Using Physically Based Hydrology Models to Improve Fine Scale Estimates of Q100 in Complex Mountain Terrain

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**Introduction**

Shifts in the timing and quantity of runoff under conditions of a warmer climate in the future will change the frequencies and magnitudes of flood and low flow risks in watersheds throughout the Pacific Northwest. Changes in extreme flow regimes pose considerable challenges to natural resource managers. The Olympic National Forest (ONF) and Olympic National Park (ONP) have formed a partnership to assess the potential effects of climate change on federal lands in the Olympic Peninsula and to revamp management practices that reflect the projected impacts.

A key component of management on the Olympic Peninsula involves maintaining the network of roads. Most of the 2180 miles (3500 km) of roads in the ONF were designed and built between 1950 and 1980 for logging purposes and are currently outdated. Within the National Park boundaries, over 140 miles (225 km) have been built for visitor use. The roads located near rivers, particularly those requiring a culvert to cross water, are at an increasing risk of inundation damage as future flooding intensifies. Any road infrastructure in disrepair near streams and rivers also threatens to impair the habitat of aquatic animals, including fish listed under the Endangered Species Act (ESA). Two foremost objectives of the ONF are to restore and protect aquatic ecosystems from aging roads and to manage for species listed as threatened or endangered under the ESA.

Road management uses the Q_{100} (or the peak flow with an estimated 100 year return frequency) as the standard gauge for stream crossing design. In the past the historical streamflow record has been used to calculate flood frequency and magnitude statistics, however under the projections of a changing climate, the baseline for this metric is expected to shift. Whereas methods applying historical streamflow records are ill equipped to capture the effects future warming temperatures, physically-based hydrologic models are designed to incorporate changes in climatic variables.

Another fundamental aspect of hydrologic management on the Olympic Peninsula is maintaining viable habitat for Pacific salmon (*Oncorhynchus* spp.),
steelhead (*O. mykiss*) and bull trout (*Salvelinus confluentus*). Several species of salmon, steelhead and bull trout were listed as threatened or endangered under the ESA in 1991. A chief consideration in preserving habitat for these protected fish is to sustain traversable streamflows during the low flow season in the summer and early fall when many salmon populations are migrating. For instance, the volume in the Elwha River dropped below average streamflows during the summer and fall of 2009 due to dry conditions during those and the previous seasons. Prolonged summer low flows have detrimental implications for migrating adult salmon and for smolts in regards to both water quality and quantity. Water resource managers typically estimate the 7-day consecutive lowest flow with a 10-year return frequency, or 7Q10, to determine low flow thresholds. Like flood frequency analyses, estimates of the 7Q10 are conventionally calculated using historical streamflow records, which would disregard the effects of projected changes in the regional climate.

In support of the effort by the ONF/ONP partnership to incorporate the potential effects of climate change in their management practices, the Climate Impacts Group and Civil and Environmental Engineering at the University of Washington conducted a comprehensive hydrologic analysis on the Olympic Peninsula. We applied the downscaled climate data derived from 10 global models to the Olympic Peninsula at a 1/16th degree (latitude/longitude) spatial resolution (see Chapter 4 of Hamlet et al. 2010 for details on hybrid delta downscaling techniques). This downscaled climate data served as the input for the Variable Infiltration Capacity (VIC) model, a macro-scale hydrologic model that simulates, among other hydrologic parameters, baseflow and run-off at a daily time-step. At each 1/16th degree grid cell these two parameters were added together and used to estimate Q_{100} and 7Q10 statistics for the historical period (1916-2006) and under 2 emission scenarios, A1B and B1, at 3 future time intervals: the 2020s (2010-2039), the 2040s (2030-2059) and the 2080s (2070-2099), (see Chapter 5 of Hamlet et al. 2010 for details about VIC).

From these extreme flow estimates, we report the ratio of the each future time interval to the historic period at each grid cell and at the spatial resolution of
12-digit hydrologic unit codes (HUCs), or the 6th level watershed classification as delineated by the USGS. The estimates of flood and low flow statistics reported here will support ONP and ONF managers to incorporate projections of climate change-induced shifts in hydrology into their management plans and climate change adaptation assessments.

