Projecting Future High Flows on King County Rivers: Phase 2

Guillaume Mauger and Jason Won
University of Washington Climate Impacts Group
June 2020

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CITATION: Mauger, G.S. and J.S. Won. 2020. Projecting Future High Flows on King County Rivers: Phase 2 Results. Report prepared for King County. Climate Impacts Group, University of Washington. https://doi.org/10.6069/67G6-H984

This work was funded via a grant from the King County Flood Control District.

ERRATA *(November 24th, 2020):* A mistake was identified in the climate data bias-correction procedure. This has been corrected, leading to an update of all online data as well as Figures 1-5 and Tables 2-4 in this report.

Purpose

Phase 1 of the current study evaluated future peak flows on the Green, Snoqualmie, and South Fork Skykomish rivers using two new regional climate model projections of future climate. Recent work has shown that regional climate model projections are better at capturing future changes in heavy rain events and are therefore likely to provide more accurate estimates of the changes in future floods. The findings from Phase 1 confirmed that two projections are not enough to reliably bracket the range in future flood magnitudes. The University of Washington has since produced an additional 11 projections. Combined with the two original simulations, the result is an ensemble of 13 regional climate model projections. The purpose of this study, Phase 2 of the work, is to evaluate the implications for flooding with this expanded set of scenarios using the same methodology used in the Phase 1 work. A secondary objective is to document improvements in the methodology that could further improve the accuracy of the projections in a possible Phase 3 effort.

Background

The purpose of the Projecting Future High Flows on King County Rivers project is to provide information on potential future flows in King County rivers to support flood hazard management decisions. This project builds on previous river flow projections (Phase 1) developed for the King County Flood Control District (FCD) by the University of Washington Climate Impacts Group (CIG; Lee et al., 2018). This previous effort was limited to running two regional weather model projections for the Snoqualmie/SF Skykomish and Green River basins. Simulations were performed using the Weather Research and Forecasting (WRF) model, described below. 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 they may not actually bracket the range of projections (e.g., Mauger et al., 2018). More model runs are needed for a more thorough evaluation 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 13 regional weather model projections (1970-2099) were obtained by CIG for King County. These new regional weather forecasting model runs were used in the current project (Phase 2) to provide additional flow projections for the Snoqualmie/SF Skykomish and Green River basins. Phase 3, which is contingent on the results of the Phase 2 effort described in the current report, would refine the approaches used in Phase 1 and expand the modeling to include the Cedar and White in addition to rerunning the Snoqualmie/SF Skykomish and Green River basins with the updated methodology. Reservoir modeling would be used to develop regulated flow projections for the Tolt, Cedar, Green, and White rivers.

The New Projections

Global Climate Model (GCM) Projections

GCM projections were obtained from the Climate Model Inter-comparison Project, phase 5 (CMIP5; Taylor et al., 2012). The 11 new GCMs added to the WRF ensemble were chosen based on Brewer et al. (2016), who evaluated and ranked global climate models based on their ability to reproduce the climate of the Pacific Northwest. These new GCMs are listed in Table 1. All of the new projections are based on the high-end RCP 8.5 scenario (Van Vuuren et al., 2011).

Mauger et al. (2018) described results from two WRF projections: (1) ACCESS 1.0, RCP 4.5, and (2) GFDL-CM3, RCP 8.5. In creating the new larger ensemble described for the current report, an error was found in the WRF boundary conditions used for the GFDL-CM3 simulation. Although the error has been corrected in the new ensemble, this means that the GFDL-CM3 results from Lee et al. (2018) should be disregarded.

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

Regional Climate Model (WRF)

Regional Climate Model simulations were produced using the Weather Research and Forecasting (WRF, http://www.wrf-model.org; Skamarock et al., 2005) community mesoscale model, following the configuration developed in previous work (e.g., Salathé et al., 2010). The model, and model configuration, are described in detail in Lorente-Plazas et al. (2018) and Mauger et al. (2018).

The new ensemble of WRF projections includes one simulation for each of the GCMs listed above, in addition to the RCP 4.5 projection developed previously for the ACCESS 1.0 GCM.

All simulations run from 1970-2099 and are archived at a 1-hour time step and a spatial resolution of 12 km.

Table 1. The twelve global climate models (GCMs) used as input to the regional model simulations. All simulations are based on the high-end RCP 8.5 greenhouse gas scenario (Van Vuuren et al., 2011). A low-end scenario was also produced for the ACCESS 1.0 model, resulting in two separate projections for this GCM.

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

Statistically Downscaled Projections (bcMACA)

The figures and tables below include the results obtained from a statistically downscaled dataset, for comparison with the new dynamically downscaled WRF projections. Described in more detail in Lee et al. (2018), we used an adjusted version of the statistically downscaled Multivariate Adaptive Constructed Analogs (MACA, Abatzoglou and Brown et al. 2012) dataset, including the observationally-based Livneh dataset (Livneh et al. 2015) that is the basis of the downscaling. Both the Livneh and MACA data were adjusted to compensate for temperature biases in the original datasets ; the corrected datasets are referred to as "bcMACA" and "bcLivneh," respectively (Mauger et al. 2016).

