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WARP to Resilience

Weather-Adapted Resource Planning

Key findings in climate data analyses for demand forecast integration

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CEC IEPR Commissioner Workshop on the California Energy Demand Forecast Results Part II

December 19, 2023

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“The difference between theory and practice is bigger in practice than in theory” —variations expressed by many

Many parties are involved and coordinating to bring climate science into the demand forecast.

Special thanks to:

- CEC demand forecast team
- CEC R&D and Energy Assessments Divisions
- Scripps, UCLA, Analytics Engine teams
- IEPR stakeholders

Image credit: Photo by Randy Fath on Unsplash.

Climate data for demand forecast

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

1. **Overview of climate data sources**
2. **Bias corrections**
3. **Recap of temperature de-trending and motivation**
4. **Results from the de-trended temperature library**
   a. Annual Cooling Degree Days (CDDs) & Heating Degree Days (HDDs)
   b. Maximum temperatures for peak demand
   c. Hourly shapes
5. **Dew point metrics**
6. **Cloud cover metrics**

Overview of 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 pt.	Cloud
WRF	Dec 2021 / Jan 2022	✓	4	3-7.0	✓	Hourly	✗	✓	✗*	✗
LOCA2	May 2023	In progress	199	2-4.5, 3-7.0, 5-8.5	✓	Daily	✓	✗	✗*	✗
WRF	Sep 2023	In progress	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 can be derived from available metrics on temperature and relative humidity.

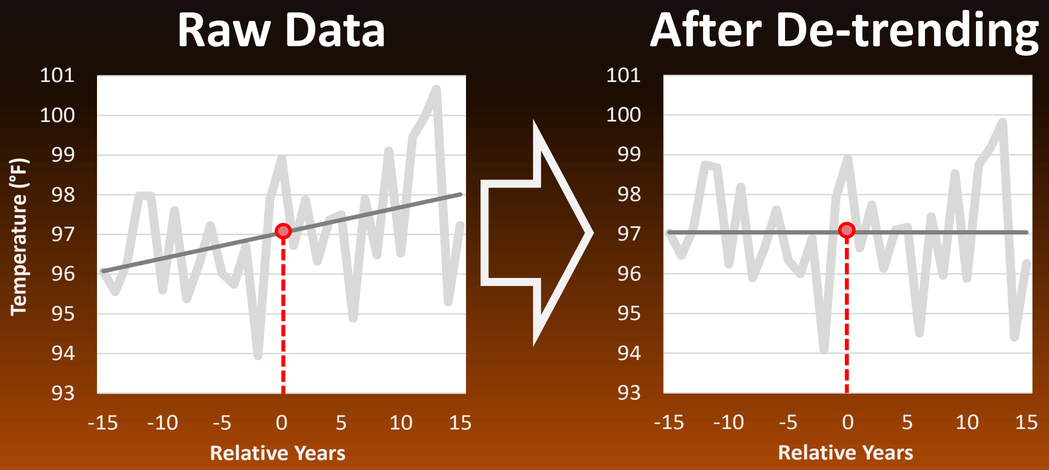
- Production > raw data repository > Cal-Adapt and Analytics Engine > (most) users
- Demand forecast requires:
  - **Hourly temp, dew point, and cloud cover**
  - **Weather station-level data**
  - **Bias-corrected to average levels, monthly peaks, hourly shape**
- We rely on the following 4 initial downscaled WRF runs:
  - **WRF_CESM2_r11i1p1f1**
  - **WRF_CNRM-ESM2-1_r1i1p1f2**
  - **WRF_EC-Earth3-Veg_r1i1p1f1**
  - **WRF_FGOALS-g3_r1i1p1f1**

Bias corrections

- **What is bias?**
  - Climate signal might be clear/robust…
  - … but baseline values, variability around climate signal, and/or time patterns may systematically deviate from historical observations
  - Additionally, gridded outputs of downscaled models may systematically deviate from observations at a point in space (e.g., weather stations)
  - Identification of bias starts with a view of how results are "really" supposed to look like and/or information on data or modeling limitations—in this case, historical replication through bias-correction is not the goal
- **A temperature localization model is our primary vehicle for addressing bias**
  - Anchors projections to temperature levels and patterns found in the historical record
  - Relies on good weather station data
  - Open code available on Analytics Engine platform
- **Remaining issues:**
  - Temperature localization model is a work in progress; residual bias at some stations, in hourly profiles
  - Localization methods for other weather variables not yet developed
  - Inherent challenges in bias-correction of extremes

Recap of temperature de-trending and motivation

Example for Illustration



Trendline shows temperatures increase by 2°F on average from 96°F to 98°F over 30-years