**Methodology**

**VIC hydrologic model**

The physically-based, macroscale hydrologic model, Variable Infiltration Capacity (VIC), was implemented at the 1/16th degree latitude and longitude spatial resolution (~11.7 sq. miles) over the Pacific Northwest as part of the Columbia Basin Climate Change Scenarios Project (Hamlet et al. 2010). This hydrologic model is spatially distributed, incorporating distinct soil layers and overlying vegetation to solve the water balance at each grid cell (Figure 1). The VIC model was used to generate daily runoff and baseflow at each VIC grid cell for a historical time period (1916 – 2006) and for three future time periods: the 2020s (2010 – 2039), the 2040s (2030 – 2059) and the 2080s (2070 – 2099). The inputs to drive the VIC model, including daily precipitation, temperature and windspeed, were derived from a historical dataset (refer to Chapter 3 of Hamlet et al. 2010 for details) and from the archived datasets of future conditions produced by the Global Climate Models (GCMs) from the IPCC AR4 report (2007). For this study, future conditions under two greenhouse gas emissions scenarios, A1B (medium) and B1 (low), were produced by 19 GCMs. The GCMs were spatially downscaled to the resolution of the VIC grid cells and bias corrected to represent a reasonable variability of storms and extreme climatic events based on the historical dataset. This downscaling method resulted in the generation of future datasets, incorporating the projected changes in climate variability and the degree of changes in future climatic conditions.
Winter temperatures, coupled with precipitation, are the principal mechanisms driving regional streamflows and provide a functional index to characterize the three types of watersheds in the Pacific Northwest (Mote et al. 2005, Hamlet et al. 2005, 2007 and Hamlet and Lettenmaier 2007). Among the variables VIC estimates are monthly precipitation and the amount of water stored as snow, or snow water equivalent (SWE). In this study, we delineate the historical distribution of the three basin types on the Olympic Peninsula by calculating the proportion of winter precipitation to peak annual SWE. Figure 2 shows monthly hydrographs that illustrate the annual streamflow behavior for the three characteristic basins in the PNW as described in Hamlet et al. (2005).
Figure 2: Simulated streamflow hydrographs for three typical basins in the PNW: rain dominant (left); transitional (middle); and snowmelt dominant (right).

**Extreme Flow Analyses**

For this study, VIC outputs of daily runoff and baseflow were summed over each grid cell to estimate the average daily streamflow of each cell. From the daily averages, the annual peak streamflows (or 7 day running average, in the case of the low flow analysis) were ranked for each time period, plotted on a quantile map and fitted to the Generalized Extreme Value (GEV) distribution using the L-moment method (Wang 1997; Hosking and Wallis 1993; Hosking 1990). Both the 100-year flood magnitude ($Q_{100}$) and the 7-day consecutive lowest flow with a 10-year return frequency ($7Q_{10}$) were estimated from the fitted probability distribution for each time period.

The $Q_{100}$ and $7Q_{10}$ analyses were also executed at the spatial scale of the 12-digit hydrologic unit codes (HUCs), or the 6th level watershed classifications, as delineated by the US Geological Survey (USGS). For this analysis, ArcGIS was used to aggregate the VIC grid cells based on their spatial overlap with the HUCs. The grid cells that intersect the borders of the HUCs were partitioned based on the fractional area of the grid cell that falls within each neighboring HUC. The baseflow and runoff were summed up over the contributing grid cells to estimate the total streamflow over each HUC. The GEV L-moment method was again applied to estimate $Q_{100}$ and $7Q_{10}$ for each HUC.