Hydrologic and Reservoir modeling

Following the intent of the Phase 2 work, all aspects of the hydrologic modeling replicate the approach used in Phase 1, as described in Lee et al. (2018). Specifically, temperature, precipitation and wind from WRF are averaged to daily and interpolated to 1/16-degree. This is so that temperature and precipitation can be bias-corrected to match the statistics of the gridded meteorological dataset developed by Livneh et al. (2015). The resulting daily temperature, precipitation, and wind values are then used as input to the MtClim (Thornton and Running, 1999; Bohn et al., 2013) routine to disaggregate to a 3-hourly time step and develop empirical estimates of humidity and radiation. The resulting meteorological inputs are then used as input to the Distributed Hydrology Soil Vegetation Model (DHSVM; Wigmosta et al., 1994) to develop estimates of naturalized (unregulated) streamflow. For the Green River, the naturalized flow results are then used with a reservoir model to simulate regulated flows at Howard Hanson Dam (USACE, 2014).

Results

This section summarizes the new results, presented alongside the previous results obtained in Phase 1. Additional data can be accessed via the project web page (https://cig.uw.edu/our-work/applied-research/effect-of-climate-change-on-flooding-in-king-county-rivers/), which is organized following the exact same approach described by Lee et al. (2018).

Naturalized flow results

Figures 1 through 4 summarize the projected changes in naturalized flows for both the Snoqualmie River near Snoqualmie and the Green River near Auburn, while Tables 2 and 3 list the projected changes across a range of sites within the two watersheds. All results are based on the “raw” (i.e.: no streamflow bias-correction) DHSVM results. Each plot shows the results for the two Phase 1 projections (ACCESS 1.0, RCP 4.5 and GFDL CM3, RCP 8.5) for comparison with the results from the new WRF ensemble. The GFDL results are included with the 11 new WRF projections – for a total of 12 RCP 8.5 WRF projections – in calculating both the median and range shown among WRF projections in each plot.

As in Phase 1, results for the statistically-downscaled bcMACA projections are shown for comparison. The statistically and dynamically downscaled results are generally in the same range for the Snoqualmie and SF Skykomish rivers, whereas – with the exception of Big Soos Creek – the dynamically downscaled projections for the Green River are smaller.

The GFDL CM3 RCP 8.5 projection (the “high-end” WRF projection used in the Phase 1 work) tends to be near the median among the monthly average changes projected by the WRF ensemble. For the extreme statistics, the results are more mixed: for the 10-year event the GFDL CM3 projection is at or near the high end of the range except at Big Soos Creek, where it is closer to the middle of the range. For the 100-year event the GFDL CM3 projection varies between the median and high end of the range, depending on location.

The ACCESS 1.0 RCP 4.5 simulation (the “low-end” WRF projection used in the Phase 1 work) projects decreases in peak flows for all locations except Big SooS Creek. For Big SooS Creek the ACCESS 1.0 RCP 4.5 projections are in the low end of the range among the WRF projections for RCP 8.5. As discussed in the Phase 1 work, this is likely an artifact of natural variability simulated by the model, in which a few large flood events have an inordinate influence on the long-term trend.

Figure 1. Monthly average naturalized flows for the Snoqualmie River near Snoqualmie for the 1980s (1970-1999) and the 2080s (2070-2099). The RCP 4.5 Dynamical Downscaling plot shows the results for just one model (ACCESS 1.0). The other three plots show the median, minimum, and maximum for all DHSVM simulations. A separate line is included in the RCP 8.5 Dynamical Downscaling plot for the GFDL CM3 results.

