1.0 MEACHAM CREEK CLIMATE CHANGE RISK ASSESSMENT

1.1 INTRODUCTION

Climate change is expected to increase stream temperatures in most rivers due in part to rising air temperature, as well as altered precipitation and snowmelt patterns that impact water levels and water flow (Battin et al., 2007, Beechie et al., 2012). Reduced regional snowpack may be the foremost impact of climate change in the Pacific Northwest, limiting summer water supply (Mote et al., 2003). Lower flows and higher air temperatures will lead to greater risk of extreme summer events in which water temperatures exceed survival thresholds. Conversely, rain on snow events in a warmer climate could magnify spring high flows, threatening both biota and channel restoration projects. Increases in stream temperature and changes in stream hydrology could have severe impacts on salmon species in the Pacific Northwest (Battin et al., 2007, Beechie et al., 2012). A key goal for the ongoing restoration and enhancement of Meacham Creek is to help ensure channel and floodplain processes are in place that will help the system adapt to a changing climate and maintain habitat conditions where salmonids and other fish species can thrive during normal weather and survive during extreme events.

The primary focus of the restoration design is on conditions that may be encountered over the first 10 years of implementation. A ten-year time horizon is not sufficient to identify a clear climate change signal, as conditions on a decadal time frame are likely to be dominated by natural oscillations such as El Niño events and the Pacific Decadal Oscillation; however, a 10-year time frame is appropriate for evaluating the benefits of the restoration plan in providing resilience against potential climate change impacts. Climate models are meant to project future climate (typically assessed with several decades of metrics) and not to predict future weather of any particular year or decade (Patte, 2014). We therefore examine a 50-year climate time horizon to evaluate the magnitude and type of climate-related risks that may be anticipated.

The trajectory of future climate is uncertain, in part because it depends on the rate of greenhouse gas emissions and other mitigation efforts that may or may not occur. Without reduction in emissions the rate of change is likely to gradually accelerate, while stronger efforts would result in stabilization. The long residence time of carbon dioxide and other greenhouse gases in the atmosphere means, however, that some continued increases in temperature and other changes in climate are locked in. A reasonable assumption for evaluating the magnitude of shorter-term (e.g., 1 to 10 year) risks is a linear interpolation relative to the 50-year time horizon – i.e., risks at 10 years can be evaluated based on one-fifth of the total change anticipated by 50 years. If the estimate is based on more pessimistic emission scenarios that do not assume rapid stabilization of emissions the linear approach is somewhat conservative in the sense that it assumes a slightly faster rate of change in the initial decade than is likely to occur.

1.2 DATA

Risks associated with climate change need to be evaluated relative to current conditions. Current condition monitoring also provides the basis for assessing how watershed processes may respond to changes in climate forcing. Fortunately, an adequate baseline on water temperature, air temperature, and flow has been collected for Meacham Creek. Figure 1 shows the location of monitoring data used for this project.

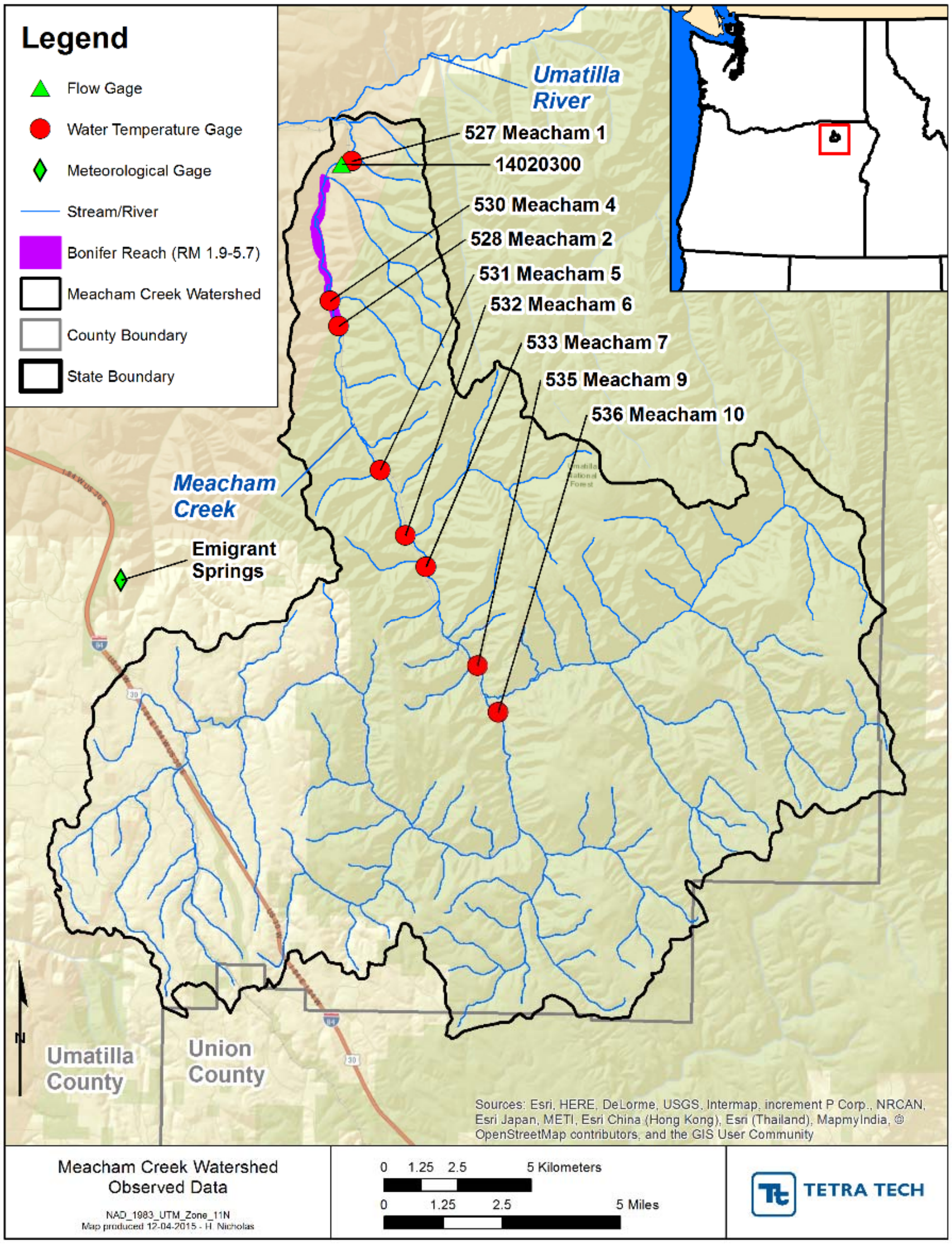

Figure 1. Meacham Creek Watershed with Flow and Temperature Monitoring Locations

1.2.1 Air and Water Temperature Data

Air and water temperatures are strongly affected by local topographic and land cover conditions, so the analysis should start with local data. It is also important that the analysis be constructed to reflect the current state of the local climate (e.g., conditions of the last several decades) rather than long-term historical climate normal given regionally averaged warming of more than 1 °C in the Pacific Northwest over the last century (Mote et al., 2014).

