right|\left(\frac{\Delta t}{\Delta t_{pw,m}} - 2\right)^2} \left(1 + \left(\frac{\Delta t}{\Delta t_{pcs,m}}\right)^2 e^2 \left(\frac{P_{max_{w,m}}}{P_{0_{w,m}}} - 1\right) e^{-2\frac{\Delta t}{\Delta t_{pcs,m}}}\right) & \Delta t \leq \Delta t_{c_{w,m}} \\ 0.0 & \Delta t > \Delta t_{c_{w,m}} \end{cases}$$



Baseline


Use the data or not use the data when an anomaly is detected?
70 years historic data is barely enough!
$\Delta T_G > 1.0\ ^0C$
Change in Temperature
Average Climate norms
$\Delta T_{norms_0} \sim 0.9^o C$
Discontinuities between historical CMIP6 ensemble and future results
$\Delta T_{ipcc_0} \sim 1.0^0 C$
$\Delta T_{hw_0} \sim 0.7^0 C$
Average HW ΔT_{hw_0}
HW data end
$\Delta T = 0$
1850
1900
HW data begin 1900 to 1950
2014 (IPCC baseline)
Fixed via CMIP6 model ensemble
Pre-industrial period – IPCC HW increase factors baseline
NOAA daily summaries

Shape function

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

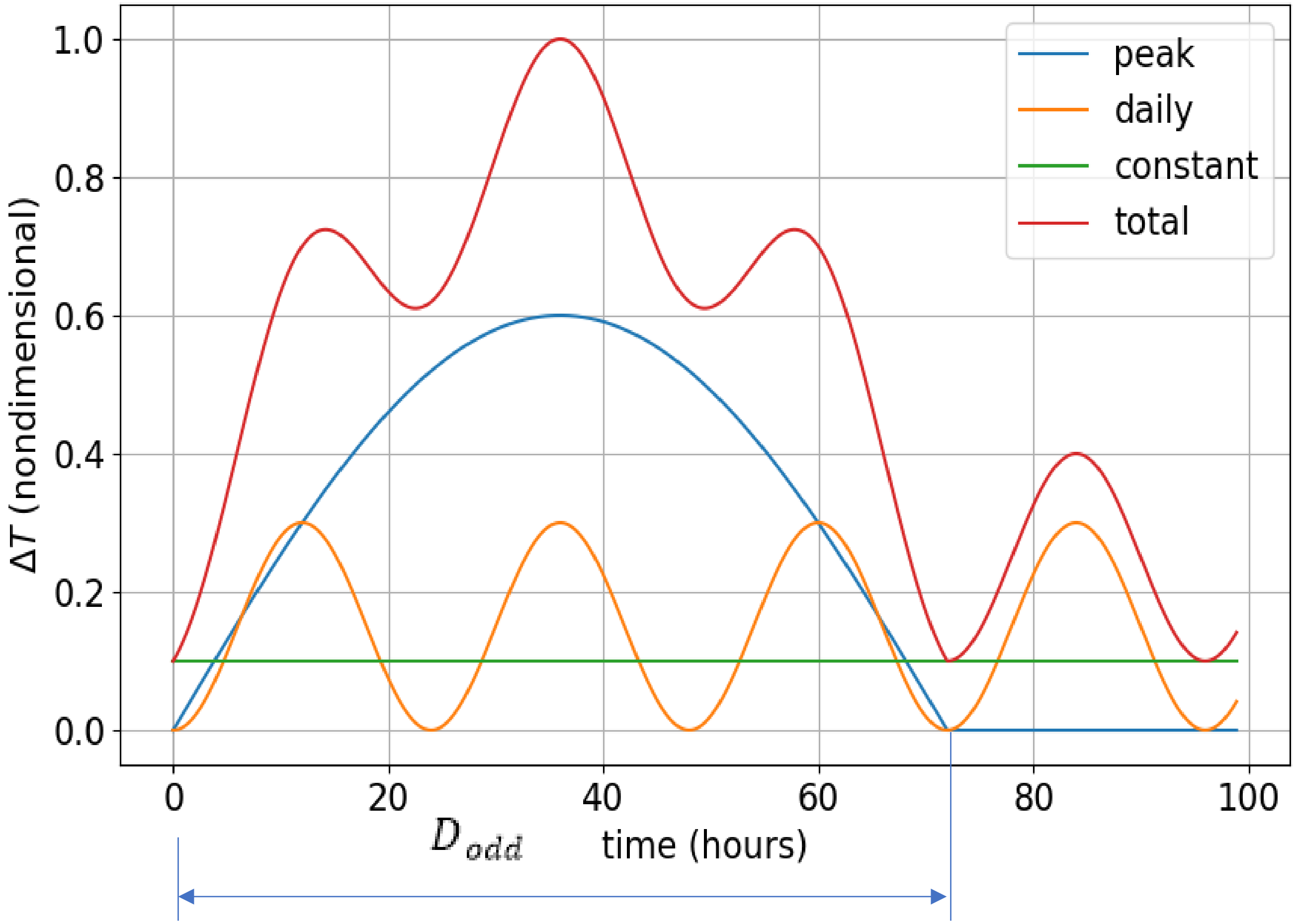
$$D_{odd} = \Delta t_{min}\left[\lfloor \frac{D}{\Delta t_{min}} \rfloor - \delta\left(\lfloor \frac{D}{\Delta t_{min}} \rfloor \mod 2\right)\right]$$

$$\Delta E = \frac{2AD_{odd}}{\pi} + BD - \frac{B\Delta t_{min}}{2\pi}\sin\left(\frac{2\pi D}{\Delta t_{min}}\right)$$

$$A = \frac{T_{max} - \frac{\pi}{2D_{odd}}E}{2 - \frac{\pi D}{2D_{odd}} + \frac{\Delta t_{min}}{4D_{odd}}\sin\left(\frac{2\pi D}{\Delta t_{min}}\right)}$$

$$B = \frac{T_{max} - A}{2}$$

$$T_{max} = A + 2B + C$$



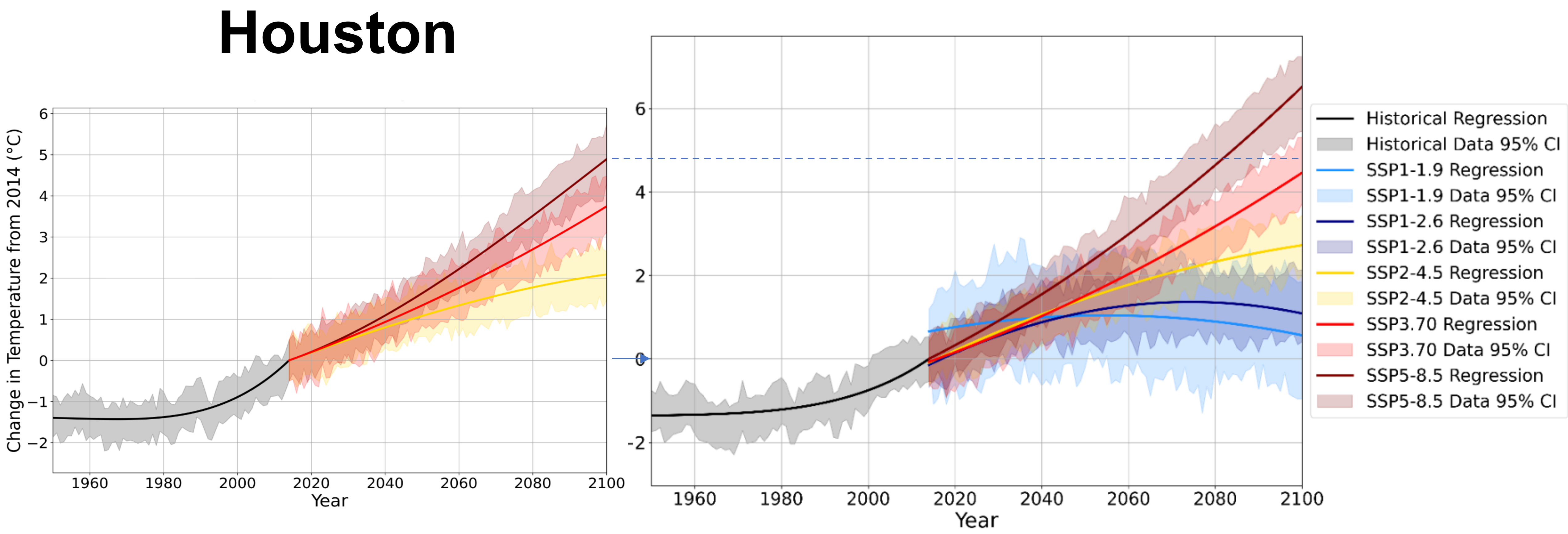
Case Study Hot and Cold Climates: Houston vs. Worcester