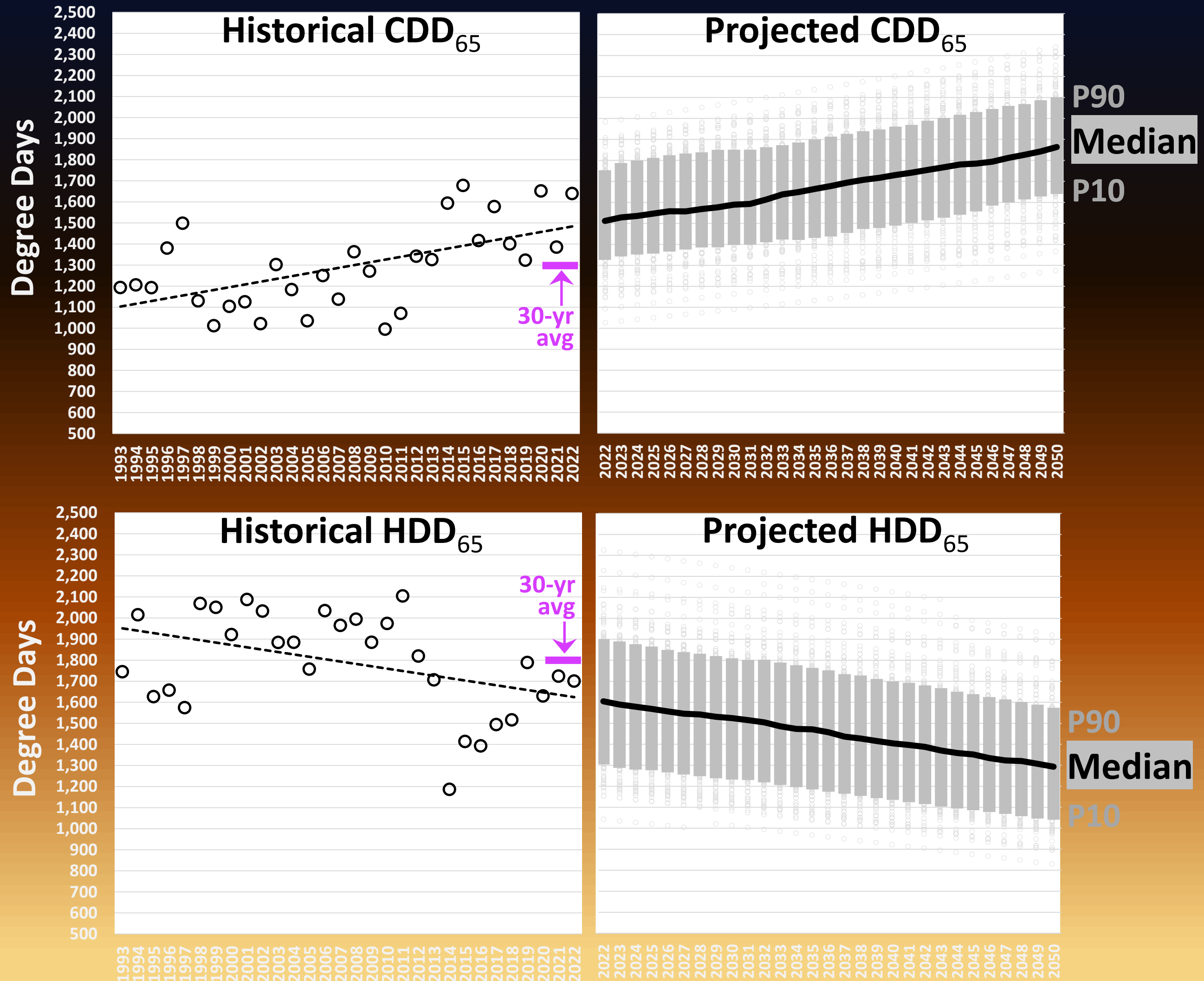
De-trending centers temperatures at 97°F as the level expected for forecast year

- **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
- **See August 18, 2023 IEPR workshop for more detail:**
  https://www.energy.ca.gov/event/workshop/2023-08/iepr-commissioner-workshop-load-modifier-scenario-development

Results from the de-trended temperature library

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

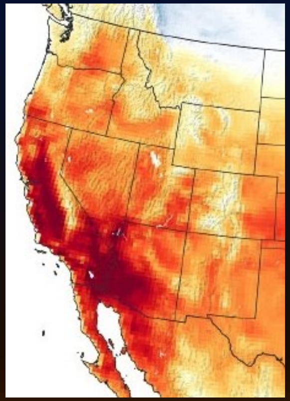
CAISO Annual CDDs and HDDs



- **For each demand forecast year:**
  - Calculate CDDs & HDDs at the station level, for each of 204 weather variants
  - Aggregate to planning area and CAISO levels
  - Select median (P50) across variants
- **Given climate trends, using historical 30-year averages 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

