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Will future climate change increase the risk of violating minimum flow and maximum temperature thresholds below dams in the Pacific Northwest?

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ABSTRACT

Detecting and avoiding environmental thresholds that lead to catastrophic change in ecological communities is an important goal, and one that is especially challenging to address over broad geographic extents. Here, we conducted a regional-scale climate vulnerability assessment (RCVA) to quantify the risk of violating thermal and minimum-flow thresholds below reservoirs. Our analysis used hybrid (process-based and empirical) models of tailwater temperature and flow driven by 4-km downscaled CMIP5 climate projections. Downscaling employed a combination of process-based models, quantile mapping, and a non-linear 'reservoir' transform function. RCVA can be applied at regional scales without proprietary and data-intensive physical models of reservoir systems or ecological models of species that comprise tailwater communities. Using RCVA, we produced ensemble projections of risk and duration of extreme high-temperature or low-flow events below federal reservoirs in the Pacific Northwest (PNW), USA. Bayesian modeling of simulated results allowed us to evaluate differences between risk under a future and baseline scenario relative to model uncertainties and to quantify uncertainty in modeled risks. Based on assumptions that historical patterns of reservoir dynamics and operation will continue, and that regulatory thresholds will not change, the risk of thermal exceedance was projected to increase by an average of 0.27 and extend into late-spring and fall (average change in duration of 10.3 d). For flow, RCVA projected an increase of 0.07 in the average risk below-thresholds flows, with an average increase in duration of 4.6 d. Both results raise concerns that cold-water salmonids of the PNW will be at increased risk under a future climate scenario.

1. Introduction

As climate warms, maintaining adequate water and water quality for freshwater biota will become more difficult, especially for cold-water fishes (Battin et al., 2007; Beechie et al., 2013; McCullough et al., 2009; Roberts et al., 2013). A primary concern is that water temperatures will exceed the thermal tolerances of fishes and other freshwater taxa, reducing the amount of habitat with suitable temperatures (Eaton and Scheller, 1996; McCullough et al., 2009). On a regional scale, aquatic communities vary in their seasonal habitat requirements. Population models have been used to evaluate responses to temperature and flow changes associated

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with climate change (Jager et al., 1999), but results from species-specific models cannot easily be generalized to diverse aquatic communities on a regional scale. In the US, local water standards have already been assigned to water bodies by states, with guidance from the US Environmental Protection Agency, and an important purpose for these standards is to protect aquatic communities. Thresholds can be used to assess the future risk of violating locally-relevant water standards in river reaches ('tailwaters') below reservoirs on broad regional scales without detailed physical (e.g., bathymetry) or biological information.

The paradigm for understanding drought and water shortages is shifting from a supply-side to a demand-side view (Mann and Gleick, 2015). On the supply side, rain-on-snow events that cause earlier snowmelt and runoff could alter the timing of reservoir inflows, particularly for river sections with a relatively large portion of their catchments near the current mid-winter snow-line (Graves and Chang, 2007; Mote et al., 2003). Yet, scientists now recognize that the indirect effects of rising air temperatures on water demands (including those of fish, irrigators, and natural vegetation) are more important than the supply of inflows driven by changing precipitation patterns (Mann and Gleick, 2015). Climate changes that alter the amount, timing, and temperatures of river flow can potentially intensify stress among competing water demands including municipal water use, irrigation, environmental flows, and hydropower generation. This is particularly true in the Pacific Northwest (PNW) (Lanini et al., 2014; Lee et al., 2009). These stresses are not limited to water availability. Future changes in climate could significantly impair habitat quality for migratory salmon and steelhead (*Oncorhynchus mykiss*) and resident salmonids (Jonsson et al., 2003; Wade et al., 2013).

Streams in the US are projected to show increased water temperatures as they track air temperatures (Kaushal et al., 2010). Historical trends have been detected. For example, Bartholow (2005) reported a rise of 0.5 °C/decade since the 1960s in the lower Klamath River, California. A warming trend has also been detected in the Lower Columbia River (Army, 2013). Crozier et al. (2011) report a rise in mean July water temperature from 16.9 °C in 1950 to 20.9 °C in 2005 below Bonneville Dam. The sequential addition of reservoirs in the Columbia River over time may have contributed to this trend, but long-term historical water-temperatures in unregulated gauges in the PNW also track the increasing historical trend in air temperatures (Isaak et al., 2012).

Thermal effects below reservoirs may differ from unregulated streams, and this has received relatively little attention at regional scales. Reservoirs can have complex effects on downstream thermal regimes in tailwaters, but in general thermal regimes are both shifted and moderated. A 'cold-block' of stored water develops during winter and downstream temperatures are therefore influenced by reservoir stratification. Reservoirs in Canada impounding more than 10% of median annual runoff reduced variation in downstream temperatures at seasonal, daily, and sub-daily time scales (Maheu et al., 2016). Regulation also increased fall temperatures (Maheu et al., 2016).

Managing risk will be more difficult as we encounter uncertain future climate conditions (Dale et al., 2018). Although freshwater ecosystems are considered at risk, infrastructure (e.g., dams, reservoirs) may be deployed in a manner that helps to manage the risk of irreversible loss of aquatic species. Because species' vulnerability to climate change are usually controlled by threshold tolerances to environmental conditions, threshold-based management is useful (Liu et al., 2015).

Climate change vulnerability assessment is a form of risk assessment used to evaluate the impacts of climate stress on specific endpoints valued by society (El-Zein and Tonmoy, 2015; Gaichas et al., 2014; Ghile et al., 2014; Higgins and Steinbuck, 2014). We developed a Regional Climate Vulnerability Assessment (RCVA) framework for regional-scale assessment of current and future risk of violating water standards in tailwaters below hydropower reservoirs. Our framework integrates several attractive features needed to make regional-scale assessments feasible. First, we assume that site-specific water standards (Coutant, 1999) adequately represent the local habitat needs of aquatic communities below reservoirs. Second, we used a hybrid modeling approach to integrate process-based with empirical models to project future changes in water temperature and flow. Climate projections from an ensemble of ten dynamically downscaled climate models (models detail is shown in Supplementary Information (SI) Table S.1) in the CMIP5 experiment (IPCC (Intergovernmental Panel on Climate Change), 2013) was bias corrected at 4-km resolution before its use as forcing in the Variable Infiltration Capacity (VIC) model to represent regional surface hydrology (Naz et al., 2016). The experimental details and future projections in 10-member 18-km dynamically downscaled ensemble are described in Ashfaq et al. (2016) and the methodology for bias correction is described in Ashfaq et al. (2010). The hybrid model incorporates this downscaled hydrology with an empirical correction to represent the local effects of reservoirs as they shift the timing and magnitude of seasonal thermal regimes downstream. In a last step, we characterized uncertainty to appropriately account for ensemble and regional variation. We demonstrated the approach for federal reservoirs in the PNW region of the US as part of an assessment of climate impacts on federal hydropower (Kao et al., 2016). At each step, the RCVA performed well against historical data and allowed us to characterize seasonal patterns in anticipated risk increases to evaluate when and where adaptive management will be most beneficial. We propose using RCVA as a threshold-based approach to managing climate risk in freshwater ecosystems (Liu et al., 2015) at scales ranging from large river basins to continental.

2. Methods

The goal of RCVA (Fig. 1) is to compare future and baseline risk of extreme events under climate change. We achieved this goal 1) by estimating risk of extreme events under current and future scenarios for each case (week, period, gage, GCM) and 2) by developing Bayesian seasonal risk models to summarize results. The main advantages of this approach are the ability to assess risk at large spatial scales and characterize uncertainty. These are summarized, along with disadvantages, in Table 1.