Study characteristics

- TMY3 data for Houston and Worcester airports
- Ran 3 Shared socio-economic pathways SSP2-4.5, SSP3-7.0, and SSP5-8.5
- Ran 4 future years 2025, 2050, 2075, and 2100. Only some SSP's for 2100 were under 6ºC
- Ran IPCC confidence intervals on heat wave shifts for 5%, 50%, and 95%
- Used 2.5e6 hours of stochastic simulation time for each month to optimize probability distribution fits. Kolmogorov-Smirnov test statistic p-test 95% confidence passed in most (but not all) cases
- Created 100 weather futures for shifted heat waves and historic cold waves per year, SSP, and confidence interval for a total of 3600 runs per location
- Used maximum number of CMIP6 ensemble results for surface temperature as available for each SSP
- Ran Medium office building International Energy Conservation Code (IECC) 2018 prototype models using EnergyPlus v 9.6.0
- No readjustment of HVAC sizing for future conditions – allow thermal discomfort to grow
- **Verification process for Tool 1 still underway**

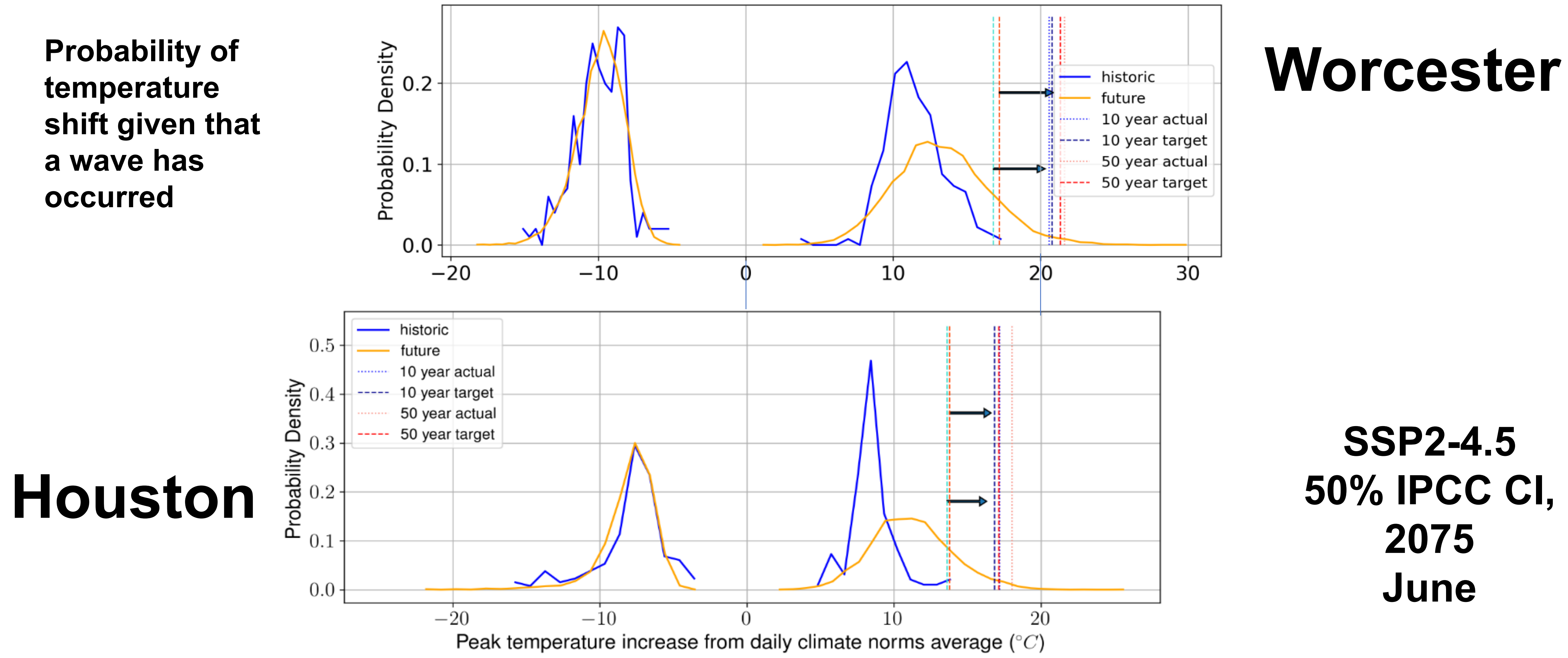
Climate scenarios

- **Polynomial fit increase in temperature added to future weather in addition to heat wave and cold snap differences**
- **Clearly more change in the North**



