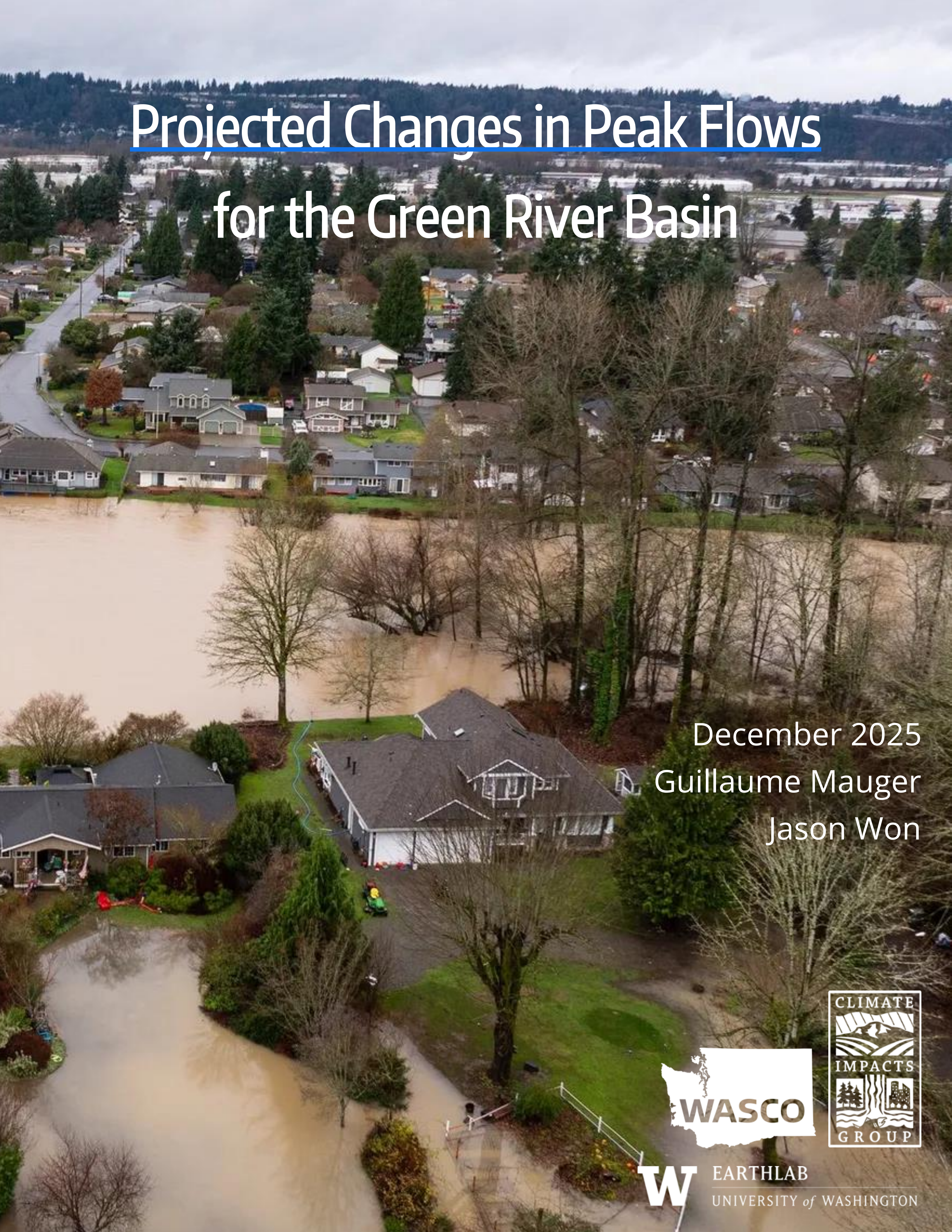

Projected Changes in Peak Flows for the Green River Basin

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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 Green 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 Green 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.

Snowpack, Precipitation and Evapotranspiration

On average for the Green River watershed, our modeling projects a median 87% decrease in April 1st Snowpack by the 2080s (relative to the 1990s, range: -48 to -97%) (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 +10% (range: -2 to +28%) and a decrease in July-August precipitation of -14% (range: -63 to +44 %; as above, for the 2080s relative to the 1990s)**. Surprisingly, our modeling projects a small *decrease* in July-August evapotranspiration for the Green River basin.

Heavy precipitation is the primary driver of flooding west of the Cascades. Models project a **+18% (range: +1 to +47%) 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 Green River.

Naturalized Flows

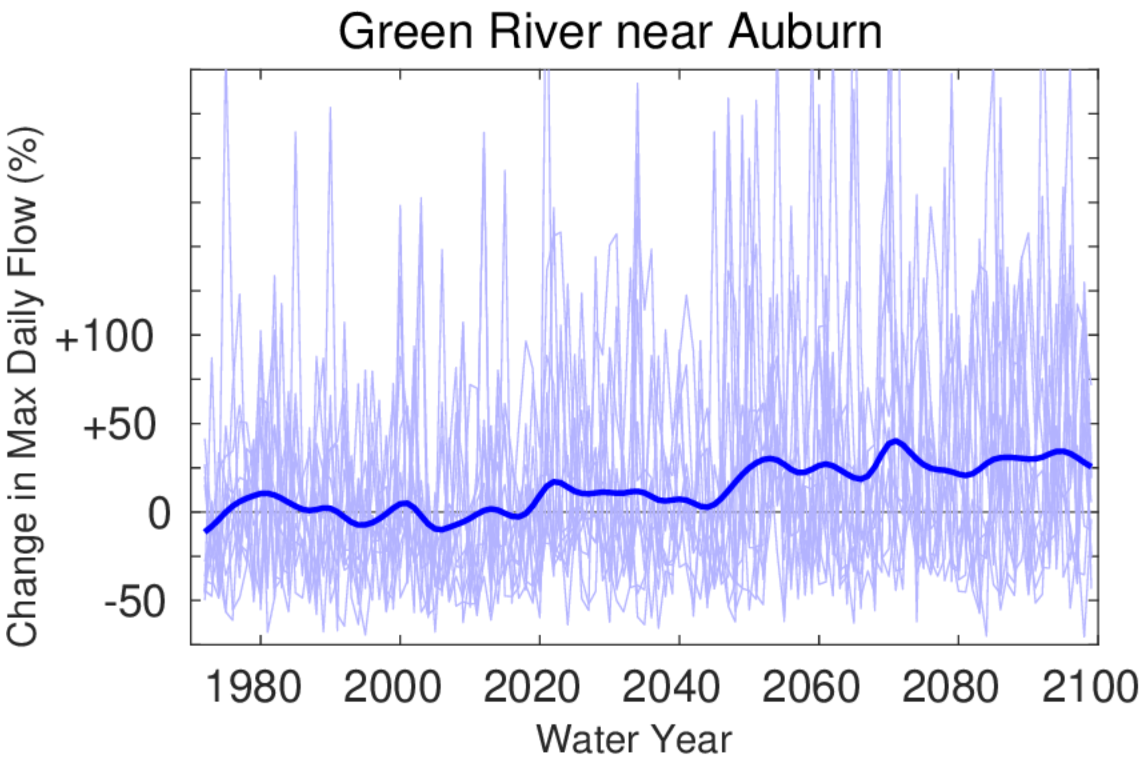

Figure ES1. Naturalized peak flows are projected to increase steadily throughout the century. Time series of peak flows for each of the 12 models analyzed in this study (light blue lines), and model average (thick blue line), for the Green River Near Auburn. All results are plotted as a percent difference, relative to the average for the 1990s (1980-2009). For readability, the model average is smoothed using an 11-point gaussian filter.

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

The Green River's hydrology is considered "rain dominant", with a winter peak in streamflow corresponding with the rainy season. Nonetheless, there is a small but important influence from snowpack, evidenced by the spring bump in historical flows for the mainstem sites. For all sites, flows drop off rapidly in late spring, with a minimum in August, 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 the Newaukum and Big Soos River sites; 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, for nearly all models, metrics, and**

time periods that we considered. Median projections for the end of the century range from about +20% to +70%, 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 well before July 1st, and late summer evapotranspiration is projected to decrease slightly in our modeling. This suggests that precipitation changes will be the most important driver of late summer flow changes. As noted above, July-August precipitation is projected to decrease. **Our streamflow modeling show a decrease in summer flows, ranging from about -30% to -40% for the mainstem sites and -6% to -15% for Newaukum and Big Soos Creeks (median projection, 2080s relative to 1990s).** The much larger decreases for the mainstem sites suggests that snowpack declines are an important driver of low flow decreases. Projected changes are similar for the water year minimum flows, though projected decreases for the two creeks are larger, suggesting a more important role for summer precipitation changes in the lowest flows of the year. It is worth noting that the model performance for low flows is good for the mainstem sites but the evaluation scores are much lower for the two creeks. Although this doesn't necessarily mean the projected changes are less accurate for Big Soos and Newaukum Creeks, we recommend further evaluation before using the results for those locations.

Regulated Flows

This section discusses the projections for *"regulated flow"* changes, obtained by modeling the effects of reservoir operations at Howard Hanson Dam.

As with most reservoirs in the region, Howard Hanson 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 and lower flows in summer. **On average, peak flows are projected to increase slightly by the end of the century (Figure ES2). Specifically, models project that the 2-year event will increase by +4%, for the 2080s relative to the 1990s** (model median, hourly peak flows for the Green River at Auburn; range: -6 to +51%). However, the results also show near-zero increases for large events (e.g. 4- and 10-year peak flows) and much larger increases for smaller events (e.g. +27% median increase for hourly flows for the Green River at Auburn, for the 2080s relative to the 1990s). **This suggests that Howard Hanson Dam is able to maintain flows below the target thresholds for the vast majority of**

floods through the end of this century, but that high flows approaching these thresholds will occur more often.

Still, flow thresholds are exceeded on occasion, and these exceedances occur more often in the future. Specifically, our projections have flows exceeding the 5,000 CFS scour threshold for the Green River at Howard Hanson Dam for about 5 days per year in the future (115 hours), on average by the 2080s, compared to about 3 days per year historically (73 hours). Similarly, **the 11,000 CFS threshold for the Green River at Auburn is projected to be exceeded 14 hours per year, on average by the 2080s, compared to about 9 hours per year historically**.

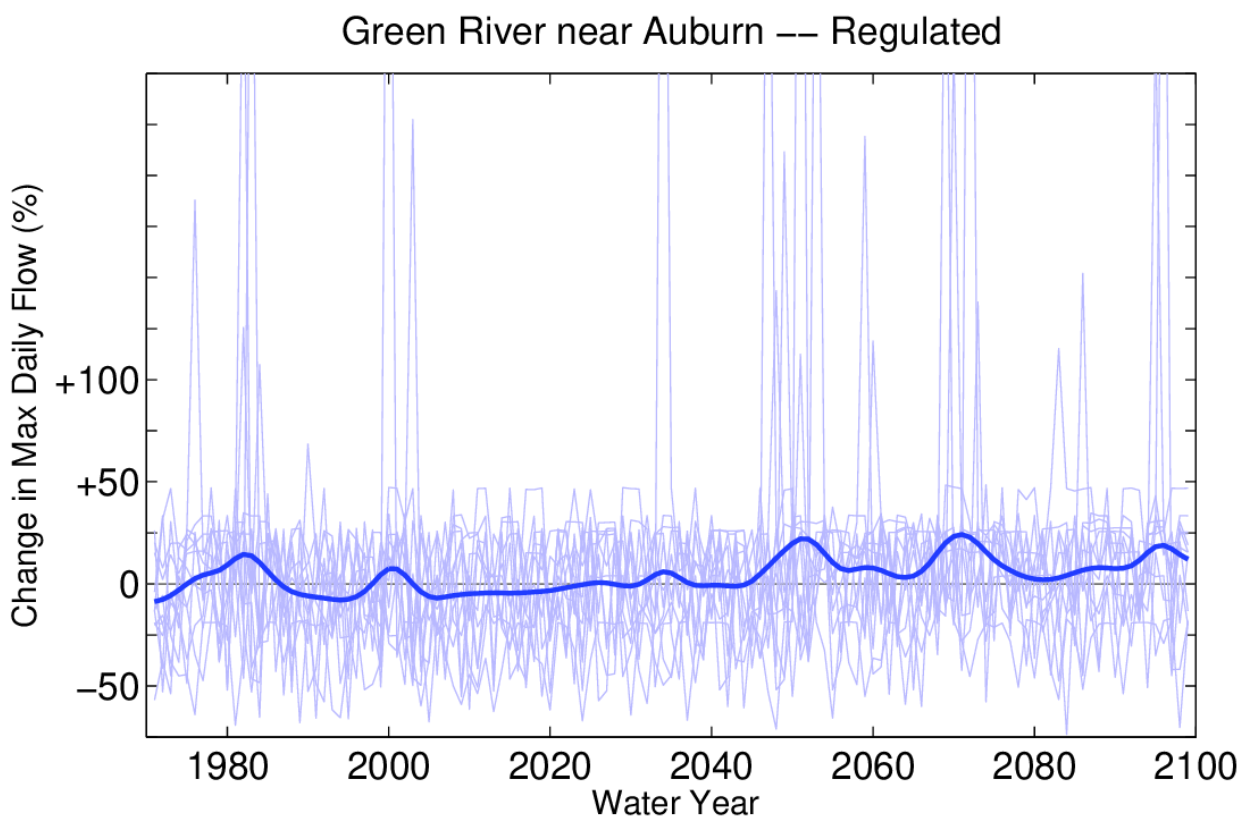

Figure ES2. Projected changes in regulated peak daily flows for each of the 12 models analyzed in this study (light blue lines), and model average (thick blue line). For each model, the plot shows the maximum in daily flows for each water year, plotted as a percent difference relative to the average for the 1990s (1980-2009). For readability, the model average is smoothed using an 11-point gaussian filter.