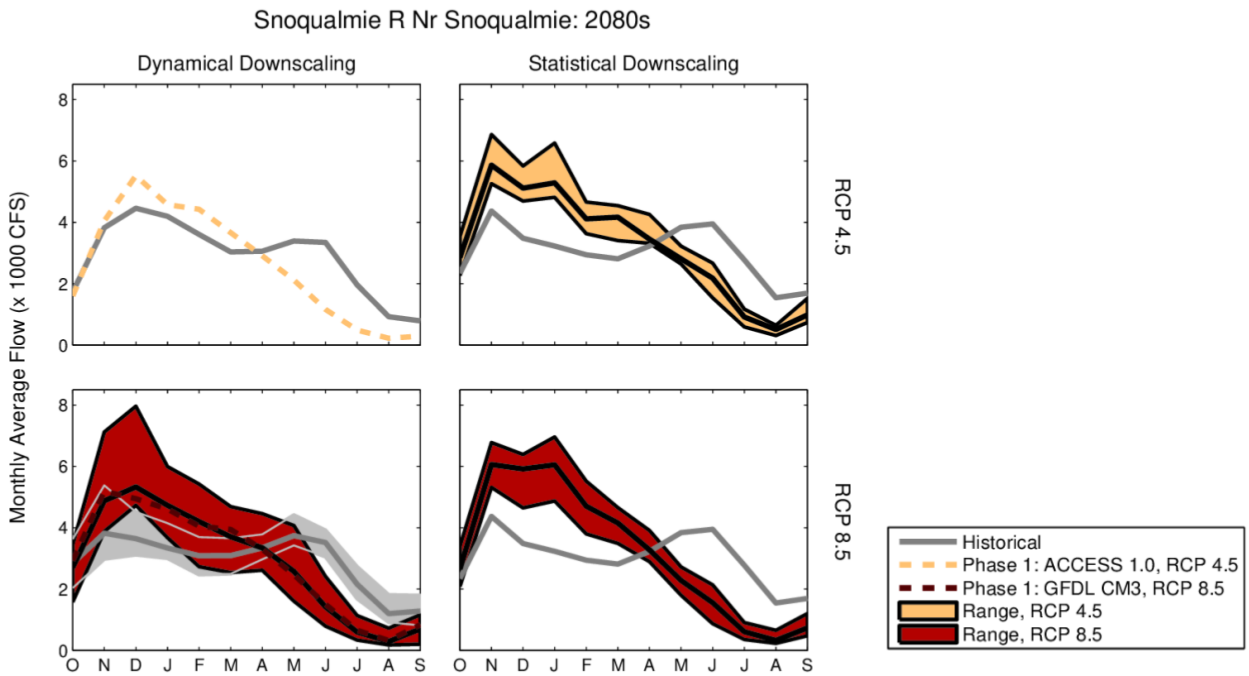
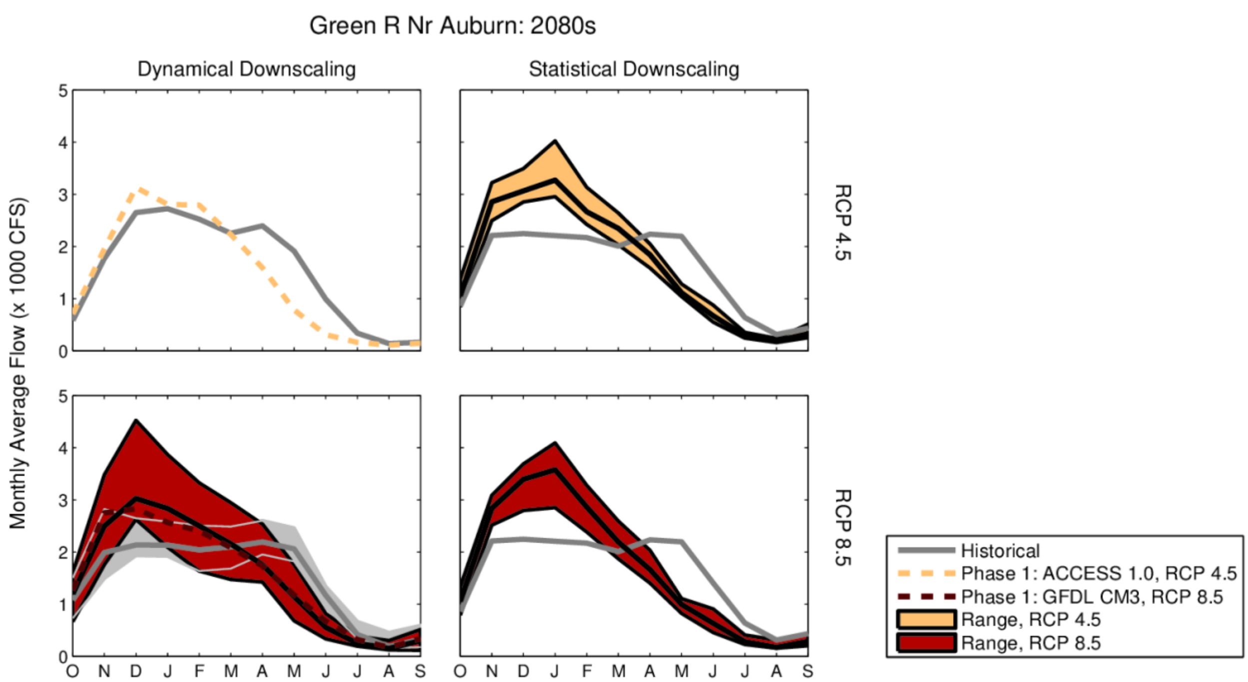


Figure 2. As in Figure 1 except showing results for the Green River near Auburn.



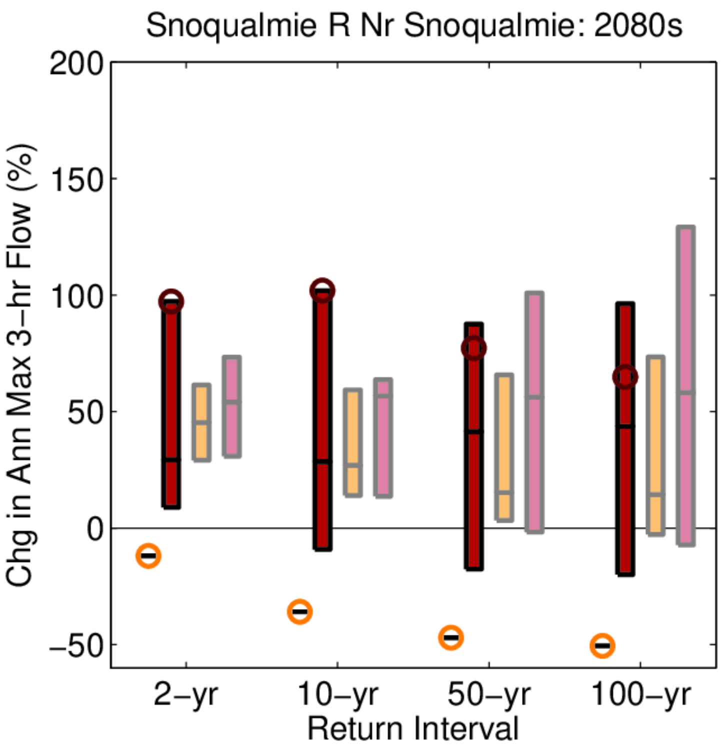
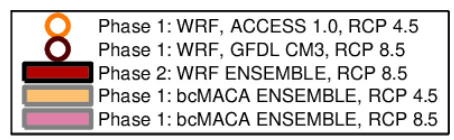


Figure 3. Percent change in peak flow statistics (2-, 10-, 50- and 100- year events) using naturalized 3-hour average flows for the Snoqualmie River near Snoqualmie, for the 2080s (2070-2099) relative to the 1980s (1970-1999). The circles and faded bars show the Phase 1 results whereas the bold red bar shows the Phase 2 results. Bars show the median, minimum, and maximum for all DHSVM simulations in each ensemble.