For observed air temperature, the weather station selected is the Natural Resources Conservation Service (NRCS) SNOw TELemetry (SNOTEL) station site 470 called Emigrant Springs. The elevation of SNOTEL site 470 is 1,158 meters, and the average elevation of the Meacham Creek Watershed is approximately 1,181 meters so this station should be representative of average air temperature for the watershed. SNOTEL site 470 has continuous air temperature data available since June 1980.

For water temperature, there are multiple gaging locations along the Meacham Creek main stem at which hourly water temperature during the summer and fall was recorded from 2005 to 2014 (see Figure 1).

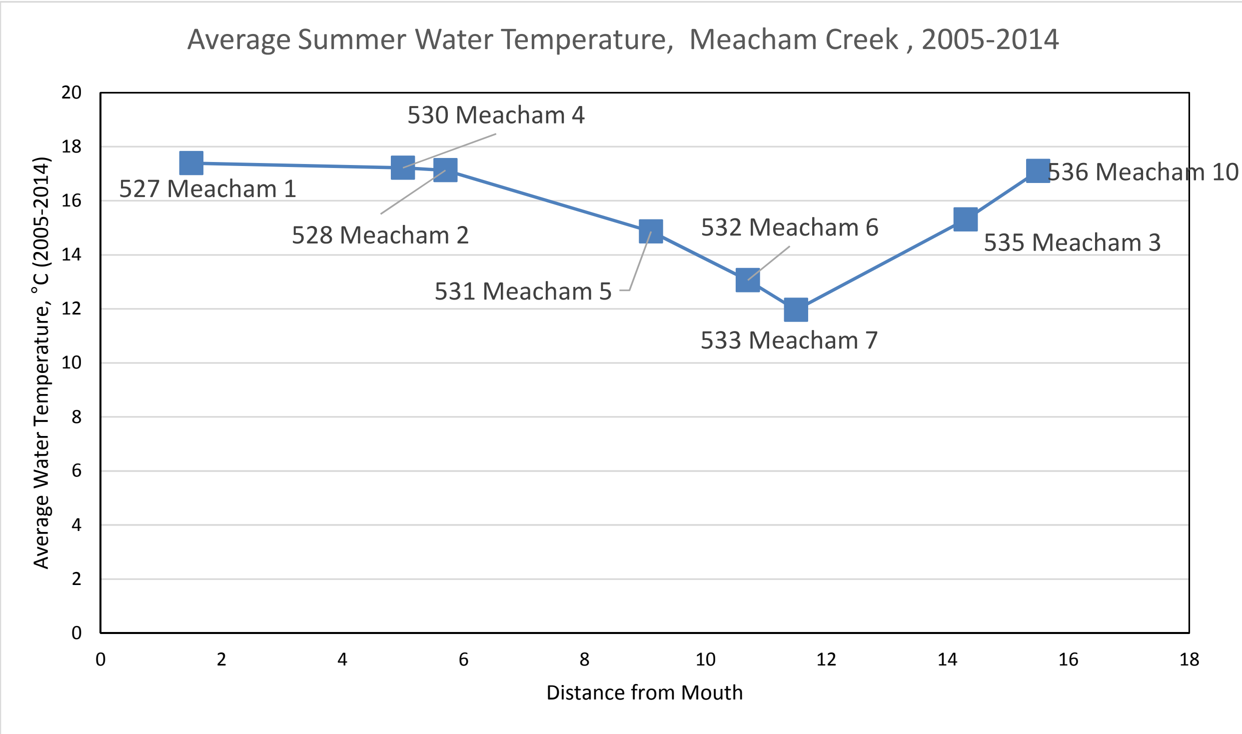

Figure 2. Average Summer Water Temperature, Meacham Creek Main Stem, 2005 to 2014

1.2.2 Flow

There is a USGS flow gage present on the downstream end of the Meacham Creek mainstem above the confluence with the Umatilla River and just downstream of the Bonifer Reach. USGS gage 14020300 ("Meacham Creek at Gibbon, Oregon") has continuous average daily discharge data and annual peak series available since 1975. This gage is used to identify long-term flow minima and maxima, and to provide a basis for estimating flow patterns under future conditions. The gage has a drainage area of 176 square miles, which is almost the entire Meacham Creek watershed.

1.3 FUTURE CLIMATE SCENARIOS

1.3.1 Selection of Future Climate Scenarios

The Intergovernmental Panel on Climate Change (IPCC) released their 5th Reassessment Report in 2013, which provides results from a round of GCM runs (CMIP5) that are appropriate for evaluating climate risks. The CMIP5 results are available in a variety of online repositories that enable rapid screening of the range of potential future outcomes predicted by the suite of GCMs. CMIP5 incorporates a number of refinements to the GCMs. It also uses a different set of greenhouse gas concentration scenarios than the emissions-based scenarios that were used in CMIP3. These greenhouse gas scenarios are now referred to as Representative Concentration Pathways (RCPs) and are based on a future target radiative forcing rather than inferring the radiative forcing from uncertain projections of future population growth, energy use patterns, and associated greenhouse gas emissions.

RCP 4.5, for example, represents radiative forcing of 4.5 W/m^2 in year 2100. RCP 8.5 includes higher greenhouse gas concentrations, and thus greater radiative forcing and higher global atmospheric temperatures than RCP 4.5. The difference among individual GCMs, however, is generally greater than the difference between RCP 4.5 and RCP 8.5 projections through at least the middle of the 21st century. The greatest impacts on precipitation and runoff do not necessarily line up with increases in temperature.

The sheer number of climate model runs and the enormous size of the model output present challenges for quick screening-level assessments. Simply put, it was not feasible to examine the results of every model and every scenario.

Mote and Salathé (2010) evaluated biases in the global-scale climate model predictions for the Pacific Northwest. No single GCM fell into the best five of the GCMs for prediction of both temperature and precipitation; likewise, no GCM fell into the worst five for both temperature and precipitation. It is thus also not appropriate to select a specific GCM based on its perceived prediction skill for the area; instead, the suite of GCMs is more appropriate for analyzing the potential ensemble range of future climates (Mote et al., 2011). This is consistent with findings of Knutti et al. (2010) and Pierce et al. (2009) that attempts to cull the best GCMs yields little difference in representing likely future change relative to a randomly selected subset of GCMs.

It is also important to note that climate models typically resolve the earth surface at a scale of about 1 degree (about 69 x 50 mi. in US) that will wash out local topographic effects. Spatial downscaling is essential for watershed analysis, so we use the bias-corrected spatially downscaled climate model output of Maurer et al. (2007), which has been adjusted to a local spatial scale and adjusted to correct for biases relative to ground-based observation stations.

To enable a manageable and cost-effective analysis, a reduced set of downscaled GCMs was selected from the RCP 8.5 scenarios that approximates the range of potential changes in temperature and precipitation. This was done through use of EPA's ClimaTools (beta tool under development at U.S. EPA Office of Research and Development, courtesy of Phillip Morefield), which performs automated summaries of monthly-level spatially downscaled GCM output from the "Downscaled CMIP3 and CMIP5

Climate and Hydrology Projections" archive at http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/ via the USGS CIDA THREDDS server (Maurer et al., 2007)[1].

