Projected Changes in Climate Extremes Affecting Seattle City Light

Guillaume Mauger, Harriet Morgan, Crystal Raymond, Jason Won

University of Washington Climate Impacts Group

Jan 2022

TABLE OF CONTENTS

CITATION: Mauger, G.S., Morgan, H., Raymond, C.L. and J.S. Won. 2021. Projected Changes in Climate Extremes Affecting Seattle City Light. Report prepared for Seattle City Light. Climate Impacts Group, University of Washington.

ACKNOWLEDGEMENT: This work was funded via a grant from Seattle City Light.

Purpose

Changes in extreme weather metrics related to heat, high winds, and lightning may have implications for Seattle City Light (SCL) operations, planning, and standards. This memo describes an updated assessment of changes in extreme winds, lightning, and heat waves for locations and metrics of interest to SCL.

Background

Regional climate model (RCM) simulations represent a distinct improvement over previous approaches to estimating historical and future weather conditions. This is especially true in areas with complex topography, where weather and climate conditions can vary significantly over short distances. For example, one study showed that regional climate model projections are needed to accurately represent changes in future flood risk (Salathé et al., 2014). This, and the subsequent studies mentioned here, are based on results from the Weather Research and Forecasting (WRF, http://www.wrf-model.org; Skamarock et al., 2008) community mesoscale model, following one of two configurations described by Salathé et al. (2010) or Chen et al. (2018). A more recent study by Mauger et al. (2019) adds some nuance to this picture, showing that the WRF biases are in the same range as the estimates produced by statistical approaches, but that the timing of events is not as well reproduced by the model. However, that study only considered historical performance, and the evaluation was primarily focused on lowland areas where statistical datasets are expected to perform best. Another comparison evaluated WRF performance for winds and waves in Puget Sound, showing better agreement than an alternative model that is commonly used in wave forecasting (Yang et al., 2019). To date, no comparisons have been made for extreme temperatures in the region.

This study builds on previous research completed by the University of Washington Climate Impacts Group (UW CIG) in close collaboration with SCL. As is the case for the current study, previous work made use of dynamically-downscaled WRF projections.

Snover et al. (2010) evaluated changes in extreme heat metrics, finding increases in the frequency and intensity of heat events and decreases in the same for cold events. However, their analysis was based on a previous generation of climate models and only one dynamically-downscaled projection. Without evaluating additional model projections, we cannot know if these changes are representative or simply unique to the one global model included in the analysis.

In a subsequent study, Salathé et al. (2015) evaluated changes in extreme winds using the three WRF simulations that were available at the time. That study found no significant changes in winds, in part because with only three model projections it is not possible to distinguish a systematic change from one that is a result of sampling. The study also evaluated results from a larger ensemble of coarse-scale global climate model projections, finding a large range among model projections, and a model-average projection that was small compared to year-to-year variability. However, the analysis also suggested that inter-model differences might be influenced by model construction. Although not the only possible explanation, it is possible that these differences would not be present in the finer-resolution WRF projections – for example, because at the 12 km WRF resolution, the topography is much more accurately represented.

The same study also evaluated changes in lightning using the composite Thunderstorm Prediction Index (Knapp et al, 2006; Knapp and Brooks, 2000). Both WRF simulations projected an increase in lightning risk over the North Cascades in spring, small decreases in summer, and the models disagreed about the changes projected for fall/winter. The projections for Seattle showed a small decrease in spring, a large decrease in summer, and again inconsistent changes for fall/winter. The study concluded that a larger ensemble of WRF projections would help determine if a systematic trend is present, while also recommending further analysis of both the lightning index and WRF representation of lightning conditions.

With support and collaboration from the Climate Impacts Group (CIG), Cliff Mass (Professor, Atmospheric Sciences, University of Washington) has recently produced a total of 12 new regional climate model projections. The purpose of the current project is to evaluate results from these new projections to better understand changes in extreme winds, lightning, and heat waves for locations and metrics of interest to Seattle City Light. ***This document summarizes the data and methods used to develop the new projections and associated fact sheets.***

Observed Data

Air Temperature and Winds

We obtained hourly weather observations for six different stations in the vicinity of the focus areas selected for their relevance to SCL operations (Table 1). We used standard data quality flags provided for each dataset to remove bad or questionable data. In order to ensure an adequate sample size for estimating the historical values for each metric, we applied the following criteria:

1. 90% of hours in each month must have valid data,
2. At least 11 of 12 months must have valid data to calculate a metric for the year.

Table 1. Weather stations used in the analysis. All sites except the I-90 bridge station provided hourly observations of temperature, humidity, and wind. The I-90 bridge station provided observations on 30-second intervals, for relating hourly average winds and gusts.

Station	Source	ID	Latitude	Longitude	Freq.	Years
Seattle Service Area						
SeaTac	NOAA ISD	72793024233	47.445N	122.314W	Hourly	1948-2020
UW ATG Building	UW Atmos	n/a	47.654N	122.309W	Hourly	1990-2020
I-90 Bridge	WSDOT	n/a	47.590N	122.270W	30 sec.	2018-2020
T-Lines						
Arlington Municipal Airport	NOAA ISD	72794504205, 72794599999	48.161N	122.159W	Hourly	1996-2020
Skagit Project						
Marblemount	RAWS	451504	48.539N	121.446W	Hourly	2003-2020
Boundary Project						
Pend Oreille	FLNRO-WMB	402	49.053N	117.413W	Hourly	1990-2020

All metrics were calculated using the entire observational record, regardless of the start and end date.

Finally, it is worth noting that the focus on hourly data (e.g., number of hours above or below a threshold) severely limits the observational data that can be used. If the extreme metrics in this study were based on daily counts, that would greatly increase the number of observational stations that could be included in the analysis. This could be something to consider for future work.

Atmospheric Soundings

There are only two locations in Washington State where atmospheric profles are consistently measured: Quileute (47.93N, 124.56W) and Spokane (47.68N, 117.63W). We obtained sounding data from NOAA's Integrated Global Radiosonde Archive (IGRA) Version 2 (Darre et al., 2016; "radiosonde" refers to the sensor package on board weather balloons). Measurements are taken twice daily and extend from the surface to the upper atmosphere. Above the surface, measurements are interpolated onto a standard set of pressure levels (e.g., 1000 hPa, 700 hPa, 500 hPa). The lightning indices described in the following section are calculated from temperature, humidity, and wind observations at a variety of pressure levels.

Lightning

We obtained lightning observations from the National Lightning Detection Network (NLDN; e.g.: Murphy et al. 2021). NOAA maintains a gridded inventory of daily lightning strikes through the Severe Weather Data Inventory (SWDI), which provides free access to NLDN data on a 4 km grid, from 1986 onward. We extracted lightning counts for grid cells in the vicinity of the atmospheric sounding stations in Quileute and Spokane.

Model Data

Global Climate Model (GCM) Projections

GCM projections were obtained from the Climate Model Inter-comparison Project, phase 5 (CMIP5; Taylor et al., 2012). The GCMs included in the WRF ensemble (Table 1) were chosen based on Brewer et al. (2016), who evaluated and ranked global climate models based on their ability to reproduce the climate of the Pacific Northwest. All of the new projections are based on the high-end RCP 8.5 scenario (Van Vuuren et al., 2011).

Additional information on model evaluation and ranking is summarized in Mauger et al. (2019). In addition, Mauger et al. (2019) discuss approaches for using RCP 8.5 projections as an analog for what might be projected for the RCP 4.5 scenario. For example, the 2080s in the RCP 4.5 projections appear to correspond approximately to the 2040s or 2050s in the RCP 8.5 projections.

Regional Climate Model (WRF)

Regional Climate Model simulations were produced using the Weather Research and Forecasting (WRF, http://www.wrf-model.org; Skamarock et al., 2005) community mesoscale model, following the configuration developed in previous work (e.g., Salathé et al., 2010). Simulations were performed using WRF version 3.2 implemented following Salathé et al. (2010, 2014). Initial and boundary conditions were provided by the following GCMs (Table 1), all driven by the high-end RCP 8.5 greenhouse gas scenario (Van Vuuren et al., 2011).

The model, and model configuration, are described in detail in Lorente-Plazas et al. (2018) and Mauger et al. (2018). Lateral boundary conditions and sea surface temperature (SST) were updated once every six hours. Thirty vertical levels were used in the model spanning from the surface to 10 hPa, with the finest vertical resolution in the boundary layer. WRF runs were initialized three months prior to the start date of each simulation as spin-up. The physics parameterizations for microphysics, cumulus parameterization, planetary boundary layer, land surface models, and longwave and shortwave radiation are summarized in Lorente et al. (2018). Although we did not perform an extensive validation of the model's performance, previous research has established that it captures the essential characteristics of local-scale weather variations in the Pacific Northwest (e.g., Dulière et al. 2011). Simulations were performed for the years 1970 through 2099. Results were archived at hourly intervals following Greenwich Mean Time (GMT, which is 8 hours ahead of local standard time in the Pacific Northwest).

The new ensemble of WRF projections includes one simulation for each of the GCMs listed in Table 1, in addition to the RCP 4.5 projection developed previously for the ACCESS 1.0 GCM. All simulations run from 1970-2099 and are archived at a 1-hour time step and a spatial resolution of 12 km.

Table 2. The twelve global climate models (GCMs) used as input to the regional model simulations. All simulations are based on the high-end RCP 8.5 greenhouse gas scenario (Van Vuuren et al., 2011). A low-end scenario was also produced for the ACCESS 1.0 model, resulting in two separate projections for this GCM.

Model	Center	Resolution	Vertical Levels
ACCESS1-0	Commonwealth Scientific and Industrial Research Organization (CSIRO), Australia/ Bureau of Meteorology, Australia	1.25 x 1.88	38
ACCESS1-3	Commonwealth Scientific and Industrial Research Organization (CSIRO), Australia/ Bureau of Meteorology, Australia	1.25 x 1.88	38
bcc-csm1-1	Beijing Climate Center (BCC), China Meteorological Administration	2.8 × 2.8	26
CanESM2	Canadian Centre for Climate Modeling and Analysis	2.8 × 2.8	35
CCSM4	National Center of Atmospheric Research (NCAR), USA	1.25 × 0.94	26
CSIRO-Mk3-6-0	Commonwealth Scientific and Industrial Research Organization (CSIRO) / Queensland Climate Change Centre of Excellence, Australia	1.8 × 1.8	18
FGOALS-g2	LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences	2.8 × 2.8	26
GFDL-CM3	NOAA Geophysical Fluid Dynamics Laboratory, USA	2.5 × 2.0	48
GISS-E2-H	NASA Goddard Institute for Space Studies, USA	2.5 × 2.0	40
MIROC5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	1.4 × 1.4	40
MRI-CGCM3	Meteorological Research Institute, Japan	1.1 × 1.1	48
NorESM1-M	Norwegian Climate Center, Norway	2.5 × 1.9	26

Hourly data were extracted for the nearest grid point to each weather station (Table 1). These constitute the “raw” WRF data for each station dataset.