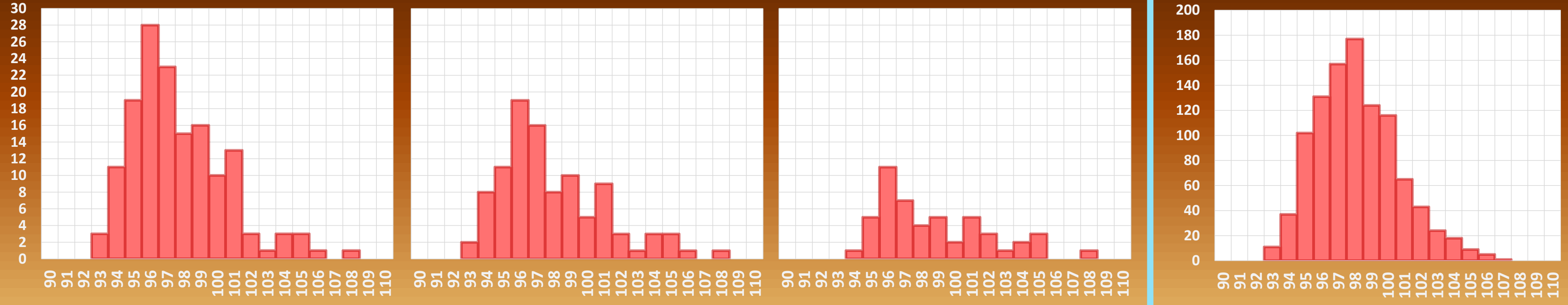
Results from the de-trended temperature library

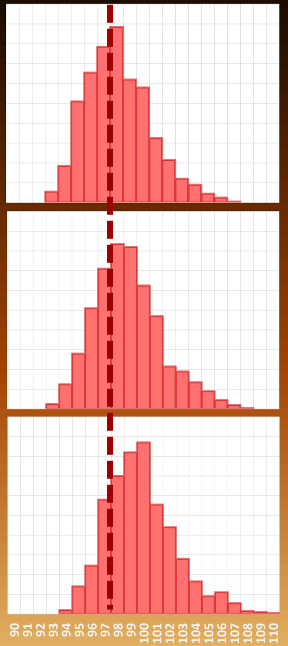
Maximum temperatures for peak demand



- **The hottest and coldest temperatures of the year are major drivers of peak demands**
- **The historical record provides limited information to distinguish a normal versus extreme year**
- **The de-trended temperature library provides a richer distribution of outcomes, adjusted with climate trends over time**

CAISO Frequency of Top 5 Hottest Days of Year

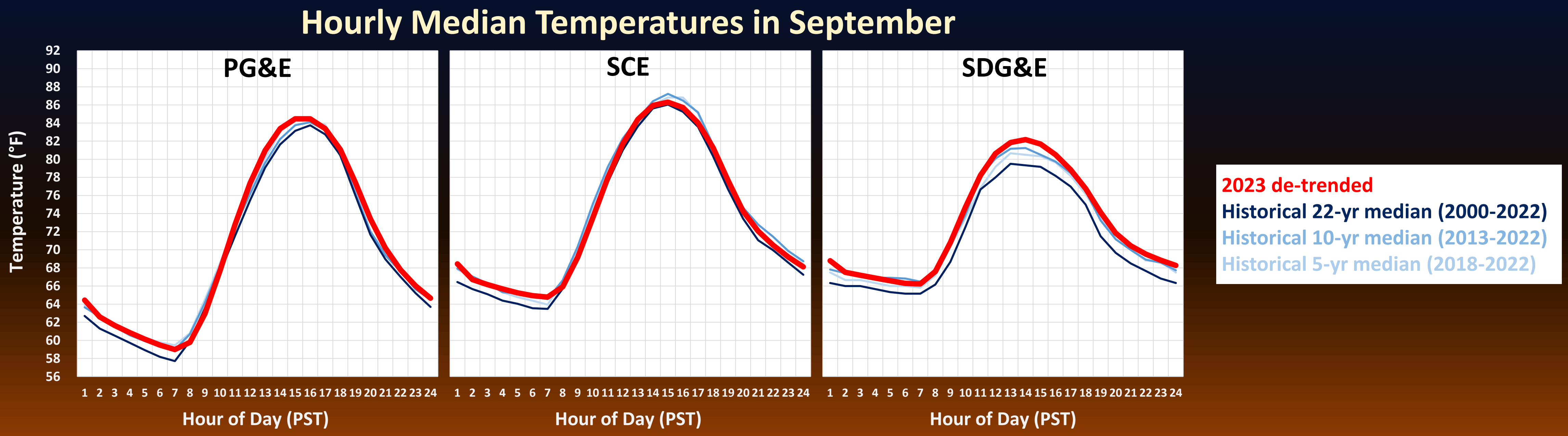




Top left image notes and credit: September 6, 2020 temperatures across the West (NASA/Joshua Stevens).