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 22 river locations across the Green 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 Green 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; given the requirements of the Federal Flood Risk Management Standard (Executive Order 13690), 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 Green 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 Green River, companions reports provide future peak flows in the Snohomish, Cedar, Green, and Puyallup river basins. In addition, a preliminary analysis will assess the implications for peak flow regulation in the major reservoirs on the Tolt, 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 A.

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.
- *Validate 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 Tukwila, Kent, Auburn, Palmer, and Below HHD 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 included in the results from the reservoir modeling.

	Station	ID	Lat. / Lon.	Years
Snowpack	Cougar Mountain	420	47.28/-121.67	1982-Now
	Lynn Lake	1069	47.2/-121.78	2008-Now
	Sawmill Ridge	1068	47.16/-121.42	2007-Now
	Stampede Pass	788	47.27/-121.34	1983-Now
Streamflow	Green R at Tukwila	12113350	47.46528/-122.2472	1960-1984
	Green R at Kent (200th st)*	12113344	47.42306/-122.2642	2011-Now
	Green R Nr Auburn*	12113000	47.31250/-122.20278	1986-Now
	Big Soos Cr	12112600	47.31250/-122.16417	1960-Now
	Newaukum Cr	12108500	47.27593/-122.05833	1944-Now
	Green R Nr Palmer*	12106700	47.30528/-121.84944	1963-Now
	Green Below HHD*	12105900	47.28389/-121.79667	1960-Now
	Green R Nr Lester	12104500	47.20778/-121.55194	1945-1993

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 adapt the meteorological 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	1981-2020
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 28^{th}.

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 C.

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. We generated the stream network based on an assumed minimum contributing area of 0.25 km^2. As shown in the figure, land cover is dominated by evergreen forest in the upper elevations while the

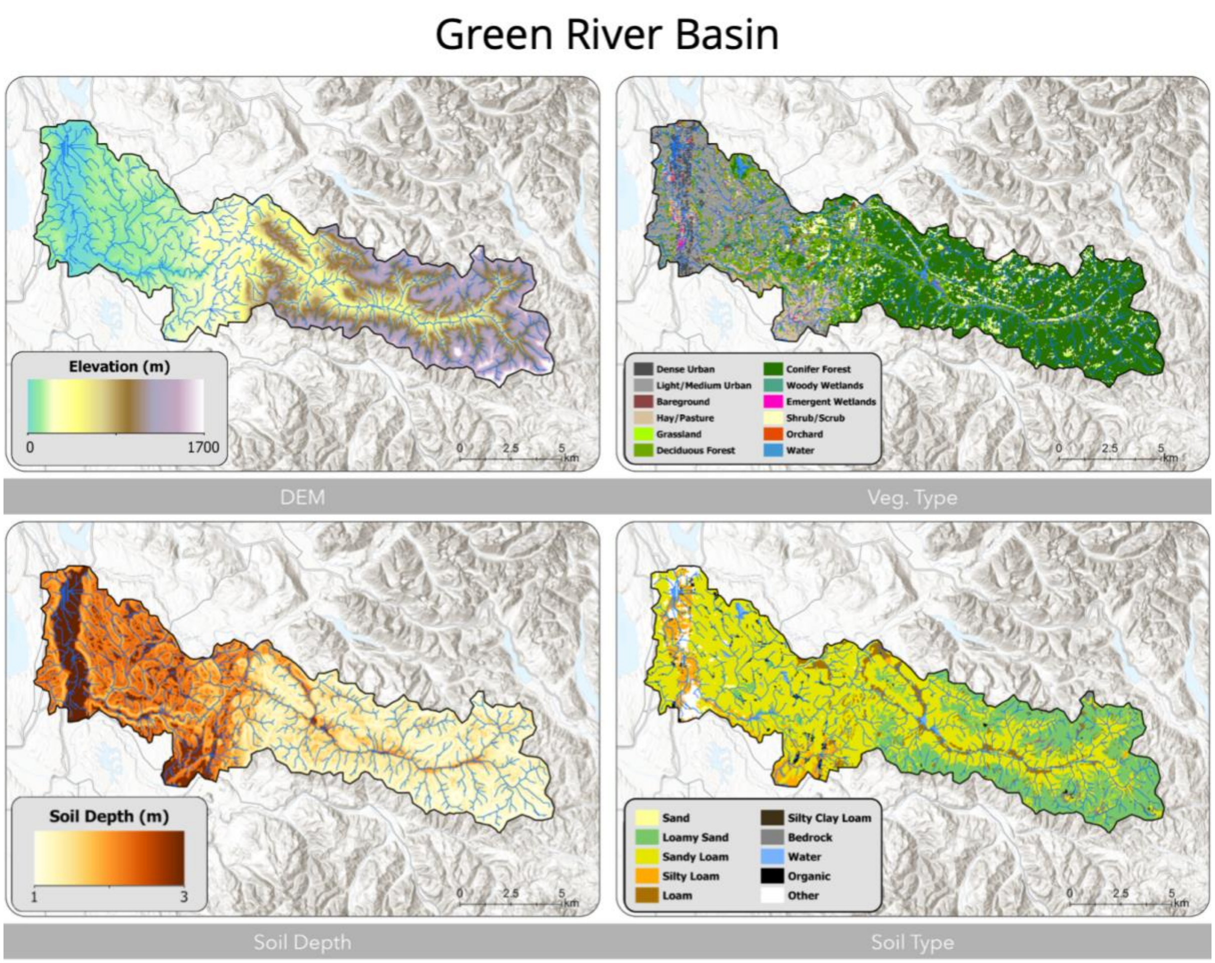

Figure 1. Maps showing elevation, soil depth, soil type, and vegetation distributions for the Green DHSVM model.

lower elevations are more developed with urban and agricultural classifications. For soils, sand 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"). 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 two additional adjustments to the meteorology: scaling temperature down by 2°C and decreasing precipitation by 20%. These changes were applied uniformly to 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 6.5°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. DHSVM uses air temperature to differentiate precipitation into rain and snow. We used a rain threshold of -1°C and a snow threshold of 0.5°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.

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	Sandy Loam	0.0028
		Silty Loam	0.00005
Exponential Decrease	0 – 10	Sandy Loam	1.0
		Silty Loam	1.0

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 adjustments that significantly improved the results. For soil depth, we found that a range of 1-3 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. In general the best model scores are for the Green River sites, especially the Green R Nr Auburn site. For the mainstem sites, Nash-Sutcliffe Efficiency (NSE) score ranges from 0.6 to 0.65, which 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") are similar – higher for the Lester site, lower for the HHD and Palmer sites, and essentially the same at Auburn. This is good news, and suggests that the model performs equally well at low flows. The Kling-Gupta Efficiency (KGE) scores corroborate the NSE scores (KGE scores tend to be higher, simply due to the way they are calculated), showing similarly good scores for the mainstem sites. In contrast with the results for the mainstem sites, the model scores for the Newaukum and Big Soos sites are very poor. This is primarily due to the large positive bias for flows in these two tributaries (Figure 2). The correlation (r^2), which is not affected by absolute biases, corroborates this – showing decent scores for both sites.

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

Table 4. Hydrologic model evaluation scores for the 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
Green R Nr Lester	0.61	0.6	0.7	0.62	0.27	-5.69
Green Below HHD	0.64	0.63	0.5	0.75	0.61	-9.84
Green R Nr Palmer	0.67	0.63	0.57	0.69	0.64	-21.05
Green R Nr Auburn	0.69	0.65	0.64	0.72	0.8	-20.69
Newaukum Cr	0.48	-0.33	0.26	0.21	0.07	-60.29
Big Soos Cr	0.56	-0.67	-0.1	-0.02	0.16	-92.3

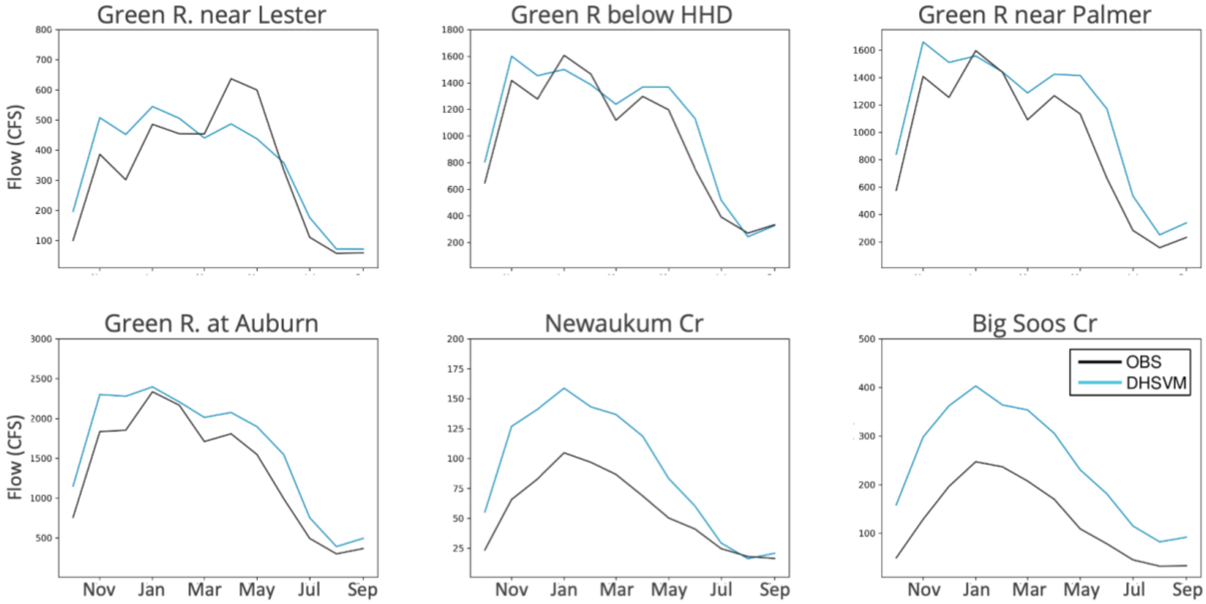

Figure 2. Observed and modeled average monthly *naturalized* flows for the six gauges listed in Table 1. Comparisons include all years in which observations and model results are available.