Error-Correcting the Erroneous Cold-Snaps in WRF

Anomalous minimum temperature events (i.e., cold snaps) were observed in the WRF model projections. Upon further investigation it was determined that these anomalies originated in the GCMs and are likely due to cold air outbreaks originating in British Columbia/Alberta. To correct the errors originating in the GCMs, we omitted all data points that were more than 35°F below the average winter temperature (December, January, February) for each water year (i.e., average winter temperature was calculated separately for each water year in the WRF projections). This threshold was chosen because it is the maximum observed difference between average winter temperature and the coldest hourly temperature in winter. This year-by-year approach was employed to ensure the long-term warming trend would not influence the detection of the cold anomalies. While this approach removed most of the cold snaps in the WRF projections, there are still some anomalous minimum temperature events in the projections. As a result, extreme metrics related to cold temperatures should be interpreted with caution.

Note that this is not the same approach used in bias correcting the hourly Sea-Tac temperatures, described in Mauger and Won (2021). In that approach, the load forecasting model could not accommodate missing data. As a result, instead of omitting the anomalous cold snaps, they were bias-corrected.

Metrics

We worked with Seattle City Light to identify 15 extreme weather metrics related to temperature, wind, and lightning (Table 3). These were selected in close collaboration with key SCL personnel, including staff interviews and a workshop on preliminary findings (described below). Metrics were selected based on relevance to SCL operations, planning and engineering standards.

Table 3. Extreme weather metrics used to evaluate the frequency of extreme temperature, wind, fire, and lightning events. The right-hand columns denote the locations for which each metric was evaluated. Metric definitions are provided in Appendix A.

Metric	Reason	Future Decade(s)	Seattle Service Area	T-Lines	Skagit Project	Boundary Project
Cold Temperatures						
Heating Degree Days	Average electricity demand for load forecasting	2021-2050, 2041-2070	✓			
Annual Minimum Temperature	Peak electricity demand, Equipment standards & ratings	2021-2050, 2041-2070	✓			
Consecutive Cold Days	Peak electricity demand for resource adequacy & distribution system planning	2021-2050, 2041-2070	✓			
Cold Extremes	Peak electricity demand for resource adequacy & distribution system planning	2021-2050, 2041-2070	✓			
Freeze-Thaw cycles	Equipment damage, Rock fall & associated road access	2021-2050, 2041-2070	✓		✓	✓
Warm Temperatures						
Cooling Degree Days	Average electricity demand for load forecasting	2021-2050, 2041-2070	✓			
Annual Maximum temperature	Peak electricity demand, Equipment standards & ratings	2021-2050, 2041-2070	✓			
Consecutive Warm Days	Peak electricity demand for resource adequacy & distribution system planning	2021-2050, 2041-2070	✓			

Metric	Reason	Future Decade(s)	Seattle Service Area	T-Lines	Skagit Project	Boundary Project
Heat Extremes	Peak electricity demand for resource adequacy & distribution system planning	2021-2050, 2041-2070	✓			
Hours with Temperatures above 86°F	Equipment standards, Transmission system planning	2021-2050, 2041-2070	✓	✓	✓	
High Winds						
Wind (Non-Consecutive high wind hours)	Outages & storm response, Wind load on equipment, Transmission system planning	2021-2050, 2041-2070	✓			
Wind (Consecutive high wind hours)	Outages & storm response, Wind load on equipment, Transmission system planning	2021-2050, 2041-2070	✓			
Number of Windstorms	Outages & storm response, Hazard mitigation, Transmission system planning	2021-2050, 2041-2070	✓			
Fire Weather						
High Wind & Low Humidity	Emergency response & hazard mitigation, Equipment upgrades	2021-2050, 2041-2070	✓			
Lightning						
Number of Strikes	Outages, Equipment standards & upgrades, Facility planning, Equipment function & standards	2021-2050, 2041-2070	✓			✓
Seasonal Timing of Strikes	Outages, Equipment standards & upgrades, Hazard mitigation	2021-2050, 2041-2070	✓			
	Equipment function & standards, Dam safety, Fire potential & response, Hazard mitigation	2021-2050, 2041-2070		✓	✓	

In addition, we calculated historical and future climate metrics using the ProcessWeather Application that was developed to provide inputs for LoadSEER, a model used for distribution planning developed by Integral Analytics. Using the WRF hourly temperature estimates as input, we used this application to produce historical and future estimates of the following temperature metrics:

- Max Low
- Max High
- Max 3-Day Weighted Avg Low
- Max 3-Day Weighted Avg High
- Max 3-Day Weighted Avg High-Low
- Min Low
- Min High
- Min 3-Day Weighted Avg Low
- Min 3-Day Weighted Avg High
- Min 3-Day Weighted Avg High-Low

Appendix B of this report includes a brief technical memo, produced by Integral Analytics (2015), that describes the ProcessWeather metrics in more detail.

Approach

This section describes the methods used to develop future projections for each of the metrics listed in Table 1.

Regional Model Bias Correction

As with all models, the WRF projections include some biases relative to observed conditions. Since biases can be different for each metric, we decided to take a tailored approach to bias adjusting model estimates separately for each metric. For threshold metrics (e.g., number of hours > 86°F), we defined the threshold in WRF based on its quantile in the observations. This corrects for biases in both the magnitude and the distribution of each variable (temperature, wind, humidity). We then evaluated changes in the frequency or duration that the percentile-based threshold is exceeded in each WRF simulation.

Wind Extremes

An additional challenge for the wind extreme metrics is that WRF does not record gusts. Instead, we evaluated changes in hourly averaged winds from WRF. To relate hourly average winds to peak gust speeds, we used the WSDOT I-90 Bridge wind data, which provides wind and gust estimates at 30 second intervals. Based on this analysis, we found that the 95th, 99th, and 99.5th percentiles in hourly average winds corresponding to maximum gusts of 30, 40, and 50 mph, respectively.

Projected Changes

To evaluate the projected change in each metric, we averaged the results over three 30-year periods: (1) historical (1981-2010), (2) 2030s (2021-2050), and (3) 2050s (2041-2070). Projections for the 2030s and 2050s are expressed as the change relative to the historical period.

For annual minimum and maximum temperature, we took the difference between the future and historical WRF estimates to obtain the projected change for these metrics. For all other metrics we used the percent change relative to historical, as opposed to the difference. We chose to use the percent change for most metrics because the absolute change can be more influenced by model biases.

Combining the WRF Projections with Observations

Given that SCL staff use observed values for each metric in current planning, we wanted all projections to scale with the observations as best as possible. To help with this, we applied the projected changes from the WRF model to the observed historical average. The result is an estimate of the absolute magnitude of each metric for each future time period. Combined with the bias-correction, this method ensures that WRF biases have a minimal impact on the results.

Workshop with SCL staff

During an hour-long webinar on February 3, 2021, CIG staff (1) provided background information on previous studies on climate extremes completed for Seattle City Light, as well as the history of the current project; (2) presented preliminary results for a subset of the metrics listed in Table 1; (3) gathered feedback on the selected climate extremes and presentation of results; and (4) discussed how these data could be used in SCL operations. During discussion, staff noted that University of Washington temperature observations are occasionally used in addition to Sea-Tac data. In response to this comment, the project team obtained temperature observations from the roof of the University of Washington Atmospheric Sciences & Geophysics building (UW ATG Building; Table 2) and used those in the analysis of all extreme temperature metrics except heating and cooling degree days. Other questions that arose during the webinar are listed in Appendix C, along with our answers to each one.

Limited Availability of Hourly Wind Observations

The availability of hourly wind observation data limited the number of SCL service area locations where we could complete analysis. For example, insufficient hourly wind data from the Arlington (Table 2) and Everett station limited the evaluation of changes in wind extremes for the “T-Lines” area between Seattle and the Skagit Project. The Tolt RAWS wind data were also unusable for two reasons: (1) a short record between 1991-1999 with very little data during winter months, and (2) the observed wind speeds ranged from 0-2 m/s, which is likely erroneous. As a result, wind extreme projections were limited to solely the Seattle Service Area geography.

Lightning

Salathé et al. (2015) evaluated changes in lightning using the composite Thunderstorm Prediction Index (TPI; Knapp et al, 2006; Knapp and Brooks, 2000). TPI is a common index used in weather forecasting; index-based approaches are commonly used with weather models since models rarely explicitly represent lightning. Other methods for estimating lightning likelihood have been explored in the literature, a brief overview of which is included in Appendix D.

However, there are a number of limitations to the approaches that are found in the literature. In particular there are relatively few studies that focus specifically on the Pacific Northwest. This is likely because lightning is much less common in the Pacific Northwest in comparison to other parts of the US. In addition, many index-based approaches require information on the sizes, types, and concentrations of ice particles in clouds. This information is not archived in the currently-available WRF simulations, nor is it clear it would be reliably estimated at the model's 12 km resolution.

Nonetheless, there are two important ways that the current study can build on Salathé et al. (2015):

1. By using observed lightning and weather conditions to validate lightning indices, and
2. By evaluating results for other lightning indices.

As described above, we used weather balloon soundings from Quileute and Spokane to obtain measurements of temperature, humidity, and winds at standard elevations throughout the atmosphere. These were compared against lightning observations from the National Lightning Detection Network (NLDN). For each site, we counted any lightning strikes occurring within a 1 degree (about 110 km) radius of the sounding location.

In addition to TPI, we evaluated the performance of the CAPE x Precipitation index proposed by Romps et al. (2014; CAPE = Convective Available Potential Energy). Since CAPE can be defined in several different ways, mainly in terms of the reference air properties that are used to estimate convective potential, we evaluated results for four different versions of CAPE:

- "CAPE" – based on the temperature and humidity at the standard 1000 hPa pressure level
- "CAPE-SFC" – based on the "surface" values for temperature and humidity, taken from the standard level of 10 m above the surface
- "CAPE-UNS" – based on the temperature and humidity that are the most unstable (most likely to initiate convection)
- "CAPE-MXD" – based on the average temperature across the lowest layer of the atmosphere (typically between 1000 and 900 hPa), as an approximation of the atmospheric boundary layer, or "mixed layer".

We found that all of the "CAPExP" indices performed nearly identically with the exception of CAPE-MXD, which generally performed worse than the other CAPE-based indices.

Figure 1 shows scatter plots of the number of lightning strikes per day, compared to the measured CAPE, precipitation, and TPI for that same day. Since CAPE and TPI can change substantially in a 24-hour period, we used the maximum daily value for each. These show some indication of a link between higher values of each index and a greater likelihood of lightning, but each plot includes thousands of points, making it difficult to discern if there is a systematic trend.

We also evaluated the correlations for all CAPExP indices and TPI, when compared against daily lightning counts. These were all very low, showing r^2 values ranging from near zero to 0.13. However correlations are not good indicators of threshold responses, and in addition may be misleading since they are disproportionately affected by anomalous values.