Results from the de-trended temperature library

Hourly shapes



- Hourly shape of temperatures impact demand patterns at the system level & across planning areas
- Base year (2023) medians estimated using 204 de-trended variants align well with historical levels
- Next step: Further refinements to the localization method to address biases identified at a small subset of weather stations, which is expected to improve the characterization of hourly shapes in demand forecasting

Dew point methodology

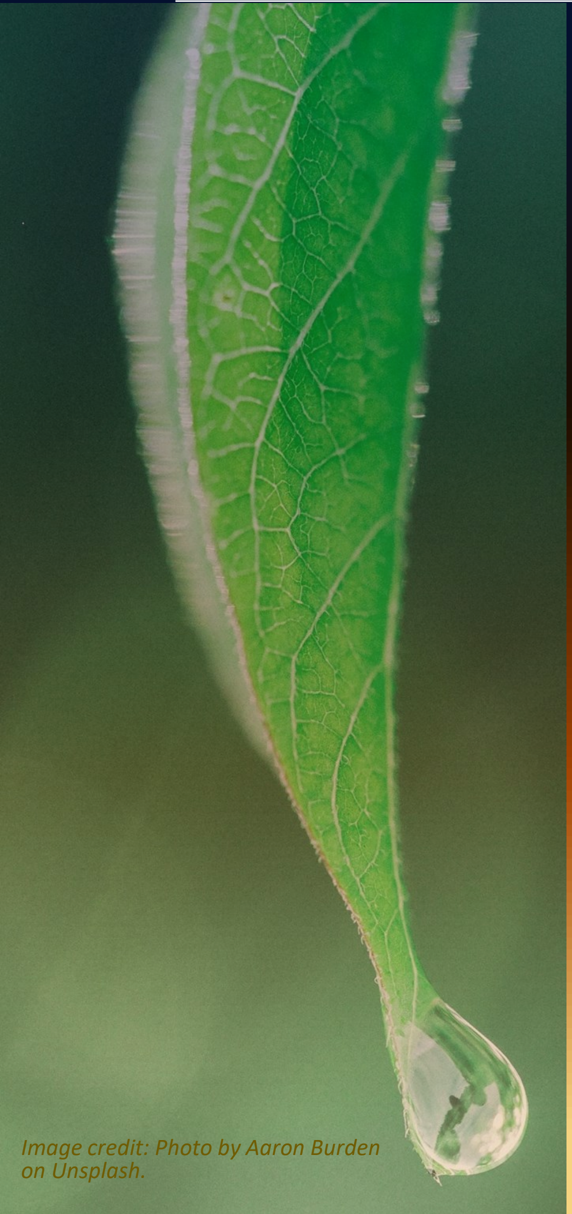
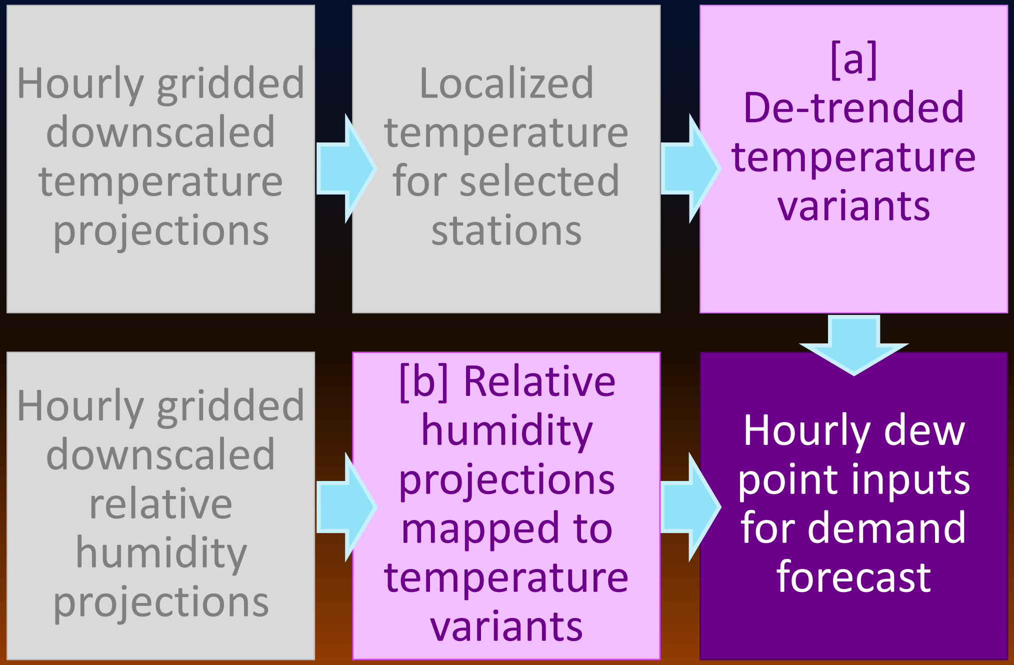