To attempt to bound the range to which adaptation may be needed, we attempted to select a scenario that is near the upper 90th percentile for increases in air temperature in the June-August summer period, a scenario that is near the 90th percentile for decreases in precipitation during the late summer August-September period, and a scenario that is near the 90th percentile for increases in precipitation during the March – May peak flow period. The seasonal biplots produced by ClimaTools are shown in Figure 3 through Figure 5. In each plot, the intersection of the dashed lines shows the ensemble mean of projected changes from a ca. 1986 baseline to the period centered around 1065 (e.g., 50 years into the future). For example, in Figure 3, the central tendency of change across all models is an increase in spring average air temperature of about 5 ½ °F and an increase in precipitation of about 11 percent – with considerable spread among the different models. Extreme outliers – such as the almost 10 °F temperature increase predicted by model 24 – seem less likely to provide accurate predictions given the weight of evidence across all models. A conservative, but more reasonable upper bound on effects is provided by moving nearer to the 90th percentile of models. For example, in Figure 3, an upper bound estimate for risks associated with increased air temperature and relatively lower precipitation (in spring) can use model 32 (MIROC-ESM-CHEM).

Based on examination of these plots, the three selected GCMs were MIROC-ESM-CHEM, GFDL-CM3, and MIROC-ESM. Summary analysis at the monthly scale does not guarantee that extremes at the scale of individual events will be captured, but the selection procedure provides a reasonable set of upper bound samples.

1.3.2 Hydrologic Responses

The bias-corrected and statistically downscaled climate archive provides daily time series of air temperature and precipitation. For the Meacham Creek analyses these climate variables need to be converted to hydrologic responses.

The U.S. Bureau of Reclamation (Reclamation, 2014) has applied the Variable Infiltration Capacity or VIC model (Gao et al., 2009; Liang et al., 1994; Liang et al., 1996) to estimate hydrologic responses from the full set of downscaled CMIP5 archived climate scenarios. The VIC model is a macro-scale hydrologic model that simulates watershed hydrology using estimates of vegetation, soil properties, topography, and daily weather variations. The Reclamation effort applied VIC on a 1/8 degree spatial scale, with approximate grid-based routing for larger streams.

As a national, GIS-based analyses on a grid, the VIC application does not provide a precise estimate of the hydrologic responses of individual watersheds. Only limited calibration has been undertaken at a few large basin sites (Brekke et al., 2014). For instance, in the Washington State application, VIC was calibrated and validated to runoff in the Columbia and Yakima rivers on streamflow at a few specific gage locations, but has not been calibrated to the many other stream gages present throughout the state.

[1] We acknowledge the World Climate Research Programme's Working Group on Coupled Modelling, which is responsible for CMIP, and we thank the climate modeling groups for producing and making available their model output. For CMIP the U.S. Department of Energy's Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals.

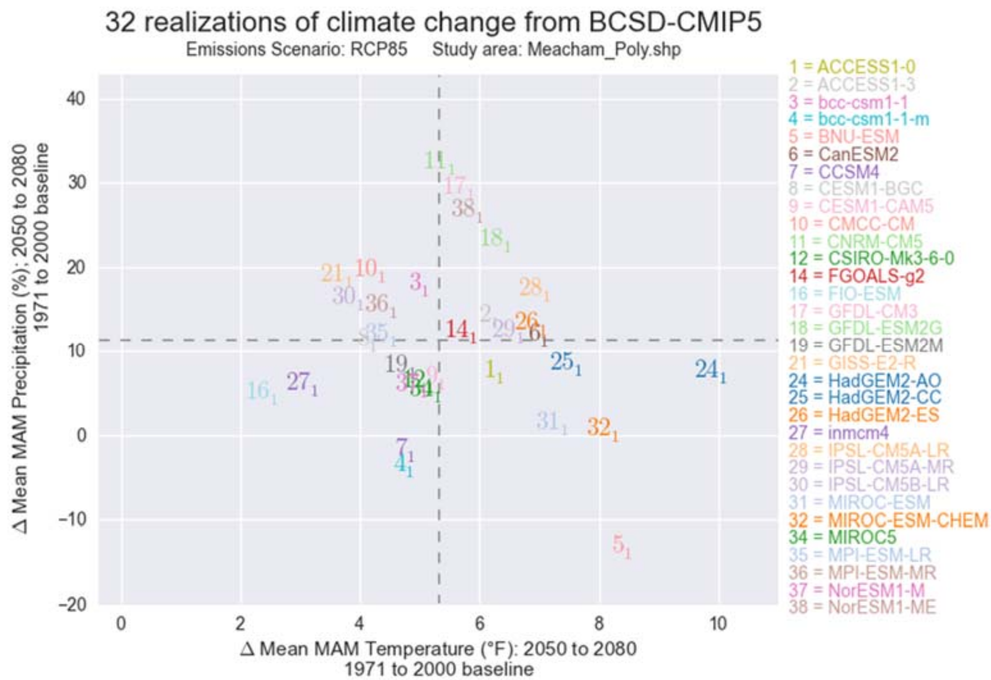

Figure 3. Biplot of Change in Precipitation and Temperature Predicted by 38 Downscaled GCMs for the Meacham Creek Watershed, Spring

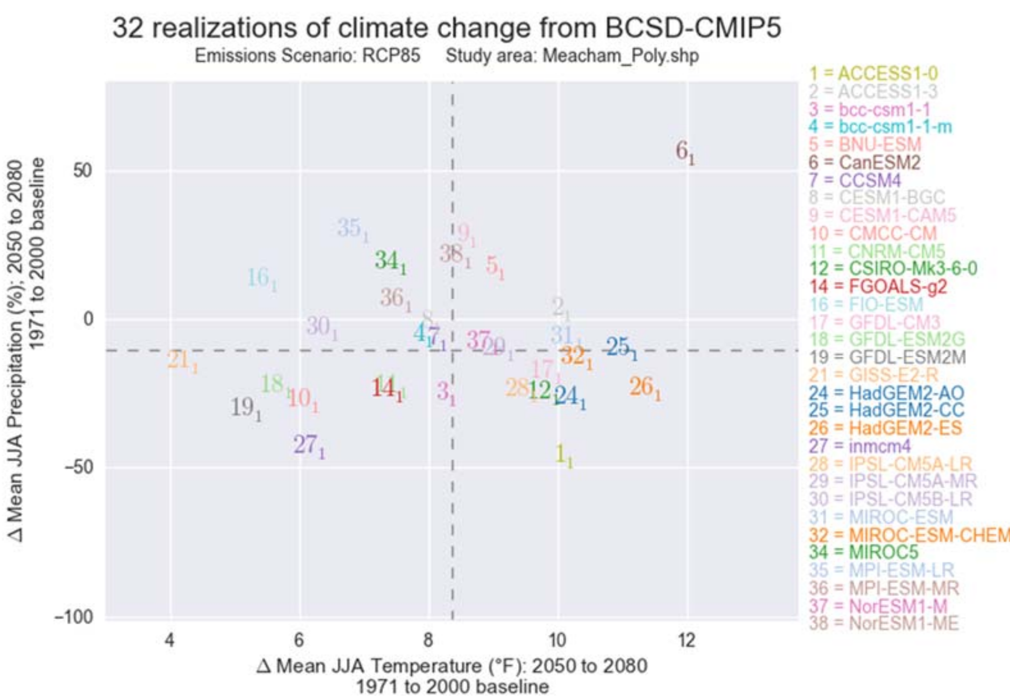

Figure 4. Biplot of Change in Precipitation and Temperature Predicted by 38 Downscaled GCMs for the Meacham Creek Watershed, Summer