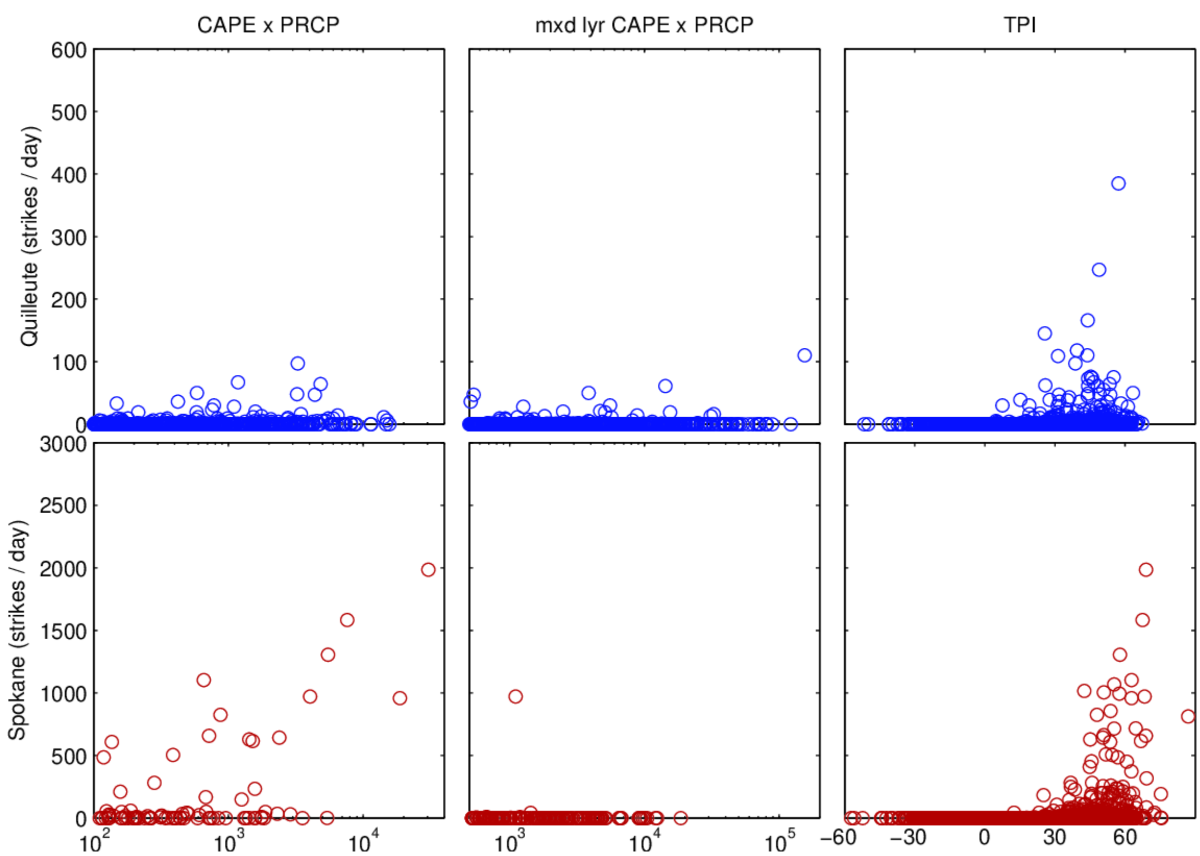

Figure 1. Scatter plots comparing lightning counts with three lightning indices: standard CAPE x precipitation (left), mixed-layer CAPE x precipitation (middle), and the Thunderstorm Prediction Index (TPI, right). Results are shown for Quileute (top) and Spokane (bottom), the two locations where weather balloons are consistently used to measure atmospheric conditions aloft.

Instead, Figure 2 includes the same information, but where we have counted the proportion of days that had lightning for a particular value of each index. Specifically, we binned the index values; for each bin, or interval, we calculated the fraction of days for which there were any lightning strikes.

From these results we can see that all three indices exhibit some positive-slope relationship with lightning probability, but that the relationship is most systematic for TPI. In addition, the TPI results suggest that the Knapp (2006) TPI thresholds of roughly 50 and 70 are likely to be good indicators of lightning probability. The results also appear to be more robust for Spokane than for Quileute, where the relationship does not appear to be strictly monotonic. This suggests that the dynamics governing lightning occurrence west of the Cascades may not be as well captured by TPI. Nonetheless, based on this initial evaluation TPI appears to be the best of the five indices we evaluated. As a result, we evaluate future lightning probability in the next section using TPI as our index. We note, however, that this was not an in-depth evaluation of lightning indices, and that more

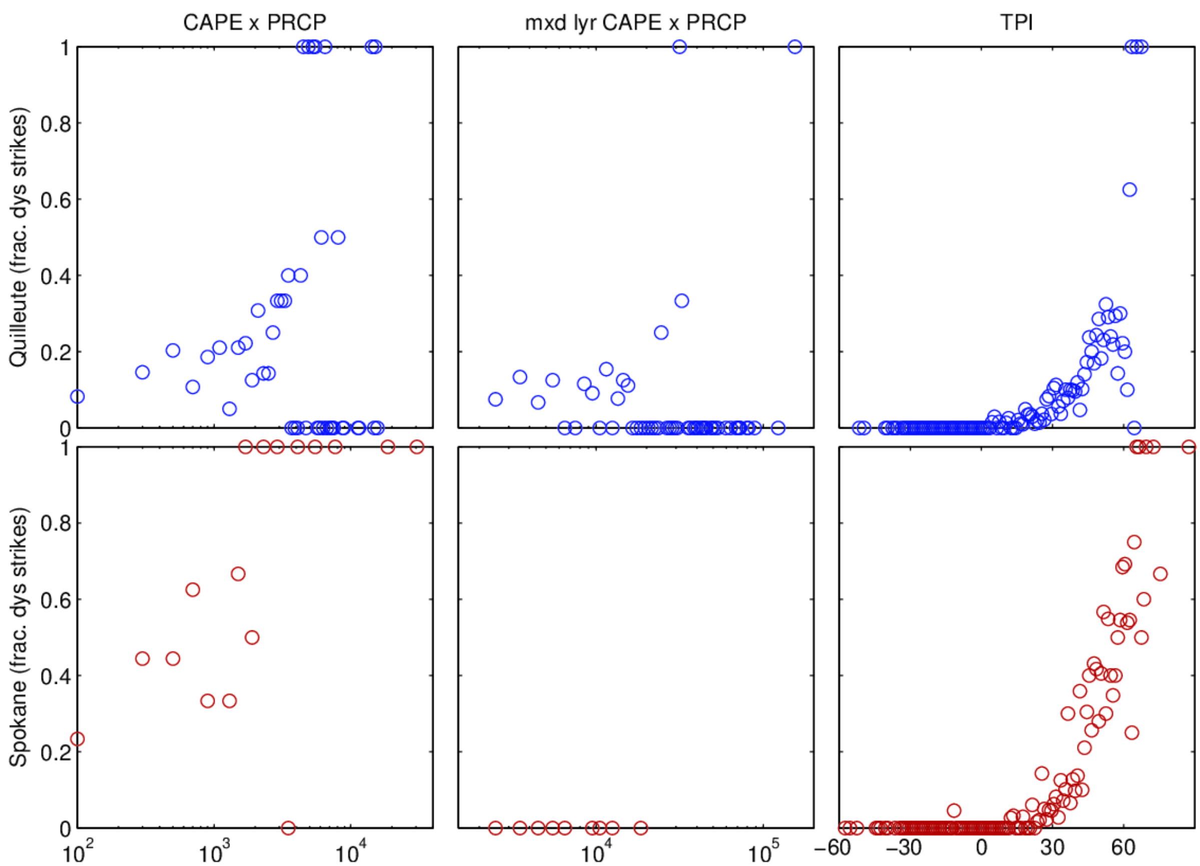

Figure 2. As in Figure 1 except the results are binned for each index and plotted against the fraction of days with lightning, which provides a rough estimate of the probability of lightning for each value of the three indices.

research would be needed to better understand the strengths and weaknesses of TPI as an indicator of lightning risk for each location of interest to SCL.

Results

Temperature and Wind Extremes

Projected changes in temperature extremes, high winds, and the fire weather metric are all summarized in the fact sheets that accompany this report. We do not summarize them here and instead refer the reader to the fact sheets to view the results.

Lightning

We did not produce fact sheets for the lightning results because we believe that further research is needed to more comprehensively evaluate approaches to estimating lightning

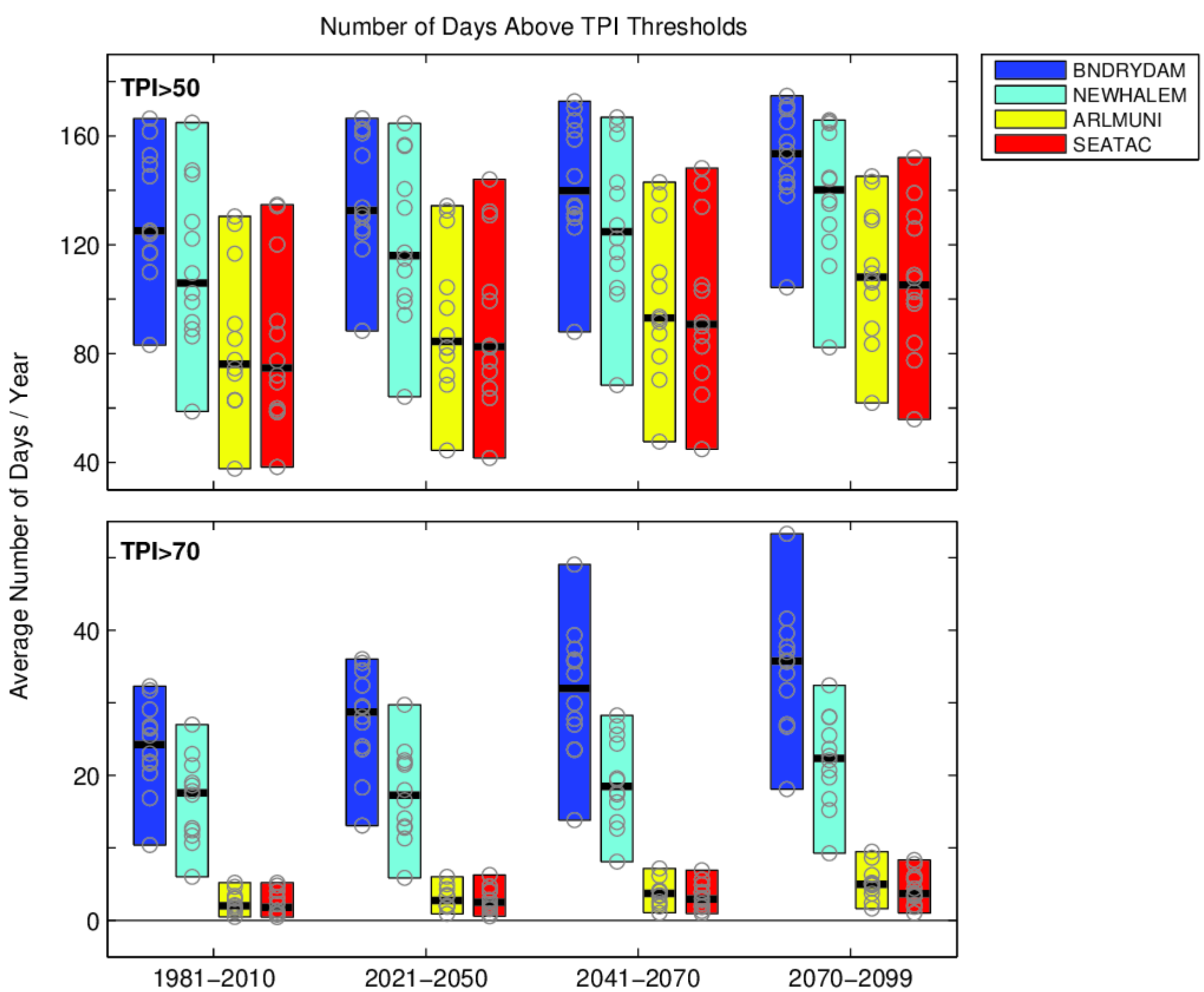

Figure 3. Average number of days per year with TPI greater than 50 (top) and 70 (bottom). Results are shown for the Boundary Project (BNDRYDAM), Skagit Project (NEWHALEM), T-Lines (ARLMUNI), and Seattle service area (SEATAC).

