Stanford | Precourt Institute for Energy

Western Interstate Energy Board

Incorporating Temperature and Precipitation Trends in Long-Term Planning

Western Interstate Energy Board and Stanford Shultz Energy Summer Fellowship Project

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About the 2022 Shultz Energy Fellows

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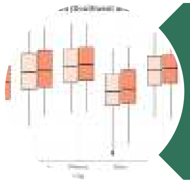
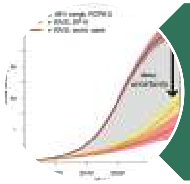
Read more about the fellows here https://energy.stanford.edu/shultz/shultz-2022-cohort

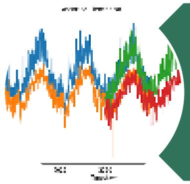
Outline



Temperature and Precipitation Data Analysis



Climate Uncertainty and Current Industry Practices



Long Term Temperature Forecasting

Recommendations and Conclusions

Background

- With climate change beginning to affect the Western Interconnection, member states requested that WIEB **analyzes recent temperature and precipitation trends**.
- Additionally, states requested that we research the **appropriate amount of historical weather data** to use for temperature and load forecasts.

Photo credit: https://www.westernenergyboard.org/

Temperature and Precipitation Data Analysis

Station Data

We began our analysis of temperature and precipitation trends across the West with **weather station data** in **20 major Western cities** – at least one in each member state/province of WIEB. For most cities, we had data from **1950-2021.**

This allowed us to uncover initial trends without major data quality concerns. All data was quality controlled by **Catalyst Cooperative.**

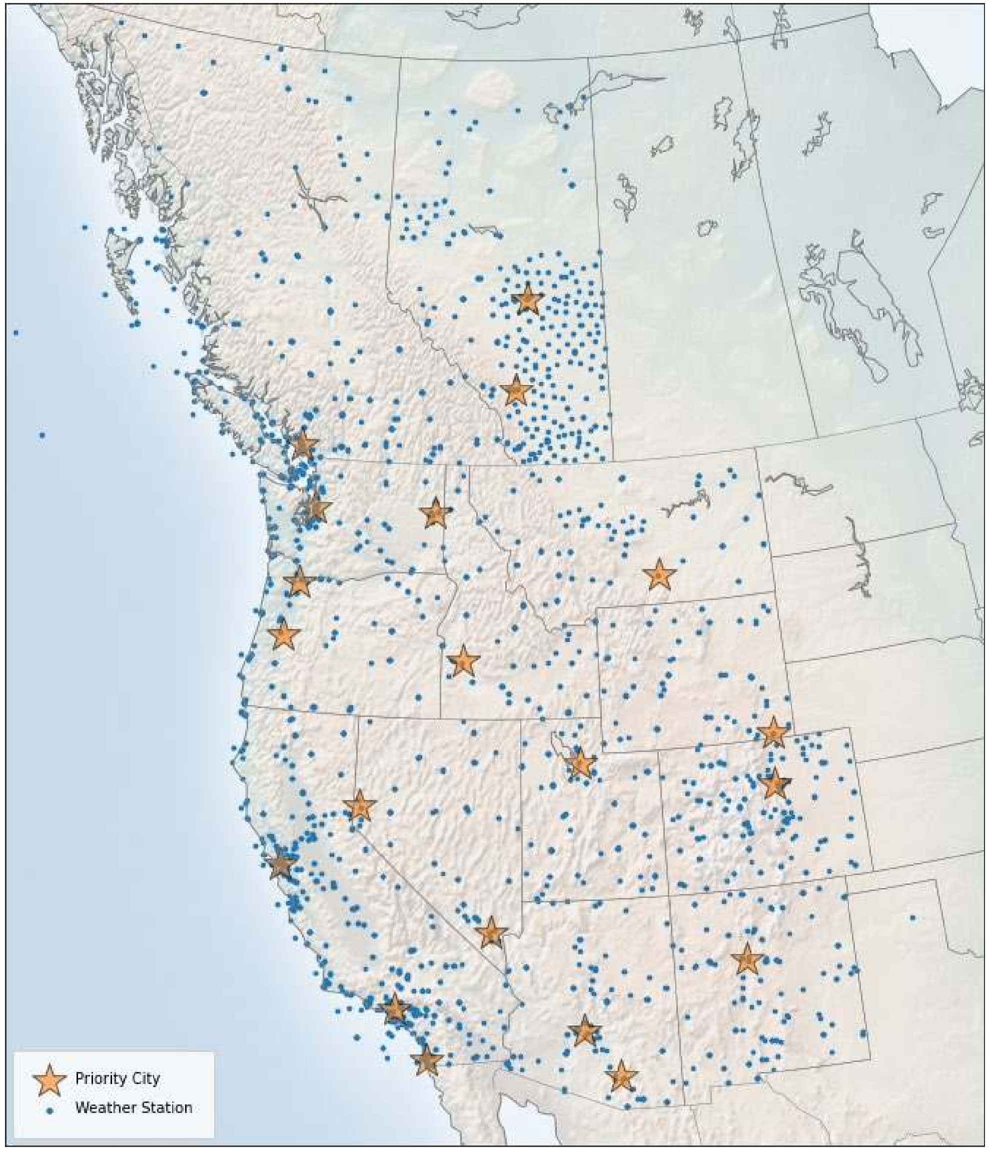
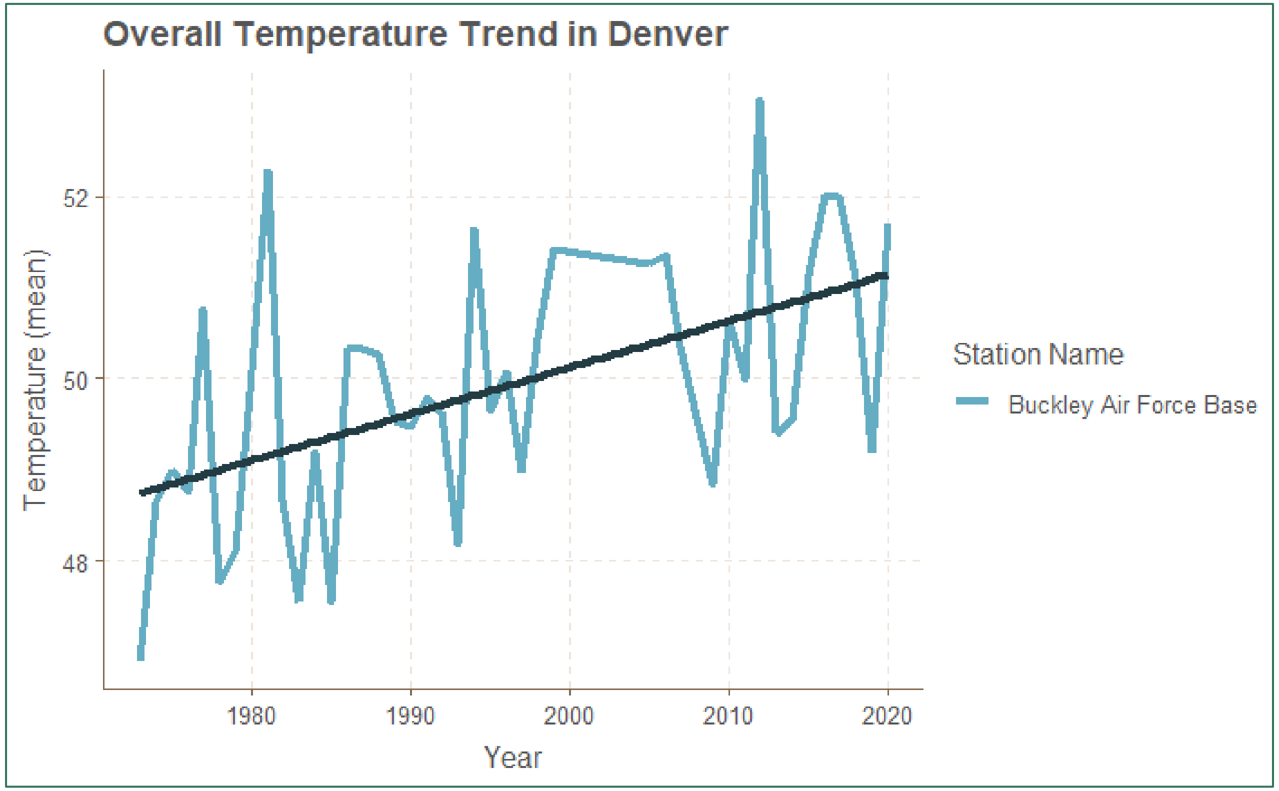


Photo credit: Trenton Bush, Catalyst Cooperative

Temperature Trend Analysis

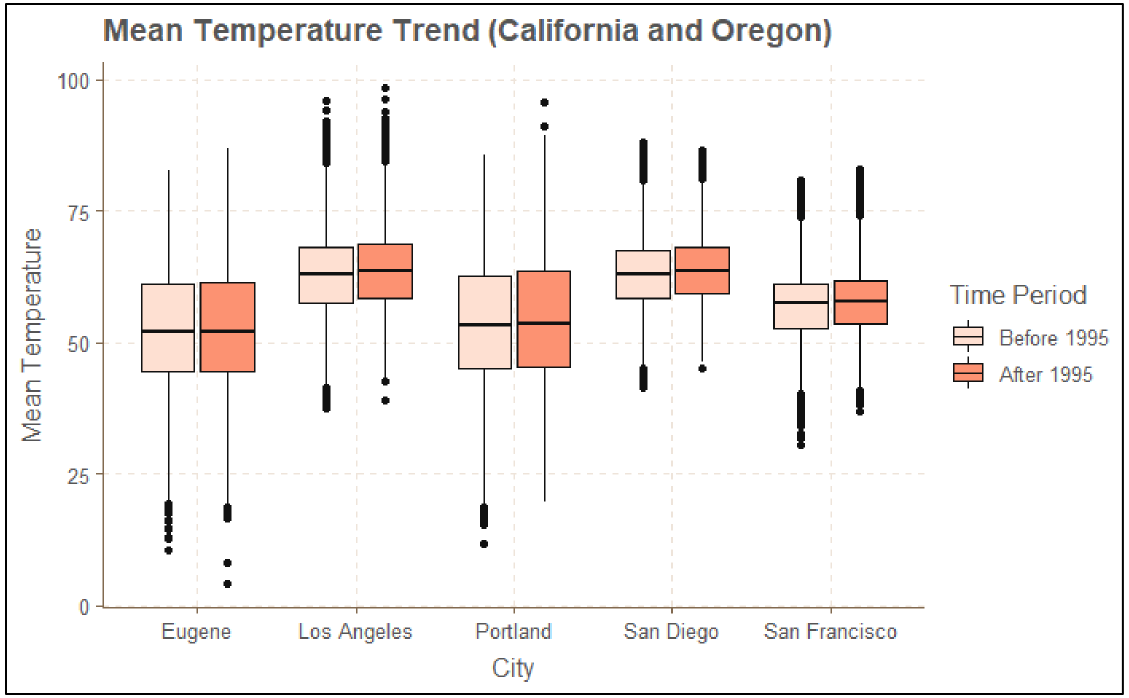


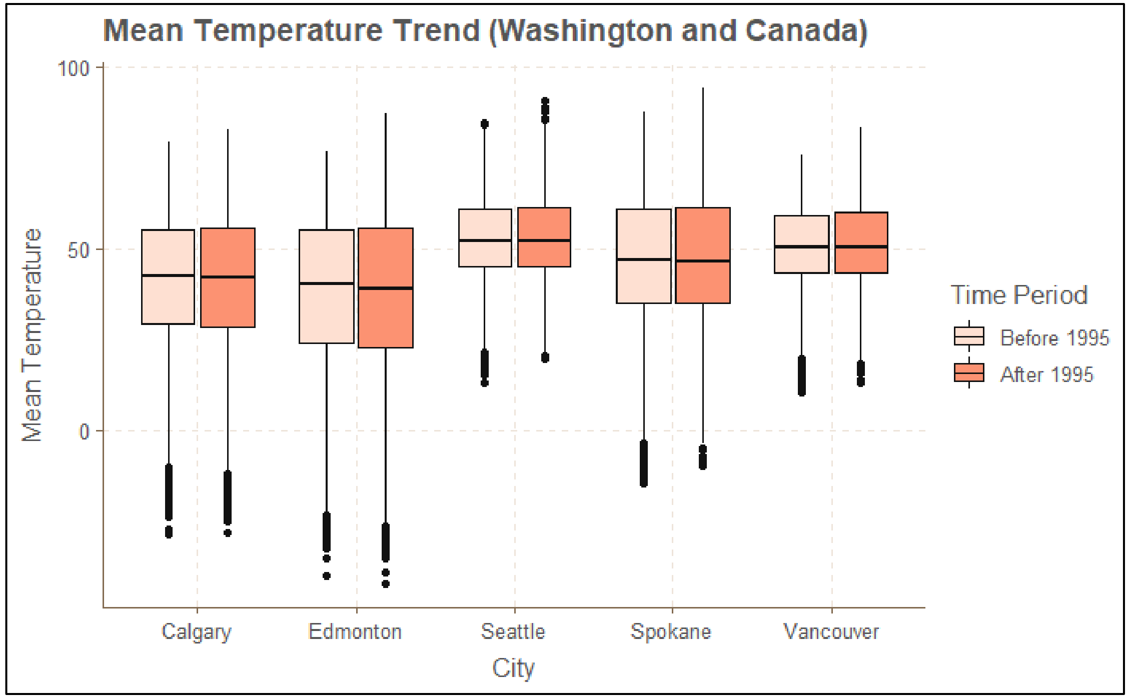
Annualized linear regression is easy to interpret and reveals a **general upwards temperature trend across all cities**. On average, temperatures have increased 1.03 degrees Fahrenheit since 1995.

However, it fails to capture seasonal trends and **smooths over extreme temperature events** that may have an outsized impact on the grid.

Temperature Trend Analysis

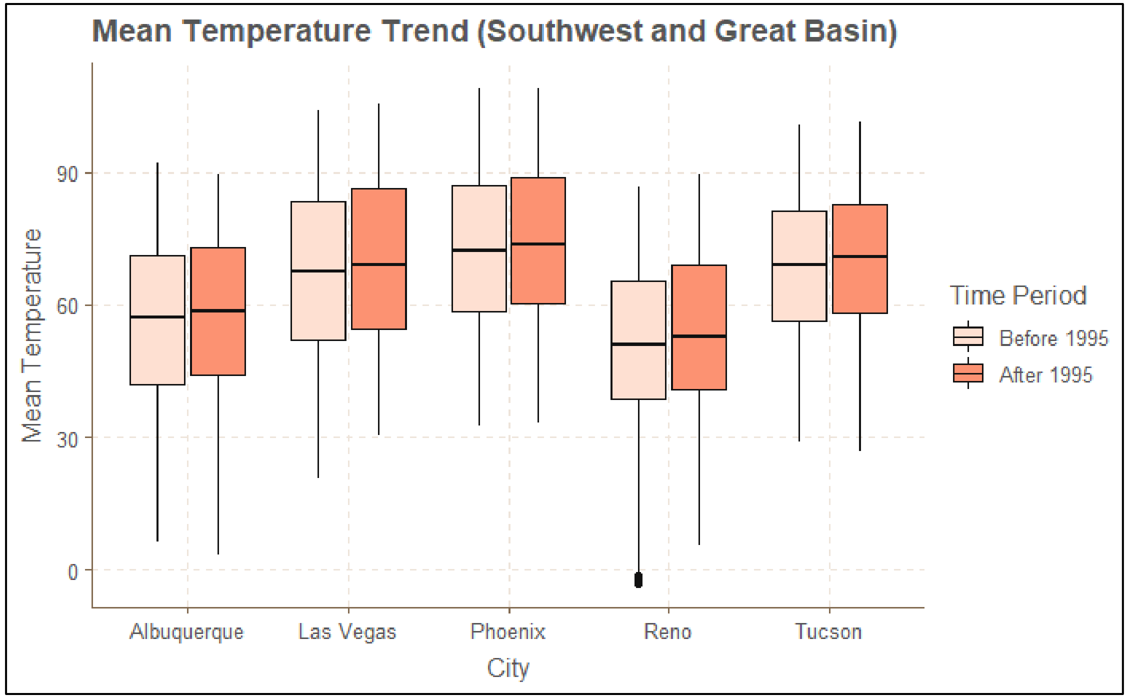
Not all regions saw the **same amount** of temperature increase. Changes in overall temperature distributions were **less pronounced** in the Pacific Northwest and Canadian cities (little to no distributional change).

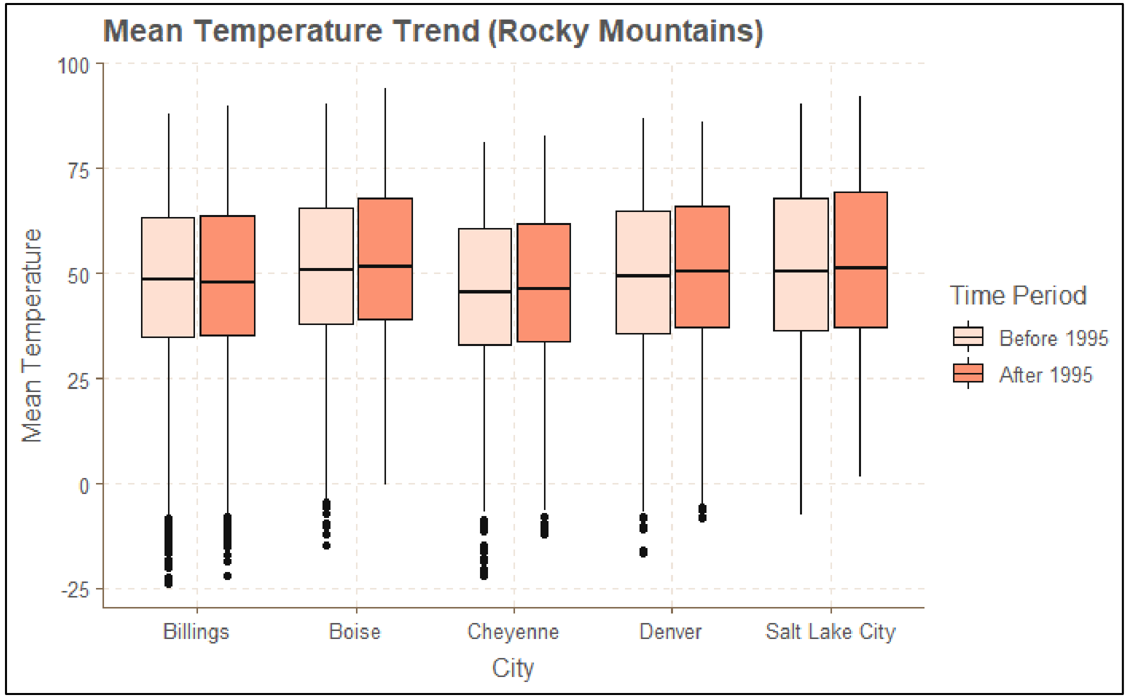




Temperature Trend Analysis

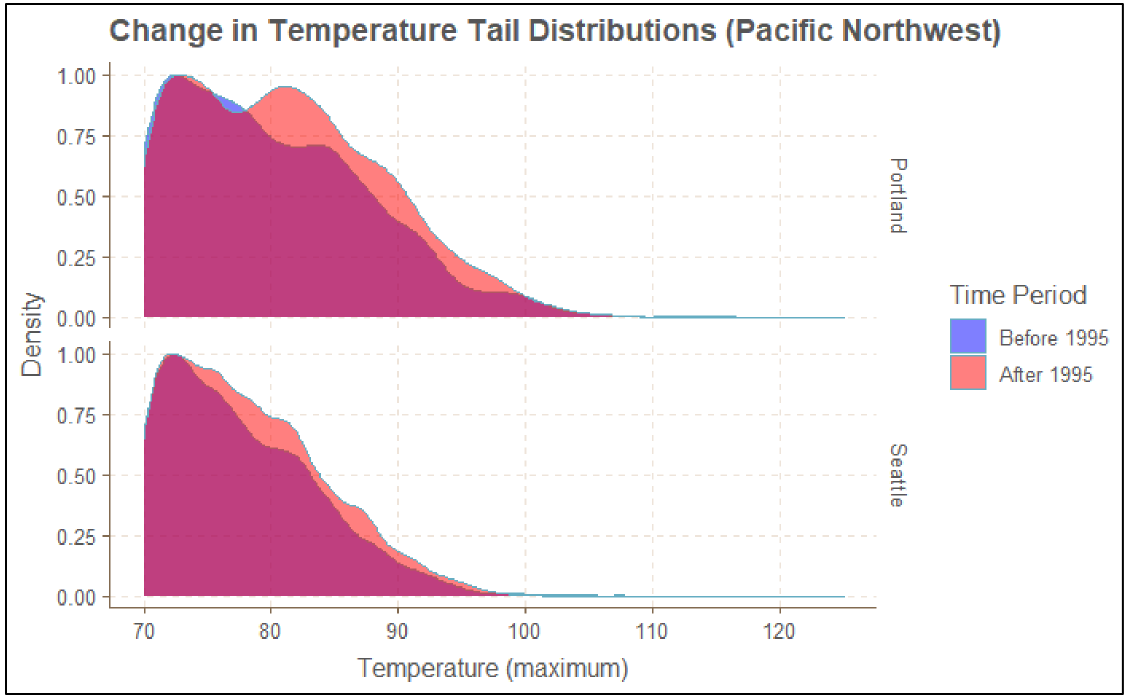
On the other hand, the Southwest and Great Basin regions saw **significant changes** in mean temperature distributions (mean increase of **2.03 degrees Fahrenheit** across both regions), the most pronounced occurring in Reno, Nevada (mean increase of **2.73 degrees Fahrenheit**).