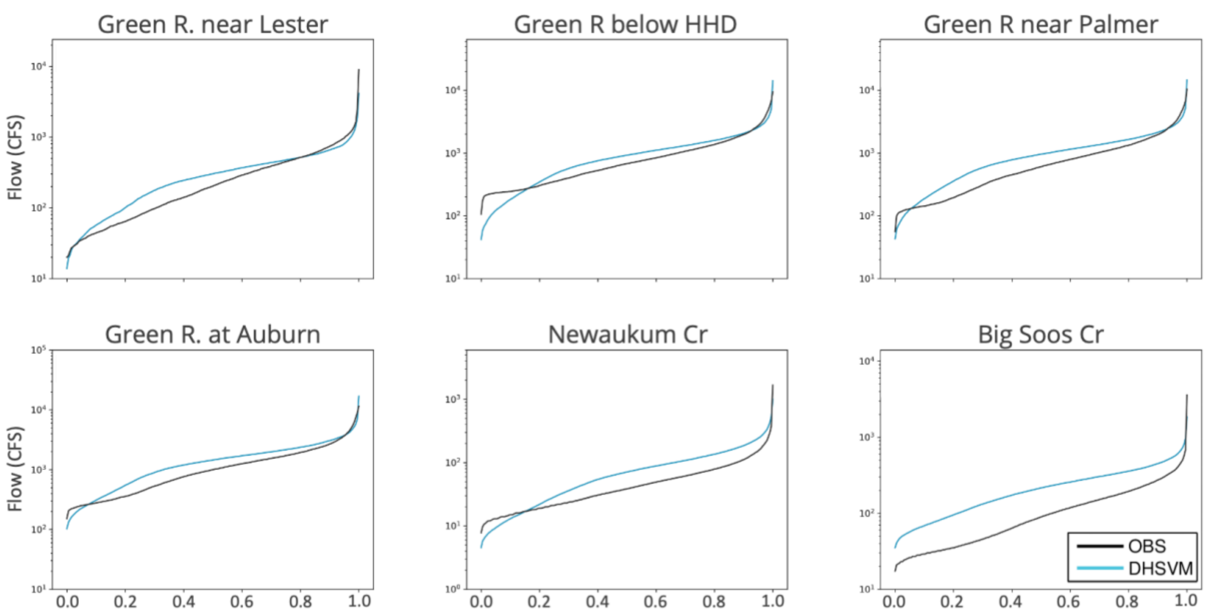

Figure 3. Observed and modeled cumulative distribution function (CDF) in daily *naturalized* flows. Comparisons include all years in which observations and model results are available.

(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 projections of the relative change (e.g. percent change in peak flows) are still likely to provide useful information, even if the historical simulations do not always align with the observations.

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 22 streamflow sites across the Green River Basin. These are listed in a companion spreadsheet to this report, along with notes about their location, source, and application.

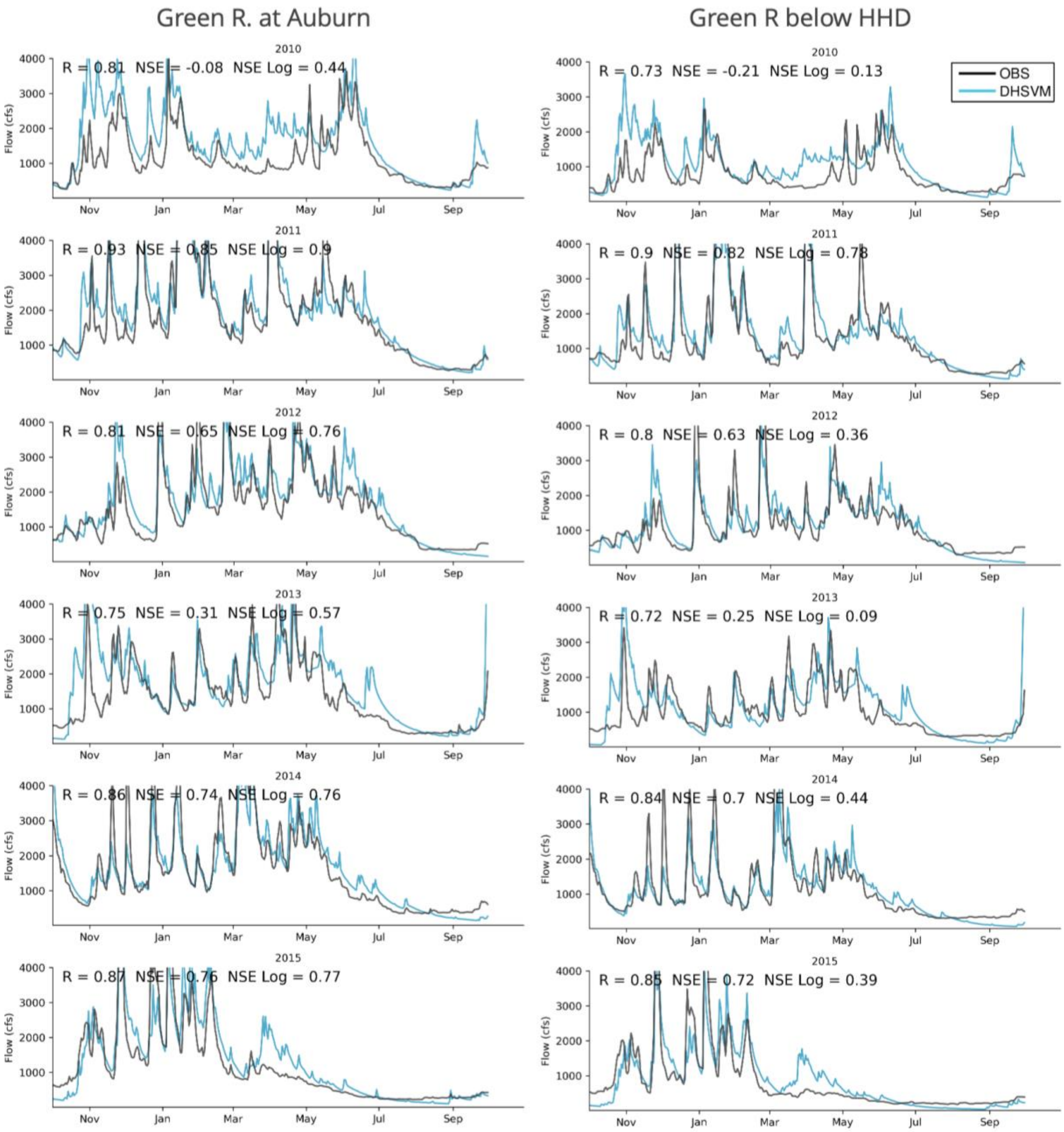

Figure 4. Observed and modeled daily flows for the Green R at Auburn and Green R below Howard Hanson Dam sites. Results are shown for water years 2010-2015; comparisons for other years are similar.

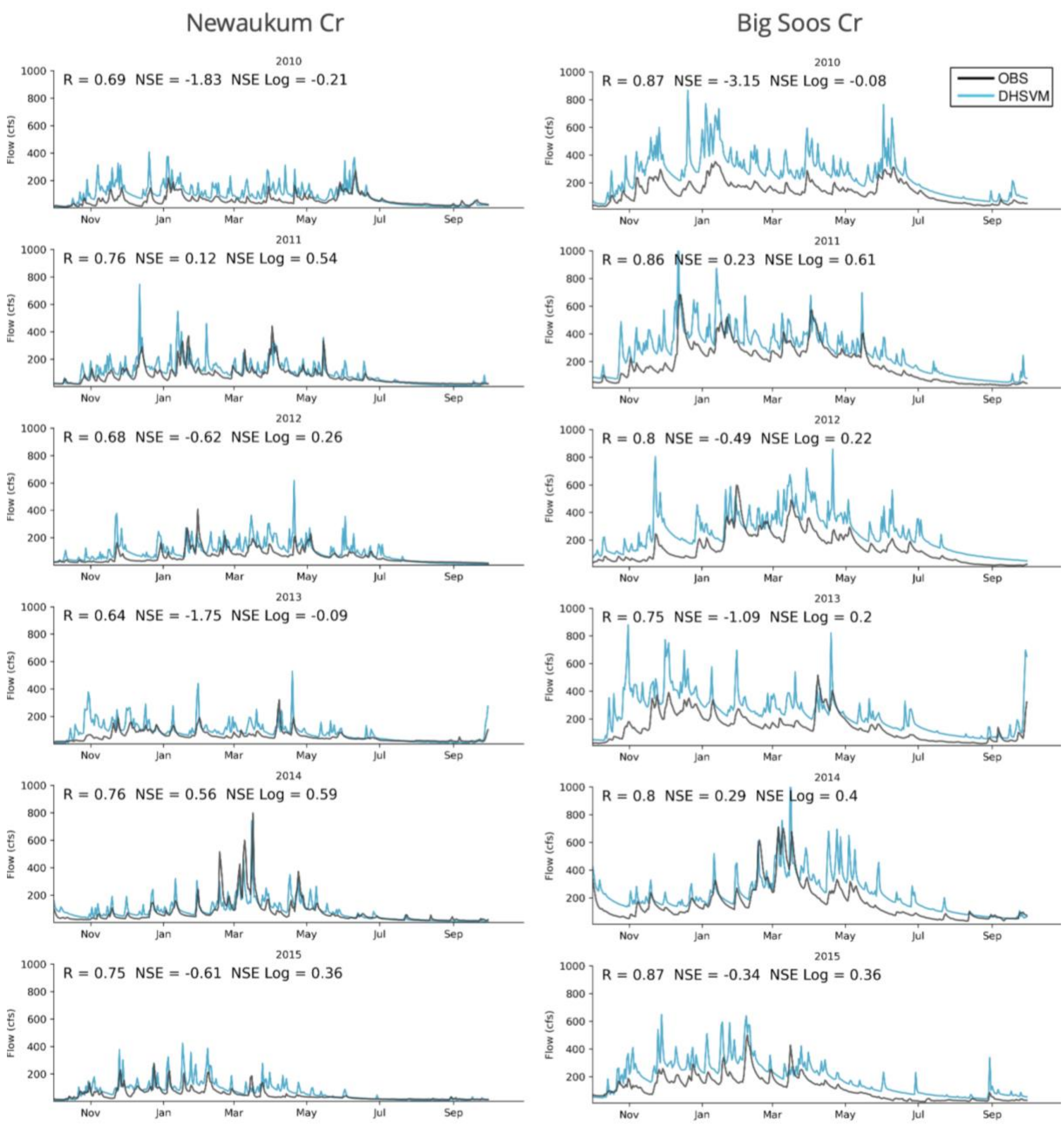

Figure 5. As in Figure 4 but for the Newaukum and Big Soos Cr sites.

Reservoir Modeling

We obtained the reservoir model for Howard Hanson Dam (HHD) from the Seattle office of the U.S. Army Corps of Engineers (USACE). The model was developed using the HEC-ResSim (https://www.hec.usace.army.mil/software/hec-ressim/; Hydrologic Engineering Center Reservoir System Simulation) software package. The model 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 Auburn gauge site. During peak flow events, operations target a maximum flow of 10,000 CFS on the rising limb and 11,000 CFS on the receding limb. Higher releases are be required, according to the Discharge Regulation Schedule, in the event that the reservoir fills beyond a certain elevation and inflows are high enough that dam safety becomes a consideration. The ResSim model for HHD runs at an hourly time step, meaning that all streamflow inputs must also be hourly.

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' tool (https://www.nwd-wc.usace.army.mil/dd/common/dataquery/www/#), using these to bias-correct DHSVM inflows to the HHD reservoir. The model also requires an estimate of local flows between HHD and the Auburn gauge site. To obtain naturalized flows at the Auburn gauge site, we took the difference between the observed USGS flows at the Auburn and Howard Hanson dam sites (Table 1), adding the naturalized flows at HHD to obtain an estimate of naturalized flows at Auburn. We used this reconstruction to bias-correct the DHSVM flows (which are also naturalized) at Auburn.

We tested multiple bias-correction approaches, using each as input to the ResSim model to evaluate their ability to reproduce the ResSim results obtained when using the naturalized observations as inputs. Specifically, our baseline ResSim simulation used the naturalized HHD flow observations from USACE along with the observed local flows between HHD and Auburn as inputs. We used this simulation as our baseline instead of observed 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 (see Mauger et al. 2016 for a description) worked best, in which corrections are applied for discrete quantile bins. In this case, we found that a bin width of 0.1% (i.e. 0-0.1, 0.1-0.2, … 99.9-100) and applying a separate bias correction for each calendar month provided the best results. The correction was applied to hourly flow estimates from DHSVM. 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 1970-2020 training period. The corrections were then applied uniformly across the entire time series (1970-2099).

