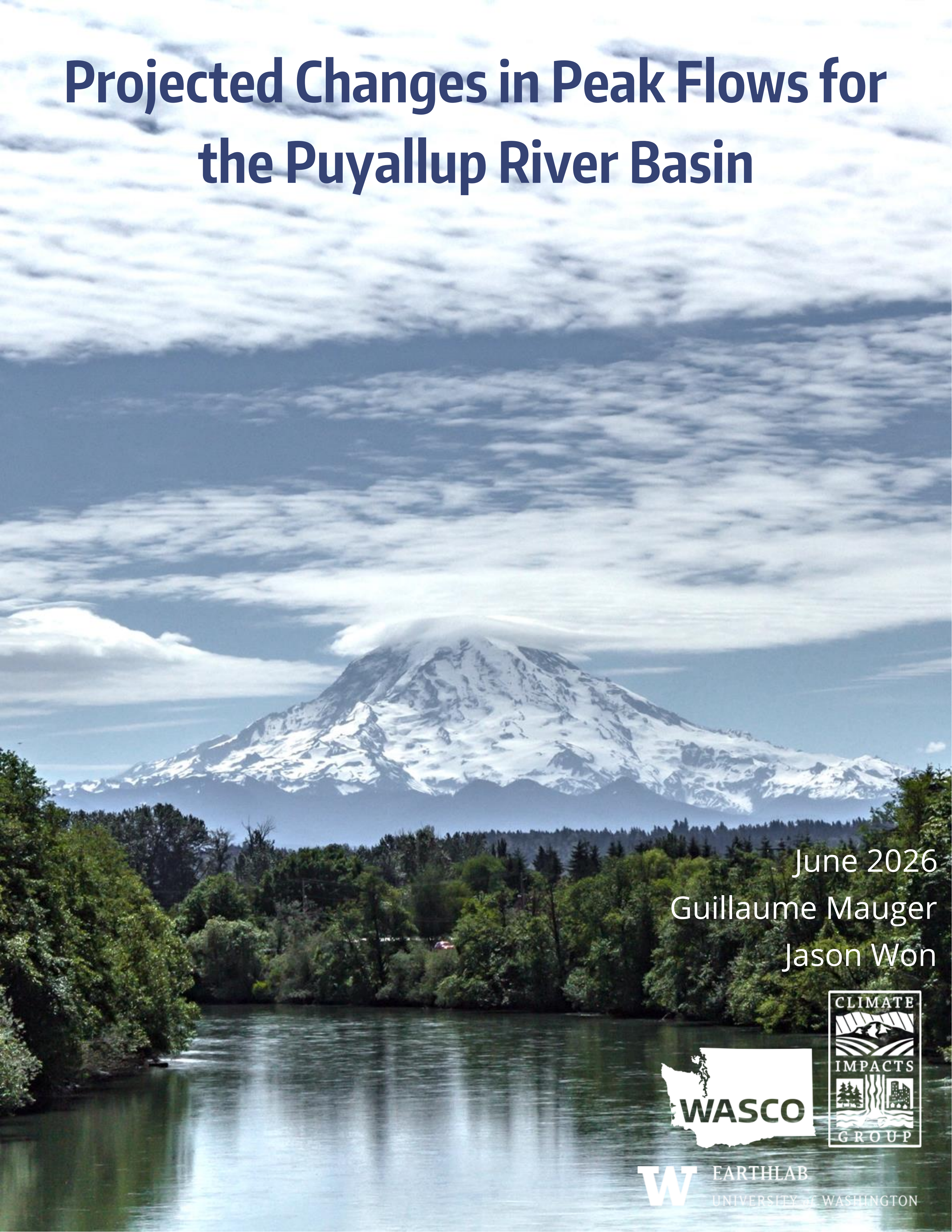
Projected Changes in Peak Flows for the Puyallup River Basin



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Contents

EXECUTIVE SUMMARY

Climate change is projected to lead to larger and more frequent river floods due to declining snowpack and more intense heavy rain events. This means that past events are no longer a reliable indicator of future flood size or frequency. This report describes new streamflow projections for the Puyallup River. The goal of this work is to support more resilient planning by developing an improved assessment of future peak flows.

This study is one part of a larger project to develop improved projections of future peak flows across four major King County rivers (the Snoqualmie / Skykomish, Cedar, Green, and White Rivers). The current report is focused on the results for the Puyallup/White River, including flow regulation at Mud Mountain Dam on the White River. As in previous phases, this work is focused on two key improvements over previous studies:

1. Using a fine-scale hydrologic model, which provides more detailed estimates of changes across the watershed, and
2. Using regional climate model projections, which research suggests are needed to accurately estimate changes in flooding (e.g. Salathé et al. 2014).

Throughout this work we have coordinated with our research partners at King County, Seattle Public Utilities, and the Seattle District of the U.S. Army Corps of Engineers.

Unlike our studies on the Snohomish or Green Rivers, in this study we were able to leverage a recent effort to model future flows on the Puyallup River using statistically-downscaled climate projections. Although statistical downscaling is considered less likely to provide accurate peak flow projections relative to regional climate model projections (or "dynamical downscaling"), it is more commonly used for climate change studies and is therefore helpful as a direct comparison with our regional climate model results.

Snowpack, Precipitation and Evapotranspiration

On average for the Puyallup River watershed, our modeling projects a median 49% decrease in April 1st Snowpack by the 2080s (relative to the 1990s, range: -18 to -61%) (all projections in this study are based on the high-end RCP 8.5 greenhouse gas scenario)**.** Declining snowpack means that more precipitation falls as rain during storms, contributing to larger floods and an associated decline in spring/summer snowmelt. Projected changes in seasonal precipitation are more uncertain, but show an **increase in winter (Oct-Mar) precipitation of +4% (range: -7 to +27%) and a decrease in July-August precipitation of -18% (range: -58 to +62%; as above, for the 2080s relative to the 1990s)**. Surprisingly, our modeling projects a small *decrease* in July-August evapotranspiration for the Puyallup River basin.

Heavy precipitation is the primary driver of flooding west of the Cascades. Models project a **+19% (range: +1 to +35%) increase in the heaviest daily rain event for each year**, again for the 2080s relative to the 1990s. This change is expected to lead to bigger and more frequent floods for the Puyallup River.

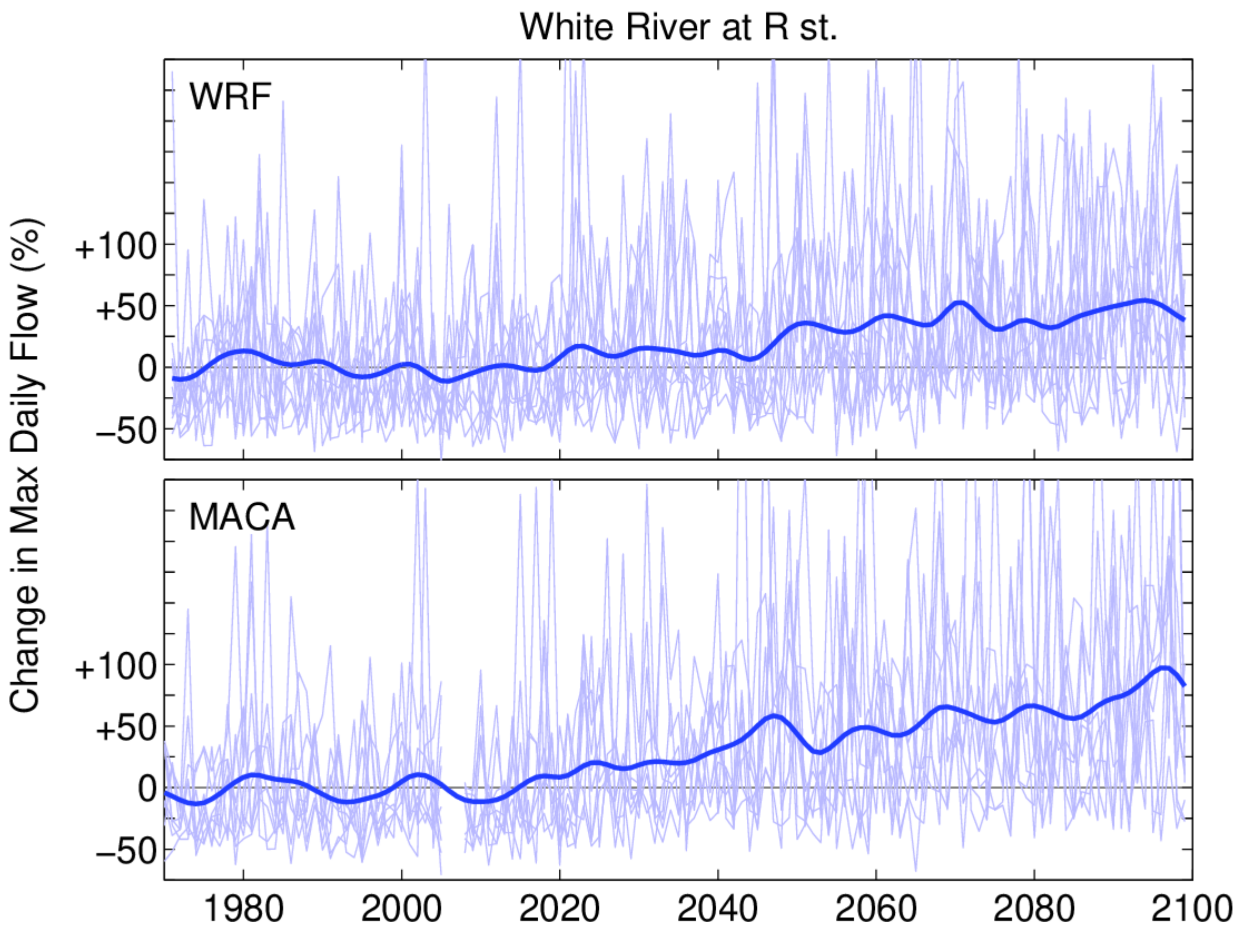

Figure ES1. Naturalized peak flows are projected to increase steadily throughout the century (in this case, "naturalized" means that the results do not account for the effect of Mud Mountain Dam). The plot shows the time series of peak flows for each of the 12 models analyzed in this study (light blue lines), and model average (thick blue line), for the White River at R st. Results from two datasets are included for comparison: The dynamically-downscaled "WRF" projections (top) that are the focus of the current study, and the statistically-downscaled "MACA" projections (bottom). All results are plotted as a percent difference, relative to the average for the 1990s (1980-2009). For readability, the model average is smoothed using an 11-point gaussian filter.

Naturalized Flows

This section discusses the projections for *"naturalized flow"* changes: Modeled changes in river flows in the absence of flow regulation at Mud Mountain Dam.

The Puyallup River's hydrology is considered "mixed rain and snow", with a dual peaks in streamflow: one in winter during the rainy season, and a second in spring due to snowmelt. For all sites, flows drop off rapidly in early summer, with a minimum in August or September, before increasing again in the fall. **Projected changes in flow reflect the combined effects of snowpack loss and the projected changes in precipitation, with a higher winter peak, a lower and earlier spring freshet, and lower flows in summer.** The changes in snowpack are negligible for South Prairie Creek and other low elevation streams; these are likely only affected by projected changes in precipitation.

Consistent with the projected increases in heavy precipitation, the median projections show an increase in peak flows across all return intervals, durations, and locations. **Peak flows are projected to increase for all locations, metrics, time periods, and nearly all models that we considered. Median projections for the end of the century range from about +5% to +50%, depending on location and flow duration (e.g. Figure ES1).**

Although not a primary focus of this study, we also analyzed changes for the summer season. Climate change can impact low flows via changes in snowpack, evaporation, and precipitation. Snowpack declines primarily result in a lengthening of the low flow season, since most snowpack is gone before July 1st, and late summer evapotranspiration is projected to *decrease* in our modeling. This suggests that precipitation changes will be the most important driver of late summer flow changes. As noted above, summer precipitation is projected to decrease. **Our streamflow modeling shows a decrease in summer flows, ranging from about -20% to -50% for the snow-influenced sites and -15% to -20% for South Prairie Creek (median projection, 2080s relative to 1990s).** The much larger decreases for the snow-influenced sites suggests that snowpack declines are an important driver of low flow decreases. Projected changes are smaller for the Puyallup River near Orting site than for the other snow-influenced site, possibly because the watershed does not have as much area at higher elevations relative to the White and Carbon River watersheds. Overall, the projected changes are similar for the water year minimum flows. It is worth noting that the model calibration prioritized peak flows. Although the model evaluation suggests good performance for low flows at most sites, we recommend further evaluation before using the low flow results.

Regulated Flows

This section discusses the projections for *"regulated flow"* changes, obtained by modeling the effects of reservoir operations at Mud Mountain Dam (MMD). Although MMD is on the White River, flows at MMD are regulated to mitigate peak flows on the lower Puyallup River (USACE 2004). Operators also strive to manage flood risks on the lower White River, though this is a secondary priority relative to the lower Puyallup River flow target.

As with most reservoirs in the region, Mud Mountain Dam operations result in lower peak flows and a shift to lower winter flows and higher flows in summer. Similar to the naturalized flow results, the projections show a tendency towards higher flows in winter

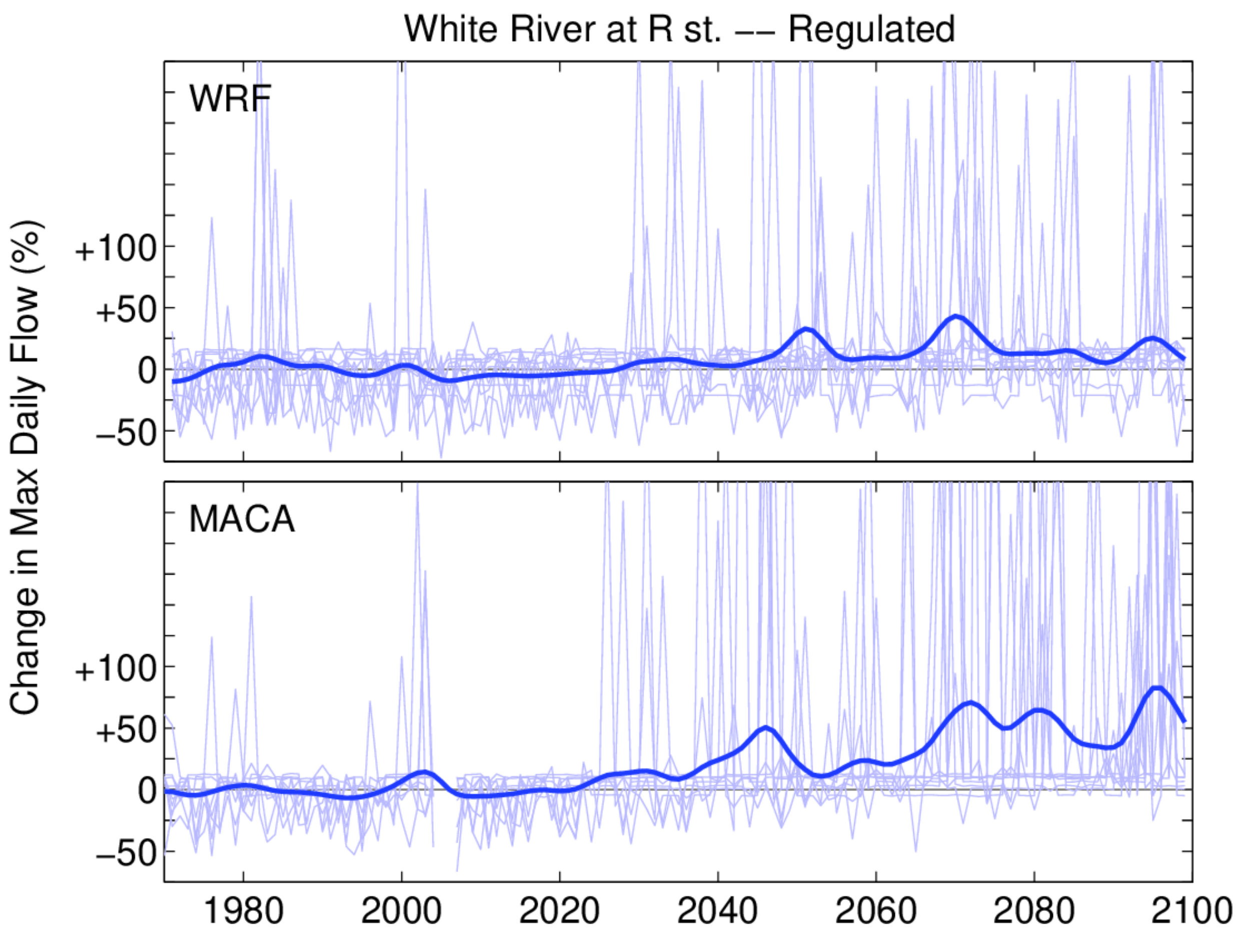

Figure ES2. <u>Regulated</u> peak flows are projected to increase steadily throughout the century (in this case, "regulated" means that the results include the effect of Mud Mountain Dam). As in Figure ES1, the plot shows the time series of peak flows for each of the 12 models analyzed in this study (light blue lines), and model average (thick blue line), for the White River at R st. Results from two datasets are included for comparison: The dynamically-downscaled "WRF" projections (top) that are the focus of the current study, and the statistically-downscaled "MACA" projections (bottom). All results are plotted as a percent difference, relative to the average for the 1990s (1980-2009). For readability, the model average is smoothed using an 11-point gaussian filter.

and lower flows in summer. **On average, peak flows are projected to increase by the end of the century (Figure ES2)**, with large changes for both the smallest and largest floods and almost no change for moderate floods (e.g. the 2-year event). Specifically, models project large increases in the 1.11-year event for dam-influenced sites (+46 to +55%, on average), almost no change for the 2-year event (+0 to +4%, on average) except at the Puyallup River at Puyallup site (+27%, on average), and modest increases in the 10-year event (+10 to +29%, on average). These results are all for daily flows; increases are similar for hourly peak flows but generally larger at longer durations.

Overall, the results show that flows exceeding the 8,000 CFS and 45,000 CFS flow targets for the White River at R st and Puyallup River at Puyallup sites, respectively, will occur both more often and be larger in the future. At the White River at R st gauge, for example, the median projection is just over 70 hours per year exceeding 8,000 CFS currently (2020s) and just over 140 hours per year by the 2080s – doubling the frequency of exceedances, relative to present-day conditions. In contrast, flows almost never exceed the 45,000 CFS target at the Puyallup gauge – flows above this level occur about 1 hour every 4 year currently (2020s), and are projected to occur about 1.7 hours per year, on average, by the 2080s. **In addition, flows that remain below but approach these thresholds will also become more common, potentially putting greater stress on the levee system.**

Using These Results

All results from the study are available online at the project website:

https://cig.uw.edu/projects/effect-of-climate-change-on-flooding-in-king-county-rivers/

This includes interactive visualizations as well as data available for download. The data files range from summary tables to raw model outputs (see Appendix D for more detail). Fine-scale modeling allows us to provide flow estimates for many locations across each watershed, ranging in size from creeks to mainstem river sites. **Our modeling assessed changes for 48 river locations across the Puyallup River watershed.** These output locations were identified in collaboration with potential users at each partner agency.

The projections can be used for any application related to changes in streamflow, particularly peak flows, within the Puyallup River basin. Possible applications include communications and engagement, planning and prioritization, and project design. For example, we have found that flood projections can provide a concrete starting point for integrated planning discussions. Another application is prioritization – identifying areas that are at the greatest risk in order to plan and focus resources. Project design is another potential application. We anticipate an increasing need for information to support climate-resilient project design. King County has already used the Snohomish River results to inform design in the lower Tolt River floodplain.

There is no universal criteria for deciding when these projections should be updated, or when an alternative dataset should be used. We recommend evaluating the needs (e.g. level of precision needed, consequences of under-design), and the strengths and weaknesses of this dataset and any alternatives, on a case-by-case basis. When feasible, best practice is to compare multiple independent estimates of change.

PURPOSE

Climate change is projected to lead to larger and more frequent river floods due to declining snowpack and more intense heavy rain events. In order to plan and design for these changes, managers need to know how flows will change over time. The purpose of this study is to provide improved projections of changes in the magnitude, duration, frequency, and timing of future peak flows on the Puyallup River.

BACKGROUND

This report is one part of a larger project to develop improved projections of future peak flows across four major King County rivers. While the current report is focused on flow projections for the Puyallup River, companions reports provide future peak flows in the Snohomish, Cedar, Green, and Puyallup river basins. In addition, a preliminary analysis assessed the implications for peak flow regulation in the major reservoirs on the Cedar, Green, and White rivers.

This is the third and latest phase of a series of efforts to better quantify future changes in peak flows on King County Rivers. All three phases are focused on two key improvements over previous studies. First: using a fine-scale hydrologic model, which provides more detailed estimates of changes across the watershed. Second: using regional climate model projections, which research suggests are needed to accurately estimate changes in flooding (e.g. Salathé et al. 2014).

The Phase 3 effort includes the three following advancements:

1. Refining the approach used in the Phase 1 and 2 efforts and applying new approaches to the existing models for the Snoqualmie/SF Skykomish and Green river basins (Lee et al. 2018, Mauger and Won 2020).
2. Developing new projections of future natural and regulated flows on the Cedar and White rivers.
3. Engaging reservoir modelers to discuss and contextualize reservoir modeling results.

For reference, the full scope of work is included in Appendix B.

In addition, unlike our studies on the Snohomish, Green, or Cedar Rivers, in this study we were able to leverage a recent effort to model future flows on the Puyallup River using statistically-downscaled climate projections. Although statistical downscaling is considered less likely to provide accurate peak flow projections relative to regional climate model projections (or “dynamical downscaling”), it is more commonly used for climate change studies and is therefore helpful as a direct comparison with our regional climate model results.

APPROACH

The current effort, Phase 3, builds on the Phases 1 (Lee et al. 2018) and 2 (Mauger and Won 2020) by testing and applying new approaches aimed at improving the accuracy of the projections. In the current work, we made the following changes:

- *Used regional climate model results for calibration.* Previous phases used a dataset that was interpolated from observations, which did not align as well with the regional climate model projections used for the future simulations.
- *Improved the bias correction of temperature and precipitation.* This is critical for calibration, and needed to ensure projections accurately represent the hydrologic response to climate change. Previous phases used a simplified approach and did not test different approaches for their effectiveness.
- *Developed hourly estimates of humidity and radiation.* Previous phases used empirical estimates of humidity and radiation, which may not apply in all contexts or locations. In this work we used humidity and radiation estimates directly from the regional model, which is more consistent with the temperature, precipitation, and wind estimates that were also obtained from the regional model.
- *Validated snow simulations, in addition to streamflow.* Although a small improvement, this provided additional information for use in model calibration. In particular, snow simulations are a more direct indicator of biases in the temperature and precipitation estimates from the regional model.

Other model updates were made but not explored in the same level of depth. Specifically, we reviewed and made updates to the soil and vegetation characteristics, the stream network, and the stream channel classifications (assumed stream channel characteristics as a function of catchment area). The subsections below describe the data used in the modeling as well as the details associated with each of the improvements listed above.

Observations

We used snowpack and streamflow observations to calibrate and evaluate the hydrologic model (Table 1).

Table 1. Observations used for model evaluation. Snowpack observations were obtained from the USDA SNOTEL network, while streamflow observations were obtained from USGS. Although flows at the Buckley, R st., and Puyallup at Puyallup sites are affected by Howard Hanson Dam, we obtained naturalized flow estimates from the U.S. Army Corps, which were used in model evaluation. Sites marked with an asterisk are affected by flow regulation at Mud Mountain Dam.

	Station	ID	Lat. / Lon.	Years
Snowpack	Burnt Mountain	942	47.04/-121.94	1999-present
	Cayuse Pass	1085	46.87/-121.53	2006-present
	Corral Pass	418	47.02/-121.46	1979-present
	Huckleberry Creek	928	47.07/-121.59	1997-present
	Mowich	941	46.93/-121.95	1998-present
Streamflow	Greenwater R. at Greenwater	12097500	47.15344/-121.63565	1989-present
	White R. below Clearwater	12097850	47.14677/-121.86011	1974-present
	White R. near Buckley*	12098500	47.15119/-121.94981	1928-2018
	White R. abv Boise Cr at Buckley*	12099200	47.17389/ -122.00806	2003-present
	White R. at R st. nr Auburn*	12100490	47.27479/ -122.20788	2009-present
	Carbon R. near Fairfax	12094000	47.02788/-122.03261	1991-present
	Puyallup R. near Orting	12093500	47.03924/-122.20787	1931-present
	South Prairie Creek	12095000	47.13954/-122.09261	1987-present
	Puyallup R. at Puyallup*	12101500	47.20843/-122.32707	1914-present

Climate Data

Global climate model (GCM) projections are coarse in spatial scale and not suitable for use as direct inputs to hydrologic modeling. As in most studies, we used “downscaling” to provide localized climate projections at a scale that is usable for input to the hydrologic model. A priority in this study was to use “dynamically downscaled” projections, or regional climate model simulations, since research suggests this approach more accurately represents changes in precipitation intensity (e.g., Salathé et al. 2014).

In this study, as in previous phases of the same work, we used regional climate model simulations performed using the Weather Research and Forecasting model (WRF; Skamarock et al. 2005). Key features of the WRF simulations used in this project are summarized in Table 2. In brief, these include an observationally-based simulation (“WRF-

NARR"), which is used for calibration, and a set of 12 climate change simulations ("WRF-CMIP5"). GCMs are described based on the acronyms provided by their developers. The 12 GCMs used to drive the WRF projections are: ACCESS1-0, ACCESS1-3, bcc-csm1-1, CanESM2, CCSM4, CSIRO-Mk3-6-0, FGOALS-g2, GFDL-CM3, GISS-E2-H, MIROC5, MRI-CGCM3, NorESM1-M. All of the new projections are based on the high-end Representative Concentration Pathway (RCP) 8.5 scenario (Van Vuuren et al. 2011). Research suggests this greenhouse gas scenario is very pessimistic, and may even be beyond what is feasible in terms of 21st century emissions (Hausfather and Peters 2020). 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, temperature changes for the 2080s in the RCP 4.5 projections appear to correspond approximately to the projections for the 2040s or 2050s in the RCP 8.5 projections. Additional information on the WRF simulations is provided in Appendix B.