For each spatial analysis, the estimates for $Q_{100}$ and $7Q_{10}$ were calculated for each downscaled GCM, emissions scenario and time period combination. The
results are shown here as the future-to-historic ratios of the magnitudes estimated for $Q_{100}$ and for $7Q_{10}$. The ratio can be thought of as the change in future flow compared to historical flow, so any ratio exceeding one represents higher future flows and those less than one indicate lower future flows. To simplify the presentation of results in this report, we averaged the outcomes over all the GCMs for each scenario and time period for the future estimates of $Q_{100}$ and $7Q_{10}$. However, the $Q_{100}$ flood ratio and $7Q_{10}$ low flow ratio were calculated for individual models and are available via an Excel spreadsheet. Also, the flood magnitudes with 2, 10, 20, 50, 200 and 500-year return intervals were calculated and are made available on the ftp site.

*Extremes Toolkit*

Researchers at the National Center for Atmospheric Research (NCAR) developed a Graphic User Interface (GUI) for the R project, an open-source statistical program. The *Extremes Toolkit* is specifically designed to analyze extreme weather and climate events by using statistical distributions (Generalized Extreme Value, Maximum Likelihood Estimate, etc.) that more robust than traditional distributions (normal, lognormal, etc.) for capturing those extreme values. Using this toolkit, we applied the Generalized Extreme Value distribution to the 12-digit HUC streamflow datasets generated by VIC for the historical and for one climate model’s simulation of future conditions (ECHAM 5 2040s). We created probability flood plots for each site comparing the historical and one future (2040s) time period, providing another tool to evaluate the projected shifts in peak flows on a site-by-site basis.

*Validation of $Q_{100}$ Estimates*

Validation of the model was performed by comparing the estimates of $Q_{100}$ and the ratio of the mean annual flood to the 100-year flood, or $Q_2:Q_{100}$, from various sources of streamflow data on the Olympic Peninsula. Six sites were
selected for validation based on their proximity to sites in the VIC routing network. The following were used for validation:

1. the [Streamstats](#) tool developed by the USGS, using [monthly precipitation](#) data archived by the Hydro-Climatic Data Network (HCDN) data, maintained by the USGS,
2. the [annual peak streamflows](#) (instantaneous) monitored by the USGS, and
3. the annual peak streamflows derived from average daily streamflow data for the [Pacific Northwest (region 17)](#) archived in the HCDN.

For the first validation approach, the Streamstats tool applies an explicit regression model to calculate basin-wide Q$_{100}$, based on the location of the watershed (Figure 3). The inputs to the model include annual precipitation, average basin elevation and drainage area. Monthly precipitation from the HCDN data archives was used to calculate the average annual precipitation for each basin. The basin area and annual precipitation were input into the Streamstats regressions to calculate Q$_{100}$ for each basin according to the spatial delineation of the regression equations over the Olympic Peninsula (Knowles and Sumioka 2001). Since the Streamstats regression equations are designed to estimate Q$_{100}$ derived from instantaneous peak flows, these estimates can be directly compared to the second validation approach: the Q$_{100}$ estimates calculated from the USGS annual peak streamflows. The instantaneous annual peak streamflows from the USGS were fitted to the GEV-L moment distribution to estimate Q$_{100}$ for the same six sites.
For the third validation procedure, the HCDN daily average streamflow data was used to determine the annual peak streamflows for each of the six validation sites. The annual peak streamflow was used to calculate $Q_{100}$ by fitting the HCDN peaks to the GEV L-moment probability distribution. The estimates of $Q_{100}$ from HCDN streamflow data are analogous to the estimates from the VIC model since both are based on annual peak flows selected from daily average streamflow.

Each validation procedure was applied to calculate the $Q_2$, or approximately the mean annual flood, with the exception of the Streamstats tool, which only estimates $Q_{100}$. The ratio of the $Q_{100}$ to $Q_2$ was determined for each site and compared among the validation procedures by applying the USGS data, HCDN data and the VIC output.

