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Filer:	Raquel Kravitz
Organization:	Lumen Energy Strategy
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WARP to Resilience

Weather-Adapted Resource Planning

Development of future weather variants for demand forecast

Presented by ONUR AYDIN and MARIKO GERONIMO AYDIN

CEC IEPR Commissioner Workshop

July 30, 2024

Lumen ENERGY STRATEGY

Development of future weather variants for demand forecast

How do we translate downscaled climate projections into workable inputs to the demand forecast models?

1. **Recap of materials from prior IEPR workshops and feedback**
2. **Overview of climate data sources and applications**
3. **Hourly de-trended temperature library**
4. **Hourly dew point metrics**

Recap of prior workshops and feedback

- **Our de-trending approach facilitates analysis of long-term trend impacts (how "normal" changes) separately from annual variability (range of what could happen in a year) in each demand forecast planning year**
- **Our work builds from IEPR's ongoing progress to bring climate science into demand forecast**
  - Many parties involved and coordinating, over many years, to develop data, serve data products, integrate analytical teams and tools, advance forecasting methodologies
  - Our analytical approach is statistical and not new climate analysis, relies on other teams' climate research and data products, extracts as much information as-is from climate projections as we can
- ***See also* our 2023 IEPR presentations supporting the demand forecast team (links at the end)**
- **Key analytical considerations**
  - Identification of bias and bias correction
  - Retention and interpretation of information on weather extremes
  - Tradeoffs of climate data for different use cases; how to develop internally-consistent planning perspectives

Climate data sources

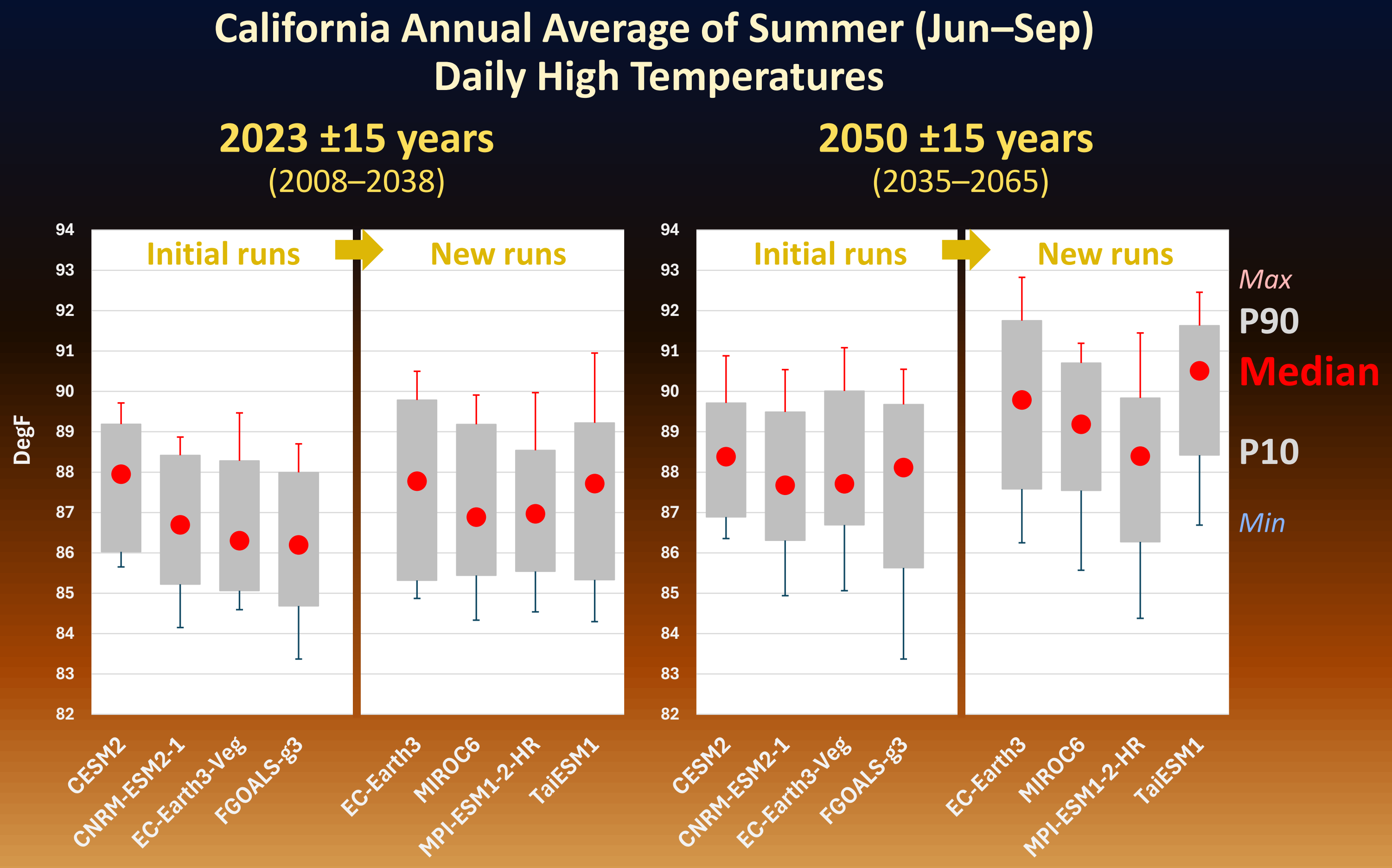
- **A suite of new downscaled climate projection model runs (GCMs) has been in production and released in phases (EPC-20-006)**
- **They vary in terms of modeling techniques, areas of focus/strength, weather variables produced, time granularity, and spatial domain**

Downscaling model	Raw data release	AE integration	# CMIP6 GCM runs	Climate scenarios (SSPs)	3km ?	Timestep	Bias correction?	3-km hourly metrics				
								Temp	Dew point	Cloud cover	Solar irr.	Wind speed
WRF	Dec 2021–Jan 2022	✓	4	3-7.0	✓	Hourly	✗	✓	✓*	✗	✗	✗
LOCA2	May 2023	✓	199	2-4.5 3-7.0 5-8.5	✓	Daily	✓	✗	✓*	✗	✗*	✓
WRF	Sep 2023	✓ *Nov 2023*	4	3-7.0	✓	Hourly	✓	✓	✓*	✗*	✓	✓

Notes:
See August 18, 2023 IEPR workshop for more information on climate projections metrics relevant to demand forecast (https://www.energy.ca.gov/event/workshop/2023-08/iepr-commissioner-workshop-load-modifier-scenario-development).
For WRF documentation *see* https://dept.atmos.ucla.edu/alexhall/downscaling-cmip6.
For LOCA2 documentation *see* https://loca.ucsd.edu.
* Dew point is derived from available metrics on temperature and relative humidity; effects of cloud cover are included in solar irradiation metrics; limited solar irradiation information from LOCA2 analysis.
** Updated from the initial 4 WRF runs listed above (released in 2021–2022) which were used for the 2023 IEPR.