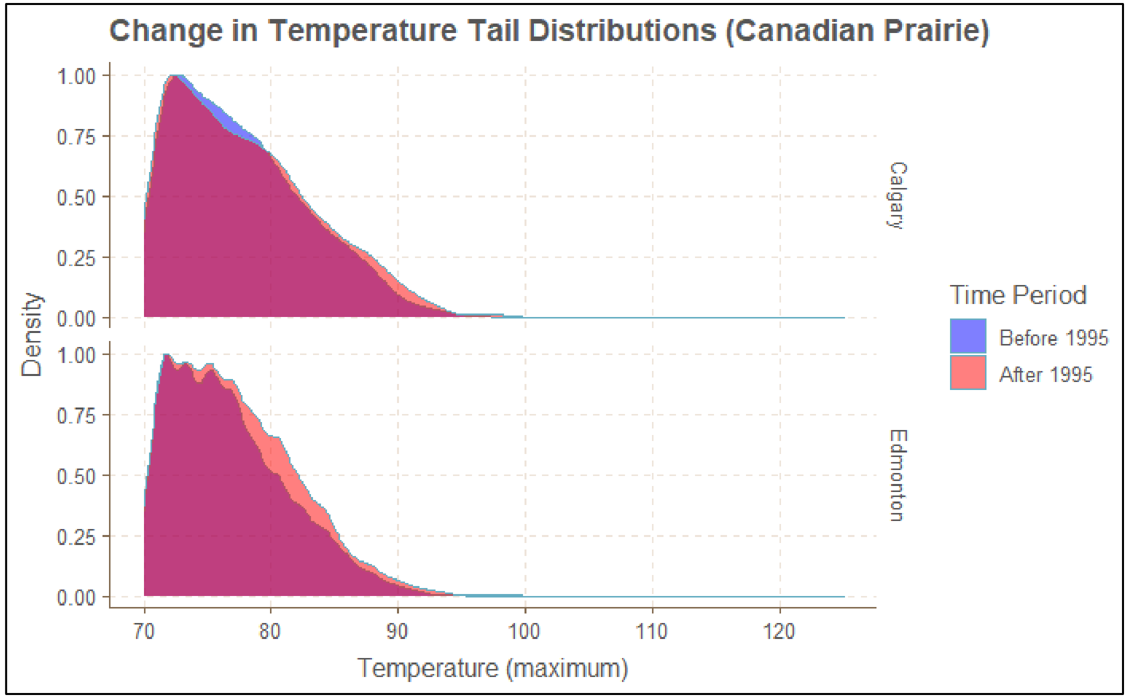




Temperature Trend Analysis

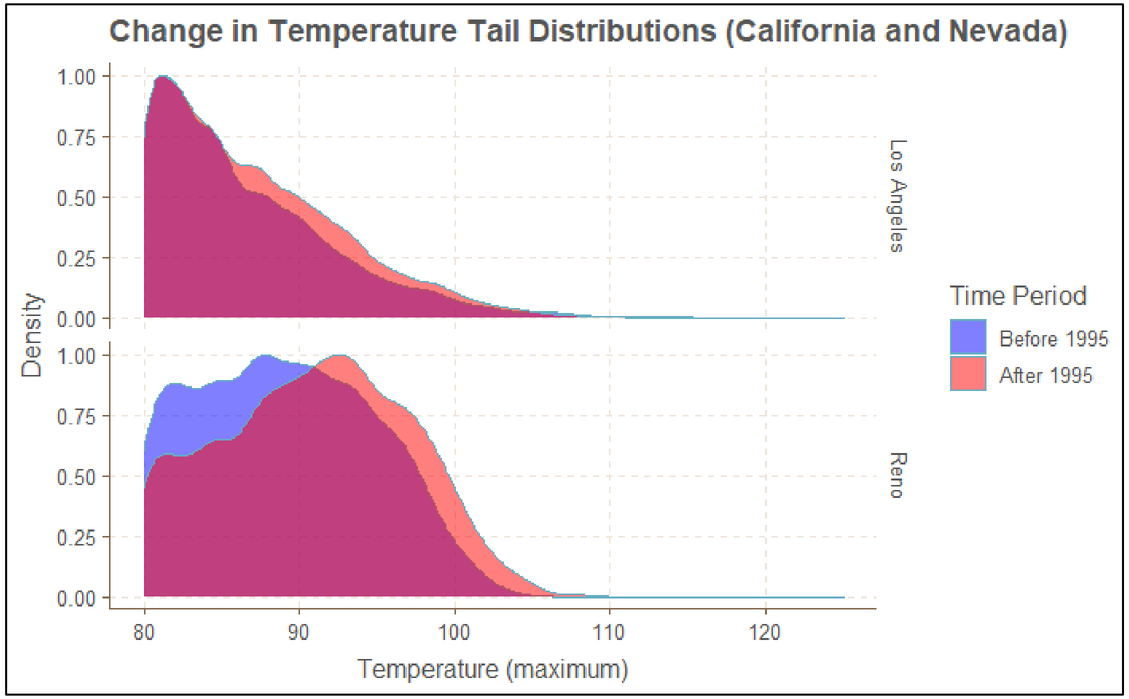
Similar geographic trends exist for temperature tail distributions – the extreme temperatures that likely have the largest impact on load, generation, and transmission.

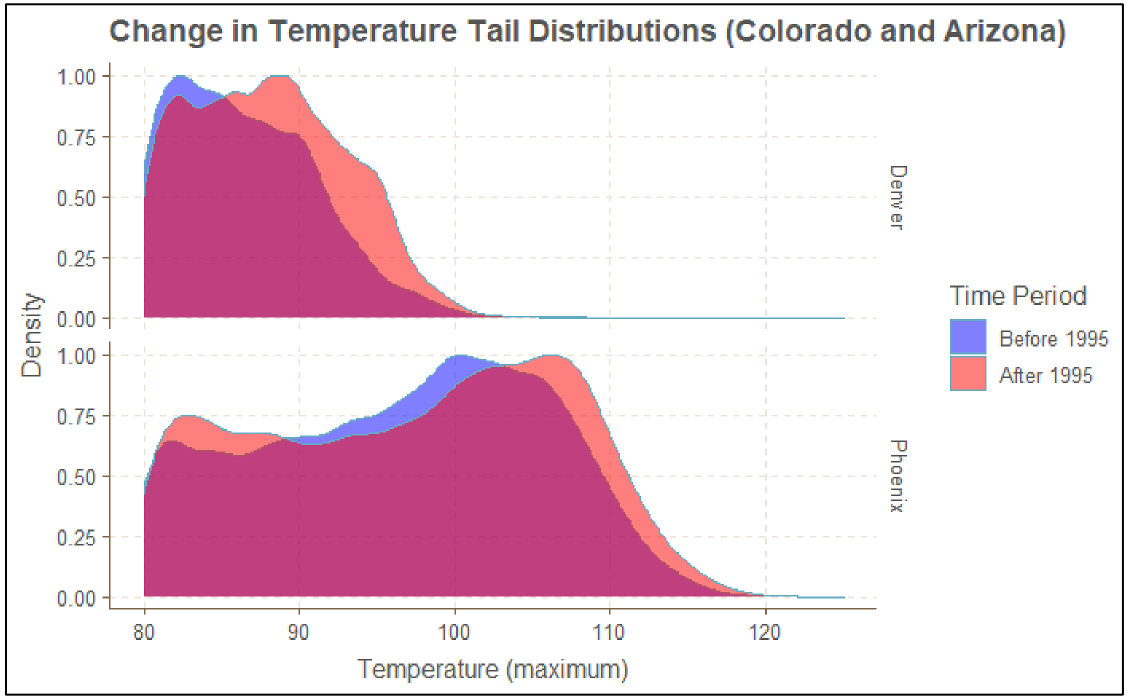




Temperature Trend Analysis

In cities in the Southwest such as Reno and Phoenix have observed **significant changes in temperature tail distributions**, with temperatures exceeding 100 degrees becoming more probable since 1995.

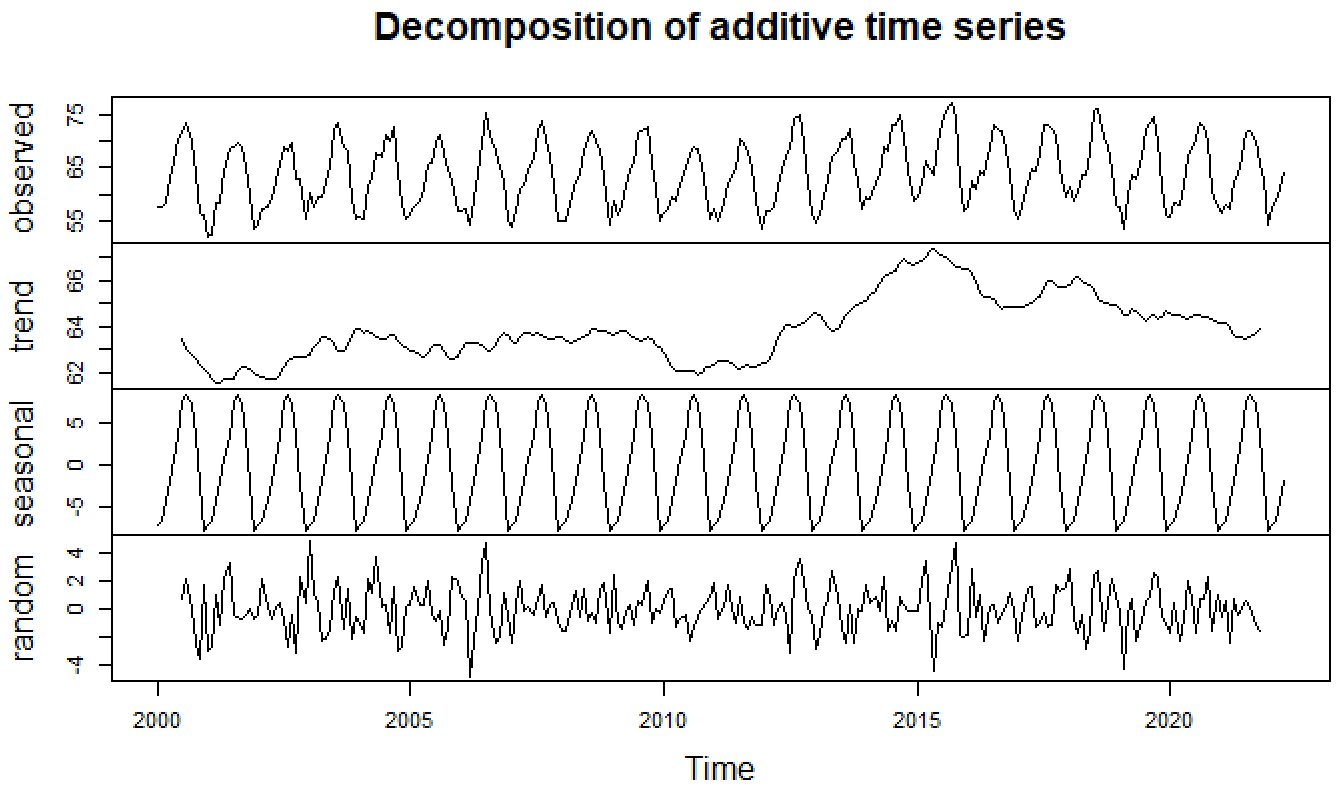




Temperature Trend Analysis

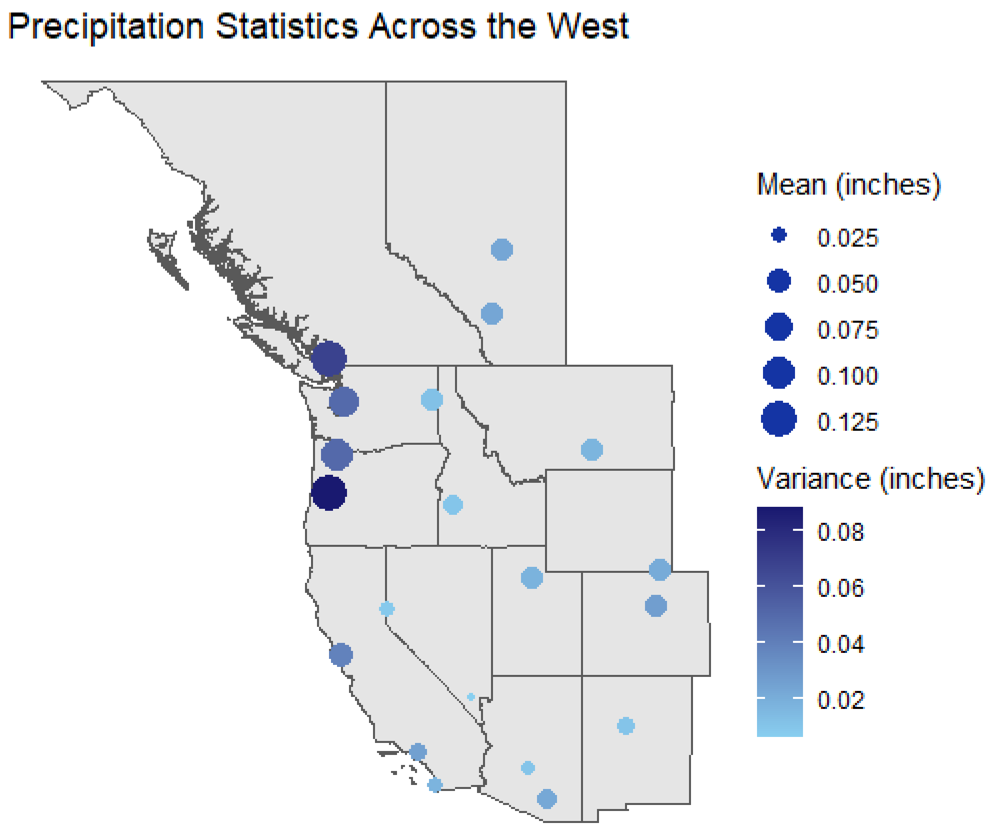
Decomposition of time series into a seasonal component, a trend, and random noise allows for a better understanding of the overall temperature trend.

Noise time series helps us understand temperature anomalies and **extreme temperature events**.



Signal decomposition of Los Angeles temperature data (from Long Beach / Daugherty Field)

Precipitation Trend Analysis



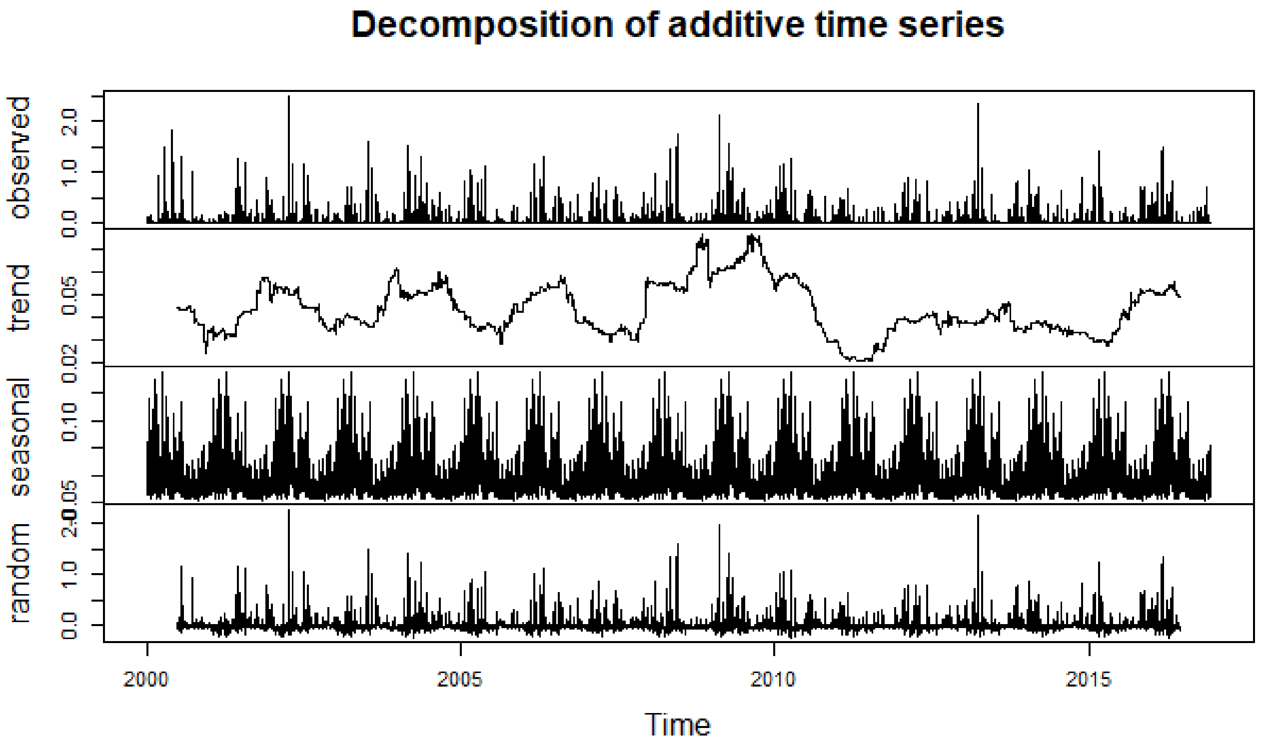
No statistically significant trends were found. The precipitation data was characterized by **distributions with high variances.**

Annualized linear regression were conducted but revealed **very low R^2 values** across the board indicate that a linear regression **does not explain most of the precipitation data**.