risk and better understand how each index performs in different locations across the Pacific Northwest. Nonetheless, we did evaluate projected changes based on the TPI index, and the projections are summarized here. As noted above, we evaluated changes for TPI thresholds of 50 and 70, since those were generally representative of relatively low and high lightning risk, respectively. We evaluate changes for the Seattle service area (Sea-Tac), the T-lines (Arlington Municipal Airport), the Skagit Project (Newhalem), and the Boundary Project.

We first consider the number of days per year that exceed each threshold. Figure 3 shows the average number of days for the historical as well as future time periods. These show that there is significantly greater lightning risk for Boundary and Newhalem than for the other two locations. Figure 4 shows the change in the number of lightning days, indicating that the four regions see increases of about the same amount in the number of days with

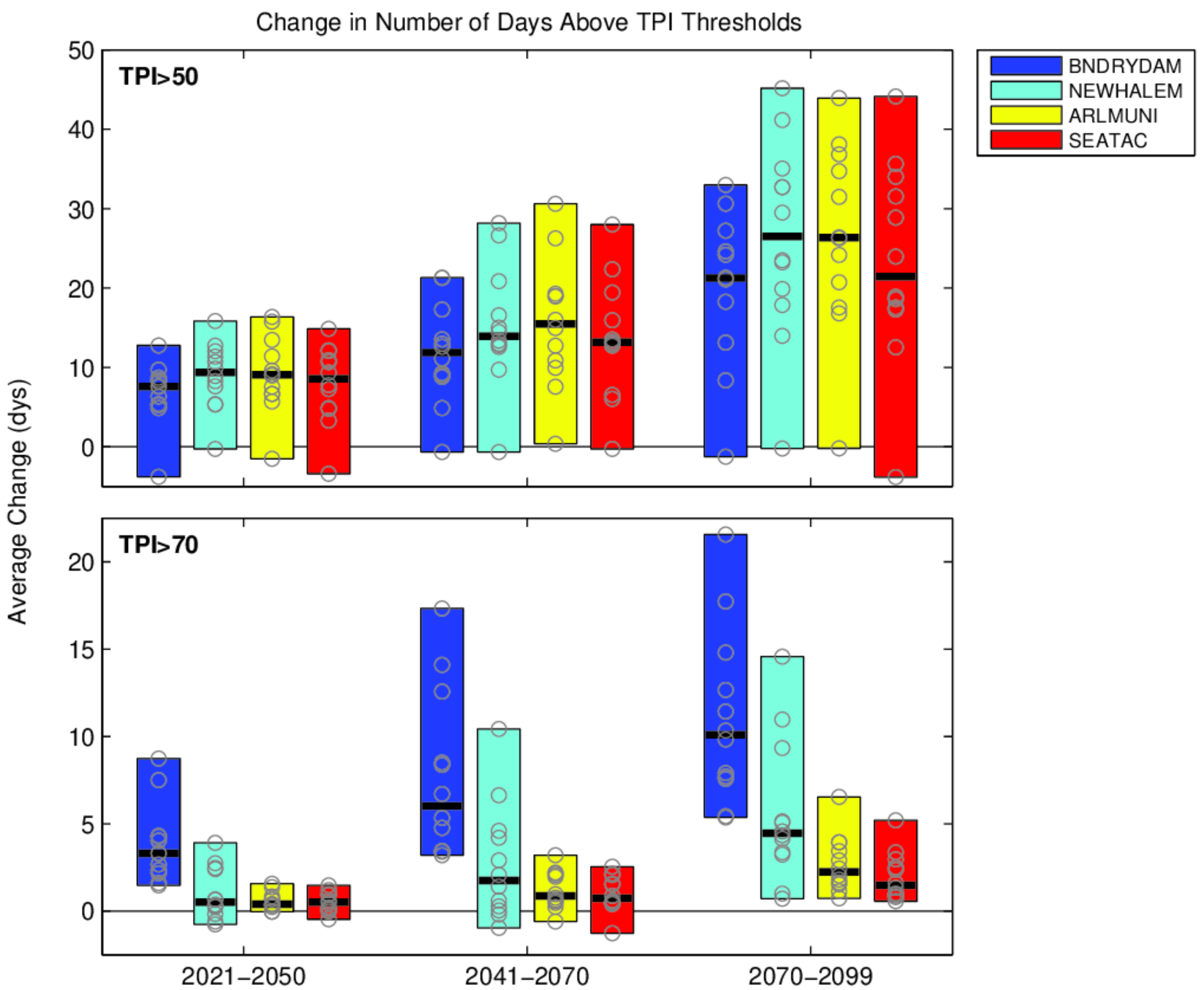

Figure 4. As in Figure 3 except showing the change in the number of days per year above each TPI threshold, relative to the average for 1981-2010.

TPI>50, but that the Boundary project is projected to see the largest and most consistent increases in the number of days with TPI>70. This is in part because TPI is so rarely above 70 for the other locations. The relative increases (not shown) are actually consistently larger for Arlington and Sea-Tac, in part because the number of days historically is so small that even small increases correspond to a large percent change at these locations.

Another factor that was discussed is the season during which lightning risk is higher. As Salathé et al. (2015) showed, there is some seasonality to lightning risk in the region, though it is not as uniquely confined to summer as in some other parts of the country. Figure 5 shows the first day of year, on average for each time period, on which TPI exceeds each threshold, while Figure 6 shows the same for the last day of the year above each threshold. The TPI>50 threshold can be exceeded almost year-round at all four locations,

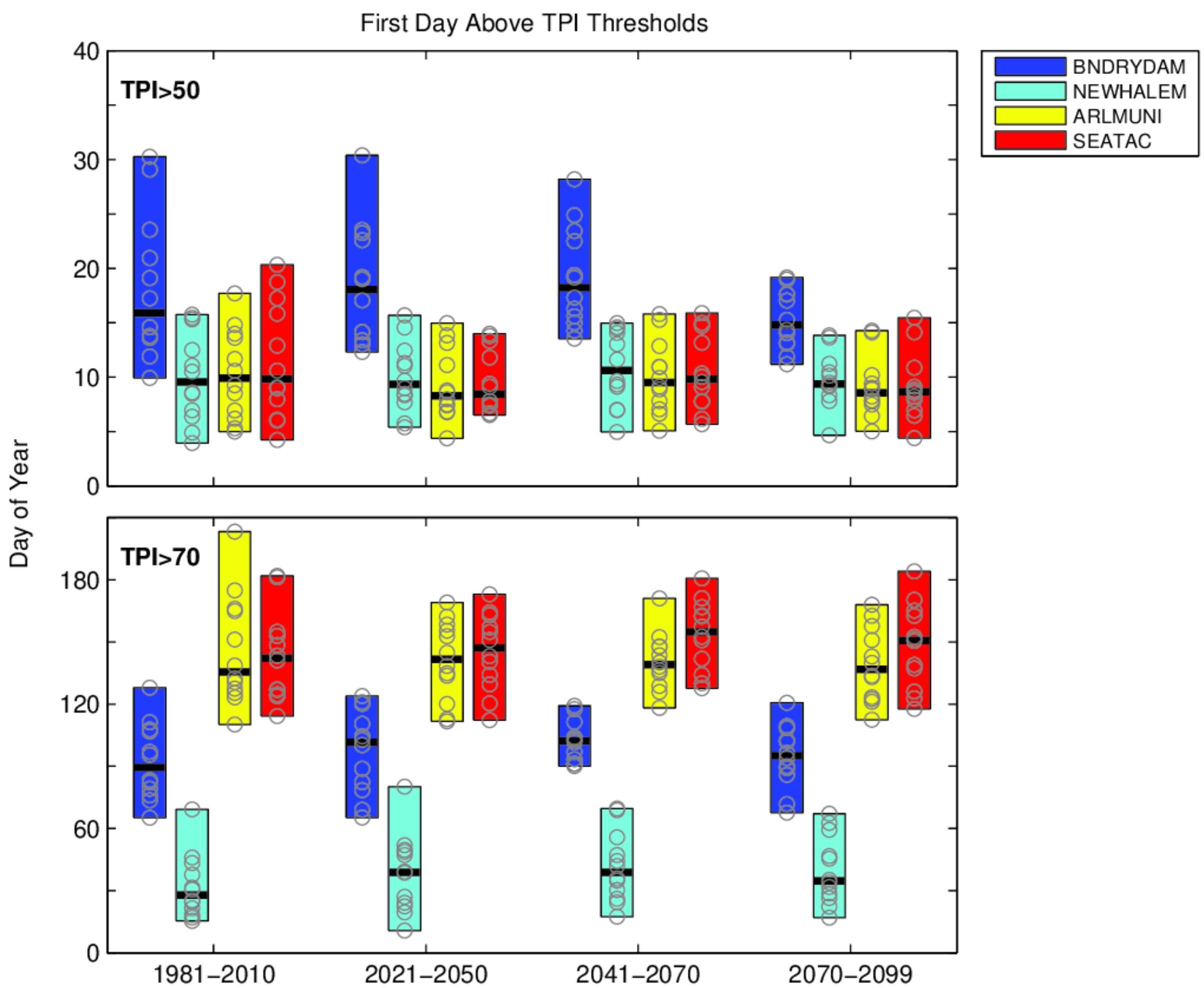

Figure 5. As in Figure 3 except showing the *first* day of year, on average, with TPI exceeding each threshold.