Previous phases of this work (Phases 1 and 2) used the same regional climate model projections, but (a) did not calibrate the hydrologic model using a regional model simulation, and (b) did not calibrate bias adjustments based on hydrologic model performance. Building on previous phases, the current study (Phase 3) devoted more time to bias-adjusting the regional model results in order to improve on the hydrologic modeling. This section describes the regional model projections, and associated bias adjustments, used as input to the hydrologic modeling.

Table 2. Dynamically-downscaled Weather Research and Forecasting (WRF) model simulations used in the current study. Additional information on these simulations is provided in Appendix B.

Name	Type	Source	Bdry. Cond.	# of Sims	Time Step	Spatial Res.	Years
WRF-NARR	Historical	PNNL	NARR	1	1 hr	6 km	1981-2015
WRF-CMIP5	Climate Change	UW Atmos. Sci.	CMIP5 (Table B1)	12	1 hr	12 km	1970-2099

Climate Data Bias-Correction

Six meteorological variables are required as input to the hydrologic model simulations: temperature (°C), relative humidity (%), precipitation (m), wind speed (m/s), incoming shortwave radiation (W/m^2), and incoming longwave radiation (W/m^2). Past experience has shown that the WRF results cannot be used directly in hydrologic modeling because of biases that lead to unrealistic hydrologic results (e.g. Mauger et al. 2021b).

For temperature and precipitation, we adapted an approach developed by Bandaragoda and Hamlet (personal communication), in which gridded averages of monthly temperature and precipitation from the PRISM dataset (Parameter Regression on Independent Slopes Model, 2022; Daly et al. 2008) are used to adjust the WRF-NARR simulation to develop a baseline correction for use in the hydrologic model. We chose to use PRISM as opposed to individual station comparisons because PRISM is based on station data while also accounting for topographic and other effects on the spatial distribution of temperature and precipitation variations.

In contrast with the Snohomish and Cedar DHSVM models, we did not provide a uniform adjustment to the WRF-NARR temperature and precipitation values. Instead, we compared each WRF-NARR grid cell with the bilinearly-interpolated PRISM values for that location. Specifically, we compared the long-term average values for each month, for the years 1981-2020. The result was a set of 12 scale factors for each variable (additive for temperature, multiplicative for precipitation), one for each calendar month,. These were applied to all time steps in the WRF-NARR simulations (e.g. all temperature estimates for any time step occurring in January were adjusted by the same amount). Since these were developed separately for each WRF-NARR grid cell, the corrections are spatially-varying, so that the long-term average for WRF-NARR matches the spatial distribution of temperature and precipitation in PRISM.

Other WRF-NARR variables were bias-corrected as well. Wind estimates were scaled down by a factor of 0.5 (50% reduction), and shortwave estimates were scaled by 0.9 (10% reduction), based on previous comparisons with observations across Washington State (Mauger et al. 2021b). Humidity estimates were not bias-corrected because initial tests suggest a joint temperature-humidity bias correction would be needed, which was beyond the scope of this study . Longwave was estimated using an empirical formulation (Dilly and O'Brien, 1998; Unsworth and Monteith, 1975), which previous research suggests is superior to WRF longwave estimates (Currier et al. 2017).

Bias-correcting the climate change (WRF-CMIP5) simulations involved first interpolating them from their native 12-km grid to the 6 km WRF-NARR grid, using a bi-linear interpolation. We then compared the historical average for each model simulation against the average for the same years (1981-2020) in the bias-corrected WRF-NARR results. This comparison provided monthly bias-correction factors, or scale factors, to be applied to each time step in the WRF-CMIP5 simulation, which were then used to create the Hydrologic model inputs. Different bias-corrections were applied to each climate model projection. Longwave was then recomputed using the same empirical formulation described above. Finally, some WRF-CMIP5 simulations do not include leap days. These were added back in by simply repeating all values for the day prior (Feb 28th), with the exception of precipitation which is set to 0.01 in./hr (0.254 mm/hr) to avoid exaggerating rainfall totals if a storm would happen to occur on Feb 28th.

Comparison with Statistically Downscaled Projections

Although this project was focused on developing dynamically downscaled projections, we were able to leverage a parallel effort using “statistical downscaling” to estimate future flows in the Puyallup river basin. Statistical downscaling uses empirical relationships to localize GCM projections, by relating temperature and precipitation variations from the GCM to observed temperature and precipitation at local scales. This required a separate DHSVM calibration, since statistical and dynamical downscaling are each based on different historical climate datasets. A technical memo describing these results is included in Appendix A; results are included for comparison in the sections below.

Hydrologic Modeling

For this study we used the Distributed Hydrology Soil Vegetation Model (DHSVM, Wigmosta et al. 1994) for all hydrologic modeling. Additional information on the model is provided in Appendix D.

Model Setup

We implemented the model at a resolution of 150 m and used a 1-hour time step for improved resolution of peak flows. The stream network, digital elevation model (DEM), vegetation type, soil type, and soil depth are all shown in Figure 1. generated the stream network based on an assumed minimum contributing area of 0.7 km^2. As shown in the figure, land cover is dominated by evergreen forest in the upper elevations while the lower elevations are highly developed with primarily light/medium and dense urban classifications. For soils, silt and loam units make up the majority of the basin. The soil depth range was used as a calibration parameter, as discussed below.

DHSVM Calibration

Calibration involved first determining if additional bias-adjustments should be applied to the meteorological inputs, then adjusting the soil properties to improve simulations. This was done manually, via sensitivity tests, in which we evaluated alternatives based on their relative ability to reproduce the observations. Specifically, we compared the time series of average annual flow, average monthly flows, daily streamflow time series, and the cumulative distribution function (alternately referred to as the “flow-duration curve”).

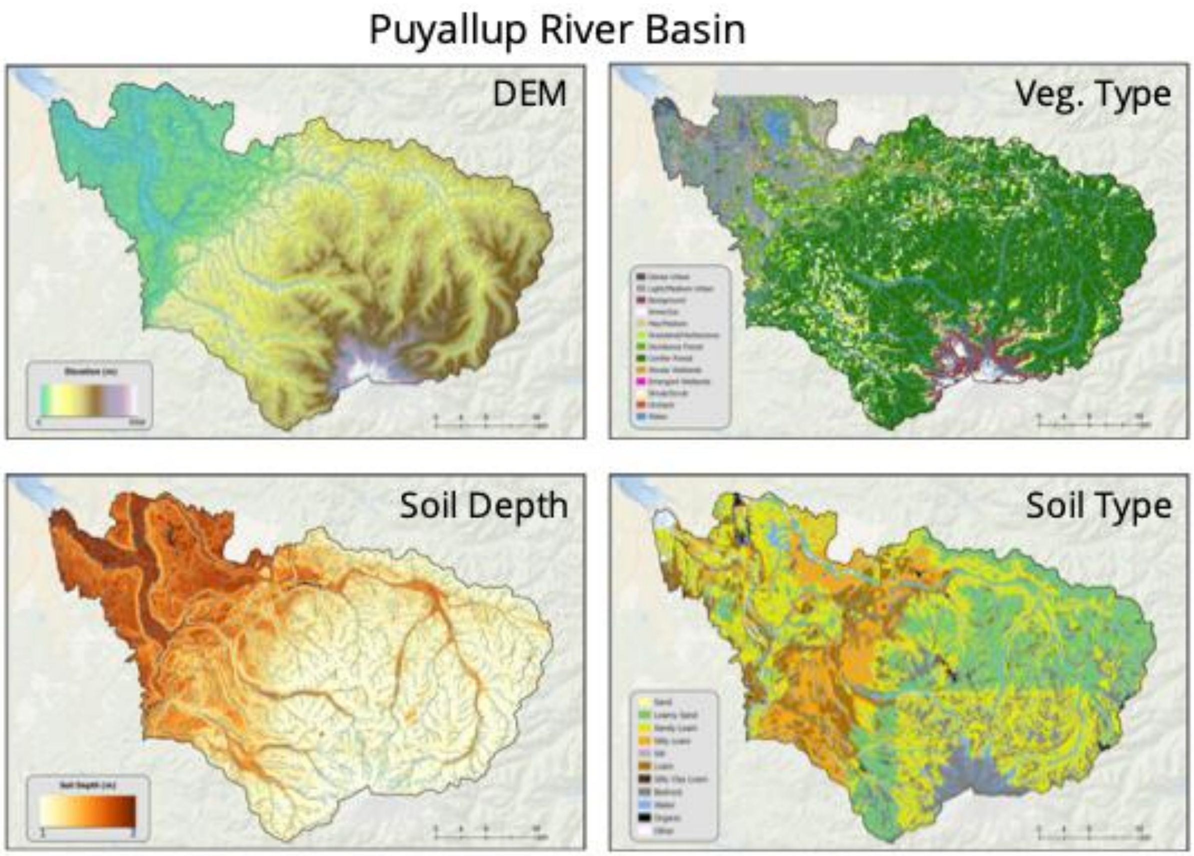

Figure 1. Maps showing elevation, soil depth, soil type, and vegetation distributions for the Puyallup DHSVM model.

Multiple criteria were used to facilitate a holistic assessment of the strengths and weaknesses of each model configuration.

Testing showed that the model performed best with additional adjustments to the meteorology, and that different adjustments were needed for the White River and Puyallup/Carbon River watersheds. For the White River watershed, we scaled temperature down by -1°C and decreased precipitation by 25%. For the Puyallup and Carbon River watersheds, we scaled temperature up by 1°C and precipitation down by 5%. These changes were applied uniformly to all grid cells within each watershed, and also uniformly across all time steps.

We made two additional adjustments to the meteorology as part of the interpolation from the 6 km meteorological data to the 150 m DHSVM grid. For temperature we assumed a constant lapse rate of 4.5°C/km (i.e.: all months have the same lapse rate). For precipitation, we used high-resolution (800 m) precipitation estimates from PRISM to distribute precipitation within each 6 km grid cell. Unlike for temperature, different precipitation adjustments were applied to each calendar month, based on a comparison between the long-term averages for PRISM and WRF-NARR.

Table 3. Parameters and soil types used in the calibration. Ranges are based on Sun et al. (2020).

Parameter	Range	Soil Type	Final
Lateral Conductivity	0.00001–0.1	Loamy Sand	0.001
		Sandy Loam	0.001
		Silty Loam	0.001
Exponential Decrease	0 – 10	Loamy Sand	1.0
		Sandy Loam	1.872572
		Silty Loam	1.145641

DHSVM uses air temperature to differentiate precipitation into rain and snow. We used a rain threshold of -2°C and a snow threshold of -2°C; these denote the minimum temperature for rain and the maximum temperature for snow, respectively. When temperatures are between these two threshold a linearly-varying mix of rain and snow is assumed. Since in our case they are set at the same temperature, the model assumes all precipitation above -2°C is rain, and all precipitation below that temperature is snow.

Additional tests evaluated the potential for adjusted soil and vegetation parameters to improve model results. We found negligible sensitivity to vegetation assumptions, but did identify two specific soil parameters that significantly improved the results. For soil depth, we found that a range of 1-5 m led to the best model agreement with the observations. We also made adjustments to the lateral conductivity and its exponential decrease with depth for select soil types (Table 3).

Model scores are shown in Table 4, and comparison plots are shown in Figures 2 through 4. All DHSVM results were compared to observed USGS flows except the White River near Buckley site, which is compared against naturalized flows obtained from USGS (see following sections on the reservoir modeling). The scores are generally comparable across the six sites analyzed, with the Nash-Sutcliffe Efficiency (NSE) score ranging from 0.52 to 0.67. This is slightly lower than preferable but better than we typically see when using regional model results as the source meteorological data (although arbitrary, an NSE above 0.7 is often viewed as a benchmark for good agreement). The NSE scores calculated based on the log-transformed flows ("NSELOG") show more variations, with excellent scores at the Buckley and Orting sites, and good scores at all of the other sites except the Greenwater River site, which scores very poorly at -0.06. This may be due to the systematic positive bias across most flow quantiles for this site (see below). The correlation (r^2), which is not affected by absolute biases, is consistent with this interpretation, since the correlations are

Table 4. Model evaluation scores for six sites listed in Table 1. Comparisons are based on daily average flows for the years 1981-2020. Metrics are the correlation squared (r^2), Nash-Sutcliffe Efficiency (NSE), NSE for log-transformed flows (NSELOG), Kling-Gupta Efficiency (KGE), root mean square error (RMSE, CFS), and average percent bias (PBIAS, %).

Site	r^2	NSE	NSELOG	KGE	RMSE	PBIAS
Puyallup R. near Orting	0.67	0.66	0.8	0.67	0.13	-5.03
Carbon R. near Fairfax	0.69	0.67	0.68	0.83	0.65	-2.48
South Prairie Cr. at SP	0.61	0.52	0.59	0.76	0.76	-4.27
Greenwater R. at Greenwater	0.62	0.61	-0.06	0.76	0.27	6.3
White R. below Clearwater	0.61	0.55	0.57	0.75	0.43	-10.61
White R. near Buckley	0.61	0.61	0.79	0.65	0.18	-4.46

similar across all sites, including the Greenwater River site. Finally, the Kling-Gupta Efficiency (KGE) scores corroborate the NSE scores, showing good scores across all six sites (KGE scores tend to be higher, simply due to the way they are calculated).

As noted above, our experience is that model scores are generally lower when using regional climate model simulations for the calibration simulation, as we have done here (i.e. by using WRF-NARR). This is likely because the simulation does not exactly reproduce the timing and intensity of precipitation events. For this reason we focus more on the comparisons between the long-term average and the cumulative distribution function (CDF) in daily flows, as shown in Figures 2 and 3. Nonetheless we include the daily flow comparisons for transparency (Figures 4 and 5). The daily comparisons show that the overall timing and magnitude of flows agrees well with observations, though the intensity and duration of storms appear to be different for the WRF-NARR simulation. This is likely one reason for the lower model scores. As noted above, we have chosen to use the dynamically downscaled projections because research indicates they provide improved estimates of the change in precipitation, particularly for extreme precipitation events.

Finally, it is important to note that historical calibration is not necessarily an indicator of accuracy in the projections. This means that relative change projections are still likely to provide useful information on potential changes in peak flows, even if the historical simulations do not always align with the observations.

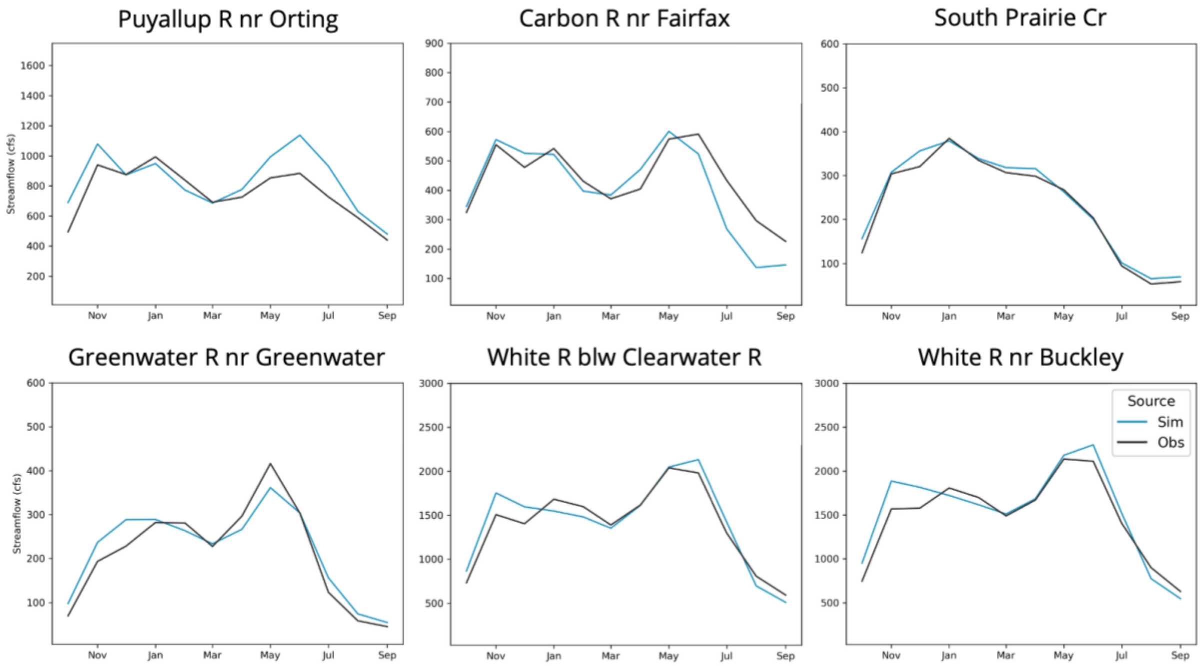

Figure 2. Observed and modeled average monthly *naturalized* flows for six gauges listed in Table 1. Comparisons include all years in which observations and model results are available.

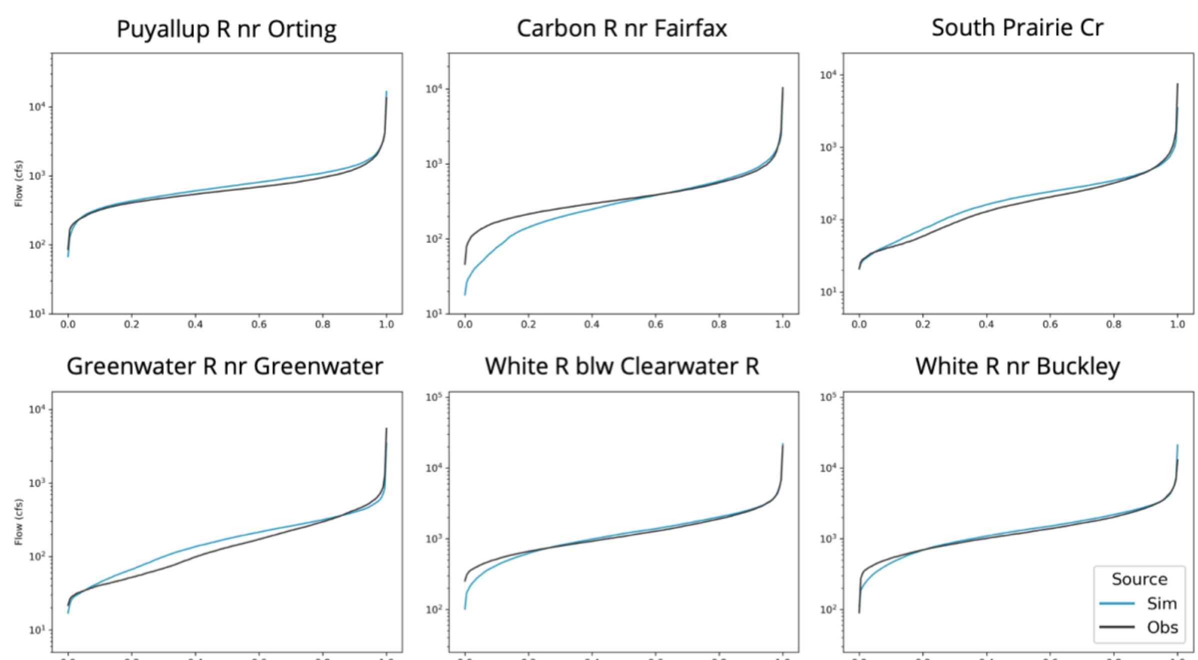

Figure 3. Observed and modeled cumulative distribution function (CDF) in daily *naturalized* flows. Comparisons include all years in which observations and model results are available.

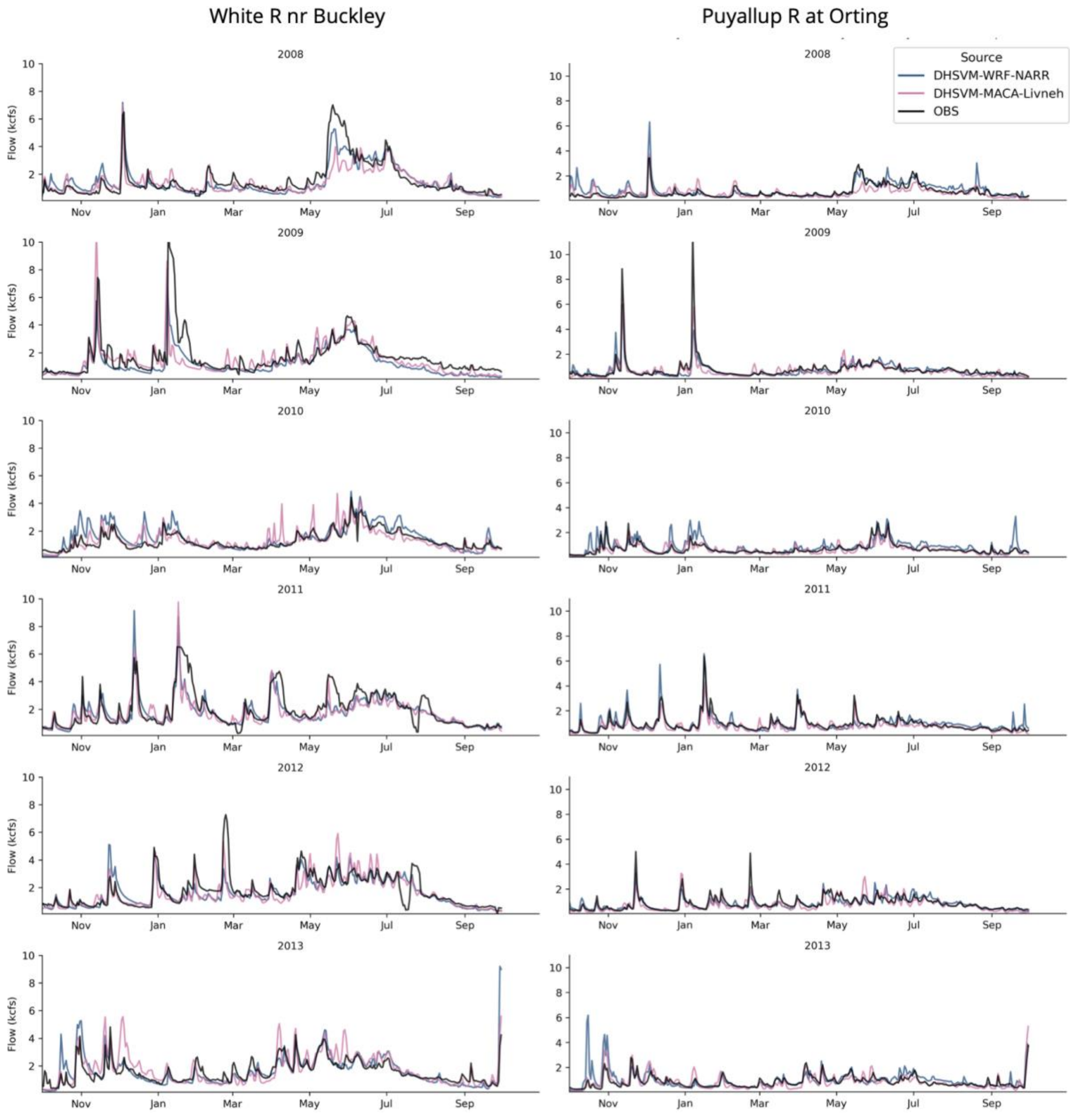

Figure 4. Observed and modeled daily flows for the White R nr Buckley and Puyallup River near Orting sites, showing results for both the WRF and MACA simulations for comparison. Results are shown for water years 2008-2013; comparisons for other years are similar.

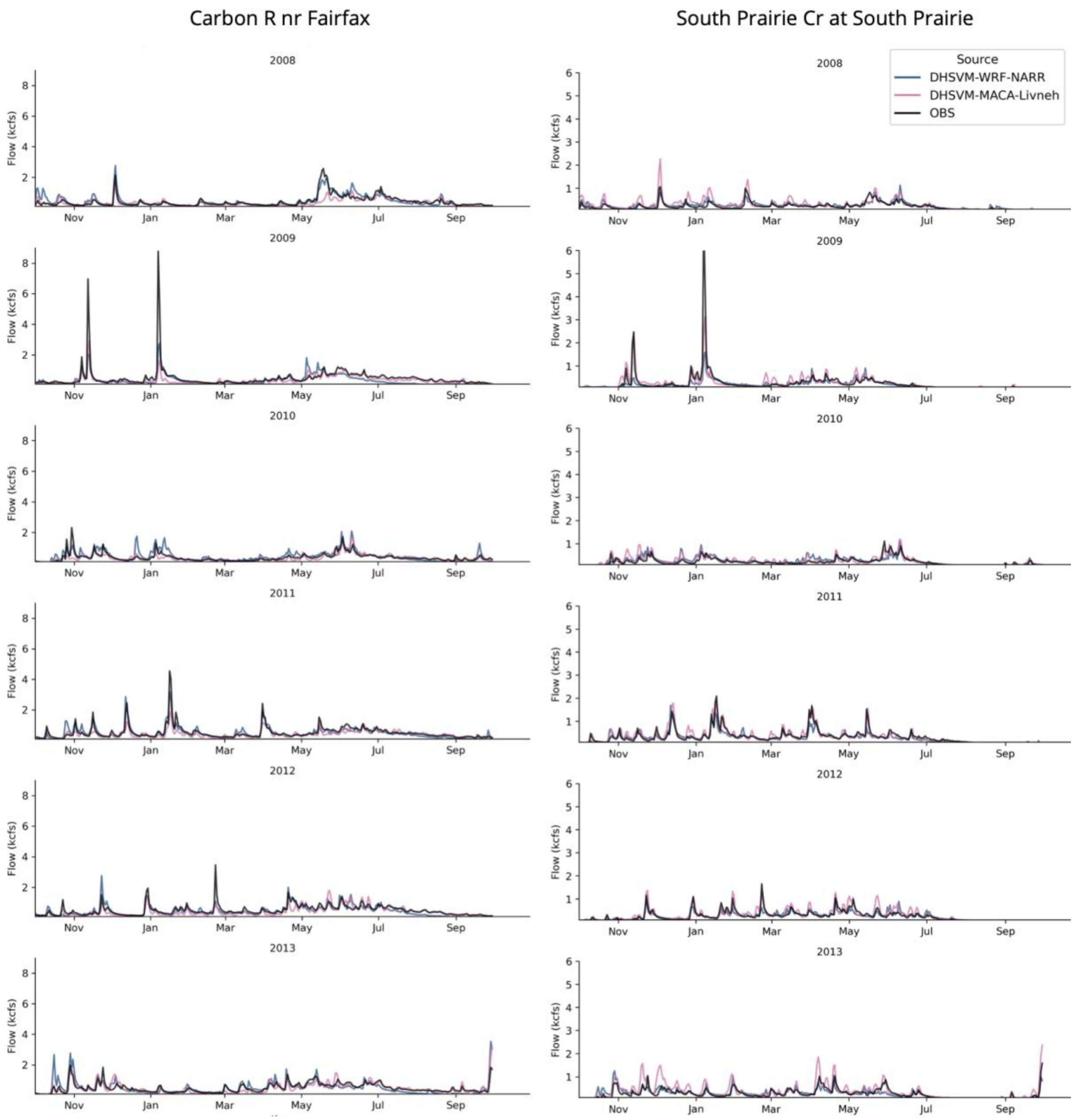

Figure 5. As in Figure 4 but for the Carbon R near Fairfax and South Prairie Cr sites.