Precipitation

Decomposition of precipitation time series reveals no discernible trend for most cities.

Annual and monthly precipitation, especially in California and the Southwest, is largely determined by short bursts of rainfall. **Understanding precipitation anomalies is more important than trying to model trends**.



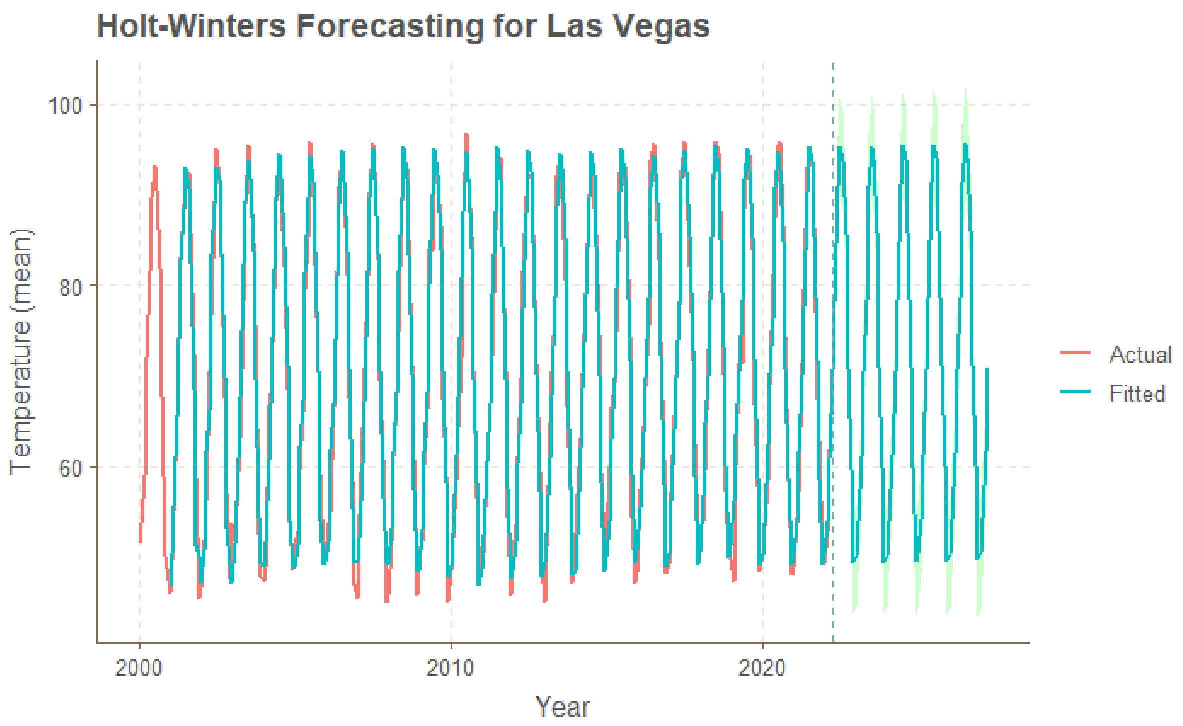
Signal decomposition of Los Angeles precipitation data (from Long Beach / Daugherty Field)

Forecasting and Training Data Analysis

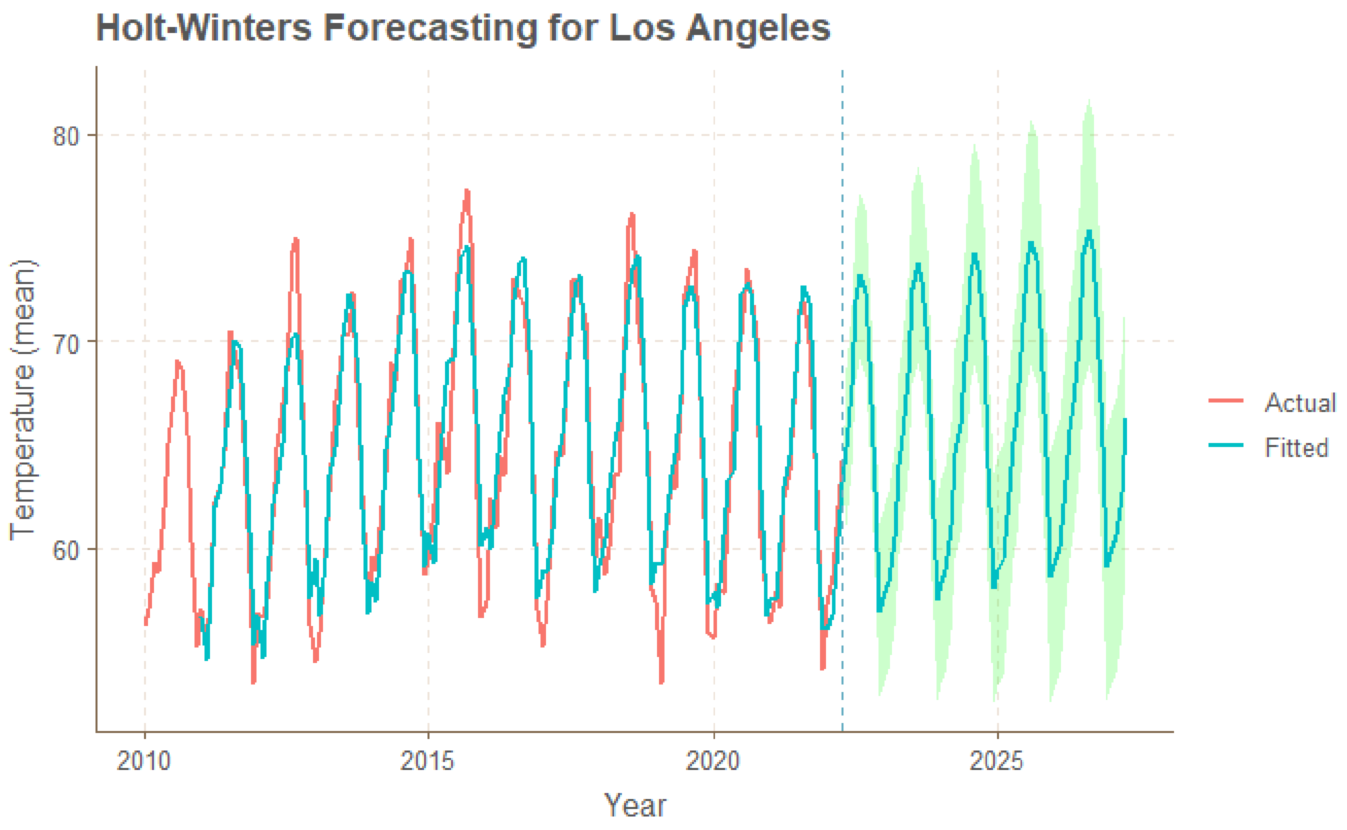
Holt Winters and SARIMA Models

To produce simple forecasts and gain a more nuanced understanding of climate trends in the West, we turned to classical statistical methods.

Example methods include Holt Winters exponential smoothing and seasonal autoregressive integrated moving average (SARIMA), both of which are widely-applied in timeseries analysis.



Temperature Trend Analysis



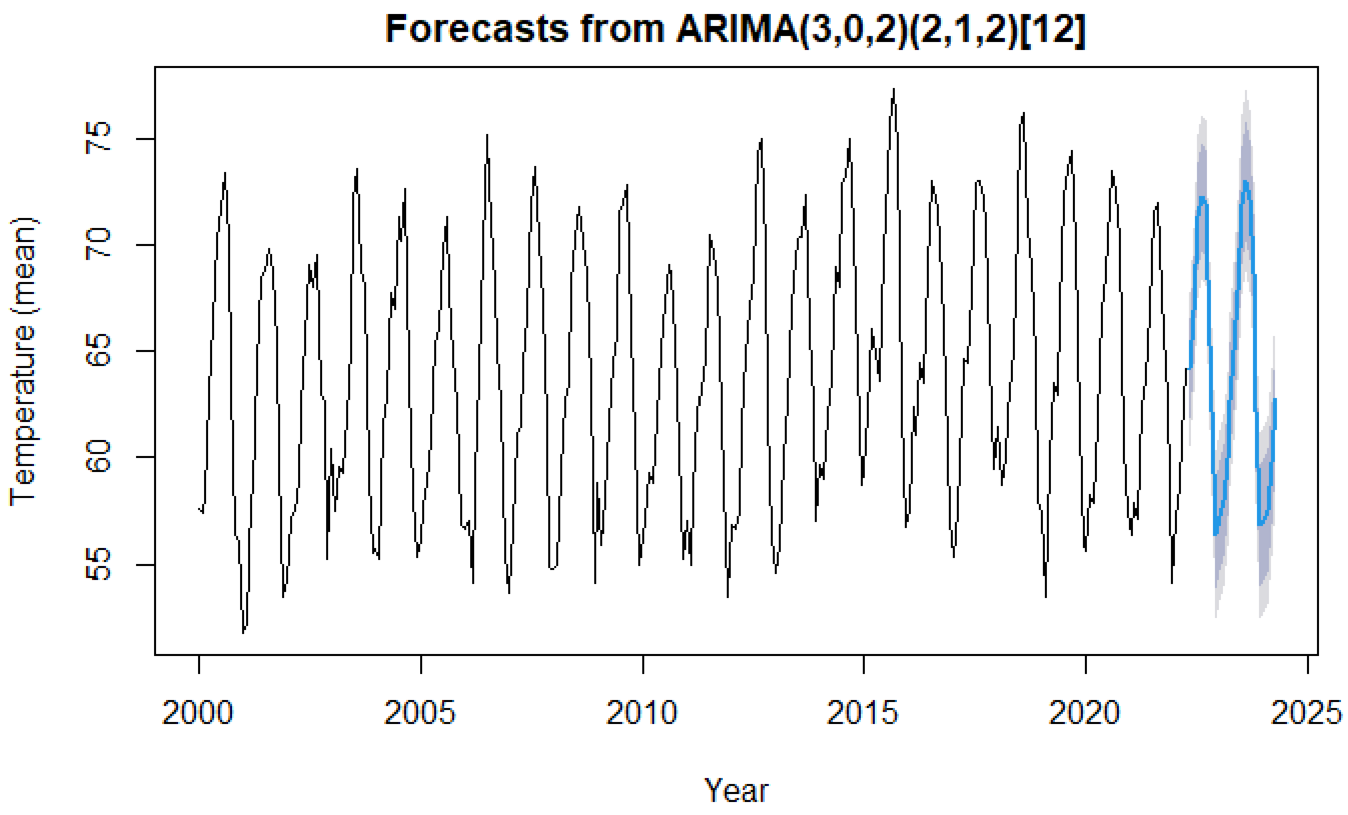
One common seasonality model that allows for accurate modeling of most periodic time series as well as relatively accurate short-term predictions is the **Holt-Winters method**.

Simple forecasts again **reveal increasing mean temperatures**, although this method doesn't provide insight into extreme weather events.

Temperature Trend Analysis

Another classical method for forecasting signals with seasonal dependence is seasonal ARIMA (SARIMA) modeling.

As with Holt-Winters modeling, SARIMA models are **relatively robust** and **produce accurate short-term forecasts** with the same trends.



Fitted SARIMA forecasts for Los Angeles temperatures, based on post-2000 data(from Long Beach / Daugherty Field)

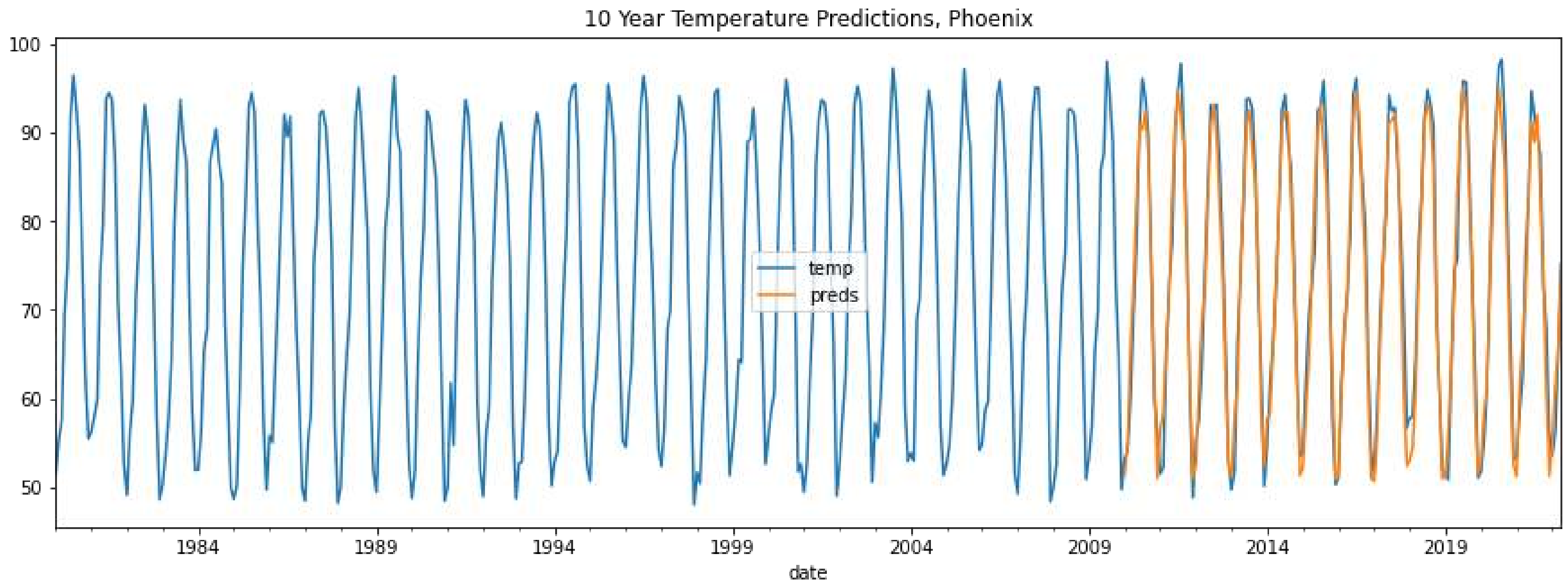
XGBoost

Later, we explored potential applications of more modern machine learning methods, including Extreme Gradient Boosting (XGBoost).

We limited our focus to lightweight machine learning models that are not excessively difficult to construct, train, and implement correctly.

Modeling Weather Trends with XGBoost

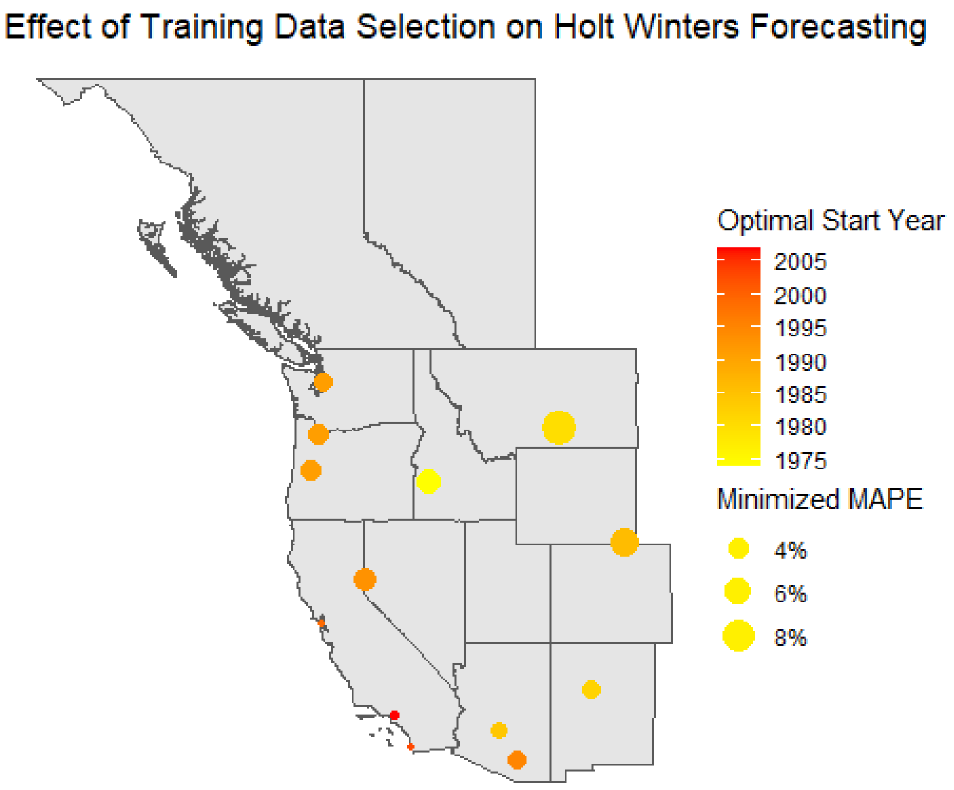
We also explored a more robust, generalizable method for predicting both temperature and precipitation trends with XGBoost. This method captured the same trends as classical methods, but with more sensitivity towards extreme events. **All three methods are viable options for forecasts seeking to produce reliable, short-term forecasts**.