We evaluated the risk of violating water standards in a projected future period relative to a current baseline. Our analysis is motivated by the need to assess risk to aquatic biota in tailwaters. In general, extreme values (i.e., high temperatures and low flows) are of the greatest interest when evaluating vulnerability of habitat supporting aquatic life (Magnuson, 2010). Two types of water standards that are regulated to protect aquatic life are stream temperature and flow. Here, we define 'risk' as the fraction of replicate

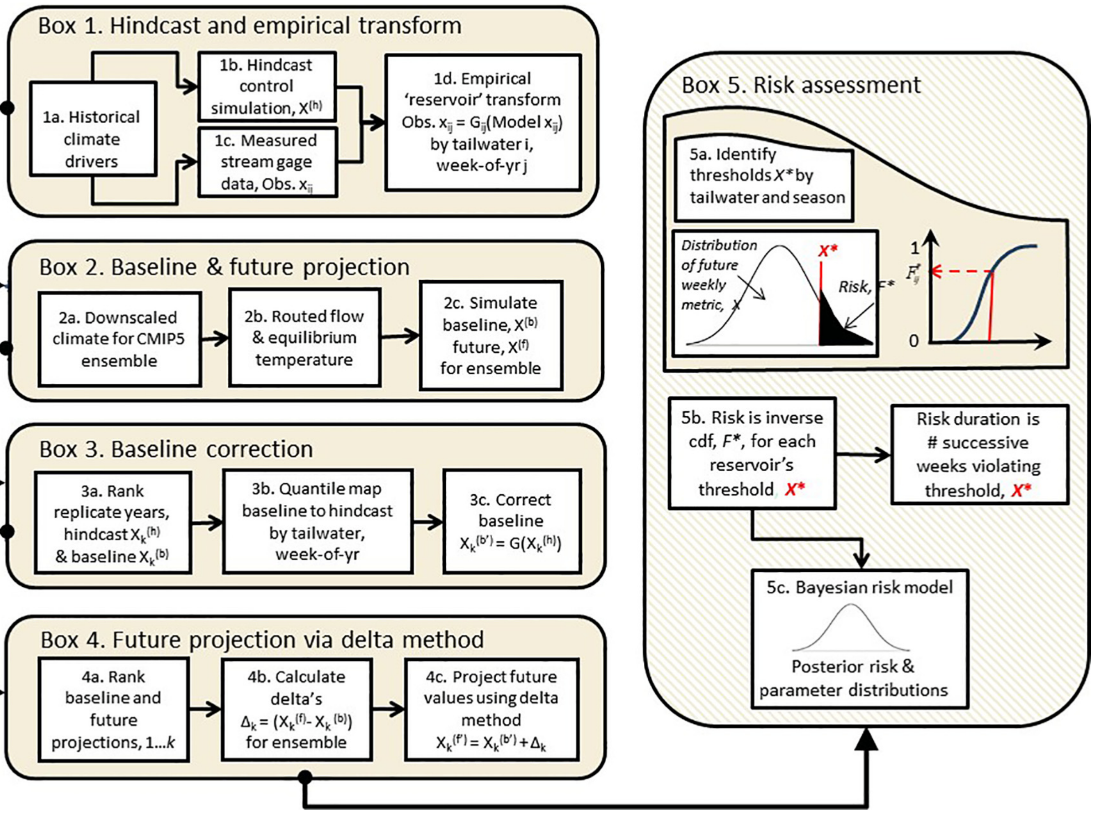


Fig. 1. Flow chart of the regional climate change vulnerability analysis (RCVA) to assess the risk of extreme water temperatures, X, exceeding site-specific thresholds, X^*. Box 1 describes development of an empirical transform using hindcast and measured data. Box 2 describes baseline and future projection using process-based flow and temperature models. Box 3 describes two-step correction of the baseline projections. Box 4. Describes the quantile mapping and delta method. Box 5. illustrates how risks are calculated from thresholds and simulated data, durations of extreme events, and Bayesian modeling to elucidate patterns in risk and characterize uncertainty. The process is identical for flow except that the threshold is a minimum.

Table 1
Advantages and disadvantages of climate change vulnerability assessment using the proposed RCVA framework in Fig. 1 with Bayesian modeling of patterns produced by hybrid models to assess risk of violating water standards in regulated rivers.

RCVA Component	Advantages	Disadvantages
Step 1. Hybrid modeling	Does not require site-specific implementation of hydrologic and water quality models for systems of reservoirs	Requires monitoring data and regulatory thresholds for flow and water temperature
	Does not assume stationary climate	Assumes reservoir operations and water quality and quantity regulations will follow historical patterns into the future
	Probabilistic risks are calculated on the whole ensemble, not from an ensemble mean.	Although the equilibrium temperature model (EWN) accounts for solar radiation and other meteorological variables, there is no input from ground water or sediments-water heat exchanges that may affect heat budgets.
Step 2. Bayesian modeling	Generality is a strength. Inference can be either to group (i.e., site, GCM) or to broader universe (region, GCM ensemble).	Bayesian post-modeling assumes a parametric model, which reduces the predictive skill relative to the hybrid projections by week and site.
	Bayesian model uncertainties are characterized through prediction of posterior risk distributions and credible intervals or posterior distributions of parameters.	Bayesian models take much longer to fit than their frequentist counterparts.
	Thresholds can be defined by using a logistic model for risk, such as the one used here.	

simulated years projected to experience an extreme event for a given GCM and site. We define 'extreme event' as water temperature above a week-and site-specific upper temperature threshold or flow below a low-flow threshold.

Our goal was to quantify the risk of failing to meet environmental thresholds in tailwater reaches below reservoirs under a baseline and future scenario. The first step was to develop empirical models for historical water temperature and flow data from hindcasted control simulations (Fig. 1, box 1). The second step used a process-based model to simulate current baseline and future water temperature and flow (Fig. 1, box 2). The third step was to apply quantile mapping to the hindcast simulation and the empirical correction (Fig. 1, box 3). Next, quantile deltas were calculated and added to the corrected baseline (Fig. 1, box 4). Risk estimation requires both environmental (e.g., regulatory) thresholds, X^* (Fig. 1, box 5) as well as projections. Risk was estimated by comparing time series of water temperature and flow against week- and tailwater-specific thresholds (Fig. 1, box 5). Durations of threshold violations were also characterized by site and time period (Fig. 1, box 5). Finally, risks calculated in step 5b were modeled using a Bayesian logistic model (Fig. 1, box 5c). This *post hoc* modeling step characterized the influences of GCM on risk and quantified whether projected changes were large relative to model uncertainty. Each component of the process in Fig. 1 is described further below.

2.1. Hybrid models to simulate tailwater temperature and flow

We developed a hybrid process-based and statistical modeling approach to simulate water temperature and flow (Fig. 1, box 1). Hybrid models combine first-principles of atmospheric dynamics and heat transfer equations with empirical modeling (Adams et al., 2013; Chen et al., 2014; Katzav, 2013). Process-based models are preferred when the future is not within the realm of past conditions because they rely on understanding underlying mechanisms. Nevertheless, to be useful, their parameters must be adjusted and calibrated against empirical data. Similarly, empirical models can use equation forms that are based on the physical processes involved (Jager et al., 2000; Katzav, 2013). RCVA uses process-based models (GCMs, climate downscaling, routing flow, equilibrium water temperature modeling) and empirical models with an equation form that describes the effects of a reservoir.

2.2. Regionally downscaled climate projections

2.2.1. Climate drivers

Here, we briefly summarize the methodology for obtaining daily flow and air temperature drivers for RCVA. The Abdus Salam International Centre for Theoretical Physics Regional Climate Model, version 4 (RegCM4, (Giorgi et al., 2012) was used to dynamically downscale results from ten global General Circulation Models (GCM) [SI Table S.1] in the CMIP5 (http://cmip-pcmdi.llnl.gov/cmip5/) archive to a 1/24° (~4 km) grid over the conterminous US (Oubeidillah et al., 2014). Downscaled meteorological variables were generated at a daily resolution for a baseline period from 1966 to 2004, and mid-term future from 2031 to 2049 (Ashfaq et al., 2013; Ashfaq et al., 2016), and these were bias-corrected using quantile mapping (QM) (Ashfaq et al., 2010). We produced weekly minimum daily average flow (*Qw*) and weekly maximum daily average water temperature (*Tw*) by using downscaled GCM meteorology as drivers (Fig. 1, box 2). Climate variables driving the water temperature model included air temperature, precipitation, relative humidity, wind speed, dew point temperature, and solar radiation.

2.2.2. Flow modeling

We estimated baseline and future river flows by using the VIC daily surface runoff and baseflow simulations (Naz et al., 2016). To simulate daily streamflow, daily surface and subsurface runoff from each grid cell simulated by the semi-distributed VIC hydrologic model (Nijssen et al., 2001) were routed to the reservoir of interest through a river network using a linear reservoir model based on Lohmann et al. (1998) (Fig. 2a–c). At this point, simulated flows were calibrated against gaged historical flows (Fig. 2d) as described by Oubeidillah et al. (2014).