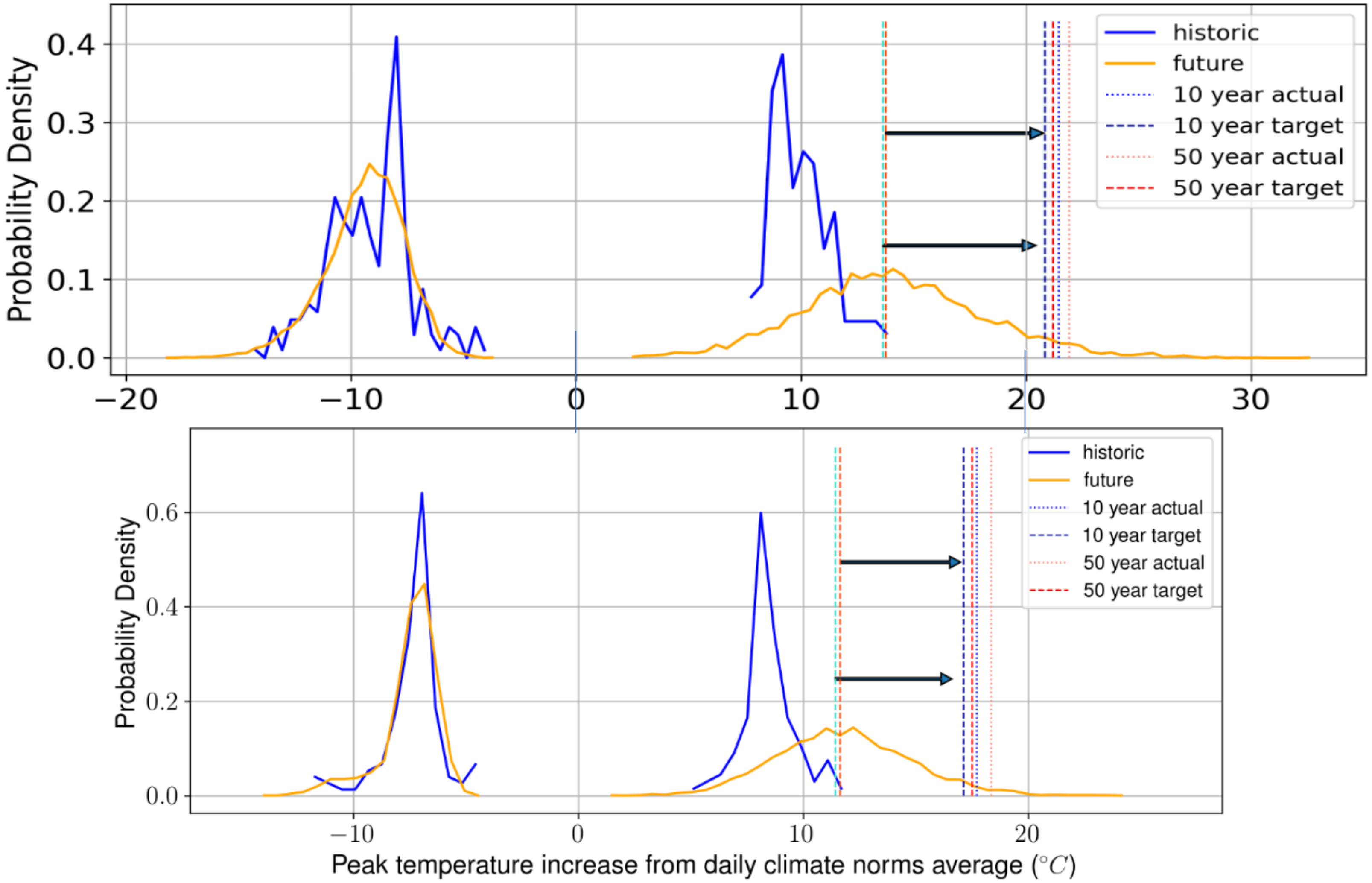
Extreme temperature shifts

Probability of temperature shift given that a wave has occurred



SSP2-4.5
50% IPCC CI,
2075
June

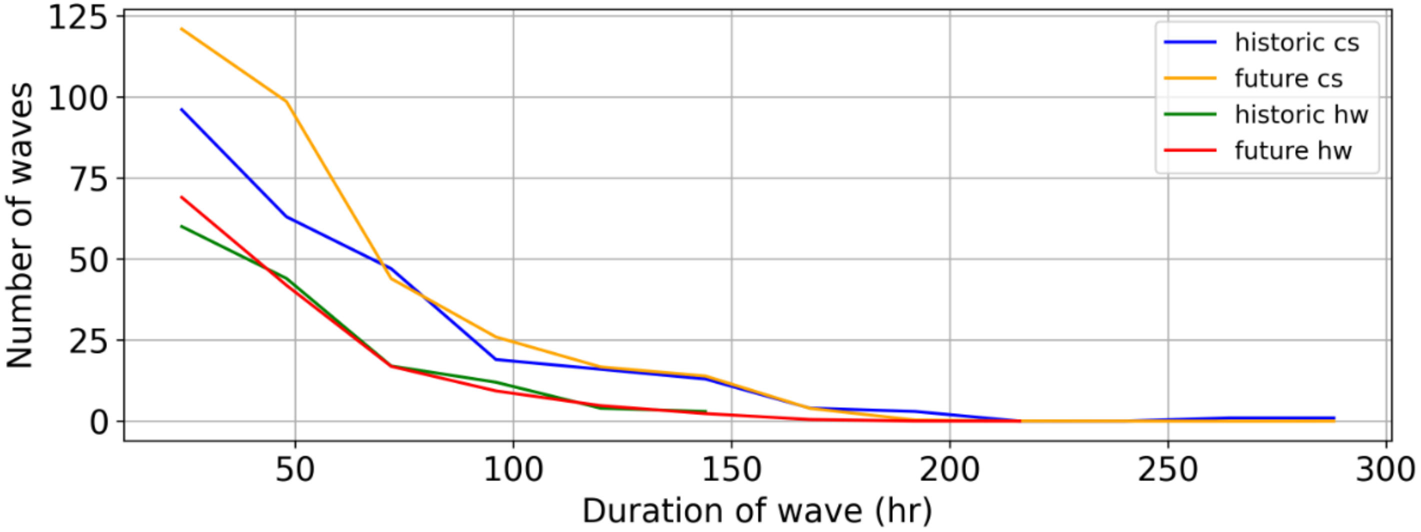
Extreme Temperature Shifts 2



SSP5-8.5
95% IPCC CI,
2075
July

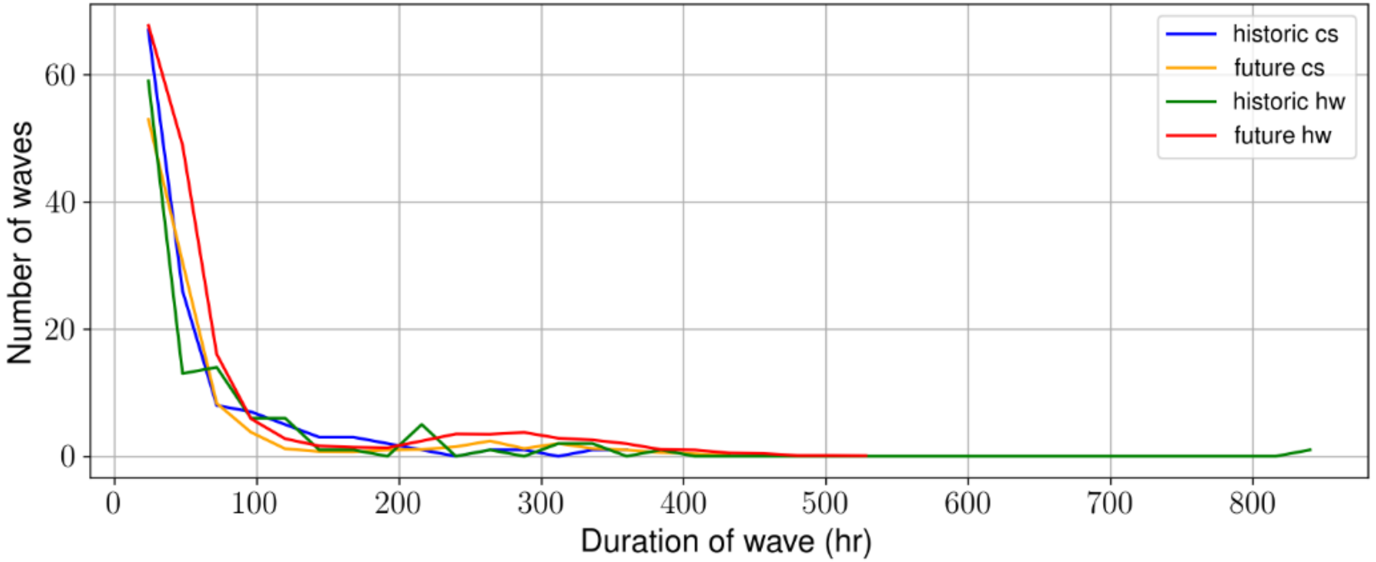