Temperature Trend Analysis

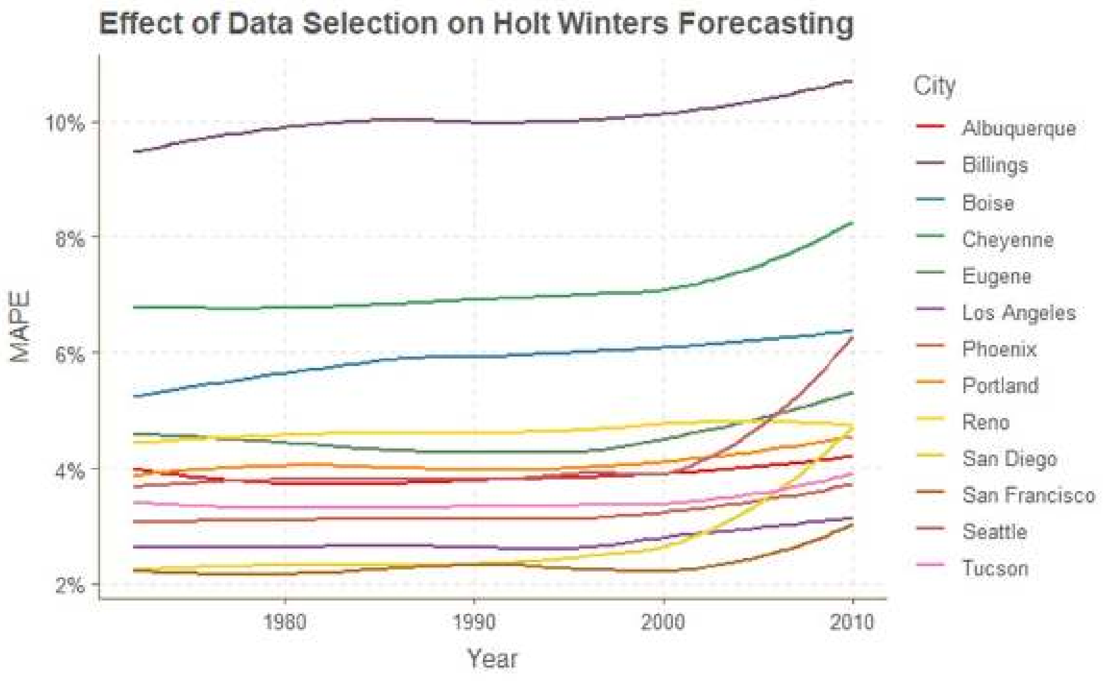
Another primary goal of our project was to understand the **impact of training data selection on forecasting**. Training data refers to the data used to fit/tune models to accurately predict historical data.

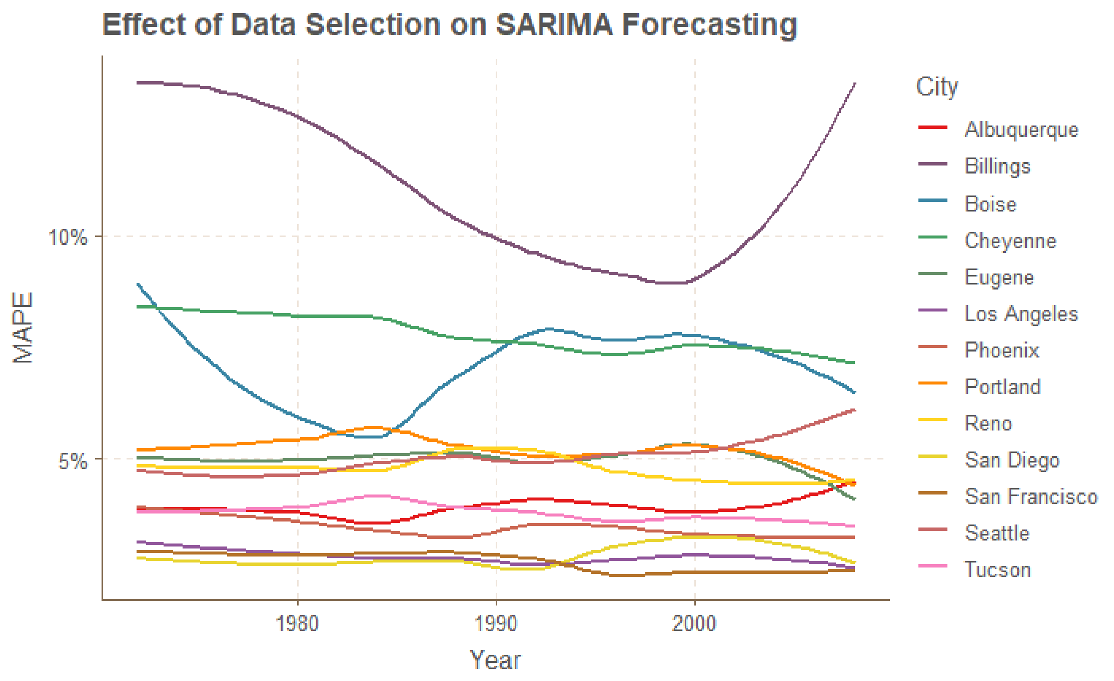
To this end, we trained classical statistical models on timeseries beginning at every year between 1972 and 2010, ending in 2016. Forecasts were all evaluated against 2016 – 2021 data.



Temperature Trend Analysis

With both classical statistical forecasting methods (Holt-Winters and SARIMA), smaller training datasets (i.e., only use more recent data to train the model) have a **minimal effect** on the model's accuracy on 2016 – 2021 temperature data.



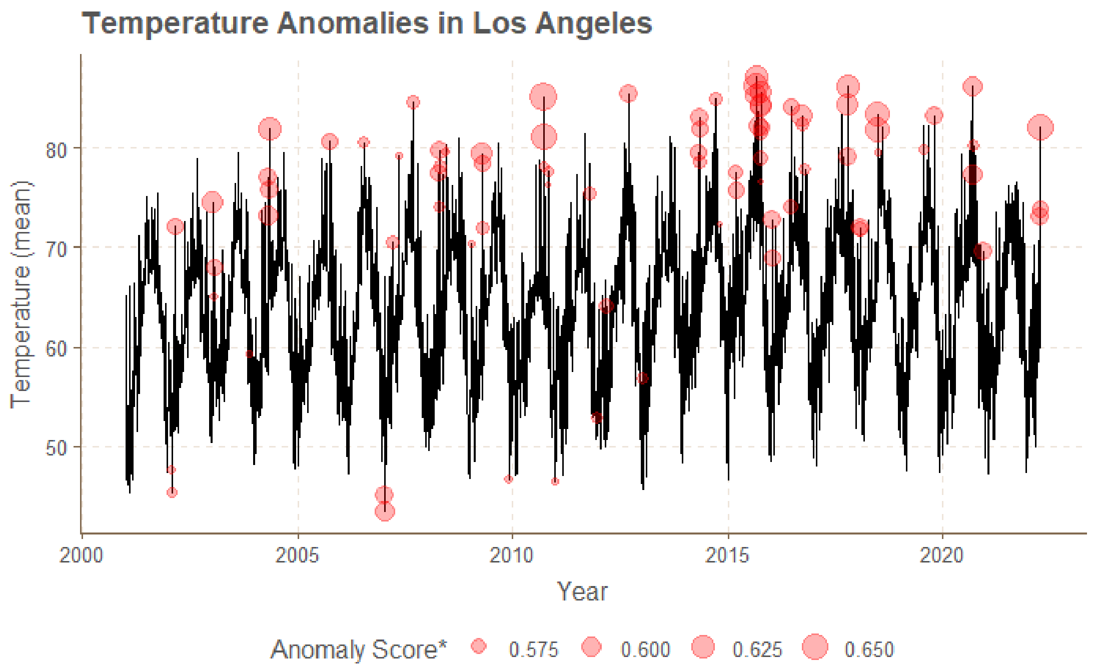


Outlier and Extreme Event Analysis

Modeling Weather Anomalies

Identifying extreme weather events and their impact on the grid will be particularly useful for regulators seeking to prevent outages in summer months.

Using an **isolation forest model**, a common tool for finding outliers in noisy datasets, we performed anomaly detection and predictions for both temperature and precipitation.

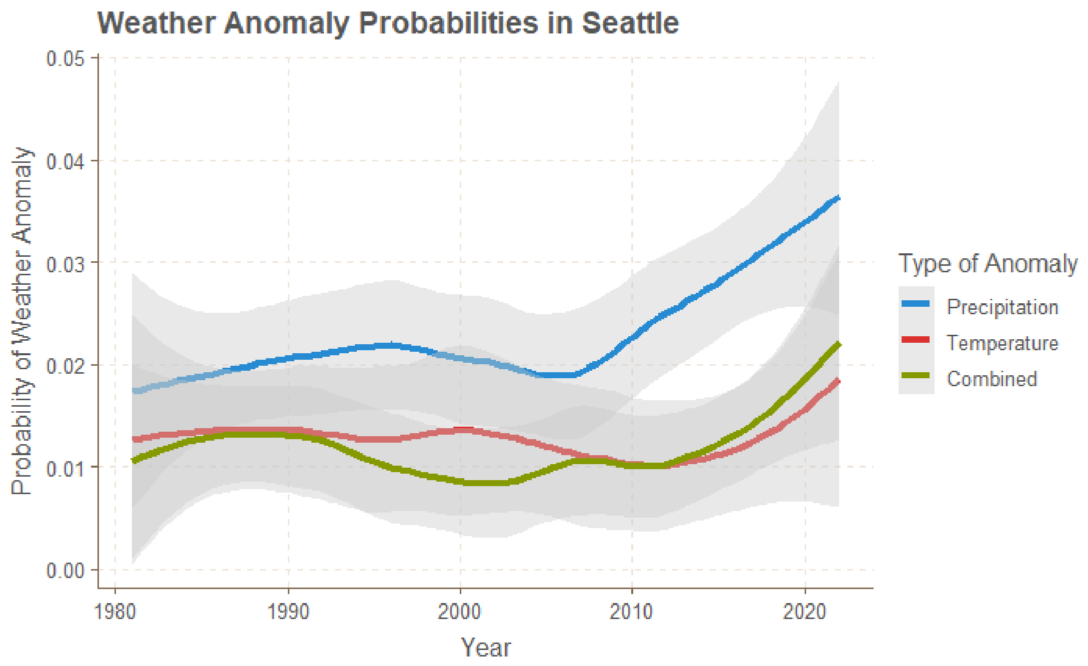


*Anomaly scores *don't* correspond directly to the severity of a weather event, but they help us understand how unlikely one is at a given time.

Modeling Weather Anomalies

By estimating the distribution of temperature and precipitation anomalies that our isolation forest model returns, we can estimate the probability of severe weather events.

This method reveals a **significant increase in the probability of weather anomalies** in all 20 Western cities since 2010.

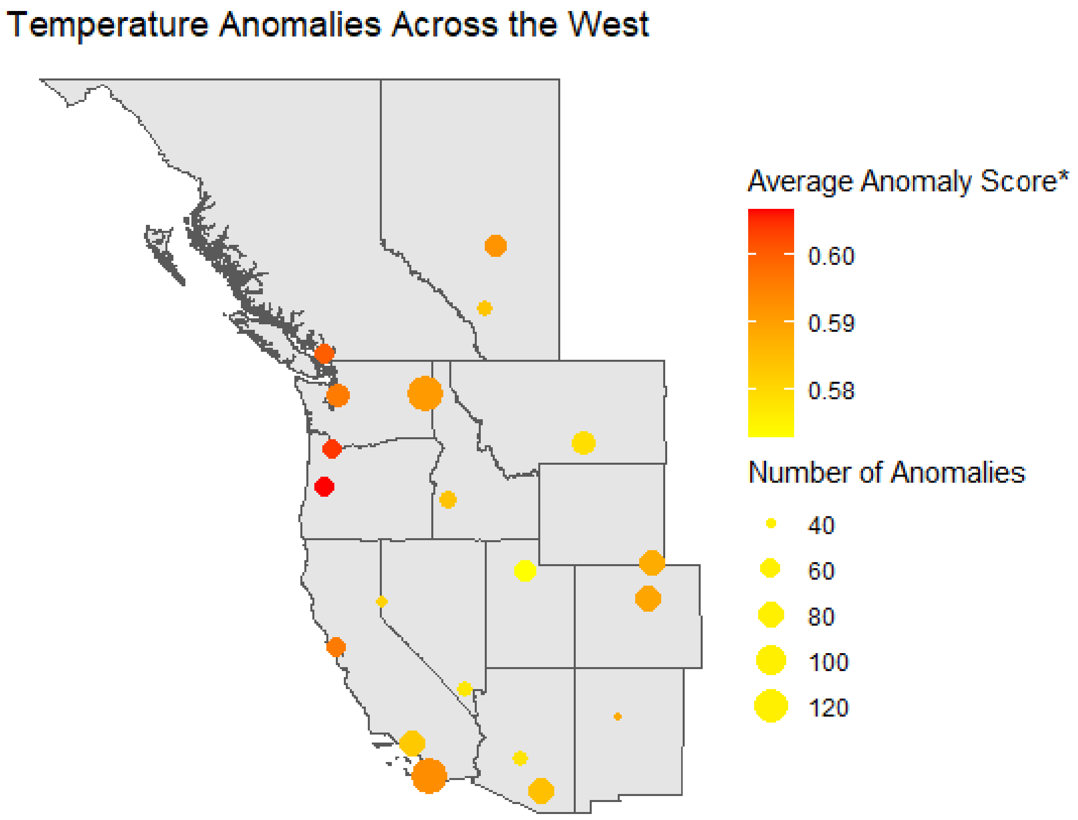


Our isolation forest model captures an across-the-board increase in anomalous weather events in Seattle in the last decade.

Modeling Weather Anomalies

San Diego, Spokane, and Tucson experienced the *most* weather anomalies.

Pacific Northwest cities (Eugene, Portland, and Vancouver in particular) had, on average, the highest anomaly scores. This can likely be attributed to the June 2021 heatwave event in the region.



Data analysis takeaways

Average temperatures are increasing

- We found that average temperatures are increasing across the West, although regional differences are present.

Extreme weather anomalies are becoming more common

- We found that extreme weather anomalies, including both extreme temperature and precipitation events, have become more likely.

Reliability of historical climate data is dependent on forecasting method

- Classical statistical methods for timeseries forecasting (Holt-Winters, SARIMA) can reliably handle recent temperature trends spurred by climate change.
- This may not generalize to less robust methods such as linear regression.

Photo credits: https://www.smithsonianmag.com/smart-news/the-western-us-is-experiencing-the-worst-megadrought-in-more-than-1200-years-180979590 / https://www.noaa.gov/media-release/noaa-adopts-technology-to-automate-weather-balloon-launches https://www.forbes.com/sites/dennismersereau/2021/05/31/how-severe-thunderstorms-shift-around-the-country-as-summer-settles-in/?sh=4b37c8cb4795

Climate Uncertainty and Current Industry Practices

Climate uncertainty

- Climate change is an evolving global problem.
- It presents enormous uncertainty in future impacts due to its complexity and sensitivity to policy decisions made by countries around the world.
- Climate change falls under **“deep uncertainty”**.

Photo credit: https://www.niehs.nih.gov/research/programs/climatechange/health_impacts/weather_related_morbidity/index.cfm

Levels of Uncertainty

- Not all uncertainty is created equal.
- The level of uncertainty depends on
  - How complex a problem is
  - The timescale
  - The number of uncontrollable variables
- The level of assurance that a decision will work in the future also depends on the consequences of being wrong.
- Many energy problems are both highly important and highly uncertain.

Climate change

Complete certainty → Total ignorance

Appropriate tool	Sensitivity analysis	Probability and statistics tools	Scenario analysis	Decision making under deep uncertainty	
Level of Uncertainty	Level 1	Level 2	Level 3	Level 4	Level 5
Context	A clear model of the future (with sensitivity)	Alternative futures (with probabilities)	Alternative future scenarios (with rankings)	Many plausible futures (unranked)	Unknown future
System Model					

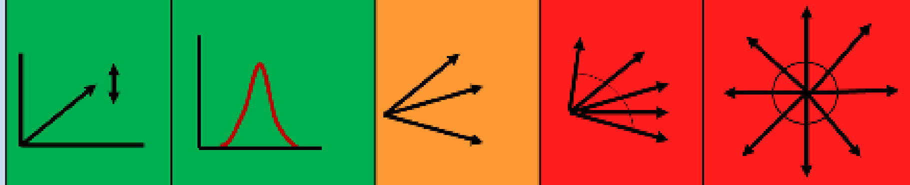
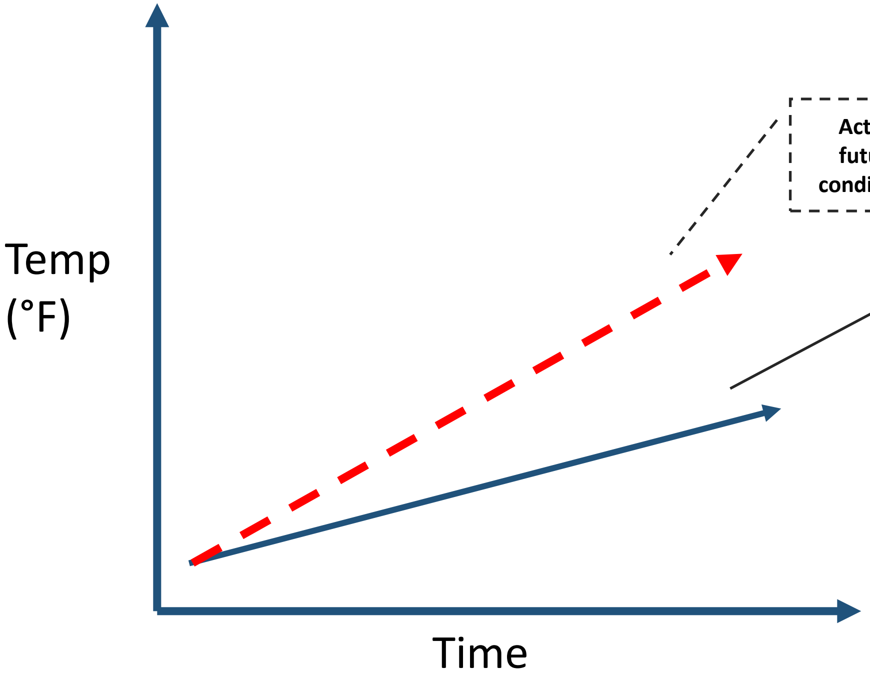
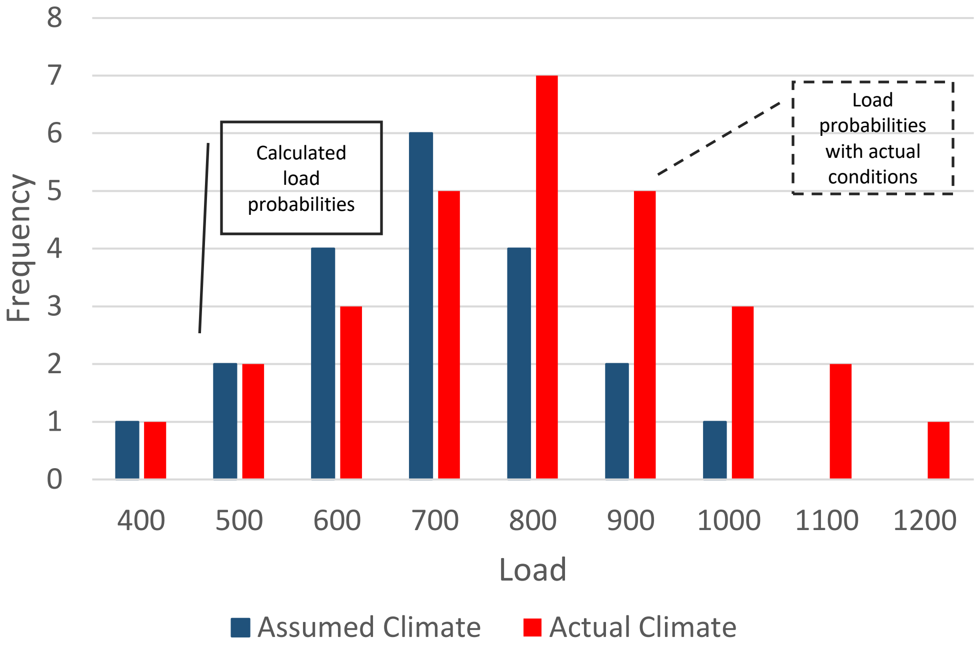


Figure adapted from work by Nathan Lee, Evan Savage, Sika Gadzanku, and Nick Laws at the National Renewable Energy Laboratory. Originally adapted from Walker (2017)

Why is a stochastic load forecast alone not enough?