VIC model performance has been evaluated across US streams at federal hydropower projects by comparing historical and simulated flows (1981–2012) and evaluating performance by calculating R^2 and Nash-Sutcliffe Efficiencies (*NSE)* at daily and monthly time scales (Naz et al., 2018; Naz et al., 2016). Performance in the PNW was better than that in most other US regions. Both *NSE* and R^2 values for daily flows exceeded 0.70 for most gages and all were above 0.5 (Naz et al., 2018; Naz et al., 2016). Our risk assessment compares *Qw* against regulatory thresholds, historical weekly minimums of daily average flows (MWAQ).

2.2.3. Water temperature modeling

Equilibrium water temperature (EWT) is the temperature at which heat fluxes between air and water are in balance. We simulated EWT per Bogan et al. (2003). EWT closely approximates the temperature of unregulated streams (Edinger et al., 1968; Null et al., 2013; Perry et al., 2012). In regional-scale studies such as this one, an EWT model is typically used because heat flux at the water surface can be calculated from air temperature and other meteorological variables simulated by mesoscale weather models and regional climate models (e.g., those used in dynamical downscaling) without local hydrologic information. Local data obtained across broad regional scales are rarely available and, when available, are highly uncertain (Null et al., 2013).

Observed stream temperature is more-closely approximated at a coarser temporal resolution (e.g., weekly or 7-d moving average) that avoids short-term lags and fluctuations from day-to-day variations in air temperature and solar radiation (Perry et al., 2012). Furthermore, regulatory thresholds are usually maximum weekly daily average temperature (MWAT). Therefore, our risk assessment uses weekly maximums of EWT, *Tw*.

2.3. Baseline correction

Here, we used a combination of QM (Ashfaq et al., 2010) and an empirical transform function to account for the effect of a reservoir (and other influences) that result in deviations between stream temperature and EWT and between modeled and measured

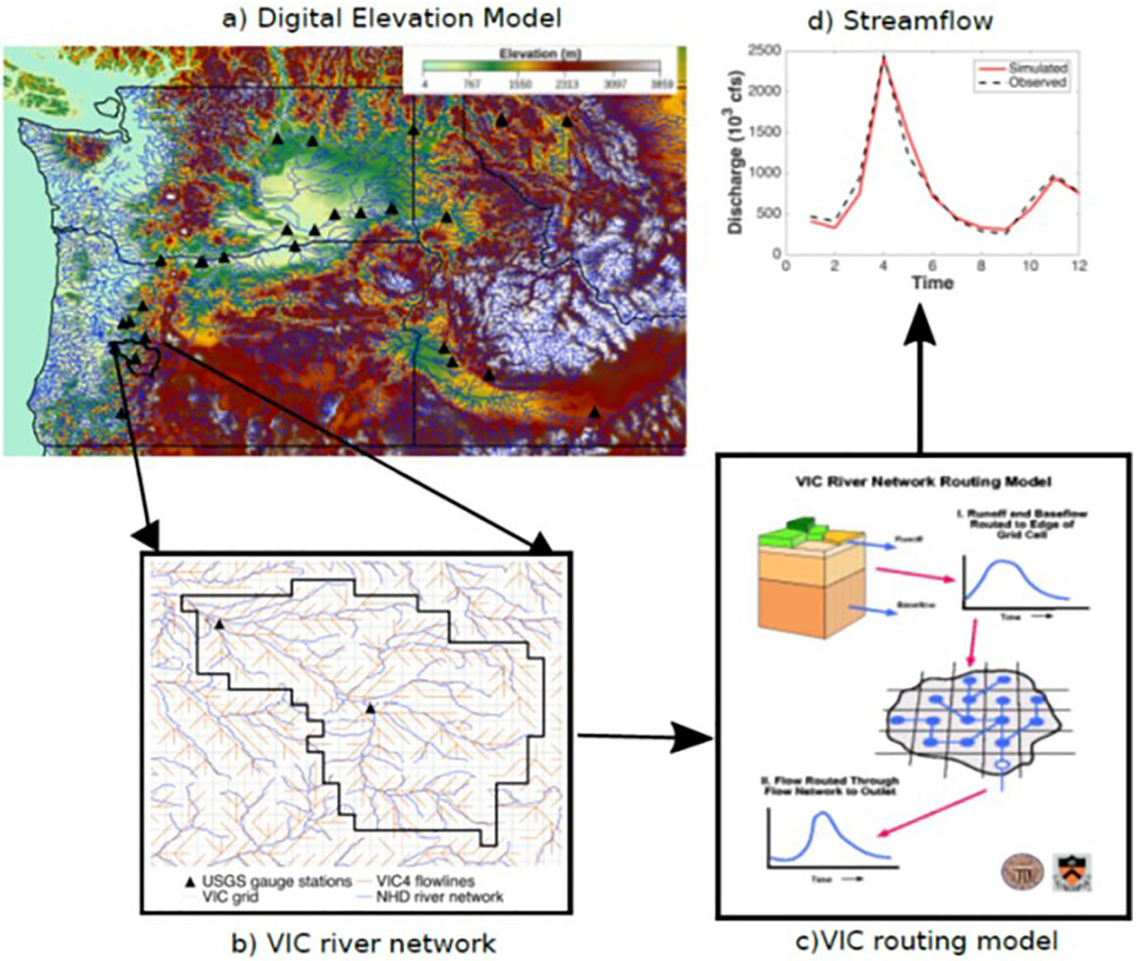


Fig. 2. Routing modeling framework. (a) Digital elevation model at 1/24 grid cell used in the routing of streamflow, b) an example of delineated watershed and river network from 1/24 digital elevation model with two USGS gauges on Willamette River, (c) a schematic of the VIC routing model (Adam et al., 2007), and (d) an example of simulated annual streamflow. Updated from Naz et al. (2018).

stream flow. The resulting hybrid model (i.e., process-based model corrected by using QM and an empirical transform) was used to adjust baseline projections.

Quantile mapping. This study focuses on the risk of extreme events (those exceeding or below an environmental threshold) and QM is the most appropriate correction when extreme values of the distributions are of interest (Smith et al., 2014). QM has also been shown to perform better than other approaches when evaluating higher moments (Lafon et al., 2013). Mapping is between the baseline and control simulations (not data) and, in a second step, a 'reservoir transform' relates the control to data. Values of both distributions were first ranked, $q = 1, \ldots, N$ for N replicate simulated years. For a baseline year's value with rank q, we mapped the corresponding ranked value from the control simulation.

'Reservoir' transform. We corrected quantile-mapped projections for the baseline period, $y^{(b)}(t)$ (Eq. (1); Fig. 1, box 3c). We applied a simple site- and month-specific empirical correction, C_k(t), relating weekly summaries of USGS observed values, $x^{(o)}$, with simulated values from the control-run, $x^{(h)}$, for each outflow gauge, k, week, t, and month of the year, $M(t)$ (Eq. (1)).

$$y_k^{(b)}(t) = \max\{x_k^{(b)}(t) + C_k(t), 0\} \tag{1}$$

The transforms used to do this represent differences between a 1981–2012 VIC-model control run driven by historical meteorology, and weekly summaries of flow and temperature measured at stream gages (Fig. 1, box 1). For temperature, models specifically represent the attenuation and seasonal lag caused by the presence of a reservoir under the assumption that historical operations will continue as they have in the past. This assumes that the temperature changes from reservoir inflow to outflow will continue to follow historical patterns.

2.3.1. Flow

For streamflow, values (cubic meters per second, cms) were log-transformed. The correction consisted of subtracting the difference between modeled and measured monthly means, but the resulting estimates remain weekly. A monthly correction produced better results and fewer missing time periods than weekly correction did.

$$\begin{aligned} C_k(t) &= \frac{1}{N_M}\sum_{t\in M(t)}(x_k^{(o)}(t) - x_k^{(h)}(t)) \\ x_k^{(h)}(t) &\equiv \text{week } t \text{ summary of hindcasted values for gage } k \\ x_k^{(o)}(t) &\equiv \text{week } t \text{ summary of measured values for gage } k \\ N_M &= \text{weeks in month } M \end{aligned} \tag{2}$$

2.3.2. Water temperature

For water temperature, we used continuous seasonal models with lags to represent the effect of reservoirs on EWT in a simple way (Eq. (3)). This 'reservoir' transform model fitted against measured tailwater stream temperatures, T. In Eq. (3), the phase shift or lag is represented by φ, amplitude by A, and mean temperature by constant m. The empirical model also corrects for other local influences not accounted for by EWT (e.g., groundwater, shading), but assumes that these will continue into the future.

$$\begin{aligned} C_k(t) &= G_k(t,\ I_x = 1) - G_k(t,\ I_x = 0) \\ G_k(t) &= m + \delta_m I_x + (A + \delta_A I_x)\sin\left(\frac{2\pi}{T}[t-(\phi + \delta_\phi I_x)]\right) \\ I_x &\equiv \begin{cases} 1, & x \text{ are weekly MWAT from measured data at gage } k \\ 0, & x \text{ are weekly MWAT from hindcasted data at gage } k \end{cases} \\ \delta_p &\equiv \text{change in parameter } p \text{ for measured data } (vs.\ \text{ simulated}) \end{aligned} \tag{3}$$

2.4. Future scenario projection

For each GCM, tailwater and week-of-the-year, w, we calculated delta values between future and baseline simulations (Fig. 1, box 2d–f). For each variable, the distribution of deltas was then formed by subtracting the qth-ranked baseline value from the qth-ranked future value (Naz et al., 2016). As future and baseline simulations had the same number of replicate years, N, we described the shift by simply using ranks, where represents the qth ranked value of $q = 1 \ldots N$. In Eq. (4), t denotes continuous weeks over time (i.e., across years), whereas $w(t)$ denotes the week-of-the-year that week t belongs to.