Duration – no shift

Duration not increased



Worcester

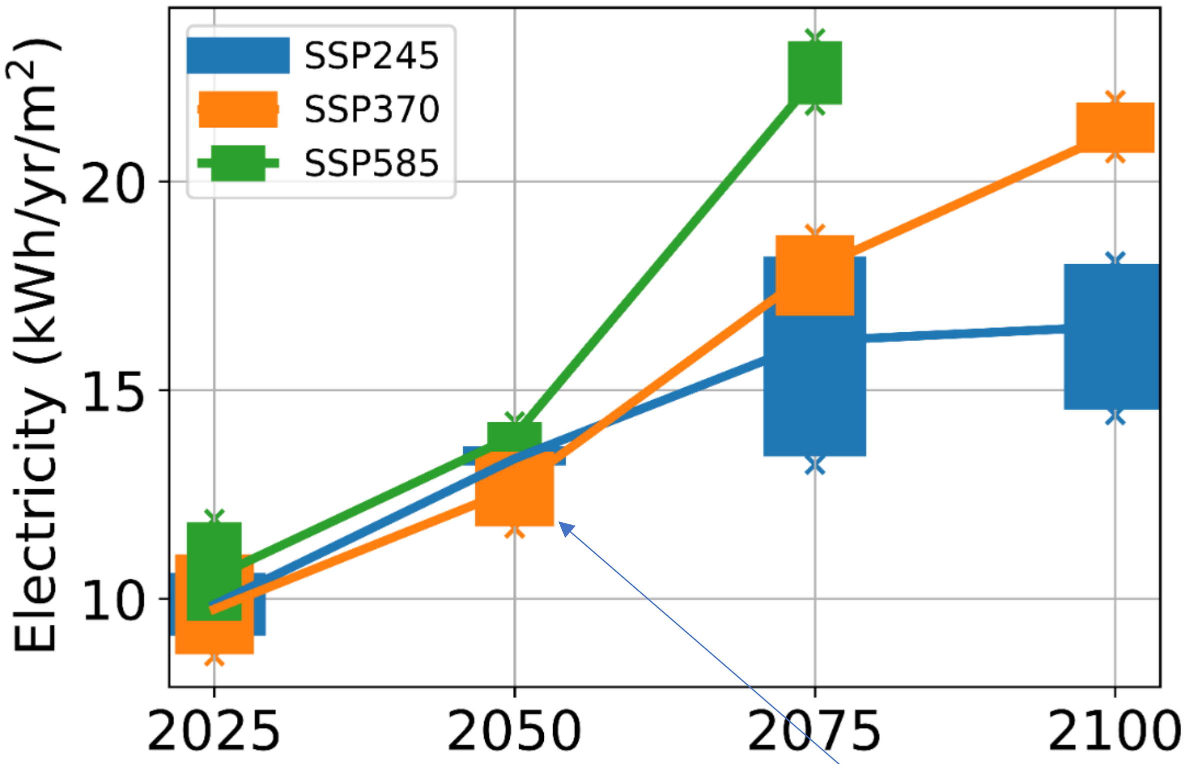
Houston



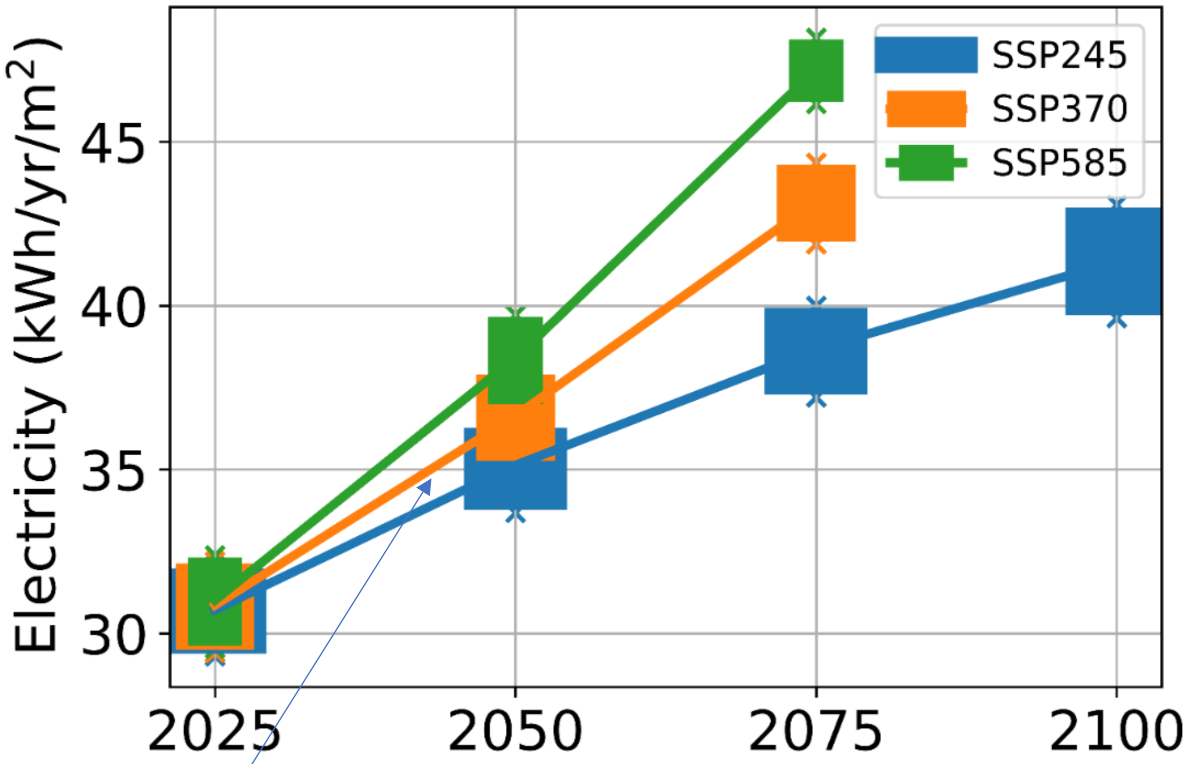
SSP5-8.5
95% IPCC CI,
2075
July

Total Building Electricity (Medium Office)

Worcester (left)



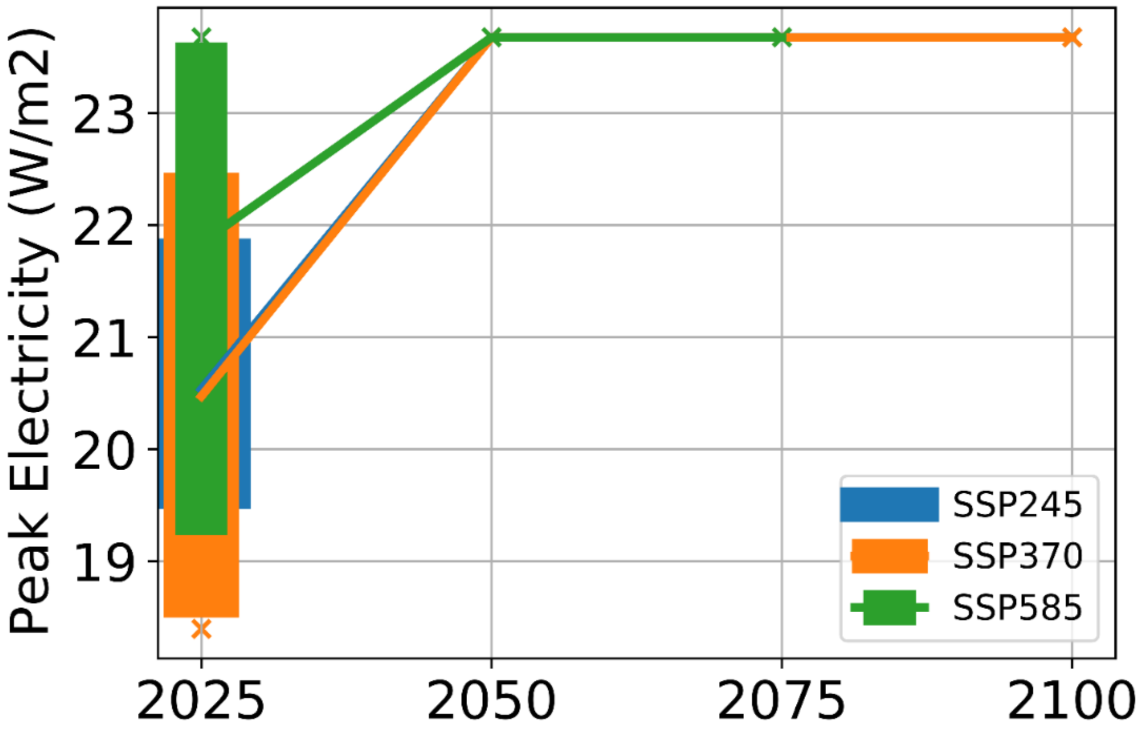
Houston (right)