- Production > raw data repository > Cal-Adapt Analytics Engine > (most) users
- Demand forecast requires:
  - **Hourly temp, dew point, cloud cover**
  - **Weather data at station-level**
  - **Bias-corrected to average levels, monthly peaks, hourly shape**
- For the 2024 IEPR we will rely on latest 4 downscaled WRF model runs**
  - **EC-Earth3 r1i1p1f1**
  - **MIROC6 r1i1p1f1**
  - **MPI-ESM1-2-HR r3i1p1f1**
  - **TaiESM1 r1i1p1f1**
- Our data selection follows guidance of (Pierce et al. 2023); *see also* (Krantz et al. 2021)

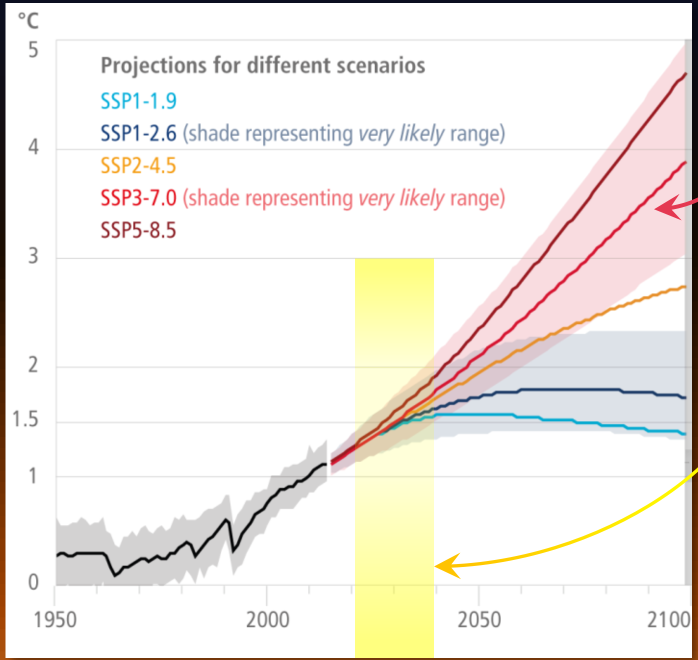
Initial vs. new WRF model results



- 4 new a-priori bias-corrected WRF runs show warmer temperature levels across California, relative to initial set of runs used for 2023 IEPR
- Summer daily maximum temperatures ~0.6°F higher on average by 2023
- Temperature spread rises over time, to above 1°F by 2050
- *See* (Rahimi 2022b) for performance evaluation of initial WRF run results

Characterization of weather extremes

IPCC Sixth Assessment Report
Global Surface Temperature Increase from Historical Period (1850–1900)

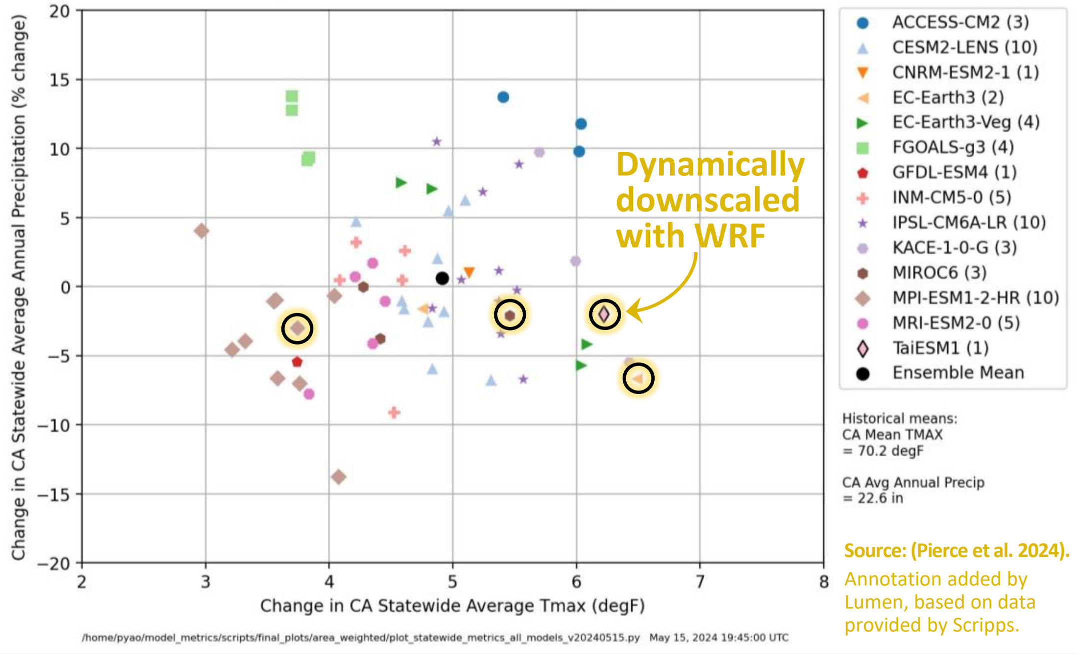


WRF modeling focuses on SSP3-7.0

Demand forecast focuses on the near/mid-term

Source: (IPCC 2022). Annotation added by Lumen. SSP = Shared Socioeconomic Pathway.

LOCA2 CA Statewide Average Precipitation vs. Tmax
Changes from LOCA2 Historical Period (1950–2014) to SSP3-7.0 (2045–2074)



Source: (Pierce et al. 2024). Annotation added by Lumen, based on data provided by Scripps.

- **Extremes differ across climate scenarios, diverge over time as uncertainty increases**
- **The SSP3 narrative relied upon in WRF analysis is consistent with renewable development and socioeconomic trends we've seen over past 10 years**

- **Chart shows 62 global climate model (GCM) runs analyzed with LOCA2 (Pierce et al. 2024)**
- **Among considerations in selection for WRF analysis: GCM performance in simulating the region including California, model independence, spread of climate signal results (Rahimi 2022a)**

Climate data localization to stations

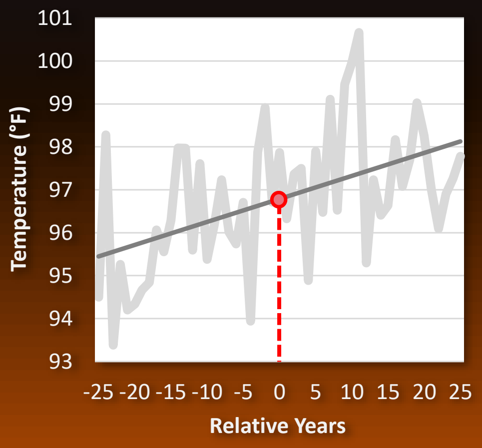
- **Demand forecast models are trained on historical observations at weather stations**
- **Localization methods used by climate scientists; generalized as needed for application by other users**
  - Temperature localization method available as a Jupyter Notebook on Cal-Adapt: Analytics Engine (analytics.cal-adapt.org)
  - Dew point localization method development initiated by the Analytics Engine team, in discussion as a potential future research area, also available as a Jupyter Notebook
  - Both use a Quantile Delta Mapping (QDM) methodology and 1981–2014 as the historical baseline period, for consistency with the underlying climate models
- **Challenges/limitations in application: challenge to localize to coastal stations, impact of quality and availability of historical data, modeling limitations & residual bias**