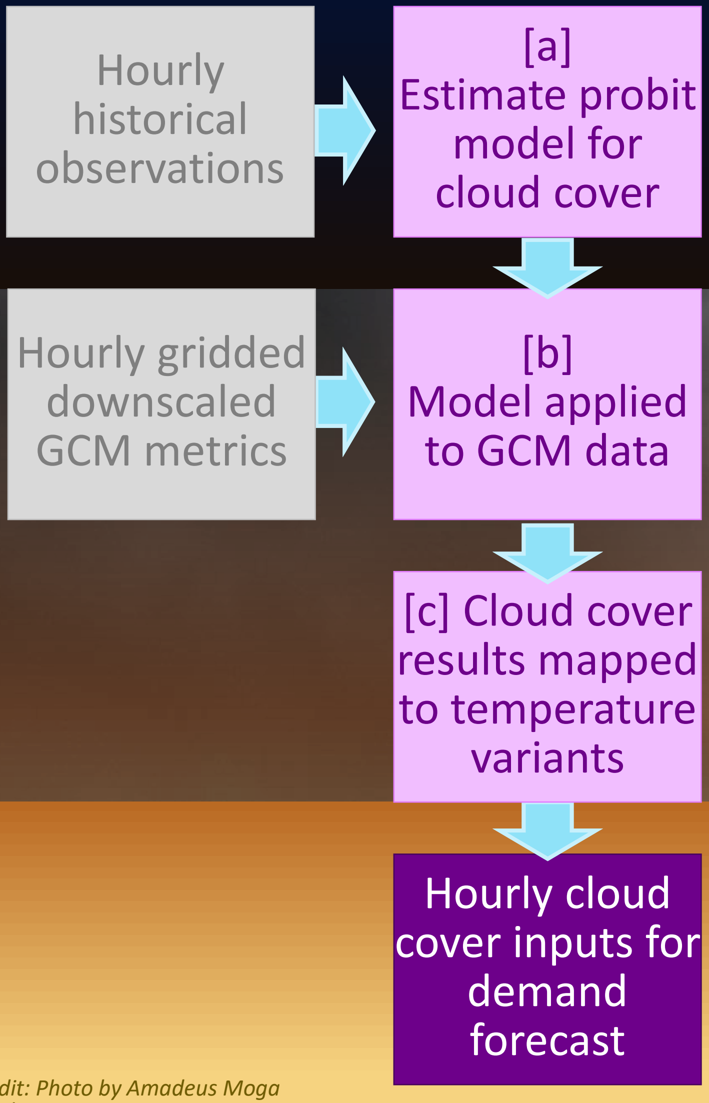
Image credit: Photo by Aaron Burden on Unsplash.

- **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)
- **No localization model currently available**



- **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

Cloud cover methodology



- **Cloud cover is a necessary input to the hourly demand forecast model**
  - The 4 downscaled GCMs used to develop the de-trended temperature library do not include a cloud cover metric
- **We estimated a model [a] for cloud cover based on historical statistical relationships between cloud cover and temperature, precipitation, and relative humidity at each weather station**
  - Using a separate multinomial probit model for each weather station
  - Dependent variable: hourly categorical cloud cover metric, simplified into 5 bins: 0, 10, 30, 70, 100 (share of cloud cover)
  - Explanatory variables: hourly precipitation, 24-hour precipitation, relative humidity, 2-part temperature spline, month, hour
- **The probit model is then applied [b] to downscaled GCM data at closest 3-km grid cell to each station**
- **Cloud cover results are then mapped to the temperature variants based on GCM and year**

Image credit: Photo by Amadeus Moga on Unsplash.

Thank you

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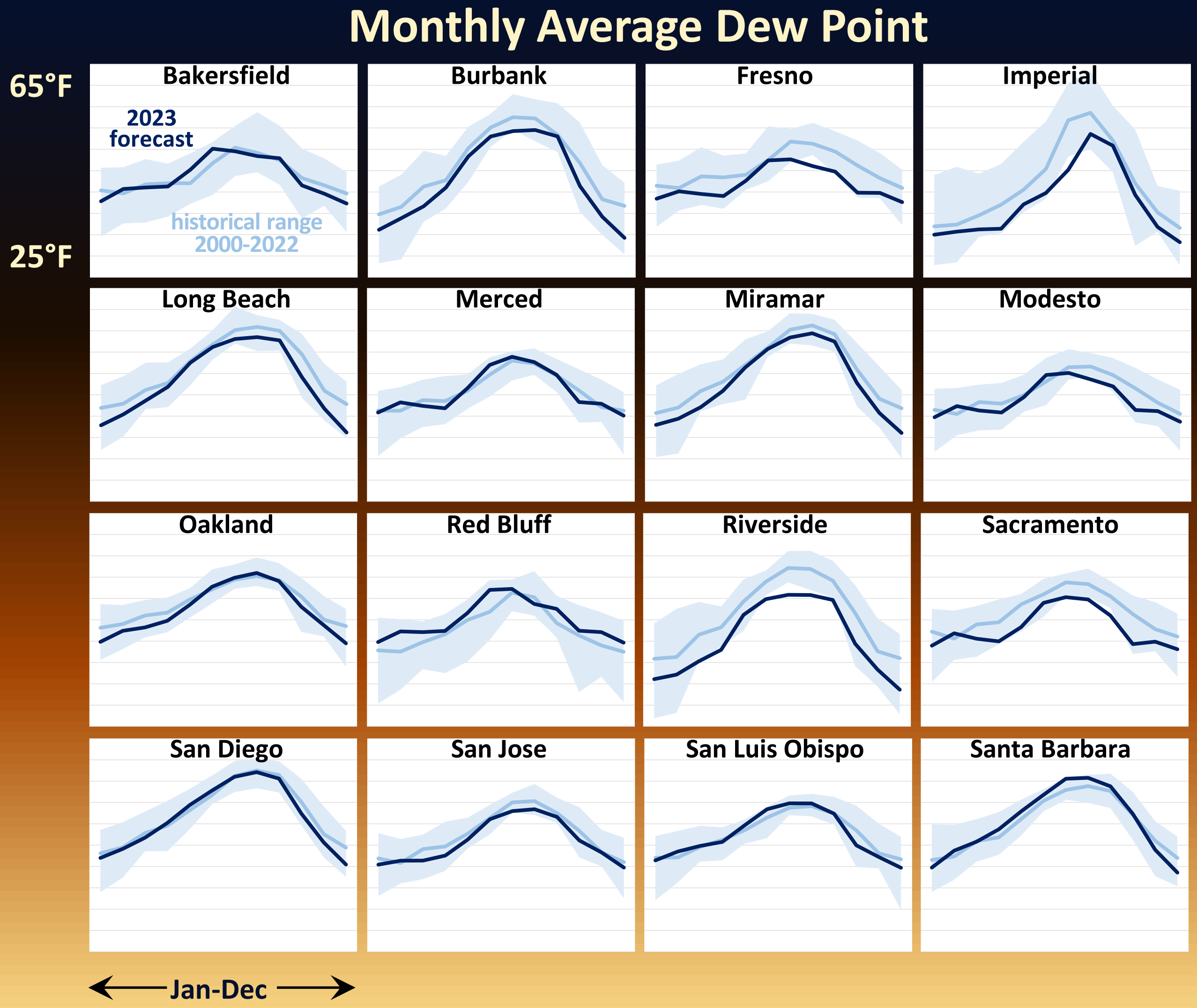
APPENDIX:
DEW POINT AND CLOUD COVER DETAILS