Table 5. Reservoir model evaluation scores for the four mainstem sites listed below Howard Hanson Dam (see 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
Green Below HHD	0.66	0.61	0.7	0.81	0.56	-0.48
Green R Nr Palmer	0.66	0.59	0.69	0.8	0.55	-0.33
Green R Nr Auburn	0.76	0.76	0.75	0.86	0.59	2.08
Green R at Kent	0.76	0.75	0.75	0.86	0.62	2.18

Table 5 – along with Figures 6, 7, and 8 – show comparisons between the ResSim results based on the bias-corrected WRF-NARR DHSVM flows ("RESSIM-WRF") and our baseline simulation ("RESSIM-NAT"), described above. For reference, observed flows from the USGS gauge sites are included as well. As noted above, 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. Apart from RMSE, for which the scores are comparable, the RESSIM scores are all 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 regulated flows downstream of Howard Hanson Dam. The scores are

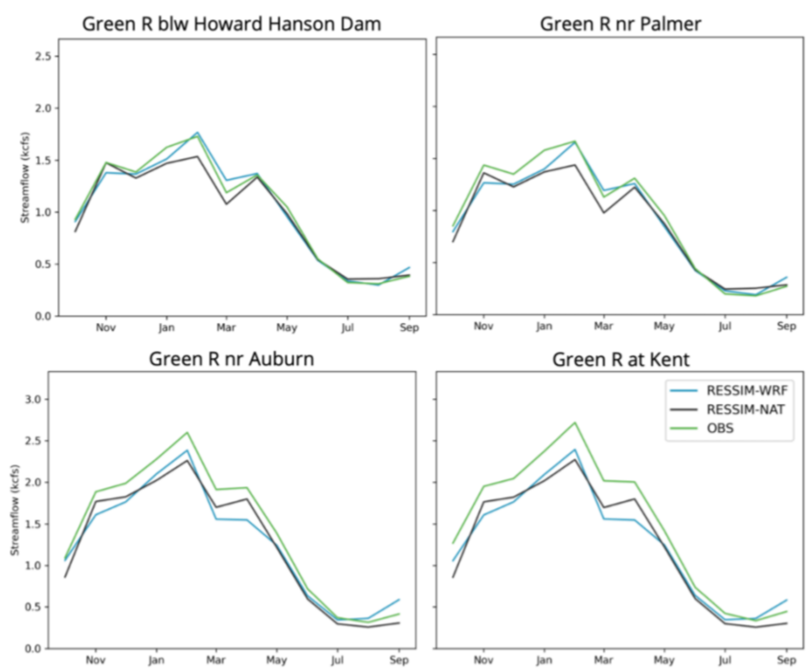

Figure 6. Average monthly *regulated* flows for four sites downstream of Howard Hanson Dam. Results are included for the observed flows at the USGS gauge (OBS, green), modeled flows using observationally-based naturalized flows (RESSIM-NAT, black), and modeled flows using the WRF-NARR DHSVM flows as inputs (RESSIM-WRF, blue). Comparisons include all years in which observations and model results are available.

better for the downstream sites (Auburn, Kent) relative to the upstream sites (HHD, Palmer). This could be due to disagreement for the highest peak flows: in the CDF comparisons (Figure 7), these are about 20% higher for RESSIM-WRF than for the baseline simulation (RESSIM-NAT). This is consistent with the monthly average flow plots, which show higher average flows for RESSIM-WRF compared to RESSIM-NAT for December-March. Notably, the USGS observations are also higher than the RESSIM-NAT results, suggesting that the RESSIM-WRF may better represent observed flows for the HHD and Palmer sites.

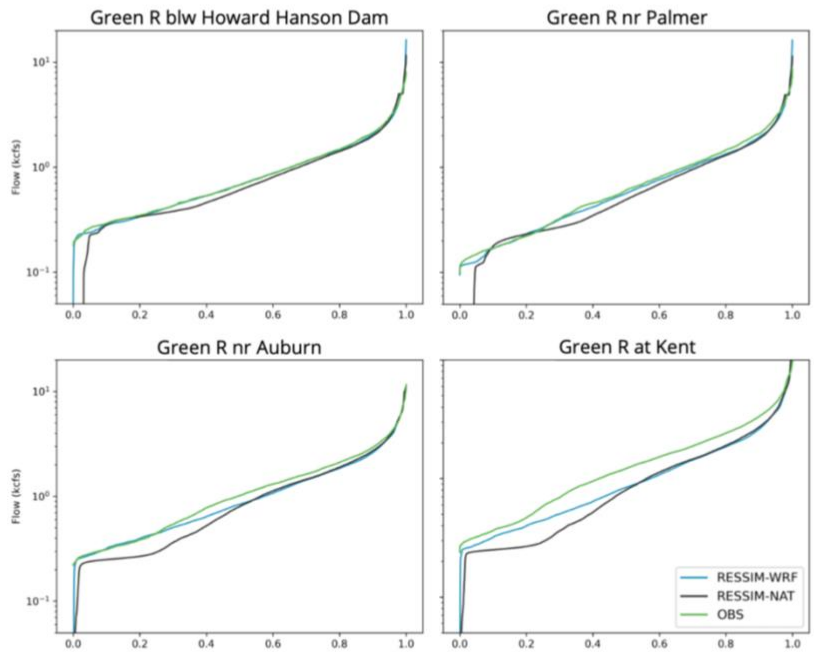

Figure 7. Cumulative distributions (CDFs) for daily *regulated* flows, for four sites downstream of Howard Hanson Dam. Results are included for the observed flows at the USGS gauge (OBS, green), modeled flows using observationally-based naturalized flows (RESSIM-NAT, black), and modeled flows using the WRF-NARR DHSVM flows as inputs (RESSIM-WRF, blue). Comparisons include all years in which observations and model results are available.

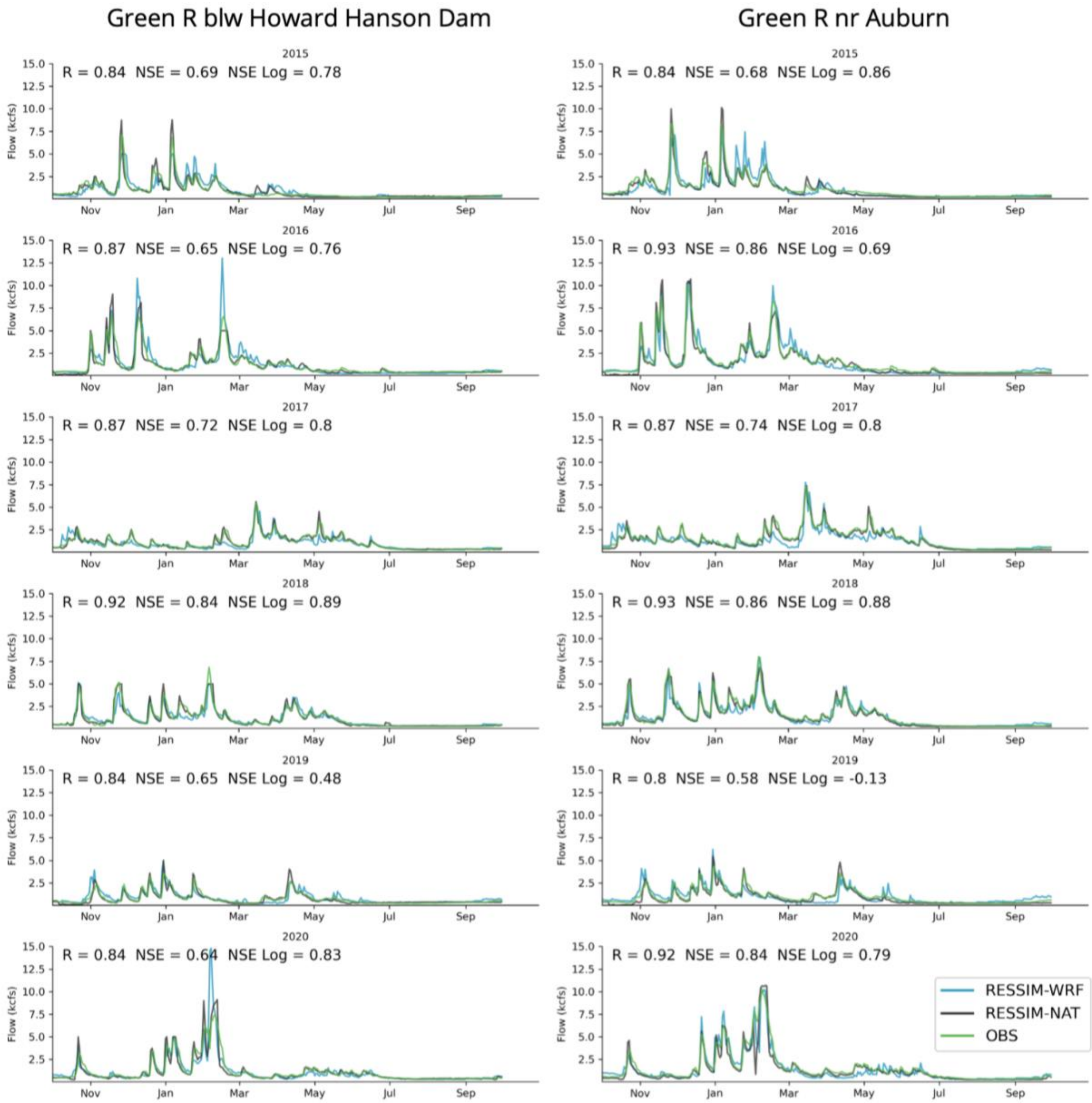

Figure 8. Time series of daily *regulated* flows for four sites downstream of Howard Hanson Dam. Results are included for the observed flows at the USGS gauge (OBS, green), modeled flows using observationally-based naturalized flows (RESSIM-NAT, black), and modeled flows using the WRF-NARR DHSVM flows as inputs (RESSIM-WRF, blue). Results are shown for water years 2015-2020; comparisons for other years are similar.

RESULTS

This section summarizes the changes in naturalized streamflow for the Green River DHSVM simulations, along with changes in regulated streamflow from the HEC-ResSim model for Howard Hanson Dam (HHD).

Apart from reservoir operations at Howard Hanson 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 E for a more in depth discussion of model assumptions and limitations.

As discussed in previous sections, all results are based on 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. 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 projections in this study are based on the high-end RCP 8.5 greenhouse gas scenario.

Snowpack, Precipitation and Evapotranspiration

On average for the Green river watershed, models project a median 87% decrease in April 1st Snowpack by the 2080s (relative to the 1990s, range: -48 to -97%). 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 +18% (range: +1 to +47%) increase in the heaviest daily rain event for each year.** 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 +10% (range: -2 to +28%).** 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 -14% (range: -63 to +44 %). Although some models disagree on the direction of change for both summer and winter, 10 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 an increase (median: +9%, range: -40% to +77%, with 9 of 12 models projecting an increase). 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: -9%, range: -36% to +17%**, with 9 of 12 models showing a decrease). This suggests that precipitation is the primary factor affecting summer decreases in flows.

Monthly Flows

Naturalized (Unregulated) Flow Projections

The Green River's hydrology is considered "rain dominant", with a winter peak in streamflow corresponding with the rainy season. Nonetheless, there is a small but important influence from snowpack, evidenced by the spring bump in historical flows for the mainstem sites (Table 6, Figure 9). For all sites, flows drop off rapidly in late spring, with a minimum in August, 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.** The changes in snowpack are negligible for the Newaukum and Big Soos River sites, because they have negligible winter snowpack to begin with. The change in heavy

Table 6. Average projected change in monthly average naturalized flows for the six river sites in Table 1. Results show the 12-model average percent change for the 2080s (2070-2099) relative to the 1980s (1970-1999). Projections are highlighted in bold when all 12 models agree on the sign of the change.

	Green R Nr Lester	Green R Below HHD	Green R Nr Palmer	Green R Nr Auburn	Newaukum Cr	Big Soos Cr
OCT	0%	+5%	+6%	+10%	+21%	+20%
NOV	+9%	+12%	+12%	+14%	+17%	**+20%**
DEC	+31%	+35%	+35%	+31%	+22%	**+22%**
JAN	**+23%**	**+26%**	**+25%**	**+23%**	+14%	**+18%**
FEB	+17%	+21%	+21%	+18%	+11%	+13%
MAR	+5%	+10%	+10%	+10%	+8%	+10%
APR	-13%	-8%	-8%	-4%	+3%	+8%
MAY	**-30%**	**-25%**	**-25%**	**-17%**	-1%	+5%
JUN	**-41%**	**-39%**	**-38%**	**-30%**	-15%	-6%
JUL	**-38%**	**-40%**	**-39%**	**-29%**	-14%	-6%
AUG	**-36%**	**-41%**	**-41%**	**-29%**	-15%	-9%
SEP	-31%	-24%	-24%	-19%	-9%	-5%

precipitation intensity likely contributes to the projected increases in winter flows for all six sites. Although the magnitude of winter increases is similar for all sites there is more model agreement for the Big Soos site. Although we have not investigated this difference, this is likely related to the spatial pattern of the precipitation projections, since snow is not a factor for Big Soos Creek. Finally, there is strong model agreement for decreases in May through August flows for the mainstem sites. Smaller decreases are also projected for late summer for the Newaukum and Big Soos sites, likely because they are only affected by decreases in summer precipitation whereas the other sites are also affected by declining snowpack.