Hourly de-trended temperature library

Motivation for de-trended temperatures

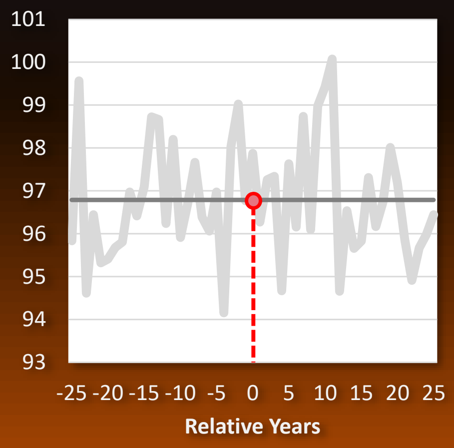
Example for Illustration

Raw Data



Trendline shows temperatures increase by 3°F on average from 95°F to 98°F over multiple decades

After De-trending



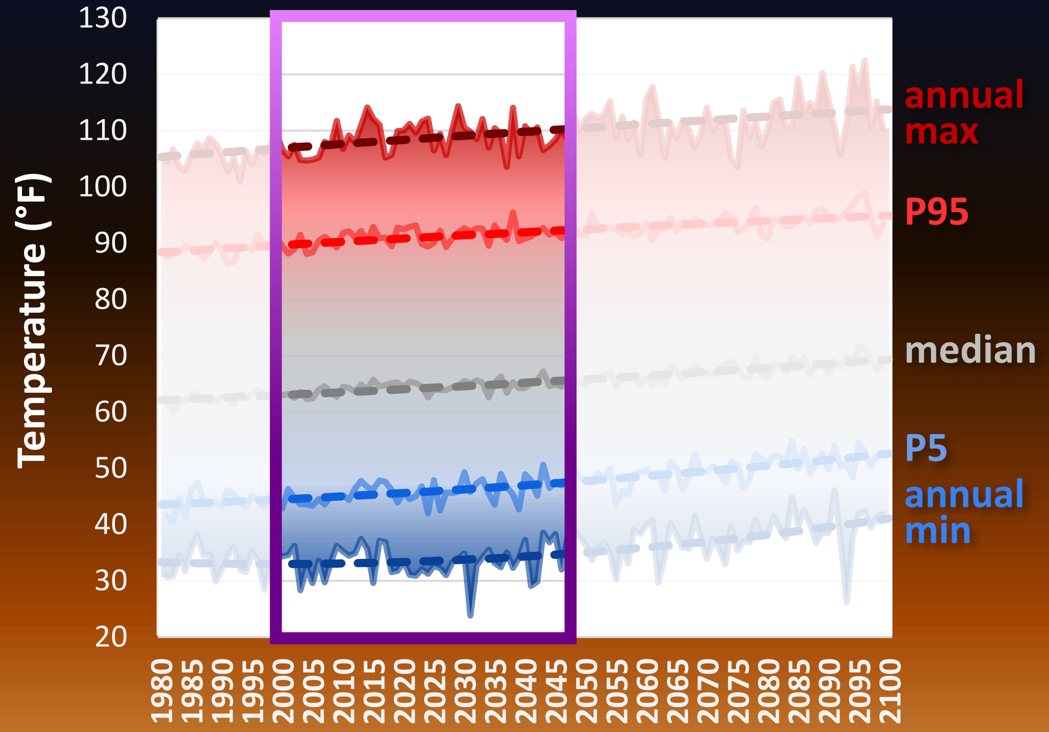
De-trending centers temperatures at 97°F as the level expected for forecast year

- **For each demand forecast year, need to understand:**
  - What can be reasonably expected
  - The range of possible outcomes in that year
  - Either/both of which may change over time
- **Increasingly difficult to harvest information on future weather risks from historical data**
  - Limited data: one realization of a range of potential outcomes
  - Rare and emerging, novel weather patterns observed *ex post*
- **De-trending harvests information on variability while reflecting expectations of the forecast year**
  - 204 weather variants (8,760 profiles) for each demand forecast year