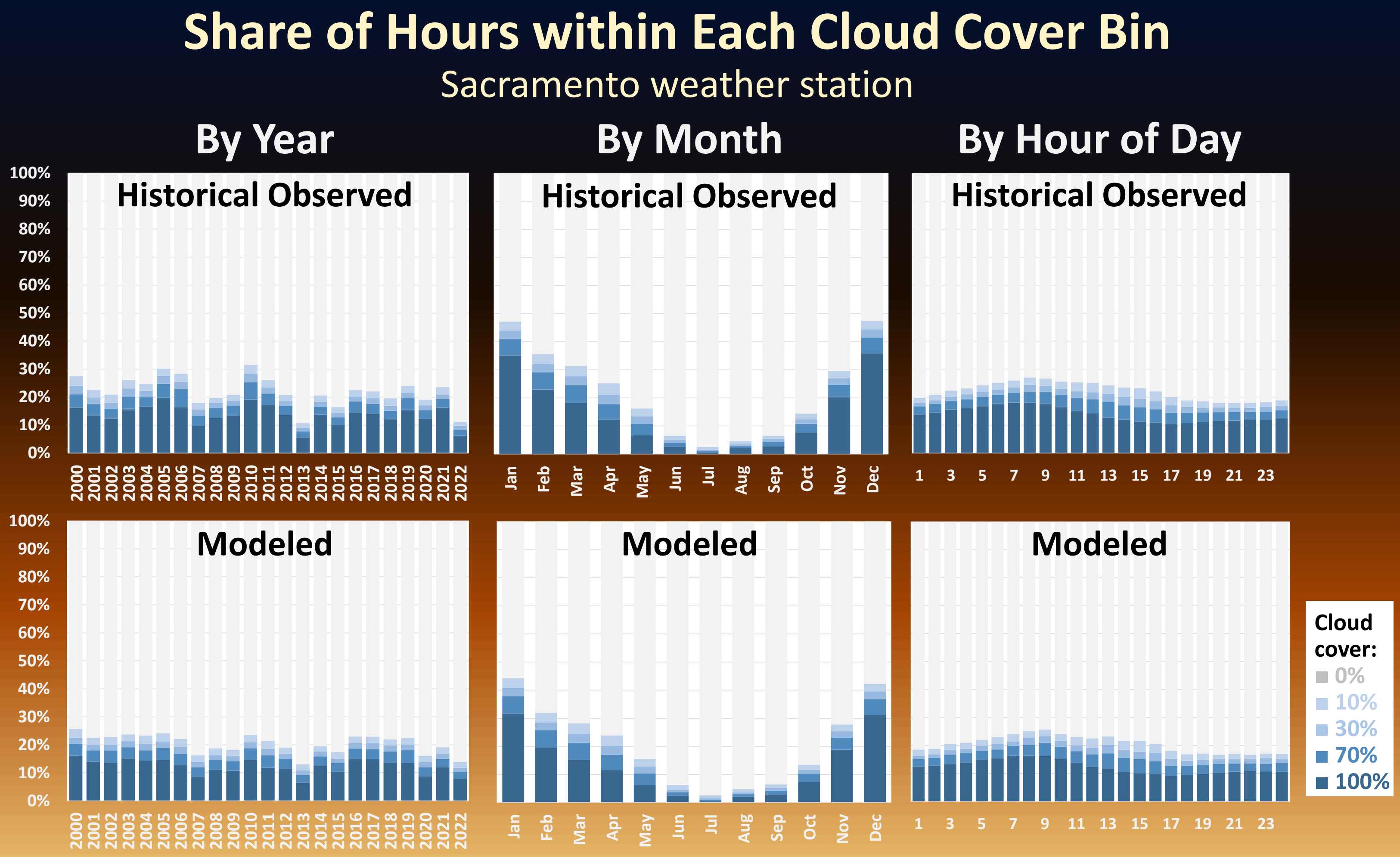
Dew point benchmark



- Projected dew points follow historical patterns
- Base year (2023) averages mostly within historical range
- Differences against historical range could be due to temperature trends, but there may also be residual bias from using 3km data (not localized)
- Biases appear to be relatively small in most cases, but important to address in future IEPR cycles by localizing relative humidity