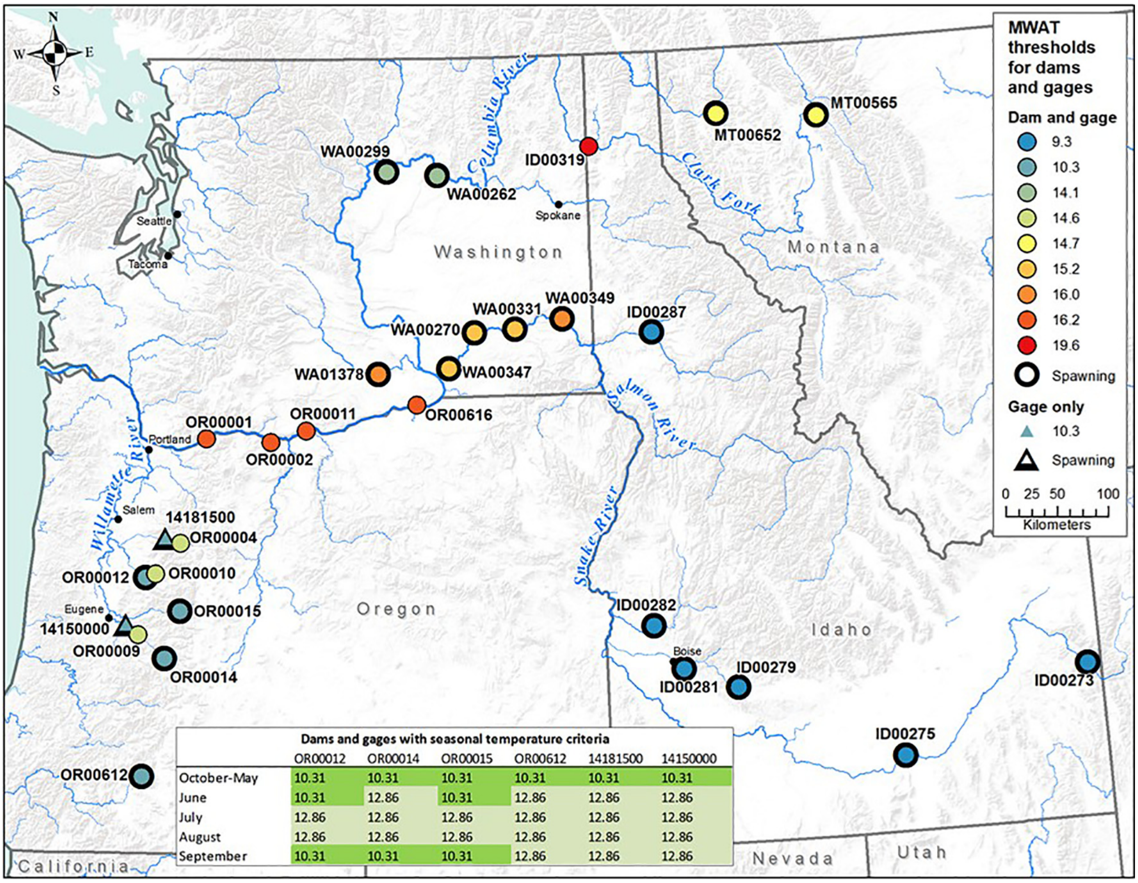
$$\begin{aligned} x_{t,q}^{(f)} &= y_{t,q}^{(b)} + \Delta_{w(t),q} = y_{t,q}^{(b)} + [x_{t,q}^{(f)} - x_{t,q}^{(b)}],\ q = 1..N \\ x_{t,q}^{(f)} &\equiv \text{Simulated future average value in week } t \text{ with rank q among years for week-of-year } w(t) \\ y_{t,q}^{(b)} &\equiv \text{Corrected average for week } t \text{ for the } q^{th} \text{ ranked year of the baseline period} \\ \Delta_{w(t),q} &\equiv \text{Projected change in water temperature in } q^{th} \text{ ranked year for week-of-year } w(t) \end{aligned} \tag{4}$$

2.5. Threshold and risk estimation

Risks were estimated (Fig. 1, box 4) as the fraction of 20 simulated 'replicate' years with extreme events (e.g., threshold exceedances) at a particular site and during a specified week and time period (current or future) (Table S.2). We used the full ensemble of downscaled GCMs in our risk calculation and evaluated variation among the ten models from the CMIP5 ensemble (Table S.1). In addition to risks for each period, we also calculated risk differences (future – baseline risk), as described by Kuss (2015), to measure the effect of future climate change on the risk of exceeding threshold values of water temperature (or falling below minimum flows). For example, if the risk of extreme events under current climate conditions is 0.5, then a +0.10 change in risk indicates that extreme events will occur during an *additional* 1 out of every 10 years in future, or 6 out of 10 years. Note that we opted not to use relative risks or odds ratios because these have statistical drawbacks when used to describe rare events (Flueck and Holland, 1976; Kuss, 2015).

Our approach relies on regulatory thresholds (X^* in Fig. 1. box 5) agreed upon by aquatic ecologists and other stakeholders to reflect local habitat requirements. Each river reach has an upper temperature threshold associated with a reach-specific designated use (Coutant, 1999). Thermal criteria reflected differences in standards among states and designated beneficial uses, which reflect local fish life histories and natural thermal conditions. The process by which we determined numeric thresholds first involved locating tailwater reaches on state-provided geospatial data describing the designated use of each water body (Fig. 3). The designated beneficial use was then identified in associated documents listing thermal criteria (Table S.2).

In the PNW, environmental thresholds usually reflect the presence of species of concern. For some tailwaters, migratory species listed under the U.S. Endangered Species Act (ESA) are present only during certain periods. In the Columbia River system, these requirements (NOAA Fisheries, 2014) are incorporated into state-designated uses, leading to seasonally varying standards. A low thermal standard is required year-round for resident and adfluvial bull trout (*Salvelinus confluentus*) and other spawning salmonids in Idaho (Upper Columbia River and Interior Snake Rivers), and for tailwaters with access to the ocean that support migratory salmon and steelhead spawning in the Willamette River, Oregon and other coastal rivers (Fig. 3). Mainstem Lower Snake and Columbia



	OR00012	OR00014	OR00015	OR00612	14181500	14150000
October-May	10.31	10.31	10.31	10.31	10.31	10.31
June	10.31	12.86	10.31	12.86	12.86	12.86
July	12.86	12.86	12.86	12.86	12.86	12.86
August	12.86	12.86	12.86	12.86	12.86	12.86
September	10.31	10.31	10.31	12.86	12.86	12.86

Fig. 3. Map of annual upper thermal thresholds (highest annual average maximum average weekly temperature) at USGS gages below selected federal reservoirs of the Pacific Northwest. Gages with heavy outlines have salmonid spawning as a designated beneficial use during some part of the year; the rest are not used by migratory fish for spawning but provide habitat for coldwater fish communities and/or serve as migration corridors for anadromous fishes. The inset table lists upper thermal thresholds (°C) for dams and gages in coastal Oregon with a different threshold during the spawning season (lighter green).

tailwaters (Washington, Oregon) have a higher year-round threshold as they do not support spawning of ESA-listed salmonids. Instead, they are used as migration corridors by anadromous species (Fig. 3).