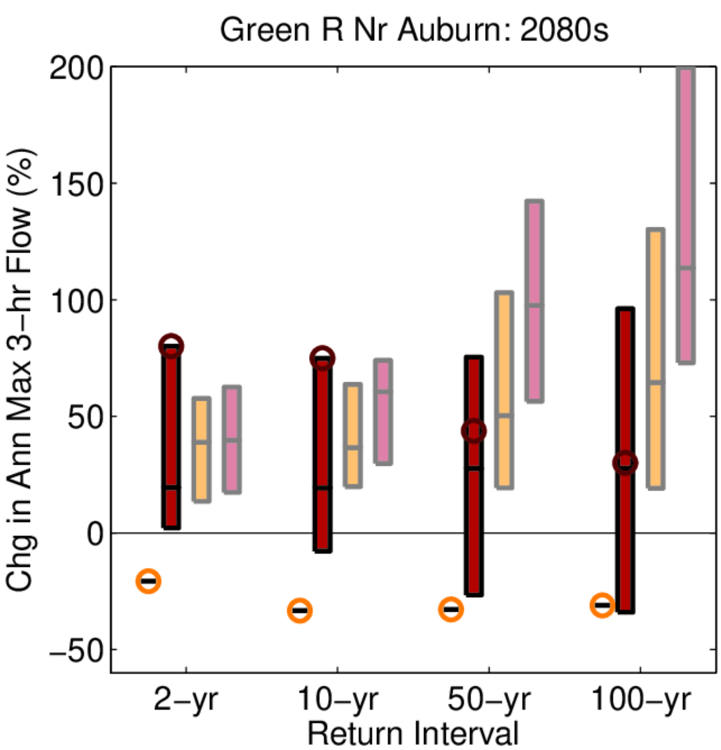


Figure 4. As in Figure 3 except showing results for the Green River near Auburn.

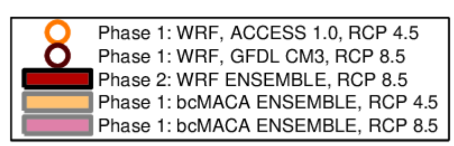


Table 2. **Percent change in the 10-year extreme in 3-hour streamflow for the 2080s** (2070-2099) relative to the 1980s (1970-1999). The Phase 1 WRF results are shown in the first two columns for the dynamically downscaled (WRF) results: ACCESS 1.0 RCP 4.5 and GFDL CM3 RCP 8.5. The next column shows the results (median, minimum, and maximum) for the ensemble of 12 RCP 8.5 WRF projections, including GFDL. The final two columns also show the Phase 1 results, in this case for the statistically downscaled bcMACA projections. These are included for comparison, showing the median, minimum, and maximum among all 10 GCM projections, for each scenario.

	Dynamical Downscaling (WRF)			Statistical Downscaling (bcMACA)	
	RCP 4.5	RCP 8.5		RCP 4.5	RCP 8.5
Site Name	ACCESS 1.0	GFDL-CM3	ENSEMBLE		
SF Skykomish R Nr Index	-32%	80%	34% (1%, 85%)	30% (7%, 52%)	48% (8%, 64%)
Skykomish R Nr Gold Bar	-31%	72%	34% (1%, 81%)	30% (7%, 49%)	47% (8%, 64%)
MF Snoqualmie R Nr Tanner	-35%	107%	35% (-3%, 107%)	30% (12%, 60%)	59% (17%, 72%)
NF Snoqualmie R Nr Snoq. Falls	-36%	90%	24% (-5%, 90%)	33% (20%, 60%)	56% (15%, 66%)
SF Snoqualmie R Abv Alice Cr	-33%	107%	36% (-5%, 107%)	40% (11%, 65%)	65% (28%, 86%)
Snoqualmie R Nr Snoqualmie	-36%	102%	29% (-9%, 102%)	27% (14%, 59%)	57% (14%, 64%)
Raging R Nr Fall City	-19%	58%	10% (-6%, 58%)	8% (-16%, 31%)	24% (-4%, 28%)
NF Tolt R Nr Carnation	-33%	61%	12% (-12%, 69%)	25% (13%, 53%)	48% (8%, 60%)
SF Tolt R Nr Carnation	-36%	68%	15% (-9%, 77%)	29% (16%, 57%)	53% (10%, 63%)
Tolt R Nr Carnation	-32%	63%	11% (-12%, 69%)	24% (14%, 55%)	47% (8%, 59%)
Snoqualmie R Nr Carnation	-34%	92%	24% (-10%, 92%)	23% (16%, 59%)	54% (12%, 59%)
Green R Nr Lester	-29%	64%	25% (-8%, 64%)	66% (35%, 104%)	85% (49%, 122%)
Green R Blw HHD	-36%	70%	20% (-11%, 70%)	44% (24%, 68%)	67% (36%, 86%)
Green R nr Palmer	-36%	71%	19% (-11%, 71%)	43% (24%, 67%)	66% (35%, 84%)
Newaukum Cr Nr Black Diam.	-13%	63%	12% (-7%, 63%)	10% (-5%, 33%)	25% (4%, 42%)
Big Soos Cr Abv Hatchery	7%	57%	39% (-7%, 94%)	8% (-3%, 39%)	23% (3%, 49%)
Green R Nr Auburn	-33%	75%	19% (-8%, 75%)	37% (20%, 64%)	61% (30%, 74%)

Table 3. As in Table 2 except showing results for the 100-year event.