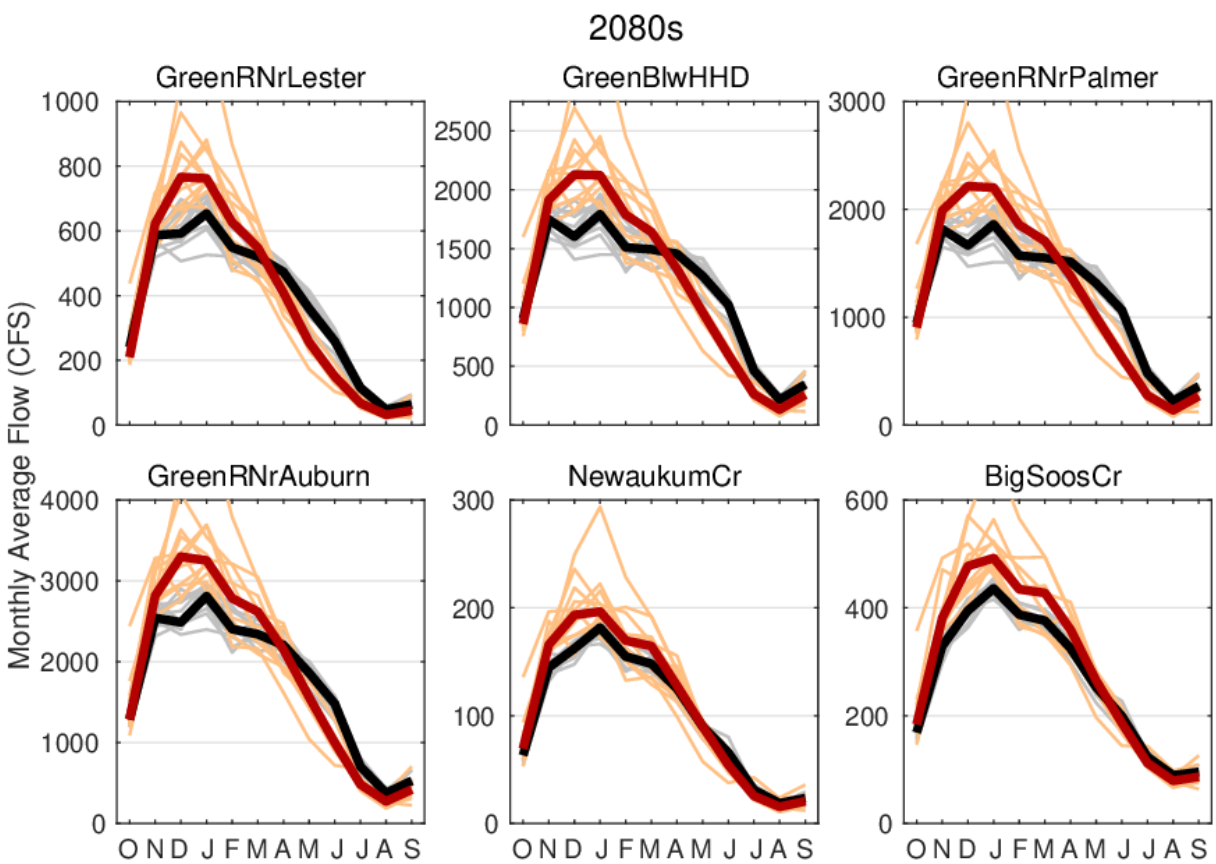

Figure 9. Historical and future monthly naturalized flows for the six sites listed in Table 1. Each line shows the results for one WRF-CMIP5 projection: historical (1980s, grey/black) and 2080s (orange/red). Thick lines show the model average, thin lines the individual model projections.

Regulated Flow Projections

Monthly average flows are projected to change in similar ways for locations affected by reservoir operations at Howard Hanson Dam (Figure 10, Table 7). However, the effect of

Figure 10. Historical and future regulated monthly flows for four 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.

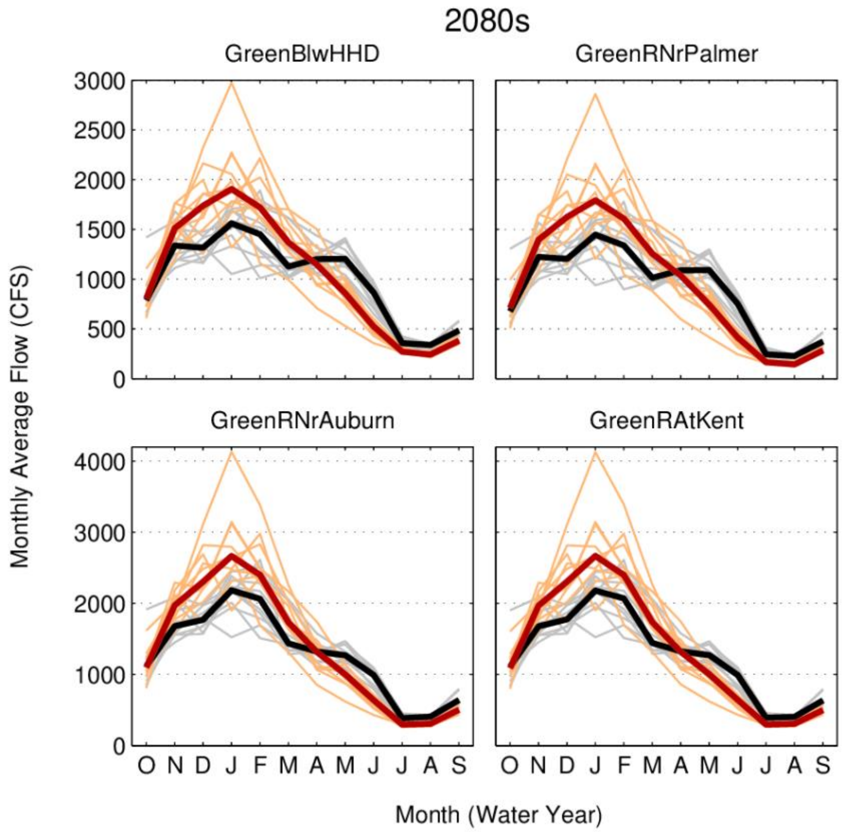

Table 7. Average projected change in monthly average regulated flows for the six river sites in Table 1. Results show the 12-model average percent change for the 2080s (2070-2099) relative to the 1980s (1970-1999). Projections are highlighted in bold when all 12 models agree on the sign of the change.

	Green R Below HHD	Green R Nr Palmer	Green R Nr Auburn	Green R At Kent
OCT	+6%	+7%	+7%	+7%
NOV	+6%	+6%	+6%	+7%
DEC	+12%	+13%	+10%	+10%
JAN	+7%	+7%	+7%	+8%
FEB	-0%	-0%	+1%	+1%
MAR	+4%	+5%	+3%	+3%
APR	-1%	-1%	+2%	+2%
MAY	-13%	-15%	-9%	-9%
JUN	-18%	-21%	-17%	-17%
JUL	**-14%**	**-20%**	**-14%**	**-14%**
AUG	**-15%**	**-20%**	**-14%**	**-14%**
SEP	-9%	-8%	-9%	-9%

regulation is clear and the projected changes differ in a few important respects. First, there is a greater range among model projections – notably, there are only two months (July and August) in which all models agree on the sign of the change in monthly flows. This is in contrast with the naturalized flow projections, which showed consistent increases in January and consistent decreases for May-August. The median projections for Nov-Jan show increases, but they are much smaller than for the naturalized flows, and there is very little change projected for February-April. The projected decreases are also less pronounced in summer, particularly for the two sites that are closer to the dam (Green R Nr Auburn, Green R At Kent). Setting aside these differences, both the regulated and naturalized flow projections show the same general pattern of higher flows in winter and lower flows in spring and summer.

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 D for the approach we use). This 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 12 models, for the Green River near Auburn. 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, Figure 12 summarizes the projections for the 2-year event, showing results for four peak flow durations, for each of the six sites featured in previous plots. Table 8 provides the same information for just the daily flow duration, juxtaposing the 2-, 10-, and 100-year projections. Although there is a range among models, **the median projections all show an increase across all return intervals, durations, and locations. Median projections for the end of the century range from about +20% to +70%, depending on location and flow duration.**

The high elevation sites generally show greater increases than the low elevation sites, likely due to the greater influence of snowpack changes at higher elevations. The projections do not show a 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 generally show smaller increases for longer durations.

The wide range among projections, even for the 2-year event, is typical of peak flow projections. It is not clear why the range is larger for the HHD, Palmer, and Auburn sites, though the fact that the range varies with duration suggests that it may be associated with differences in heavy precipitation projections among models. Middle elevations tend to receive the most intense precipitation, which could result in greater uncertainty for these areas as well. Further investigation would be needed to better understand why the models differ so dramatically in their projections, and what this suggests about likely changes in future flooding.

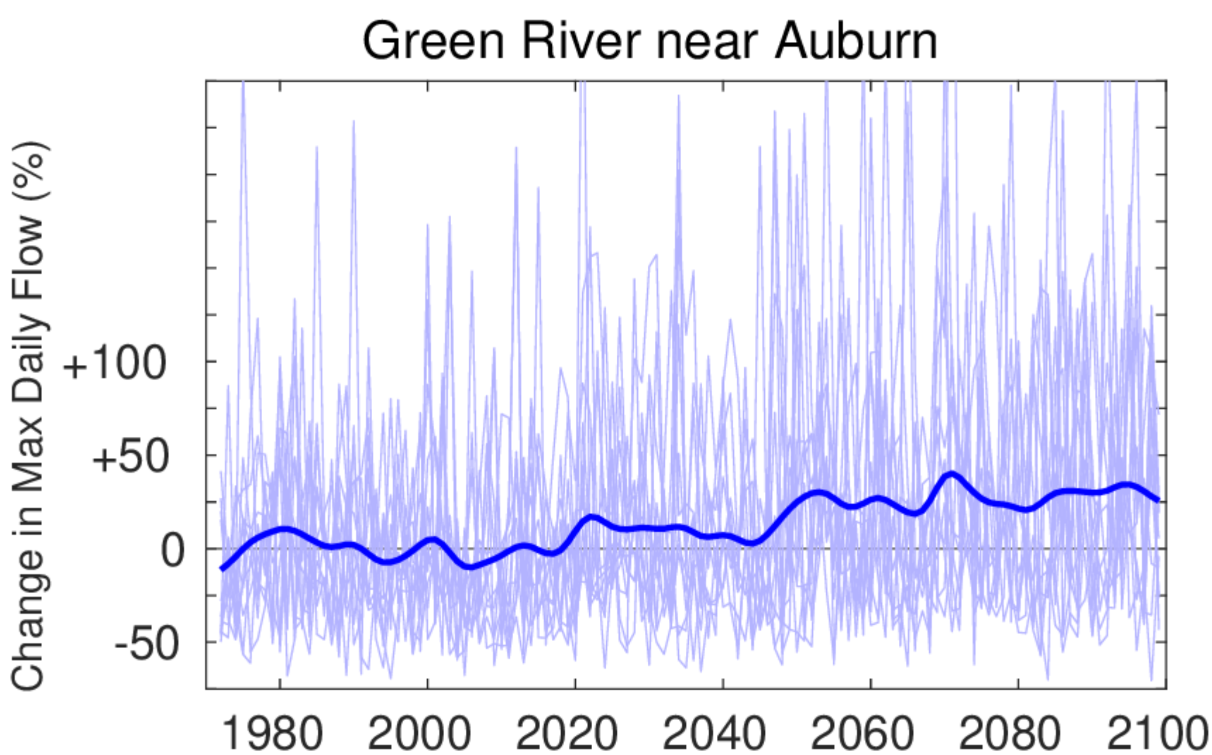

Figure 11. Projected changes in <u>naturalized</u> peak daily flows for each of the 12 models analyzed in this study (light blue lines), and model average (thick blue line). For each model, the plot shows the maximum in daily flows for each water year, plotted as a percent difference relative to the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

Table 8. Projected change in naturalized peak daily flow extremes for four streamflow sites. Results are provided for the 2080s (2070-2099) relative to the 1980s (1970-1999).