Sensitivity Analysis

To determine the relative sensitivity to changes in future climate demonstrated by the current method used to calculate $Q_{100}$, we applied the downscaled precipitation data from the global climate models to the USGS Streamstats tool. This analysis was performed for each 1/16th degree grid cell using
historical precipitation data and the multi-model average precipitation data projected for the future time period of the 2040s. The results were compared to the VIC output for the historical and the 2040s time periods. We also created a hybrid map overlaying the projected change in the Q_{100} from the VIC estimate (2040s:historical) over the historical Q_{100} results generated by the USGS Streamstats tool.

**Results & Conclusions**

*Basin characterization*

A critical factor shaping the patterns of streamflow projections on the Olympic Peninsula is the geography of the region and its influence on the climate and atmospheric circulation. The dominant features on the Peninsula are the Olympic Mountains, which arise steeply in the center of the Peninsula and create divergent climatic conditions on different margins of the Peninsula. Because the prevailing winds are from the southwest in the winter, the northeastern region of the Peninsula is relatively drier (~50 cm/year rainfall) with a markedly more continental climate due to the rain shadow effect of the Olympic Mountains. The mountainous ridges of the Olympics are among the wettest areas in the continental US, receiving > 600cm rainfall/year (Peterson et al. 1997). The coastal, western side of the Peninsula is characterized by a wetter, maritime climate (~400 cm/year rainfall).

These geographic and climatic features largely govern the behavior of watersheds on the Olympic Peninsula because they determine the proportion of snowmelt-to-rainfall that contributes to streamflow. Figure 4 shows the historical spatial distribution of watershed types on the Olympic Peninsula based on the proportion of precipitation to SWE. The red tones denote rain-dominated basins (up to about a 0.25 ratio), the yellow and orange colors indicate transitional basins, with a mixed runoff of rain and snow (~0.3 – 0.5 ratio), and the blue shades represent the few snow-dominated basins on the Peninsula (>0.6 ratio). Warming
trends shift snowmelt dominant and transient snow basins towards more rain dominant behavior, and are associated with increasing winter flows and decreasing summer flows (Mantua et al. 2010; Elsner et al. 2010).

Figure 4 Ratio of Snow Water Equivalent to October to March precipitation for the historical simulation.

Flood output

Results of the future to historic flood ratio for individual VIC grid cells indicate a range of responses, contingent on the snowmelt contribution to the runoff generated in the cell. Figure 5 shows that initially, in the 2020s, the mid-elevation grid cells are first to respond to warmer temperatures with slightly
higher 100-year flood magnitudes. Whereas many of the lower elevation grid cells that are predominantly rain fed do not demonstrate a notable sensitivity to increased temperatures. Towards the end of the century, most of the grid cells show an increase in the 100-year flood magnitude, with the mid elevation cells undergoing greater flood severity than the lower elevation cells. This chronological trend of increasing flood intensity is swifter in the A1B emissions scenario than the B1 scenario due to more rapid warming projected in the former. The pattern of a quicker hydrologic response to the climatic forcings in the A1B scenario compared to the B1 scenario is consistent for all simulations, so we show only the results from A1B for the remainder of this report.

![Ratio of 100-year Flood Statistics (21st Century ÷ 20th Century)](image)

Figure 5 Ratio of the future to historic 100-year flood magnitude for the A1B (top panel) and the B1 (bottom panel) scenarios at the 1/16th degree spatial resolution. Maps are shown for the 2020s (left), 2040s (middle) and 2080s (right). Black lines indicate major roads.

The flood ratio results for the 12-digit HUCs show a similar spatial pattern of elevated flood magnitude through each time period as the grid cell analysis (Figure
6, only A1B scenario shown). Furthermore the magnitude of increased flooding severity is on par with the grid cell level analysis. Again, the mid-elevation regions demonstrate a greater sensitivity to flooding due to future warming and are the first to respond, particularly the northern and eastern watersheds.

Figure 6 Ratio of the future (2040s) to historic 100-year flood magnitude for the A1B scenario only at the 12-digit HUC spatial resolution.