	Dynamical Downscaling (WRF)			Statistical Downscaling (bcMACA)	
	RCP 4.5	RCP 8.5		RCP 4.5	RCP 8.5
Site Name	ACCESS 1.0	GFDL-CM3	ENSEMBLE		
SF Skykomish R Nr Index	-51%	38%	40% (-11%, 123%)	26% (-10%, 104%)	41% (-10%, 87%)
Skykomish R Nr Gold Bar	-52%	38%	39% (-0%, 113%)	23% (-12%, 94%)	43% (-10%, 95%)
MF Snoqualmie R Nr Tanner	-49%	53%	51% (-16%, 100%)	14% (-7%, 67%)	47% (-8%, 114%)
NF Snoqualmie R Nr Snoq. Falls	-54%	55%	40% (-16%, 135%)	23% (-5%, 94%)	62% (-9%, 126%)
SF Snoqualmie R Abv Alice Cr	-49%	50%	47% (-23%, 90%)	38% (-9%, 90%)	73% (27%, 160%)
Snoqualmie R Nr Snoqualmie	-51%	65%	44% (-20%, 96%)	14% (-3%, 73%)	58% (-7%, 129%)
Raging R Nr Fall City	-25%	96%	24% (-22%, 96%)	25% (-27%, 77%)	61% (-9%, 132%)
NF Tolt R Nr Carnation	-41%	55%	44% (-7%, 122%)	19% (-2%, 125%)	73% (2%, 148%)
SF Tolt R Nr Carnation	-48%	52%	39% (-12%, 142%)	29% (-1%, 123%)	86% (5%, 159%)
Tolt R Nr Carnation	-41%	61%	43% (-11%, 119%)	18% (-3%, 122%)	71% (1%, 147%)
Snoqualmie R Nr Carnation	-48%	79%	40% (-18%, 103%)	17% (2%, 82%)	68% (-6%, 141%)
Green R Nr Lester	-37%	2%	19% (-42%, 114%)	137% (117%, 198%)	190% (112%, 288%)
Green R Blw HHD	-41%	12%	22% (-43%, 109%)	77% (39%, 159%)	133% (89%, 201%)
Green R nr Palmer	-41%	14%	23% (-42%, 108%)	75% (35%, 156%)	129% (85%, 200%)
Newaukum Cr Nr Black Diam.	-0%	127%	25% (-17%, 129%)	17% (-18%, 72%)	50% (18%, 129%)
Big Soos Cr Abv Hatchery	60%	82%	81% (-19%, 214%)	-8% (-32%, 59%)	11% (-15%, 128%)
Green R Nr Auburn	-31%	30%	28% (-34%, 96%)	65% (19%, 130%)	114% (73%, 200%)

Regulated flow results

This section summarizes the regulated flow results, obtained by using the DHSVM naturalized flow results as input to the USACE model for Howard Hanson Dam. Although 3-hourly results are available, the regulated flow analysis focuses on daily and 3-day average flows. There are two reasons for this: (1) the reservoir model is limited to a daily time-step, and (2) these durations were recommended by USACE (Ken Brettman, personal communication) as key metrics for assessing possible changes in regulation. As above, additional results can be accessed via the project web page (https://cig.uw.edu/our-work/applied-research/effect-of-climate-change-on-flooding-in-king-county-rivers/).

An important limitation of the reservoir modeling performed here is that it assumes future regulated flows will be managed exactly as they have been in the past. This is unlikely to be true. Given that HHD can currently accommodate a >100-year event, it is likely that the changes in future regulated flows are overestimated for events below the 100-year return period.