We used the maximum weekly average temperature for the warmest 7-d period (MWAT) as a metric because average daily temperatures were available below more reservoirs than extreme temperatures were (in rare situations where average daily temperatures were missing, we imputed them using the average of minimum and maximum daily values). MWAT is used as the thermal water standard for many states, although other metrics have significant advantages and may be adopted in future (McCullough, 2010). In some cases, we converted other criteria (e.g., maximum daily average (MDAT), maximum daily maximum (MDMT), maximum weekly maximum (MWMT) [mean of weekly maxima, for warmest 7-d period]) to MWAT (Essig et al., 2003).

Minimum flow thresholds below reservoirs are more varied and complex than thermal criteria. For privately-owned hydropower projects, flow regulations depend on the anticipated hydrologic-year type, which is estimated based on the previous year's snowpack and other short-term indicators of future inflows. In some states (e.g., Idaho), reservoirs may not have legal obligations to maintain minimum flows. Although rule curves exist for most federal reservoirs, these are not easily accessible and may not be reflected in historical operations. Laws governing the timing of reservoir releases are complex, involving prior water rights for irrigation and other purposes, Biological Opinions under the Endangered Species Act, and authorizing legislation for flood control. Given this complexity, a historical estimate provides a workable solution. We estimated MWAQ thresholds from *Qw* below each reservoir during the historical period.

2.6. Duration modeling of species-specific risk

The focus of this study is on risk associated with violating regulatory thresholds, regardless of duration. However, the duration of extreme events is important when assessing ecological risk. For example, the stressful impacts of high temperatures on salmonids increase with duration. In streams where diurnal (or other) fluctuations in temperature limit exposures, individuals are able to recover and therefore tolerate higher temperatures (Farless and Brewer, 2017). By contrast, longer exposures increase risk of infection and growth of pathogenic diseases or parasites that can contribute to pre-spawn and incubation mortality (Tillotson and Quinn, 2017).

To facilitate future species-specific risk modeling, we calculated the average duration of violations measured in weeks (Fig. 1, box 5). Although not fully modeled here, we present the methodology for using these duration estimates to assess changes in survival for salmonids. For a particular species of concern, one can estimate survival as a function of duration information to measure the exposure to stress. In the case of flow, this might use relationships between survival and the duration of dewatering of redds (nests). For exposure to high temperatures, laboratory experiments can be used to quantify the duration of time to 50% or 100% mortality (upper lethal temperatures). For example Selong et al. (2001) developed relationships between exposure duration of bull trout based on 60-d trials. For fall Chinook salmon, Jager (2011) used similar relationships to develop a multiplicative model for survival that assumed independence among time periods. This kind of information can be used to evaluate risk to individual species of concern as a function of the duration of exposure under future climate scenarios.

2.7. Bayesian uncertainty

As a last step, we developed *post hoc* logistic models of projected risk from the hybrid models (Fig. 1. box 5c) (Gelman and Hill, 2007). This *post-hoc* modeling allowed us to: 1) understand how risk differences varied in response to covariates (effects of site and season), 2) 'test' for a change in risk (credible intervals on the indicator variable for time period), and 3) simplify communication of results (i.e., to aggregate results for all combinations of two periods, 52 weeks, 10 GCMs, and 20 or 23 sites). Note that a periodic function of day-of-year, *t*, was used as a temporal sinusoidal smoother to describe seasonal patterns.

We extended the approach suggested by Kuss (2015) to evaluate the influences of season (week of the year), and time period (baseline vs. future) on risk. We identified a model form for risk, $p_k = E\,(Y_k/n_k)$ that could represent nested variance structure in the simulation design (i.e., multiple models) by specifying both fixed and random effects, Eq. (5). Let Y_k , a binomial random variate, B $(\boldsymbol{n_k},\ \boldsymbol{p_k})$, represent the number of years with extreme events (i.e., above temperature threshold or below flow threshold) for n_k simulated replicate years. After expanding the simulated data to a binary form (i.e., threshold exceeded or not), we used the R-package 'glmer' to model risk proportions, $\boldsymbol{p_k} = Y_{\boldsymbol{k}}/n_{\boldsymbol{k}}$, where n_k = number of years, specifying a logit link function, g (Eq. (5)). Vector **k** indicates the case [i.e., site, week-of-year *t*, and time period (baseline or future)]. The model included random effects, **b**, on the model intercept for GCM. Mixed models of the form shown in Eqn (5) were used to compare risk with and without GCM influences on the intercept.

$$
\begin{gathered}
g\,(p_k) = \log\left(\frac{p_k}{1-p_k}\right) = \mathbf{x}'\mathbf{b} + \mathbf{y}'\boldsymbol{\beta}, \\
\text{where}\,\mathbf{b} \sim \mathbf{N}(\mathbf{0},\,\sigma^2\mathbf{I}),\ x = I\,(GCM)\,(\text{random effect}) \\
\mathbf{y}_k = \begin{cases} I\,(period) \\ I\,(site) \\ \sin\left(\frac{2\pi t}{52}\right) \\ \cos\left(\frac{2\pi t}{52}\right) \end{cases} \text{for case}\ \ \mathbf{k} = \{\text{period, site, t}\}
\end{gathered}
\tag{5}
$$

To characterize uncertainty, we re-fitted the model using a Bayesian approach with the R-package, 'stan.glmer' (Stan Development Team, 2016). We specified weakly-informative priors recommended by Gelman et al. (2008) as follows. We assigned the intercept a T-distribution centered at zero with degrees of freedom, df = 7 and scale = 10. For all parameters that did not vary by case, we used a T-distribution with df = 1 and scale = 10 as the prior. For the random effects (GCM-specific intercepts), we specified a gamma prior distribution with shape parameter = 10 and scale = 1 on parameters of the covariance matrix. Two independent chains sampled each posterior distribution by using Hamiltonian Markov Chain Monte Carlo (MCMC). We simulated each chain for 5000 iterations with a warmup period of 2000 iterations and determined that two MCMC chains converged (see SI). Uncertainty was quantified by the posterior distributions of modeled (temporally smoothed) risk based on 3000 draws of one chain for each variable. Convergence was evaluated in three ways, 1) by comparing overlap among chains (Fig. S.1), 2) evaluating overlap between final posterior distributions (Fig. S.2), and 3) ensuring that *Rhat* statistics comparing chains were within 0.1 of 1 (Sorensen et al., 2016).

We present the posterior distribution of the coefficient *Is.mid* [*I(period)* in Eq. (5)], which measures the effect of climate period (baseline versus future) on risk. When this distribution does not overlap zero, the climate signal is strong enough to be detected despite year-to-year variation and other sources of uncertainty in RCVA risk estimates. We also produced ridge plots to visualize the posterior distributions of risk by month (averaged over site, GCM, and week).

3. Results

3.1. Model-data comparisons

To evaluate the effectiveness of using empirical correction, we compared hybrid simulated *Tw* and *Qw* for the control run (Daymet drivers, 1966 to 2004) against corresponding measured values based on data from USGS gauges (Fig. 1, box 1c and d). We use two measures of goodness of fit for model predictions. The root-mean-square-error (RMSE) measures accuracy as the magnitude of residual error in the original units (e.g., °C or log-cms) and is essentially a measure of bias. Correlation measures the strength of the

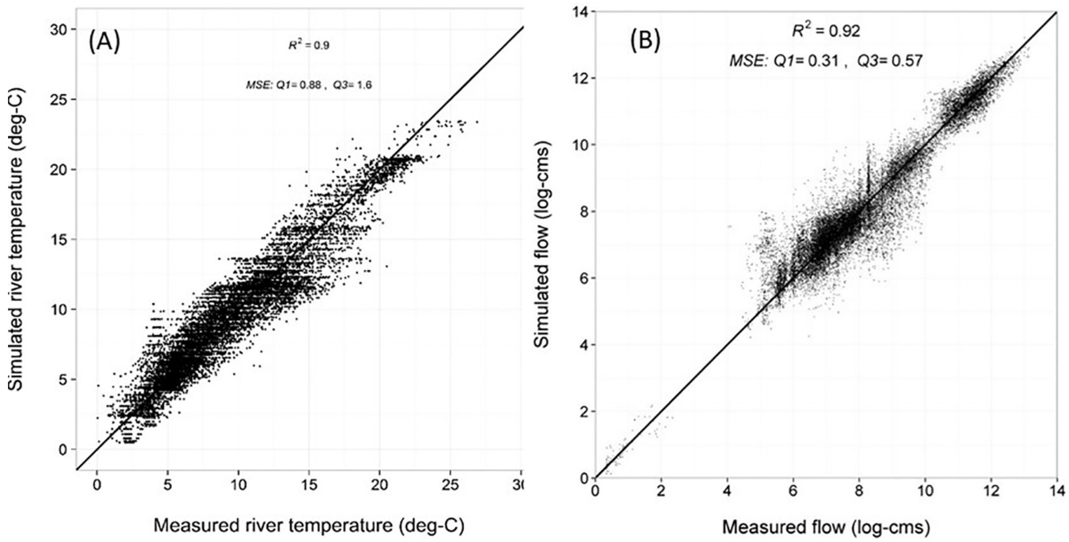


Fig. 4. Comparison of measured and hybrid-model simulated (A) weekly minimum temperature (*Tw*, °C) and (B) log weekly minimum average flow (*Qw*, cms) for the control run for the period 1966–2004.