	Site	Median	25th / 75th	min / max
2 yr	Green R nr Lester	+30%	+8% / +48%	-12% / +61%
	Green R blw HHD	+22%	+7% / +45%	+2% / +79%
	Green R nr Palmer	+22%	+6% / +44%	+1% / +78%
	Green R nr Auburn	+16%	+7% / +38%	+1% / +67%
	Newaukum Cr	+12%	+4% / +32%	-3% / +43%
	Big Soos Cr	+20%	+8% / +31%	-1% / +38%
10 yr	Green R nr Lester	+28%	+2% / +50%	-1% / +75%
	Green R blw HHD	+28%	+8% / +65%	+2% / +90%
	Green R nr Palmer	+28%	+8% / +65%	+1% / +89%
	Green R nr Auburn	+25%	+6% / +62%	+4% / +81%
	Newaukum Cr	+30%	+12% / +51%	-1% / +76%
	Big Soos Cr	+29%	+21% / +49%	+4% / +73%
100 yr	Green R nr Lester	+32%	-3% / +89%	-34% / +109%
	Green R blw HHD	+36%	+2% / +100%	-19% / +171%
	Green R nr Palmer	+37%	+3% / +100%	-19% / +174%
	Green R nr Auburn	+40%	+11% / +101%	-22% / +147%
	Newaukum Cr	+73%	+16% / +120%	-9% / +159%
	Big Soos Cr	+73%	+28% / +99%	-11% / +203%

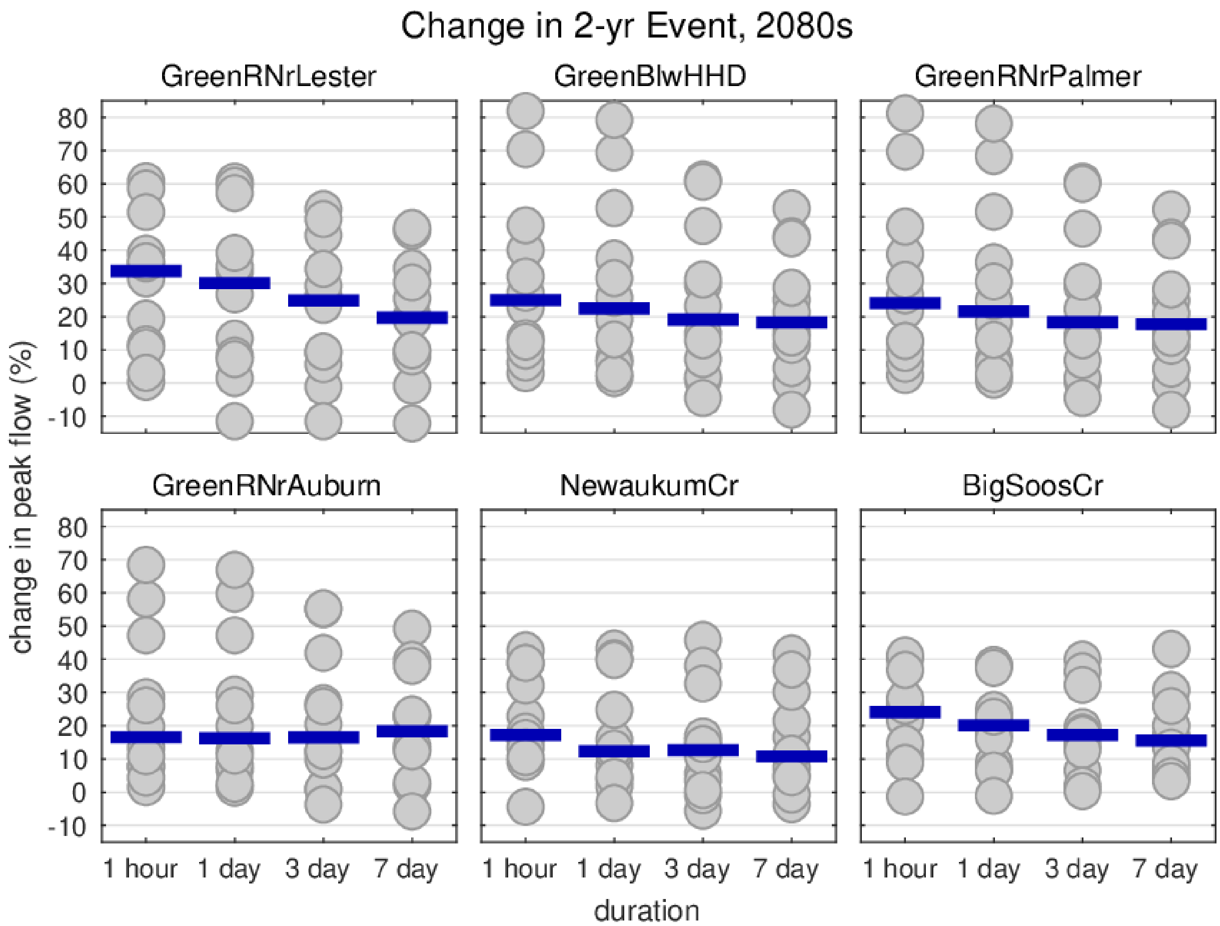

Figure 12. Projected change in the 2-year naturalized peak flow for the six sites listed in Table 1. Results are in percent, relative to the 1980s (1970-1999), for four different durations: 1 hour, 1 day, 3 day, and 7 day average flows. Each dot shows the result for one GCM projection, while the blue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

Regulated Peak Flow Projections

The regulated peak flow changes are generally projected to be much smaller than those for naturalized flows, and there is a larger spread among models. Figure 13, for example, shows about a 10-15% average increase in the maximum daily peak flow, about half of the change projected for naturalized peak flows at Auburn (Figure 11). Another difference from the naturalized peak flows is the magnitude of the peaks. Although not shown, the absolute flows show that the vast majority of regulated peak flows are effectively capped at the 11,000 CFS flow target at Auburn. Instead, the projected increase in peak flows is a result high flows below that threshold occur more frequently. That is, although most high flow events remain below the 11,000 CFS flow target, high flows below that limit occur more often in the future.

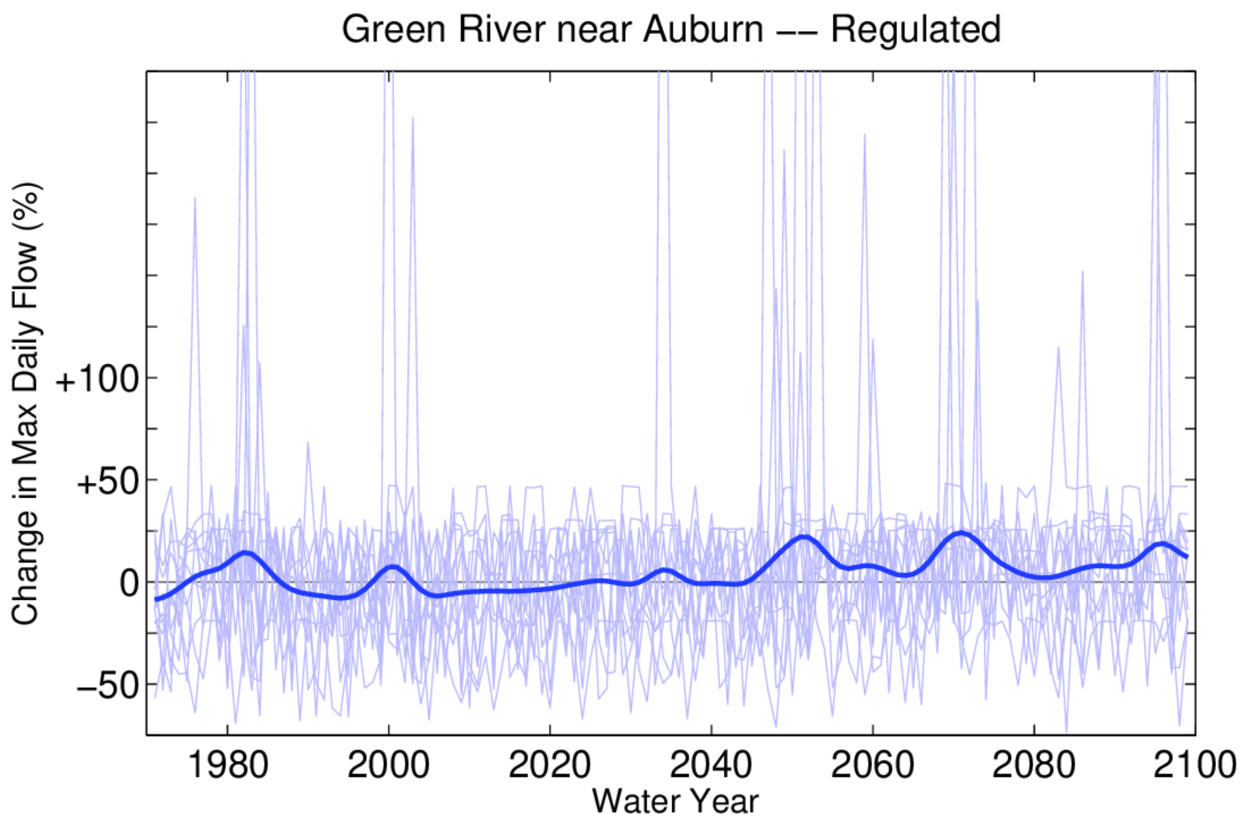

Figure 13. Projected changes in regulated peak daily flows for each of the 12 models analyzed in this study (light blue lines), and model average (thick blue line). For each model, the plot shows the maximum in daily flows for each water year, plotted as a percent difference relative to the average for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

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; we calculated 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, we do not recommend assessing changes for extremes that are greater than the 10-year event.

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 15 and Table 9 show the projected changes for select return intervals in daily flows.

Figure 14. Projected change in the cumulative distribution of <u>regulated</u> 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.

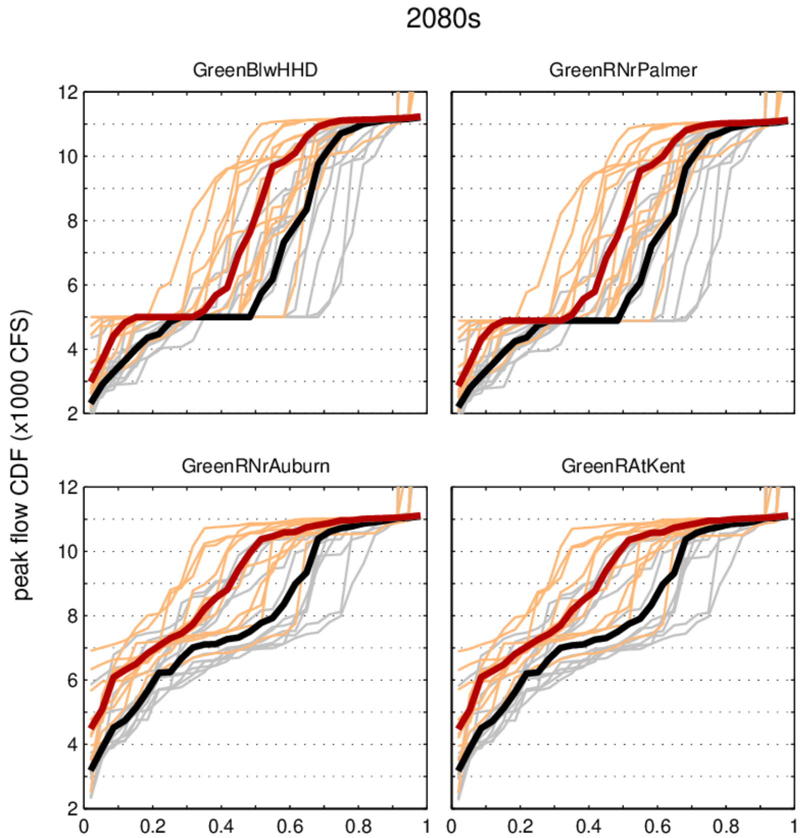

Figure 15. Projected change in the 2-year regulated peak flow for four sites downstream of Howard Hanson Dam. Results are in percent, relative to the 1980s (1970-1999), for four different durations: 1 hour, 1 day, 3 day, and 7 day average flows. Each dot shows the result for one GCM projection, while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

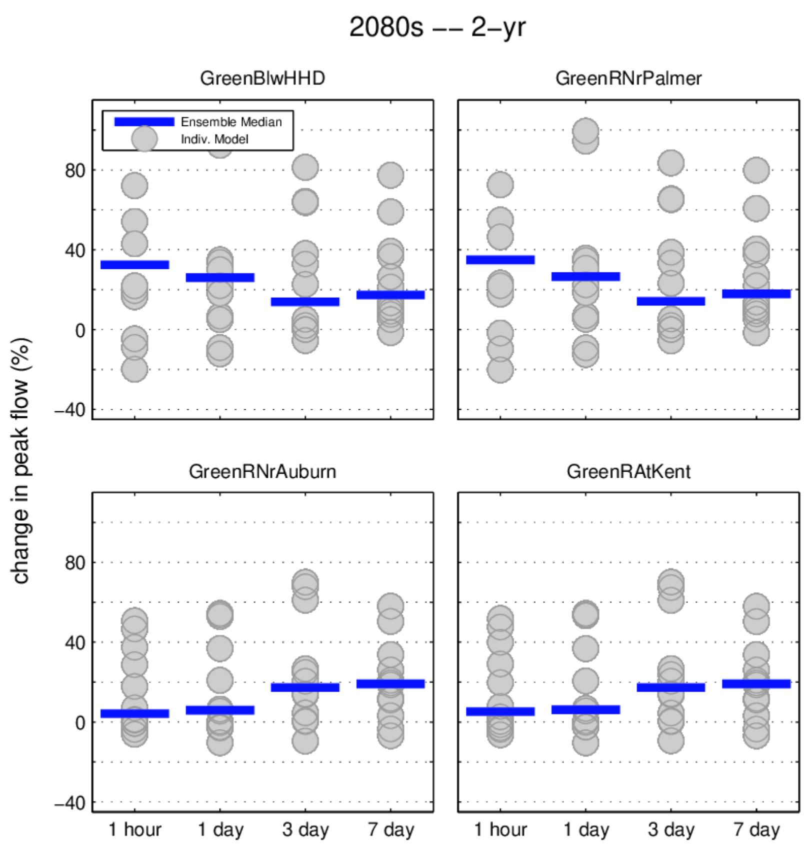

Table 9. Projected change in regulated peak daily flow extremes for four streamflow sites downstream of Howard Hanson Dam. Results are provided for the 2080s (2070-2099) relative to the 1980s (1970-1999).