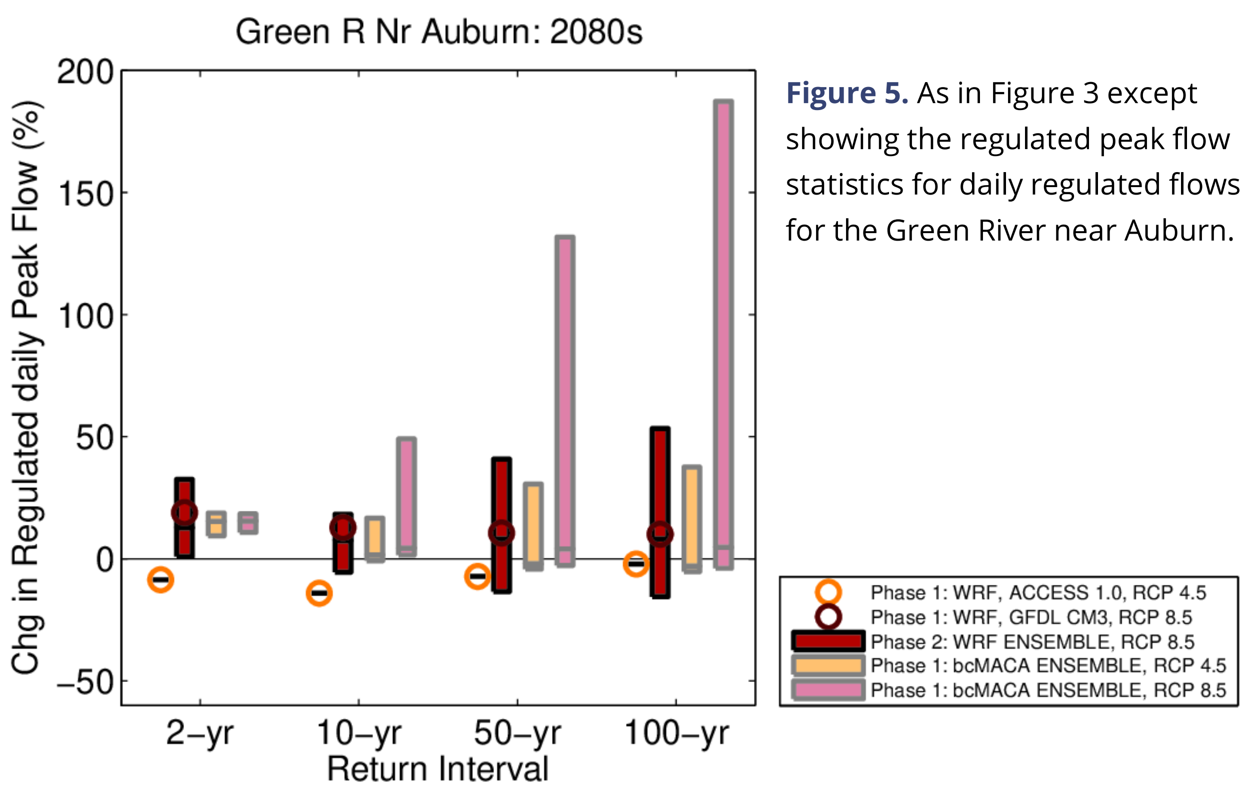


Figure 5. As in Figure 3 except showing the regulated peak flow statistics for daily regulated flows for the Green River near Auburn.

As in Phase 1, results for the statistically-downscaled bcMACA projections are shown for comparison. Although the median projection for the statistically (bcMACA) and dynamically (WRF) downscaled results tend to agree, the high end of the range among WRF projections is much lower than for bcMACA.

Relative to Phase 1, these results show that the GFDL CM3 RCP 8.5 projection (the "high-end" WRF projection from Phase 1) tends to be closer to the middle of the range among the ensemble of RCP 8.5 WRF projections, rather than representing the high end as originally intended. As with the unregulated flow results, the ACCESS 1.0 RCP 4.5 projection (the "low-end" WRF projection from Phase 1) is generally at or below the low end among the RCP 8.5 WRF projections.

Table 4. **Percent change in regulated peak flow statistics for the Green River near Auburn.** Results are shown for the 2-, 10-, 50-, and 100-year annual (water year) peak flow statistics for both 1- day and 3-day average flows, for the 2050s (2040-2069) and 2080s (2070-2099), relative to the 1980s (1970-1999). The Phase 1 results are shown in the first two columns for the dynamically downscaled (WRF) results: ACCESS 1.0 RCP 4.5 and GFDL CM3 RCP 8.5. The next column shows the results (median, minimum, and maximum) for the ensemble of 12 RCP 8.5 WRF projections, including GFDL. The bcMACA projections are included for comparison, showing the median, minimum, and maximum among all 10 GCM projections for each scenario.

			Dynamical Downscaling (WRF)			Statistical Downscaling (bcMACA)	
			RCP 4.5	RCP 8.5		RCP 4.5	RCP 8.5
Agg.	Freq.	Decade	ACCESS 1.0	GFDL CM3	ENSEMBLE		
daily	2-yr	2050s	8%	22%	5% (-8%, 22%)	9% (5%, 19%)	12% (1%, 18%)
		2080s	-9%	23%	11% (-1%, 24%)	15% (9%, 19%)	15% (11%, 18%)
	10-yr	2050s	-2%	15%	5% (-3%, 26%)	1% (-9%, 46%)	8% (-6%, 29%)
		2080s	-14%	15%	8% (-3%, 15%)	2% (-1%, 17%)	4% (2%, 49%)
	50-yr	2050s	-10%	13%	7% (-8%, 50%)	-2% (-14%, 124%)	8% (-11%, 87%)
		2080s	-7%	11%	5% (-9%, 36%)	-2% (-4%, 31%)	4% (-3%, 132%)
	100-yr	2050s	-12%	13%	8% (-9%, 63%)	-2% (-15%, 173%)	9% (-12%, 123%)
		2080s	-2%	10%	4% (-10%, 48%)	-3% (-5%, 38%)	5% (-4%, 187%)
3-day	2-yr	2050s	2%	33%	12% (-8%, 33%)	9% (5%, 21%)	16% (-1%, 21%)
		2080s	-15%	35%	15% (2%, 36%)	18% (8%, 22%)	19% (11%, 23%)
	10-yr	2050s	-5%	20%	8% (-5%, 25%)	3% (-10%, 43%)	8% (-3%, 25%)
		2080s	-18%	18%	9% (-1%, 21%)	5% (-0%, 13%)	6% (4%, 38%)
	50-yr	2050s	-10%	15%	7% (-8%, 22%)	3% (-15%, 98%)	7% (-8%, 62%)
		2080s	-6%	9%	9% (-8%, 17%)	1% (-6%, 15%)	5% (-1%, 70%)
	100-yr	2050s	-11%	14%	7% (-9%, 22%)	2% (-17%, 129%)	8% (-9%, 82%)
		2080s	3%	6%	6% (-11%, 21%)	1% (-7%, 16%)	5% (-2%, 91%)