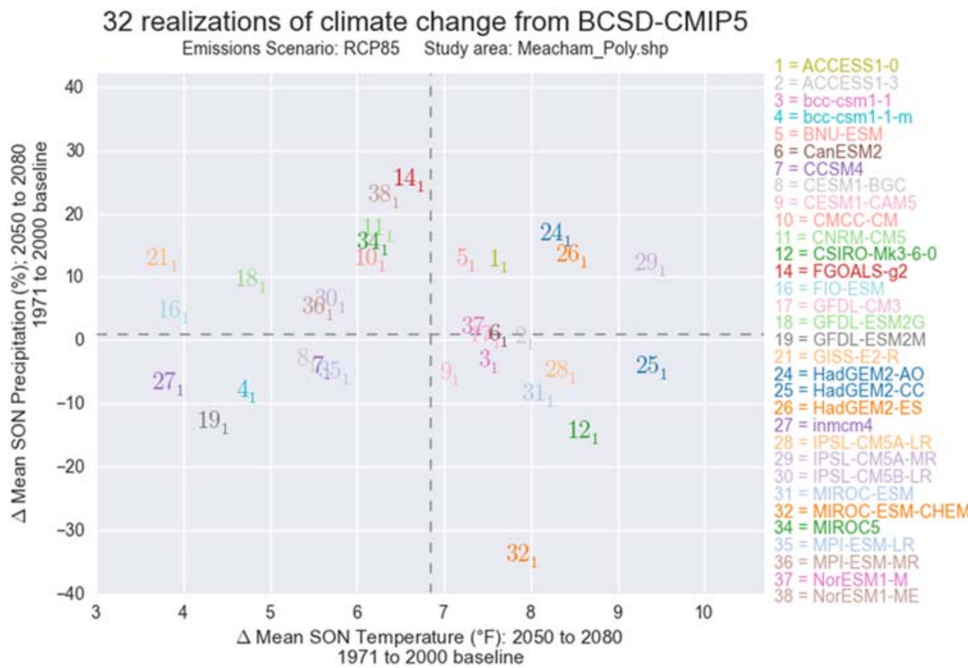

Figure 5. Biplot of Change in Precipitation and Temperature Predicted by 38 Downscaled GCMs for the Meacham Creek Watershed, Fall

As a result, the VIC model results do not provide reliable predictors of the actual magnitude of streamflow on smaller streams and rivers; however, they do provide a reasonable representation of relative changes in streamflow responses. Therefore, the results of GCM-based VIC runs are best used as an indicator of the potential relative changes in watershed streamflow responses that may occur under future climates. These relative changes can then be applied to historic series of watershed high and low flow extremes using statistical methods as described in the next section.

1.4 METHODS: CONVERTING CLIMATE SCENARIOS TO ESTIMATES OF LOCAL IMPACT

1.4.1 Air Temperature Deltas

Daily maximum air temperature was used to compute 7-day average daily maximum (7dAM) air temperatures for historical and future time periods (1976-2005 and 2051-2080, respectively). The difference between the 90th percentile 7dAM air temperatures for both periods were compared using results from the MIROC-ESM-CHEM GCM, with a difference of 6.58 degrees Celsius. This critical temperature difference was used as an additive delta to increase the observed 7dAM air temperatures to the predicted future climate air temperature regime.

1.4.2 Water Temperature

The water temperature analysis focuses on the annual maximum of the 7-day average of daily maximum temperatures (7dAM), which is a commonly used basis for evaluating temperature impairments relative to support of salmonid populations and is the form in which Oregon's numeric criteria for water temperature are expressed (ODEQ, 2008). Maximum stream temperature predictions under future climate are based on regression analysis as recommended by the Forest Service (http://www.fs.fed.us/rm/boise/AWAE/projects/stream_temperature.shtml). A properly constructed regression approach can provide useful results without the large effort needed to construct and calibrate a detailed, physically based water temperature model. Mantua et al. (2010) used a stream temperature regression model to evaluate water temperature distributions in Washington State under future climate conditions. They did this using a logistic regression approach developed by Mohseni et al. (1998) that depends on air temperature and the natural limitations on the range of water temperature response imposed by the freezing point below and enhanced evaporative cooling at the higher end. While Mantua's model was developed for weekly average stream water temperature, a similar form can be used to predict 7-DADMax temperatures.

The Mohseni model for weekly stream temperatures takes the following form:

$$T_S = \mu + \frac{\alpha - \mu}{1 + e^{\gamma(\beta - T_a)}}$$

In this equation, T_S is the predicted weekly average stream water temperature in Celsius, and T_a is the average weekly air temperature. The variables μ (minimum stream temperature), α (maximum stream temperature), γ (steepest slope of the function), and β (air temperature at the inflection point of the logistic curve) are all fitting parameters.

Mohseni models were fit to all 8 monitoring stations along Meacham Creek with generally consistent results. The three stations in or near the Bonifer Reach (527M1, 530M4, and 528M2) had root mean squared errors (RMSE) of 1.19 to 1.35 °C and generally track data well (e.g., Figure 6). Model parameters for these stations are shown in Table 1.

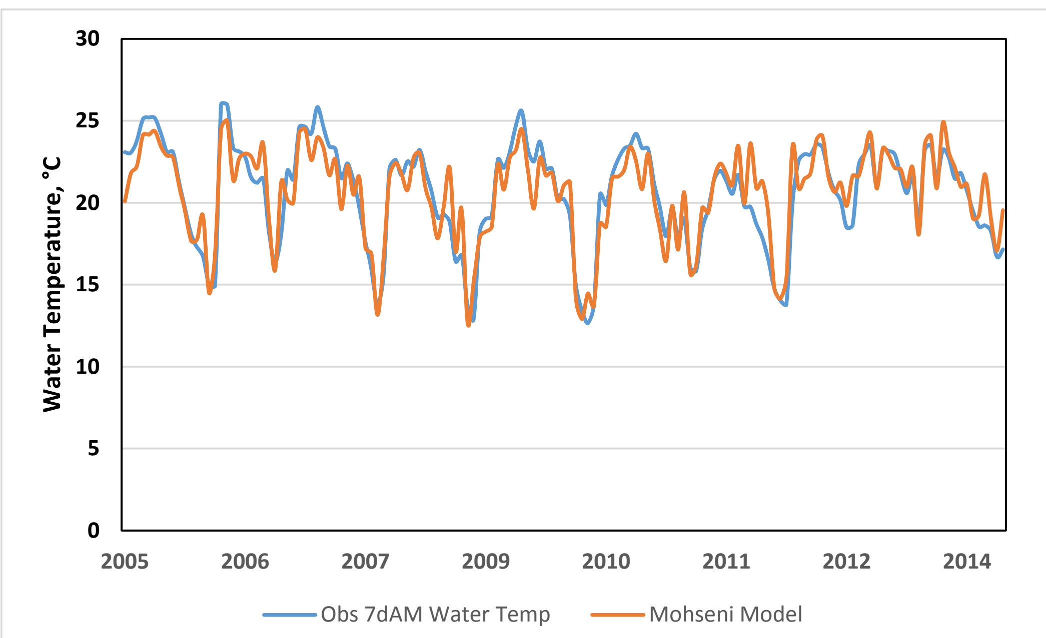

Figure 6. Mohseni Model fit to 7-day Average Water Temperature, Meacham Creek Station 527

Table 1. Mohseni Model optimized Parameters for Meacham Creek 7dAM Temperature

Parameter, Statistic	528M2	530M4	527M1
α	31.07	29.47	32.21
μ	0.00	0.00	0.00
γ	0.09	0.08	0.08
β	13.18	12.43	15.50
RMSE (°C)	1.35	1.19	1.35

1.4.3 Flow

Climate risks are evaluated relative to both high and low flows. In both cases, the interest is in extreme values, such as the 100-year flood peak and 7-day 10-year recurrence low flow (7Q10), which are best analyzed with extreme value theory.