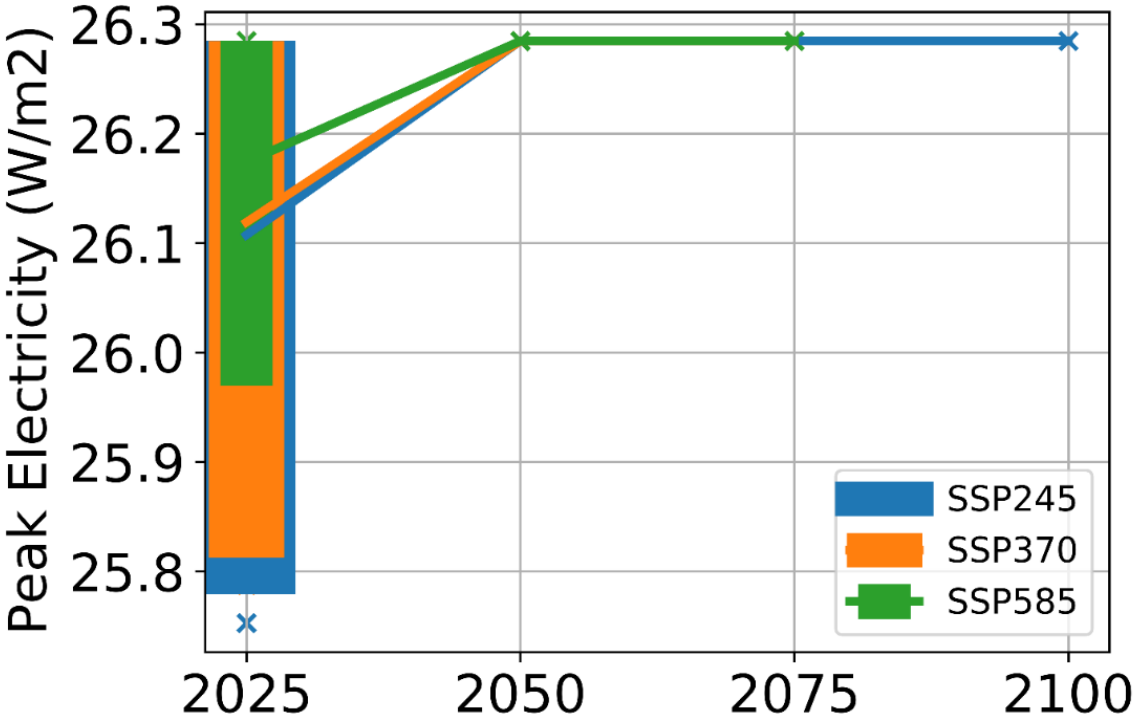


Hypothesis: Southern climates have differences between climate scenarios sooner

Building HVAC Peak Electricity

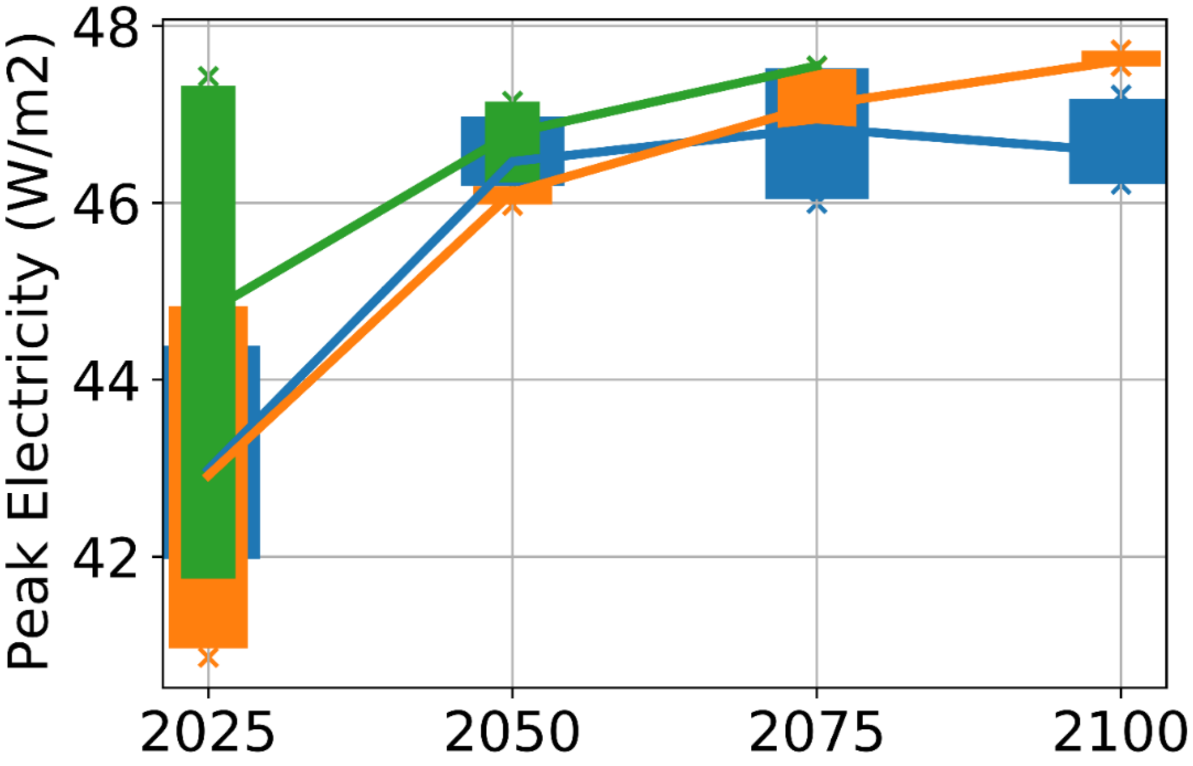
Predicted need for new equipment sizes by 2050