DHSVM Outputs

DHSVM provides results at pre-identified streamflow locations. The fine-scale resolution of DHSVM allows us to include flow estimates for locations ranging from creeks to mainstem river sites. **Working with our partner agencies, we identified 48 streamflow sites across the Puyallup River Basin.** These are listed in Appendix E as well as a companion spreadsheet to this report that includes notes about their location, source, and application.

Reservoir Modeling

We obtained the reservoir model for Mud Mountain Dam (MMD) from the Seattle office of the U.S. Army Corps of Engineers (USACE). The model was developed using the HEC-ResSim (Hydrologic Engineering Center Reservoir System Simulation) software package, and is designed to represent operations of the reservoir based on simulated or observed inflows both above and below the dam, down to the primary control point at the Puyallup River at Puyallup gauge site. During peak flow events, operations target a maximum flow of 45,000 CFS (USACE 2004). In addition, operators strive to keep flows under 8,000 CFS at the White River at R st gauge site, due to flood risks associated with channel aggradation in the lower White River. In both cases, higher releases may be required, according to the Discharge Regulation Schedule, if the reservoir were to fill prior to the end of a flood event. The ResSim model for MMD runs at an hourly time step.

Streamflow estimates from the DHSVM model, as shown in previous sections, exhibit some biases relative to observations. We obtained naturalized flows from the USACE Dataquery 2.0 tool (https://www.nwd-wc.usace.army.mil/dd/common/dataquery/www/#), using these to bias-correct DHSVM inflows to the MMD reservoir. The model also requires an estimate of local flows between MMD and the White River at R st., and between the White River at R st. and Puyallup R at Puyallup gauge sites (Table 1). These are simply calculated as the differences between the observed USGS flows at each site, using both the White River near Buckley site (12098500) and the White River above Boise Cr at Buckley (12099200) site for the observed outflows from Mud Mountain Dam (two sites were used to maximize the temporal overlap between observed and modeled flows).

We tested multiple bias-correction approaches, using each as input to the ResSim model to evaluate their ability to reproduce the observationally-based ResSim results. Specifically, our baseline ResSim simulation used the naturalized flow estimates from USACE along with the observed local flows between MMD, White River at R st, and Puyallup River at Puyallup as inputs. We used this simulation as our baseline instead of direct observations of flows, in order to separate biases in the bias-corrected DHSVM inputs from limitations in the ResSim model itself, which is known to be an approximation for actual flow regulation at the reservoir (e.g. simplified operations, no accounting for weather forecasts). Our tests showed that the quantile-based “percentile delta” correction worked best, in which corrections are applied for discrete quantile bins (see Mauger et al. 2016 for a more in-depth description). In this case, we found that a bin width of 1% (i.e. 0-1, 12, … 99-100) and applying a separate bias correction for each calendar month provided the best results. The correction was applied to hourly flow estimates from DHSVM, using the naturalized flows at

Table 5. Reservoir model evaluation scores for the four mainstem sites listed below Mud Mountain Dam (see Table 1). Comparisons are based on daily average flows for the years 1981-2020. Metrics are the correlation squared (r2), Nash-Sutcliffe Efficiency (NSE), NSE for log-transformed flows (NSELOG), Kling-Gupta Efficiency (KGE), root mean square error (RMSE, CFS), and average percent bias (PBIAS, %).

Site		r^2	NSE	NSELOG	KGE	RMSE	PBIAS
Mud Mtn Dam Outlet	**WRF-NARR**	0.76	0.75	0.79	0.86	0.59	-0.6
	MACA-Livneh	0.72	0.71	0.74	0.81	0.7	0.94
White R at R st	**WRF-NARR**	0.76	0.75	0.77	0.87	0.62	-0.51
	MACA-Livneh	0.74	0.73	0.74	0.84	0.7	-0.8
Puyallup R at Puyallup	**WRF-NARR**	0.77	0.77	0.82	0.88	1.25	0.35
	MACA-Livneh	0.81	0.81	0.83	0.85	1.17	2.97

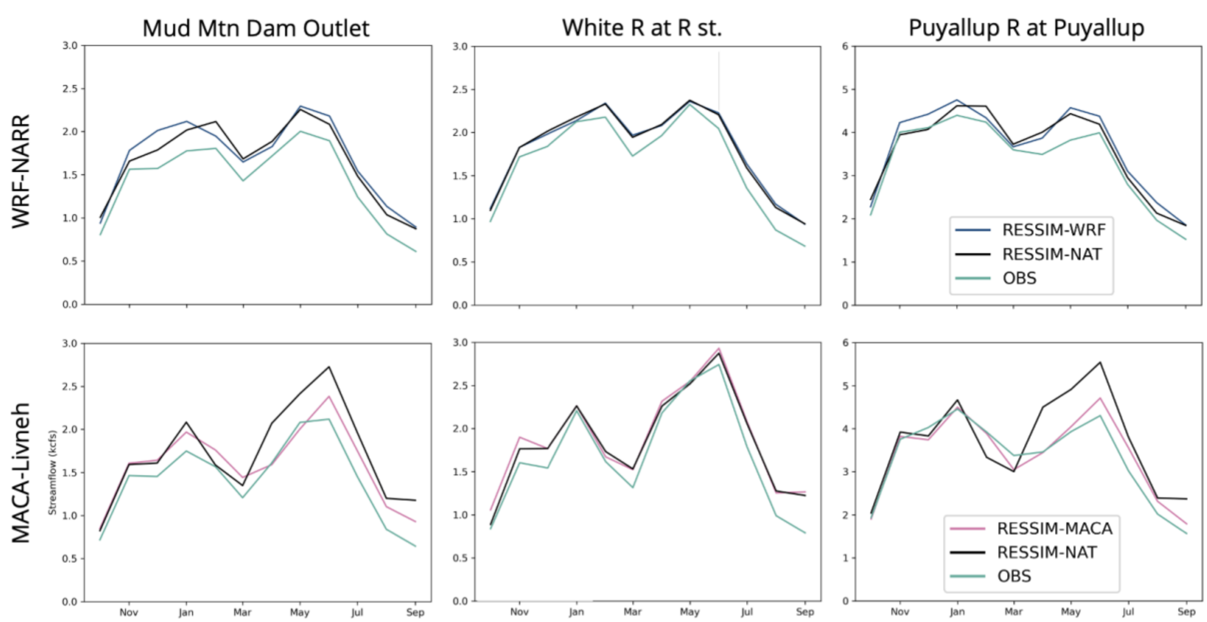

Figure 6. Average monthly *regulated* flows for three sites downstream of Mud Mountain Dam. Results are included for the observed flows at the USGS gauge (OBS, green), modeled flows using observationally-based naturalized flows (RESSIM-NAT, black), and modeled flows using the WRF-NARR DHSVM flows as inputs (top row, RESSIM-WRF, blue) and the MACA-Livneh DHSVM flows (bottom row, RESSIM-MACA, blue). Comparisons include all years in which observations and model results are available, hence the different averages even for observed and naturalized flows.

MMD and the observed local flows (differences described above) as the reference datasets for the bias correction. For the climate change simulations (WRF-CMIP5), the bias corrections were developed based on comparisons between the naturalized flow observations and modeled historical flows, using a training period of 2010-2020 for WRF-NARR and 2010-2012 for MACA-Livneh. The corrections were then applied uniformly across the entire time series (1970-2099 for WRF-CMIP5 and 1950-2099 for MACA-CMIP5).

Table 5 – along with Figures 6, 7, and 8 – show comparisons between the ResSim results based on the bias-corrected DHSVM flows ("RESSIM-WRF", "RESSIM-MACA") and our baseline simulation ("RESSIM-NAT"), described above. For reference, observed flows from the USGS gauge sites are included in the figures. Since the ResSim model does not perfectly represent actual reservoir operations, we expect some divergence between the observations and ResSim results. Nonetheless, these show that the DHSVM model, and bias correction, perform quite well at reproducing both the baseline simulation and even the observed flows. Overall, the RESSIM scores are generally comparable to or better than the naturalized flow comparisons above (Table 4). Although this is a bit of an apples-to-oranges comparison, it indicates that our RESSIM results are a good representation of the

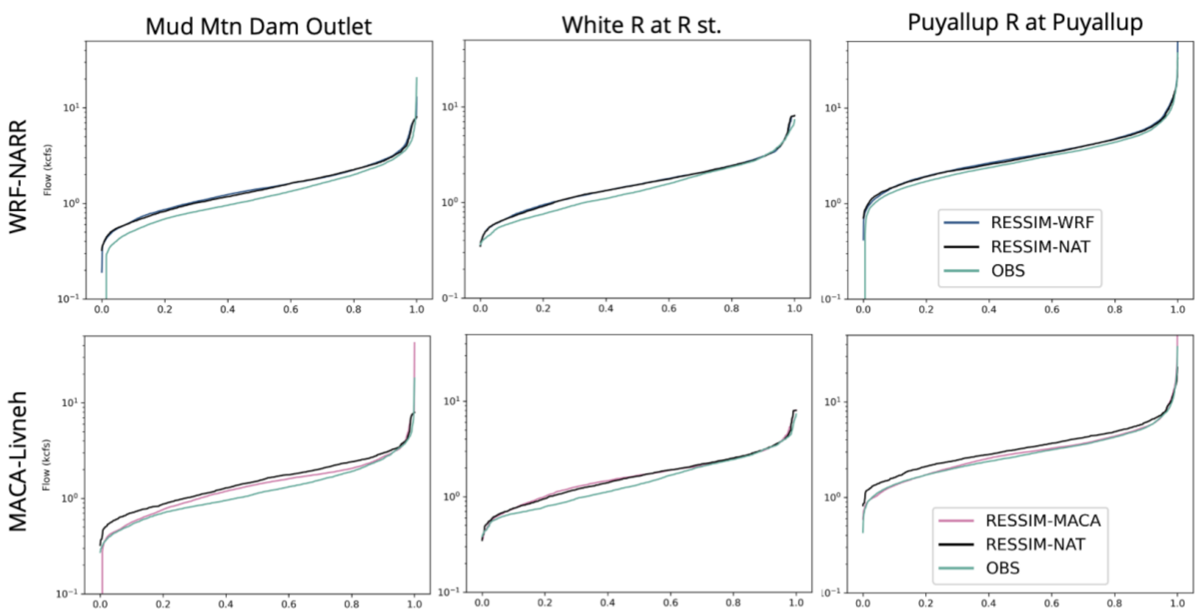

Figure 7. Cumulative distributions (CDFs) for daily *regulated* flows for three sites downstream of Mud Mountain Dam. Results are included for the observed flows at the USGS gauge (OBS, green), modeled flows using observationally-based naturalized flows (RESSIM-NAT, black), and modeled flows using the WRF-NARR DHSVM flows as inputs (top row, RESSIM-WRF, blue) and the MACA-Livneh DHSVM flows (bottom row, RESSIM-MACA, blue). Comparisons include all years in which observations and model results are available, hence the different averages even for observed and naturalized flows.

regulated flows downstream of Mud Mountain Dam. The scores are very similar for the statistically downscaled ("RESSIM-MACA") and dynamically-downscaled ("RESSIM-WRF") simulations. Notably, the model simulations seem to outperform the naturalized flow simulations in the monthly average comparisons (i.e.: they match the observations better than the naturalized flow simulation). With the CDF comparisons, we can see that the ResSim results depart from the observations, particularly for flows below the median value.

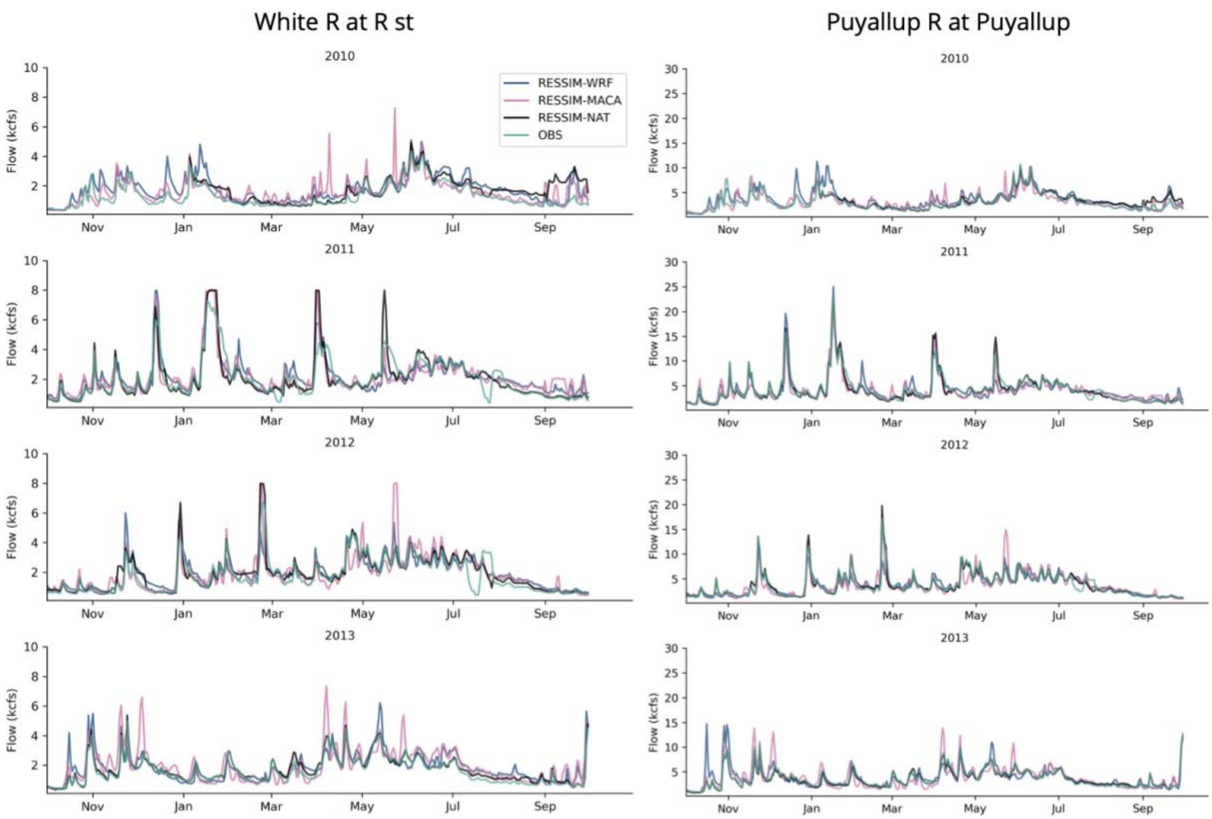

Figure 8. Time series of daily *regulated* flows for two sites downstream of Mud Mountain Dam. Results are included for the observed flows at the USGS gauge (OBS, green), modeled flows using observationally-based naturalized flows (RESSIM-NAT, black), and modeled flows using the WRF-NARR and MACA-Livneh DHSVM flows as inputs (RESSIM-WRF and RESSIM-MACA, respectively; blue). Results are shown for water years 2010-2013 because those are the only years for which all datasets overlap.

RESULTS

This section summarizes the changes in naturalized streamflow for the Puyallup River DHSVM simulations, along with changes in regulated streamflow from the HEC-ResSim model for Mud Mountain Dam (MMD).

Apart from reservoir operations at Mud Mountain Dam, the results do not account for other practices that impact flows. However most water diversions occur during the summer season and are unlikely to substantially affect peak flows. Similarly, the results do not account for changes in land cover, either due to changes in development patterns, land management or wildfire. These changes could have a big impact on flooding, especially on smaller tributaries where the proportional impact from any land use changes would be greater. None of these effects are included in the current analysis. See Appendix F for a more in depth discussion of model assumptions and limitations.

As discussed in previous sections, all results are based on one of two climate datasets. First, the bias-corrected hourly WRF-CMIP5 projections (i.e.: dynamical downscaling, including temperature, precipitation, humidity, wind, and shortwave radiation), and empirical longwave estimates selected based on previous research. And second, the statistically-downscaled MACA-CMIP5 projections, which are a daily dataset that are then disaggregated to 3-hourly for the hydrologic modeling (see Appendix A for more information). Although the climate data are bias-corrected, no bias-correction is applied to the streamflow estimates. To control for biases in the projections, our results focus on percent changes in streamflow whenever possible (i.e., we calculate the percent change for a given GCM projection relative to the historical estimate from that same GCM). Some of the results are nonetheless presented using absolute flow estimates, because these are often more readily translated into impacts. Finally, all of the dynamically-downscaled projections in this study are based on the high-end RCP 8.5 greenhouse gas scenario.

Finally, although we present results from both the dynamically-downscaled (WRF) and statistically-downscaled (MACA) projections, our summary and discussion emphasizes the dynamically-downscaled results. There are two reasons for this. First, research suggests that dynamically-downscaled projections provide more accurate estimates of the change in precipitation, particularly for flooding (e.g. Salathé et al. 2014). Second, we were directly involved in calibrating and evaluating the dynamically-downscaled projections.

Snowpack, Precipitation and Evapotranspiration

On average for the Puyallup river watershed, the dynamically-downscaled simulations project a median -49% decrease in April 1st Snowpack by the 2080s

(relative to the 1990s, range: -18 to -61%). Declining snowpack means that more precipitation falls as rain during storms, contributing to larger floods and an associated decline in spring/summer snowmelt. The effect of snowpack loss on flooding is exacerbated by projected changes in precipitation: **models project a +19% (range: +1 to +35%) increase in the heaviest daily rain event for each year (2080s relative to 1990s).** Since rainfall intensity is the primary driver of flooding in this region, this change is expected to lead to bigger and more frequent floods. **The change in winter (Oct-Mar) precipitation is smaller and more uncertain, showing a projected increase of +4% (range: -7 to +27%).** Still, the projected change is consistent with the effects of declining snowpack and intensifying heavy rain events. **Late summer (Jul-Aug) precipitation, in contrast, is projected to decrease, by -18% (range: -58 to +62%).** Although some models disagree on the direction of change for both summer and winter, 9 of 12 models project an increase in winter precipitation, and 9 of 12 models project a decrease in late summer precipitation for the 2080s. The projections are much more uncertain for September precipitation but suggest a decrease (median: -1%, range: -46% to +52%, with only half of the models projecting a decrease). In summer, another potential climate change effect is evaporation. Surprisingly, our models project a **small decrease in late summer evapotranspiration (median change for Jul-Aug: -6%, range: -24% to +19%**, with 8 of 12 models showing a decrease). This suggests that precipitation is the primary factor affecting summer decreases in flows.

Table 6. Average projected change in monthly average *naturalized* flows for six river sites in Table 1. Results show the model average percent change for the 2080s (2070-2099) relative to the 1980s (1970-1999), for both the WRF and MACA projections. Projections are highlighted in bold when all models agree on the sign of the change.

	Puyallup R nr Orting		Carbon R nr Fairfax		South Prairie Cr		Greenwater R		White R blw Clearwater		White R nr Buckley	
	WRF	MACA	WRF	MACA	WRF	MACA	WRF	MACA	WRF	MACA	WRF	MACA
OCT	+19%	+2%	-1%	-4%	-5%	-5%	-13%	-18%	+1%	-14%	+1%	-14%
NOV	**+31%**	**+36%**	+18%	**+50%**	+1%	**+23%**	+4%	**+44%**	**+24%**	**+45%**	**+22%**	**+42%**
DEC	**+52%**	**+68%**	**+41%**	**+101%**	+13%	**+48%**	+33%	**+113%**	**+53%**	**+100%**	**+49%**	**+95%**
JAN	**+33%**	**+65%**	+24%	**+108%**	+5%	**+45%**	**+27%**	**+134%**	**+37%**	**+114%**	**+35%**	**+106%**
FEB	**+31%**	**+62%**	+25%	**+107%**	+5%	**+40%**	+19%	**+139%**	**+31%**	**+113%**	+28%	**+105%**
MAR	+26%	**+39%**	+21%	**+76%**	+4%	**+20%**	+9%	**+101%**	+22%	**+82%**	+20%	**+75%**
APR	+14%	+9%	+7%	**+33%**	-2%	-7%	-12%	**+28%**	+3%	**+27%**	+3%	**+24%**
MAY	-4%	**-23%**	**-18%**	-13%	-9%	**-42%**	**-36%**	**-43%**	**-21%**	**-25%**	**-20%**	**-26%**
JUN	**-17%**	**-35%**	**-37%**	**-39%**	-20%	**-59%**	**-44%**	**-71%**	**-38%**	**-50%**	**-37%**	**-51%**
JUL	**-26%**	**-34%**	**-49%**	**-50%**	-16%	**-64%**	**-38%**	**-78%**	**-45%**	**-62%**	**-44%**	**-62%**
AUG	**-29%**	**-40%**	**-53%**	**-55%**	-17%	**-54%**	**-33%**	**-70%**	**-42%**	**-64%**	**-41%**	**-64%**
SEP	-11%	**-42%**	-32%	**-52%**	-19%	**-46%**	**-31%**	**-57%**	-26%	**-57%**	-26%	**-56%**

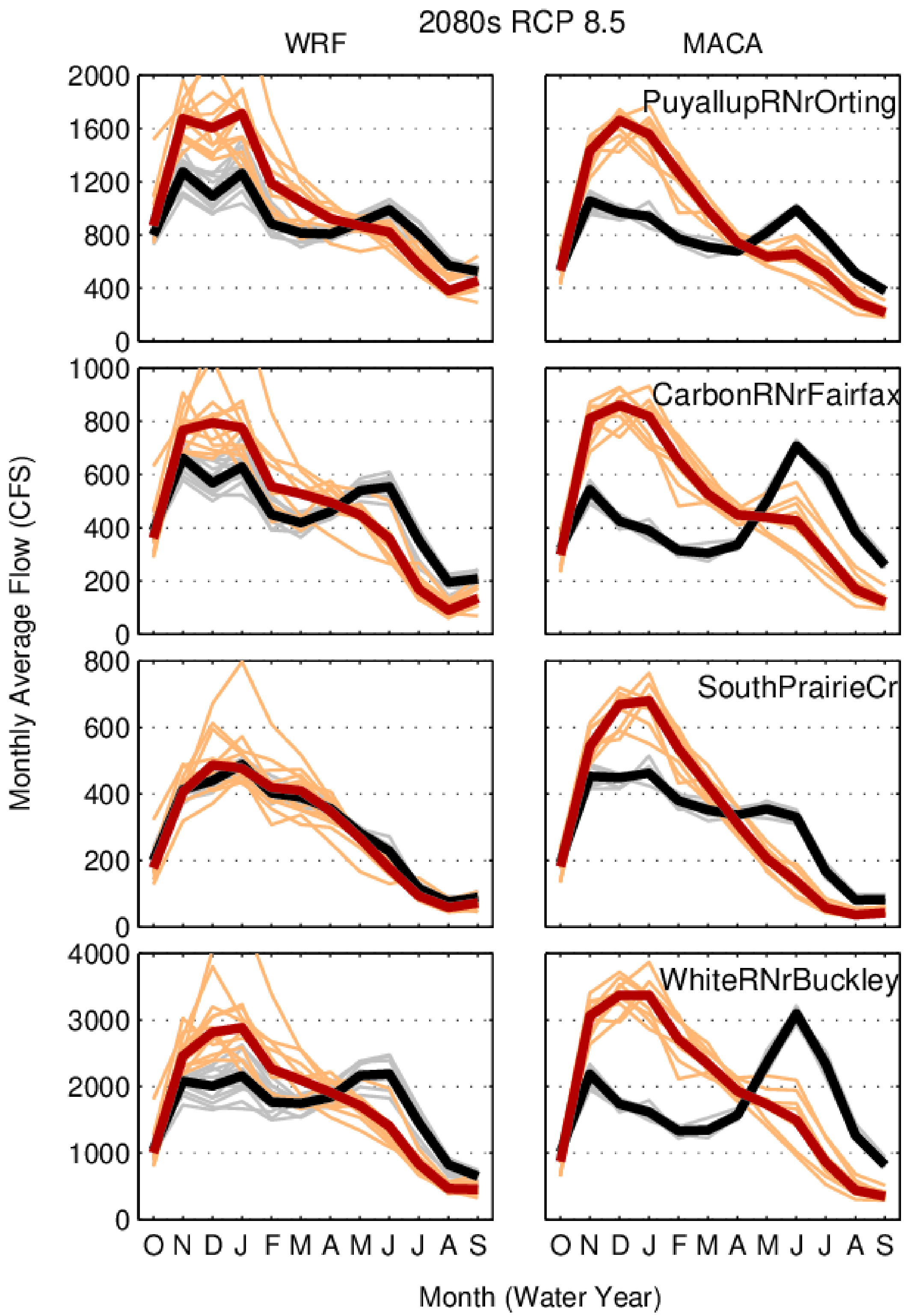

Figure 9. Historical and future monthly *naturalized* flows for four sites listed in Table 1. Each line shows the results for one WRF-CMIP5 or MACA-CMIP5 projection: historical (1980s, grey/black) and 2080s (orange/red). Thick lines show the model average, thin lines the individual model projections.