The areas projected to undergo the most notable rise flood severity are the mid-elevation, transitional basins located in the northeastern part of the Olympic Peninsula. Since the northeastern portion of the Peninsula maintains a cooler, continental climate in the winter, it receives more snow than the warmer, maritime western edge. Small increases in temperatures at mid-elevation will provoke a greater proportion of winter precipitation to fall as rain, producing instantaneous run-off, rather than accumulating as snow. These results are consistent with previous studies that have established the heightened sensitivity of transitional
basins to warmer temperatures resulting from their position at mid-elevation ranges (Hamlet et al. 2007, Mantua et al. 2010).

The northeastern aspect of the Olympic Mountains feed the Elwha, the Dungeness, the Quilcene, the Dosewallips and the Duckabush Rivers. All of these northeast-originating basins display transitional behavior to varying degrees, depending on the winter temperatures at the elevation of the headwaters. As the temperatures warm and more precipitation falls as rain, these basins are projected to undergo more severe winter peak flows due to an expansion of the contributing basin size (Hamlet and Lettenmaier 2007).

Higher winter peak flows are detrimental to overwintering salmon redds because they become more prone to scour. Furthermore depending on the timing of peak flows, juvenile salmon and parr could get washed downstream before they are ready to migrate. In terms of road infrastructure, increased flood magnitudes, regardless of timing, could trigger more wash outs and overtopping of culverts for roads near these rivers and their tributaries. Such occurrences could further exacerbate the impairment to aquatic habitats for fish.

*Extremes Toolkit Plots*

Using the Extremes Toolkit designed for the R statistical program, we generated sets of four probability plots for each 12 digit HUC. Here we present the results from one HUC, located near the headwaters of the Dungeness River. The plots shown in Figure 7 are as follows for the historical simulation:

1. probability (upper left) of the modeled peak values compared to the empirical peak values supplied by the VIC model,
2. quantile plot (upper right), comparing the the modeled and empirical quantiles,
3. magnitude of peak values versus the return period (lower left), and
4. a histogram of the density of the values’ distribution (lower right).

The closer the values are to the diagonal line of upper two plots is an indication of how well the modeled values match the observed values. The return level plot
shows the probability of exceedence for a given peak magnitude and the blue lines delineate the 95% confidence interval. Note that the confidence interval expands the higher the return interval, an indication of greater uncertainty with projections farther into the future.

Figure 7 Plots generated from the Extreme Toolkit for the historical peak streamflows generated for the 12 digit HUC near the headwaters of the Dungeness River.

For each site, these probability plots can be compared between the future and historical simulations. The future simulation is shown here for one model only for the 2040s time period (Figure 8).
Figure 8 Plots generated from the Extreme Toolkit for the future peak streamflows generated under the projected conditions (2040s) of the ECHAM 5 model for the 12 digit HUC near the headwaters of the Dungeness River.

We additionally provide a database of the extreme streamflow results from the historical run and for each model run in an Excel Spreadsheet. The Spreadsheet is designed to interactively produce values and plots of the magnitude of peak flows and low flows for a given return interval for each 12 digit HUC.

Low flow output
The results for the ratio of the future to historic 7Q10 at the spatial resolution of the VIC cells indicate that the mid-elevation areas are the first to respond with more extreme low flows (Figure 9, results shown only for A1B scenario). As the snowmelt contribution diminishes through the 21st century with warmer temperatures, the spatial severity of low flows broadens to lower elevation cells, where the lowest flows occur in the summer.

**Ratio of Low Flow (7Q10) Statistics**

(21st Century ÷ 20th Century)

![Figure 9](image)

Figure 9 Ratio of the future-to-historic low flow statistic (7Q10) for the 2020s (left), 2040s (middle) and 2080s (right) under the A1B scenario simulation only at the 1/16th degree spatial resolution. Black lines indicate major roads.

The 12-digit HUC spatial analyses for 7Q10 demonstrate a comparable geographic distribution of low flow severity to the grid cell analysis (Figure 10, A1B scenario only). The more intense low flows initially occur at the mid elevation basins at the start of the 21st century. By the end of the century, the increased intensity of low flows expands to lower elevation basins, particularly on the western side of the Olympic Peninsula.
Figure 10 Ratio of future (2040s)-to-historical 7Q10 based on 12-digit HUC delineation for the under the A1B scenario at the 12-digit HUC spatial resolution.