A stochastic load profile does not account for uncertainty in the assumptions behind the climate forecast





Review of utility IRPs

- To support our analysis, we conducted interviews and a review of utility IRPs to understand how weather data are currently used in load forecasting and resource adequacy.
- We spoke with load forecasters at:
  - The California Energy Commission
  - The Northwest Power and Conservation Council
  - Puget Sound Energy
  - WAPA
  - Holy Cross Energy

Photo credit: https://www.latimes.com/environment/story/2020-07-01/want-jobs-and-clean-energy-this-overlooked-technology-could-deliver-both

Review of utility IRPs

- We looked at how utilities:
  - Use weather data in their load forecasts
  - Incorporate climate change
  - Analyze uncertainty in future weather trends
  - Incorporate weather data in resource adequacy

Photo credit: https://www.clearwaycommunitysolar.com/blog/all-about-renewable-power/about-solar-and-wind-power/

Uncertainty Analysis and Modeling of Weather Data in IRPs

**Based on the most recent publicly available IRP we could find for each utility*

Based on our IRP review, we formed some recommendations to address on what we saw

These are examples of utility forecasting practices and our recommendations for improvement

Problem: Assuming historical weather

- Several utilities base their load forecast on weather data from in its service territory, using daily mean temperatures 2000-2019.
- This method may obscure climate trends not already present in current data that may appear in the future.

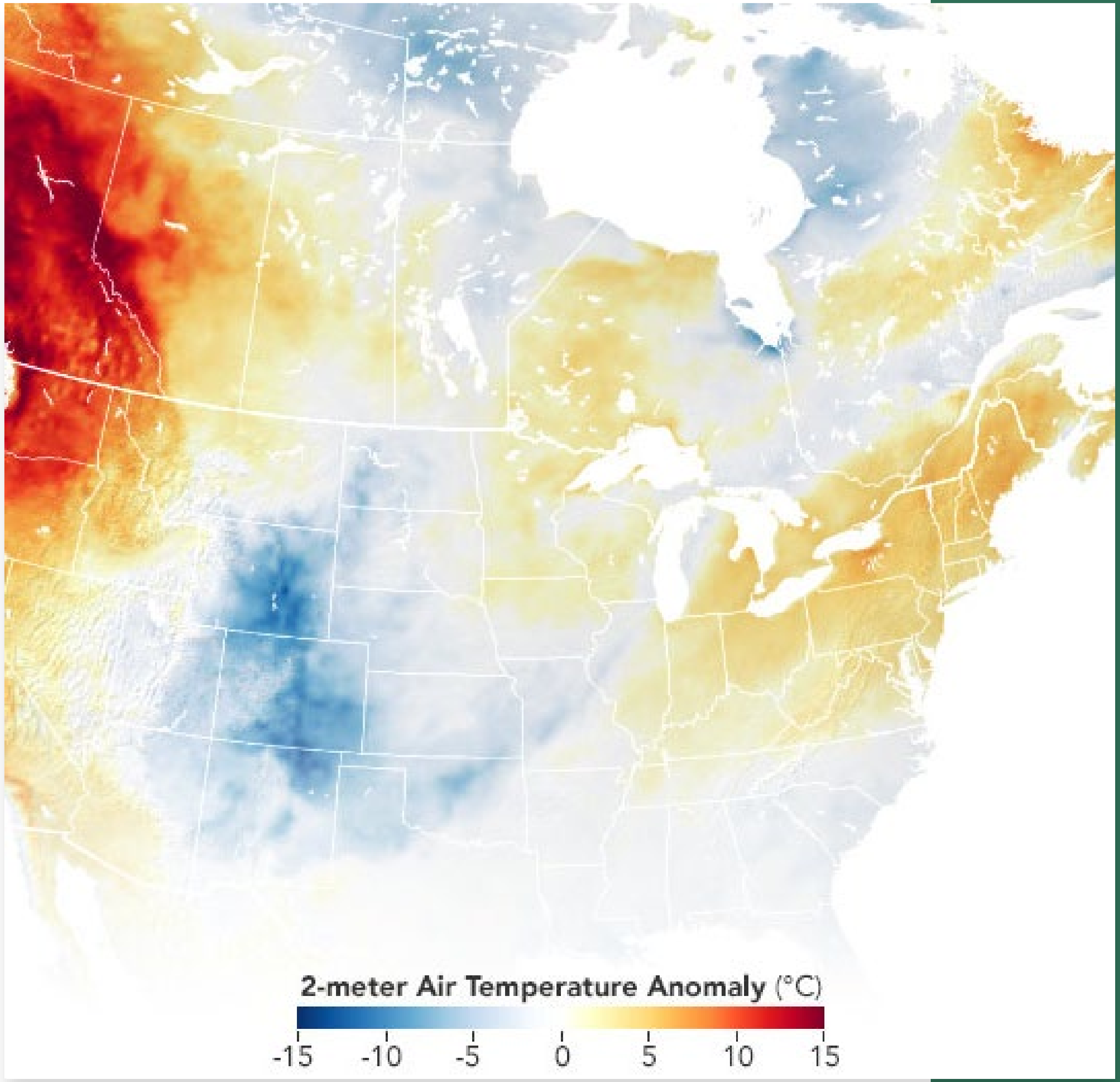
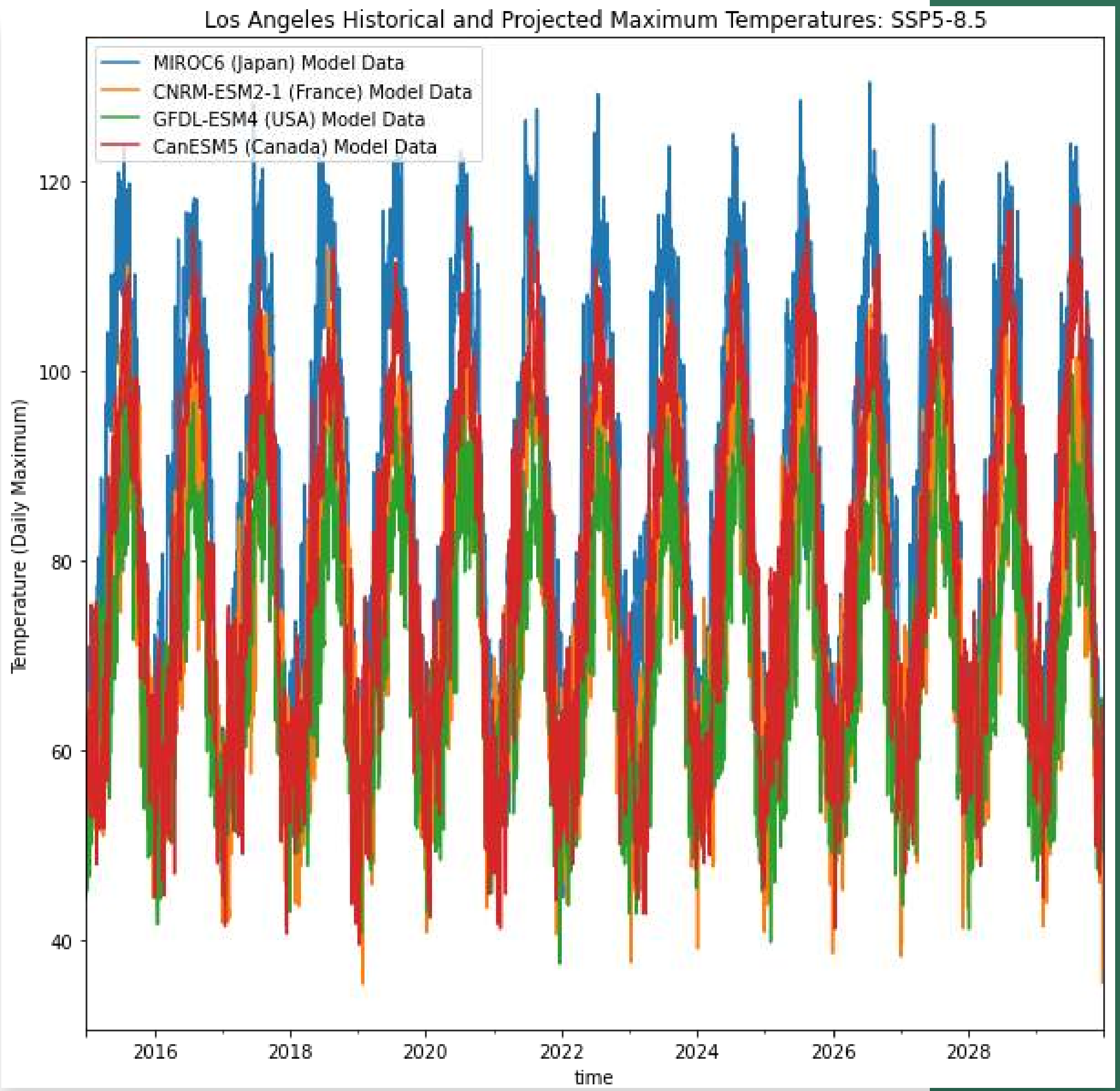


Photo credit:
https://en.wikipedia.org/wiki/2021_Western_North_America_heat_wave

Solution: Using historical and climate model data

- Utilities moves to using an ensemble model that takes into account historical data and multiple global climate models to predict future temperatures.
- This method better captures long-term climate trends and captures some uncertainty in climate forecasts.



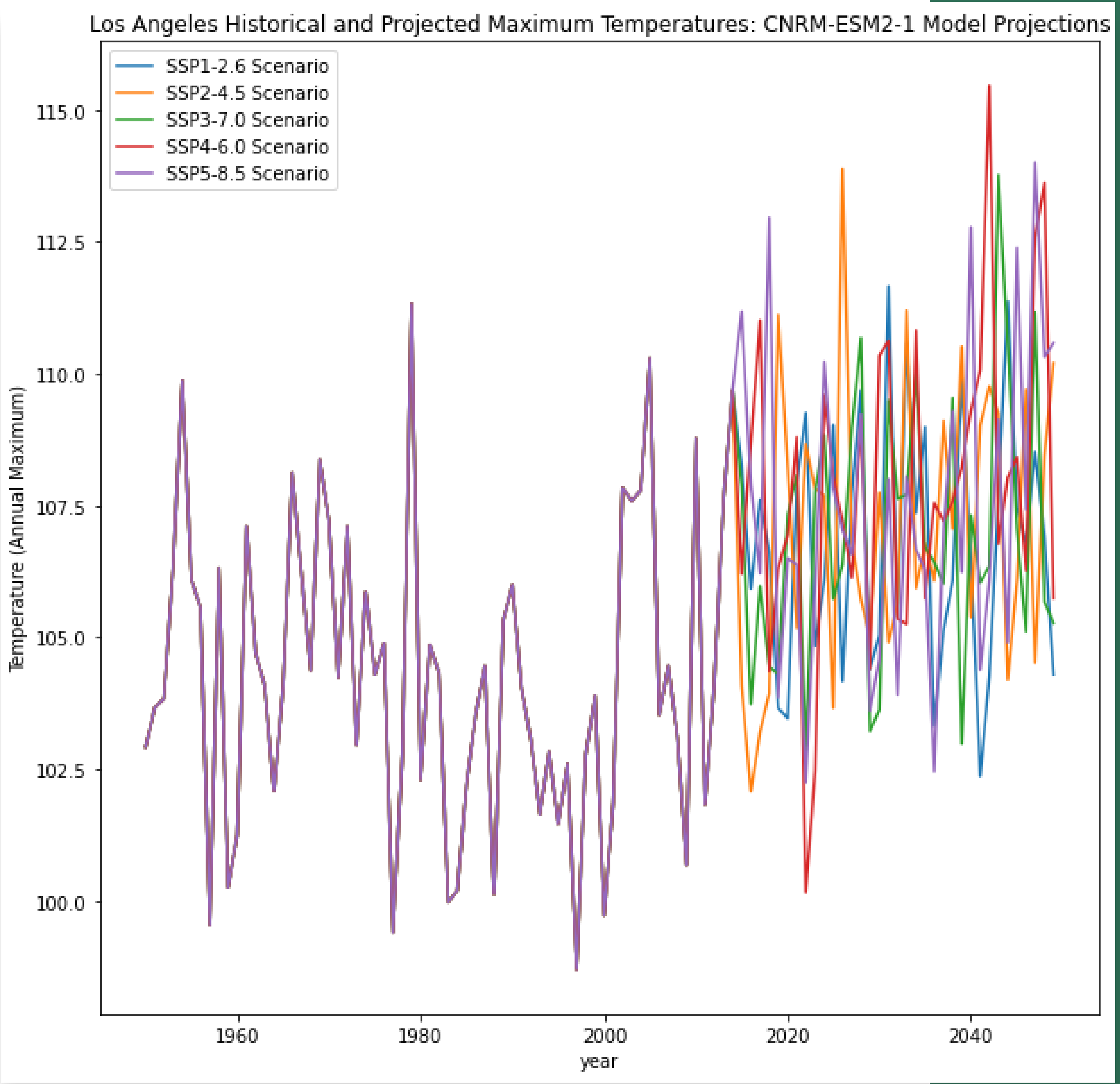
Problem: Assuming consistent peak producing temperatures

- Several utilities base their long-term peak load forecast on load growth factors and historic peak-producing temperatures.
- The increase in extreme temperatures we found in the data indicates that current peak producing temperatures are unlikely to remain constant in the future, a trend confirmed by climate scientists.

Photo credit: https://www.cnet.com/pictures/inside-a-power-grid-control-room-photos/

Solution: Generating peak load forecast with climate models

- Utilities update its long-term peak load forecast using a variety of climate models and explores the impact of different climate change scenarios on peak load.
- More on this later.



Problem: Assuming consistent air conditioning growth

- Some utilities assumes air conditioning load growth will be consistent with historic levels.
- EIA projects air-conditioning energy use to grow faster than any other use in buildings (EIA 2020).
- Obringer et al (2021) predict US air conditioning load will exceed grid capacity, with AC load growing 5%–8.5%.

Photo credit: https://southern-energy.com/maximize-multifamily-hvac-performance/

Solution: AC growth study, uncertainty analysis

- Utilities perform an in-depth study of AC growth over the next few decades in its service territory, simulating the impact that a variety of growth scenarios will have on loads.
- Conduct scenario analysis and account for the transition to heat pumps.
- Utilities and regulators encourage more efficient AC units.

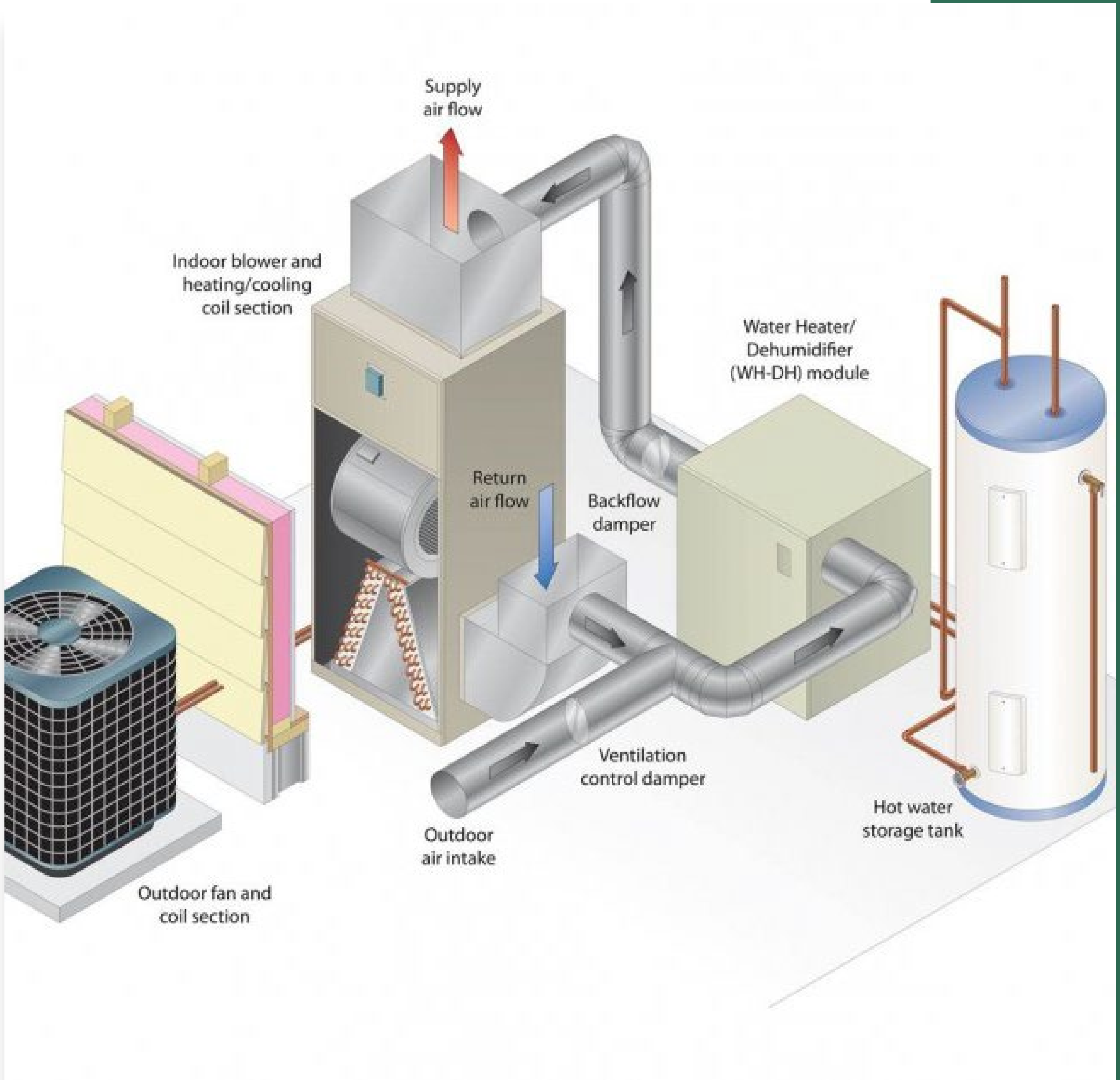


Photo credit: https://www.energy.gov/eere/buildings/downloads/air-source-integrated-heat-pump

State of the industry conclusions

Peak load forecasting must account for climate change

- We found that assuming historical weather patterns for long-term peak load forecasting is no longer a reliable assumption.

Long-term load forecasts should include climate modeling

- Forecasts should be based on climate models to capture climate change’s impact on extreme events.

Compound events of increased load and decreased generation are likely

- According to many authors, planners must account for increased load and decreased generation due to climate change and consider regional and compounding effects.