Monthly Flows

Naturalized (Unregulated) Flow Projections

The Puyallup River's hydrology is considered "mixed rain and snow", with two peaks in streamflow corresponding with (1) the rainy season, in mid-winter, and (2) the snowmelt season, in spring. For all sites, flows drop off rapidly in late spring, with a minimum in September, before increasing again in the fall. **Projected changes reflect the combined effects of snowpack loss and the projected changes in precipitation, with a higher winter peak, a lower and earlier spring freshet, and lower flows in summer** (Table 6, Figure 9). The changes in snowpack are negligible for the South Prairie Creek site, because it has negligible winter snowpack to begin with. The change in heavy precipitation intensity likely contributes to the projected increases in winter flows for all six sites. The magnitude of streamflow changes (winter increases, summer decreases) is larger and there is more model agreement for the snow-influenced sites. This is expected, since changes in snowpack are more pronounced and occur sooner than projected changes in precipitation.

Regulated Flow Projections

Monthly average flows are projected to change in similar ways for locations affected by reservoir operations at Mud Mountain Dam (Figure 10, Table 7). The effect of regulation is clear with a general reduction in winter flows and an increase in summer flows, especially

Table 7. Average projected change in monthly average *regulated* flows for three river sites in Table 1. Results show the model average percent change for the 2080s (2070-2099) relative to the 1980s (1970-1999), for both the WRF and MACA projections. Projections are highlighted in bold when all models agree on the sign of the change.

	White R nr Buckley (Mud Mtn Dam)		White R at R st.		Puyallup R at Puyallup	
	WRF	MACA	WRF	MACA	WRF	MACA
OCT	+2%	-16%	+2%	-15%	+7%	-8%
NOV	**+24%**	**+47%**	**+23%**	**+43%**	+23%	**+39%**
DEC	**+53%**	**+100%**	**+50%**	**+92%**	**+44%**	**+74%**
JAN	**+38%**	**+110%**	**+37%**	**+102%**	**+29%**	**+75%**
FEB	**+35%**	**+119%**	**+33%**	**+109%**	+28%	**+79%**
MAR	+26%	**+86%**	+24%	**+74%**	+21%	**+52%**
APR	+3%	**+25%**	+3%	**+22%**	+6%	**+14%**
MAY	**-22%**	**-25%**	**-21%**	**-25%**	**-15%**	**-24%**
JUN	**-39%**	**-51%**	**-38%**	**-50%**	**-32%**	**-45%**
JUL	**-43%**	**-59%**	**-41%**	**-58%**	**-36%**	**-50%**
AUG	**-39%**	**-59%**	**-37%**	**-57%**	**-33%**	**-51%**
SEP	**-27%**	**-53%**	**-25%**	**-52%**	**-21%**	**-47%**

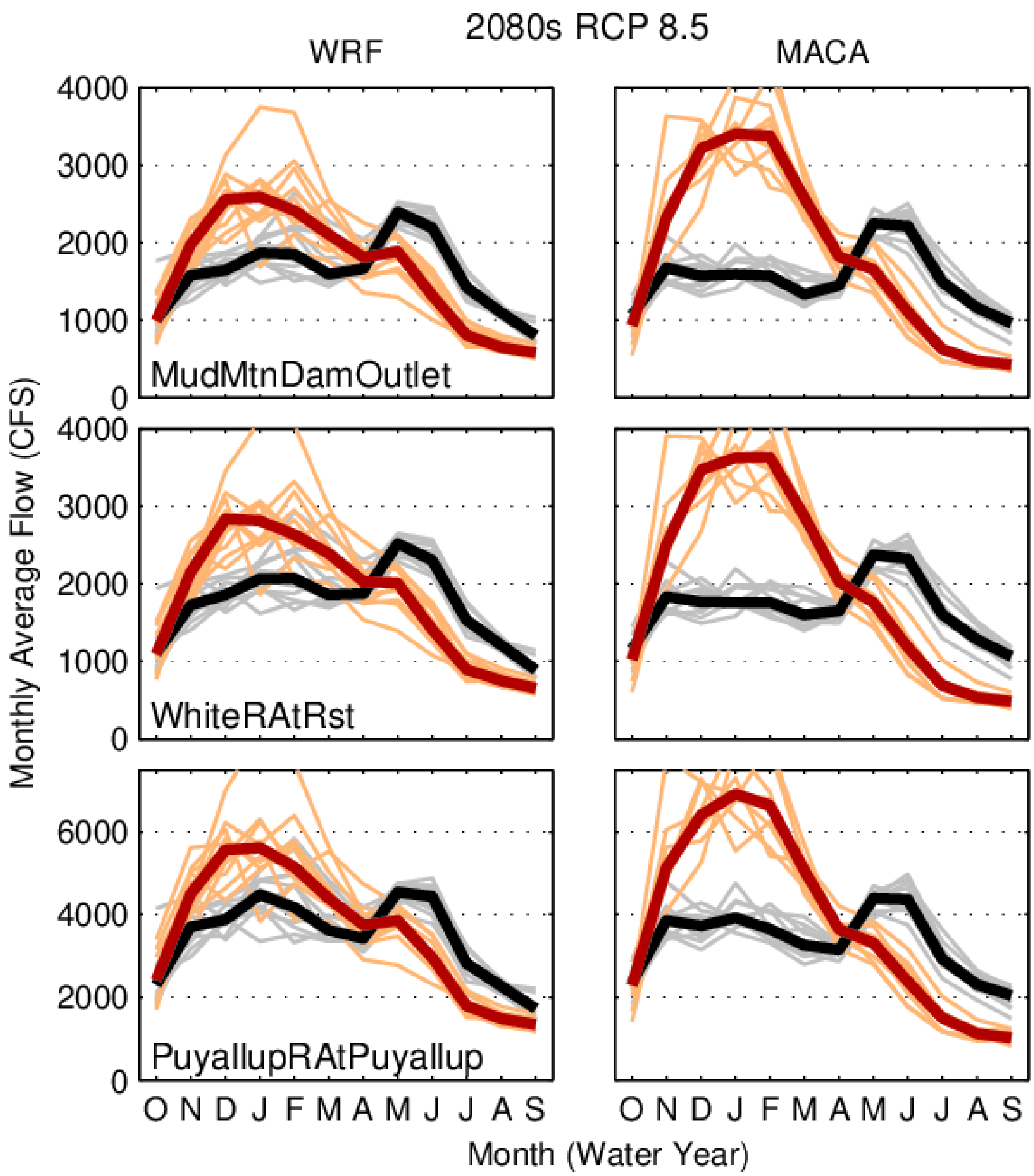

Figure 10. Historical and future *regulated* monthly flows for three sites listed in Table 1. Each line shows the results for one WRF-CMIP5 projection: historical (1980s, grey/black) and 2080s (orange/red). Thick lines show the model average, thin lines the individual model projections.

in late summer, relative to the naturalized flows. Nonetheless, the results are very consistent with the naturalized flow projections: climate change results in higher flows in winter (Nov-Mar) and lower flows in spring and summer (May-Sep), and there is high agreement among models. For the regulated flow projections, models only differ on the direction of change around the inflection points between increases and decreases (Oct, Mar, Apr). As with the naturalized flow results, the projections are more extreme for MACA than for WRF and there is less of a spread among models. **Notably, for both MACA and WRF, regulated Aug-Sep flows for the 2080s are about as low as the naturalized flow projections for the 2080s**, suggesting that reservoir storage may not be able to augment summer flows in the future.

Peak Flows

Naturalized (Unregulated) Peak Flow Projections

Naturalized peak flows are projected to increase for nearly all models, return intervals, and time periods that we considered. Assessing trends in extremes is difficult, since they are by definition rare events (see Appendix E for the approach we use). This

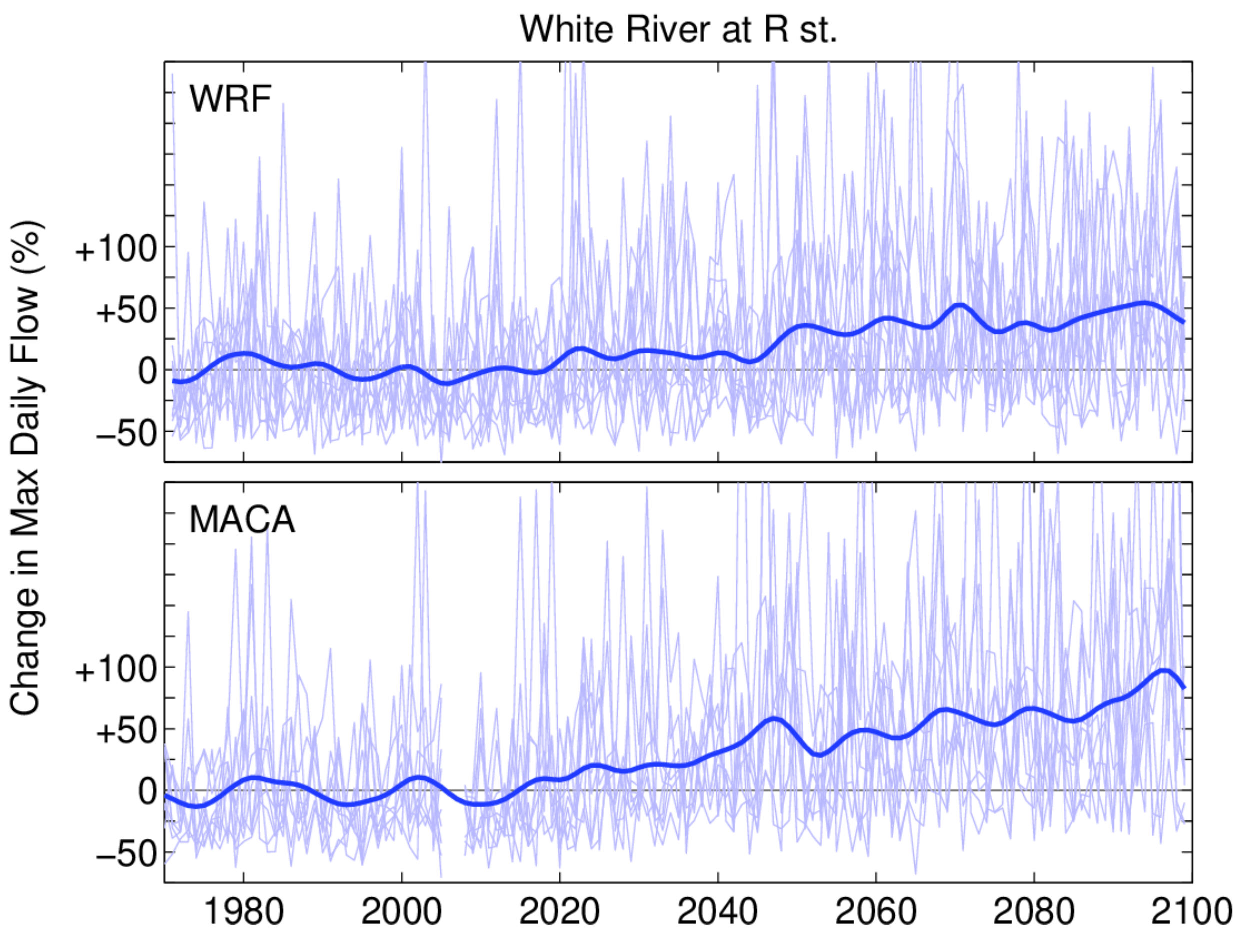

Figure 11. Projected changes in *naturalized* peak daily flows for each of the models analyzed in this study (light blue lines), and model average (thick blue line). The top plot shows results from the dynamically-downscaled projections (WRF-CMIP5), while the bottom plot shows results from the statistically-downscaled projections (MACA-CMIP5). For each model, the plot shows the maximum in daily flows for each water year, plotted as a percent difference relative to the average for the 1990s (1980-2009). For readability, the model average is smoothed using an 11-point gaussian filter.

means the projected changes are more sensitive to sample bias. This uncertainty is likely greater for the largest events such as the 50-year or 100-year return interval events. We recommend treating the results for these larger events with caution. In contrast, the smaller and more frequent extreme events are likely well-captured by the 30-year sampling periods and therefore less influenced by natural variability. To illustrate the episodic nature of peak flows, Figure 11 shows the time series of the maximum daily flow for each water year, for all models, for the White River at R st. While the average across all models increases fairly steadily throughout the century, the big events in each model simulation punctuate the record at random intervals. This means that the extreme statistics, particularly for the big events like the 50- and 100-year floods, can fluctuate a lot from decade to decade, even if the long-term average shows a steady rise over time.

In order to provide a more detailed look at the statistics, Table 8 summarizes the projections for the daily flow duration, juxtaposing the 2-, 10-, and 100-year projections for each of the six sites featured in previous plots. Figure 12 provides results for multiple durations (3-hour through 7-day) for the 2-year event. Although there is a range among models, **the median projections all show an increase across all return intervals, durations, and locations. For the dynamically-downscaled WRF results, the median**

Table 8. Projected change in *naturalized* peak daily flow extremes for six streamflow sites. Results are provided for the 2080s (2070-2099) relative to the 1980s (1970-1999), for the high-end RCP 8.5 scenario.

	site	WRF RCP 8.5		MACA RCP 8.5	
		median	min / max	median	min / max
2-yr	Puyallup R nr Orting	+46%	+32% / +101%	+57%	+25% / +83%
	Carbon R nr Fairfax	+25%	+15% / +80%	+82%	+48% / +106%
	South Prairie Cr at SP	+5%	-6% / +51%	+35%	+19% / +56%
	Greenwater R	+40%	-10% / +66%	+76%	+40% / +91%
	White R blw Clearwater	+48%	+18% / +88%	+84%	+46% / +102%
	White R nr Buckley	+44%	+14% / +86%	+80%	+44% / +98%
10-yr	Puyallup R nr Orting	+41%	+23% / +102%	+58%	+39% / +87%
	Carbon R nr Fairfax	+33%	+12% / +84%	+79%	+63% / +107%
	South Prairie Cr at SP	+19%	-8% / +70%	+45%	+19% / +63%
	Greenwater R	+38%	-1% / +80%	+90%	+67% / +158%
	White R blw Clearwater	+39%	+16% / +90%	+92%	+72% / +138%
	White R nr Buckley	+37%	+14% / +87%	+88%	+68% / +129%
100-yr	Puyallup R nr Orting	+33%	+1% / +123%	+45%	+13% / +132%
	Carbon R nr Fairfax	+38%	-9% / +109%	+57%	+21% / +196%
	South Prairie Cr at SP	+48%	-11% / +123%	+55%	+2% / +126%
	Greenwater R	+42%	-50% / +113%	+91%	+10% / +221%
	White R blw Clearwater	+40%	-26% / +109%	+82%	+24% / +242%
	White R nr Buckley	+41%	-28% / +109%	+75%	+24% / +240%

projections for the end of the century range from about +5% to +50%, depending on location and flow duration. Projections from the statistically-downscaled MACA projections are higher and more consistently positive.

The high elevation sites generally show greater increases than the low elevation sites, likely due to the greater influence of snowpack changes. The projections do not show a

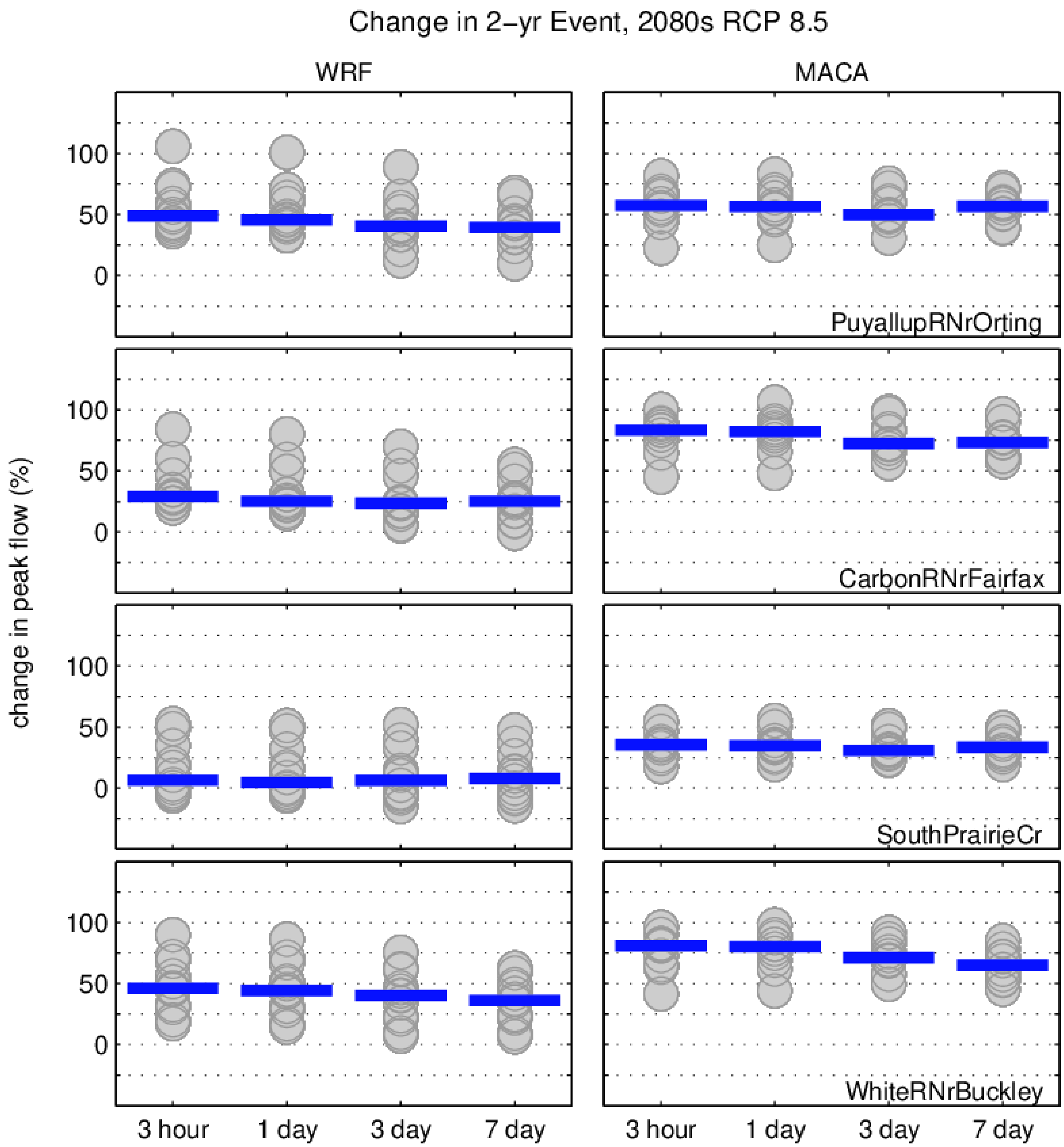

Figure 12. Projected change in the 2-year *naturalized* peak flow for the six sites listed in Table 1. Results are in percent, relative to the 1980s (1970-1999), for four different durations: 3 hour, 1 day, 3 day, and 7 day average flows. Each dot shows the result for one GCM projection, while the blue bars show the median of the 12 models.

consistent relationship with duration, though some sites show a weak tendency for smaller increases at longer durations. This is consistent with the precipitation projections, which also tend to show smaller increases for longer durations.

The wide range among models, even for the 2-year event, is typical of peak flow projections. The range among projections is also greater for the dynamically-downscaled WRF projections relative to the statistically-downscaled MACA projections. This is consistent with previous research (Salathé et al. 2014).

Regulated Peak Flow Projections

Regulated peak flows are projected to increase across nearly all durations, quantiles, and models, but the increases are generally smaller than for naturalized flows. On the White River, the changes are most important for both the smallest and largest floods, whereas little change in projected for moderate floods. In contrast, peak flows are projected to increase across the board for the Puyallup mainstem site. As with all of the results, the projected increases are systematically larger for the statistically-downscaled (MACA) results compared to the dynamically-downscaled (WRF) projections. Figure 13, for example, shows about a 10-15% average increase in the maximum daily peak flow for the WRF projections, about a third of the change projected for naturalized peak flows at the White River at R st site (Figure 11). Similarly, the MACA projections show about a 50-75% increase for regulated flows (Figure 13), compared to a 75%-100% increase for naturalized flows. For the remainder of this section, our summary is focused on the results for the dynamically-downscaled WRF projections.

Assessing peak flow statistics is more complicated for regulated flows because they do not necessarily adhere to an extreme value distribution. Based on discussions with staff at the U.S. Army Corps and King County, we decided not to use an extreme value fit to assess changes in peak flows. Instead, we chose to only consider changes in the empirical CDF of peak flows. We can still calculate the results for specific return intervals, using quantiles from the empirical CDF. Specifically, we estimated quantiles using the Cunnane (1978) plotting position. However, since we compare 30-year periods to assess changes (e.g. 1980-2009, 2070-2099), we only have 30 peak flow values for each time period. Given this limited sample size, our analysis is primarily focused on extremes that are smaller than the 10-year event. As discussed below, future work could explore approaches to better characterizing changes for larger floods.

For a more detailed look at the peak flow projections, Figure 14 shows the historical and future peak daily flow CDFs for the four sites for which regulated flows were estimated.

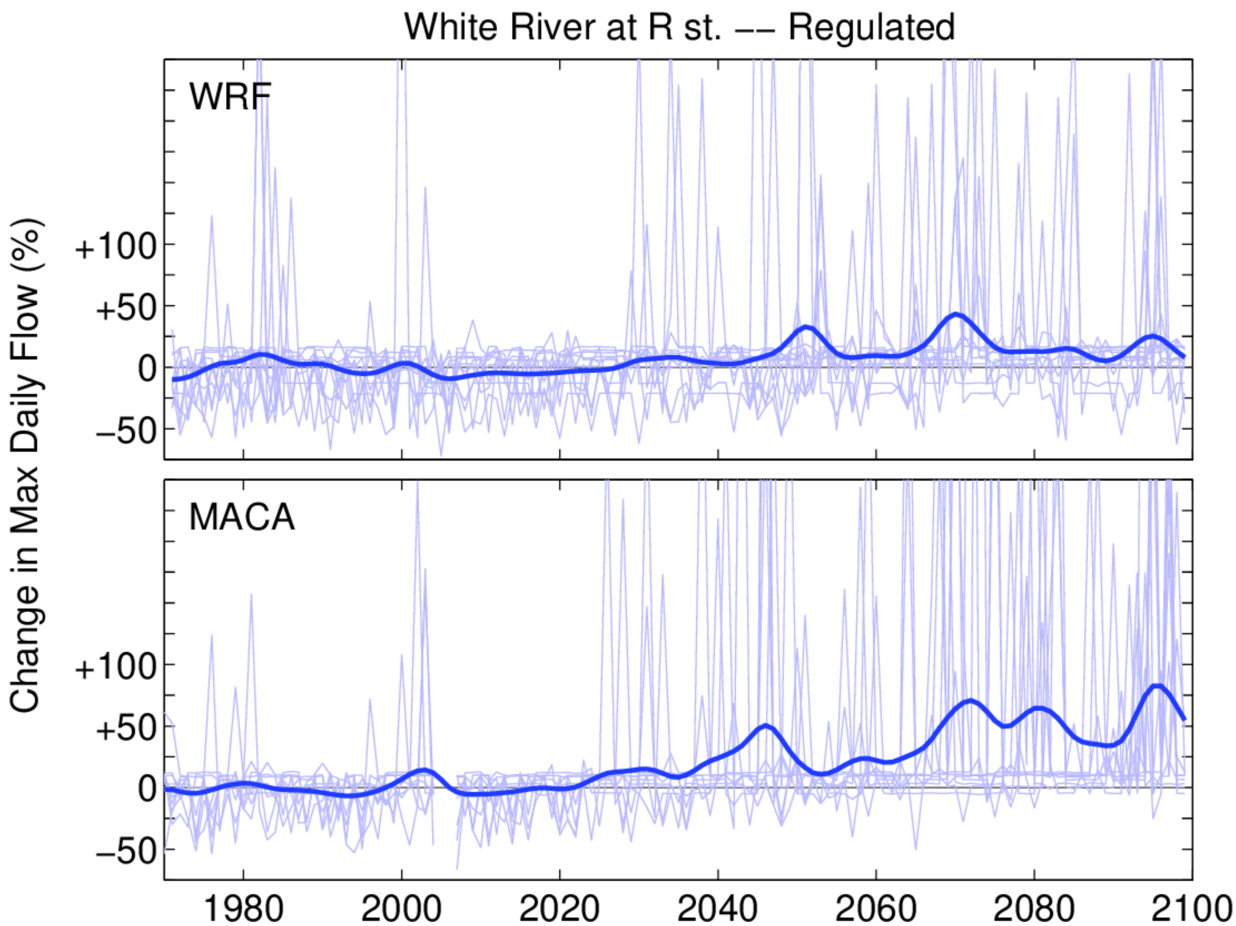

Figure 13. Projected changes in *regulated* peak daily flows for each of the 12 models analyzed in this study (light blue lines), and model average (thick blue line). For each model, the plot shows the maximum in daily flows for each water year, plotted as a percent difference relative to the average for the 1990s (1980-2009). For readability, the model average is smoothed using an 11-point gaussian filter.

Figure 15 and Table 9 show the projected changes for select return intervals in daily flows, calculated using the empirical quantiles as described above.