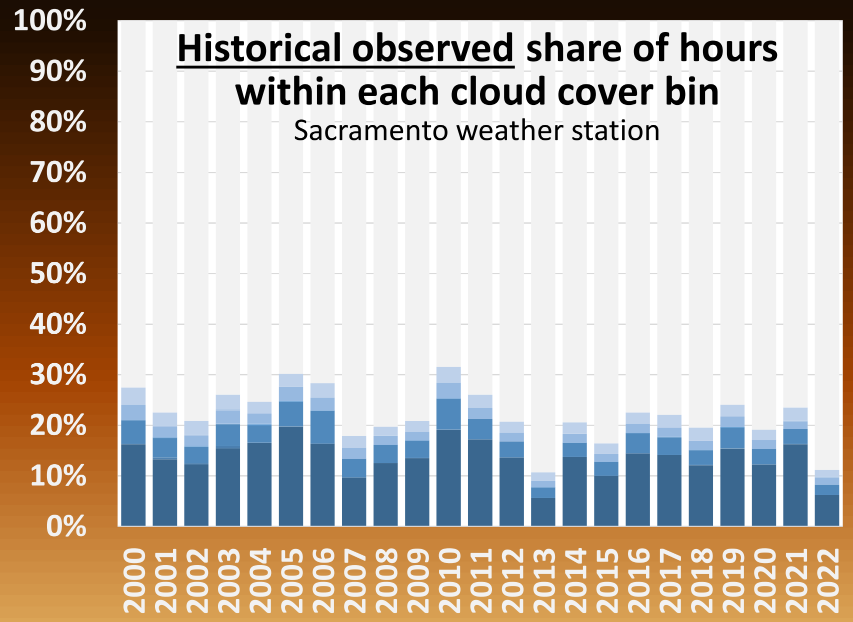
Cloud cover benchmark

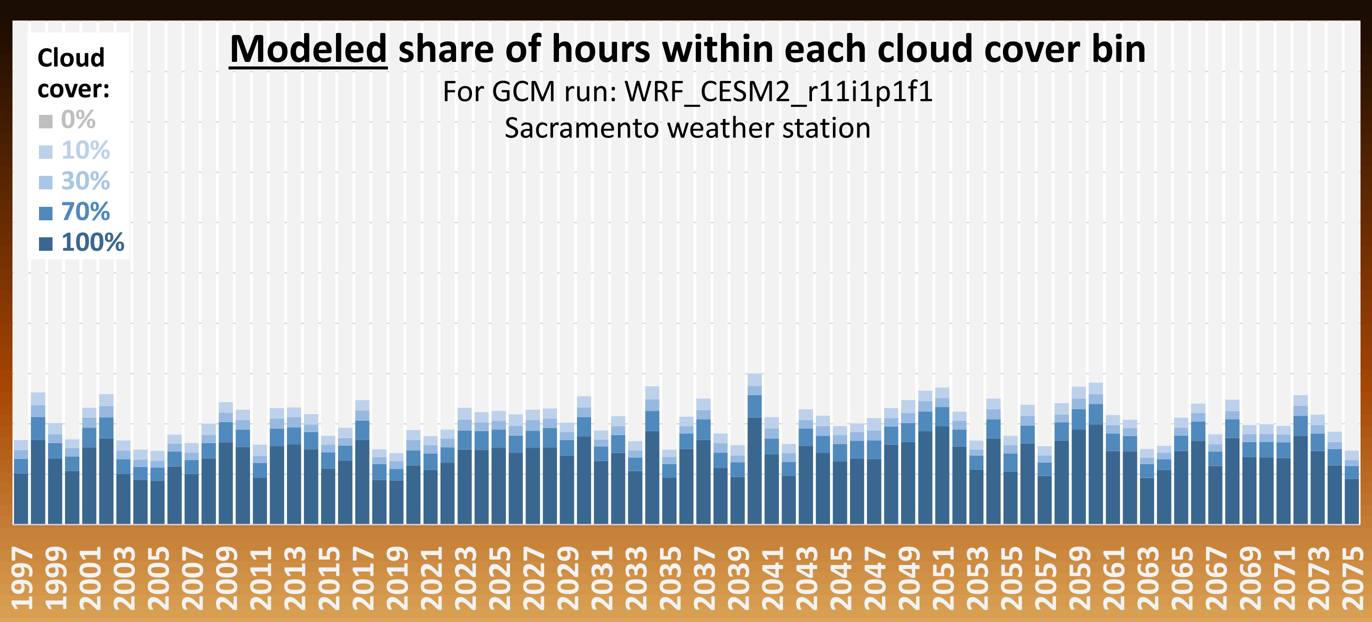
- **Graphs show the share of hours (y-axis) with cloud cover at 0%, 10%, 30%, 70%, or 100% (stacked bars)**
- **In each year 2000–2022**
  - Observed vs. "predicted" by probit model
- **Model captures cloud cover variability and patterns across years, months, and hours**