Hourly de-trended temperature library

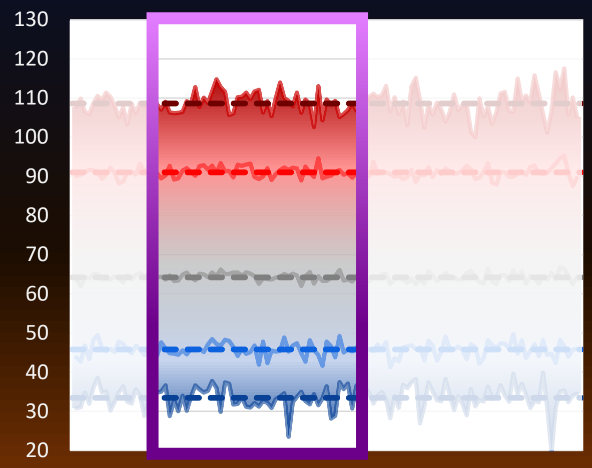
De-trending by temperature levels

Historical & Projected Temperatures
Example: Riverside Station*

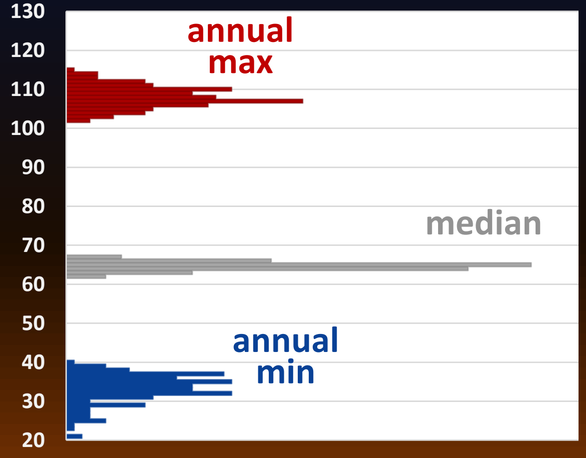


*Example of station-level data for illustration

De-trended Temperatures
Base Year 2023



Frequency Distribution
Multiple Climate Models



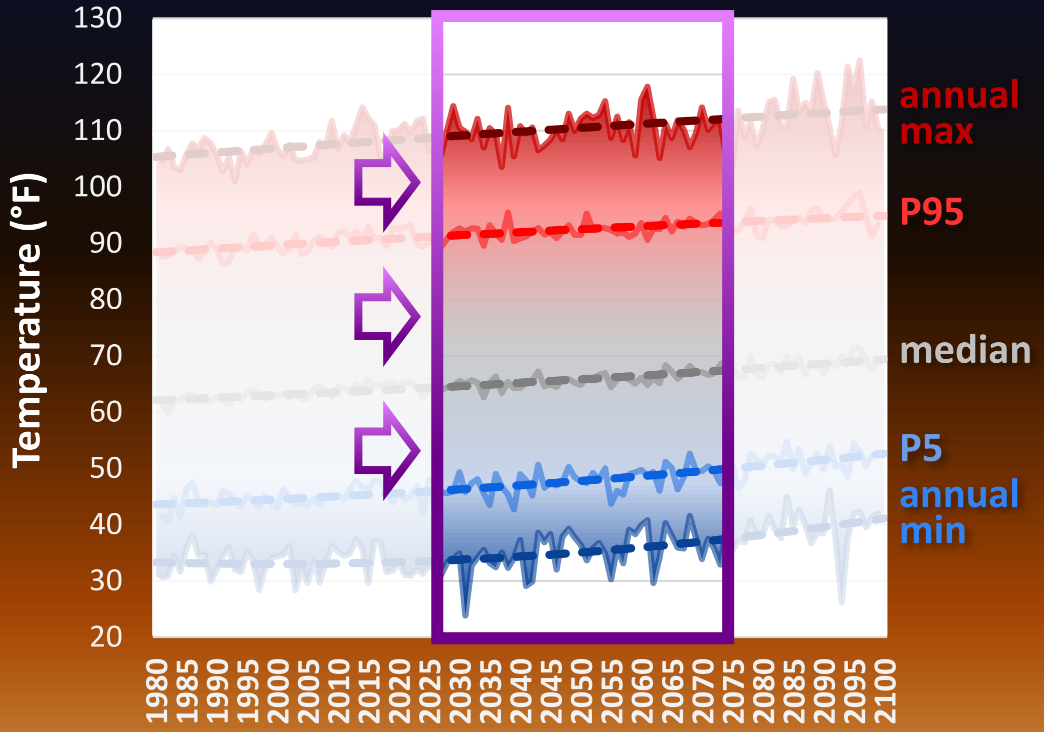
- De-trending by temperature level (quantile) recognizes that anticipated climate change effects are not uniform
- Preserves hourly chronological order and correlations across weather events in original climate projections
- Rolling window avoids the use of weather patterns from distant past/future that may not be applicable for the forecast year