Summary

Naturalized Flows: the GFDL CM3 RCP 8.5 WRF projection, chosen to represent the high-end of the range in the Phase 1 work, generally does represent the high end of the range among the RCP 8.5 WRF projections for the 10-year flood event. However, it does not reliably represent the high end of the range for the 100-year event or for monthly average flows. The ACCESS 1.0 RCP 4.5 projection is almost universally below the minimum among the 12 RCP 8.5 WRF projections. However, upon inspection we found that the time series for the ACCESS 1.0 RCP 4.5 happens to include a few anomalously large events early in the record. This is likely not representative of the expectations for RCP 4.5 and is instead likely an artifact resulting from the challenges in assessing trends in rare events. Although such variability could also affect positive trends, inspection of the trend for the GFDL CM3 RCP 8.5 simulation does not show a similar dependence on a small handful of large events.

Regulated Flows: In contrast with the naturalized flow results, the GFDL CM3 RCP 8.5 WRF projection is not representative of the high end of the range among the RCP 8.5 WRF projections. The ACCESS 1.0 RCP 4.5 projection is, however, at or below the minimum for nearly every duration and return interval considered.

Recommendations for Phase 3

There were three main limitations to the Phase 1 study of changing flood risk in King County rivers:

1. Results were based on only two regional climate model simulations of the future. This is insufficient to determine if changes are representative of what one would find from a larger set of regional climate model projections.
2. Only the Snoqualmie, SF Skykomish, and Green were evaluated. Other rivers in King County (e.g., Cedar, White) may respond differently to climate change.
3. The modeling included a number of methodological choices that could be improved upon, and doing so could have a significant effect on the results.

The first issue has been resolved as part of the Phase 2 work presented above, while the second and third would be addressed in a possible Phase 3 effort.

The second issue would be addressed by simply replicating our approach for additional rivers in King County. Other rivers are likely respond differently to climate change, in particular due to the different amount and temperature of winter snowpack in each basin. How these rivers respond, and how each exhibits different vulnerabilities, will be important for planning. New simulations for the Cedar River would also make it possible to simulate the effects of regulation on both the Cedar and the South Fork Tolt. Flow regulation would also be simulated for Mud Mountain Dam on the White River.

The remainder of this section describes changes in the methodological approach used to develop future floods, and how these might affect the results:

BIAS CORRECTION OF TEMPERATURE AND PRECIPITATION: In the Phase 1 & 2 work, WRF hourly temperature and precipitation inputs were bias-corrected to match the spatial pattern and time series from the interpolated daily dataset described by Livneh et al. (2015). This was done in order to ensure consistency with the statistically-downscaled MACA projections, which are derived using meteorology from Livneh et al. (2015). Unfortunately, however, this negates the primary benefit of using the WRF dataset. The Livneh et al. (2015) dataset is likely less reliable in areas with few observations or complex terrain – both of which are the case for the mountainous areas that are the source of flooding in King County rivers. In addition, research indicates that WRF provides a more accurate characterization of changes in extremes; by bias-correcting to Livneh et al. (2015), this advantage may also be lost. Several studies have since developed approaches to bias-correcting the WRF inputs without compromising the benefits provided by WRF. A new bias-correction would affect the magnitude and spatial distribution of weather events used as input to the hydrologic model, but would not alter their sequencing. ***The primary benefit of this change would be to improve the characterization of the spatial distribution of temperature and precipitation. This could affect flooding by altering the relative contribution of flood waters among tributaries to each river, and could also have an effect on the sensitivity of flooding to climate change.***

ESTIMATING HUMIDITY AND RADIATION INPUTS: The Phase 1 & 2 work used the "MtClim" empirical formulation to estimate 3-hourly humidity and radiation, instead of using the estimates provided directly by WRF. There are two principle disadvantages to this: (1) it is based on a daily time step, so sub-daily weather variations are not accounted for, and (2) results may not be consistent with the physics-based predictions of the WRF model. Recent work has shown that empirical approaches such as MtClim outperform WRF for longwave radiation but that WRF is likely to outperform MtClim for humidity estimates. Results for shortwave are ambiguous. In all cases, results will be improved if humidity and radiation inputs are developed at the 1-hourly WRF time step. WRF radiation and humidity estimates could also be bias-corrected based on comparisons with observations. In Phase 3, we propose to replace the MtClim humidity with that obtained directly from WRF, to use the MtClim longwave estimate obtained from hourly WRF data, and to test the effect of using MtClim vs WRF for the shortwave estimates. ***The primary benefits of this change would be to (1) provide more accurate sub-daily estimates of weather variations, including precipitation, and (2) improve the simulation of snowpack and, potentially, evapotranspiration. These could all have an effect on the magnitude and volume of flood peaks.***