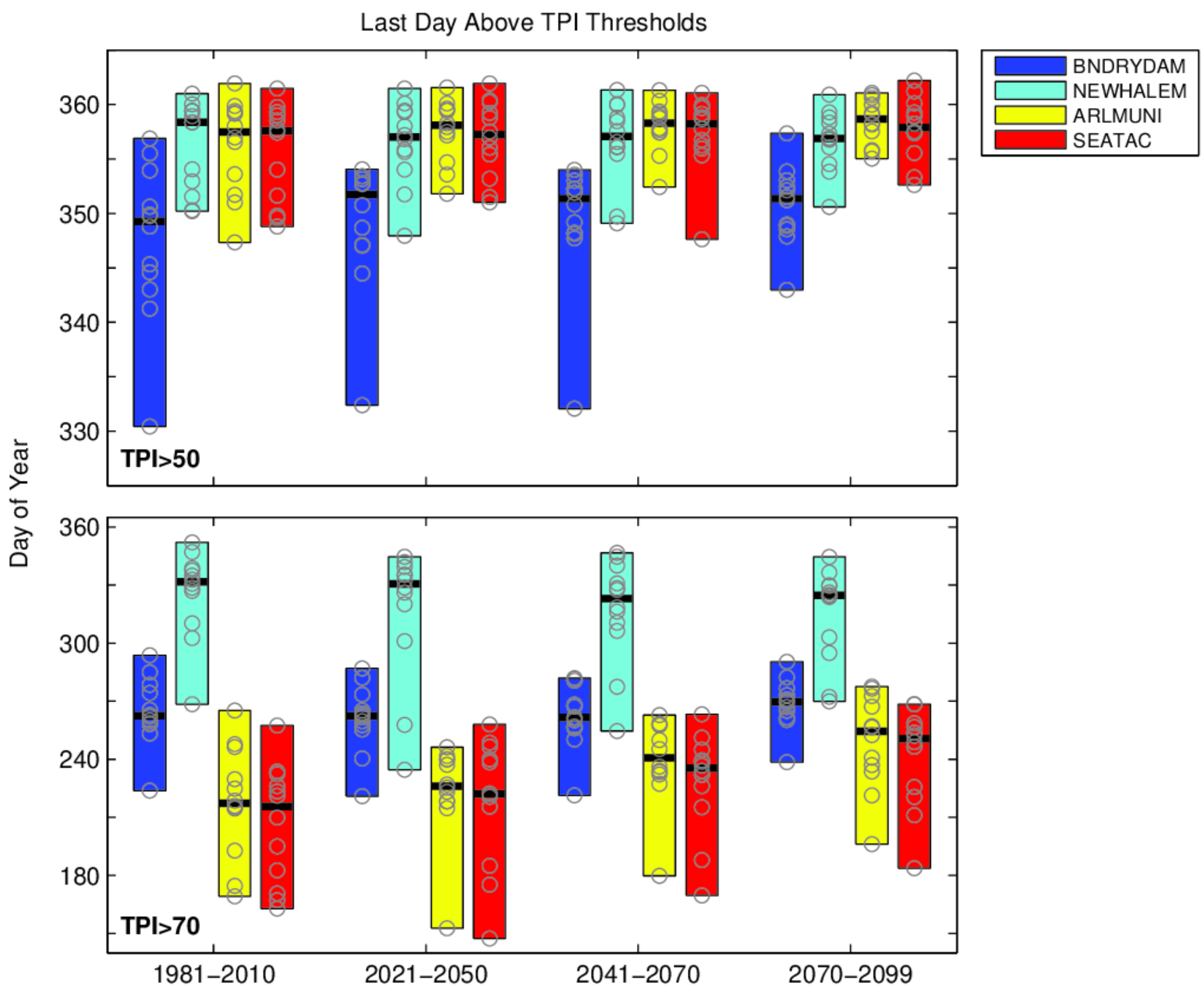

Figure 6. As in Figure 3 except showing the *last* day of year, on average, with TPI exceeding each threshold.

suggesting that it will not be a good indicator of changes in lightning seasonality. For TPI>70, however, there are notable differences among the four locations. Newhalem continues to exceed this threshold nearly year-round, while for Skagit and Arlington the first and last exceedances are around 100 days apart, on average. Boundary is in between these two extremes, showing first exceedances around April 1st (day of year = 90) and last exceedances around October 1st (day of year = 270). Figure 7 shows the changes in the first and last dates for days with TPI>70. These show that models disagree on the sign of the change, and the model average changes are also generally small for both dates at all four locations. However there does seem to be some tendency for the last exceedance to be occurring later in the future at Seattle and Arlington.

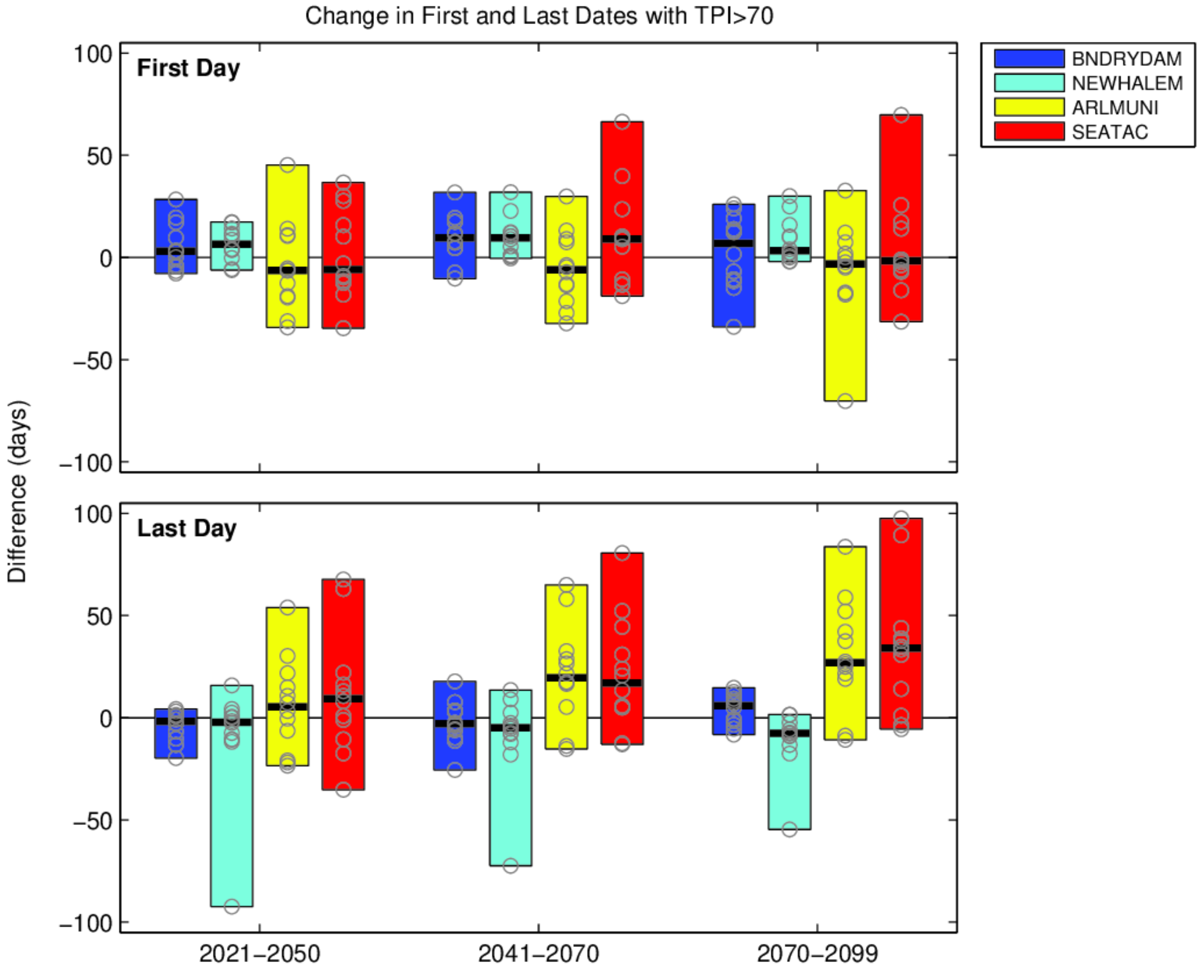

Figure 7. Change (days) in the first and last day of year, on average, with TPI>70.

Future Work

This analysis evaluated projected changes in extreme weather metrics relevant to Seattle City Light operations, planning, and standards. The process of identifying and evaluating the relevant metrics provided an opportunity to identify knowledge gaps and potential areas for future work. The areas for future work identified below are largely related to additional metric analysis. During the February 3rd workshop, SCL staff expressed interest in evaluating additional extreme metrics including projected changes in:

- heating degree day and cooling degree day analysis for UW ATG
- daily minimum temperatures associated with equipment to cooling in summer (e.g., number of days with TMIN below 30°C)
- atmospheric river frequency and intensity
- snow cover
- flood risk (Skagit and Boundary areas)
- low streamflow and high stream temperatures (Skagit Project area)
- east wind events
- temperature metric evaluation in the Tolt and Cedar area
- change in wind speed and direction after heavy rain (can push against 'hardened' poles).
- place the SeaTac and UW ATG factsheet plots on the same axis scale
- expand lightning evaluation to (a) evaluate additional lightning metrics and/or develop new ones, and (b) more thoroughly explore their performance for different locations across the PNW

References

Brewer, M. C., & Mass, C. F. (2016). Projected changes in western US large-scale summer synoptic circulations and variability in CMIP5 models. Journal of Climate, 29(16), 5965-5978. https://doi.org/10.1175/JCLI-D-15-0598.1

Cramer, O. P. 1957. Frequency of dry east winds over northwest Oregon and Southwest Washington. Pacific Northwest Forest and Range Experiment Station. U.S. Department of Agriculture Forest Service. Portland, OR. https://www.fs.usda.gov/treesearch/pubs/26050

Chen, X.D., Leung, L.R., Gao, Y., Liu, Y., Wigmosta, M., Richmond, M., 2018. Predictability of extreme precipitation in western US watersheds based on atmospheric river occurrence, intensity, and duration. Geophys. Res. Lett. 45 (21), 11693–11701. https://doi.org/10.1029/2018GL079831

Durre, Imke; Xungang, Yin; Vose, Russell S.; Applequist, Scott; Arnfield, Jeff. (2016) Integrated Global Radiosonde Archive (IGRA), Version 2. NOAA National Centers for Environmental Information. https://doi.org/10.7289/V5X63K0Q. Accessed June 2021.

Knapp, D. I., Range, W. S. M., Barker, E., Brooks, G. R., & Rentschler, S. (2006, February). Comparisons and verification of an automated thunderstorm potential index output to manual products. In 12th Conference on Aviation Range and Aerospace Meteorology. https://ams.confex.com/ams/Annual2006/webprogram/Paper100953.html

Knapp, D. I., & Brooks, G. R. (2000, September). Use of a new thunderstorm potential index for 12-hour forecasts using mesoscale model data. In Preprint, 9th Conf. on Aviation, Range, and Aerospace Meteorology. J54-58.