Hourly de-trended temperature library

De-trending for future years

Historical & Projected Temperatures

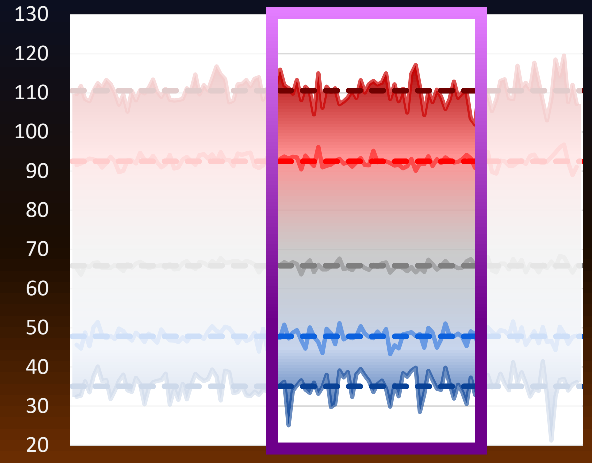
Example: Riverside Station*



*Example of station-level data for illustration

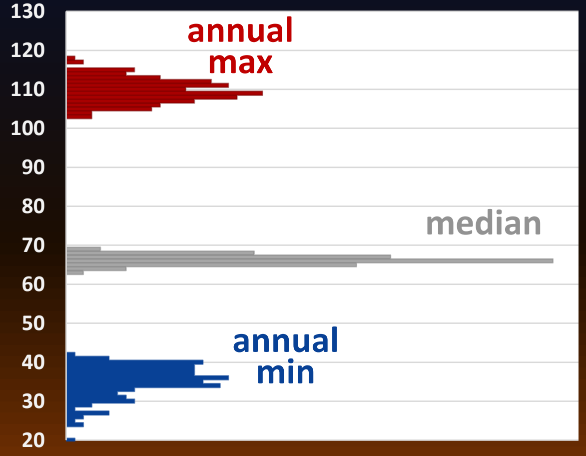
De-trended Temperatures

Future Year 2050



Frequency Distribution

Multiple Climate Models

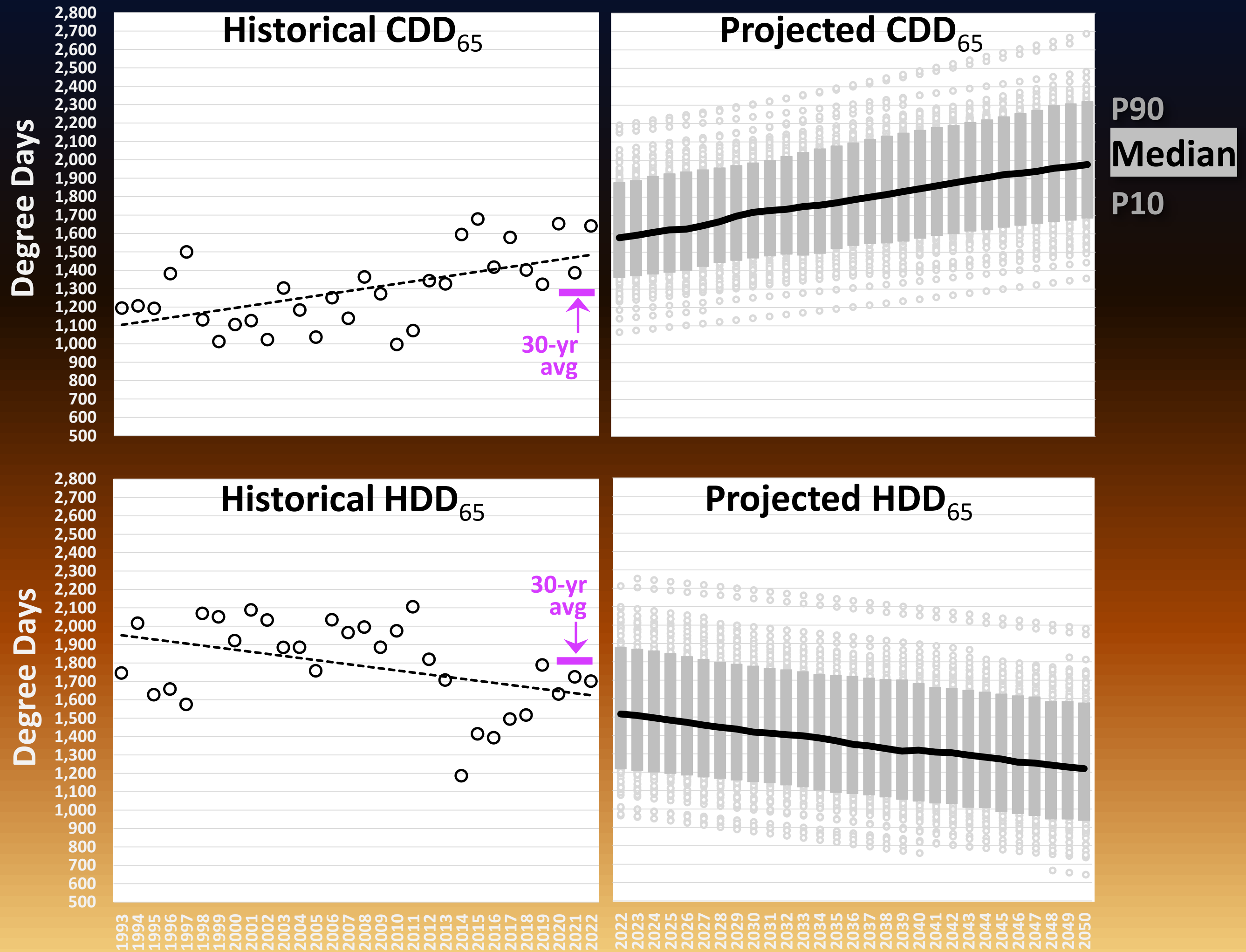


- Center of the rolling window used to develop weather variants shifts with the forecast year
- Expectations for each temperature level moves along the long-term trendline (shown in dashes)
- Variability around that expectation also changes as new future years are considered and past years are gradually dropped

Hourly de-trended temperature library

Cooling degree days (CDDs) & heating degree days (HDDs)

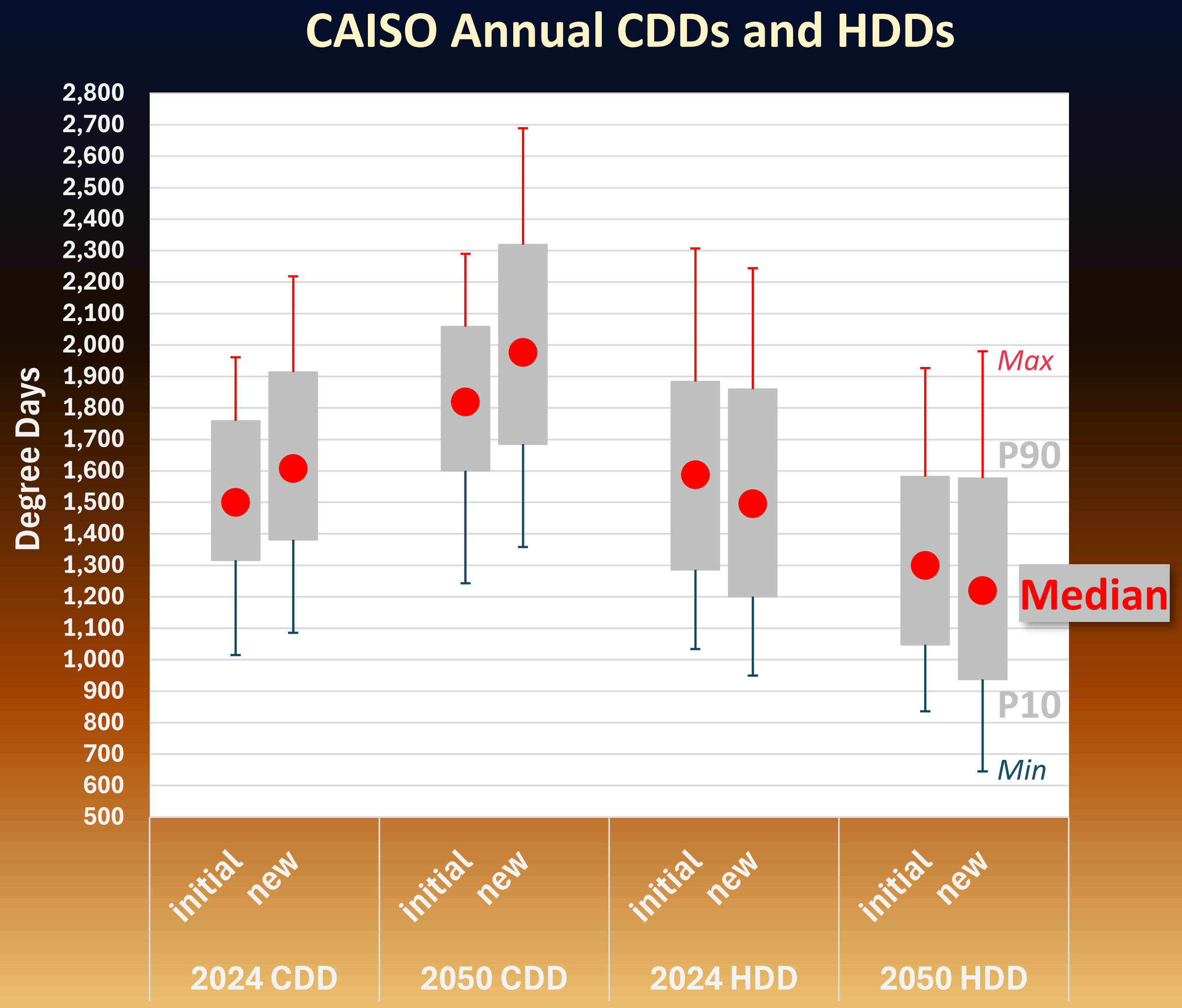
CAISO Annual CDDs and HDDs



- **CDD/HDD key input to consumption forecast**
- **For each demand forecast year:**
  - Calculate CDDs and HDDs at the station level, for each of 204 weather variants using the 4 new bias-corrected WRF runs
  - Aggregate to planning area and CAISO level
  - Select median and 1-in-x across variants
- **Given climate trends, using historical data would significantly understate CDDs and overstate HDDs**
- **Resulting projected CDDs & HDDs:**
  - Align well with historical trends
  - Enable a more detailed look at the range of potential outcomes in a given forecast year
  - Tie back to the de-trended temperature library and specific variant(s) that may be explored in the hourly demand forecast models

Hourly de-trended temperature library

CDDs & HDDs in initial vs. new WRF model results



- **With the new a-priori bias-corrected WRF runs, CDD levels are higher and HDD levels are lower, relative to the initial runs used for 2023 IEPR demand forecast**
- **Preliminary results also show a larger range of potential outcomes across weather variants**
  - Important for weather normalization process and stochastic analyses
  - E.g., For 2050 forecast year, median CDD based on new WRF runs are near the P90 level previously estimated using initial WRF runs. The new P90 levels are as high as the absolute maximum across 204 variants.