- (Mukherjee and Nateghi 2019, Turner et al. 2019, Burillo et al. 2019, Solaun and Cerdá 2019, Cole et al. 2020, Voisin et al. 2020, Bartos and Chester 2015, Stenclik et al. 2021, Murphy, Lavin, and Apt 2020, O’Connell et al. 2019, Lu et al. 2010)

Photo credits: https://www.powermag.com/nyiso-workers-now-living-at-grid-control-centers/
https://fortune.com/2017/07/07/australian-tesla-grid-scale-battery/
https://www.newsweek.com/hoover-dam-celebrates-90th-anniversary-record-low-water-levels-1607723

Long Term Temperature Forecasting

Planning for Uncertainty: A Framework

Based on interviews with load forecasting experts and long-term planners at utilities from across the West, we created an easy-to-use tool to generate peak temperature forecasts for any location in the region.

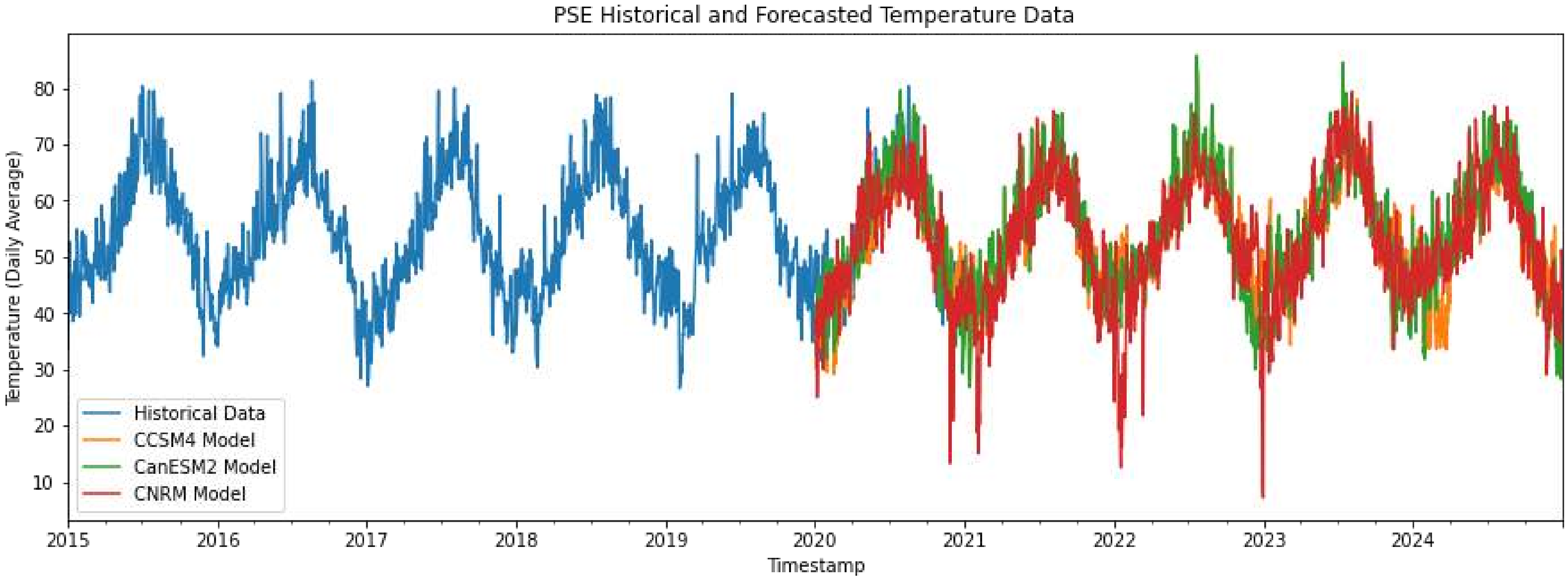
Our recommendations and methodology are largely based on the procedures and modeling efforts at:

1. The River Management Joint Operation Committee (RMJOC)
2. The Northwest Power and Conservation Council (NWPCC)
3. Puget Sound Energy (PSE)

After extensive literature review, we found that these organizations (all of whom collaborate for long-term planning) planned extremely well for climate change-induced uncertainty in temperature and precipitation trends.

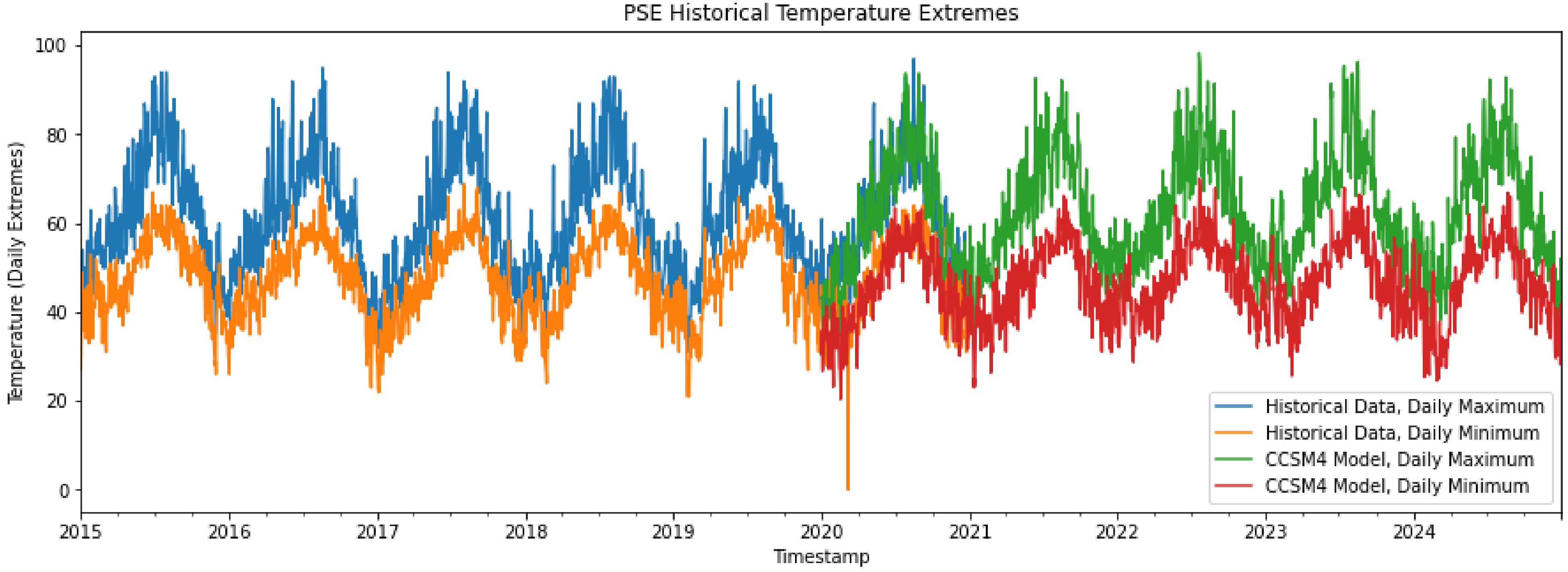
Planning for Uncertainty: A Framework

Using Coupled Model Intercomparison Project 6 (CMIP6) general circulation model (GCM) data that the RMJOC, NWPCC, and PSE all use captures a wide array of climate possibilities.

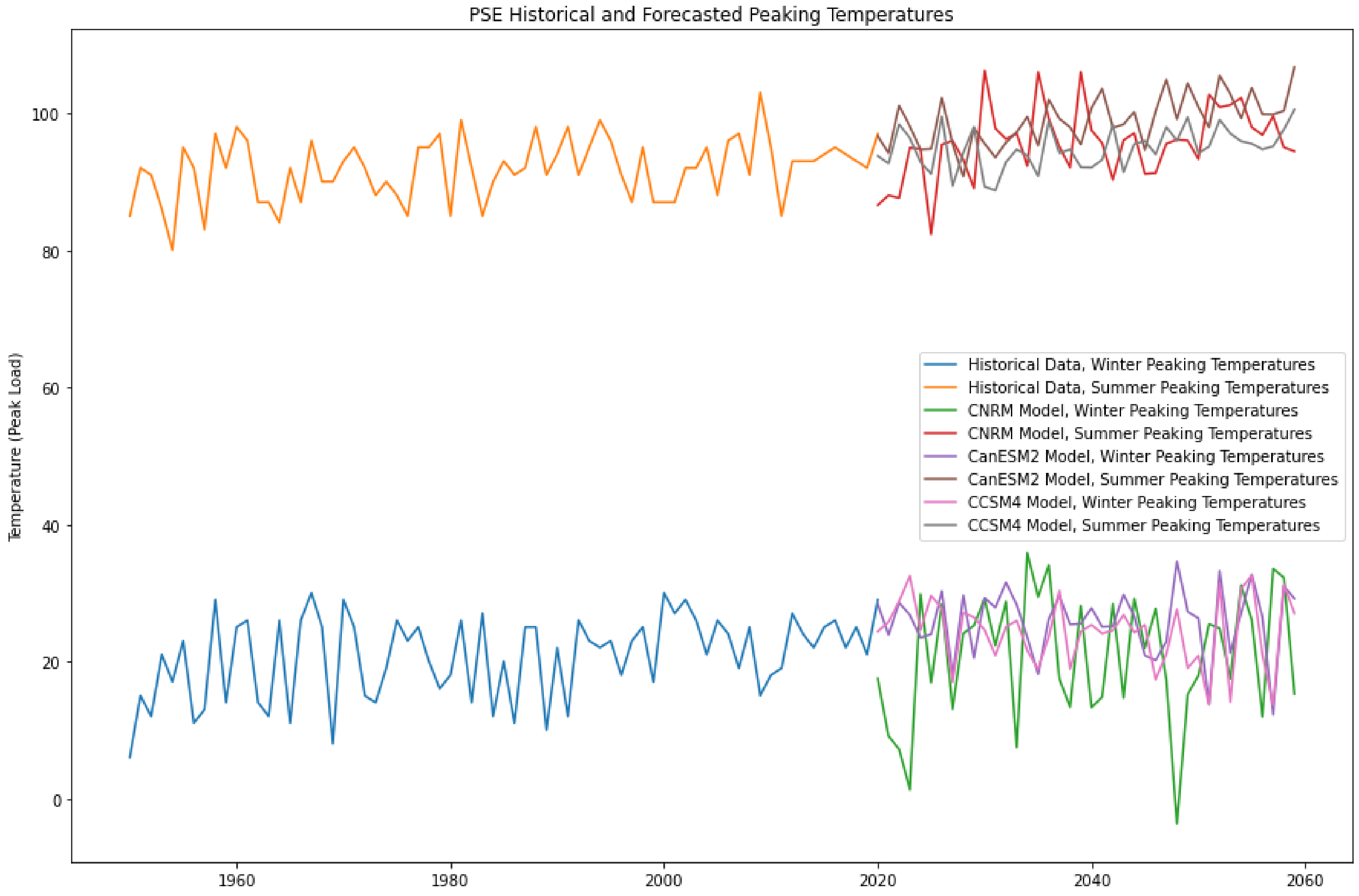


Planning for Uncertainty: A Framework

Using daily minima and maxima, the NWPCC and PSE use three climate models (curated by the RMJOC) and historical data to project trends in peak temperatures (i.e., temperatures that will result in peak load).

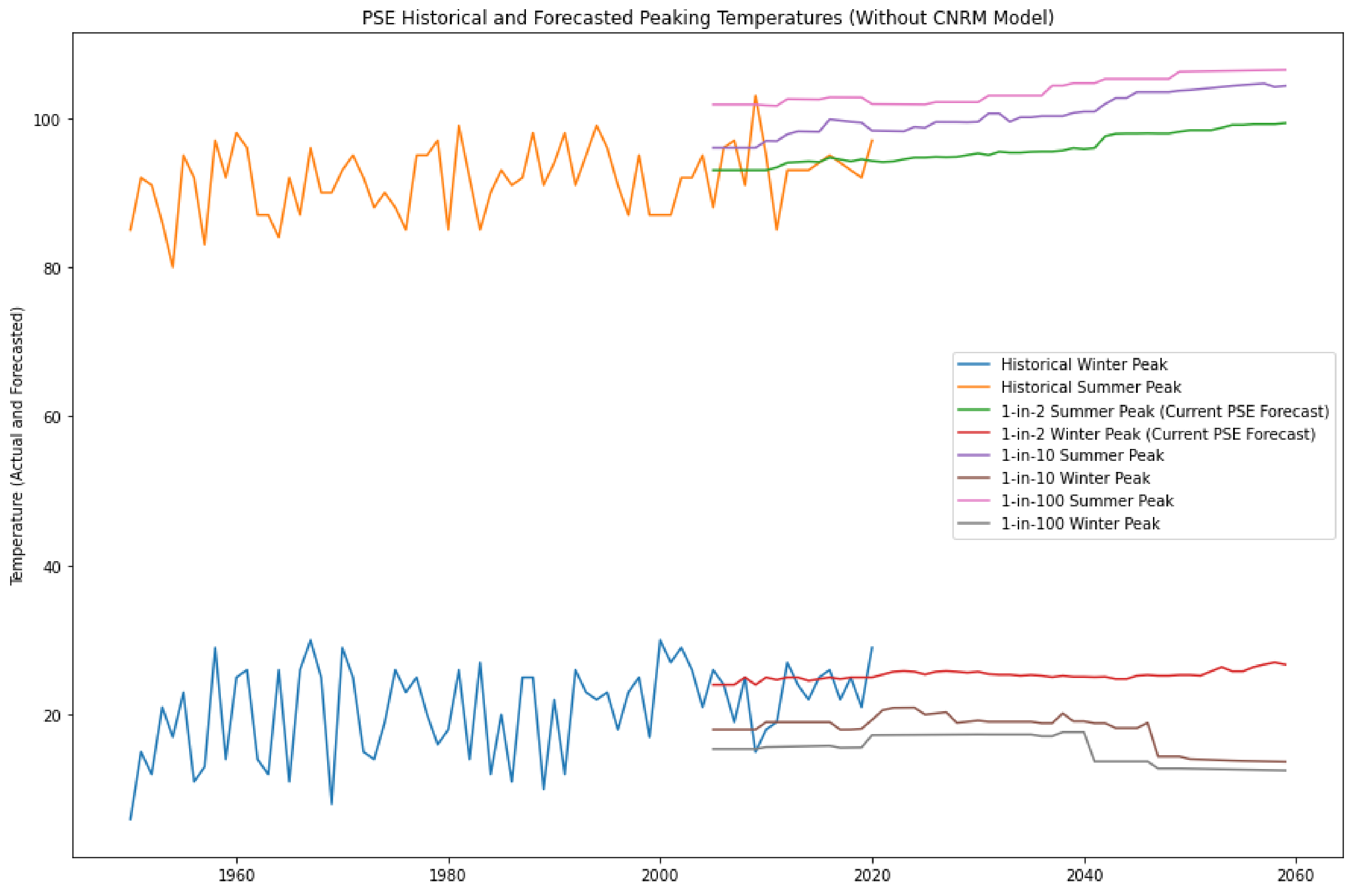


Planning for Uncertainty: A Framework



Using common peak hours for both winter and summer, the methodology presented by PSE combines historical peak temperatures with modeled peaks to produce a **30-year forecast**.

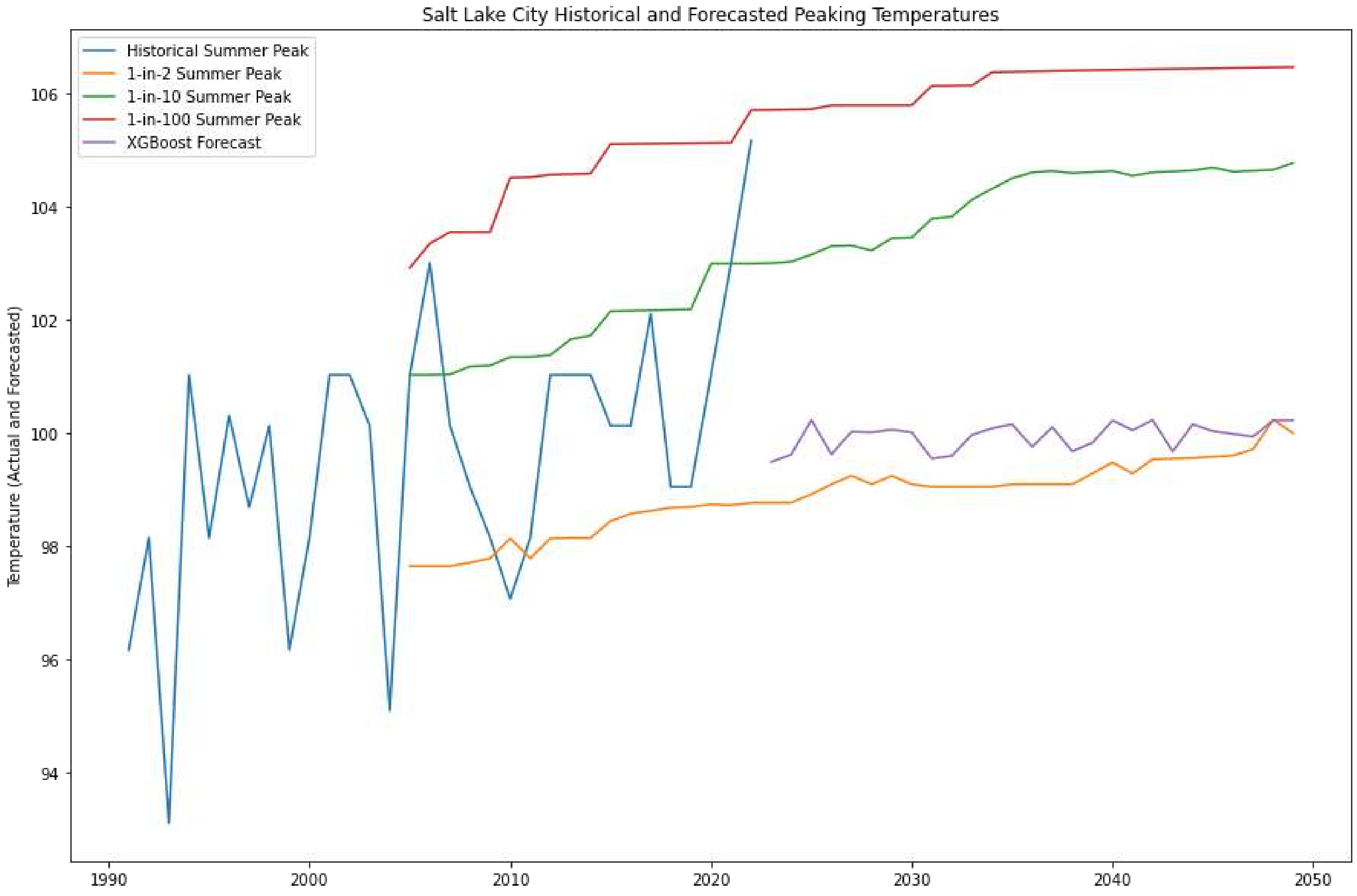
Planning for Uncertainty: A Framework



We modified PSE's peak hour assumptions slightly (i.e., including a broader range of peak hours for winter) so that they generalize better to other locations.

Additionally, we **calculated more extreme peaks** (1-in-10 and 1-in-100) to capture a greater range of uncertainty.