Cloud cover results

- Results reflect a historical statistical relationship among cloud cover, precipitation, relative humidity, temperature, month, hour of day, and location
- Next steps will be to incorporate data from newer downscaled GCMs, including some form of localization and/or bias-correction





* Weather variants are based on forecast year +/-25 years, for consistency with de-trended temperatures. For example, the base year (2023) forecast uses the above cloud cover results for 1998–2048.

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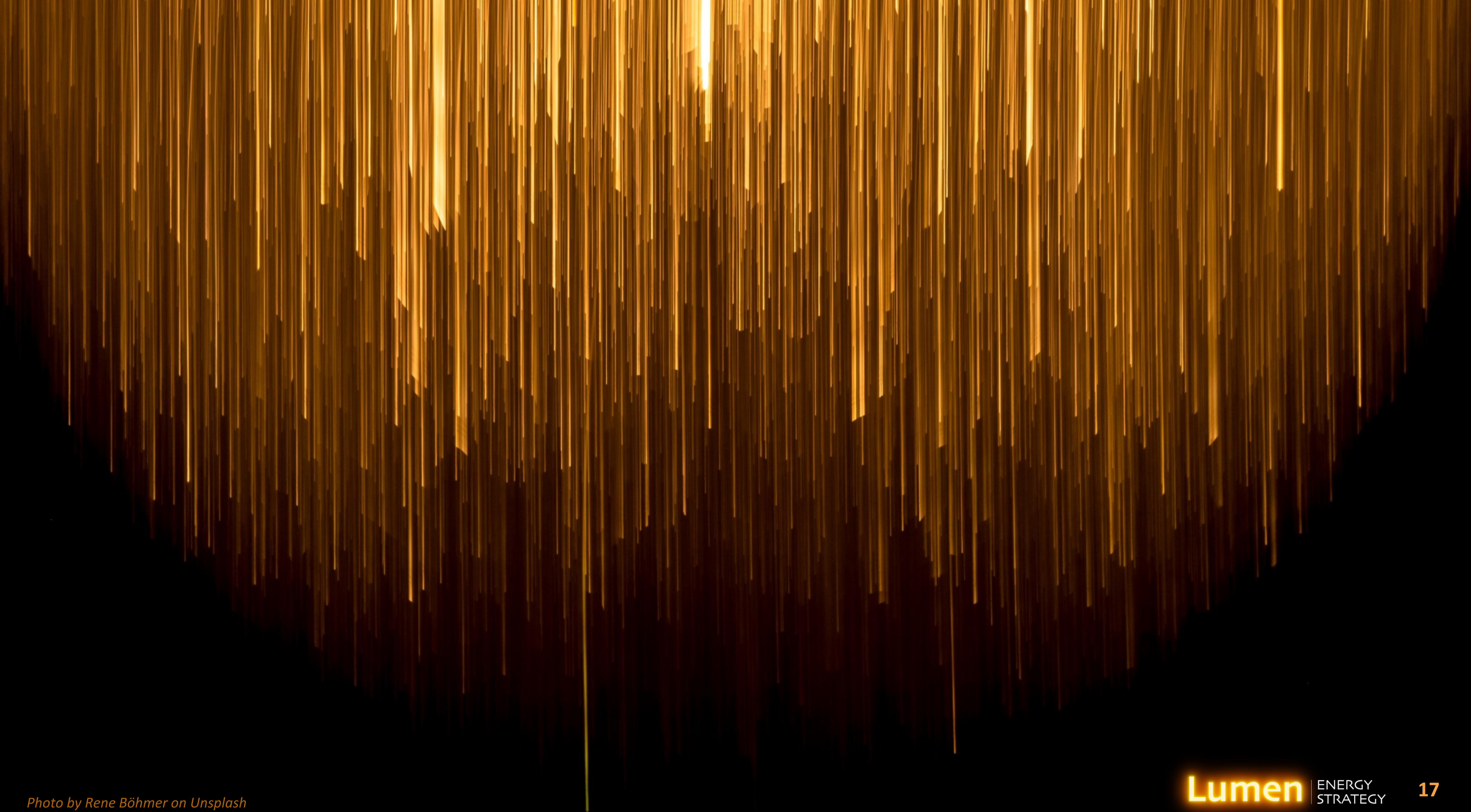

Photo by Rene Böhmer on Unsplash