The results for Mud Mountain Dam outflows and the White River at R st are similar. They confirm that peak flows rarely exceed 8,000 CFS at both sites. Specifically, the middle of the distribution shows no change. This is expected, since for these moderate floods, the reservoir is able to keep flows at or below 8,000 CFS. However, the **projections show flows above 8,000 CFS becoming both larger and more frequent for the White River at R st.** For example, the WRF model average for the historical simulations only has flows exceeding 8,000 CFS substantially for the largest events (corresponding approximately to the 50-year event), whereas by the 2080s, these 8,000 CFS limit is exceeded starting at about the 10-year event. The largest floods at these sites are also projected to increase in

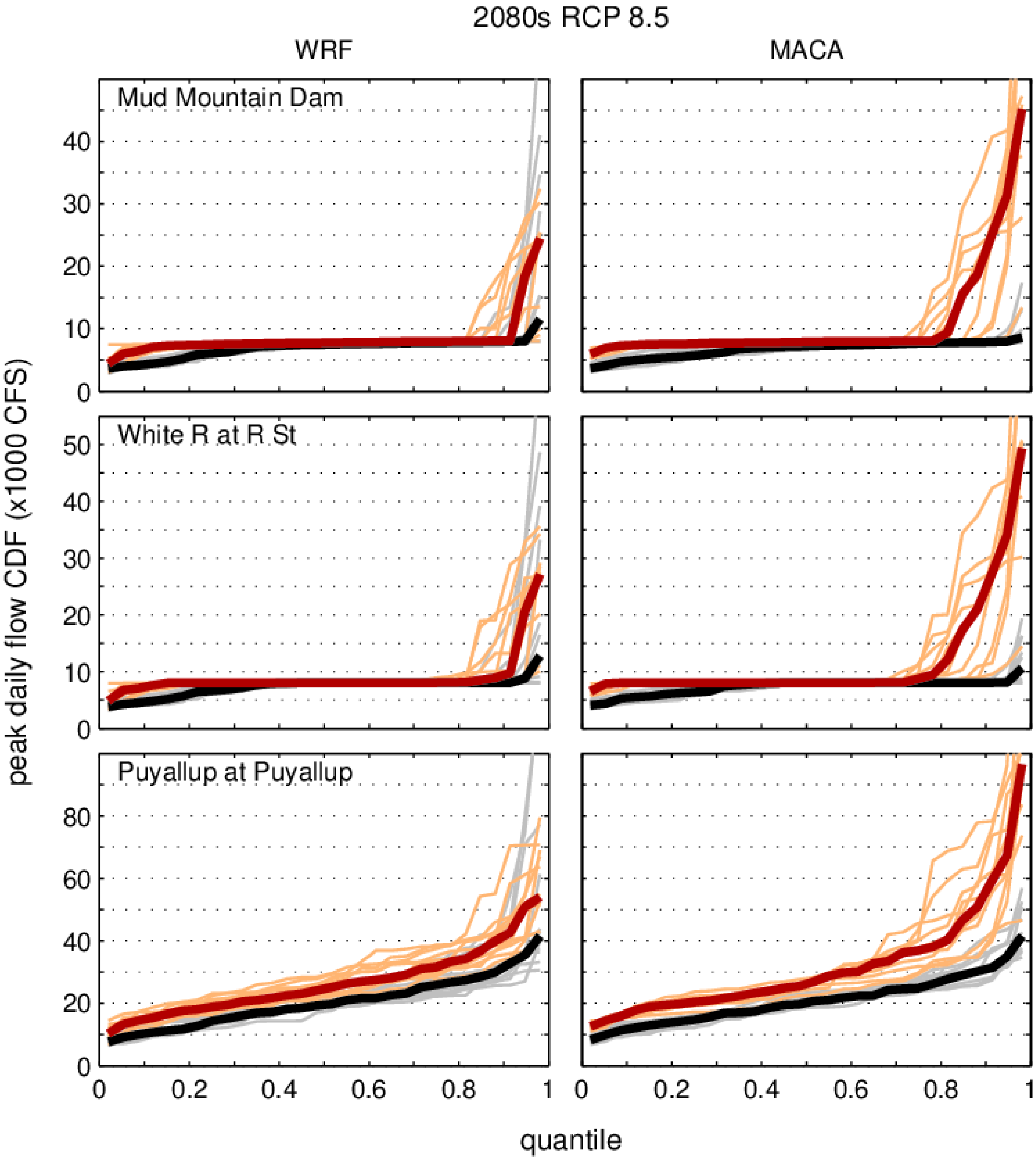

Figure 14. Projected change in the cumulative distribution of regulated peak flows (x1000 CFS), at the daily duration, for four sites downstream of Howard Hanson Dam. Each line shows the results for one WRF-CMIP5 projection: historical (1980s, grey/black) and 2080s (orange/red). Thick lines show the model average, thin lines the individual model projections.

magnitude. At the highest quantile (approximately a 50-year event), the average of the WRF projections is nearly 24,000 CFS, whereas historically it is under 13,000 CFS. As noted above, this extreme end of the distribution is subject to greater uncertainty with an empirical CDF. Nonetheless, the sign of the change is clear: models consistently show increases in the largest events at R st., and that they exceed the 8,000 CFS flow target more frequently.

The other change that is evident is in the lower end of the distribution. Historically, these smaller floods did not require releases approaching the 8,000 CFS limit – flows reached this limit starting at just under the 2-year event. By the 2080s, in contrast, the average model projection has flows reaching 8,000 CFS at R st about twice as often, starting at about the 1.3-year event.

Regulated peak flows at the Puyallup River at Puyallup gauge behave differently than those on the lower White River because of the greater influence of unregulated flows from areas in the Puyallup watershed that are not upstream of Mud Mountain Dam. This is evident in the results, which generally show a more uniform increase across all quantiles (in contrast, the White River sites have a threshold response that is reflective of the flow targets at MMD). Nonetheless, the results show that historically, flows remain below the 45,000 CFS limit for the Puyallup River at Puyallup gauge across all quantiles whereas in the future they may not. Specifically, for the 1980s the model average maximum of the CDF, corresponding approximately to a 50-year event, is 43,000 CFS. By the 2080s, in contrast, the model average maximum of the CDF increases to 57,000 CFS, well above the 45,000 CFS flow target.

In order to provide a direct comparison with Figure 12, Figure 15 shows the projected changes in the 2-year event across four durations, ranging from 3 hours to 7 days. As illustrated in Figure 14, there is essentially no change in the 2-year event for the White River sites – these floods already reach 8,000 CFS historically, and Mud Mountain Dam is able to keep them at or below this limit in the future. In contrast, the 2-year event for the 3-day and 7-day durations has historically been well below 8,000 CFS (on average, about 3,900 and 3,400 CFS, respectively). Figure 15 shows that all models project an increase in the magnitude of these longer-duration events, and that the increases are particularly substantial for the 7-day duration. This again suggests that flows approaching the 8,000 CFS target will occur more frequently in the future.

In contrast, projections for the Puyallup River at Puyallup show a fairly uniform increase across all durations. This is consistent with the naturalized flow results (Figure 12), which makes sense given the smaller proportional influence of Mud Mountain Dam on this location. Nonetheless, the regulated flow projections show smaller increases than the

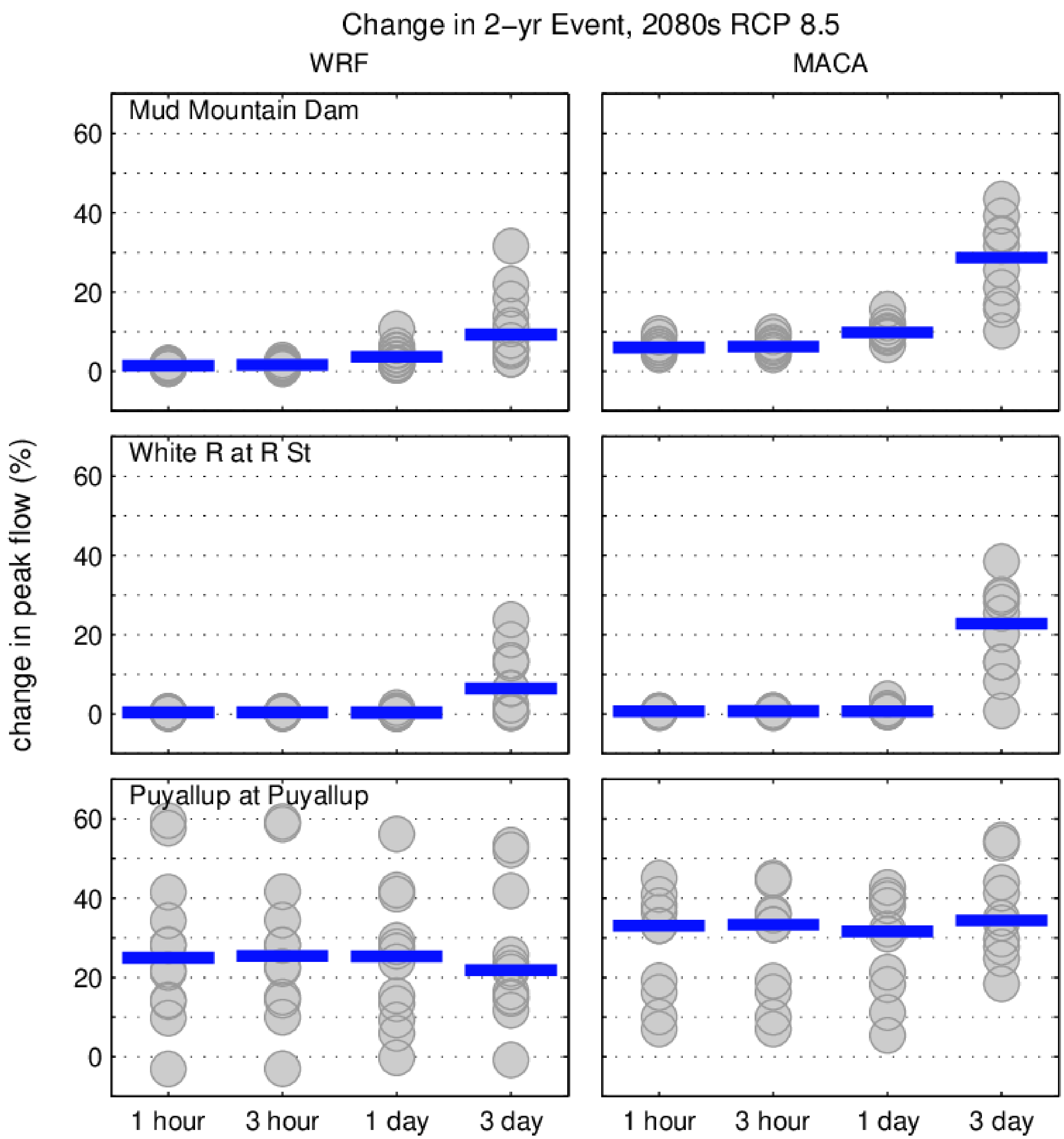

Figure 15. Projected change in the 2-year *regulated* peak flow for four sites downstream of Mud Mountain Dam. Results are in percent, relative to the 1980s (1970-1999), for four different durations: 1 hour, 1 day, 3 day, and 7 day average flows. Each dot shows the result for one GCM projection, while the blue bars show the median of the 12 models.

Table 9. Projected change in regulated peak daily flow extremes for three streamflow sites downstream of Mud Mountain Dam. Results are provided for the 2080s (2070-2099) relative to the 1980s (1970-1999).

	Site	WRF RCP 8.5 median	WRF RCP 8.5 min / max	MACA RCP 8.5 median	MACA RCP 8.5 min / max
1.11-yr	**Mud Mtn Dam Outlet**	+59%	+19%/+82%	+54%	+26%/+90%
	White R at R st	+60%	+13%/+82%	+50%	+22%/+82%
	Puyallup R at Puyallup	+49%	+4%/+82%	+39%	+19%/+70%
2-yr	**Mud Mtn Dam Outlet**	+4%	+1%/+12%	+9%	+7%/+16%
	White R at R st	+0%	+0%/+1%	+1%	+0%/+1%
	Puyallup R at Puyallup	+26%	-1%/+57%	+29%	+11%/+43%
10-yr	**Mud Mtn Dam Outlet**	+2%	-0%/+144%	+168%	+2%/+371%
	White R at R st	+14%	+0%/+197%	+180%	+15%/+394%
	Puyallup R at Puyallup	+24%	+7%/+128%	+65%	+24%/+121%

naturalized flow projections, indicating that there is a moderating influence on floods due to flow regulation at Mud Mountain Dam.

Overall the results suggest that the reservoir can continue to meet the 8,000 CFS and 45,000 CFS flow targets at the White River at R st and Puyallup River at Puyallup, respectively, for the majority of floods. However, increases in inflows to Mud Mountain Dam, combined with increases in naturalized peak flows for locations unaffected by the dam, do result in future floods that are both more frequent and larger for the Puyallup River at Puyallup. This includes more frequent and larger exceedances above the flow targets, as well as high flows just below these flow targets occurring more often. The latter events could put more stress on the levee system, even if the risk of overtopping is averted.

Another way to evaluate changes is in terms of the number of times flow thresholds are exceeded, now and in the future. Figure 16 shows the average number of hours per year that flows exceed 8,000 CFS at the White River at R st gauge and 45,000 CFS at the Puyallup River at Puyallup gauge. Both show fairly consistent increases over time. **At the R st gauge, the median projection is just over 70 hours per year exceeding 8,000 CFS currently (2020s) and just over 140 hours per year by the 2080s – doubling the frequency of exceedances, relative to present-day conditions. In contrast, flows almost never exceed the 45,000 CFS target at the Puyallup gauge – flows above this level occur about 1 hour every 4 year currently (2020s), and are projected to occur about 1.7 hours per year, on average, by the 2080s.** Of course, this is the average value per year. In reality each year will be different, with some years showing no exceedances and others more extended stretches above these flow levels. Regardless, the results consistently show increases in the frequency of flows exceeding flow targets at each of the control points for Mud Mountain Dam.

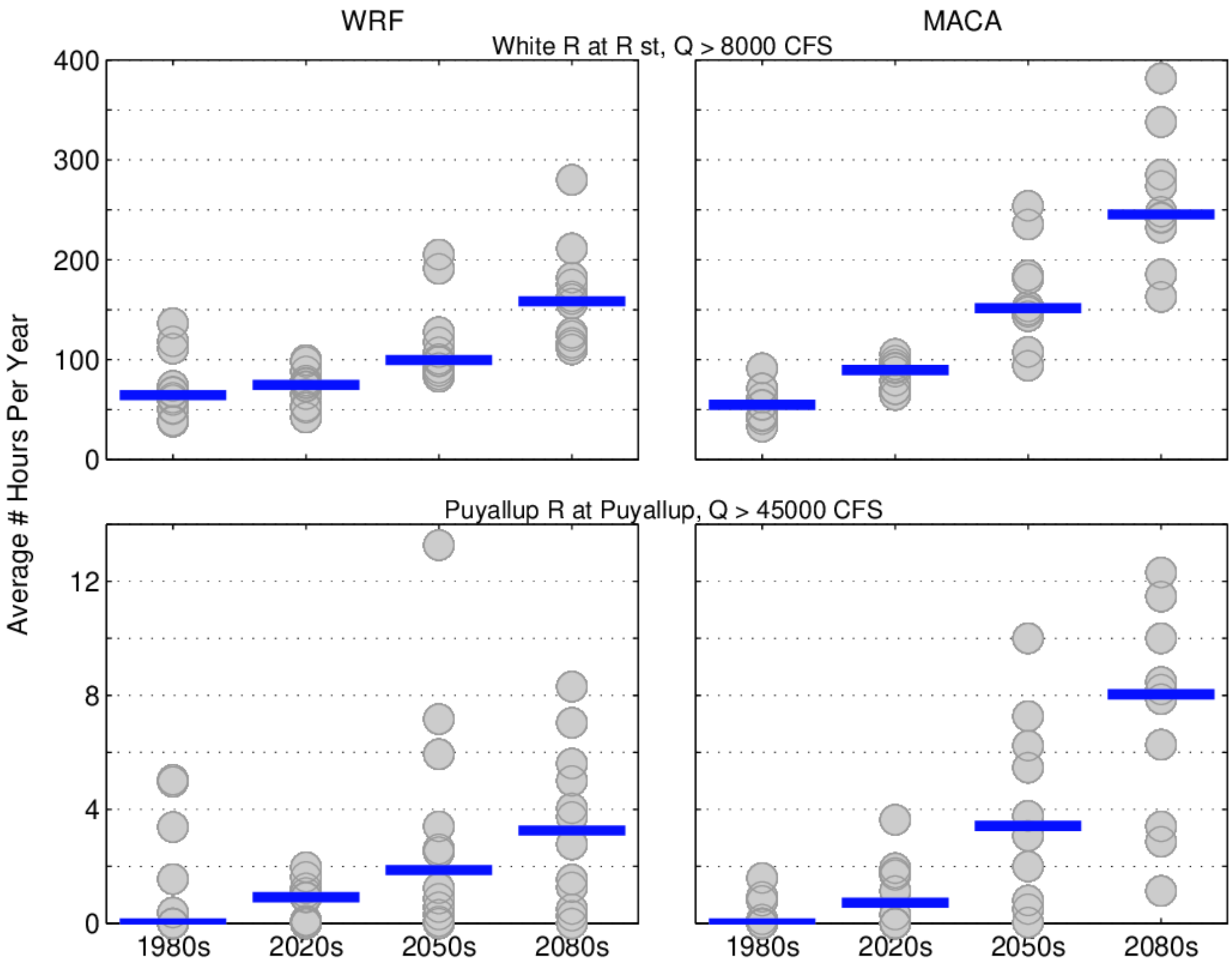

Figure 16. Number of hours with *regulated* hourly flows above 8,000 CFS for the White River near R st gauge location (top), and above 45,000 CFS for the Puyallup River at Puyallup gauge location (bottom). Each plot shows the average, for each of the 12 GCM projections, for four 30-year periods: 1980s (1971-1999), 2020s (2010-2039), 2050s (2040-2069), and 2080s (2070-2099). Each dot shows the result for one GCM projection, while the blue bars show the median of the 12 models.

Low Flows

Naturalized Low Flow Projections

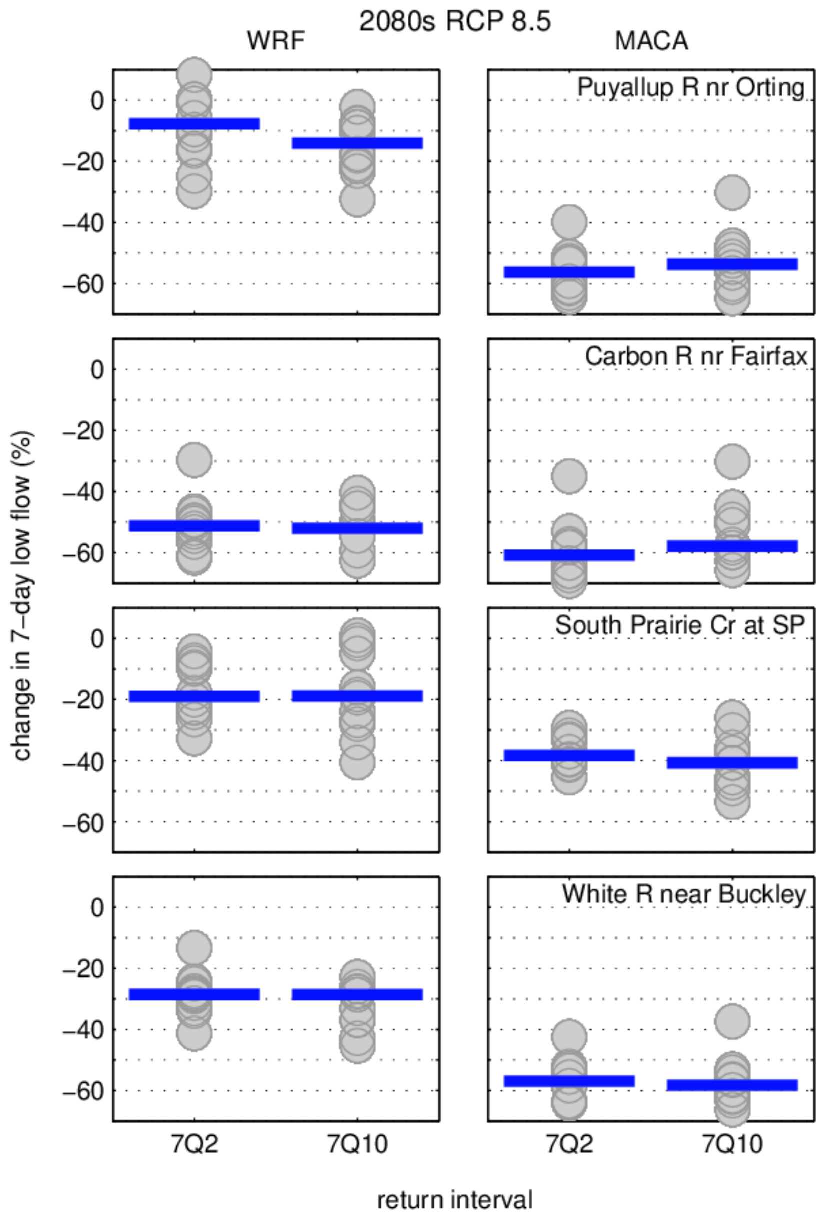

Figure 9. As in Figure 6 except showing the projected change in *naturalized* low flows. Results are shown in percent, relative to the 1980s (1970-1999), for the 2-, and 10-year extremes in 7-day minimum flows. Each dot shows the result for one GCM projection, while the blue bars show the median of the 12 models.

Naturalized low flows are projected to decrease for nearly all models, durations, return intervals, and time periods that we considered (Figure 17, Table 10). Although there is some contrast between the snow-influenced and rain-dominated sites (e.g. South Prairie and Carbon River), the projections for the Puyallup River near Orting are more similar to those for South Prairie Cr than the other snow-influenced sites. In addition, the range among models is smaller for low flows than for the peak flow projections.

Although not shown in these results, another difference with the peak flow projections is that changes appear to be occurring sooner for low flows. Results vary among models and metrics, but some suggest that the region has already experienced modest decreases in low flows (i.e., comparing the 2020s to the 1980s in the current simulations). This again suggests that snowpack is playing a role in the projected changes, since trends in precipitation have not been detected to date. **Overall, median projections for the end of the century range from about a +10% to +50% decrease.**

Table 10. Projected change in naturalized low flow extremes for six gauge locations listed in Table 1. Results are provided for 7-day average low flows, for the 2080s (2070-2099) relative to the 1980s (1970-1999).

	site	WRF RCP 8.5		MACA RCP 8.5	
		median	min / max	median	min / max
2-yr	Puyallup R nr Orting	-10%	-34% / +3%	-52%	-61% / -30%
	Carbon R nr Fairfax	-51%	-60% / -26%	-54%	-66% / -22%
	South Prairie Cr at SP	-20%	-34% / -4%	-39%	-47% / -29%
	Greenwater R	-32%	-41% / -26%	-49%	-58% / -42%
	White R blw Clearwater	-27%	-38% / -10%	-56%	-64% / -36%
	White R nr Buckley	-27%	-36% / -12%	-56%	-64% / -38%
10-yr	Puyallup R nr Orting	-17%	-35% / -5%	-43%	-59% / -16%
	Carbon R nr Fairfax	-53%	-69% / -40%	-45%	-59% / -11%
	South Prairie Cr at SP	-20%	-41% / +2%	-42%	-55% / -26%
	Greenwater R	-32%	-39% / -13%	-54%	-64% / -43%
	White R blw Clearwater	-31%	-43% / -21%	-56%	-65% / -34%
	White R nr Buckley	-30%	-44% / -21%	-56%	-65% / -34%

Regulated Low Flow Projections

We did not evaluate regulated low flow projections, because this was not the focus of our reservoir modeling. Doing so would require a more detailed evaluation of the hydrologic model performance during summer, and maybe additional calibration. Additional work may also be needed to ensure water management choices are adequately captured in the reservoir model.

DISCUSSION

Efforts to integrate dynamical downscaling in hydrologic modeling are few and far between, and it is even more rare to do so using fine-scale hydrologic modeling as we have done here. The use of dynamical downscaling is particularly important in Western Washington given that rain intensity is by far the most important contributor to flooding, and statistical downscaling is unlikely to accurately represent future changes in precipitation (e.g. Salathé et al. 2014).

The previous two phases of this effort also combined dynamical downscaling with fine-scale hydrologic modeling. One of the key advances in this third phase of the work was to use the dynamical downscaling for the historical simulation used in model calibration in addition to the climate change simulations. This ensures greater consistency between historical and future simulations, and likely greater accuracy in the change estimates, since the calibration is more compatible with the projections. To do this we had to identify and correct biases in the dynamically downscaled projections, which proved challenging. Future work could evaluate other dynamically downscaled projections (e.g. Rahimi et al. 2024) or further refine the bias corrections applied here.

Our results are consistent with previous projections in several respects. We find rapid and accelerating decreases in snowpack, and an associated change in streamflow among the sites with the greatest amount of upstream snowpack (e.g. White River near Buckley). Specifically, these locations show increasing flows in winter and decreasing flows in late spring and early summer. Winter flows are further boosted by higher intensity rain events, and there is an associated increase in peak flows. Our extreme precipitation projections are also very similar in magnitude to those from previous studies (e.g. Warner et al. 2015), though they had not previously been incorporated in a hydrologic modeling study.

Our naturalized flow results are generally consistent with the results of our Snohomish and Green River studies (Mauger et al. 2025, Mauger and Won 2025). Specifically, the peak flow projections for the daily 2-yr and 10-yr events show an increase ranging from about +15 to +30% by the end of the century, and the projected changes occur earlier and are generally larger for the snow-influenced sites. Although the model skill scores are similar, the Puyallup model generally performs better for low flows than the Green and Snohomish models. Another difference in the current study is that the Puyallup DHSVM model was more difficult to calibrate, in particular because the meteorological biases were different for the White River and Puyallup/Carbon River basins. Finally, this study included results that are based on statistically-downscaled projections, for comparison with the dynamically-downscaled projections.

As in the Green River study, we evaluated regulated flows using the HEC-ResSim model developed by the U.S. Army Corps of Engineers. Overall, the projections show the expected shift to higher flows in winter along with higher peak flows and lower flows in summer. Importantly, the regulated flow projections show that the cap of 8,000 CFS for the White River at R st and 45,000 CFS for the Puyallup River at Puyallup are nearly always met. Nonetheless, the projections show that flows more frequently exceed these thresholds in the future, and that the magnitude of the overshoot is projected to increase substantially. In addition, we find that flows at or just below these thresholds occur more frequently in the future. Even without overtopping, this could put stress on levees and increase the risk of failure.