Lorente-Plazas, R., Mitchell, T.P., Mauger, G., Salathé, E.P., 2018. Local Enhancement of Extreme Precipitation during Atmospheric Rivers as Simulated in a Regional Climate Model. American Meteorological Society, 19:1429-1446. https://doi.org/10.1175/JHM-D-17-0246.1

Mauger, G.S. and J.S. Won. 2021. Bias-Corrected and Dynamically-Downscaled Hourly Temperature Projections for Sea-Tac. Report prepared for Seattle City Light. Climate Impacts Group, University of Washington.

Mauger, G.S., J.S. Won, 2019. Expanding the ensemble of precipitation projections for King County. Report prepared for the King County Department of Natural Resources. Climate Impacts Group, University of Washington, Seattle.

https://cig.uw.edu/publications/expanding-the-ensemble-of-precipitation-projections-for-king-county/

Mauger, G.S., J.S. Won, K. Hegewisch, C. Lynch, R. Lorente Plazas, E. P. Salathé Jr., 2018. New Projections of Changing Heavy Precipitation in King County. Report prepared for the King County Department of Natural Resources. Climate Impacts Group, University of Washington, Seattle. https://cig.uw.edu/publications/new-projections-of-changing-heavy-precipitation-in-king-county-2/

Mauger, G.S., S.-Y. Lee, C. Bandaragoda, Y. Serra, J.S. Won, 2016. Refined Estimates of Climate Change Affected Hydrology in the Chehalis basin. Report prepared for Anchor QEA, LLC. Climate Impacts Group, University of Washington, Seattle. https://doi.org/10.7915/CIG53F4MH

Salathé, E.P., Leung, L.R., Qian, Y., Zhang, Y. 2010. Regional climate model projections for the State of Washington. Climatic Change 102(1-2): 51-75, doi: 10.1007/s10584-010-9849-y. https://doi.org/10.1007/s10584-010-9849-y

Salathé Jr, E. P., Hamlet, A. F., Mass, C. F., Lee, S. Y., Stumbaugh, M., & Steed, R. (2014). Estimates of twenty-first-century flood risk in the Pacific Northwest based on regional climate model simulations. Journal of Hydrometeorology, 15(5), 1881-1899. https://doi.org/10.1175/JHM-D-13-0137.1

Skamarock, W. C., Klemp, J. B., Dudhia, J., Gill, D. O., Barker, D., Duda, M. G., ... Powers, J. G. (2008). A Description of the Advanced Research WRF Version 3 (No. NCAR/TN-475+STR). University Corporation for Atmospheric Research. https://doi.org/10.5065/D68S4MVH

Snover, A. K., A. F. Hamlet, S.-Y. Lee, N. J. Mantua, E. P. Salathé, Jr, R. Steed, I. Tohver. 2010. "Seattle City Light Climate Change Analysis: Climate change impacts on regional climate, climate extremes, streamflow, water temperature, and hydrologic extremes." Prepared for The City of Seattle, Seattle City Light by The Climate Impacts Group, Center for Science in the Earth System, Joint Institute for the Study of the Atmosphere and Ocean, University of Washington. June. https://cig.uw.edu/publications/seattle-city-light-climate-change-analysis/

Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2012). An overview of CMIP5 and the experiment design. Bulletin of the American Meteorological Society, 93(4), 485-498. https://doi.org/10.1175/BAMS-D-11-00094.1

Van Vuuren, D., J. Edmonds, M. Kainuma, K. Riahi, A. Thomson, K. Hibbard, G. Hurtt, T. Kram, V. Krey, J. Lamarque, T. Masui, M. Meinshausen, N. Nakicenovic, S. Smith, S.

Rose, 2011: The representative concentration pathways: an overview. Climatic Change, 109: 5-31. http://dx.doi.org/10.1007/s10584-011-0148-z

Appendix A – Metrics Definitions

Table A1. Definitions for each extreme weather metrics used to evaluate the frequency of extreme temperature, wind, fire, and lightning events. The right-hand column lists the units for each metric.

Metric	Definition	Units
Cold Temperatures		
Heating Degree Days	Annual sum of degrees below a base temperature of 65°F, as measured by the daily mean temperature.	°F-days
Annual Minimum Temperature	Minimum hourly temperature for the calendar year.	°F
Consecutive Cold Days	Longest stretch of consecutive days with minimum temperature at or below 25°F for the calendar year.	days
Cold Extremes	Annual number of hours below 14°F	hours
Freeze-Thaw cycles	Number of days with maximum temperature above freezing and minimum temperature below freezing.	days
Warm Temperatures		
Cooling Degree Days	Annual sum of degrees above a base temperature of 65°F (units: °F-days), as measured by the daily mean temperature.	°F-days
Annual Maximum temperature	Maximum hourly temperature for the calendar year.	°F
Consecutive Warm Days	Longest stretch of consecutive days with maximum temperature above 85°F for the calendar year.	days
Heat Extremes	Annual number of hours above 98°F	hours
Hours with Temperature above 86°F	Number of hours with hourly average temperature >86°F.	hours
High Winds		
Wind (Non-Consecutive high wind hours)	Number of hours with gusts above 30, 40, and 50 mph.	hours
Wind (Consecutive high wind hours)	Maximum number of consecutive hours with gusts above 30, 40, and 50 mph.	hours
Number of Windstorms	Number of storms between August and October. A “storm” is defined as a 48-hour period in which gusts at any point exceed 30, 40, and 50 mph.	none

Metric	Definition	Units
Fire Weather		
High Wind & Low Humidity	Number of days per year when hourly RH is less than 36% and wind speed is greater than 9 mph for at least 2 hours out of the day. Based on Cramer (1957).	days
Lightning		
Number of Strikes	Number of cloud-ground lightning strikes within a designated geographic area.	none
Seasonal timing of strikes	Day of year with highest likelihood of lightning.	day of year

Appendix B – Integral Analytics Memo

Integral Analytics – LoadSEER Weather Analysis Discussion

Summary

Intentionally, there are multiple approaches/methods to Calculate Weather Probabilities in LoadSEER. In general, LoadSEER has 3 applications of weather: Annual Circuit Peak Forecasting, Monthly/Seasonal Energy Forecasting, and Hourly Load Shape Forecasting. Each application of weather requires a different set of weather statistics: annual temperature stats, HDD/CDD, and hourly temperature, respectively. In all applications, we recommend starting with 30 years of historic hourly temperature to support the analysis. It is also common to collaborate with our clients to ensure consistency with system and distribution planning groups.

Applications

In the first two applications (annual peak, and monthly/seasonal energy forecasting), we calculate percentiles on historically observed temperature values directly, and choose a temperature value near the 95th percentile to determine a corresponding 1-in-10 temperature (this decision varies dependent upon the amount of available historic temperature observations). Similarly, we choose a percentile between the 50th and 75th for 1-in-2, and between 75th and 90th for 1-in-5. This approach is applied to both temperature and HDD/CDD statistics, where we calculate 30 years of HDD and CDD values.

1) **Annual Circuit Peak Forecasting-** Regression analysis of annual Circuit Peak Loads vs Temperature. We calculate weather statistics for each weather station, by (1) starting with hourly data (8760 * 30 years), (2) find the max temperature per year (i.e., 30 values), and then (3) use a Percentile function on the dataset from step #2 to get the different percentiles (2, 5, 10, 25, 75, 90, 95, 98). This gives us a starting point and relationships between, say, 1-in-2 and 1-in-10 temperatures at the weather station.

   The LoadSEER-FIT application does not always apply the 1-in-X temperature from the weather station directly to a circuit's peak regression model, as the historic peaks for a given circuit may have occurred on days with lower or higher average temperatures compared to averages of all days at a station. In these cases, we use the relationship (percent difference) between 1-in-2 and 1-in-10 at the station, and apply it to the given circuit's 1-in-2 temperature, based on the average of the observed temperatures on the days that circuit peaked.

   a. Optional Weather Statistics for load driven by hot temperatures:
      i. Max Low Temperature
      ii. Max High Temperature
      iii. Max 3-Day Weighted-Avg Low Temperature
      iv. Max 3-Day Weighted-Avg High Temperature
      v. Max 3-Day Weighted-Avg Low-High Interaction
   b. Optional Weather Statistics for load driven by cold temperatures:
      i. Min Low Temperature
      ii. Min High Temperature
      iii. Min 3-Day Weighted-Avg Low Temperature
      iv. Min 3-Day Weighted-Avg High Temperature
      v. Min 3-Day Weighted-Avg Low-High Interaction

2) **Monthly/Seasonal Circuit MWH Forecasting-** Econometric regression analysis of monthly/seasonal Circuit MWH usage. We use the CDD and HDD statistics from the weather station for each circuit assigned to that station. The 1-in-X CDD and HDD are calculated using a Percentile function on the dataset of past available weather history at each station, to get different percentiles (2, 5, 10, 25, 75, 90, 95, 98).

   a. Weather Statistics for load driven by hot temperatures:

Integral Analytics – LoadSEER Weather Analysis Discussion

i. CDD

b. Weather Statistics for load driven by cold temperatures:

i. HDD

In the third application (hourly load modeling), we build an hourly load vs hourly temperature regression model, apply 30 years of hourly temperature values. We calculate percentiles on the resulting loads (8760 x 30), and choose a predicted **load** near the 95th percentiles to determine a corresponding 1-in-10 load. We often refer to this application as a load normalization method, by including other variables (such as day of week), to distinguish it from univariate weather normalization analysis.

3) **Hourly Load Shape Modeling and Forecasting-** For example**,** we assume that 30 years represents the maximum range of loads for planning, and we are able to simulate 30 years of load forecasts in our models and 30 years of weather. Assuming these load forecasts are normally distributed, and using 2 tail tests, the following probabilities of observations result, see FIGURE 1 below as an *example*.

   The highest value is assumed to be 3.5 standard deviations above the mean, and shown as the Max Forecast in both cases. Within the peak load month, we simulate 20 weekdays across 30 years of weather, totaling 600 forecasts. Given this quantity, we expect 1 observation of the 600 to lie within 2.56 Std Dev, or the 99th percentile, as a two tail statistical test result. Since we only have 30 years of simulated data, we expect 3 times this amount, or 3 such results across 100 years of forecasts, if we were to have done that. We can call this 3 in 100 year result, loosely speaking, a 1 in 33 or 1 in 30 year possibility. The more useful load forecast value is the 95th confidence level, with an expected 5 observations in our data, and loosely a 1 in 7 or 1 in 10 year possibility. The 90th percentile value should produce 9 load forecasts at or above this level, in our 30 years of data, or loosely speaking, a 1 in 3 to 1 in 5 year possibility.