linear association between predicted and measured values and varied between 0.81 and 0.99 for individual gages. The skill of the hybrid models is illustrated for water temperature (Fig. 4A) and flow (Fig. 4B) in PNW tailwaters. For *Tw*, median RMSE was 1.26 °C, with inter-quartile range 0.88–1.6 °C. For log-transformed *Qw*, median RMSE was 0.36 with inter-quartile range 0.31–0.57 log-cms. Uncertainty in the model performance is reflected in the vertical spread of data points in Fig. 4.

3.2. Reservoir effects on water temperature

Estimated parameters for Eq. (3) describe the effect of historical reservoir operations on water temperatures (Table 2). Parameter δ_m estimates change in average annual temperature. Compared with water temperatures simulated by the process-based EWT model, measured tailwater temperatures were lower (δ_m), with damped amplitude (δ_A) and an average thermal lag of more than three weeks (δ_Φ). An inverse relationship was evident across gages between change in amplitude and thermal lag (Fig. 5).

3.3. Future scenario projection

For 14.5% of weeks-GCM-gages, we projected risk of exceedance to be higher under the future scenario. An aggregated rose diagram shows that the average risk of weekly temperatures, *Tw*, exceeding MWAT thresholds was highest between spring and fall, and that there were no months with a net decrease in risk (Fig. 6A). At several sites risk (frequency of exceedance events) in early summer increased by 0.2, as shown by site-specific rose diagrams (Fig. S.3A).

Our results suggest that annual future risk of violating historical thresholds will change for weekly minimum average flow. However, risk differences for *Qw* were less than 4%. Site-specific rose diagrams showing differences among sites are presented in Fig. S.3B. When averaged across sites, the risk of below-threshold flows showed a pattern of higher risk from fall to summer and lower risk from spring and late winter (Fig. 6B). The magnitudes of change in risk associated with historical minimum-flow thresholds were considerably lower than those for water temperature criteria (mean 0.07 versus 0.27).

Duration was also calculated from simulated results. The average change in the duration of extreme events for below-threshold flows was 4.6 d and the average change for high temperature exceedances was 10.3 d. The geographic distributions of changes in duration are presented (Fig. 7). Durations increased least in the lower Columbia River basin and two sites in Montana. Durations of low-flow events were projected to increase in the Upper Columbia, Upper Snake, and Willamette Basins. Sites with notable increases

Table 2
Average estimated parameters for Eq. (2) quantify seasonal shifts in temperature associated with reservoir and other local influences leading to differences in seasonal patterns between EWT simulated temperatures (control simulations) and measured tailwater temperatures. Gage specific values can be obtained from the corresponding author.

River basin	m (°C)	A	Φ	δ_m	δ_A	δ_Φ
Mountain/Upper Columbia	9.47	12.40	14.74	−2.06	−6.60	5.41
Interior Snake	12.90	14.90	15.00	−3.90	−7.13	3.87
Columbia	14.05	13.82	14.29	−0.88	−4.16	3.28
Coastal	12.99	11.67	14.62	−3.96	−7.21	4.52

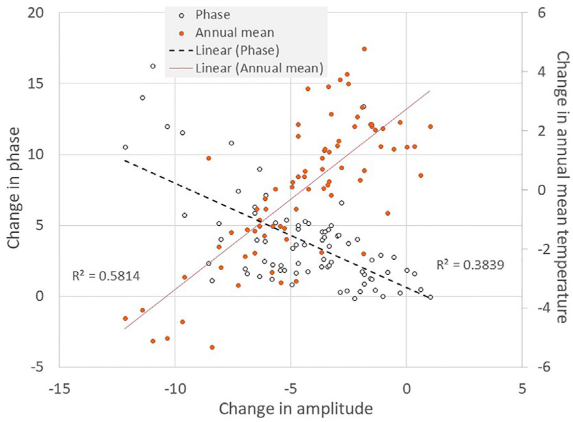


Fig. 5. Reservoir effect on seasonal patterns in tailwater temperatures as estimated by deltas in Eq. (3) for gages below federal reservoirs in the Pacific Northwest. Generally, the seasonal amplitude (°C) and annual average temperature (filled circles) decreased and the phase shift (lag in d, open circles) increased.

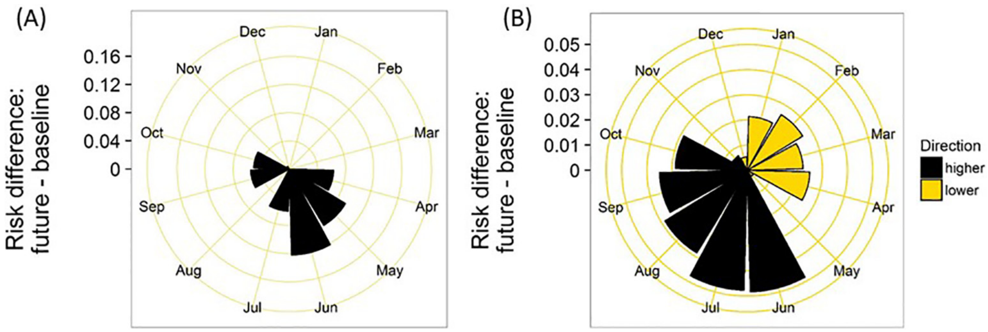


Fig. 6. Aggregate (mean) seasonal patterns of change in risk of A) exceeding MWAT and B) falling below mean weekly average flow, MWAQ based on the RCVA hybrid model for tailwaters. Note difference in scale. Black wedges indicate increases and gold wedges indicate average decreases in risk from the baseline to future period.

in the duration of high temperatures were one gage in the Middle Fork Willamette River (14145500) and two tributaries of the Middle Snake River (13206000 and 13190565) (Fig. 7).

3.4. Bayesian uncertainty

3.4.1. Preliminary analyses

We compared mixed models with site as a fixed and random effect, and with GCM as a random nested effect or excluded (due to low variance). For water temperature, the model with site as a fixed effect and GCM as a random effect produced the lowest AIC [122,924 versus 124,165 (random site, nested GCM model), 124,165 (random, crossed site and GCM model), and 123,333 (random site model without GCM)]. The same model form (site as fixed effect) was adopted for flow.

3.4.2. Bayesian posteriors

Posterior distributions are valuable for assessing whether the effects of covariates and the magnitudes of projected changes in risk are large relative to hybrid-model uncertainties, as represented by our Bayesian hierarchical model. Convergence was demonstrated by the overlap in two MCMC chains (Fig. S.1) and the posterior distribution of parameters associated with them (SI Fig. S.3). We achieved an *Rhat* very near one for all parameters estimated indicating that the chains converged in fitting the seasonal risk models for both water temperature and flow. Having satisfied ourselves that the chains have converged, we reported parameter estimates and credible intervals for all parameters (Tables S.3 and S.4) derived from posteriors from two chains.

We tested for a detectable change in risk between the baseline and future period. The lack of overlap with zero of the posterior distribution of *Is.mid* gives us confidence that the risk of extreme events will increase for water temperature (Fig. 8A) and for flow (Fig. 8B).

In addition to providing credible intervals on parameters, the Bayesian model produced posterior distributions that approximate uncertainty associated with RCVA risk projections. An example of series of posteriors by month is shown in Fig. 9. The posterior distributions for temperature exceedances were bimodal from spring to fall (Fig. 9A). Risk of below-threshold flows were generally lower in magnitude (Fig. 9B).