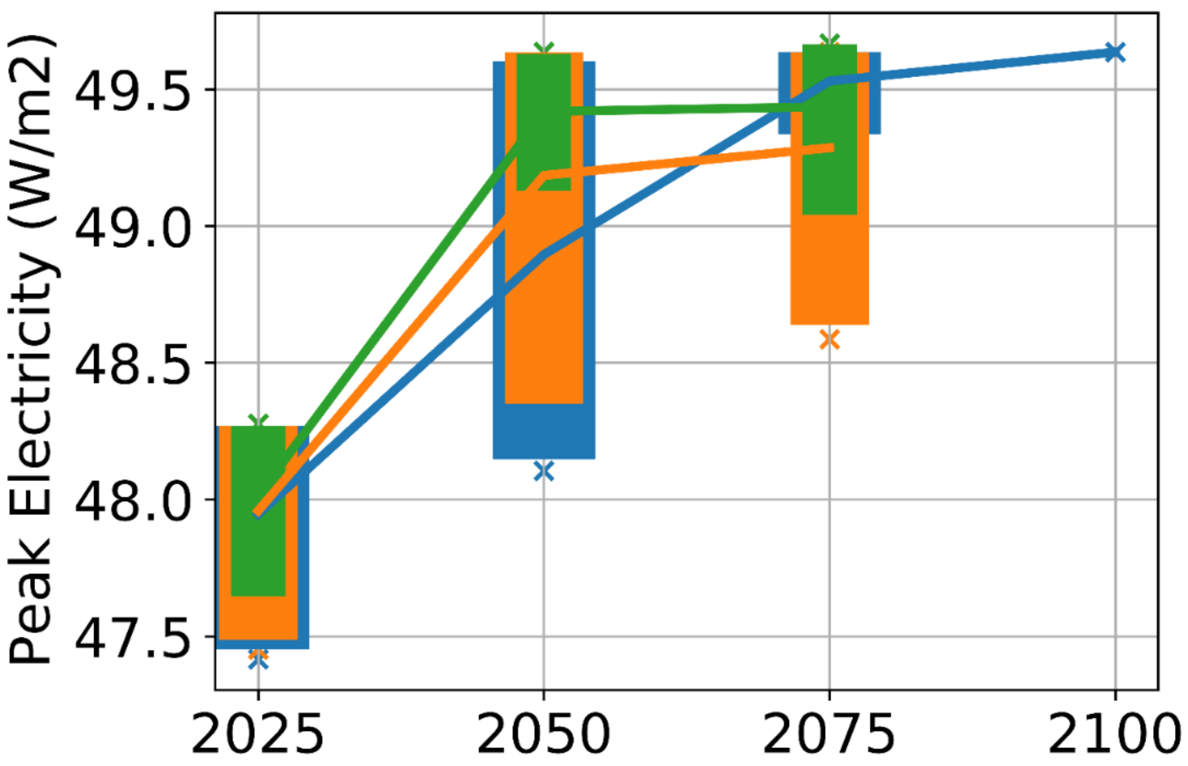




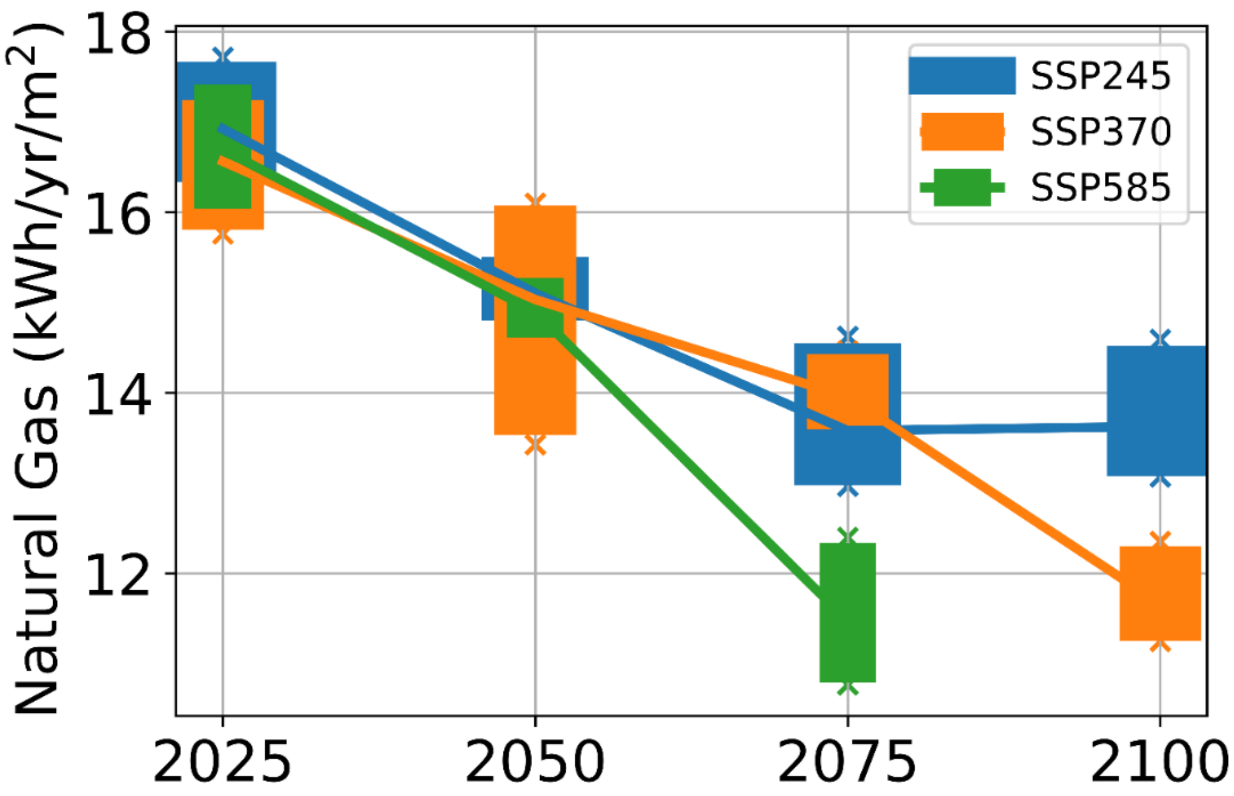
Peak Electricity

Much larger increases of peak electric load in Worcester

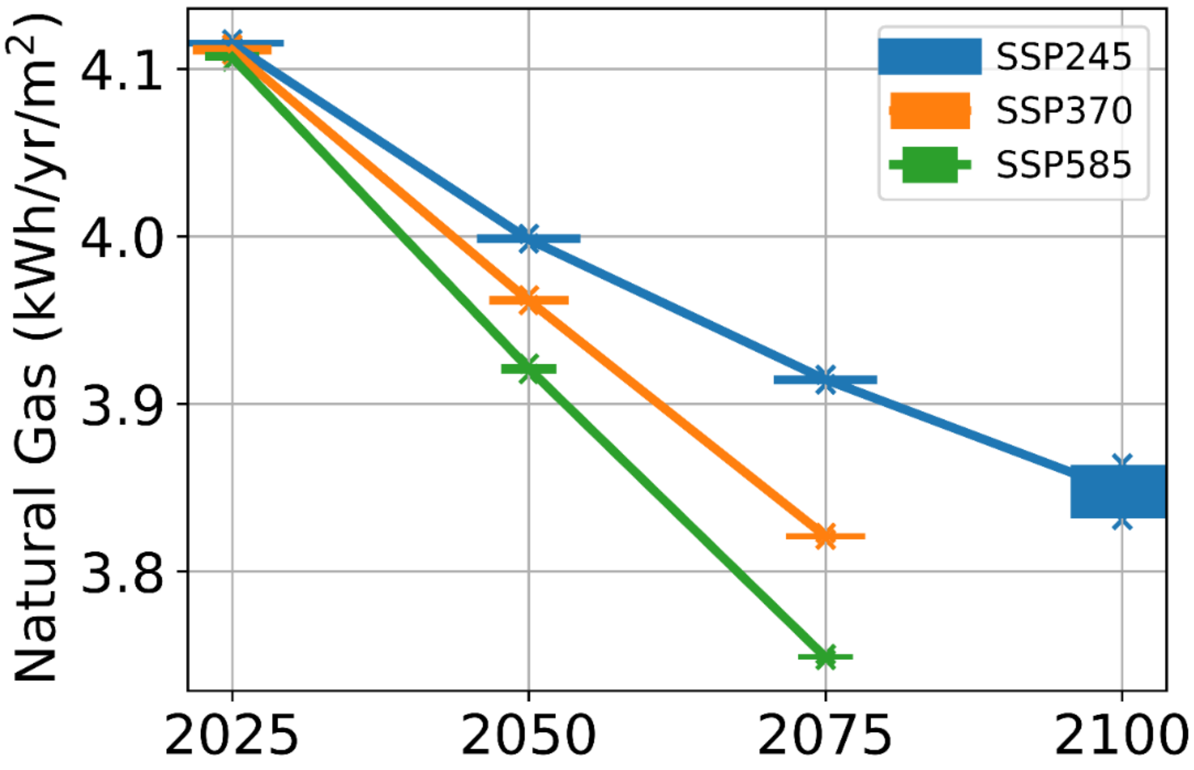




Natural Gas

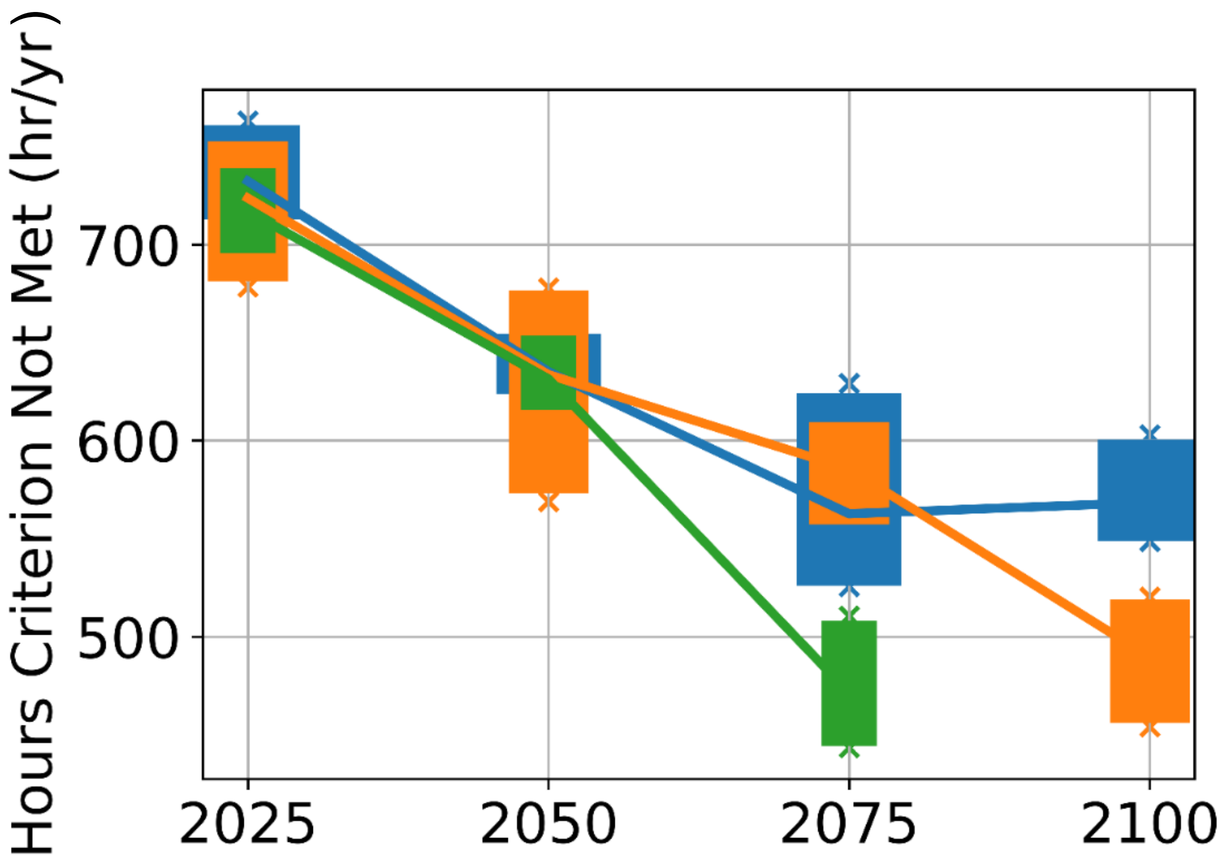