	Site	Median	25th / 75th	min / max
1.11 yr	Green R blw HHD	+22%	+4% / +52%	-7% / +72%
	Green R nr Palmer	+22%	+4% / +55%	-7% / +75%
	Green R nr Auburn	+26%	+7% / +49%	-19% / +63%
	Green R at Kent	+26%	+6% / +49%	-19% / +64%
2 yr	Green R blw HHD	+26%	+6% / +64%	-12% / +116%
	Green R nr Palmer	+27%	+6% / +65%	-12% / +118%
	Green R nr Auburn	+6%	-1% / +45%	-10% / +54%
	Green R at Kent	+6%	-1% / +45%	-10% / +54%
10 yr	Green R blw HHD	+0%	-0% / +1%	-2% / +7%
	Green R nr Palmer	+0%	-0% / +1%	-2% / +7%
	Green R nr Auburn	+1%	-0% / +1%	-1% / +4%
	Green R at Kent	+1%	-0% / +1%	-1% / +4%

These results confirm that peak flows rarely exceed 11,000 CFS anywhere, and even then only in a few isolated instances. In addition, HHD outflows remain less than the 5,000 CFS scour threshold for everything below roughly the 2-year event (quantile of 0.50). **The most important changes are for flows below the 0.70 or 0.80 quantile (approximately the 3- or 4-year events). For these events, the changes can be important, with over a 20% increase in the model median projection for the lowest quantiles (e.g. 1.11-yr event, Table 9).** Although the plots in Figure 14 look as though the changes for the 2-year event should be just as big for Auburn as for HHD, the projected increases for each individual model are much smaller, leading to the smaller overall increase for the downstream sites.

Overall the results suggest that the reservoir can continue to meet the 11,000 CFS Auburn flow target through the end of the century, but higher outflows below that threshold will be occurring more often, potentially putting stress on the levee system. For instance, Figure 14 shows that at Auburn, peak flows exceed 10,000 CFS over 50% of the time by the 2080s (i.e. on average at least once every other year), whereas historically this occurred in about 30% of years (i.e. from approximately a 2- to a 3-year event).

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 5,000 CFS at the HHD gauge and 11,000 CFS at the Auburn gauge. Both show steady increases over time. **At the HHD gauge, the median projection is just over 80 hours per year exceeding 5,000 CFS currently (2020s) and just under 120 hours per year by the 2080s; nearly a 50% increase. Similarly, flows exceed 11,000 CFS at the Auburn gauge about 10 hours per year currently (2020s), and this is projected to increase to about 14 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.

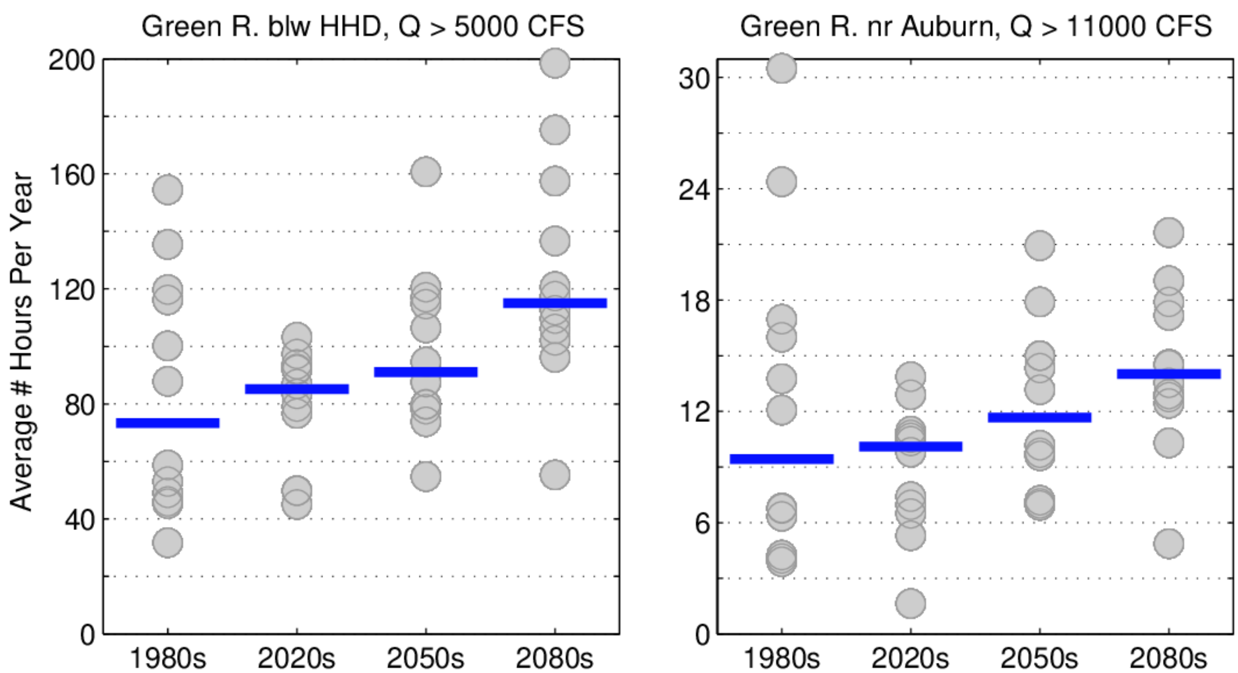

Figure 16. Number of hours with regulated hourly flows above 5,000 CFS for the Green River below Howard Hanson Dam gauge location, and above 11,000 CFS for the Green River near Auburn gauge location. Results show the average, for each of the 12 GCM projections, for four 30-year periods: 1980s (1971-1999), 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

Naturalized low flows are projected to decrease for nearly all models, durations, return intervals, and time periods that we considered (Figure 17, Table 10). There appears to be some contrast between the snow-influenced and rain-dominated sites, however changes for Newaukum Creek are close to those for the mainstem sites. 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

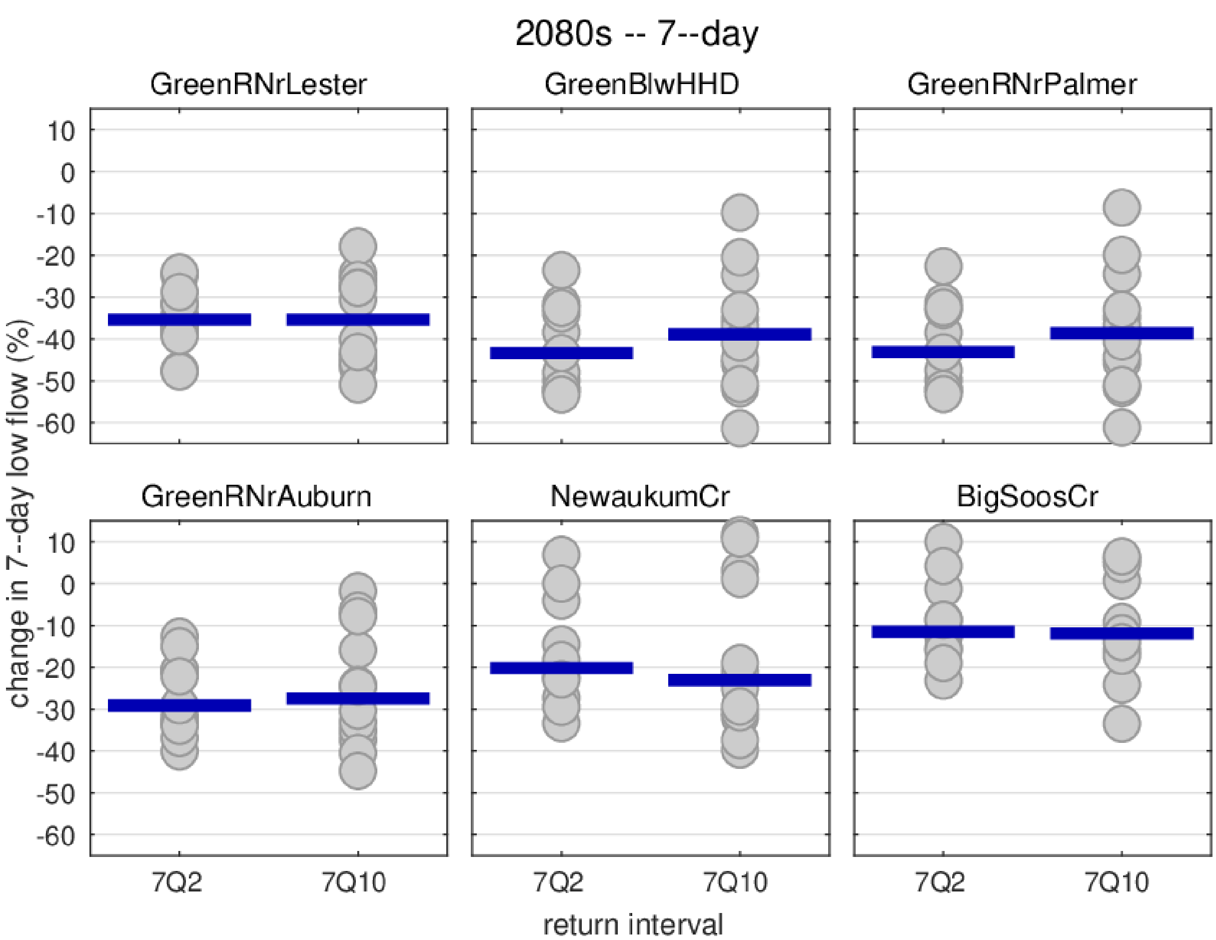

Figure 9. As in Figure 6 except showing the projected change in low flows. Results are shown in percent, relative to the 1980s (1970-1999), for the 2-, and 10-year extremes in 7-day minimum flows. Each dot shows the result for one GCM projection, while the blue bars show the median of the 12 models.

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 40% decrease.**

Table 10. Projected change in low flow extremes for all streamflow sites. Results are provided for 7-day average low flows, for the 2080s (2070-2099) relative to the 1980s (1970-1999).

	Site	Median	25th / 75th	min / max
2 yr	Green R nr Lester	-35%	-39% / -30%	-48% / -24%
	Green R blw HHD	-43%	-51% / -33%	-53% / -24%
	Green R nr Palmer	-43%	-51% / -33%	-53% / -23%
	Green R nr Auburn	-29%	-34% / -21%	-40% / -13%
	Newaukum Cr	-20%	-25% / -9%	-33% / +7%
	Big Soos Cr	-12%	-16% / -5%	-23% / +10%
10 yr	Green R nr Lester	-35%	-45% / -27%	-51% / -18%
	Green R blw HHD	-39%	-48% / -29%	-61% / -10%
	Green R nr Palmer	-39%	-48% / -29%	-61% / -9%
	Green R nr Auburn	-28%	-36% / -12%	-45% / -2%
	Newaukum Cr	-23%	-31% / +2%	-40% / +12%
	Big Soos Cr	-12%	-17% / +3%	-34% / +6%

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. Green River near Lester). 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.