	Percentile 2 Tail	Z Score	Normal Distribution Percent Value	Maximum Number Expected in 100 years	Number Expected In 30 Yrs of Simulation	"1 in X" Year Approximation
Data Modeling Has:						
30 Years	**90th**	**1.65**	**4.97%**	**30**	**9**	**3**
20 Weekdays	**95th**	**1.96**	**2.52%**	**15**	**5**	**7**
1 Months	**99th**	**2.56**	**0.54%**	**3**	**1**	**30**
600 Load Forecasts	**Max**	**3.5**	**0.02%**	**1**	**1**	**100**

FIGURE 1 – CONCEPTUAL EXAMPLE OF HOURLY LOAD DISTRIBUTION AND 1-IN-X APPROXIMATION.

Additional Comments

The methods described above are flexible and we often implement variations of them according to our clients and their unique climate. Below is a brief summary of generalized implementations we seen and or used in the past.

1. When only one weather variable, e.g., temperature, is used in the model, collect data on the highest temperature value in each of the years of history. Assuming 30 years, this means you have 30 data points to draw from in establishing the probability thresholds. Options include:
   a. Compute the mean and standard deviation of the 30 data points and using the standard deviation add 1.645 times to the mean for a 1 in 10 level (10% chance of being higher). This assumes the data is normally distributed.
   b. One could do the same assuming a different probability distribution such as a log normal or an extreme value distribution.

Integral Analytics – LoadSEER Weather Analysis Discussion

   c. Another option is to just ignore the type of distribution and sort the data from high to low. For thirty data points, the third highest could be used as the 1 in 10 temperature.

2. Finally, one could apply the peak forecasting model to the 30 data points and then evaluate the 1 in 10 using the estimated loads and one of the methods a through c above.
3. If multiple weather variables, e.g., temperature and humidity on a 1day and the maximum temperature for the prior day, are included in the forecasting model, one must go to a weather index. This involves simulating the model through the 30 years of daily weather data where the weather data for the day is configured the same way as for the forecasting model. For example, it might be the high temperature for the day and the humidity at the time of the high temperature and the maximum temperature for the prior day. After simulating the model through 30 years of daily weather data (for a summer peak, probably all days June through September for 30 years), pick the highest load values from each of the thirty years. Then, one can use methods a through c above to identify the 1 in 10 load. From that, one can identify the 1 in 10 weather conditions.

Appendix C – Q&A from SCL Extremes Webinar

The following questions arose during our webinar with SCL staff on February 3rd, 2021. We have included detailed answers below for each.

Can we say where in the service area lightning will be more likely? Seem to see more at higher elevations.

Our modeling is not detailed enough to provide the spatial distribution of current or future lightning. Our focus in this project is on assessing the change in the likelihood of lightning in the future, on average, for each focus area (Seattle, Skagit, Boundary, etc.)

SCL staff sometimes use UW temperature observations in addition to Sea-Tac. These observations are used to generate fine scale load forecast for a few northern substations to assess peak loads.

- We have obtained temperature observations from the roof of the UW ATG building and used those in our analysis of all extreme temperature metrics except heating and cooling degree days.

Could you provide results for temperatures in the foothills of the Tolt/Cedar?

We have gridded data that could be analyzed for this area: our models cover all of the Pacific Northwest. However, when we inspected the observations for the Tolt (RAWS network) they were either too limited (temperature) or seemed to have major biases (wind). As a result we didn't calculate any changes for these locations. In future work our modeling could still be used to assess changes, we would simply not be able to use the observations in order to bias-adjust the results.

We typically have to plan around "normal" weather conditions. How is that defined in the climate models, historically and in the future? How could I look at a moving window definition of "normal" conditions?

We define "normal" as the 30-year average condition. In this project we are using 1981-2010 for the historical time period and 2021-2050 and 2051-2080 for the future time periods. Our results take the change between each future time period and our historical time period, and apply these to the observed value as used by SCL. We do this to minimize the effect of biases in the models, and to ensure the results are as directly applicable to SCL operations as possible.

In this project we looked at the differences from historical to just two discrete future periods. We could instead take a moving window approach in which we calculate the "normal" for 1981-2010, 1982-2011, 1983-2012, etc., on through 2070-2099. We have provided data files with hourly temperature and wind data for 1970-2099; these could be used to calculate each metric and the associated moving average "normals".

Does the future dataset include La Nina/El Nino cycles?

Yes. Each model includes variability, including El Niño and other natural cycles. Research suggests that these natural cycles will not change substantially as a result of climate change. The timing and magnitude of these is random and cannot be predicted. For example: there is no way of knowing if 2051 will be an El Niño, neutral, or a La Niña, nor is it possible to know how strong of an event it might be. This is why we define "normal" as the 30-year average condition: doing so averages out these natural (and unpredictable) fluctuations, so that we can instead focus on the long-term trend.

There are multiple model projections for the future. How do we select which one to use?

We do not recommend picking just one model: models are not always consistently at one end of the range, when compared to other models, and there are no clear "winners" – models that outperform others across the board.

Instead, we recommend taking the average and range among the 12 regional climate projections. In some cases it may be sufficient to consider only the average projection while in others you may want to consider more pessimistic projections (e.g.: the 90th percentile). The best approach depends on your risk tolerance and the opportunity costs associated with planning for larger impacts.

We would like to see flood and drought risk in addition to fire risk. This is important for fish as well as for resource adequacy in both the Skagit & Boundary projects, as well as the Tolt and the Cedar Rivers.

This isn't the focus of our current project. However, the following resources may be helpful:

(1) Recent streamflow modeling has been completed for the Skagit River watershed that includes high and low flows:
http://www.skagitclimatescience.org/projected-changes-in-streamflow/

(2) The CIG has just developed a new tool for looking at projected changes in precipitation extremes across the region:
https://cig.uw.edu/projects/heavy-precipitation-projections-for-use-in-stormwater-planning/

(3) The CIG is working with King County and SPU to develop improved current and future streamflow estimates for the Snoqualmie, Cedar, Green, and White Rivers. This work is ongoing; past reports are available here:
https://cig.uw.edu/our-work/applied-research/effect-of-climate-change-on-flooding-in-king-county-rivers/

How might Atmospheric Rivers change in the future? In terms of both frequency and intensity?

We are not considering precipitation in the current project. However, the CIG has just developed a new tool for looking at projected changes in precipitation extremes across the region: https://cig.uw.edu/projects/heavy-precipitation-projections-for-use-in-stormwater-planning/

Research on this topic is ongoing. For example, the following article summarizes a recent study finding that "windy ARs" tend to bring more precipitation than those with lower winds: https://eos.org/articles/atmospheric-rivers-have-different-flavors. See also Warner et. al., 2015, for a classic paper on the topic. We have not reviewed the literature comprehensively, but could do so in future work.

System planning typically uses 30°C (~85°F) in their line rating for summertime heat and this standard is for SCL's entire system. Should they be higher? Should the standards be different for difference locations? (e.g., Seattle vs the Skagit project)

We provide results for two relevant metrics:

1. Warm Spells: Number consecutive days with daily maximum temperatures above 85°F. Provided for the Seattle Service Area.
2. Hours > 86°F: Number of hours with hourly average temperature above 86°F. Provided for the Seattle Service Area, T-Lines, and Skagit Project.

These will provide measures of high temperatures and how these are projected to change over time. This information could be reviewed to determine if the planning threshold should be adjusted.

Daily minimum temperatures allow equipment to cool in summer; nighttime cooling is critical and could be less effective in the future. Could you add a metric to account for this, such as the number of days with TMIN below 30°C?

This would be straightforward to add but is beyond the scope of our current project. Would this work as a definition of the metric: Number of days in July-September with TMIN<30°C? It sounds like this would be most important to assess for Sea-Tac and the UW observations.

We are interested in changes in snowpack. Can you provide projections for this?

This is not the focus of the current project. Some information may be available as part of the Bandaragoda et al. work mentioned above:

http://www.skagitclimatescience.org/projected-changes-in-streamflow/
Their hydrologic models accounts for changes in snowpack and glaciers.

East wind events could be an important predictor for low streamflow conditions. Did you consider wind direction?

We focused on peak wind events, using the WindWatch thresholds, and winds/humidity associated with fire. In both cases we found that there wasn't a strong dependence on the local wind direction. Nonetheless, this is something that could be studied more in a future project: east wind events do bring warm and dry conditions in summer, and should be a good indicator of short time-scale fluctuations in flows. Local wind direction is influenced by many factors and may not be a good indicator of regional winds, so future work should consider wind from stations across the region as an indicator (e.g.: Enumclaw may be a good choice, located west of a "gap" in the Cascade range).

Appendix D – Bibliography of Lightning Literature

The following citations and brief synopses provide a preliminary look at the literature on lightning observations and modeling. *This list is not comprehensive and is best viewed as a starting point for further investigation.*

Battan, L. J. (1965). Some factors governing precipitation and lightning from convective clouds. Journal of Atmospheric Sciences, 22(1), 79-84.

> Early paper associating CG lightning with Precipitation intensity. Focused on southern AZ.

Blanchard, D. O. (1998). Assessing the vertical distribution of convective available potential energy. Weather and Forecasting, 13(3), 870-877.

> Makes the case for using “NCAPE” (CAPE normalized over the layer depth that is used for integration). Most valuable in areas depth of free convection is shallow or CAPE is small. Seems like main point is that it is similar to LI, so it might be redundant to using the TPI (Knapp, 2006).

Bright, D. R., Wandishin, M. S., Jewell, R. E., & Weiss, S. J. (2005, January). A physically based parameter for lightning prediction and its calibration in ensemble forecasts. In Preprints, Conf. on Meteor. Appl. of Lightning Data, Amer. Meteor. Soc., San Diego, CA (Vol. 3496, p. 30).

> Introduces the “Cloud Physics Thunderstorm Parameter” (CPTP). Combined with precipitation, this can be used as a proxy for thunderstorm potential. Focus of the paper is on thunderstorms, but the verification statistics include lightning. Focus is CONUS; results are not separated by region.

$$CPTP = \begin{cases} \dfrac{(\text{-}19°\mathrm{C} - T_{EL})(CAPE_{\text{-}20} - K)}{K}, & T_{LCL} > \text{-}10°\mathrm{C} \\ 0, & T_{LCL} \leq \text{-}10°\mathrm{C} \end{cases}$$

$$T_{LCL} = Temperature\ of\ most\ unstable\ parcel\ at\ its\ LCL$$

$$T_{EL} = Equilibrium\ Level\ Temperature\ (should\ be \leq \text{-}20°\text{C})$$

$$CAPE_{\text{-}20} = CAPE\ in\ the\ 0°\text{C}\ to\ \text{-}20°\text{C}\ layer$$

$$K = empirical\ constant. Typically\ 100\ J/kg\ \ over\ CONUS$$

Changnon, S. A., & Changnon, D. (2001). Long-term fluctuations in thunderstorm activity in the United States. Climatic Change, 50(4), 489-503.

Evaluated long-term fluctuations and trends in thunderstorm occurrence for 86 high-quality station records across CONUS. Measurements stem from actually hearing thunder at a NWS office. Found upward trend in PNW.