As with the pattern of increased flooding severity, mid-elevation basins are projected to respond initially with more intense low flows and the intensification expands to lower basins throughout the Olympic Peninsula. However, spatially this trend proliferates more notably on the western, more maritime region of the Olympic Peninsula. Affected basins include the Quinault, the Queets, the Hoh and the Sol Duc. These rivers on the western side of the Peninsula are predominantly rain-fed with very little snowmelt contribution and undergo the lowest flows in the summer season when the rain inputs are minimal. As projected temperatures rise through the 21st century, what small snowmelt contributions from high elevation glaciers these western basins receive will diminish further, incurring even lower flows in the summertime. Additionally, with warmer temperatures, the degree of evapotranspiration in the summer will further intensify low flows.
The intensification of low flows throughout the Olympic Peninsula has detrimental implications for adult spawning salmon and steelhead migrating upstream in the summer months; and for the rearing habitat for salmon with a stream-type life history (juveniles that remain in freshwater for 1+ years). Another consideration of intensified summer low flows is the increased water temperatures concurrent with these projections. All of the threatened salmon species, steelhead and bull trout depend on cool waters for habitat and cannot withstand water temperatures above a certain threshold (McCullough 1999, Richter and Kolmes 2005, Mantua et al. 2010). These rivers also provide a mainstay for fishing among Native American populations that inhabit the western part of the Olympic Peninsula, including the Quinault, the Hoh and the Quileute Indian Reservations.

Validation of $Q_{100}$ Estimates

The inter-comparisons of $Q_{100}$ estimates indicate the discrepancies among the methods and data sources to calculate this statistic. Side-by-side comparisons of the estimates generated from the USGS Streamstats tool, which uses annual precipitation, and the USGS peak flow data, fitted to the GEV-L moment distribution, show the similarities of the absolute numbers (Figure 11), with the exception of the Queets River. These estimates are both trained on the instantaneous peak flow, which explains the comparable results.
Figure 11 Estimates of the $Q_{100}$ magnitude using (1) the USGS Streamstats tool (green) and (2) the USGS instantaneous peak streamflow data (red), fitted to the GEV-L moment distribution.

The corresponding comparisons of $Q_{100}$ estimates generated by fitting HCDN data and VIC data to the GEV-L moment distribution indicate similar results (Figure 12), again with a divergence for the Queets River estimates. Both of these data sources tend to underestimate the absolute value $Q_{100}$ compared to the Streamstats and USGS because the HCDN and VIC estimates are derived from average daily flows, rather than instantaneous peak flows.
A sensible way to even out the incongruities among the various methods and data sources used to calculate $Q_{100}$ is to assess the ratio of the mean annual flood ($\sim Q_{2.33}$) to $Q_{100}$. This tends to smooth the inherent disparities that arise in the absolute values. Here, we show the ratio of the estimates of $Q_{100}$ and $Q_2$ for each site and validation method (with the exception of Streamstats, which only estimates $Q_{100}$). Figure 13 demonstrates that the ratio among the methods are comparable, even though the raw numbers, or absolute values, can vary markedly (compare Figures 9 and 10).
Figure 13 Ratio of $Q_{100}/Q_2$ estimates from three data sources.

Sensitivity analysis

Comparing the future shifts in the estimates of $Q_{100}$ using the USGS Streamstats tool to the VIC estimates indicates the overall insensitivity of the Streamstats tool to changing climate conditions. Figure 14 shows spatial plots of the differences in flood magnitudes of the historical and future climate conditions for each method. Since Streamstats only uses annual precipitation as the principal driver of flood estimates in its regression model, it is not responsive to temperature changes in climate projected by the downscaled GCMs. In contrast, the VIC model has a fully integrated snow model that runs in parallel to the hydrologic model, and therefore depicts the susceptibility of watersheds to the increased snowmelt and associated flooding projected with future warming.
Figure 14 Estimates of the $Q_{100}$ magnitude from the USGS Streamstats tool (left panels) and from the VIC model (right panels). The top two maps show the historical conditions and the bottom two maps show results from the 2040s.