The regulated peak flow projections suggest that flow targets on both the lower White and Puyallup rivers may not always be met in the future. Several important points should be emphasized about these results. First, the reservoir model does not account for the role of weather forecasts, which can allow operators to evacuate water in advance of oncoming storms. This means our results are likely pessimistic. Future work could evaluate the potential for reductions when accounting for weather forecasts. Second, one hypothesis might be that the secondary flow target on the White River increases the risk of exceedances on the lower Puyallup. However, we ran a model test with the White River flow target removed and found that future flows still exceeded the lower Puyallup for nearly all the same events, with only small reductions in peak flows as a result of the change. Finally, it is possible that future inflows are simply high enough that no amount of regulation at Mud Mountain Dam could ensure that flow targets are met. For example, across the 12 WRF-CMIP5 projections, there are about 50 events with regulated flows that exceed 45,000 CFS at the Puyallup R at Puyallup gauge. For those events, natural flows on the Puyallup (i.e. upstream of the confluence with the White River) exceed 45,000 CFS for 22 of them. This means that for nearly half of Puyallup River flow exceedances, no amount of regulation at MMD could keep flows below the 45,000 CFS target. For many of the remaining events models project very high inflows to Mud Mountain Dam, exceeding 50,000 CFS in some instances. This last explanation – future inflows are projected to be much higher – is likely the most important. Future research could further evaluate these projections to better understand their cause(s) and associated modeling uncertainties.

For summer, our models project a decrease in July-September precipitation and, surprisingly, a *decrease* in summer evapotranspiration. The precipitation projection is consistent with the findings of previous studies (e.g. Mauger et al. 2015). However, the projections show almost no change for July and September. In addition, there is a very wide range among models for all three months, suggesting low confidence in these findings.

The decrease in summer evapotranspiration is unexpected. In marine-influenced areas like western Washington, we expect relative humidity to track with warming, minimizing changes in evapotranspiration. Still, it is surprising to see a projected decrease in evapotranspiration, in particular given a recent study suggesting models tend to overestimate increases in evapotranspiration (Milly and Dunne 2017, the methods evaluated in this study include the Penman-Monteith approximation used in DHSVM). Instead, our modeling projects a decrease in summer evapotranspiration. In analyzing our Snohomish model results, we found that this was due to a projected increase in humidity, and that this increase is enough to more than compensate for the projected increase in temperature. The same is likely true for the Puyallup River results.

As noted above, this was the first time we used dynamical downscaling in both model calibration and the climate change simulations. In doing so, we confirmed that the biases in regional climate model simulations must be corrected in model calibration, and that these biases vary in space and with weather conditions. We chose not to apply corrections that vary with weather conditions, as doing so objectively would be challenging. Instead, we applied uniform corrections based on low-elevation comparisons with the observationally-based PRISM dataset. We also found that adding sub-grid variations from the PRISM 800m precipitation climatology significantly improved the simulations. Finally, research is ongoing into potential changes in extreme precipitation and other factors related to flood risk in the WRF-CMIP5 projections. As noted above, future work could further explore potential changes and assess uncertainties in climate change projections.

Two key limitations of the hydrologic modeling used this study are that we do not model deep or confined groundwater, and we do not consider possible changes in land cover and water management. Each of these could alter the response of the watershed to climate change, though they are likely most important for low flows. Finally, our hydrologic model (DHSVM) only has a simplified routing scheme (Wigmosta and Perkins 2001) and does not account for overbank flow during flood events. Uncertainties in flow routing could be more important for flood projections.

Another consideration is that all of our projections are based on the high-end RCP 8.5 greenhouse gas scenario (VanVuuren et al. 2011). This scenario is exceptionally high: well above what is considered the likely range for 21st century emissions (e.g. Hausfather and Peters 2020). In this respect, the current projections may overestimate the potential changes this century.

Future work to address these and other limitations is discussed in Appendix G.

Finally, there is no universal criteria for deciding when to update these projections, or use the results of another study in lieu of the current one. This is especially true given that the model is better calibrated for some locations and metrics, and less so for others. Alternative hydrologic projections already exist for the Puyallup River basin (e.g. Chegwidden et al. 2019), though based on statistical downscaling and coarse-scale hydrologic modeling. Dynamically downscaled simulations have also recently been developed for the newer CMIP6 projections (e.g. Rahimi et al. 2024), but these have not been used to develop hydrologic projections in the region. Regardless, alternative projections do exist and more will be developed in the future. As with any adaptation decision, the best way to decide which to use is to first consider the decision context: What level of precision is needed? Will the results affect what decision is made? What are the consequences of under-design? etc. Then if warranted, compare the performance – and projected changes – for different datasets. This will help clarify when the choice of approach makes a difference in the findings, and the strengths and weaknesses of each.

APPENDIX A: STATISTICALLY DOWNSCALED FLOW PROJECTIONS

The following sections describe the inputs, calibration, and results from the statistically downscaled DHSVM projections.

Model Inputs

The Distributed Hydrology Soil Vegetation Model (DHSVM) was implemented at a 90-m resolution for the entirety of the Puyallup River Basin. The model domain was derived from a 90-m Digital Elevation model (DEM) that was resampled from the original 30-m USGS DEM. To achieve proper routing, the DEM was also filled to eliminate sinks. The vegetation inputs utilized in this study was the 2016 National Land Cover Dataset (NLCD), which was resampled from its original resolution of 30-m to 90-m. The soil data used in this study were derived from SSURGO dataset with some locations filled by STATSGO dataset. These datasets were reclassified to the 13 main USDA soil types based on percentage of sand, silt, and clay. The stream network applied in the study is generated by an ArcPy module developed for DHSVM, and a threshold of 50-grids was used for network initiation. This threshold was selected to align with the NHD flowlines, the Google Earth imagery, while distinguishing between fluvial process and the channel flow process. Channel properties were calculated based on the study by Carson and Jackson (2001). The soil depth map was generated along with the stream network, based on the elevation and the topographic gradient of the basin with DHSVM utility tools.

The model was set up to produce streamflow estimates for the sites listed in Table A1. The sites were identified on the network based on the coordinates and descriptions provided by the CIG. The DEM for the 90m DHSVM resolution was edited so that the resulting stream network correctly matched the observed stream network, and to include the locations of interest. Due to limitations in what can be resolved at the 90m resolution, and the fact that DHSVM only output streamflow at downstream end of each stream channel network, streamflow at some sites were not saved at the exact coordinate but at the nearest possible location (such as at a downstream end of channel segment).

The model was implemented at the 1/16-degree resolution of the observationally based historical dataset used in calibration (Livneh et al. 2015) and future projections from the statistically downscaled Multivariate Adaptive Constructed Analogs dataset (MACA, Abatzoglou and Brown 2012). The Livneh et al. (2015) and MACA projections are produced at a daily time step, and include only temperature, precipitation and wind. In contrast, the DHSVM model was implemented using a 3-hour time step and requires precipitation, temperature, wind, downward longwave radiation, downward shortwave radiation, and relative humidity as inputs. To obtain 3-hourly meteorological inputs, we disaggregated the daily Livneh and MACA data using the mountain microclimate simulator (MTCLIM), with the daily precipitation and temperature as inputs.

Table A1. Locations included in streamflow simulation results

USGS Site	Location Name	Location Ref
	White R at R St nr Auburn	WhtAtRst
12100496	WHITE RIVER NEAR AUBURN, WA	WhtNrAub
12100500	WHITE RIVER NEAR SUMNER, WA	WhtNrSum
	Clear Creek at confluence with Puyallup R.	ClrAtPuya
	Canyon Creek at confluence with Clear Cr	CanyonAtConf
12101500	PUYALLUP RIVER AT PUYALLUP, WA	Puyallup
	Clarks Creek at 52nd St E	ClarkAt52
	Clarks Creek at Stewart Ave E	CarkAtStew
	Puyallup R at 5th st Bridge at Puyallup	PuyaAt5th
	Squally Creek at confluence with Clear Cr	SquaAtClr
	Swan Creek at confluence with Clear Cr	SwanAtConf
	Clear Cr at confluence with Mainstem Clear Cr	ClrAtClr
12096500	Puyallup R at Alderton	Alderton
12099600	BOISE CREEK AT BUCKLEY, WA	BoiseAtBuck
12100000	WHITE RIVER AT BUCKLEY, WA	WhtAtBuck
12099200	WHITE RIVER ABOVE BOISE CREEK AT BUCKLEY, WA	WhtAbvBoise
	Clarks Creek near Hatchery	ClarkNrHatch
12097500	GREENWATER RIVER AT GREENWATER, WA	GreenAtGreen
	Ball Creek at confluence with Puyallup R.	BallAtConf
12097850	WHITE RIVER BELOW CLEARWATER RIVER NR BUCKLEY, WA	WhiteBlwClear
12097000	WHITE RIVER AT GREENWATER, WA	WhtAtGrn
12098500	WHITE RIVER NEAR BUCKLEY, WA	WhtNrBuck
12095000	South Prairie Cr at South Prairie	SouthPrairie
	White River Below Clearwater River near Buckley Subbasin 2	WhtBlwClrSB2
12097820	Clearwater River near Buckley	ClrNrBuck
	South Prairie Creek at Arline Rd E #1	SPatRD1
	White River Below Clearwater River near Buckley Subbasin 1	WhtBlwClrSB1
	Horsehaven Creek near Mouth	HorseNrMth
	Horsehaven Creek at 188th St E	HorseAt188
	Card Creek at Pioneer Way	CardCrAtPi
	Huckleberry Creek near Greenwater	HuckNrGrn
	Card Creek near Card Rd.	CardCrNrRd
12093500	PUYALLUP RIVER NEAR ORTING, WA	Orting
12094000	CARBON RIVER NEAR FAIRFAX, WA	Carbon
	Below Winthrop Glacier	BlwWinG
12092000	PUYALLUP RIVER NEAR ELECTRON, WA	Electron
	Below Emmons Glacier	BlwEmmG

Model Calibration

The DHSVM streamflow were calibrated by comparing them against the USGS streamflow observations. Se selected the USGS sites that were representative of multiple scales and locations of the basin while avoiding sites influenced by regulations. The calibration period was chosen to include major flood events in the basin around WY2008, WY2009, and/or WY2011, and the validation period were chosen to include the common period of records among different USGS gauges.

For the Puyallup River branch the calibration sites included are South Prairie (USGS 12095000), Orting (USGS 12092000), Electron (USGS 12093500), Carbon (USGS 12094000), and Puyallup River at Alderton (12096500). On the White River the calibration sites were White River Below Clearwater River NR Buckley (USGS 12097850) and Greenwater River at Greenwater (USGS 12097500).

Key parameters that were calibrated include the soil lateral conductivity for key soil types, soil porosity, snow albedo parameters, rain/snow threshold, temperature lapse rate, and vegetation fractional cover. The range of those parameters considered for calibration and the final parameter selection were listed in Table A2. We also tested the model sensitivity to the soil depth by applying various multipliers to adjust it. Our analysis revealed that the adjustments made to soil depth, as well as soil properties such as porosity and conductivity, appear to compensate for or enhance each other in terms of soil water storage and drainage capabilities. As a result, we selected a soil depth multiplier of 0.95 (depth range 1.43-1.9m), which produced reasonable hydrological response in both regular and high flow conditions and subsequently further calibrated the soil property parameters.

Table A2. Parameter range and final parameter value of calibration.

Parameter Name	Range for calibration	Puyallup	White River
Temperature Lapse Rate (°C/km)	[-4.0, -7.5]	-6.6	-6.5
Rain Threshold (°C)	[-2, 2]	-1	-2
Snow Threshold (°C)	[-2, 4]	-1	-2
Accumulation Lambda	[0.70, 0.99]	0.9	0.9
Melt Lambda	[0.6, 0.90]	0.6	0.6
Accumulation Min	[0.75,0.90]	0.78	0.78
Melt Min	[0.50,0.90]	0.7	0.7
Fractional cover for key forest types	[0.40, 0.85]	0.65	0.8

In our calibration approach, we utilized an auto-calibrator in conjunction with manual adjustments to the parameters. The auto calibrator used in this study was the Multi-objective Complex Evolution (MOCOM-UA) global optimization method. At the beginning, we identified the initial parameters and their ranges based on the physical range of parameters and experience with the model applications in the area. The auto-calibrator was used as information for parameter sensitivity to help with initial manual calibration. The modeler then conduced additional tests and adjustments to the parameters to until the calibration was finalized.

During the modeling process, we observed slightly different responses among the sub-watersheds, specifically the Puyallup River Branch and the White River Branch within the HUC8 level Puyallup River Basin. As a result, we calibrated those two sub-watersheds separately. Parameters such as snow albedo parameters exhibited similarities between the two sub-watersheds, we then unified certain parameters without significantly compromising the performance of each sub watershed. The heterogenous parameters were converted to a spatial map as inputs to the model.

Calibration Results

The calibration and validation results were shown in Figures A1 through A8. The statistics for calibration and validation are summarized in Table A3. The model generally performs well among two subbasins Puyallup Branch and the White River branch. The flood events that occurred in WY2008, WY2009, and/or WY2011 were considered extreme events in the area and their magnitude posed challenges for the model performance during the calibration period. Simulating extreme events with hydrological models is often limited by factors such as resolution and accuracy of the meteorology data, as well as sometimes the model structure such as the time step. Therefore, the selection of the model parameters also took account of the balance of performances between the extreme events and the regular flow conditions by balancing the NSE vs. logNSE stats. The calibration did show

Table A3. Performance statistics for calibration/validation

Subbasin	Site	Daily (NSE/logNSE)		Monthly (NSE/logNSE)	
		Calibration	Validation	Calibration	Validation
Puyallup and Carbon	Alderton	0.705/0.622	*Limited Data*	0.821/0.787	*Limited Data*
	South Prairie	0.637/0.816	0.799/0.846	0.722/0.851	0.870/0.922
	Electron	0.626/0.451	0.634/0.452	0.485/0.365	0.635/0.418
	Orting	0.729/0.574	0.734/0.598	0.761/0.681	0.697/0.710
	Carbon	0.539/0.646	0.621/0.684	0.539/0.632	0.627/0.680
White	White Blw Clearwater	0.643/0.747	0.794/0.804	0.721/0.787	0.831/0.892
	Green at Green	0.503/0.728	0.731/0.850	0.581/0.743	0.828/0.883

limitations in the relatively higher elevation sites. This could be resulted from several reasons. The higher elevation subbasins are at zones where the phase of precipitation (rain vs. snow) becomes more critical for flood generation, yet the metrology data does suffer some limitation in higher elevations. Overall speaking the model calibration showed reasonably good NSE/logNSE statistics at majority of the sites.

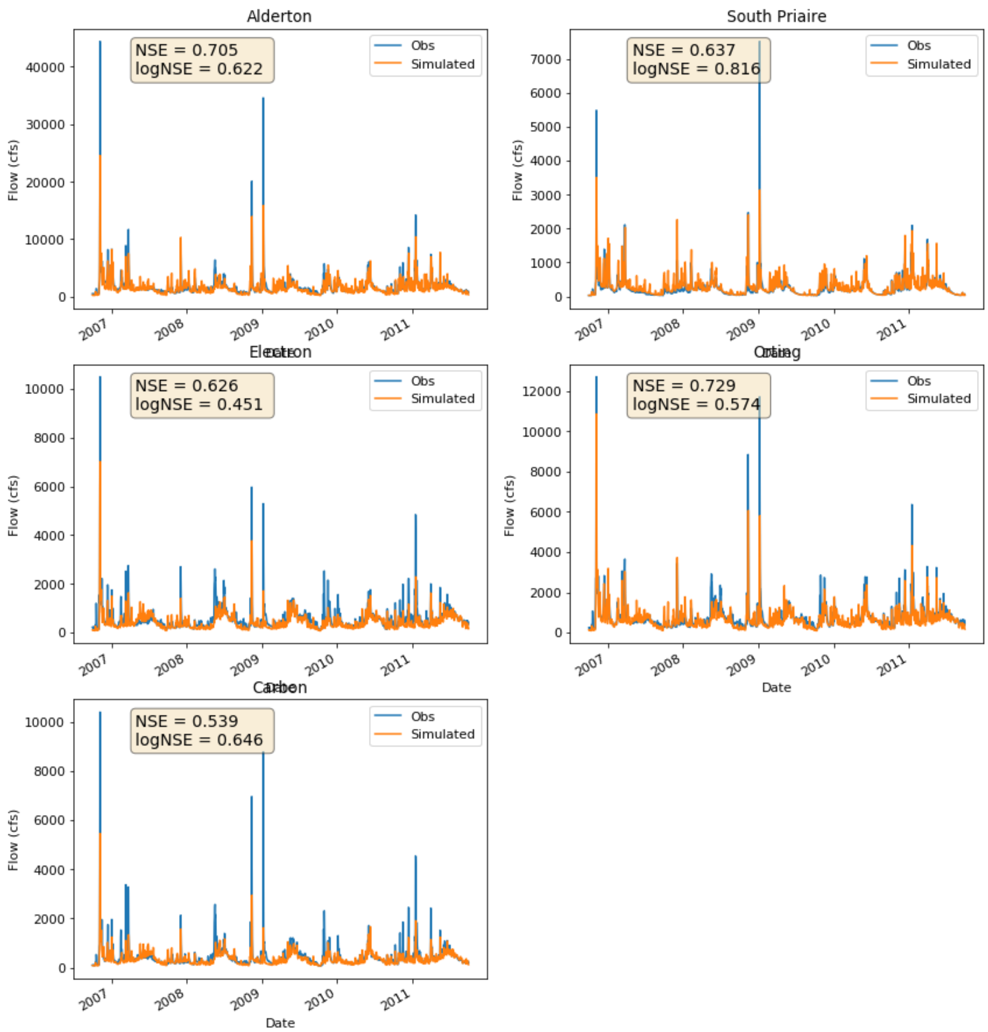

Figure A1. Daily time series for calibration periods at USGS sites in Puyallup and Carbon basins

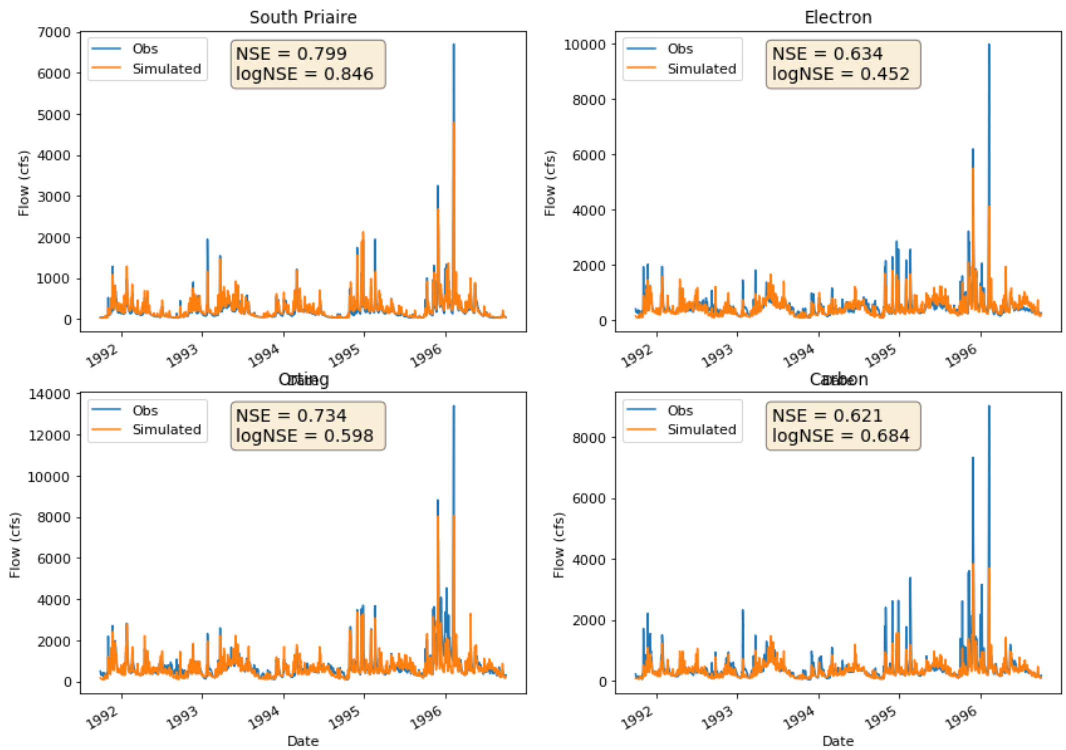

Figure A2. Daily streamflow for validation periods at USGS sites in Puyallup and Carbon basins

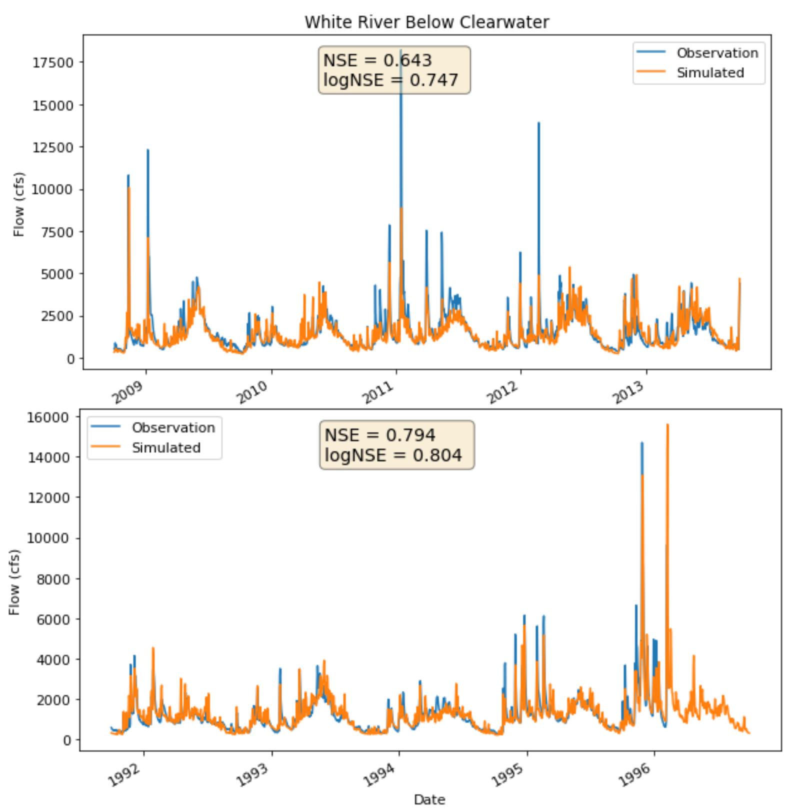

Figure A3. Daily streamflow for calibration and validation periods at White River Below Clearwater

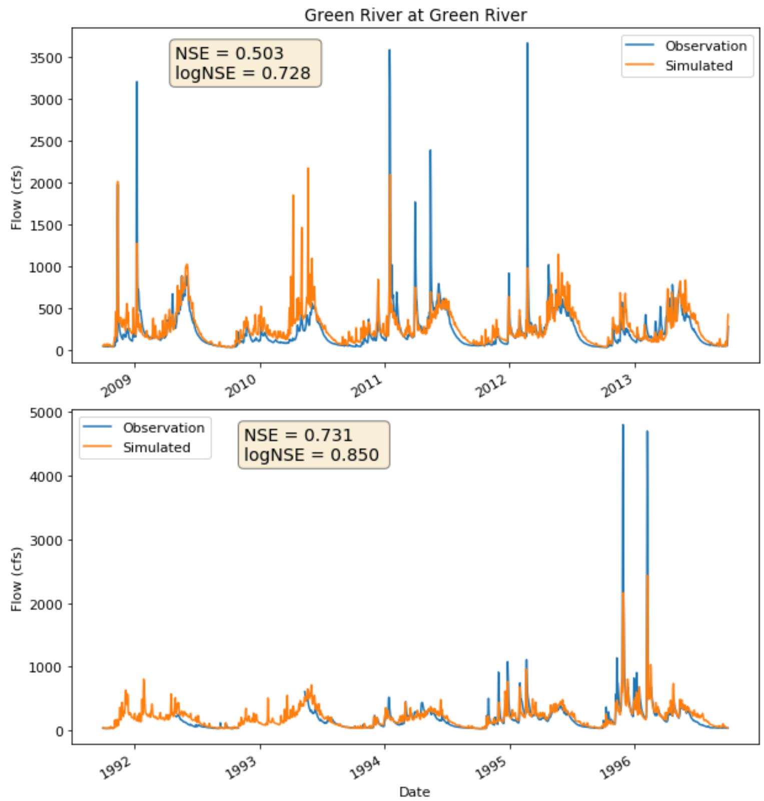

Figure A4. Daily time series of streamflow for calibration and validation periods at Green River at Green River