Hourly dew point metrics

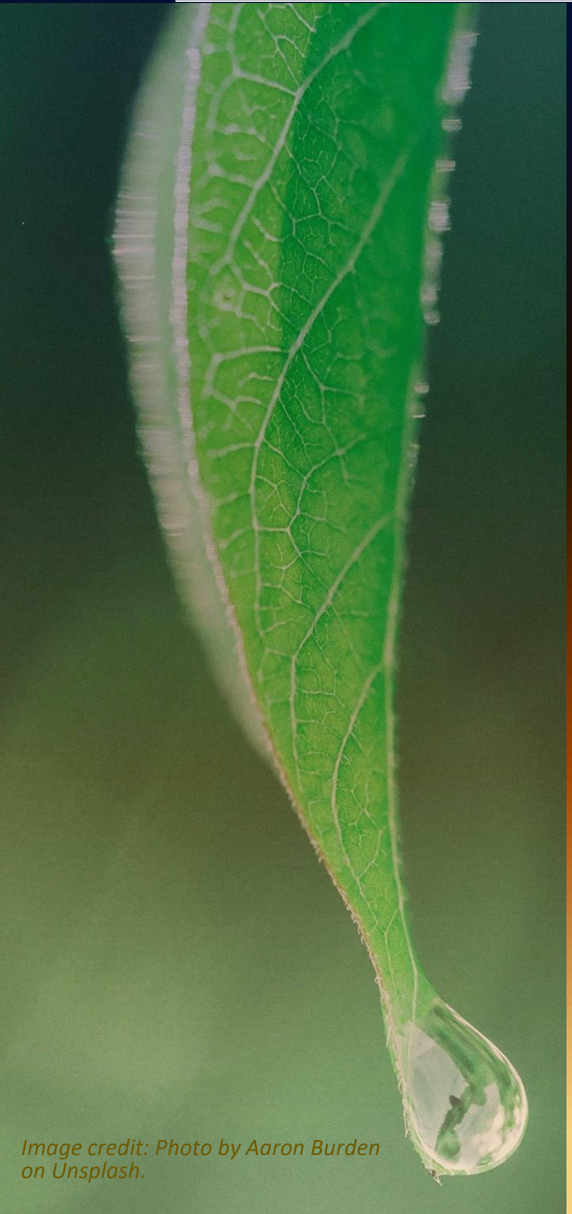
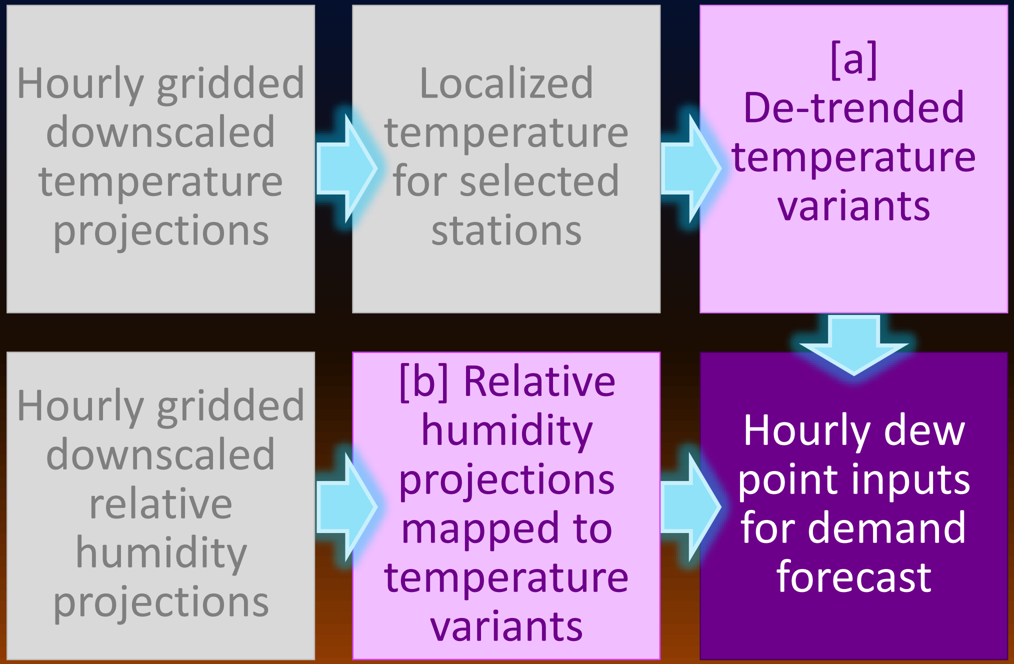


Image credit: Photo by Aaron Burden on Unsplash.

- **Dew point is a necessary input to the hourly demand forecast model**
  - Dew point indicates the air's absolute moisture content
  - High dew points are a better measure of human discomfort than relative humidity (Wallace et al. 2006)



- **Derived dew point from de-trended temperatures [a] and relative humidity at closest 3-km grid cell to each station [b]**
  - For each of the 204 variants corresponding to each demand forecast year, and at each station
  - Preserves the physical relationship between projected relative humidity and de-trended temperatures
  - Applies the same formulas used by Cal-Adapt

THANK YOU

LEARN MORE ABOUT *WARP TO RESILIENCE* AND JOIN OUR MAILING LIST FOR STUDY UPDATES
www.lumenenergystrategy.com/resilience

APPENDIX

Appendix

Selected references

IPCC (Intergovernmental Panel on Climate Change). 2022. *Climate change 2022: mitigation of climate change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge University Press, Cambridge, UK and New York, NY, USA. April 2022. doi: 10.1017/9781009157926. https://www.ipcc.ch/.

Krantz, Will, David Pierce, Naomi Goldenson, and Daniel Cayan. 2021. *Memorandum on evaluating global climate models for studying regional climate change in California.* UCLA andScripps Institution of Oceanography. Prepared under California Energy Commission agreement number EPC-20-006. November 29, 2021. https://www.energy.ca.gov/media/7264.

Pierce, David W., Daniel R. Cayan, Stefan Rahimi, and Julie Kalansky. 2023. *Data adoption justification memo (for California's Fifth Climate Change Assessment): LOCA version 2 hybrid downscaling*. Scripps Institution of Oceanography, UCSD & UCLA. Prepared under California Energy Commission agreement number EPC-20-006. December 2023. https://www.energy.ca.gov/programs-and-topics/topics/research-and-development/climate-data-and-analysis-working-group-c-dawg.

Pierce, David W., Julie Kalansky, Stefan Rahimi, Josh Mumford, Peter Yao, and Dan Cayan. 2024. "Toward targeted case studies of extremes." Climate Data and Analysis Working Group. Hosted by the California Energy Commission Sustainability & Health Unit and Energy Research & Development Division. May 17, 2024. https://www.energy.ca.gov/programs-and-topics/topics/research-and-development/climate-data-and-analysis-working-group-c-0.

Rahimi, Stefan. 2022a. *Memo on the development and availability of dynamically downscaled projections using WRF.* UCLA. Prepared under California Energy Commission agreement number EPC-20-006. April 2022. https://www.energy.ca.gov/sites/default/files/2022-09/20220907_CDAWG_MemoDynamicalDownscaling_EPC-20-006_May2022-ADA.pdf.