Even more so than with temperature, flow estimates need to be adjusted to reflect local conditions and to eliminate biases that may be present in climate model predictions of local watershed conditions. Quantile mapping (QM) methods, otherwise known as cumulative distribution function (CDF) matching methods, have long been used as a method to correct for local biases in GCM output. The method first establishes a statistical relationship or transfer function between model outputs and historical observations, then applies the transfer function to future model projections (Panofsky and Brier, 1968) and has been successfully used as a downscaling method in various climate impact studies (e.g., Hayhoe et al., 2004).

Using the notation of Li et al. (2010), for a climate variable *x*, the QM method can be written as:

$$\hat{x}_{m-p.adjst.} = F^{-1}_{o-c}\left(F_{m-c}(x_{m-p})\right)$$

where *F* is the CDF of either the observations (o) or model (m) for observed current climate (c) or future projected climate (p), and F^{-1} is the inverse cumulative distribution function. Each CDF has a corresponding set of parameters, θ. The bias correction for a future period is thus done by finding the corresponding percentile values for these future projection points in the CDF of the model for current observations (e.g., applying the fitted parameters for $F_{m\text{-}c}$ to the model projected future values, $x_{m\text{-}p}$), then re-applying the inverse of the fit to observed data ($F_{o\text{-}c}^{-1}$) to determine the adjusted percentiles of the future distribution.

A weakness of the QM method is that it assumes that the climate distribution does not change much over time, and that, as the mean changes, the variance does not change, which is likely not true (e.g., Milly et al., 2008). To address this, Li et al. (2010) proposed the equidistant quantile mapping (EQM) method, which incorporates additional information from the CDF of the model projection. The method assumes that the difference between the model and observed value during the current calibration period also applies to the future period; however, the difference between the CDFs for the future and historic periods is also taken into account. This is written as:

$$\hat{x}_{m-p.adjst.} = x_{m-p} + F^{-1}_{o-c}\left(F_{m-p}(x_{m-p})\right) - F^{-1}_{m-c}\left(F_{m-p}(x_{m-p})\right)$$

Applying the EQM method results in the creation of a series of climate-adjusted and observation-adjusted future annual extreme values. Finally, an extreme value distribution is fit to the adjusted future series, which can then be used to predict estimates of any desired recurrence interval.

The analysis of both high and low extreme flow values in Meacham Creek is accomplished through application of the Gumbel distribution (Chow, 1964), a two-parameter, extreme value distribution that is frequently used for analysis of flood recurrence and can be applied for either extreme high values (right-skewed) or low values (left-skewed). The two parameters of the Gumbel distribution are the mode or location (u) and the dispersion or scale (α), which can be related to the mean and variance (see Benjamin and Cornell, 1970), while the distribution has a fixed skewness. We use the Gumbel distribution rather than the log-Pearson Type III distribution recommended by the U.S. Water Resources Council (1967) because the latter distribution depends on the local and regional skew and it is unlikely that the climate model output is capable of accurately estimating higher-order moments such as skew.

The EQM method with the Gumbel distribution is readily implemented through the SciPy package for the Python programming language (http://scipy.org) using the *gumbel_r* (right-skewed) and *gumbel_l* (left-skewed) functions, both of which support methods for the cumulative distribution function (*.cdf(x, loc, scale)*) and inverse cumulative distribution function (*.ppf(q, loc, scale)*), along with parameter fitting to data (*.fit*). The relevant distributions for the Meacham Creek analysis are then:

- $F_{m\text{-}c}$: Gumbel fit to climate model annual maximum (or 7-day minimum) series for the historical period.
- $F_{o\text{-}c}$: Gumbel fit to observed historical annual maximum (or 7-day minimum) series
- $F_{m\text{-}p}$: Gumbel fit to climate model annual maximum (or 7-day minimum) series for the future period

In the archived climate model runs, the historical period runs through 2005, and model projections run from 2006 through 2100. The nominal future period for analysis is 2065, which is represented by a 30-year time slice, 2050-2079. Current conditions are also represented by a 30-year time slice, 1976 – 2005. The start date for the current conditions representation is also consistent with the available gage data for Meacham Creek.

As an example of the process, consider updating the flood frequencies with results from the GFDL-CM climate model as downscaled and filtered through VIC. The historical annual maximum series, which range from 878 to 5,930 cfs, is shown in Figure 7.

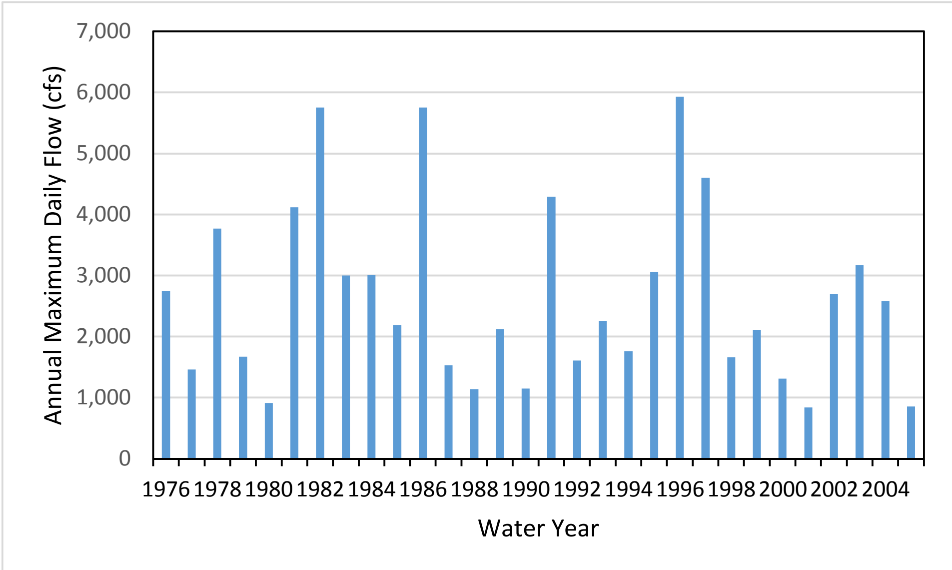

Figure 7. Annual Maximum Daily Flow Series, Meacham Creek (USGS 1402300)

The Gumbel extreme-value models were fit using depth units of mm/d over the watershed to correspond to the format of the VIC output. Parameter estimates are shown in Table 2. It will first be noted that the GCM model fit has parameters that are very different from the historical observations, with a smaller location parameter. This indicates that the VIC model is biased low relative to observations – which is why we need to use the EQM method for adjustment. The historical and future GCM fits do show an increase in location, which in turn indicates an increase in predicted values, although adjusted by a change in scale, which is inversely related to the event of a given recurrence. These changes are translated back to the historical observations to produce the adjusted future extreme value model.