The relative sensitivities of each method to future climatic shifts is illustrated in Figure 15, which shows the spatial distribution of changing climate conditions that each model is able to capture. The VIC results demonstrate a wider
spectrum of climate variability distributed throughout the Olympic Peninsula spatially, and a greater sensitivity to flooding with warmer temperatures, particularly at mid-to-higher elevations.

**Ratio of the Future:Historic 100-year Flood**

Figure 15 Ratio of the 2040s to the historical Q_{100} estimated from the USGS Streamstats tool (left map) and from the VIC model (right map).

A hybrid method combining the estimates from the USGS Streamstats tool with the VIC model highlights the strengths of each method to calculate flood statistics. The Streamstats tool more realistically depicts the absolute value of Q_{100}, whereas the VIC model is better capable of capturing the projected responses of these watersheds to a changing climate. A map fusing the assets of these two methods is illustrated in Figure 16. This map superimposes the Q_{100} change projected in the VIC model (2040s:historical) over the historical Q_{100} absolute values estimated from the Streamstats tool.
Figure 16 A hybrid map of change in $Q_{100}$ (future:historical) estimated by the VIC model overlaid the $Q_{100}$ estimate from the Streamstats tool.

**Excel Data Bases**

The future-to-historic ratios of $Q_{100}$ and $7Q_{10}$ are calculated at each grid cell and at the spatial resolution of 12-digit HUCs, and are reported in the following excel spreadsheets:

- grid_cell_flood_stats_ONP.xls
- grid_cell_7q10_stats_ONP.xls
- huc12_7q10_stats_ONP.xls
- huc12_flood_stats_ONP.xls
Each spreadsheet has four worksheets: three data sheets and one plot sheet. For “grid_cell_flood_stats_ONP.xls” as an example, the worksheets of “flood_stats_2020s_A1B”, “flood_stats_2040s_A1B” and “flood_stats_2080s_A1B” include flood statistics for each time period (see Figure 17) and the worksheet of “Plot_flood_stats” has flood statistics and plots for a specified grid cell (see Figures 18 and 20).

Figure 17 Screen shot showing the worksheet of “flood_stats_2020s_A1B” for “grid_cell_flood_stats_ONP.xls”: the columns A to T (top) and the columns T to AM (bottom).
On the worksheet of "flood_stats_2020s_A1B" which shows flood statistics for the 2020s, columns A to M, N to Z and AA to AZ are statistics for 20, 50, 100-year flood statistics, respectively (see Figure 17). Each grid cell name which is latitude and longitude (lat_lon) information is stored in the columns A, N, and AA. The grid cell name is used to specify the figures and tables on the worksheet of “Plot_flood_stats” as explained later. The columns B, O, and AB indicate flood frequency with 20, 50, and 100-year. The columns C, P, AC are historical values related to flood frequency. For example, the column C shows historical flood magnitude of 20 year return intervals (Q_{20}) (see Figure 17). The columns D to M, Q to Z and AD to AM are estimated Q_{20}, Q_{50}, and Q_{100} values for each A1B scenarios (specified in row 3). The worksheets of “flood_stats_2040s_A1B” and “flood_stats_2080s_A1B” have same format of “flood_stats_2020s_A1B” but include flood values for the 2040s and 2080s, respectively.

The worksheet of “Plot_flood_stats” shows tables and figures related to a grid cell specified on B3 (Figure 18). VLOOKUP function is used to search three data
worksheet mentioned above and return the flood statistics of the grid cell specified on B3. As a result, tables and figures are automatically updated when B3 is changed. For example, when you copy a grid cell name of 46.90625-122.96875 from the column A on the data worksheets and phase it on B3, the tables and figures on the worksheet of “Plot_flood_stats” show the flood statistics for the grid cell of 46.90625-122.96875 as shown in Figures 18 and 20.