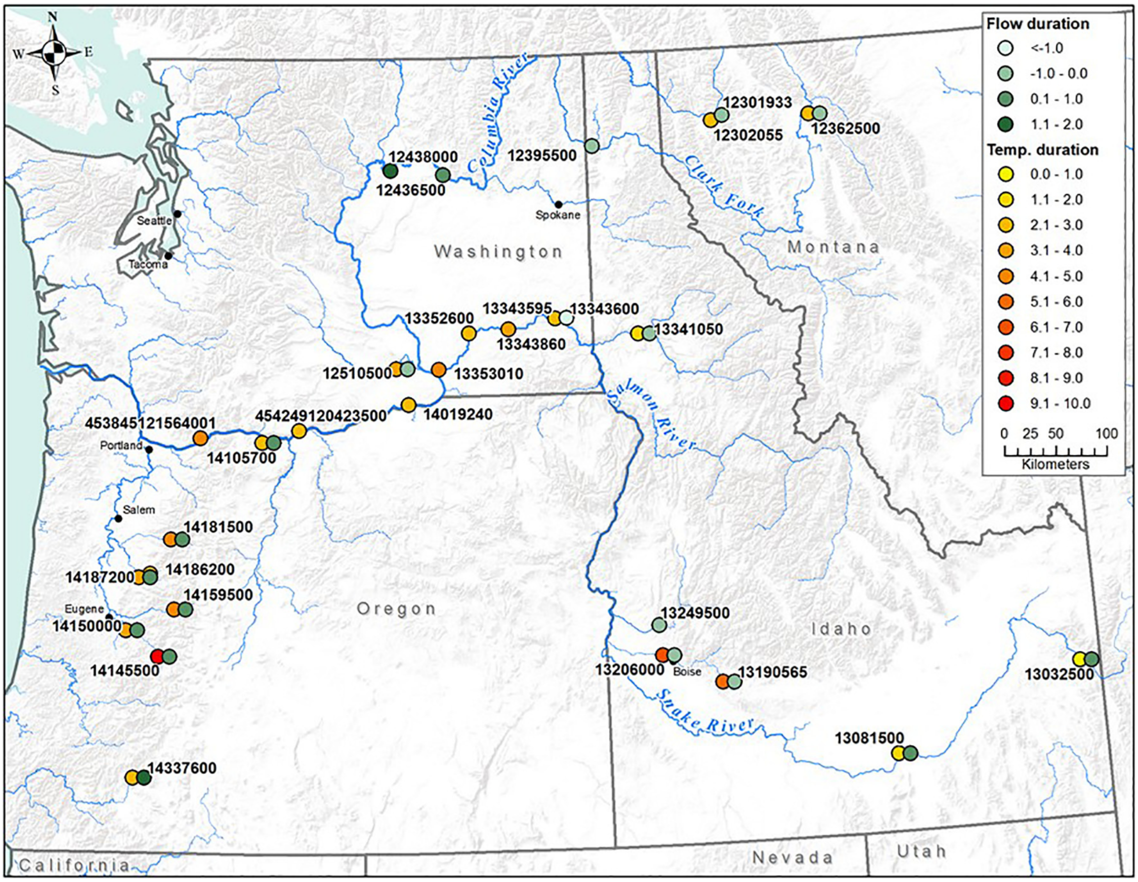


Fig. 7. Map of gages identified by USGS id. Symbols indicate the projected change in the average duration (weeks) that weekly maximum of average daily temperature thresholds (MWAT, °C) were exceeded and that minimum flows fell below minimum weekly average daily flow thresholds (MWAQ, cms). At several gages, we had data for one variable but not the other.

4. Discussion

When deciding where and when to mitigate, it is important to know where thresholds are in danger of being crossed (Wu and Skelton-Groth, 2002). This will be especially important in a non-stationary future. The RCVA framework described here can be used to implement threshold-based management to reduce vulnerabilities (Liu et al., 2015). Here, we evaluated seasonal and spatial patterns to understand when and where water thresholds will be most at risk of being violated under a future climate scenario. We found that risk was projected to increase most during spring and fall, with the maximum monthly averages of weekly changes for individual sites just under 0.2 (Fig. 7; Fig. S.3A). Under the future scenario, we found that risk and duration of events exceeding thermal thresholds increased most in coastal tailwaters that support salmonid spawning and in tributaries of the Middle Snake River basin (Fig. 7).

Previous projections have suggested that lower flows and warmer stream temperatures may coincide during summer (Beechie et al., 2013; Miles et al., 2000; Wu et al., 2012). This is a concern because episodes of warm temperature and drought would elevate thermal stress on aquatic biota (Battin et al., 2007; Wu et al., 2012). Here, tailwaters were projected to experience co-occurring risks from spring to fall. However, projected changes in risk of low-flow violations were not as large as those projected for temperature. Increases in risk were less than 0.05 for flow (Fig. S.3B) and the maximum increase in duration of low-flow events was ∼eight days (Fig. 9).

Reservoir releases to meet thermal requirements of cold-water biota in summer (the season for which we projected the highest risk) coincide with times when human demand for hydropower generation of electricity for cooling is high. This demand is likely to follow the same pattern projected by our increase in risk by extending into late spring and fall. However, timing the release of the cold-water block to lower temperatures in fall might present a significant future challenge (Marce et al., 2010; Matthews et al., 2015). Where water storage is limited, winter releases may be needed to meet flood-control requirements (Lanini et al., 2014; Raymondi et al., 2013). As a result, less stored water would be available to protect fish in spring and fall (Miles et al., 2000; Mote et al., 2003; Payne et al., 2004).

Increased risks of elevated temperatures are likely to have high biological significance for ESA-listed salmonids. Not only do high

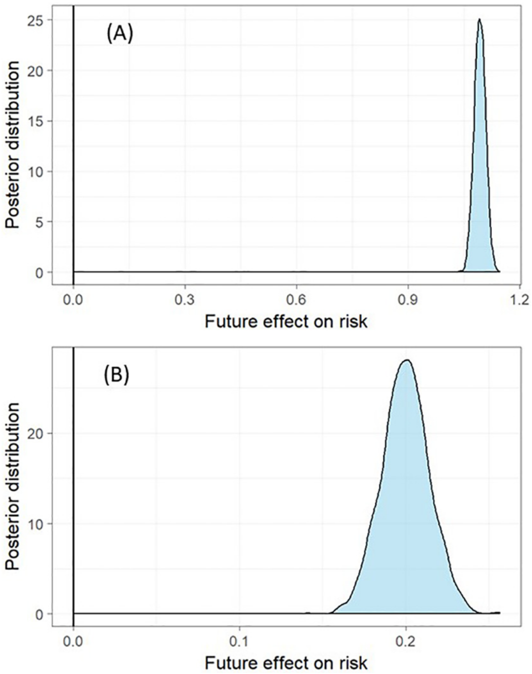


Fig. 8. Posterior distributions of parameter *Is.mid,* which indicates the effect of future period (0 = baseline; 1 = future) on risk. Note that there is zero credibility associated with *Is.mid*, having a zero or negative effect on the risk of (A) exceeding weekly maximum average temperature (MWAT, °C) or (B) extreme low flows (MWAQ, cms).

water temperatures have direct effects, but indirect adverse effects are mediated by dissolved oxygen (lower saturation) and disease (McCullough et al., 2009). The coastal Willamette River basin and the Columbia River basin provide habitat for migratory steelhead and salmon. The seasons during which we project increased risk are biologically important for steelhead that spawn in spring and other migratory salmon that spawn in summer and fall (e.g., fall and spring Chinook salmon, sockeye salmon (*O. nerka*), coho salmon (*O. kisutch*)). High temperatures can delay upstream migration and cause degradation of eggs carried by females (Ferre et al., 2012; McCullough et al., 2009). High pre-spawn mortality has been linked to thermal experience of adult sockeye salmon, particularly at high densities when dissolved oxygen is depleted (Tillotson and Quinn, 2017).

Inland basins (e.g., the Snake River, Idaho) support resident salmonids such as bull trout. Bull trout have the lowest thermal requirements among North American salmonids. Fifty percent of bull trout were killed by exposure to water temperatures above 20 °C for 60 days (Selong et al., 2001). Salmonids typically move upstream into tributaries or to areas with groundwater influence, seeking optimal thermal conditions for spawning. Consequently, spawning populations of bull trout are rarely found where summer temperatures exceed 13 °C (Jones et al., 2014). In tributaries of the Snake River basin, Idaho, simulated future temperature-exceedance events spanned an additional five to six weeks compared to the baseline period (Fig. 9). In Idaho tailwaters that support bull trout spawning, this increased duration might cause populations to retreat to cooler headwaters (Eby et al., 2014; Rieman et al., 2007).