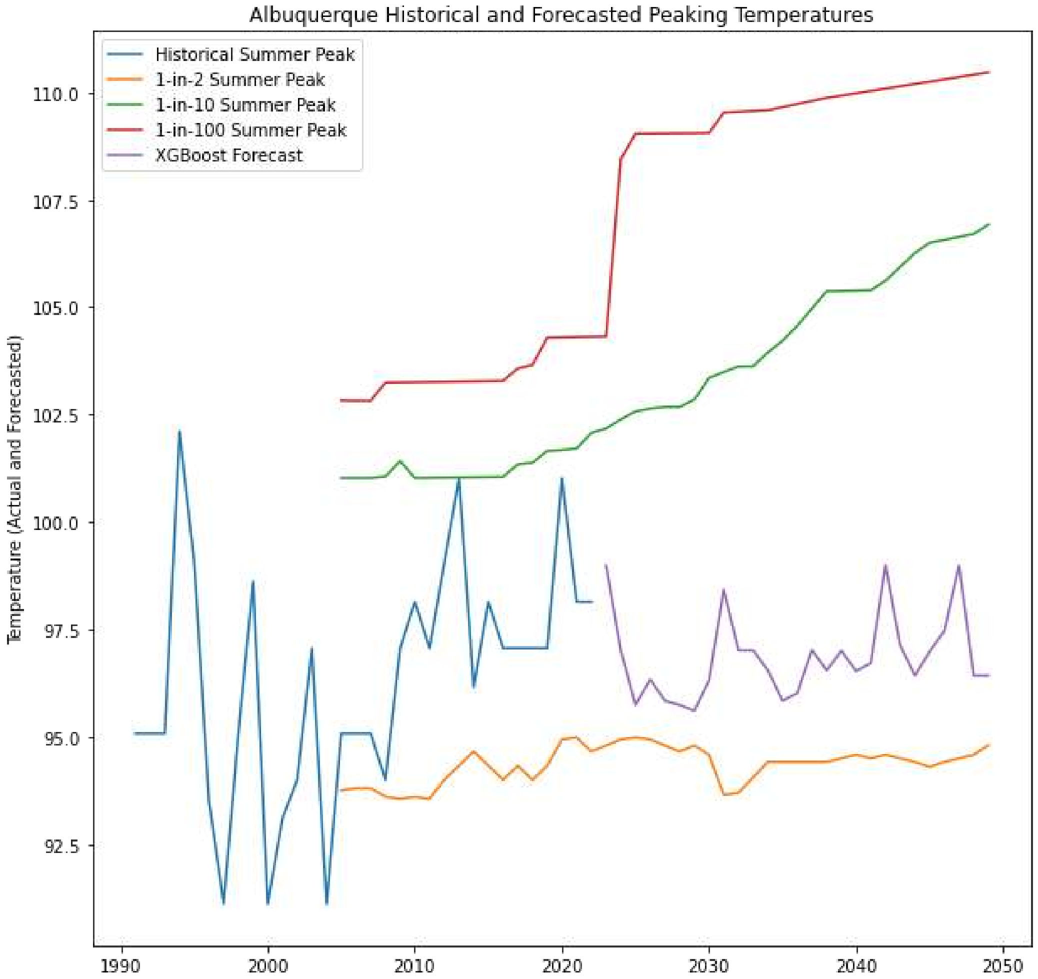
Planning for Uncertainty: A Framework



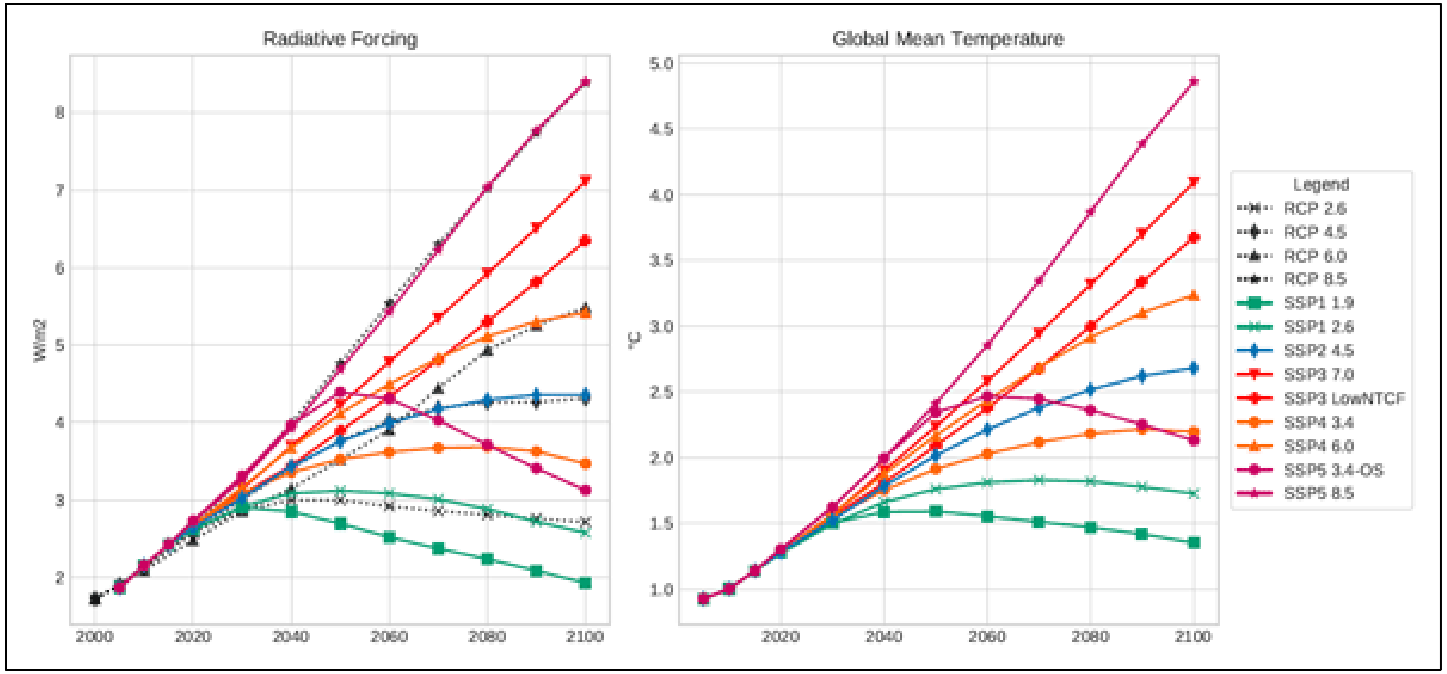
Finally, our framework utilizes XGBoost to find the **optimal relationship between climate model projections and historical temperatures**.

The final result is a robust forecast with **several levels of uncertainty**.

Planning for Uncertainty: A Framework



Planning for Uncertainty: A Framework



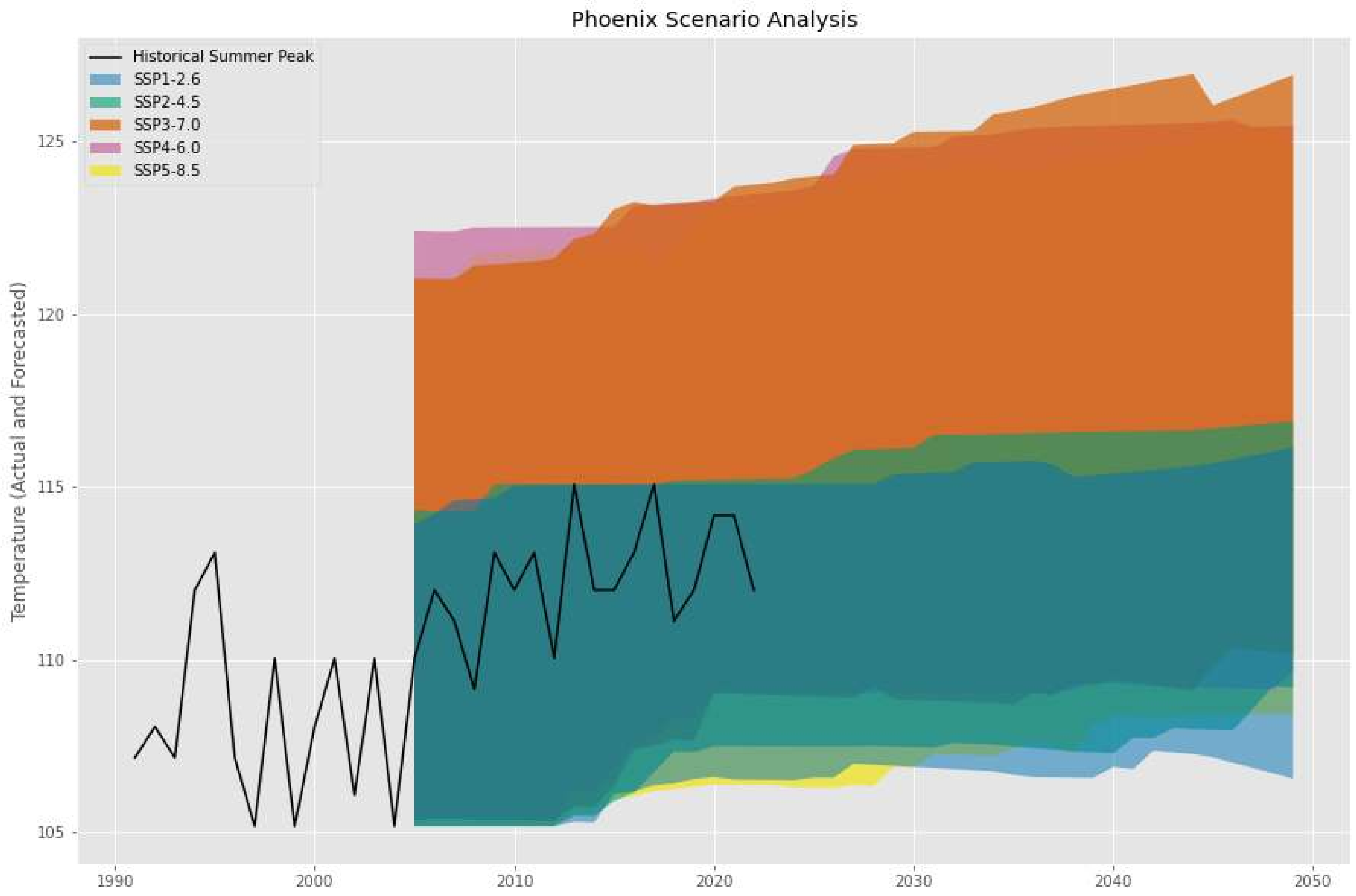
CMIP6 climate scenarios explore different **shared socioeconomic pathways** (SSPs) and **radiative forcing scenarios** by 2100 (RCP scenarios from CMIP5) in conjunction.

Photo credit:
https://gmd.copernicus.org/articles/12/1443/2019/

Using CMIP6 climate models also allows for **scenario analysis**.

The CMIP6 GCMs utilize a wide variety of assumptions about socioeconomic growth, radiative forcing, and total carbon emissions to project global mean temperatures (and other climate indicators) until 2100.

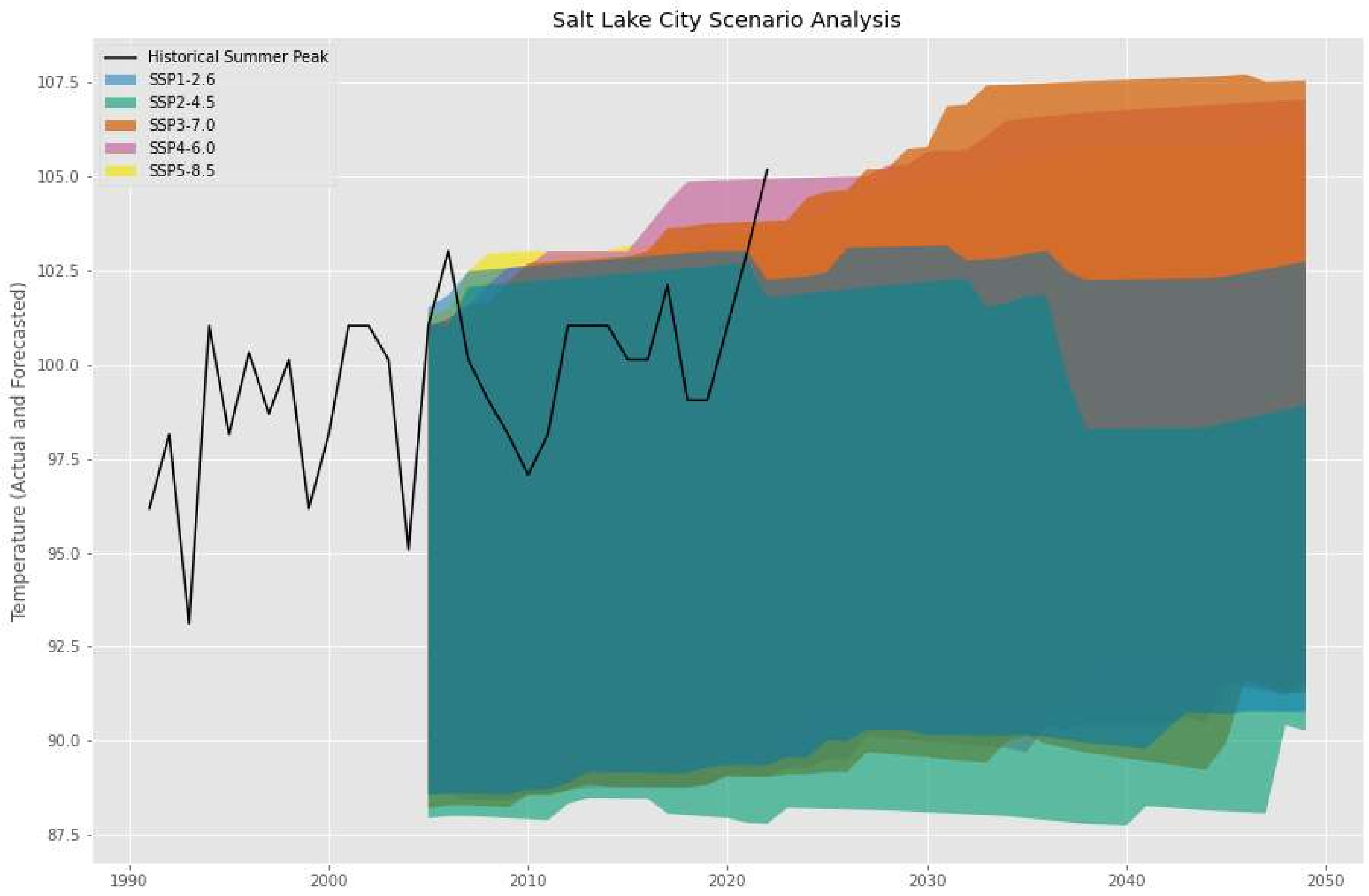
Planning for Uncertainty: A Framework



With our framework, planners can also explore **the various climate pathways used in all CMIP6 climate models**.

The plot on the left, which displays 95% confidence intervals for all 5 climate scenarios for the city of Phoenix, demonstrates the **extreme degree of uncertainty posed by climate change**.

Planning for Uncertainty: A Framework



In cities such as Salt Lake City, historical peak temperatures **have already exceeded the 95% confidence intervals of the more optimistic climate projections.**

This phenomenon illustrates the importance of **including a multitude of climate change projections in forecasting**

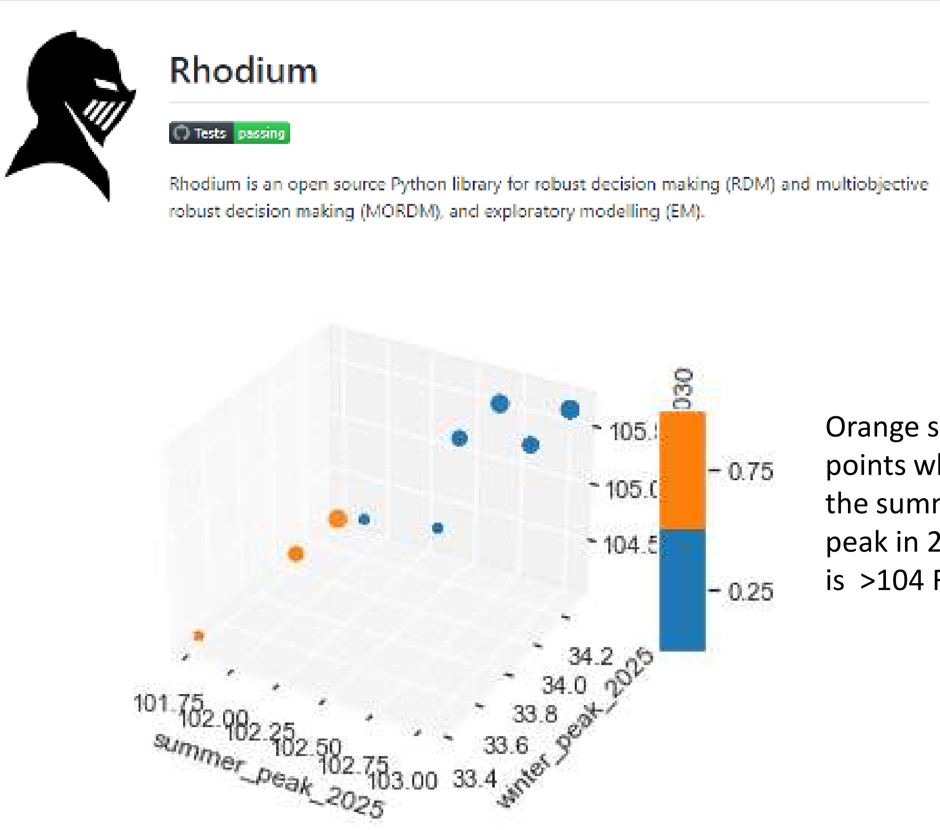
Planning for Uncertainty: A Framework

- Our framework for long-term peak temperature forecasting allows users to explore:
  - A variety of climate models widely used in the forecasting world.
  - Several different climate scenarios that consider socioeconomic growth and emissions.
  - The capabilities advanced forecasting techniques such as XGBoost.
- This generalizable framework implements many of the recommendations that we've made throughout this presentation, allowing anyone with some Python experience **to see our recommendations for long-term temperature planning in action.**

Planning for Uncertainty: Further uncertainty analysis

Rhodium

- Rhodium is an open-source Python library for robust decision making that can be perform sophisticated uncertainty analysis on pre-built models.
- We used Rhodium on our forecasting tool for Puget Sound Energy by varying summer and winter peak start hour and adding additional noise to simulate more extreme weather anomalies.