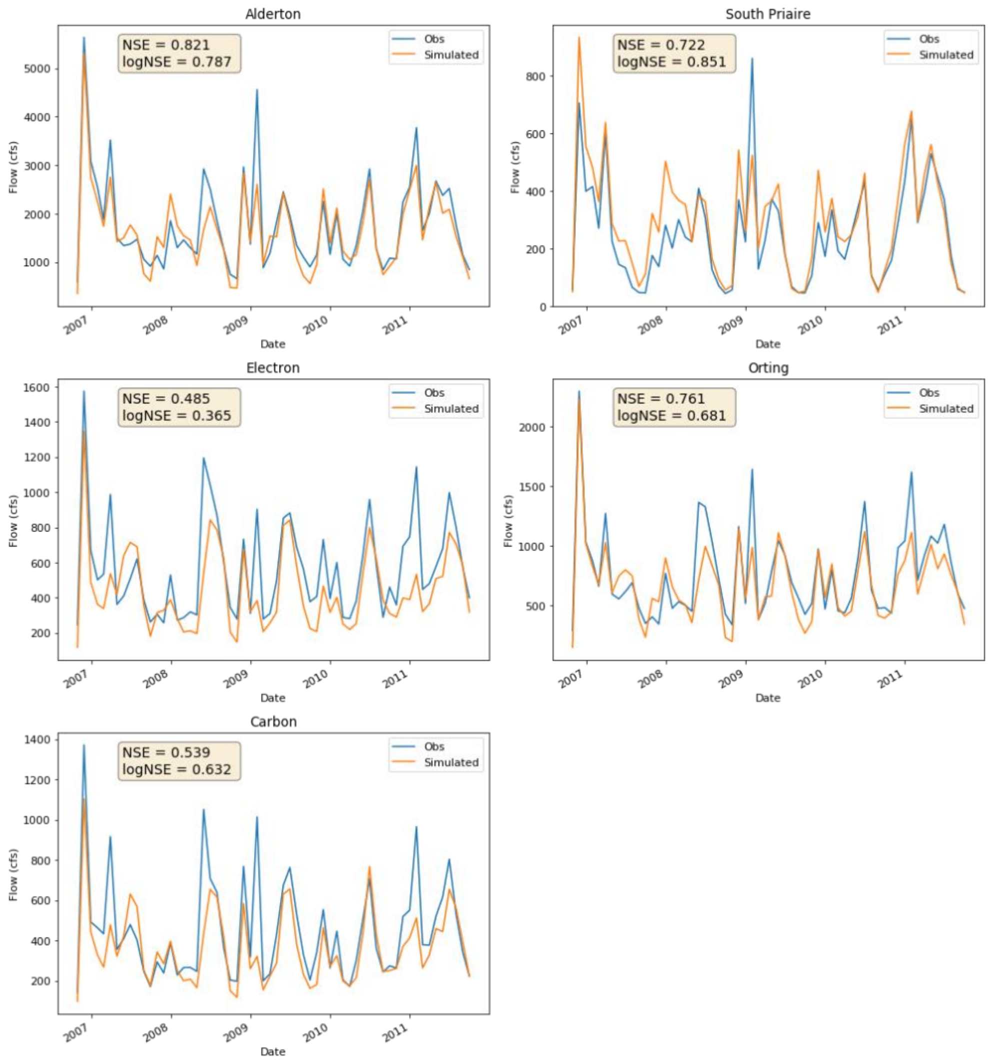

Figure A5. Monthly time series for calibration periods at USGS sites in Puyallup River Branch

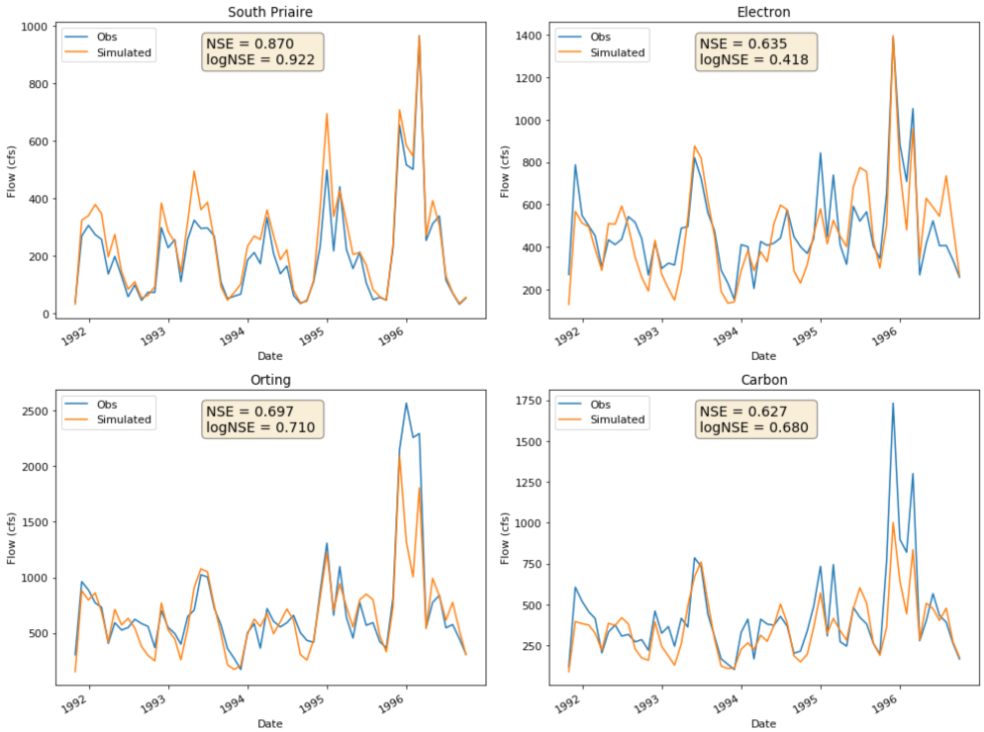

Figure A6. Monthly time series for validation periods at USGS sites in Puyallup River Branch

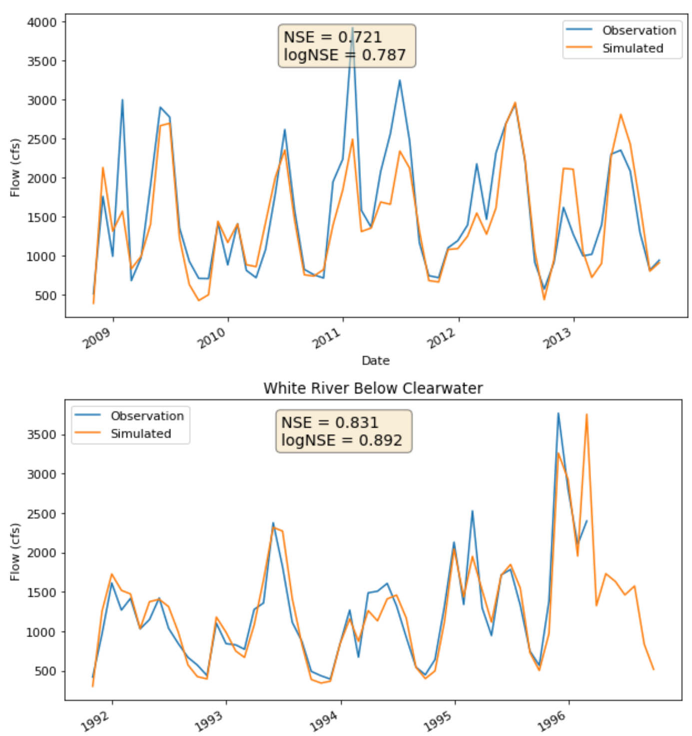

Figure A7. Monthly time series of streamflow for calibration and validation periods at White River Below Clearwater

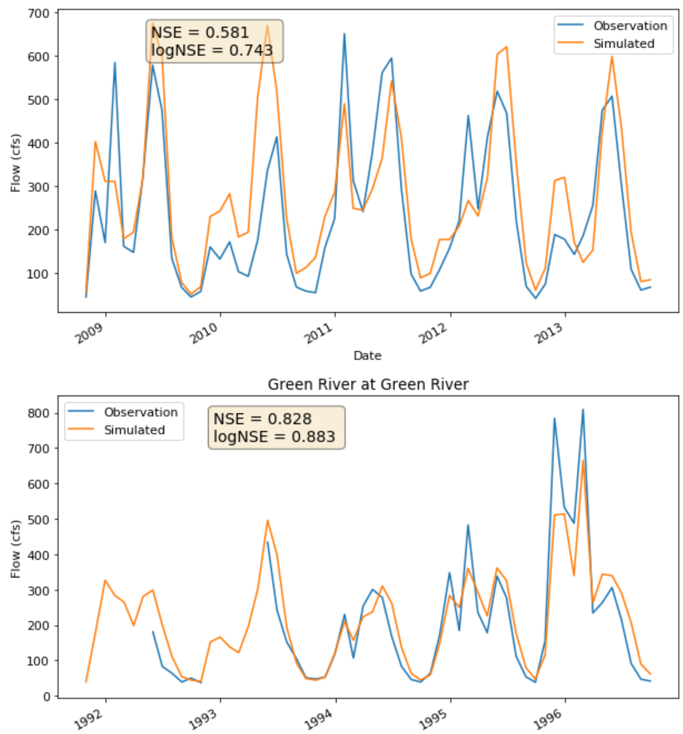

Figure A8. Monthly time series of streamflow for calibration and validation periods at Greenwater River at Greenwater

GCM Simulations

For the statistically downscaled projections, we used the Multivariate Adaptive Constructed Analogs (MACA, Abatzoglou and Brown 2012). As with all statistically downscaled projections, the MACA projections are developed using an observationally based historical dataset. In this case, the training dataset is described in Livneh et al. (2015), as described in the calibration section above.

MACA includes 10 GCM projections, each of which has a historical, spanning 1950 through 2005, and two future scenarios, which go from 2006 through 2099. The future projections include one based on a low (RCP 4.5) and a high (RCP 8.5) greenhouse gas scenario.

Preliminary Results

Figure 9 shows boxplots of the results for the historical and two future climate scenarios (RPC4.5, and RPC8.5) for each of the ten 10 GCMs. Each subplot represents a monthly flow boxplot for a specific GCM, with the GCM name indicated in the legend suffix. The three distinct colors represent different scenarios. The results show that for most of the GCMs, both RCP4.5 and RCP8.5 scenarios exhibit higher winter flow and slightly lower summer flow compared to historical. For some GCMs this pattern is also associated with a shift in timing of the flow.

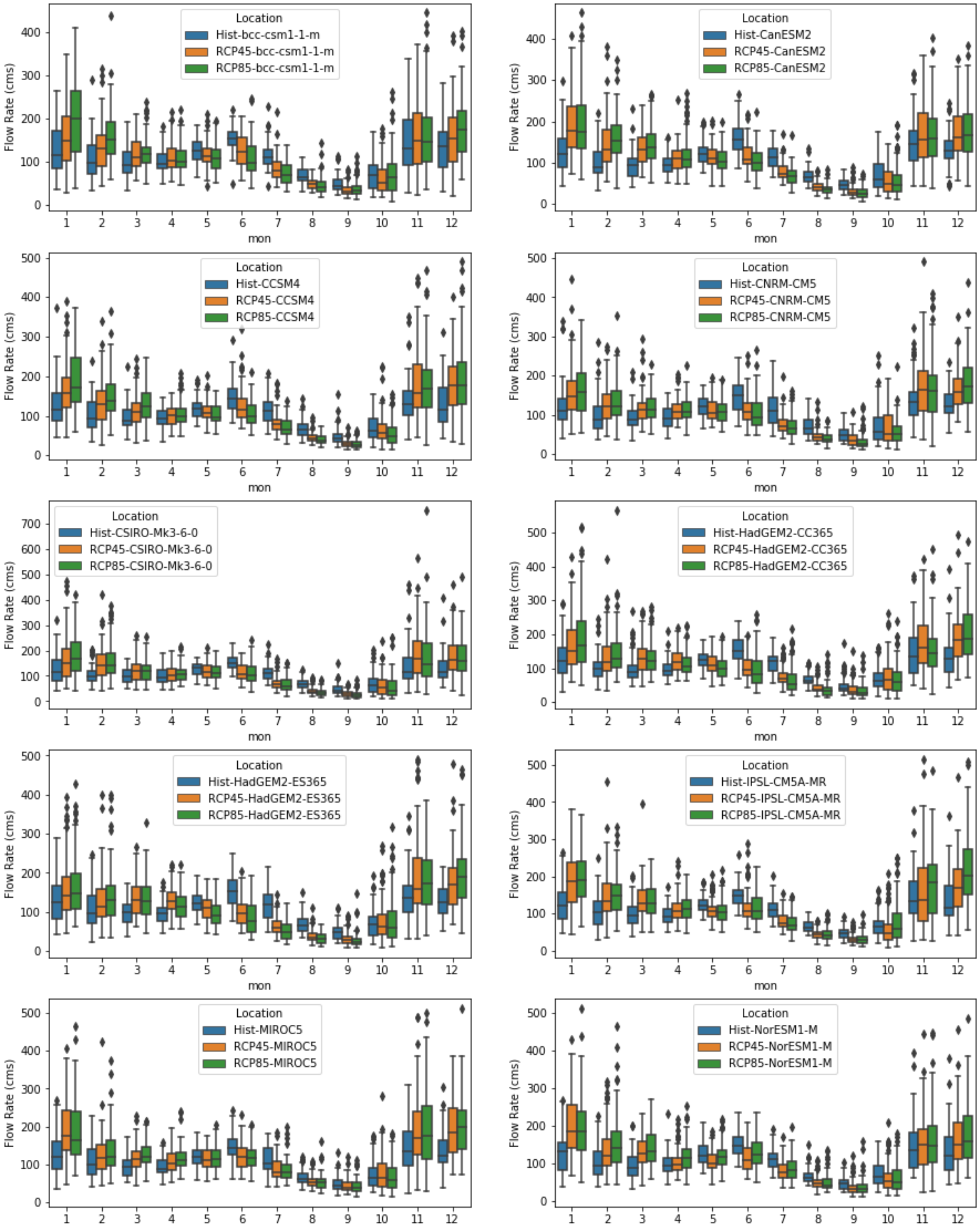

Figure A9. Boxplot of monthly average streamflow at Puyallup outlet (Puyallup at Puyallup).

APPENDIX B: SCOPE OF WORK

University of Washington Scope of Work

Projecting Future High Flows on King County Rivers: Phase 3

Objectives

1. Refine approach used in the Phase 1 and 2 efforts, applying new approaches to the existing models for the Snoqualmie/SF Skykomish and Green river basins.
2. Develop new projections of future natural and regulated flows on the Cedar and White rivers.
3. Engage reservoir modelers to discuss and contextualize reservoir modeling results.

Background

The purpose of the Projecting Future High Flows on King County Rivers project is to provide improved projections of changes in the magnitude, duration, frequency, and timing of future peak flows on King County rivers. This information will support improved assessments of flood risk for use in to flood hazard management. This project builds on previous river flow projections (Phases 1 & 2) developed for the King County Flood Control District (FCD) by the University of Washington Climate Impacts Group (CIG; Lee et al., 2018). The Phase 1 effort was limited to running two regional weather model projections, which were selected to bracket potential effects on flows in the Snoqualmie/SF Skykomish and Green River basins. While these two model projections were intended to provide upper and lower bounds on the potential impacts of climate change on future river flows, subsequent analyses by King County and CIG suggest that this may not be the case (e.g., Mauger and Won 2019). More model runs are needed for a more thorough understanding of possible future flood conditions.

As part of a separate project funded by King County's Wastewater Treatment Division (WTD), the output from a total of 12 regional weather model projections (1970-2100) have been obtained by CIG for King County. In Phase 2, these new regional weather forecasting model runs were used to provide additional flow projections for the Snoqualmie/SF

Skykomish and Green River basins. This document describes Phase 3, which includes the three major advancements described above under Objectives.

As outlined below, FCD funding will be used to refine the approaches used to develop accurate hydrologic model projections and process the results, develop the new hydrologic models for the Cedar and White River, and engage reservoir managers in contextualizing the results of the reservoir models.

Scope of Work

Task 1. Develop and Test Changes in Methodology

Selected methodological changes based on information provided in Phase 2 will be tested using the Snoqualmie and Green River models to evaluate their relative effect on predicted future flows relative to the model runs conducted as part of Phase 1 (Lee et al., 2018) and Phase 2 of this project. These are detailed in Mauger and Won (2020) and include the following:

- Improved bias correction of temperature and precipitation
- Develop hourly estimates of humidity and radiation
- Review soil and vegetation characteristics
- Validate snow simulations, in addition to streamflow
- Improve stream channel classifications
- Optimize hydrologic model calibration
- Tailor streamflow bias correction for reservoir modeling needs
- Contextualize reservoir modeling by engaging directly with managers.

Each of these would represent an improvement over the Phase 1 and 2 modeling; by quantifying the improvements we can better understand how the results may change as a result of putting them in place. The final three bullets will be informed by discussions with reservoir operations modelers described under Task 4 below; these may be evaluated at a later stage, pending the timing of the Task 4 work.

CIG will communicate the results of these tests and a decision will be made by the team regarding which methodological changes will be incorporated into the modeling framework going forward. Methodological testing results will be documented by CIG in a presentation provided to the King County project team.

Outcome: Communication of the effect of selected methodological changes on future flow projections. Determination of which methodological changes to implement as part of Phase 3.

Deliverables: Electronic copy of slide presentation.

Task 2. Develop and Calibrate River Hydrologic Models for the Cedar and White River Basins

CIG will develop and calibrate the Distributed Hydrologic Soil Vegetation model (DHSVM) for the Cedar and White river basins. With assistance from King County, CIG will obtain reservoir inflows and/or naturalized flows for the Cedar and SF Tolt rivers, based on what is available from Seattle Public Utilities (SPU), and for the Whiter River from the US Army Corps (USACE), for use in model calibration. Model development and calibration will be consistent with the Snoqualmie/SF Skykomish and Green river models developed in previous work for the Flood Control District, including the methodological refinements developed in Task 1 above.

Outcome: Calibrated hydrologic models of the Cedar and White river basins.

Deliverables: Tabular and graphical reporting on model performance.

Task 3. Run Hydrologic Models, Process Output, and Compare Scenario Results

CIG will run the Cedar and White river basin models for the 12 regional climate model projections CIG will summarize flood frequency statistics for all model runs and make comparisons consistent with the tabular and graphic results developed in the Phase 1 and Phase 2 reports. Additional summary statistics will be provided for snowpack, which may help in the interpretation of future flow changes and for approximating reservoir operations in Task 4d below.

Outcome: A total of 12 dynamically-downscaled projections of future un-regulated river flows for the Snoqualmie/SF Skykomish, Green, Cedar, and White river basins.

Deliverables: Tabular and graphical comparisons of scenario results.

Task 4. Model Reservoir Operations and Effects on High Flows

The primary objective of this task is to estimate changes in regulated peak flows in the future based on changes in inflows due to climate change but with current reservoir operations. CIG will collaborate with reservoir managers (SPU and USACE) for each river to determine and carry out the most appropriate method for estimating or modeling future regulated flows.

Task 4a: Obtain White and Green River reservoir models. CIG, with assistance from King County, will obtain the White and Green River reservoir operations models from the US Army Corps of Engineers (USACE). In addition to the daily time-step model, we will discuss the potential to apply the hourly time-step model with USACE collaborators. This work builds on existing discussions with USACE collaborators, focused most recently on flooding in the lower White River.

Task 4b: Establish a Memorandum of Agreement among SPU, King County, and CIG that will define the terms and conditions of the collaboration on projecting future regulated flows for the Cedar and Tolt rivers. King County, CIG, and SPU will establish an agreement outlining the terms of collaboration for this portion of the study, including opportunities for reviewing outcomes and deliverables, expectations on the timing of review periods, and the process for resolving any concerns or disagreements regarding the methods, content, and results described in the deliverables. The goal of this agreement is to provide adequate review opportunities and time to ensure that SPU's reservoir system and operations are adequately characterized, while completing deliverables on schedule.

Task 4c: Evaluate future reservoir operations on the Cedar/Tolt Rivers. Once an agreement is established, CIG will work with SPU to estimate future regulated peak flows on the Cedar and Tolt Rivers. The most appropriate methods to use for this will be determined in collaboration between CIG and SPU and may involve working with SPU to apply the existing reservoir model or using alternative and/or simplified approaches to estimate potential future regulated flows. This could involve a census of historical flood events, simplified calculations based on single flood events in the future, a sensitivity analysis based on assumed reservoir conditions prior to and during future flood events, or other approaches. The work under Task 4c will be subject to the review terms established by the Agreement defined under Task 4b.

Task 4d: Synthesize future regulated flow estimates. CIG will summarize flood frequency statistics for the new regulated flow estimates, comparing them to the previous model runs and the unregulated peak flow results.

> **Outcome:** Synthesis of the approaches, limitations, and information needs associated with estimating future regulated peak flows on the White, Green, Cedar, and SF Tolt Rivers. A total of 12 dynamically-downscaled projections of future regulated peak river flows for the Snoqualmie/SF Skykomish, Cedar, Green, and White river basins.

Deliverables: Brief technical memo summarizing the findings on model performance, limitations, and future research needs, and the projected changes in peak regulated flows, for each basin.

Task 5. Report Results

CIG will produce draft and final reports describing the methods and results of the river flow projections results for each river basin:

- Snoqualmie/SF Skykomish River
- Green River
- Cedar River
- White River

CIG will also present the project results at one King County lunch-and-learn and give one presentation to the FCD if requested.

Outcome: Reports documenting methods and scenario results for the Snoqualmie/SF Skykomish, Green, Cedar, and White river basins.

Deliverables: Reports documenting methods and scenario results for the Snoqualmie/SF Skykomish, Green, Cedar, and White river basins.

Task 6: Application to Floodplain Management

CIG will participate in a workshop organized by WLR to discuss the results and potential applications to floodplain management in King County. This workshop will include regional partners invited to the Phase 1 workshop, held August 1, 2017. WLR will draft a report summarizing the implications of CIG's analysis for floodplain management actions, as well as priorities for additional analysis that may be necessary to further guide floodplain management.

Outcome: Workshop presentation and participation by CIG.

Deliverables: Presentation describing the methods and results. WLR will produce a report summarizing the workshop discussion of implications for floodplain management.

APPENDIX C: CLIMATE PROJECTIONS

Observationally-Based Historical Climate Dataset

Past hydrologic studies have typically used interpolated estimates of daily weather on model grid cells (e.g., Hamlet et al. 2013, Chegwidden et al. 2019). A novel aspect of the current approach is that we use dynamically downscaled historical meteorology, as is done for the climate change simulations. This has a number of advantages. First, we are able to use hourly meteorology as opposed to daily; a significant improvement given that instantaneous flows – the basis for many regulations and design standards – are not well correlated with daily-average flows, whereas the correlation is high for hourly flows. Second, regional models have been shown to better represent spatial variations in weather variables, particularly in complex topography or where observations are sparse. Finally, by using the same regional climate model for both the historical and climate change simulations, we ensure that the hydrologic model is better adapted to our approach for assessing future changes in hydrology.

For this historical dataset we used an implementation of WRF developed by Ruby Leung and colleagues at the Pacific Northwest National Laboratory (PNNL; hereafter, we refer to the historical WRF simulation as "WRF-NARR"). The dataset is produced using WRF version 3.2, with a model domain covering all of the western U.S., at an hourly time step and a spatial resolution of 6 km (Chen et al. 2018). Boundary conditions are taken from the North American Regional Reanalysis (NARR; Mesinger et al. 2006), and the simulation spans the years 1981-2015. Reanalysis datasets are essentially internally-consistent collections of weather observations; they are created by combining massive amounts of environmental observations in a Bayesian model framework that synthesizes them into the best estimate of the atmospheric state for each time step. NARR is produced for North America at a spatial resolution of 32 km.

Future Climate Dataset

A new ensemble of regional climate model projections was recently produced in collaboration with Cliff Mass in UW's department of Atmospheric Sciences (hereafter referred to as "WRF-CMIP5"). GCM projections were obtained from the Climate Model Inter-comparison Project, phase 5 (CMIP5; Taylor et al. 2012). GCMs were primarily selected 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. The new ensemble of WRF projections includes one simulation for each of the GCMs listed in Table B1. All of the new projections are based on the high-end Representative Concentration Pathway (RCP) 8.5

Table C1. The twelve global climate models (GCMs) used as input to the regional model simulations. Horizontal resolution is given in degrees latitude × degrees longitude; "Vertical Levels" refers to the number of layers in the atmosphere model for each GCM. All simulations are based on the high-end RCP 8.5 greenhouse gas scenario (Van Vuuren et al. 2011).

Model	Center	Resolution	Vertical Levels
ACCESS1-0	Commonwealth Scientific and Industrial Research Organization (CSIRO), Australia/ Bureau of Meteorology, Australia	1.25° × 1.88°	38
ACCESS1-3	Commonwealth Scientific and Industrial Research Organization (CSIRO), Australia/ Bureau of Meteorology, Australia	1.25° × 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

scenario (Van Vuuren et al. 2011). Research suggests this greenhouse gas scenario is very pessimistic, and may even be beyond what is feasible in terms of 21st century emissions (Hausfather and Peters 2020).

Simulations were performed using WRF version 3.2, implemented following Salathé et al. (2010, 2014). The innermost domain, at 12-km resolution, encompasses the U.S. Pacific Northwest. Simulations span the years 1970-2099 at an hourly time step. The model, and model configuration, are described in detail in Lorente-Plazas et al. (2018) and Mass et al. (2022). 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, temperature changes for the 2080s in the RCP 4.5 projections appear to correspond approximately to the projections for the 2040s or 2050s in the RCP 8.5 projections.

APPENDIX D: HYDROLOGIC MODEL

We modeled the hydrology of each watershed using the Distributed Hydrology Soil Vegetation Model (DHSVM, Wigmosta et al. 1994). DHSVM is an open-source model maintained by PNNL (http://dhsvm.pnnl.gov/). DHSVM has been widely applied in the mountainous western United States (e.g., Storck et al., 1998, Bowling and Lettenmaier, 2001; Whitaker et al., 2003) and for assessing the impacts of climate change (e.g., Elsner et al. 2010, Vano et al. 2010, Cuo et al. 2011, Cristea et al. 2014, Naz et al. 2014, Murphy and Rossi 2019, 2020, Mauger et al. 2016, Lee et al. 2018, Mauger et al. 2020) and land use (e.g., Sun et al. 2013, Cuo et al. 2009, 2011) on streamflow.