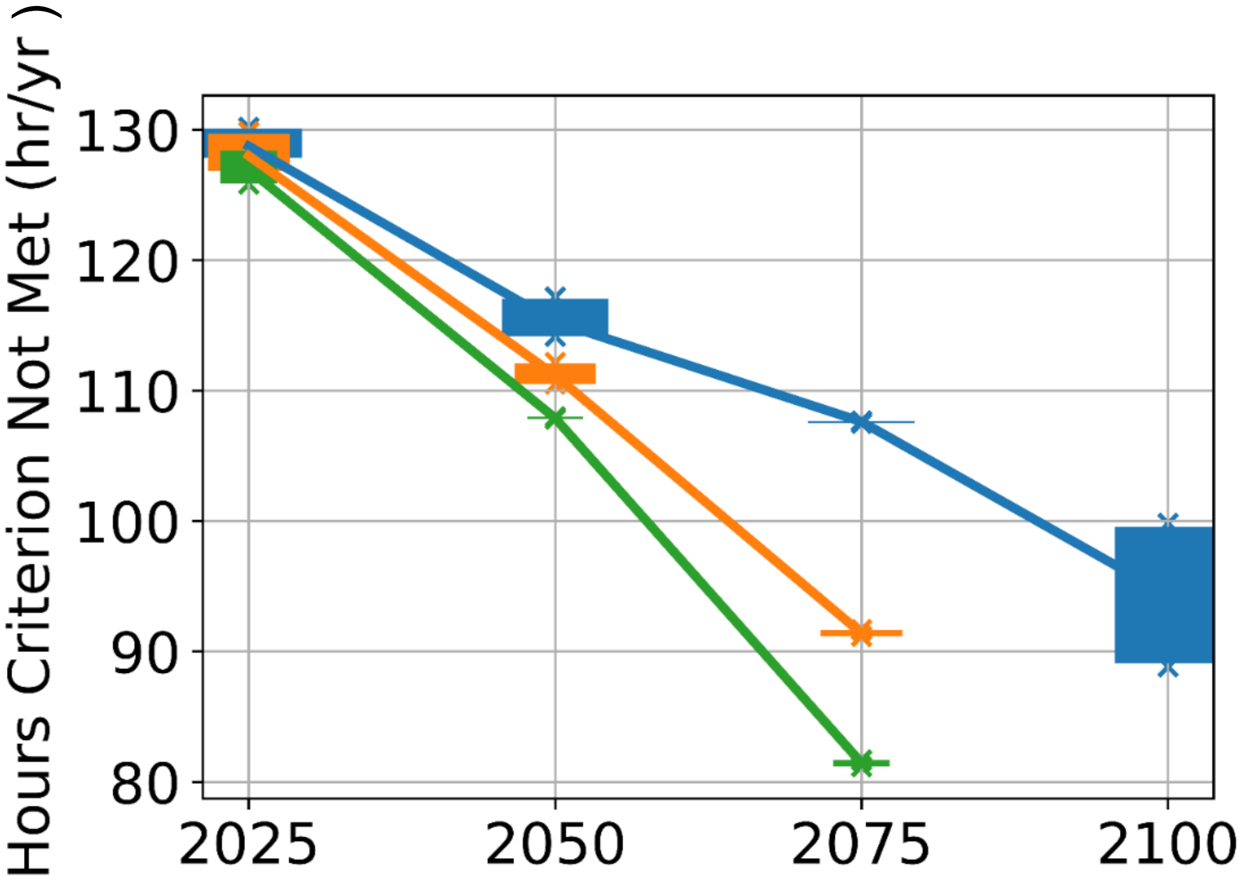
Natural Gas (kWh/yr/m^2)
18
16
14
12
2025
2050
2075
2100
SSP245
SSP370
SSP585



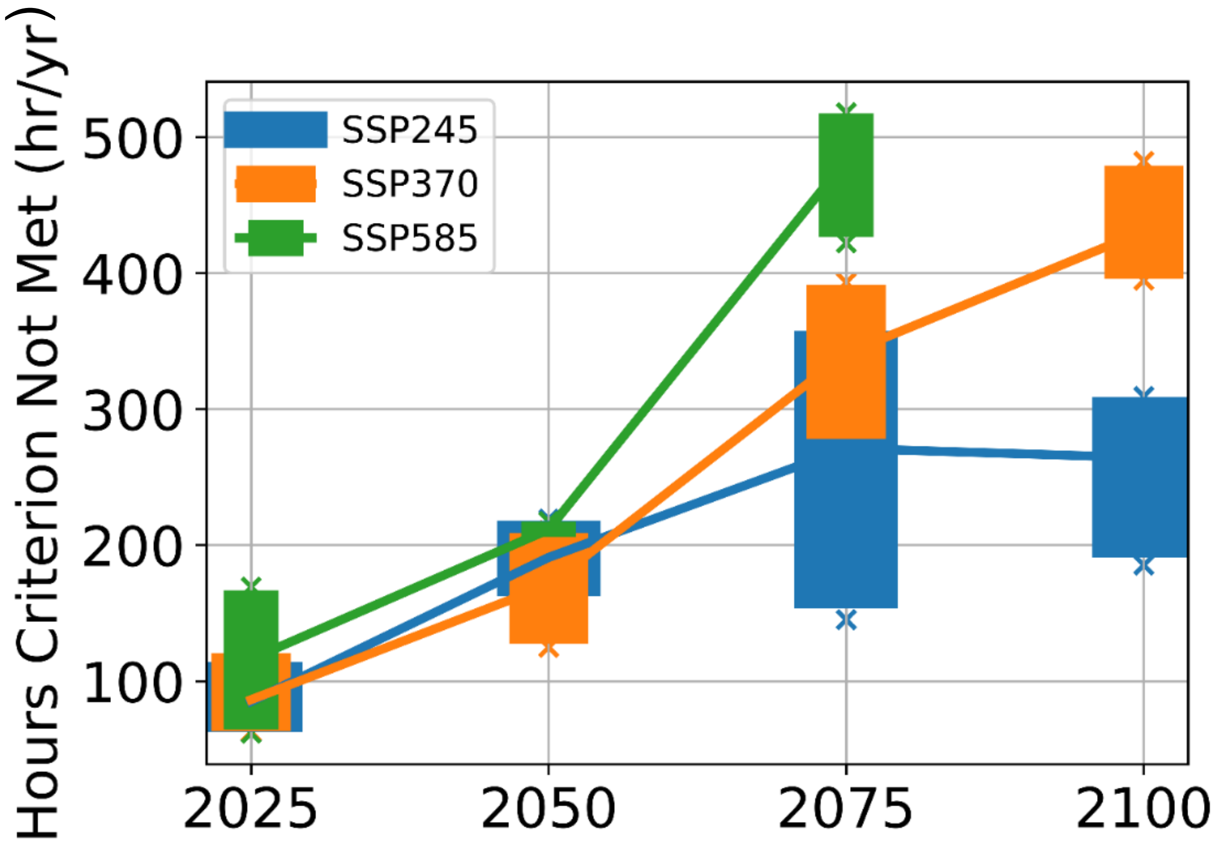
Natural Gas (kWh/yr/m^2)
4.1
4.0
3.9
3.8
2025
2050
2075
2100
SSP245
SSP370
SSP585