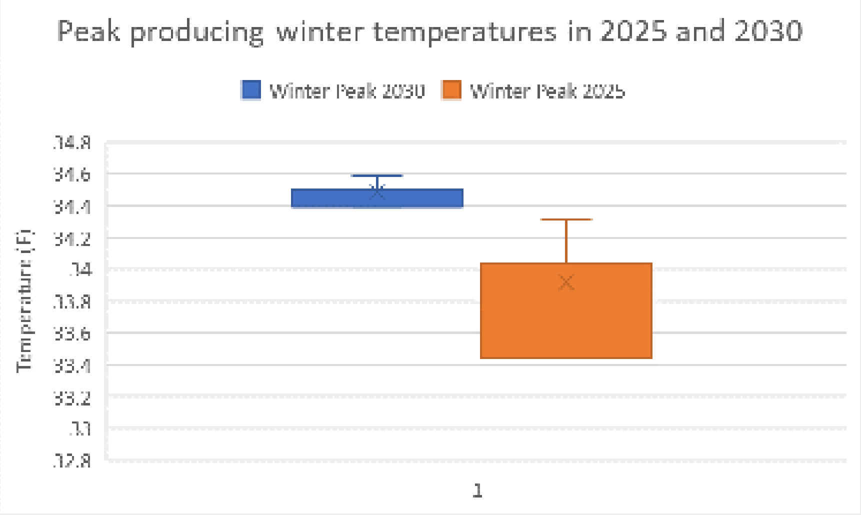


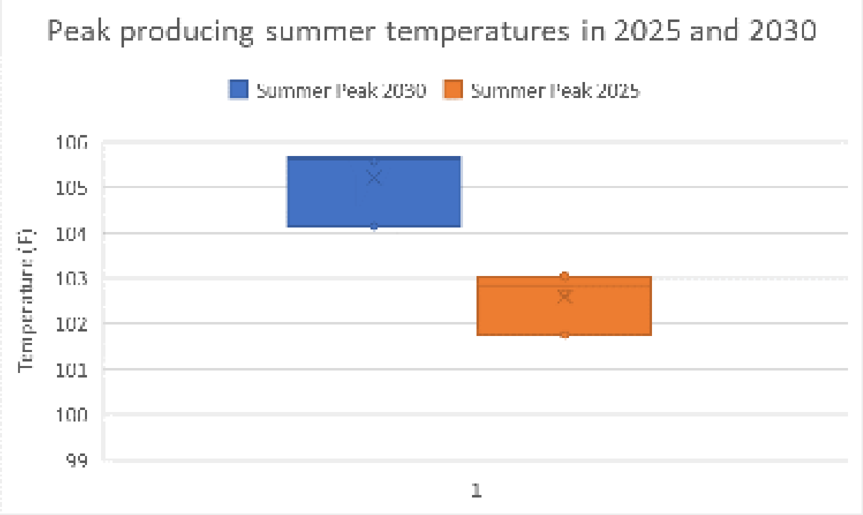
Orange shows points where the summer peak in 2030 is >104 F

The example figure above shows the relationship between summer and winter peak in 2025.

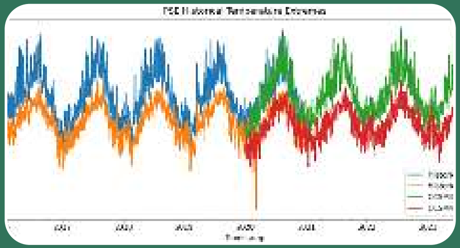
Planning for Uncertainty: Further uncertainty analysis

- The top figure shows a box and whisker plot for the resulting range of winter seasonal peaks achieved. A similar study could inform a resource adequacy analysis.
- The bottom figure shows same for summer temperatures.
- This analysis projects small uncertainty ranges for winter peaks, and around 2 degrees of additional uncertainty for summer peaks.



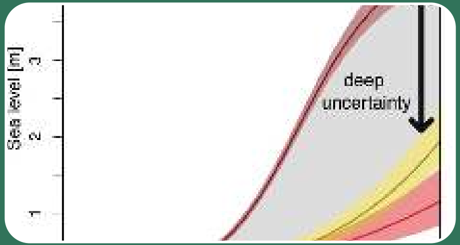


Long-term temperature forecasting conclusions



Long-term temperature forecasting can be relatively straightforward

- We were able to produce long-term temperature forecasts for minimal cost using open-source climate models and weather data.



Conducting scenario analysis or deep uncertainty analysis reveals hidden risk

- Our scenario analysis through the peak temperature forecasts and deep uncertainty analysis through Rhodium revealed climate risk that could be hidden in a traditional load forecast.

The temperature forecast tool developed by Jake Hofgard will be open-source

- The tool Jake developed will be open-source and available for stakeholders to use in to explore climate change's impact on temperatures in their region.

Photo credits: https://www.nature.com/articles/s41598-017-04134-5
https://www.marcobeltempo.com/open-source/simplify-mit-license/

Recommendations and Conclusions

We need new tools and strategies to address climate change

$

Business as usual

An incorrect forecast could result in ***resource adequacy problems*** or an ***oversized and costly system, and increasing risk***

Sophisticated modeling and uncertainty analysis

Climate modeling and uncertainty analysis can pave the way to ***preventing overbuilding and costly resource adequacy issues, and minimizing risk***

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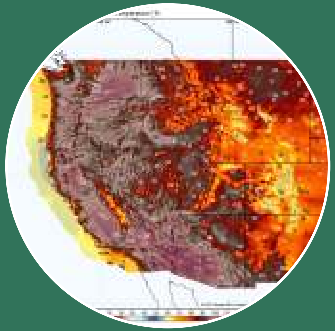
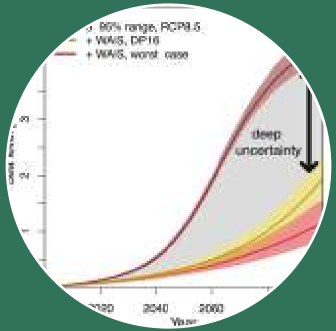
Top 3 Recommendations for Long-Term Load Forecasting



Climate change must be included in the **primary energy and peak load** forecasts



Uncertainty analysis of the underlying weather assumptions in the forecast with methods **sufficient for high levels of uncertainty**

Continually updated climate models to reflect the **most likely climate scenarios** and potential for warming (i.e., CMIP5 to CMIP6)

Photo credits: https://www.nature.com/articles/s41598-017-04134-5
https://www.washingtonpost.com/weather/2021/06/22/heat-wave-pacific-northwest-historic/
chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://www.wcrp-climate.org/images/modelling/WGCM/CMIP/CMIP6FinalDesign_GMD_180329.pdf

Top 3 Recommendations for Resource Adequacy

Account for **firm generation decreases** as climate change progresses, especially in **hydropower and thermal generators**

Consider **compound events**; future weather events that **decrease generation availability and increase peak load** simultaneously

Consider **regional effects**, and ensure all BAs are not relying on the same resources which may be stressed more frequently under climate change

Photo credits: https://cronkitenews.azpbs.org/2022/03/17/lake-powell-water-levels-drop-historically-low-level / https://www.bbc.com/news/business-39735802 https://www.wecc.org/epubs/StateOfTheInterconnection/Pages/Western-Interconnection.aspx

Recommendations for Policymakers and Regulators

Could require utilities to consider multiple climate scenarios

- Regulators could require utilities to consider multiple climate scenarios in their main load forecast in the IRP process.

Consider adding greater safety margin to meet peak load

- Policymakers and regulators could increase the PRM or require peak load to be calculated based on more extreme climate scenarios.

Could update capacity requirements to account for decreased generation

- Policymakers and regulators could increase the PRM or require that thermal and hydropower capacity be modeled with reduced generation during temperature extremes.

Photo credits: https://oilcity.news/wyoming/energy/2019/10/16/can-wyoming-law-delay-coal-plant-closures/
https://www.windpowerengineering.com/how-three-battery-types-work-in-grid-scale-energy-storage-systems/
https://www.reuters.com/world/us/brutal-heat-wave-persists-us-west-oregon-wildfire-rages-2021-07-12/

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Questions?

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References

Auffhammer, Maximilian, Patrick Baylis, and Catherine H. Hausman. 2017. “Climate Change Is Projected to Have Severe Impacts on the Frequency and Intensity of Peak Electricity Demand across the United States.” *Proceedings of the National Academy of Sciences* 114 (8): 1886–91. https://doi.org/10.1073/pnas.1613193114.

Bailey, Stephanie. 2022. “ADOPTED Final 2021 Integrated Energy Policy Report Volume IV California Energy Demand Forecast,” February, 111.

Bartos, Matthew D., and Mikhail V. Chester. 2015. “Impacts of Climate Change on Electric Power Supply in the Western United States.” *Nature Climate Change* 5 (8): 748–52. https://doi.org/10.1038/nclimate2648.

Burdick, Aaron, Nick Schlag, Adrian Au, Roderick Go, Zachary Ming, and Arne Olson. 2022. “Lighting a Reliable Path to 100% Clean Electricity: Evolving Resource Adequacy Practices for a Decarbonizing Grid.” *IEEE Power and Energy Magazine* 20 (4): 30–43. https://doi.org/10.1109/MPE.2022.3167572.

Burillo, Daniel, Mikhail Chester, Benjamin Ruddell, and Nathan Johnson. 2017. “Electricity Demand Planning Forecasts Should Consider Climate Non-Stationarity to Maintain Reserve Margins during Heat Waves.” *Applied Energy* 206 (November): 267–77. https://doi.org/10.1016/j.apenergy.2017.08.141.

Burillo, Daniel, Mikhail V. Chester, Stephanie Pincetl, Eric D. Fournier, and Janet Reyna. 2019. “Forecasting Peak Electricity Demand for Los Angeles Considering Higher Air Temperatures Due to Climate Change.” *Applied Energy* 236 (February): 1–9. https://doi.org/10.1016/j.apenergy.2018.11.039.

CAISO. 2022. “2022 Summer Loads Resource Assessment.” California Independent System Operator.

Carvallo Bodelon, Juan Pablo, Nan Zhang, Benjamin Leibowicz, Thomas Carr, Maury Galbraith, and Peter H. Larsen. 2020. “Implications of a Regional Resource Adequacy Program on Utility Integrated Resource Planning: Study for the Western United States,” November. https://escholarship.org/uc/item/8n98r73t.

Cole, Wesley, Daniel Greer, Jonathan Ho, and Robert Margolis. 2020. “Considerations for Maintaining Resource Adequacy of Electricity Systems with High Penetrations of PV and Storage.” *Applied Energy* 279 (December): 115795. https://doi.org/10.1016/j.apenergy.2020.115795.

“Comments of Andrew Dessler: Electric Weather Preparadness Standard - Phase 2.” 2022.

Coughlin, Katie, and Charles Goldman. 2008. “Physical Impacts of Climate Change on the Western US Electricity System: A Scoping Study.” LBNL-1249E, 944431. https://doi.org/10.2172/944431.

Craig, Michael, Stuart Cohen, and Jordan Macknick. n.d. “A Review of the Potential Impacts of Climate Change on Bulk Power System Planning and Operations in the United States.” Golden, CO: National Renewable Energy Laboratory (NREL).

Eckstrom, Carly, and Xuesi Shen. 2018. “Resource Adequacy in the West: Current State of Affairs and Ideas for the Future.” Western Interstate Energy Board.

EIA. 2020. “EIA Projects Air-Conditioning Energy Use to Grow Faster than Any Other Use in Buildings.” Energy Information Administration. March 13, 2020. https://www.eia.gov/todayinenergy/detail.php?id=43155.

Fan, Shu, Kittipong Methaprayoon, and Wei-Jen Lee. 2009. “Multiregion Load Forecasting for System With Large Geographical Area.” *IEEE Transactions on Industry Applications* 45 (4): 1452–59. https://doi.org/10.1109/TIA.2009.2023569.

Gidden, M. J., Riahi, K., Smith, S. J., Fujimori, S., Luderer, G., Kriegler, E., van Vuuren, D. P., van den Berg, M., Feng, L., Klein, D., Calvin, K., Doelman, J. C., Frank, S., Fricko, O., Harmsen, M., Hasegawa, T., Havlik, P., Hilaire, J., Hoesly, R., Horing, J., Popp, A., Stehfest, E., and Takahashi, K.: Global emissions pathways under different socioeconomic scenarios for use in CMIP6: a dataset of harmonized emissions trajectories through the end of the century, *Geosci. Model Dev.*, 12, 1443–1475, https://doi.org/10.5194/gmd-12-1443-2019, 2019.

Khoshrou, Abdolrahman, and Eric J. Pauwels. 2019. “Short-Term Scenario-Based Probabilistic Load Forecasting: A Data-Driven Approach.” *Applied Energy* 238 (March): 1258–68. https://doi.org/10.1016/j.apenergy.2019.01.155.

“Legal and Policy Brief of the California Independent System Operator Corporation: Order Instituting Rulemaking to Establish Policies, Processes, and Rules to Ensure Reliable Electric Service in California in the Event of an Extreme Weather Event in 2021.” 2021.

Li, Shuya, David W. Coit, and Frank Felder. 2016. “Stochastic Optimization for Electric Power Generation Expansion Planning with Discrete Climate Change Scenarios.” *Electric Power Systems Research* 140 (November): 401–12. https://doi.org/10.1016/j.epsr.2016.05.037.

Lu, Ning, Todd Taylor, Wei Jiang, Chunlian Jin, James Correia, L. Ruby Leung, and Pak Chung Wong. 2010. “Climate Change Impacts on Residential and Commercial Loads in the Western U.S. Grid.” *IEEE Transactions on Power Systems* 25 (1): 480–88. https://doi.org/10.1109/TPWRS.2009.2030387.

References Continued

Mukherjee, Sayanti, and Roshanak Nateghi. 2019. “A Data-Driven Approach to Assessing Supply Inadequacy Risks Due to Climate-Induced Shifts in Electricity Demand.” *Risk Analysis* 39 (3): 673–94. https://doi.org/10.1111/risa.13192.

Murphy, Sinnott, Luke Lavin, and Jay Apt. 2020. “Resource Adequacy Implications of Temperature-Dependent Electric Generator Availability.” *Applied Energy* 262 (March): 114424. https://doi.org/10.1016/j.apenergy.2019.114424.

NERC. 2021. “2021 Summer Reliability Assessment.” North American Electric Reliability Corporation.

Obringer, Renee. 2022. “US Household Air Conditioning Use Could Exceed Electric Capacity in next Decade Due to Climate Change.” AGU Newsroom. February 3, 2022. https://news.agu.org/press-release/us-household-air-conditioning-use-could-exceed-electric-capacity-in-next-decade-due-to-climate-change/.

Obringer, Renee, Roshanak Nateghi, Debora Maia-Silva, Sayanti Mukherjee, Vineeth Cr, Douglas Brent McRoberts, and Rohini Kumar. 2022. “Implications of Increasing Household Air Conditioning Use Across the United States Under a Warming Climate.” *Earth’s Future* 10 (1): e2021EF002434. https://doi.org/10.1029/2021EF002434.

O’Connell, Nathalie Voisin, Macknick, and Fu. 2019. “Sensitivity of Western U.S. Power System Dynamics to Droughts Compounded with Fuel Price Variability.” *Applied Energy* 247 (August): 745–54. https://doi.org/10.1016/j.apenergy.2019.01.156.

“Opening Testimony of Jeff Billington on Behalf of the California Independent System Operator Corporation: Order Instituting Rulemaking to Establish Policies, Processes, and Rules to Ensure Reliable Electric Service in California in the Event of an Extreme Weather Event in 2021.” 2021.

Puget Sound Energy. 2022. “RP Stakeholder Meeting: Energy Planning Process next Steps for 2022.” January 20.

Sobhani, Masoud, Tao Hong, and Claude Martin. 2020. “Temperature Anomaly Detection for Electric Load Forecasting.” *International Journal of Forecasting* 36 (2): 324–33. https://doi.org/10.1016/j.ijforecast.2019.04.022.

Solaun, Kepa, and Emilio Cerdá. 2019. “Climate Change Impacts on Renewable Energy Generation. A Review of Quantitative Projections.” *Renewable and Sustainable Energy Reviews* 116 (December): 109415. https://doi.org/10.1016/j.rser.2019.109415.

Steinberg, Daniel C., Bryan K. Mignone, Jordan Macknick, Yinong Sun, Kelly Eurek, Andrew Badger, Ben Livneh, and Kristen Averyt. 2020. “Decomposing Supply-Side and Demand-Side Impacts of Climate Change on the US Electricity System through 2050.” *Climatic Change* 158 (2): 125–39. https://doi.org/10.1007/s10584-019-02506-6.

Stenclik, Derek, Aaron Bloom, Wesley Cole, Gord Stephen, Armand Figueroa Acevedo, Rob Gramlich, Chris Dent, Nick Schlag, and Michael Milligan. 2021. “Quantifying Risk in an Uncertain Future: The Evolution of Resource Adequacy.” *IEEE Power and Energy Magazine* 19 (6): 29–36. https://doi.org/10.1109/MPE.2021.3104076.

Tebaldi, C., Debeire, K., Eyring, V., Fischer, E., Fyfe, J., Friedlingstein, P., Knutti, R., Lowe, J., O'Neill, B., Sanderson, B., van Vuuren, D., Riahi, K., Meinshausen, M., Nicholls, Z., Tokarska, K. B., Hurtt, G., Kriegler, E., Lamarque, J.-F., Meehl, G., Moss, R., Bauer, S. E., Boucher, O., Brovkin, V., Byun, Y.-H., Dix, M., Gualdi, S., Guo, H., John, J. G., Kharin, S., Kim, Y., Koshiro, T., Ma, L., Olivié, D., Panickal, S., Qiao, F., Rong, X., Rosenbloom, N., Schupfner, M., Séférian, R., Sellar, A., Semmler, T., Shi, X., Song, Z., Steger, C., Stouffer, R., Swart, N., Tachiiri, K., Tang, Q., Tatebe, H., Voldoire, A., Volodin, E., Wyser, K., Xin, X., Yang, S., Yu, Y., and Ziehn, T.: Climate model projections from the Scenario Model Intercomparison Project (ScenarioMIP) of CMIP6, *Earth Syst. Dynam.*, 12, 253–293, https://doi.org/10.5194/esd-12-253-2021, 2021.

Turner, S. W. D., N. Voisin, J. Fazio, D. Hua, and M. Jourabchi. 2019. “Compound Climate Events Transform Electrical Power Shortfall Risk in the Pacific Northwest.” *Nature Communications* 10 (1): 8. https://doi.org/10.1038/s41467-018-07894-4.

Voisin, Nathalie, Ana Dyreson, Tao Fu, Matt O’Connell, Sean W. D. Turner, Tian Zhou, and Jordan Macknick. 2020. “Impact of Climate Change on Water Availability and Its Propagation through the Western U.S. Power Grid.” *Applied Energy* 276 (October): 115467. https://doi.org/10.1016/j.apenergy.2020.115467.

Walker, Warren E., and Vincent A. W. J. Marchau. 2017. “Dynamic Adaptive Policymaking for the Sustainable City: The Case of Automated Taxis.” *International Journal of Transportation Science and Technology*, Connected and Automated Vehicles: Effects on Traffic, Mobility and Urban Design, 6 (1): 1–12. https://doi.org/10.1016/j.ijtst.2017.03.004.

Wang, Pu, Bidong Liu, and Tao Hong. 2016. “Electric Load Forecasting with Recency Effect: A Big Data Approach.” *International Journal of Forecasting* 32 (3): 585–97. https://doi.org/10.1016/j.ijforecast.2015.09.006.

WECC. 2020. “The Western Assessment of Resource Adequacy Report.” Salt Lake City, UT: Western Electricity Coordinating Council (WECC).