The DHSVM is a physically-based, spatially-distributed hydrological model that accounts for physical processes affecting the distribution of precipitation, partitioning of rain vs. snow, and tracking the movement of water on and through landscapes. The model represents the spatial distribution of evapotranspiration, snow cover, soil infiltration and moisture, and runoff across a watershed in a distributed fashion, requiring model inputs of geographic and climate information (Wigmosta et al. 2002; Figure C1). The model simulates one or more unsaturated soil layers and a saturated bottom layer. Subsurface flow in the saturated zone is based on a quasi-equilibrium approach described by Wigmosta and Lettenmaier (1999). The DHSVM represents snow accumulation and melt by calculating the full surface energy balance independently at each model grid cell, accounting for terrain

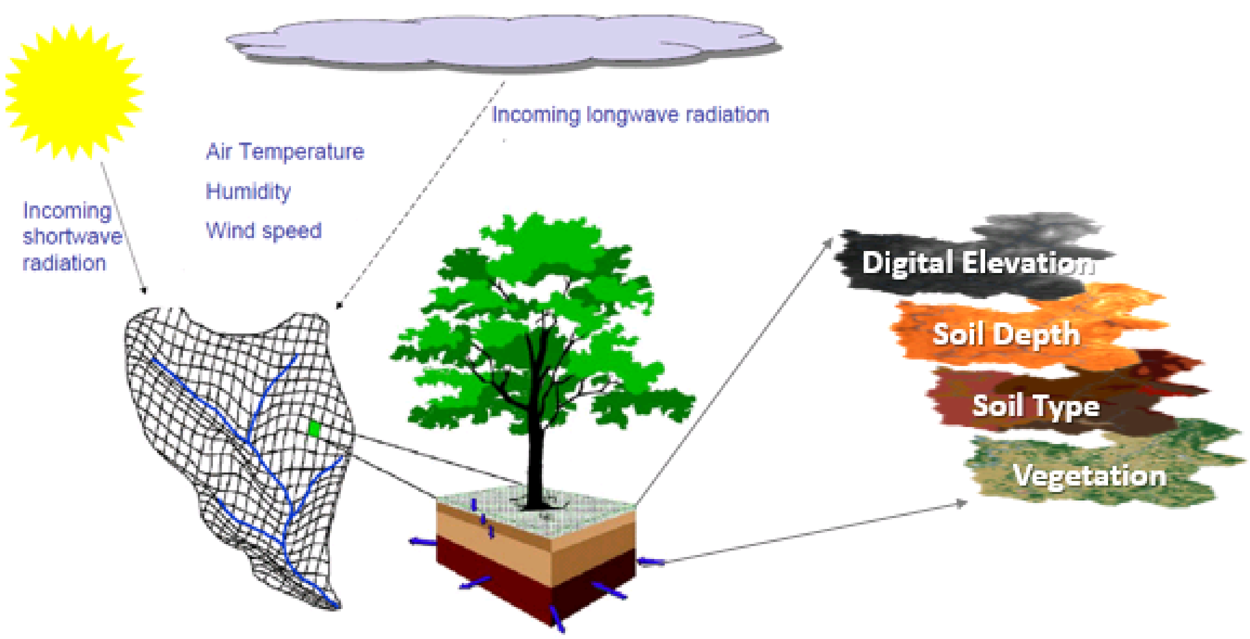

Figure D1. Diagram of DHSVM model and its inputs.

shading effects, radiation attenuation, wind modification and snow-canopy processes (Wigmosta et al. 1994, Storck 2000, Storck et al. 2002, Andreadis et al. 2009, Sun et al. 2018, Sun et al. 2019). Prior research has shown that DHSVM snow simulations are sensitive to the choice of both incoming shortwave and longwave radiation, with melt initiation and rate more sensitive to longwave than shortwave radiation (Hinkelman et al. 2015). Stream channel routing is performed using a linear storage routing algorithm (Wigmosta and Perkins 2001), which allows the user to produce hydrographs at any location along the channel network. Typical spatial resolution of DHSVM implementations range from about 10 m to 200 m.

Model Version

For this study we used DHSVM version 3.2, which includes a number of updates, most notably a new canopy gap component with enhanced radiation transmittance schemes and physical processes controlling snowpack evolution in forest gaps (Sun et al. 2018, https://github.com/pnnl/DHSVM-PNNL).

Topography and Stream Network

The digital elevation models (DEM) were downloaded from the National Elevation Dataset (http://viewer.nationalmap.gov/basic/; Elevation products, 3DEP). The DEM provides a base layer of spatial information and is used to generate watershed boundaries using ArcGIS hydrology modeling tools. DHSVM-PNNL Python scripts that drive ArcGIS tools are used to develop a stream network based on a user-defined contributing area. Simulated streamflows are routed through the stream network based on flow direction relationships from upgradient (higher elevation) to downgradient (lower elevation) grid cells and stream channel segments.

Land Cover

We generated the land cover grids based on the National Land Cover Database 2016 update (NLCD; Homer et al. 2020, Jin et al. 2019, Yang et al. 2018). This is the most recent national land cover product, with a 16-class land cover classification scheme applied at a spatial resolution of 30 meters based on Landsat satellite data and created by the Multi-Resolution Land Characteristics Consortium (Homer et al. 2015). Land cover grids were resampled

Table D1. Land cover classifications used as input to the DHSVM model.

ID	NLCD IDs	Land Cover Type
1	23, 24	Dense Urban (>75%)
2	21, 22	Light / Medium Urban (<75%)
3	31	Bare Ground
4	12	Snow / Ice
5	81	Hay / Pasture
6	71	Grassland/Herbaceous
7	41, 43	Mixed / Deciduous Forest
8	42	Conifer Forest
9	90	Woody Wetlands
10	95	Emergent Herbaceous Wetl.
11	52	Shrub / Scrub
12	82	Orchard
13	11	Water

to the DHSVM resolution then converted to the 13 default classifications used in DHSVM (Table C1).

Soil Parameters

The Digital General Soil Map of the United States, or STATSGO dataset (NRCS 2017) was developed for regional and national studies designed for broad planning and management uses requiring estimates of soil characteristics. The soil units are distributed as spatial and tabular datasets with 1-kilometer resolution for the conterminous United States. Soil parameters were converted to the 16 default soil types used in DHSVM (Table C2).

Soil Depth

Soil depths are defined empirically based on elevation and local slope using DHSVM-PNNL Python scripts (https://github.com/pnnl/DHSVM-PNNL). The algorithm generates thin soils on steep slopes and ridge tops and thick soils on gentle slopes and in depressions, within a user-defined defined range.

Table D2. Soil types used in the DHSVM model, and select parameters for each. The table lists the properties of the top soil layer, although in many cases the same properties applies to the second and third soil layers. Soil types that are included in the Puyallup DHSVM model are highlighted in bold. The "Other" category applies to developed areas.

ID	Soil Type	Basin Area (%)	Bulk Density (kg/m^3)	Field Capacity	Lateral Cond. (m/s)	Exp. Dec.	Vertical Cond. (m/s)
1	**Sand**	**0.9**	**1492**	**0.08**	**0.1**	**3**	**0.5**
2	**Loamy Sand**	**22.6**	**1520**	**0.10**	**0.001**	**2**	**0.3**
3	**Sandy Loam**	**37.4**	**1569**	**0.14**	**0.01**	**1.872572**	**0.3**
4	**Silty Loam**	**11.6**	**1419**	**0.30**	**0.001**	**1.145651**	**0.00009**
5	Silt	0.02	1280	0.28	0.00002	1	0.00009
6	**Loam**	**13.0**	**1485**	**0.20**	**0.00008**	**0.5**	**0.0008**
7	**Sandy Clay Loam**	**0.3**	**1600**	**0.27**	**0.00002**	**1**	**0.00002**
8	Silty Clay Loam	0	1381	0.36	0.00002	1	0.000009
9	Clay Loam	0	1600	0.31	0.00002	1	0.000009
10	**Sandy Clay**	**10.6**	**1565**	**0.31**	**0.00002**	**1**	**0.000002**
11	**Silty Clay**	**2.1**	**1346**	**0.37**	**0.00002**	**1**	**0.000009**
12	**Clay**	**1.1**	**1394**	**0.36**	**0.00002**	**1**	**0.000002**
13	**Bedrock**	**0.4**	**1650**	**0.05**	**0.00002**	**1**	**0.000002**
14	Water	0	1394	0.36	0.00002	1	0.000002
15	Organic	0	1485	0.29	0.00002	1	0.000009
16	Other	0	1600	0.27	0.00002	1	0.000009

APPENDIX E: POST-PROCESSING APPROACH

All streamflow results are provided at the model time step of 1 hour. Results for each of the 12 WRF-CMIP5 simulations are provided in both time series format (1970-2100) and averaged over four 30-year time periods: “1980s” (1970-1999), “2020s” (2010-2039), “2050s” (2040-2069), “2080s” (2070-2099). We use 30 years because it is the convention in climate change studies – chosen as a compromise between the need to detect changes over time while minimizing sensitivity to random short-term variability. For reference, results are also provided for the WRF-NARR simulation (1981-2020) and the observations.

For each of the above time periods, we computed extreme statistics by fitting a GEV distribution with L-moments to estimate extreme statistics – following the methodology described in Salathé et al. (2014) and Tohver et al. (2014) – based on findings that indicate it is superior to the Log-Pearson Type 3 distribution (Rahman et al. 1999 & 2015, Vogel et al. 1993, Nick et al. 2011).

One challenge with the extreme statistics is that 30-year periods require extrapolation to encompass the rarest events (e.g., 50-year, 100-year, 500-year). Although extrapolation leads to greater uncertainty in the flood frequency estimates, it is common practice in flood studies as we rarely have enough observed data to encompass these rare events. Nevertheless, the effects of this greater uncertainty should be considered when using the extrapolated data.

A Focus on the Relative Changes

In order to minimize the effect of model biases on the projections, we recommend focusing on the change in flows, relative to the historical baseline provided by each WRF-CMIP5 simulation. By considering only the relative change, you remove any absolute biases that may be present in the model estimates. If the long-term change is desired, relative to the climate of the past, we recommend using the “1980s” as the baseline. If changes relative to present-day conditions are desired, we recommend using the “2020s” as the baseline.

Accessing the Results

All model results can be obtained from the project website:

https://cig.uw.edu/projects/effect-of-climate-change-on-flooding-in-king-county-rivers/

This includes interactive visualizations, raw model results, and summary data files. Figure D1 illustrates the file structure for the DHSVM results. Time series files and 30-year averages are provided. These are included in separate files for each model: one for the WRF-NARR simulation and one for each of the WRF-CMIP5 simulations (labeled according to the names of the GCMs listed in Table 2). Files are labeled according to the model and metric evaluated. For example, the peak flow time series files include the suffix "_PeakFlows.csv", while the peak flow statistics have the suffix "_PeakStats.csv".

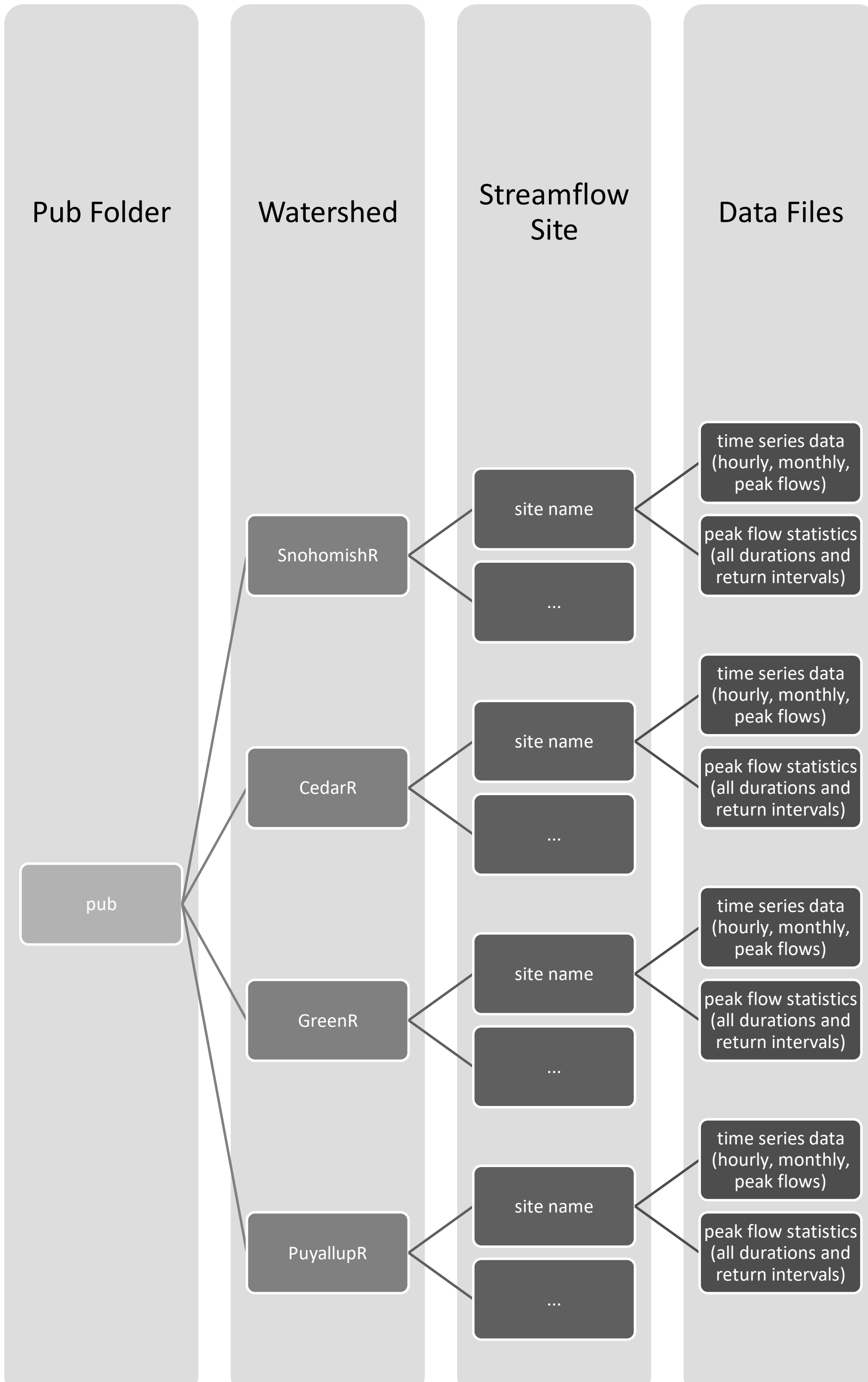

Figure E1. Data structure for the model results.

Table E1. Output locations included in model results, in alphabetical order by name. Each location is a streamflow site of interest, either because it is a gauge location or because it was requested by one of the project partners. Sites marked with an asterisk are included in the results from the reservoir modeling.

Name	Source	Location	Years	MACA?
Ball Creek at confl. with Puyallup R.	N/A	47.163N / 122.218W	N/A	Y
Ball Creek at Military Rd.	N/A	47.151N / 122.240W	N/A	N
Below Emmons Glacier	N/A	46.894N / 121.595W	N/A	Y
Below Winthrop Glacier	N/A	46.941N / 121.707W	N/A	Y
Boise Creek at Buckley, WA	USGS 12099600	47.176N / 122.017W	1987-2025	Y
Boise Creek at SE 268th	N/A	47.190N / 121.984W	N/A	N
Boise Creek at SR 410	N/A	47.190N / 121.932W	N/A	N
Canyon Creek at confl. with Clear Cr	N/A	47.221N / 122.375W	N/A	Y
Carbon R nr Fairfax	USGS 12094000	47.028N / 122.031W	1910-Present	Y
Card Creek at Pioneer Way	N/A	47.082N / 122.186W	N/A	Y
Card Creek nr Card Rd.	N/A	47.065N / 122.183W	N/A	N
Clarks Creek at 52nd St E	N/A	47.210N / 122.341W	N/A	Y
Clarks Creek at Stewart Ave E	N/A	47.201N / 122.342W	N/A	Y
Clarks Creek at Tacoma Rd nr Puyallup	USGS 12102075	47.198N / 122.336W	1995-2022	N
Clarks Creek nr Hatchery	N/A	47.177N / 122.317W	N/A	Y
Clear Cr at confl. with Mainstem Clear Cr	N/A	47.221N / 122.376W	N/A	Y
Clear Creek at confl. with Puyallup R.	N/A	47.236N / 122.393W	N/A	Y
Clearwater R nr Buckley	USGS 12097820	47.128N / 121.801W	2011-Present	Y
Greenwater R	USGS 12097500	47.154N / 121.634W	1989-Present	Y
Horsehaven Creek at 188th St E	N/A	47.085N / 122.225W	N/A	Y
Horsehaven Creek nr Mouth	N/A	47.106N / 122.238W	N/A	Y
Huckleberry Creek nr Greenwater	N/A	47.060N / 121.606W	N/A	N
Lake Tapps Div. Canal at 218th Ave E	N/A	47.197N / 122.140W	N/A	N
Lake Tapps Outlet Works	N/A	47.238N / 122.204W	N/A	N
Mud Mountain Dam Outlet	N/A	47.140N / 121.933W	N/A	N
Puyallup R at 5th st Bridge at Puyallup	USGS 12101470	47.199N / 122.286W	2010-Present	Y
Puyallup R at Alderton	USGS 12093500	47.185N / 122.228W	2006-Present	Y
Puyallup R at Puyallup	USGS 12106500	47.209N / 122.326W	1914-Present	Y
Puyallup R nr Electron	USGS 12092000	46.904N / 122.020W	1909-Present	Y
Puyallup R nr Orting	USGS 12093500	47.039N / 122.207W	1931-Present	Y
Red Creek at confl. with White R	N/A	47.157N / 121.971W	N/A	N
South Prairie Crat SP	USGS 12095000	47.140N / 122.091W	1949-Present	Y
South Prairie Creek at Arline Rd E #1	N/A	47.128N / 122.134W	N/A	Y
Squally Creek at confl. with Clear Cr	N/A	47.222N / 122.379W	N/A	Y

Name	Source	Location	Years	MACA?
Swan Creek at confl. with Clear Cr	N/A	47.234N / 122.394W	N/A	Y
White R abv Boise Cr at Buckley	USGS 12099200	47.174N / 122.008W	2003-Present	Y
White R abv Tailrace	N/A	47.239N / 122.234W	N/A	N
White R at Buckley, WA	USGS 12100000	47.174N / 122.019W	1977-2003	Y
White R at Greenwater, WA	USGS 12097000	47.147N / 121.646W	1929-1975	Y
White R at Pacific	USGS 12100498	47.260N / 122.237W	stage only	N
White R at R St nr Auburn	USGS 12100490	47.275N / 122.207W	2010-Present	Y
White R blw Clearwater	USGS 12097850	47.147N / 121.859W	1974-Present	Y
White R blw Canyon Creek	N/A	47.147N / 121.861W	N/A	N
White R abv WF White River	N/A	47.108N / 121.600W	N/A	Y
White R blw WF White River	N/A	47.133N / 121.623W	N/A	Y
White R nr Auburn	USGS 12100496	47.266N / 122.229W	1987-2009	Y
White R nr Buckley	USGS 12098500	47.151N / 121.949W	1928-2003	Y
White R nr Sumner	USGS 12100500	47.250N / 122.243W	1945-1971	Y

APPENDIX F: GUIDE TO INTERPRETING THE RESULTS

Interpretation of these results, particularly given the focus on rare extreme events, can be challenging. Following are a few considerations to keep in mind when reviewing the results:

- The greenhouse gas scenario used in this study (RCP 8.5, Van Vuuren et al. 2011) is a very high-end scenario. Research suggests this greenhouse gas scenario is very pessimistic, and may even be beyond what is feasible in terms of 21st century emissions (Hausfather and Peters 2020). Since future emissions are unlikely to be this high, future warming and associated impacts are likely to be than the current results imply. Mauger et al. (2019) discuss approaches for using RCP 8.5 projections as an analog for what might be projected for the low-to-moderate RCP 4.5 scenario. For example, temperature changes for the 2080s in the RCP 4.5 projections appear to correspond approximately to the projections for the 2040s or 2050s in the RCP 8.5 projections.
- Historical calibration is not a guarantee of accuracy in the projections. This is particularly important for the Tolt River, where the calibration did not perform as well as the other locations where model results were evaluated. However, the point also applies to locations where the model is well calibrated: this does not necessarily guarantee the projections will be accurate. In a perfect world we would use multiple different approaches to assess future changes in streamflow; where these agree would indicate higher confidence in the results. Doing so was beyond the scope of the current study. Instead, we focused on using methods that research suggest are most likely to accurately represent future changes – for example, using regional model projections as opposed to the previous statistically downscaled datasets as input to the hydrologic modeling. For the Tolt River, we expect that relative changes in flows will still be a useful indicator of future changes, even if the historical simulations show lower flows than the observations.
- Projected changes will always be governed by a combination of random variability and long-term trends due to climate change. This is particularly true for changes in extremes: Since by definition these events are rare, it is difficult to accurately assess how rapidly they will change. Although even the 2080s projections can be significantly influenced by natural variability, it can be helpful to focus on these late century projections since this is when the projected changes will be largest relative to natural variability.
- The WRF model used in this study has a spatial resolution of 12 km. This spatial resolution is sufficient to estimate variations in weather conditions across the

watershed, but may be too coarse to represent important variations within the watershed. For example, typical spacings between ridges and valleys are generally much shorter than 12 km, meaning that differences in conditions across these features may be missed by the model. These variations could have important implications for both current and future flows, and would not be captured in the current modeling.

- A limitation of complex hydrologic models such as DHSVM is that there are more parameters to tune than there are observations with which to estimate them. This means that it is possible for calibration to lead to "the right answer for the wrong reason". This is an especially challenging issue with climate change, since a model that performs well under current conditions may not be able to accurately capture changes in flow under future climate conditions. We have tested the model calibration in multiple ways in order to avoid this pitfall. This issue is also more likely to affect low flows than peak flows, since low flows are more affected by assumptions about soil and vegetation properties, channel characteristics, and biases in humidity, wind, and radiation. Nonetheless, we cannot be sure that the issue does not remain, even for peak flows.

- Shallow unconfined groundwater, as in any basin with permeable soils, will always play an important role by absorbing precipitation and releasing it to streams over the days and weeks following a rain event. The DHSVM model can approximate these shallow groundwater processes via its three soil layers. In contrast, DHSVM is not able to capture deep or confined groundwater. Although deep or confined aquifers are unlikely to play a major role in the hydrology of Skookum and Kennedy Creeks, we note that such processes would not be captured in DHSVM and, if important, a different model would be needed to capture such changes.

- In a recent study comparing evapotranspiration estimates, Milly and Dunne (2017) found that most hydrologic models dramatically overestimate future changes in evapotranspiration. This includes the Penman-Monteith method used in DHSVM. This could have important implications for summer flows, and would be important to estimate correctly in any future study evaluating the implications of possible changes in land cover. This is one reason we recommend exploring alternate ways of estimating potential changes in low flows.

- This project has focused on quantifying the changes in streamflow due to climate change. To assess climate vulnerability, two other pieces of information are needed:

(1) the "sensitivity" to these changes – how impacts scale with future changes, and (2) the "adaptive capacity" – how much these changes can be mitigated by changes in land use and water management or salmonid life history characteristics. Work to better understand these complementary aspects of vulnerability would help clarify if and when the current projections pose a problem for management.

- The current work does not account for changes in land cover, whether due to natural or human causes. In reality, changes in land cover due to property ownership, population growth, wildfire, or a variety of other factors could all have consequences for both streamflow and water temperature. None of these are accounted for in the current study. Instead, these results are meant to quantify changes in streamflow and water temperature in the absence of other changes, providing a benchmark for comparison with other management or policy choices that may affect instream conditions.

The science of climate change will continue to evolve over time due to changes in greenhouse gas scenarios, global climate models, downscaling approaches, and the hydrologic and stream temperature modeling used to make localized streamflow and water temperature estimates. In addition, further refinements to the existing approach could result in improved model estimates of current and future conditions.

APPENDIX G: FUTURE WORK

As outlined in previous sections, there are limitations to the modeling used in this study. Addressing these limitations could lead to changes in the projections and provide greater confidence in the accuracy of the results. We recommend two general approaches to updating and refining these projections over time, with the goal of improving the information available for planning:

1. Update these models as methods and approaches improve over time, and
2. Develop independent estimates of likely changes in streamflow.

Now that the models have been developed, less work is needed to further refine them and thereby improve on the climate projections. Additional work could simply involve revisiting model calibration and further exploring the parameter space to ensure the models provide the best estimates possible. For example, DHSVM testing could determine if model performance could be improved with further adjustments to the climate inputs or changes to the soil parameters. Larger efforts at model improvement could involve gathering new data (e.g. to fill in gaps in weather observations), testing new approaches to developing the meteorological inputs (e.g., different regional climate model implementations), or integrating the results obtained from groundwater and reservoir models. Streamflow modeling could also be integrated with impact models to assess implications for flooding and ecosystems.

Independent estimates of climate change impacts would also bring greater confidence to the results. As above, these can be fairly simple to undertake or more complex. One possibility, in order to better understand baseline conditions, would simply be to evaluate existing observations (air temperature, precipitation, streamflow, water temperature, etc.), to determine if changes have already been observed. Another fairly simple option would be to consider notable past events as analogs for future conditions: for example, by looking at how low flows respond to conditions such as a summer heat wave or the time elapsed since the last rain event. Ideally such analyses would consider impacts (e.g. on infrastructure, ecosystems), relating these to particular climate conditions. Once sensitivities like these have been quantified, they can be compared to climate projections to see how often such conditions may occur in the future. A more involved way to obtain independent estimates of changes would be to use other models. Numerous other hydrologic models are available, each of which has advantages and disadvantages. Similarly, the impacts on regulated peak flows could be further explored. Regardless of the approach – whether refining existing models or developing new independent estimates of change – further examination of the results will lend greater confidence to the findings, thereby providing better support for climate-resilient planning.

Planning requires more than just understanding the implications of climate change. In addition, managers need to know which interventions are likely to be needed, which are most effective, and how the answers to these questions vary across the watershed. As above, some questions can be answered with relatively little effort. For example, the existing models presented in this study can be used to look at the implications of land cover change on streamflow and stream temperature. This can involve very detailed planning scenarios (e.g., targeted riparian buffers) or coarser testing meant for illustration purposes (e.g., estimating flows and water temperature under pre-settlement conditions). For example, the Tulalip Tribe is currently modeling the impacts of forest management on flow and stream temperature. Additional work could involve other models that capture forest dynamics (e.g., VELMA, Mckane 2014) or more complex ecosystem management decision support models (EMDS, Murphy et al. 2018).

Finally, we emphasize that these are questions that many communities and tribes around the region are asking. From a modeling point of view, the domain of the regional climate model used to develop these projections covers the entire Pacific Northwest, and the models used here can be applied elsewhere provided observations can be obtained or estimated for use in calibration. This means that the same approach used here could be applied to other watersheds and communities around the region, and that there may be opportunities collaborate with these communities as they work to interpret similar results and put them to use. As interest in this work grows, additional coordination may be warranted to capitalize on economies of scale.

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