Table 2. Gumbel Parameter Estimates for Annual Maximum Daily Flow (mm/d)

	Location (u)	Scale (α)
Historical Observations	10.60	5.77
GFDL-CM, 1976-2005	6.07	2.32
GFDL-CM, 2051-2080	8.08	2.98
Adjusted Future	12.61	6.43

Prediction of an extreme high flow, Q_T, of a given recurrence, *T* (years), is accomplished using a frequency factor, K_T, and the mean (μ) and standard deviation (σ) of the distribution:

$$Q_T = \mu + K_T \sigma$$

For the Gumbel distribution, the frequency factor is given by (Chow, 1964):

$$K_T = -\frac{\sqrt{6}}{\pi}\{0.577 + \ln[\ln(T) - \ln(T-1)]\}$$

The mean and standard deviation of the right-skewed Gumbel distribution are related to the location and scale parameters through (Bras, 1990):

$$\mu = u + \frac{0.577}{\alpha}, \quad \sigma^2 = \frac{1.645}{\alpha^2}$$

Application of these equations allows estimation of future high extremes of any desired recurrence based on the adjusted future parameter distribution obtained through application of the EQM method. A similar analysis can be applied to the series of annual minima using a left-skewed Gumbel distribution, which is a symmetric mirror image of the right-skewed distribution (see Benjamin and Cornell, 1970).

1.5 RESULTS

1.5.1 Future Water Temperature

Using the calibrated Mohseni model parameters, the future climate air temperature deltas from MIROC-ESM-CHEM (Section 1.4.1) were used to predict 7-day water temperature series under mid-century climate at the Meacham Creek temperature monitoring locations in and near the Bonifer Reach. Average summer 7-day water temperatures are predicted to increase on average by about 3.2 °C across the Meacham Creek monitoring stations in and near Bonifer Reach (Table 3). Note that the water temperature response is buffered relative to the change in atmospheric temperature: Water temperature is predicted to change relative to the change in air temperature at the 7-d scale (about 6.58 °C) by a ratio of about 0.48. This is somewhat less than the “typical” ratio of changes in summer average water temperature to change in air temperature of 0.67 reported by Isaak et al. (2011).

The 7dAM water temperatures increase by a similar amount, on average; however, the highest 7dAM for the 10-year monitoring period is predicted to increase by a smaller amount (Table 4) as the GCM predicts greater air temperature increases for cool years than for warm years.

Table 3. Average Summer 7-day Water Temperatures (°C), based on 2005-2014 Monitoring and MIROC-ESM-CHEM Climate Projections

Station	Observed	Future (ca. 2065)	Difference
527M1	20.6	23.9	3.3
528M2	21.8	25.0	3.2
530M4	20.8	23.6	2.9

Table 4. Highest Summer 7dAM Water Temperatures (°C), based on 2005-2014 Monitoring and MIROC-ESM-CHEM Climate Projections

Station	Observed	Future (ca. 2065)	Difference
527M1	26.0	27.4	1.4
528M2	27.6	28.0	0.4
530M4	25.6	26.4	0.8

1.5.2 Future High Flows

Future daily peak flows were estimated using the EQM statistical methods described in Section 1.4.3 to adjust the annual maximum series observed at USGS gage 14020300. Gumbel distributions were fit to both the observed (1976-2005) and adjusted future (ca. 2065) annual peaks for both the GFDL-CM3 and MIROC-ESM GCMs. The fitted extreme value distribution was then used to predict daily flood flows of different recurrence intervals, as shown in Table 5 and Figure 8. These results suggest an increase in the magnitude of potentially damaging flood flows, as is expected for a warmer climate in which the intensity of rainfall events and rapidity of snowmelt increases. For example, the 100-yr 24-hr flow is projected to increase by up to 21 percent by mid-century. The statistical model can provide predictions beyond the 100-year recurrence, but these are not presented as the estimates based on model fit to 30 years of data are highly uncertain.

Table 5. 24-hr Peak Flow Recurrences for Historical (1976-2005) and Future (ca. 2065) Climate Projected by GDFL-CM3 and MIROC-ESM

Recurrence Interval (years)	Observed Historical High Flows (cfs)	GDFL-CM3 Future High Flows (cfs)	MIROC-ESM Future High Flows (cfs)
2	2,370	2,789	2,564
10	4,396	5,046	5,152
25	5,416	6,183	6,454
50	6,173	7,026	7,420
100	6,924	7,863	8,379

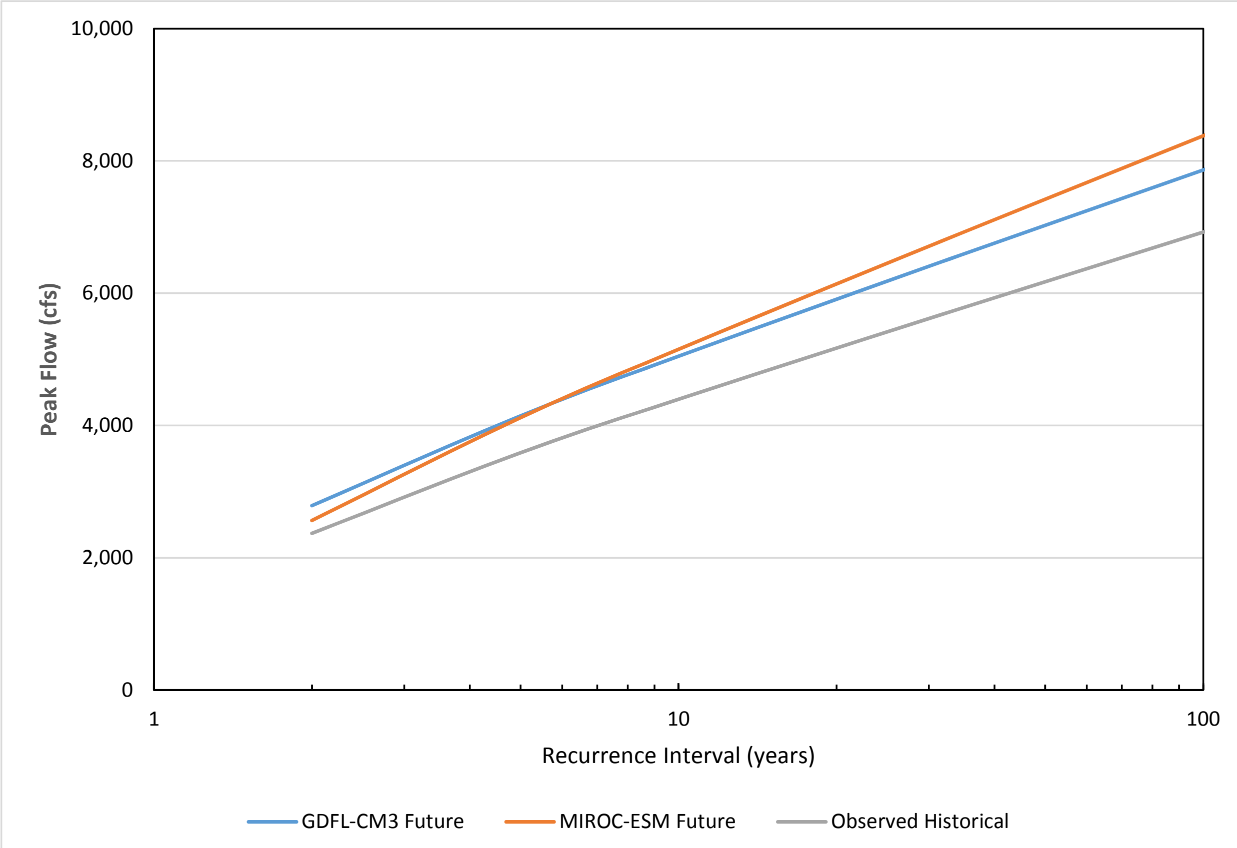

Figure 8. Peak Daily Flow Recurrence Curves for Meacham Creek at Gage for Historical Conditions and Mid-Century Conditions Predicted by GDFL-CM3 and MIROC-ESM Models