REVISIT SOIL AND VEGETATION CHARACTERISTICS: The Phase 1 & 2 studies used the STATSGO dataset to determine soil types and the NLCD 2011 (Homer et al., 2015) land cover estimates. Although the finer-scale SSURGO dataset does not cover all of the two watersheds, there may be additional potential to refine or adjust the soil definitions in Phase 3. For example, to ensure that valley-bottom soils are not conflated with soils that are found on steep slopes. Similarly, the translation from STATSGO to DHSVM soil types could be further examined to ensure an adequate level of detail and accuracy. The vegetation cover could similarly be evaluated to test the effect of different approaches for translating between NLCD and DHSVM. In particular the approach to representing developed areas to ensure that these capture the consequences for surface and sub-surface runoff. Finally, we recommend performing a sensitivity test in which the land cover is adjusted to approximate conditions prior to european settlement of the region. This could be a helpful way to "measure" the effect of climate change, via comparison with the impacts of human-induced changes in land cover. ***The primary benefits of these changes would be to (1) better represent the distribution of soils and vegetation cover, which could have an effect on the duration and magnitude of flood peaks, and (2) provide a reference for comparing the effects of land cover and climate change on flooding.***

VALIDATE SNOW SIMULATIONS (NOT JUST STREAMFLOW): In the Phase 1 & 2 work, the DHSVM model was calibrated entirely based on streamflow simulations. This is just one constraint on model performance and does not ensure that the model is accurately representing important process that could contribute to flooding. By first evaluating snow simulations from the model – via both point comparisons with SNOTEL and a qualitative evaluation of snow-covered area – the DHSVM model can be further tested to ensure that the model configuration and meteorological inputs are not resulting in biased estimates of snowpack in the basin. This is particularly useful as a way of testing the meteorological inputs, since snow is sensitive to temperature, precipitation, wind, humidity, and radiation. In Phase 3 we propose to begin by validating the model's snow simulation before proceeding to subsequent phases of model adjustment and calibration. ***The primary benefit of this change would be to improve the characterization of snowpack, an important contributor to current and future flooding in King County rivers.***

IMPROVE STREAM CHANNEL CLASSIFICATIONS: The Phase 1 & 2 work used the default stream channel classifications provided by DHSVM – these classificaitons are used to set stream channel width, depth, and roughness, which affect routing time. Recent work has shown that the choice, and construction, of stream channel classifications can have an important effect on the timing and magnitude of flood peaks, includng the relative timing of peaks among tributaries. We propose to revisit the stream classifications in the Phase 3 work to determine if there is an important effect on flood peaks, and if so refine the approach in order to improve their characterization. ***The primary benefit of this change would be to produce more accurate estimates of the timing and magnitude of flood peaks.***

OPTIMIZE HYDROLOGIC MODEL CALIBRATION: The Phase 1 & 2 work employed the automated MOCOM-UA calibration algorithm (Yapo et al., 1998). Although this same autocalibration approach should be used in future work, there are a number of limitations to the previous approach: (1) a limited number of parameters were considered, (2) the model was calibrated to monthly flows, whereas the objective of the project was to characterize peak flows, and (3) only the default metrics were used in the optimization. Regarding this last point, the default optimization metrics tend to not be well adapted to climate change studies, both because model sensitivity to climate variations is more important than the exact magnitude of flood peaks (e.g.: the correlation may be more applicable than the nash-sutcliffe efficiency), and because the primary objective is to have the cumulative distribution (or flow-duration curve) match the observations, not necessarily the exact timing of events. In Phase 3 we propose to perform a more thorough set of sensitivity tests to identify important parameters for calibration, evaluate the calibration using key peak flow metrics as opposed to monthly averaged flows, and test several different optimization metrics for use with MOCOM-UA. ***The primary benefits of these changes would be to (1) improve the accuracy of the flood estimates, and (2) ensure that the model is not optimized to match current flows at the expense of reducing the accuracy of the climate change projections.***

TARGETED STREAMFLOW BIAS-CORRECTION: Bias-corrected streamflows are needed as input for subsequent modeling – for example, in order to run reservoir, stream temperature, or habitat models. In the Phase 1 & 2 work we applied a bias-correction approach that had been developed in a parallel project evaluating changes in extreme precipitation. Although relatively general, this approach may not be well adapted to reservoir modeling. In addition, it may actually be preferable to scale the observed historical record to match the projected changes rather than bias-correcting the climate change simulations. Although a thorough investigation of this topic is likely beyond the scope of a Phase 3 effort, we propose to perform an initial evaluation by validating historical simulations of the reservoir model and exploring its sensitivity to changes in flood characteristics and antecedent conditions. Based on the results of these tests, we would then implement an updated approach to streamflow bias-correction and/or modeling future reservoir operations. ***The primary benefit of this change would be to improve the accuracy of the regulated flow estimates by tailoring the bias-correction to minimize model inaccuracies that could affect the reservoir model results.***

CONTEXTUALIZE AND REFINE RESERVOIR MODELING: The Phase 1 & 2 work used the daily time step reservoir model developed by the Army Corps for Howard Hanson Dam (HHD). The primary way in which this work could be improved is in the interpretation of the results: reservoir models are imperfect representations of actual operations and may overestimate the impacts of climate change. In Phase 3 we propose to engage more closely with reservoir operators at SPU and the Army Corps to ensure that the results are properly interpreted and contextualized. There is also a secondary way in which the Phase 1 & 2 results could be improved: the Army Corps has a partially-completed HHD model that operates at a 1-hour time step. In Phase 3, this model could be finalized so that hourly climate change simulations could be performed for HHD. A similar approach could be taken for Mud Mountain Dam, for which CIG has recently produced a daily time-step model. ***The primary benefits of this work would be to (1) ensure the regulated flow results are accurately interpreted and contextualized, and (2) produce hourly instead of daily estimates of regulated flow peaks for Howard Hanson and Mud Mountain Dams.***

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