The ranges B9:N12, O9:AA12 and AB9:AN12 show flood statistics for the 2020s, 2040s and 2080s (Figure 18). Each time period contains Q_{20}, Q_{50}, and Q_{100} values for historical runs, ten A1B future scenarios and the average of ten A1B scenarios. For the 2020s as an example, the range C10:C13 shows historical flood magnitudes with 20, 50, and 100-year return intervals, the range D10:M13 includes Q_{20}, Q_{50}, and Q_{100} values for each A1B scenarios and the range N10:N13 has the average of 10 A1B scenarios for each flood frequency (see Figure 19).

100 year flood magnitudes for each time period are selected from the range B9:AN12 and rearranged in the range B43:M46 (see Figure 20). In other words, the range B44:M46 shows only 100 year flood magnitudes for historical and 10 A1B climate change scenarios for each time period as shown in Figure 20. The range
N44:N46 shows the average of the future 100 year flood magnitudes for the each time periods. The range O44:O46 shows the ratio of the average of future scenarios to historical 100 year flood magnitude for the 2020s, 2040s and 2080s.

Figure 20 Screen shot showing 100 year flood statistics for each time period on the worksheet of “Plot_flood_stats”.

There are four figures on the worksheet of “Plot_flood_stats” as shown in Figure 21. The left figure shows 100 year flood for different time periods (related to the range B43:O46) and the rest figures show flood statistics of Q20, Q50 and Q100 for the 2020s (related to the range B9:N12), 2040s (related to the range O9:AA12), and 2080s (related to the range AB9:AN12). Blue circles show historical value, solid red circles represent flood statistics for each A1B scenario and black lines are the average of 10 A1B scenarios. For the left figure, blue circle is historical 100 year flood, solid red circles show estimated 100 year flood for each A1B scenarios for the 2020s, 2040s, and 2080s and black lines show the average of ten A1B scenarios for each time period (see Figure 21). As the time moves to the end of the 21st century, red solid circles and black lines are getting higher.

`huc12_flood_stats_ONP.xls` has same format of “grid_cell_flood_stats_ONP.xls” which are explained above but uses huc name instead of grid cell name. `grid_cell_7q10_stats_ONP.xls` and `huc12_7q10_stats_ONP.xls` have similar format of “grid_cell_flood_stats_ONP.xls” and “huc12_flood_stats_ONP.xls” but include 7Q10 information instead of flood statistics.
Conclusions

The hydrologic modeling studies carried out during this study project increased winter flood risk over essentially all of the Olympic Peninsula due increased winter precipitation and warmer temperatures. Most low-lying areas show about a 10% increase in $Q_{100}$ by the 2040s in the simulations. The largest changes in flood risk in the simulations are seen at the highest elevations in the Olympics, where loss of snowpack and higher freezing levels during storms combine with increased storm intensity to produce dramatic increases in flood risk. In the most sensitive areas, the magnitude of $Q_{100}$ increases by more than 60% by the 2040s.

Similarly, essentially all of the Olympic Peninsula is projected to see decreases in 7Q10 values due to reductions in snowpack and decreasing summer precipitation in the climate change scenarios. The moderate and high elevation areas are the most sensitive, with a 20-40 percent reduction in 7q10 values projected for the 2040s.

Figure 21 Screen shot showing figures on the worksheet of “Plot_flood_stats”.
Statistical tools like Streamstats, and physically based hydrologic models like VIC have different strengths and weaknesses. Hybrid products that use the base $Q_{100}$ value from streamstats combined with a percent change from VIC for the future may be the most viable approach for guiding culvert design and other engineering or road management decisions.

Several previous studies have demonstrated the need for collaborative, ongoing discourse among scientists and managers of the Olympic National Park and Forest lands, particularly within the context of climate change (Halofsky et al. 2011, CCSP 2008). This study reinforces the necessity for a cooperative effort among scientists, managers and decision-makers to adapt to a changing climate.
References