500 STANLEY A. CHANGNON AND DAVID CHANGNON

Figure 7. Regions based on linear trends of the 100-year values at 86 stations. Up is for increasing trend significant at the 10% or lower level, flat is essentially no significant trend up or down, and down is for decreasing trends significant at the 10% or lower level.

Clark, S. K., Ward, D. S., & Mahowald, N. M. (2017). Parameterization-based uncertainty in future lightning flash density. Geophysical Research Letters, 44(6), 2893-2901.

CAM5 intercomparison among lightning parameterizations. Global. Found best correlation with satellite obs for parameterizations based on cloud top height or "cold cloud depth". No maps/details on regional performance of each.

Dementyeva, S. O., Ilin, N. V., & Mareev, E. A. (2015). Calculation of the lightning potential index and electric field in numerical weather prediction models. Izvestiya, Atmospheric and oceanic physics, 51(2), 186-192.

Validation of the Lightning Potential Index (LPI) for various WRF microphysics parameterizations. Spatial domain is “European Russia”. LPI is not applicable in our case because we lack the microphysics information needed.

Estberg, G. N., Norris, S., & Hutten, K. M. (2008). Year-in-advance prediction of lightning activity for the pacific northwest. Northwest Science, 82(2), 151-157.

Use climate indeces to forecast lightning activity one year in advance, using a simple linear combination of MEI (Multivariate ENSO Index) and WNPMI (Western N Pac. Monsoon Index) values from the year prior. The model explains 30% of the variance in the observations (r^2=0.3), and these indices may not be reliably reproduced by GCMs.

Finney, D. L., Doherty, R. M., Wild, O., Stevenson, D. S., MacKenzie, I. A., & Blyth, A. M. (2018). A projected decrease in lightning under climate change. Nature Climate Change, 8(3), 210-213.

Study builds on previous work by same author (notably their 2014 paper), comparing microphysical (“IFLUX”) to cloud top height (“CTH”) approaches for estimating lightning rates. Whereas CTH estimates universally show increases in lightning frequency, IFLUX shows a decrease. Study focuses on global average change, and the biggest differences between the approaches are in the tropics. The maps make it difficult to discern the differences for the PNW but it looks like the results are similar except east of the Rockies and in BC.

Kaltenböck, R., Diendorfer, G., & Dotzek, N. (2009). Evaluation of thunderstorm indices from ECMWF analyses, lightning data and severe storm reports. Atmospheric Research, 93(1-3), 381-396.

Analysis of severe storms database in Europe to see how those can be predicted from atmospheric conditions. Most relevant to lightning: CAPE is a good tool for distinguishing between ordinary thunderstorms and those that contain a significant amount of hail – needed for lightning generation.

Knapp, D. I., Range, W. S. M., Barker, E., Brooks, G. R., & Rentschler, S. (2006, February). Comparisons and verification of an automated thunderstorm potential index output to manual products. In 12th Conference on Aviation Range and Aerospace Meteorology.

Updated report on Thunderstorm Potential Index (TPI). Suggest a threshold value of ~50% can be used for presence/absence of thunderstorms. TPI tends to overforecast lightning in summer. Study considered full CONUS; difficult to interpret figures so unclear how performance is different for PNW.

For model grid cells with elevations below 850 hPa:

$$TPI = (0.1795 + 0.0073 \cdot K - 0.0149 \cdot LI + 0.0008 \cdot SWEAT) \cdot 100$$

$$K = T_{850} + Td_{850} - T_{500} - DD_{700}$$

$$LI = T_{500,envir} - T_{500,parcel}$$

$$SWEAT = 12 \cdot Td_{850} + 20 \cdot (TT - 49) + 2 \cdot WSpd_{850} + WSpd_{500} + 125 \cdot (\sin 850\ v\ 500\ wind\ dir + 0.2)$$

$$TT = (T_{850} - T_{500}) + (Td_{850} - T_{500})$$

For model grid cells with elevations above 850 hPa:

$$TPI_{850} = (0.2101 + 0.7611 \cdot PW - 0.054 \cdot LI) \cdot 100$$

Krause, A., Kloster, S., Wilkenskjeld, S., & Paeth, H. (2014). The sensitivity of global wildfires to simulated past, present, and future lightning frequency. Journal of Geophysical Research: Biogeosciences, 119(3), 312-322.

GCM simulations of future wildfire, accounting for changes in lightning. Uses the cloud top height relationship of Price & Rind (1992). Wildfire results seem really noisy; may not be worth considering.

Meijer, E. W., Van Velthoven, P. F. J., Brunner, D. W., Huntrieser, H., & Kelder, H. (2001). Improvement and evaluation of the parameterisation of nitrogen oxide production by lightning. Physics and Chemistry of the Earth, Part C: Solar, Terrestrial & Planetary Science, 26(8), 577-583.

Focused on NOx forecasts for Europe. Found best correlation between lightning and convective precipitation in ECMWF forecasts.

Owens, M. J., Scott, C. J., Lockwood, M., Barnard, L., Harrison, R. G., Nicoll, K., ... & Bennett, A. J. (2014). Modulation of UK lightning by heliospheric magnetic field polarity. Environmental Research Letters, 9(11), 115009.

Example of a class of studies showing observational evidence for a link between solar activity and lightning. This paper focuses on the polarity of the "Heliospheric Magnetic Field" (HMF). The study only considered 5 years (2001-06) but suggests a ~50% difference in lightning activity in response to changes in polarity. However this is probably not relevant for climate studies since the polarity flips about every 7-14 days, on average, on Earth – and there is no indication of a long-term trend. In addition, studies appear to disagree on the sign of HMF effects depending on the length of record and location evaluated.

Petersen, W. A., & Rutledge, S. A. (1998). On the relationship between cloud-to-ground lightning and convective rainfall. Journal of Geophysical Research: Atmospheres, 103(D12), 14025-14040.

Calculated "rain yields", in kg/flash, calculated on a monthly basis as the ratio of convective rain mass to cloud-to-ground flash count. Reviews results from other studies; most non-tropical locations center around 10^8 kg/fl. Study did not consider PNW.

Price, C., & Rind, D. (1992). A simple lightning parameterization for calculating global lightning distributions. Journal of Geophysical Research: Atmospheres, 97(D9), 9919-9933.

Early paper on lightning proxies. Presents an empirical relationship -- based on data from Florida, New Mexico, and New England – relating flash rate to the ~5th power of cloud top height. Also shows first-principles argument for a 5th power relationship. Separate parameterization, over oceans, uses an exponent of ~1.7.

Price, C., & Rind, D. (1994). Possible implications of global climate change on global lightning distributions and frequencies. Journal of Geophysical Research: Atmospheres, 99(D5), 10823-10831.

Early paper estimating change in lightning frequency due to a doubling of CO2. Uses cloud top height parameterization from Price & Rind (1992); based on the GISS model (resolution 8°x10°!!).

Reeve, N., & Toumi, R. (1999). Lightning activity as an indicator of climate change. Quarterly Journal of the Royal Meteorological Society, 125(555), 893-903.

Observational study finding a strong correlation between monthly land wet-bulb temperature and lightning activity. Finds best correlation in the Northern Hemisphere, but even there the r^2=0.32. No specifics for PNW.

Romps, D. M., Seeley, J. T., Vollaro, D., & Molinari, J. (2014). Projected increase in lightning strikes in the United States due to global warming. Science, 346(6211), 851-854.

Original CAPExP lightning paper. Found high correlation with obs (time series comparisons across CONUS) and large sensitivity to CC (+12+/-5%/degC). Only evaluated year 2011 and precip data didn't include PNW.

Romps, D. M., Charn, A. B., Holzworth, R. H., Lawrence, W. E., Molinari, J., & Vollaro, D. (2018). CAPE times P explains lightning over land but not the land-ocean contrast. Geophysical Research Letters, 45(22), 12-623.

CAPExP evaluation over CONUS. Find that best approach is to use contemporaneous and collocated CAPE and P. Validations show that CAPExP calculated by NARR correlates best with observations. Also looked at diurnal cycle and land-ocean contrast.

Romps, D. M. (2019). Evaluating the future of lightning in cloud-resolving models. Geophysical Research Letters, 46(24), 14863-14871.

Use cloud-resolving models to produce lightning proxies: (1) CAPExPrecip, (2) PW10 (precip rate when vertical velocity is >10m/s, (3) IFLUX (vertical ice flux at 440hPa), and (4) IxG (Ice x Graupel concentrations). Compared against observed flashes. All are decent; IFLUX agrees best with obs. Only #1 can be calculated from WRF output. Projected increase with CC of ~10%/degC. All results for CONUS; unclear how results would be different for just PNW.

Rorig, M. L., & Ferguson, S. A. (1999). Characteristics of lightning and wildland fire ignition in the Pacific Northwest. Journal of Applied Meteorology, 38(11), 1565-1575.

Found that soundings from Spokane can be used to differentiate between dry and wet lightning. Specifically, based on the dewpoint depression at 850 hPa and the temperature difference between 850 and 500 hPa.

Stolz, D. C., Bilsback, K. R., Pierce, J. R., & Rutledge, S. A. (2021). Evaluating empirical lightning parameterizations in global atmospheric models. Journal of Geophysical Research: Atmospheres, 126(4), e2020JD033695.

Evaluates lightning proxies, but is only focused on the tropics – due to use of TRMM data.

Tapia, A., Smith, J. A., & Dixon, M. (1998). Estimation of convective rainfall from lightning observations. Journal of Applied Meteorology, 37(11), 1497-1509.

Another study looking at lightning as a proxy for precipitation. Focused on Florida so probably not applicable to PNW. Also based on radar observations which cannot be used to look at future changes.

Tippett, M. K., & Koshak, W. J. (2018). A baseline for the predictability of US cloud-to-ground lightning. Geophysical Research Letters, 45(19), 10-719.

Spatially explicit expansion of Romps (2014) CAPExP proxy. Uses spatially explicit CAPE and precipitation, but does not use a spatially explicit constant of proportionality – unclear why. Correlations indicate good performance for PNW.

Tippett, M. K., Lepore, C., Koshak, W. J., Chronis, T., & Vant-Hull, B. (2019). Performance of a simple reanalysis proxy for US cloud-to-ground lightning. International Journal of Climatology, 39(10), 3932-3946.

> Builds on 2018 study, looking at regional variations in the relationship between “CP” (CAPExP) and CG flash counts. Main issue for the PNW is that CP is shows a very muted seasonal cycle relative to lighting observations. The “warm season” (May-Oct) results are fairly well correlated with the observations, suggesting there is some potential to improve results by focusing the CP proxy on those months.

Yair, Y. (2018). Lightning hazards to human societies in a changing climate. Environmental research letters, 13(12), 123002.

> Review paper summarizing changing societal exposure to lightning. Covers more than just climate change – also urbanization, UHI effect, aerosols. Nearly all modeling studies project an increase in lightning occurrence in the future because warmer air, at the same humidity, holds more water. No discussion of negative feedbacks such as potential increases in stability. Cites Finney et al. (2014) result showing that microphysical proxies project smaller changes than proxies based on cloud top height.