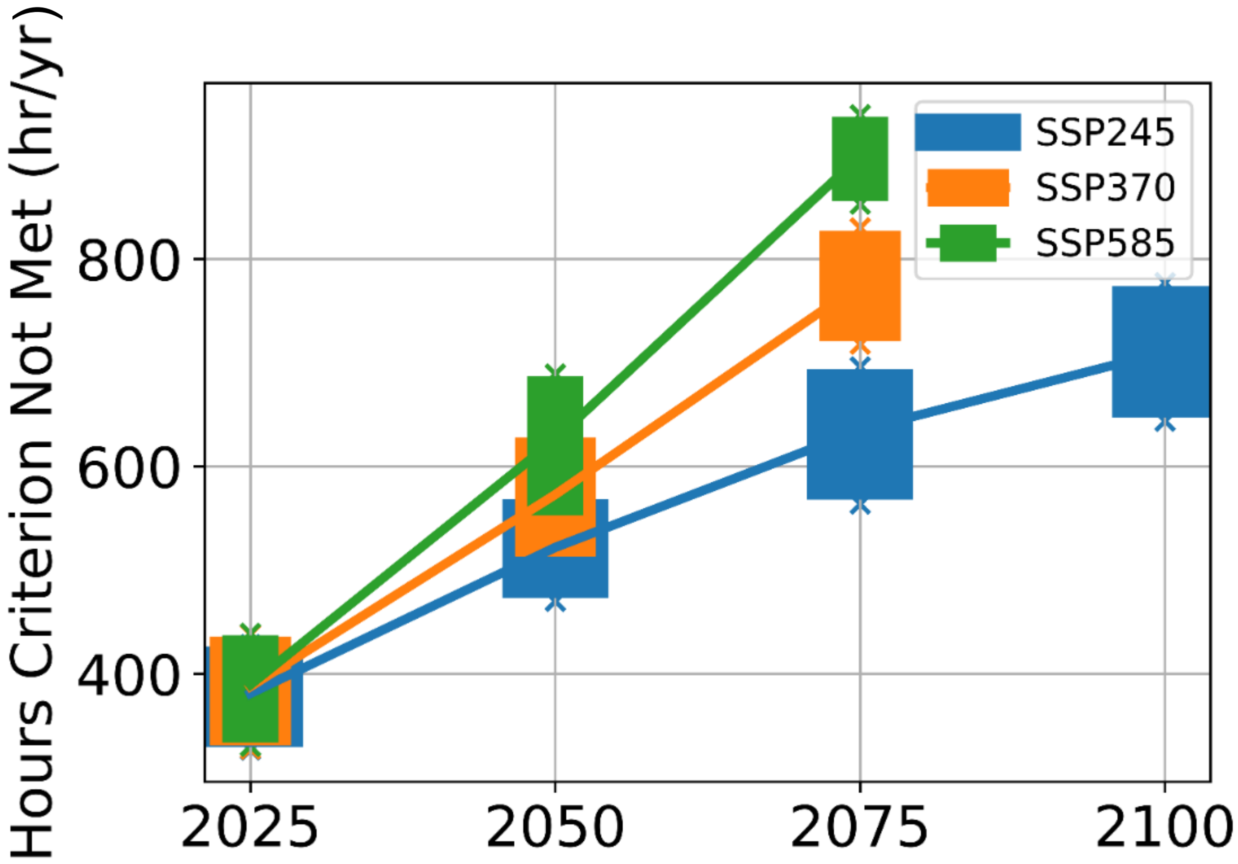
Heating setpoint





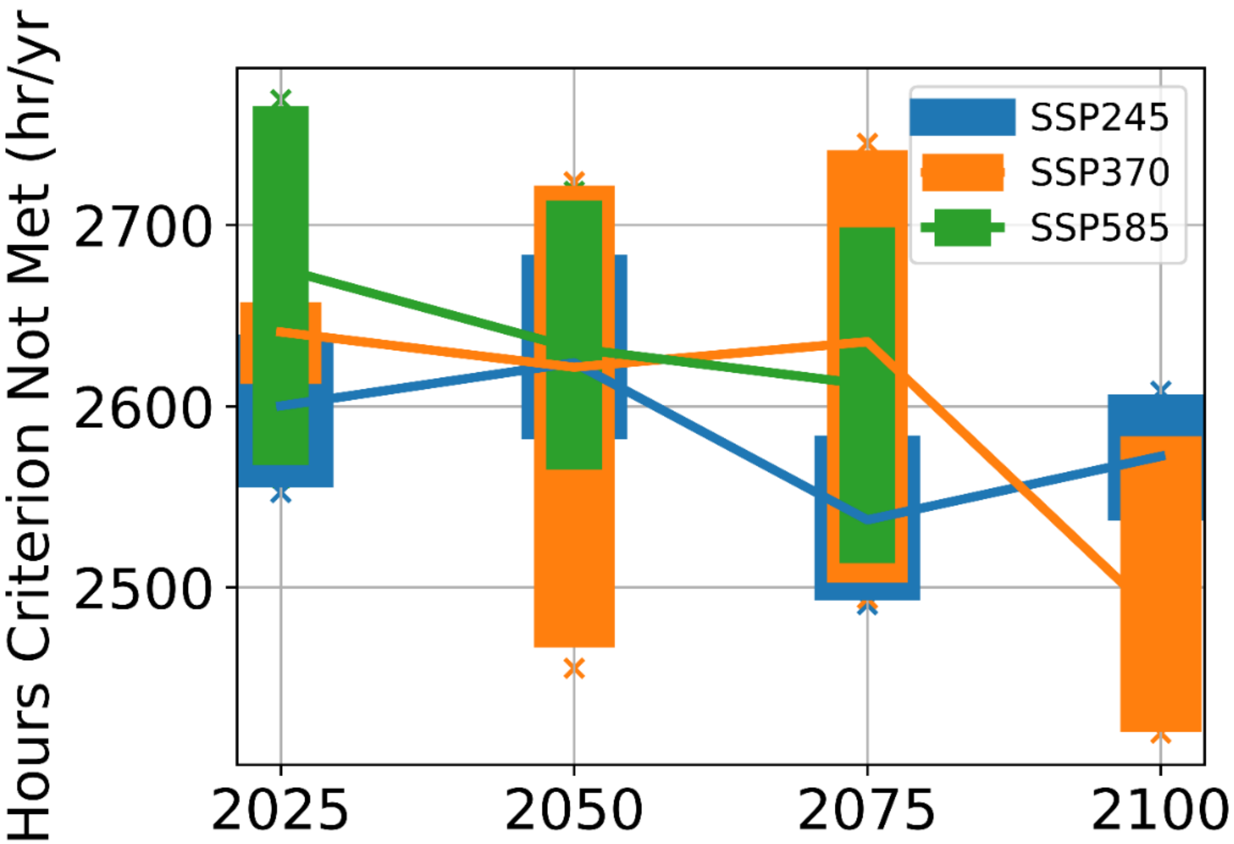
Cooling Setpoint

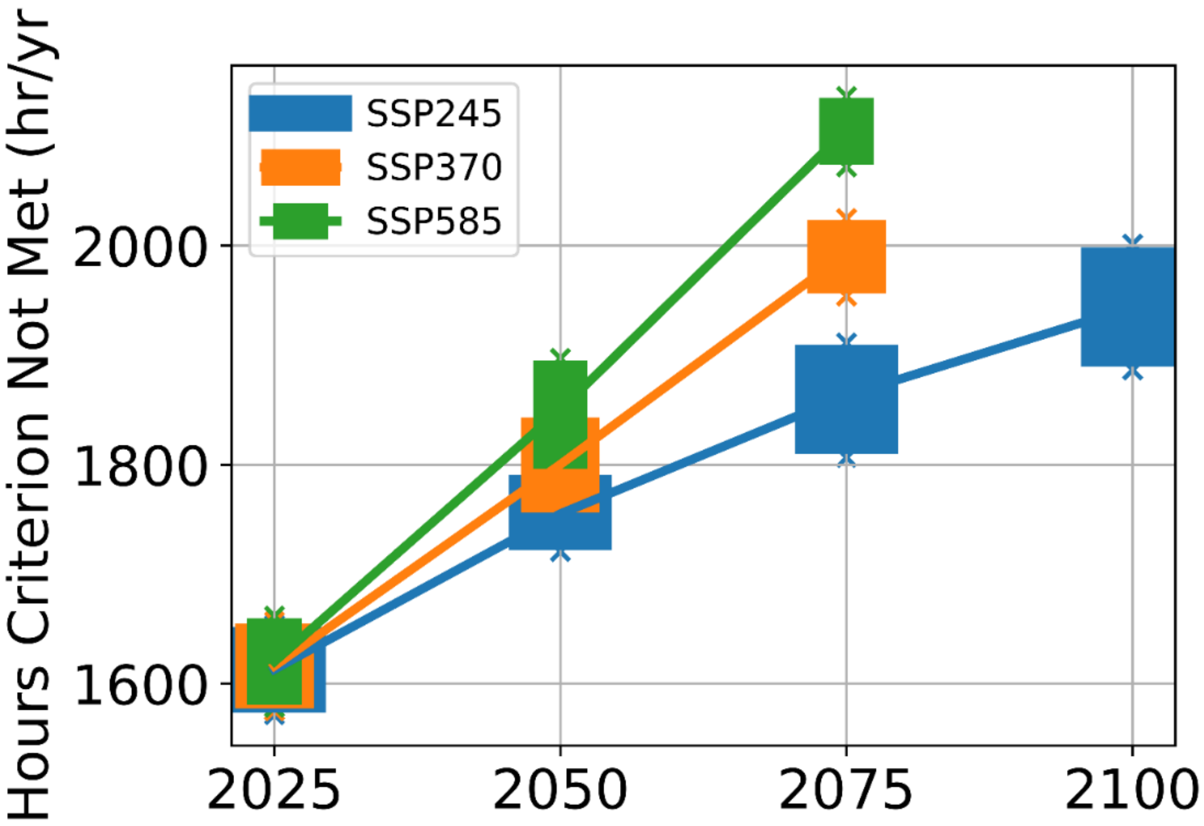




ASHRAE Standard 55-2004 thermal comfort

- **Overall thermal comfort will increase in the north but decrease in the south**





- The study performed shows promise for using Tool 1 to conduct BEM studies of future climates
- Probably > 100 runs per future scenario are needed.
- Better statistical ways of analyzing the vast output data are under development
- There are marked differences between southern and northern climates
    - Southern heat wave changes are less extreme shifts than Northern
    - Southern has less difference into the future than Northern
    - When HVAC sizing kept constant southern thermal comfort will reduce while northern will increase
    - Electricity use for Northern climates increases 2-3 times as much as Southern as air-conditioning begins to run much more.
- Much more work is needed to look at resilience metrics that isolate performance during heat waves
- Tool 1 needs to be connected to Regional Climate Modeling
- Mapping of Tool 1 study for 12 climate zones is underway

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Questions?

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