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Lumen's related materials from 2023 IEPR workshops (https://www.energy.ca.gov/data-reports/reports/integrated-energy-policy-report/2023-integrated-energy-policy-report/2023-iepr):

August 18, 2023: IEPR Commissioner Workshop on Load Modifier Scenario Development

Projected climate trends and patterns of interest to California's energy system, by Mariko Geronimo Aydin, Lumen Energy Strategy. https://efiling.energy.ca.gov/GetDocument.aspx?tn=251703

Development of future weather variants for demand forecast, by Onur Aydin, Lumen Energy Strategy. https://efiling.energy.ca.gov/GetDocument.aspx?tn=251702

December 19, 2023: IEPR Commissioner Workshop on the California Energy Demand Forecast Results Part II

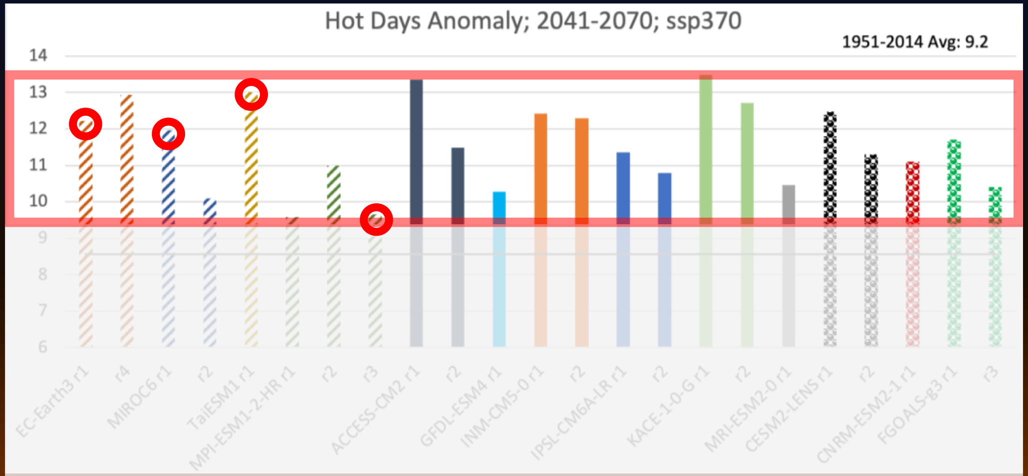
Key findings in climate data analyses for demand forecast integration, by Mariko Geronimo Aydin and Onur Aydin, Lumen Energy Strategy. https://efiling.energy.ca.gov/GetDocument.aspx?tn=253658

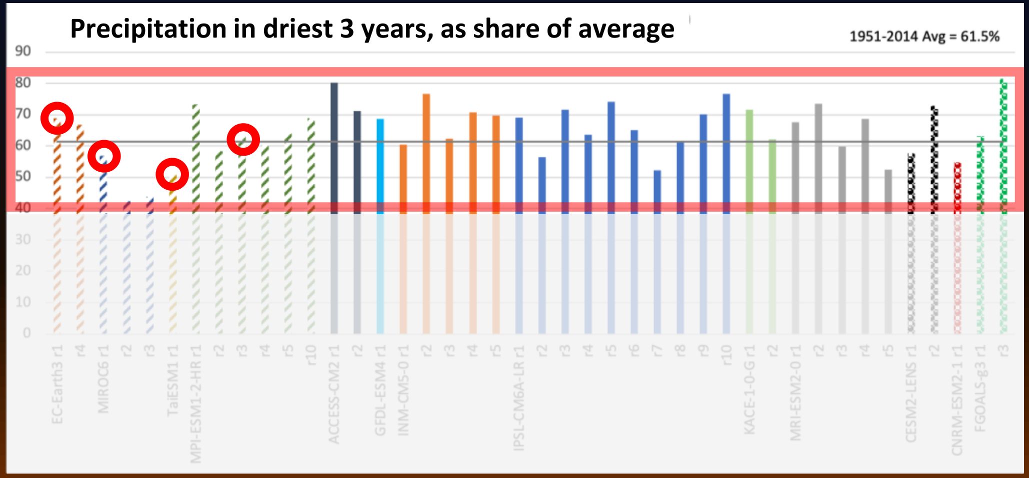
Appendix

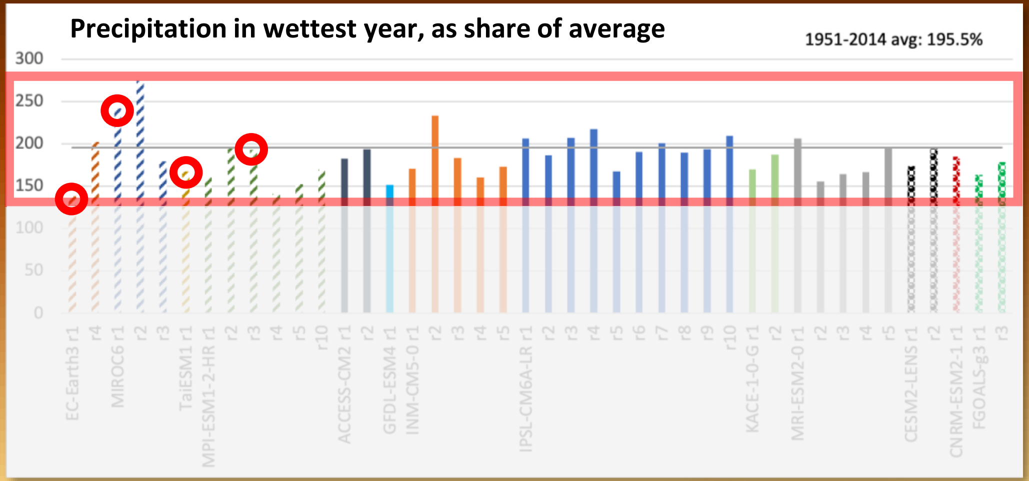
GCM runs used in LOCA2 vs. WRF

LOCA2 California Statewide Average Temperature and Precipitation Metrics

Future Extremes in SSP3-7.0 (2041–2070) vs. Historical Period Average (1951–2014)







- **Charts show a selection of global climate model (GCM) runs analyzed with LOCA2 (Pierce et al. 2024)**
- **Part of their work is to identify target extremes to use in scenario planning and stress tests**

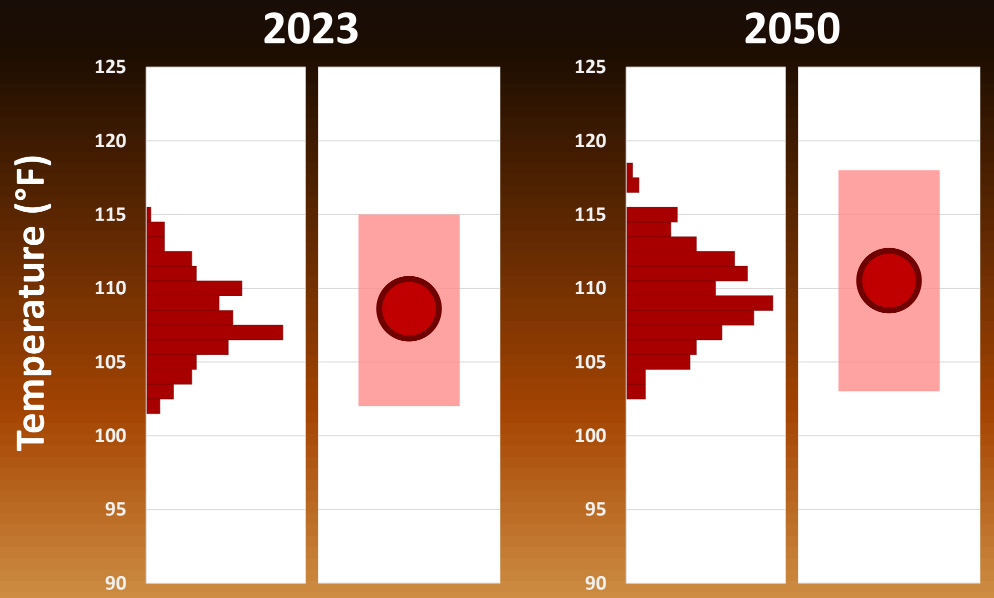
Source: (Pierce et al. 2024).
Annotation added by Lumen.