1.5.3 Future Low Flows

Similar statistical methods can be used to estimate the future probability distribution of 7-day average low flows. The approach is similar to that developed by the USGS for estimating low-flow frequencies using the log Pearson III distribution (Riggs, 1972). Here, recurrence intervals for 7-day average low flows under future climate were estimated by applying the EQM method with the left-skewed Gumbel distribution. Results are shown in Table 6 and Figure 9

Annual low flows for both climate scenarios for historical and future periods were scaled to the low flow timeseries of the observed flow at USGS gage 14020300. The low flows were scaled using the EQM with the left-skewed Gumbel Method, then future flow volumes were tabulated at various recurrence intervals. The climate model projections show a decrease in 10-yr low flows but a possible slight increase in low flows at larger recurrence intervals. This occurs because the climate models predict a change in both the location and the scale of the Gumbel distribution under future climate.

Table 6. 7-day Low Flow Recurrences for Historical (1976-2005) and Future (ca. 2065) Climate Projected by GDFL-CM3 and MIROC-ESM

Recurrence Interval (years)	Observed Historical Low Flows (cfs)	GDFL-CM3 Future Low Flows (cfs)	MIROC-ESM Future Low Flows (cfs)
2	9.9	7.0	3.5
10	6.9	5.4	2.7
25	5.4	4.5	2.3
50	4.3	3.9	2.0
100	3.2	3.3	1.7

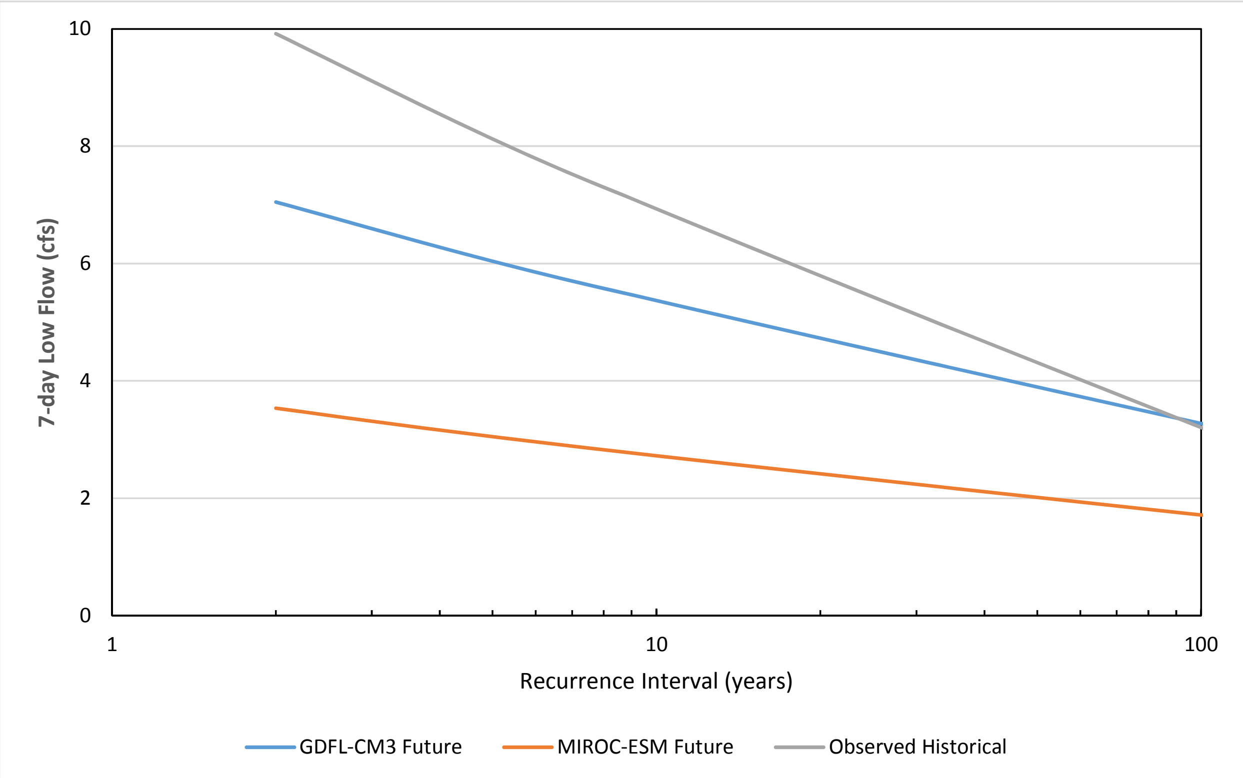

Figure 9. 7-day Low Flow Recurrence Curves for Meacham Creek at Gage for Historical Conditions and Mid-Century Conditions Predicted by GDFL-CM3 and MIROC-ESM Models

For low flows, there is particular interest in 7Q10 flow, the 7-day low flow that occurs, on average, once every 10 years. The estimated 7Q10 flow under recent historical conditions at USGS gage 14020300 is estimated at 6.93 cfs. By 2065, a flow of 6.93 cfs or less is estimated to occur on average about every 2.2 years for the GDFL-CM3 climate projections and essentially every year for the MIROC-ESM climate projections.

1.6 SUMMARY

A rapid scoping analysis was undertaken to evaluate potential changes in water temperature, high flows, and low flows in Meacham Creek under potential changes in climate through approximately 2065. These results suggest that planning and design should account for increases in average 7-day water temperatures on the order of 3.2 °C by 2065 and increases in critical 7-day summer water temperatures on the order of 1.4 °C. Assuming a linear trend, these are equivalent to increases of 0.64 and 0.28 °C over the next 10 years.

Peak flows are expected to increase, while critical low flows will decrease. The 100-yr 24-hr flood flow is estimated to increase by up to 21 percent by mid-century (4.2 percent over 10 years). The 7Q10 low flow is estimated to decrease, possibly by more than half by mid-century. Over the next ten years this trend equates to a decrease of approximately 12 percent.

The scoping analyses presented here could be further refined in several ways. For flows, the VIC model projections are not calibrated to Meacham Creek and may introduce biases (although the EQM approach is designed to minimize the impacts of such biases). A site-specific and calibrated watershed response model could improve the representation of hydrologic response to changes in climate forcing. For prediction of critical water temperatures, the Mohseni model is fit to site data, but is also an empirical approach that assumes that the underlying relationship between air temperature and water temperature does not change under future climate. A more detailed temperature response model could be used to assess the impact of changes in other meteorological inputs, such as humidity, as well as the influence of changes in critical period flow on water temperature. Finally, evaluation of the full suite of available climate model projections would provide additional information on the range of potential responses of both flow and water temperature to which adaptation may be needed.