4.1. Climate adaptation

This study adds to a growing body of evidence that measures should be considered to reduce risk to aquatic life in the PNW. Conservation plans for ESA-listed species now address threats posed by climate change (McClure et al., 2013; NOAA Fisheries, 2014). Ensuring that populations have access to thermal refuge is one logical priority. As a general rule, barriers to thermal mixing (including dams) help to maintain thermal heterogeneity and cold-water refuges (Jager et al., 1999; McCullough et al., 2009). However, barriers to movement should be avoided because they prevent fishes and other species from tracking suitable habitat. Dams located in headwaters would provide additional upstream storage (to replace snowpack) without impeding fish movements (Jager et al., 2015).

Consistent adaptation in the way hydrosystems can be managed to avoid risks identified here. Although the basic seasonal template for reservoir operation is unlikely to change (e.g., winter drawdown), regulation to moderate untimely low flows and shifts in the timing of pulse or augmentation flows might be needed to moderate temperatures during migration (Buccola et al., 2013; Poff et al., 2016). In tailwaters, temperature-control features at dams, such as selective-depth reservoir withdrawal and cooling, can be used to avoid downstream violations in water quality during critical times (Buccola et al., 2013). Off-channel mitigation involving watershed management might also be important. For example, actions that promote groundwater recharge, riparian zones that provide shading to headwater streams (Wu and Skelton-Groth, 2002), and management of wildfires (Isaak et al., 2010; Rosenberger et al., 2015) are all relevant to maintaining suitable instream habitat for spawning salmonids. Hatcheries, which produce a significant fraction of salmonids, use water sources that may also be impacted by rising temperatures (Hanson and Ostrand, 2011).

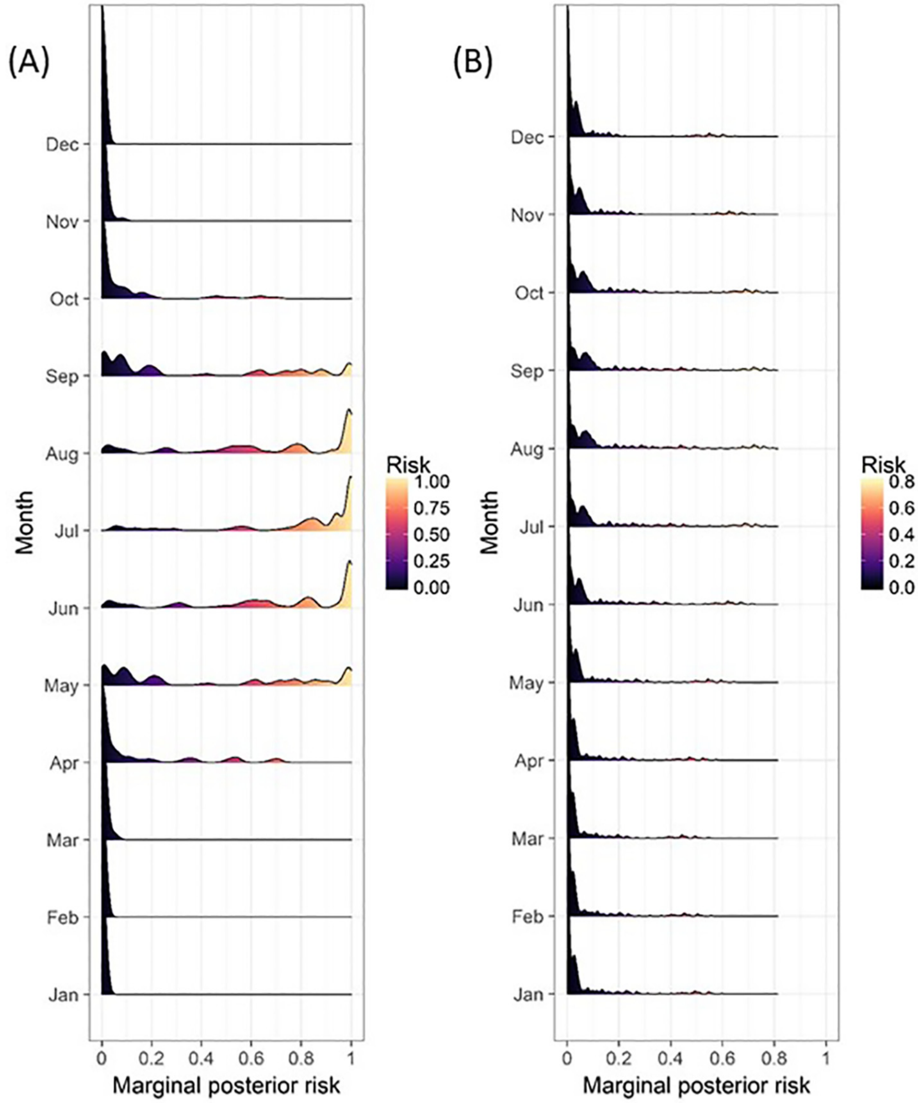


Fig. 9. Ridge plots for the marginal posterior distribution of risk of (A) exceeding weekly temperature thresholds (MWAT, °C) and (B) falling below weekly flow thresholds (MWAQ, cms) for the future scenario. Distributions describe variation among replicates in average risk for sites, GCMs and weeks within a month.

4.2. Future directions

We see three future opportunities for improving or extending RCVA. These include 1) refining the 'reservoir' model, 2) assembling national-scale information on minimum flow requirements or standards, and 3) bridging from assessments based on regulatory thresholds to assessment of species-specific risks through duration modeling (illustrated below).

A main advantage of the RCVA framework presented here is the ability to produce well-founded climate-risk projections at large regional scales without complex integrated physical models of reservoir systems that require proprietary information or information not available at national scale from US agencies such as the US Corps of Engineers. The approach here assumed that the reservoir 'transform' of temperature would not change under future climate due to in-reservoir processes or changes in operation. It may not be unreasonable to assume a continued pattern of seasonal releases, which are constrained by legal requirements. However, further adjustments to the model, including perhaps a more mechanistic representation, would be needed to evaluate scenarios that involve future changes in reservoir stratification or operation, especially when near thresholds. This might be accomplished by summarizing responses simulated by process-based models to operations for a taxonomy of hypothetical reservoirs with attributes such as upstream storage volume, type of operation (Jager and Bevelhimer, 2007; McManamay et al., 2016), or configuration (elevation) of dam-release infrastructure. While our results are informative, analysis with more process-based modeling of the reservoir physics and operations will be required to evaluate the assumptions we have made here.

A second future need is to improve the specificity of regulatory thresholds or standards (especially for flow) or, alternatively, to translate from durations of extreme events based on regulatory thresholds to biological threats to specific species of local concern. Our risk assessment for flow measures where and when flow conditions under the future scenario are likely to elevate (or lower) stress for aquatic biota compared with past flows, but this should not be construed as an assessment of regulatory risk. Collection of minimum flow requirements of private hydropower dams, ancillary data such as snowpack needed to define them, and reservoir elevations across the US would allow further refinements of risk assessments.

Finally, regional risk assessments focused on species of concern are possible when projected changes in duration are estimated. An approach is outlined here, but additional research and data are needed to carry out a full ecological risk assessment. Research to understand regional differences in competing seasonal water demands and national-scale monitoring data to track water will be important when developing strategies to reduce future vulnerabilities, and relevant information can help owners of hydropower projects to consider future climate as part of the relicensing process in the US (Viers, 2011).

5. Conclusions

In this study, we demonstrated the use of regional climate vulnerability assessment (RCVA) to characterize risks associated with changes in water temperature and flow in tailwaters of reservoirs across a large region for a future scenario. This scenario is assumed to continue past seasonal patterns of reservoir operation and continued regulatory thresholds for water temperature (and standards for flow). We also projected changes in the duration of extreme (above- or below-threshold) events and indicate how these might be used to evaluate risk to individual species. Although tailwaters have been touted as potential thermal refuges, our results showed a higher risk of thermal exceedances (average of +0.27) extending into in late-spring and fall and over longer durations (average change of 10.3 d). For flow, RCVA projected an increase of 0.07 in the average risk below-thresholds flows, with an average increase in duration of 4.6 d. We highlight the significance of these projected risks for ESA-listed salmonids in the Pacific Northwest and suggest future refinements to the RCVA approach needed to address questions about climate adaptation.

Conflicts of interest

We confirm that the results presented here were not influenced by any potential conflicts of interest associated with funding source.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.crm.2018.07.001.

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