Changes in distribution of temperatures

Distribution of potential outcomes influenced by both upward trends and increased variability in projected temperatures.
Different effects on normal (e.g., 1-in-2 years) and more extreme (e.g., 1-in-10 years) conditions.

Annual Maximum Temperatures

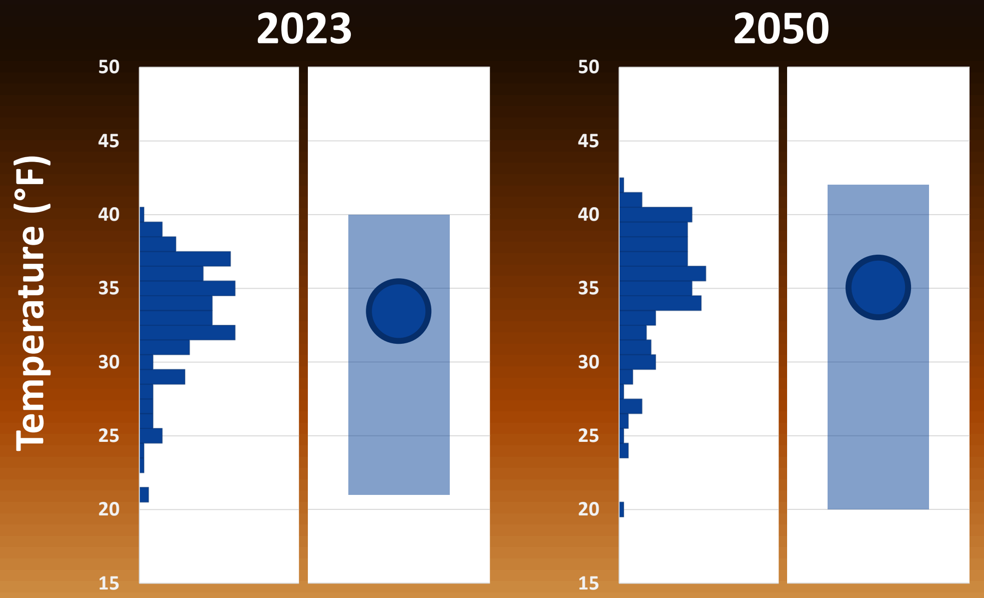
Example: Riverside Station*



*Example of station-level data for illustration

Annual Minimum Temperatures

Example: Riverside Station



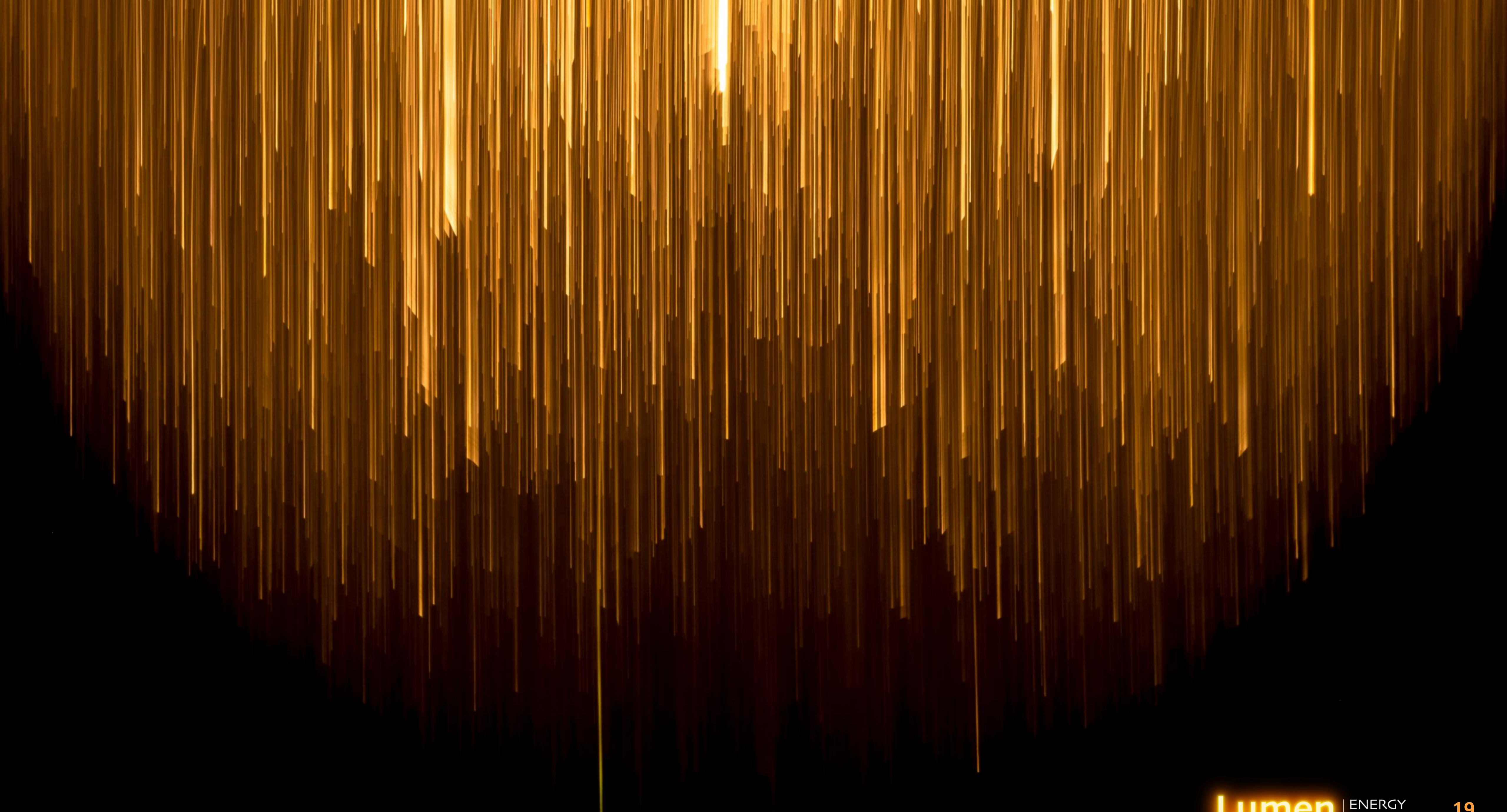


Photo by Rene Böhmer on Unsplash