1.7 REFERENCES

Battin, J., M.W. Wiley, M.H. Ruckelshaus, R.N. Palmer, E. Korb, K.K. Bartz, and H. Imaki. 2007. Projected impacts of climate change on salmon habitat restoration. PNAS, 104(16): 6720-6725.

Beechie, T., H. Imaki, J. Greene, A. Wade, H. Wu, G. Pess, P. Roni, J. Kimball, J. Stanford, P. Kiffney, and N. Mantua. 2012. Restoring salmon habitat for a changing climate. *River Research and Applications*, 29(8): 939-960. doi:10.1002/rra.2590: 22.

Benjamin, J.R. and C.A. Cornell. 1970. *Probability, Statistics, and Decision for Civil Engineers.* McGraw-Hill, New York.

Bras, R.L. 1990. *Hydrology: An Introduction to Hydrologic Science.* Addison-Wesley, Reading, MA.

Brekke, L., A. Wood, and T. Pruitt. Downscaled CMIP3 and CMIP5 Hydrology Projections. Bureau of Reclamation Science and Technology Program.

Chow, V.T. 1964. *Handbook of Hydrology*. McGraw-Hill, New York.

Gao, H., Q. Tang, X. Shi, C. Zhu, T.J. Bohn, F. Su, J. Sheffield, M. Pan, D. Lettenmaier, and E.F. Wood. 2010. Water-Budget Record from Variable Infiltration Capacity (VIC) Model. Chapter 6 in *Algorithm Theoretical Basis Document for Terrestrial Water Cycle Models*. http://grid1.cos.gmu.edu:8090/OPeNDAPClient/ATBD_Chapter6_doc.pdf.

Hayhoe, K., D. Cayan, C.B. Field, P.C. Frumhoff, E.P. Maurer, N.L. Miller, S.C. Moser, S.H. Schneider, K.N. Cahill, E.E. Cleland, L. Dale, R. Drapek, R.M. Hanemann, L.S. Kalkstein, J. Lenihan, C.K. Lunch, R.P. Neilson, S.C. Sheridan, and J.H. Verville. 2004. Emissions pathways, climate change, and impacts on California. *Proceedings of the National Academy of Sciences of the U.S.A.*, 101: 12,422-12,427, doi:10.1073/pnas.0404500101.

Isaak, D.J., S. Wollrab, D. Horan, and G. Chandler. 2011. Climate change effects on stream and river temperatures across the northwest U.S. from 1980–2009 and implications for salmonid fishes. *Climatic Change*. doi:10:1007/s10584-011-0326-z.

Knutti, R., R. Furrer, C. Tebaldi, J. Cermak, and G.A. Meehl. 2010. Challenges in combining projections from multiple climate models. *Journal of Climatology*, 23(10):2739–2758.

Li, H., J. Sheffield, and E.F. Wood. 2010. Bias correction of monthly precipitation and temperature fields from Intergovernmental Panel on Climate Change AR4 models using equidistant quantile matching. *Journal of Geophysical Research: Atmospheres*, 115: D10101, doi:10.1029/2009JD012882.

Liang, X., D.P. Lettenmaier, E.F. Wood, and S.J. Burges. 1994. A simple hydrologically based model of land surface water and energy fluxes for GSMs. Journal of Geophysical Research, (99)D7:14415–14428.

Liang, X., E.F. Wood, and D.P. Lettenmaier. 1996. Surface soil moisture parameterization of the VIC-2L model: Evaluation and modifications. *Global Planetary Change*, 19:137–159.

Mantua, N., I. Tohver, and A. Hamlet. 2010. Climate change impacts on streamflow extremes and summertime stream temperature and their possible consequences for freshwater salmon habitat in Washington State. *Climatic Change*, 102: 187-223. doi:10.1007/s10584-010-9845-2.

Maurer, E. P., L. Brekke, T. Pruitt, and P. B. Duffy. 2007. Fine-resolution climate projections enhance regional climate change impact studies. *EOS, Trans. AGU*, 88(47), 504

Milly, P.C.D., J. Betancourt, M. Falkenmark, R.M. Hirsch, Z.W. Kundzewicz, D.P. Lettenmaier, D.P., and R.J. Stouffer. 2008. Stationarity is dead: Whither water management? *Science*, 319: 573-574, doi:10.1126/science.1151915.

Mohseni, O., H.G. Stefan, and T.R. Erickson. 1998. A nonlinear regression model for weekly stream temperatures. *Water Resources Research*, 34(10): 2685-2692.

Mote, P.W., E.A. Parson, A.F. Hamlet, W.S. Keeton, D. Lettenmaier, N. Mantua, E.L. Miles, D.W. Peterson, D.L. Peterson, R. Slaughter, and A.K. Snover. 2003. Preparing for climatic change: The water, salmon, and forests of the Pacific Northwest. *Climatic Change*, 61: 45–88.

Mote, P.W., and E.P. Salathé. 2010. Future climate in the Pacific Northwest. *Climatic Change*, 102(1–2):29–50. doi:10.1007/s10584-010-9848-z.

Mote, P., L. Brekke, P.B. Duffy, and E. Maurer. 2011. Guidelines for constructing climate scenarios. *EOS, Transactions of the American Geophysical Union*, 92(31):257–258.

Mote, P., A.K. Snover, S. Capalbo, et al. 2014. *Ch. 21: Northwest. Climate Change Impacts in the United States: The Third National Climate Assessment*. J.M. DeMelillo, T.C. Richmond, and G. W. Yohe, eds., U.S. Global Change Research Program, Washington, DC.

ODEQ. 2008. Temperature Water Quality Standard Implementation – A DEQ Internal Management Directive. Oregon Department of Environmental Quality. http://www.deq.state.or.us/wq/pubs/imds/Temperature.pdf.

Panofsky, H.A., and G.W. Brier. 1968. *Some Applications of Statistics to Meteorology*. Pennsylvania State University, University Park, PA

Patte, D. 2014. Climate Trends and Projections – A Guide to Information and References. U.S. Fish and Wildlife Service Pacific Region. http://teaming.com/sites/default/files/2014%20Downscaled%20Modeling%20Summary_Sept%2019.pdf.

Pierce, D.W., T.P. Barnett, B.D. Santer, and P.J. Gleckler. 2009. Selecting global climate models for regional climate change studies. *Proceedings of the National Academy of Sciences*, 106(21):8441–8446.

Reclamation. 2014. Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections: Release of Hydrology Projections, Comparison with Preceding Information, and Summary of User Needs. U.S. Department of the Interior, Bureau of Reclamation, Technical Services Center, Denver, CO.

Riggs, H.C. 1972. Low-flow Investigations. Chapter B1 in Book 4, Hydrologic Analysis and Interpretation, Techniques of Water-Resources Investigations of the United States Geological Survey. U.S. Geological Survey, Washington, DC. http://pubs.usgs.gov/twri/twri4b1/pdf/twri_4-B1_a.pdf.

U.S. Water Resources Council. 1967. A Uniform Technique for Determining Flood Flow Frequencies. Bulletin 15. U.S. Water Resources Council, Washington, DC.