Although generally similar, our naturalized flow results differ from our findings for the Snohomish River study (Mauger et al. 2025), in two key respects. First, the peak flow projections differ among sites, and the increases do appear to be greater for snow-influenced sites. It is not clear why this effect would be more notable on the Green River relative to the Snoqualmie or Skykomish rivers, though the much larger basin size for the Snohomish could buffer the effect of snowpack declines. A second difference is that the model does a better job of capturing low flows, and there is a smaller range among low flow projections.

In addition, 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 11,000 CFS for the Green River at Auburn is nearly always maintained, even through the end of the century. Although this flow target is not exceeded very often, there are a handful of instances in which regulated peak flows do exceed the 11,000 CFS target, and the frequency is projected to increase over time. Flows exceeding the 5,000 CFS scour threshold for Green River at Howard Hanson Dam are more common, and also projected to increase over time. Overall, we find that peak flows rarely exceed the flow thresholds set for each location, but that high flows approaching these levels occur more often in the future.

There are some unexpected findings in these simulations. First, although the July-August precipitation projections are similar to the findings of previous studies (e.g. Mauger et al. 2015), our models project a slight increase in precipitation for September, suggesting an earlier end to the dry season in the future. There is a very wide range among models for September precipitation changes, suggesting low confidence in this finding.

Second, our models project a *decrease* in summer evapotranspiration. 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 Green 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.

Two key limitations of the naturalized flow projections 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 model only has a simplified routing scheme (Wigmosta and Perkins 2001) and does not account for overbank flow during flood events. These and other issues are discussed in Appendix E.

An important limitation of the regulated flow projections is that the modeling assumes no forecast: all reservoir operations are based on current conditions only. This means that our results are likely an overestimate of the impacts, since with forecasts operators can likely release additional water ahead of an approaching storm.

One other 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.

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 Green 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: 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 B: 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 B1. 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 C: 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

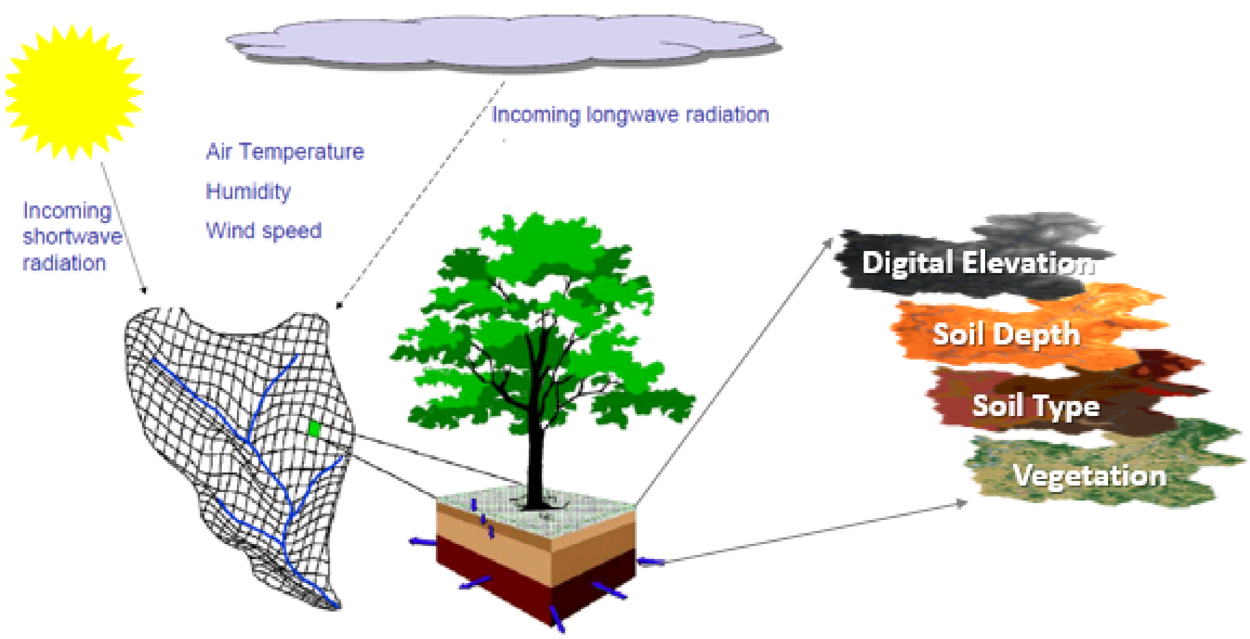

Figure C1. Diagram of DHSVM model and its inputs.

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 C1. 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 C2. 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 Green 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	**0.5**	**1492**	**0.08**	**0.1**	**3**	**0.5**
2	**Loamy Sand**	**23.2**	**1520**	**0.10**	**0.001**	**1**	**0.3**
3	**Sandy Loam**	**59.3**	**1569**	**0.14**	**0.0028**	**1**	**0.3**
4	**Silty Loam**	**6.2**	**1419**	**0.30**	**0.00002**	**1**	**0.00009**
5	Silt	0	1280	0.28	0.00002	1	0.00009
6	**Loam**	**4.2**	**1485**	**0.20**	**0.00008**	**0.5**	**0.0008**
7	Sandy Clay Loam	**0.2**	**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	**1.1**	**1565**	**0.31**	**0.00002**	**1**	**0.000002**
11	Silty Clay	**1.3**	**1346**	**0.37**	**0.00002**	**1**	**0.000009**
12	Clay	**1.1**	**1394**	**0.36**	**0.00002**	**1**	**000002**
13	**Bedrock**	**2.9**	**1650**	**0.05**	**0.00002**	**1**	**000002**
14	**Water**	0	1394	0.36	0.00002	1	000002
15	Organic	0	1485	0.29	0.00002	1	0.000009
16	**Other**	0	1600	0.27	0.00002	1	0.000009

APPENDIX D: POST-PROCESSING APPROACH

All streamflow results are provided at the model time step of 1 hour; results are provided for all of the sites listed in Table D1. 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).

Table D1. 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.

Location	Source	ID	Location	Years
Auburn Mill Cr	King Co.	41a	47.368N / 122.249W	1989-2006
Big Soos Cr abv Hatchery nr Auburn	USGS	12112600	47.313N / 122.164W	1960-Present
Burns Cr--near Lones Levee	N/A	Green09	47.279N / 122.110W	N/A
Champion Cr	N/A	Green08	47.205N / 121.560W	N/A
Charley Cr	N/A	Green02	47.259N / 121.780W	N/A
Crisp Cr mouth	King Co.	40d	47.285N / 122.081W	1994-Present
Cristy Cr (Flaming Geyser Park)	N/A	Green10	47.273N / 122.021W	N/A
Gale Cr	N/A	Green03	47.263N / 121.727W	N/A
Gold Cr Nr RM 76	N/A	Green05	47.225N / 121.624W	N/A
Green R at 200th St at Kent*	USGS	12113344	47.423N / 122.264W	2011-Present
Green R at Purif. Plant nr Palmer*	USGS	12106700	47.305N / 121.849W	1963-Present
Green R at Tukwila	USGS	12113350	47.465N / 122.247W	1960-1984
Green R blw Howard Hanson Dam*	USGS	12105900	47.284N / 121.797W	1960-Present
Green R nr Auburn*	USGS	12113000	47.313N / 122.203W	1986-Present
Green R nr Lester	USGS	12104500	47.208N / 121.552W	1945-1993
Green R abv Twin Camp Cr nr Lester	USGS	12103380	47.182N / 121.388W	1992-1999
Green River blw Intake Cr nr Lester	USGS	12103400	47.212N / 121.420W	1966-1977
Newaukum Cr nr Black Diamond	USGS	12108500	47.276N / 122.058W	1944-Present
North Fork Green R	N/A	Green01	47.298N / 121.772W	N/A
Rock Cr Nr RM 81	N/A	Green06	47.203N / 121.532W	N/A
Smay Cr	N/A	Green04	47.225N / 121.609W	N/A
Sunday Cr	N/A	Green07	47.217N / 121.448W	N/A

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".

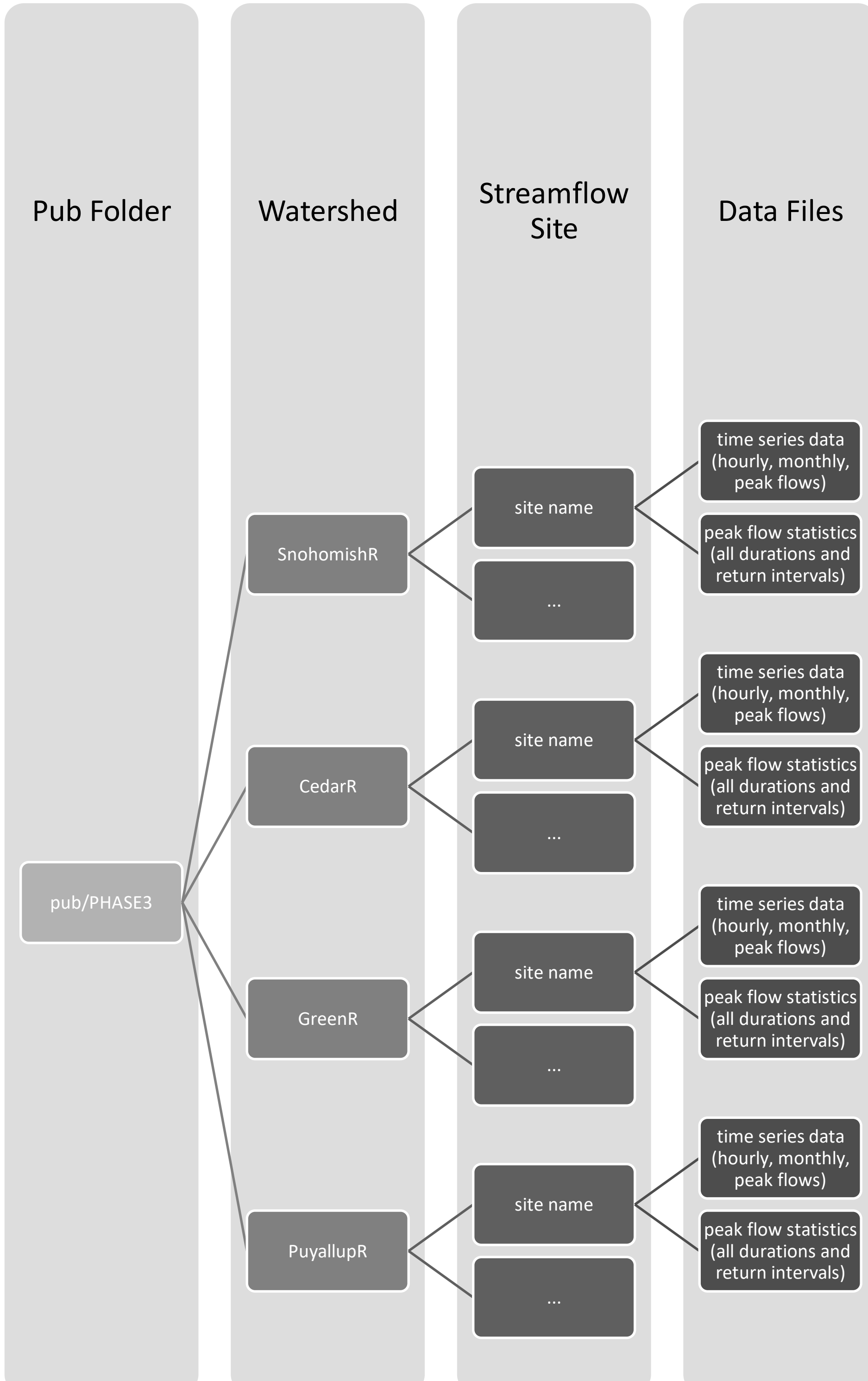

Figure D1. Data structure for the model results.

APPENDIX E: 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 Big Soos and Newaukum Creeks, where the calibration did not perform as well as the other locations where model results were evaluated. Future projections may still be accurate for these locations, regardless of historical model performance. Conversely, greater historical accuracy at the well-calibrated sites 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. Overall, we expect that relative changes in flows will still be a useful indicator of future changes, even when the historical simulations show disagreement with 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 F: 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. Similarly, reservoir modeling could evaluate the effect of weather forecasts on operations, which would likely result in lower peak flows since reservoirs can be drawn down in anticipation of approaching storms. Streamflow modeling could also be integrated with other 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. 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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