Climate change and stream temperature projections in the Columbia River basin: habitat implications of spatial variation in hydrologic drivers

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Abstract

Water temperature is a primary physical factor regulating the persistence and distribution of aquatic taxa. Considering projected increases in air temperature and changes in precipitation in the coming century, accurate assessment of suitable thermal habitat in freshwater systems is critical for predicting aquatic species responses to changes in climate and for guiding adaptation strategies. We use a hydrologic model coupled with a stream temperature model and downscaled General Circulation Model outputs to explore the spatially and temporally varying changes in stream temperature for the late 21st century at the subbasin and ecological province scale for the Columbia River Basin. On average, stream temperatures are projected to increase 3.5 °C for the spring, 5.2 °C for the summer, 2.7 °C for the fall, and 1.6 °C for the winter. While results indicate changes in stream temperature are correlated with changes in air temperature, our results also capture the important, and often ignored, influence of hydrological processes on changes in stream temperature. Decreases in future snowcover will result in increased thermal sensitivity within regions that were previously buffered by the cooling effect of flow originating as snowmelt. Other hydrological components, such as precipitation, surface runoff, lateral soil water flow, and groundwater inflow, are negatively correlated to increases in stream temperature depending on the ecological province and season. At the ecological province scale, the largest increase in annual stream temperature was within the Mountain Snake ecological province, which is characterized by non-migratory coldwater fish species. Stream temperature changes varied seasonally with the largest projected stream temperature increases occurring during the spring and summer for all ecological provinces. Our results indicate that stream temperatures are driven by local processes and ultimately

require a physically-explicit modeling approach to accurately characterize the habitat regulating the distribution and diversity of aquatic taxa.

1. Introduction

The temporal and spatial variability of stream temperature is a primary regulator of the life-history, behavior, ecological interactions, and distribution of most aquatic species (Peterson and Kwak, 1999). For example, metabolic processes in ectothermic freshwater organisms (e.g., fishes, amphibians, invertebrates) are directly regulated by water temperature (Angilletta, 2009), and thus the persistence of populations and the rate of energy flow through aquatic ecosystems is dependent on the thermal characteristics of a local habitat (Woodward et al., 2010). Moreover, much like terrestrial species, the timing of important life-history traits such as reproduction and migration is heavily dependent on seasonal thermal regimes (Johnson et al., 2009; Woodward et al., 2010). Additionally, stream temperature plays a large role in chemical kinetic rates and is important for governing stream management for recreation as well as urban and industrial water supplies. Therefore, to better understand hydrologic systems and to better manage water resources in a changing environment, it is critical to predict the potential effects of climate variability and change on stream temperature, and to characterize how these changes affect the distribution and diversity of freshwater taxa.

Potential impacts of climate change on stream temperatures have been widely estimated using field investigations and modeling studies (Webb and Nobilis, 1994;Mohseni et al., 2003;Caissie, 2006;Hari et al., 2006;Nelson and Palmer, 2007;Webb et al., 2008;Isaak et al., 2010;van Vliet et al., 2011;Null et al., 2013;Ficklin et al., 2013). At larger spatial scales, regional regression models have been used to predict the impacts of climate change on stream temperatures (Mohseni et al., 1998;Mohseni and Stefan, 1999;Mohseni et al., 1999;Erickson and Stefan, 2000;Bogan et al., 2003;Webb et al., 2003;Stefan and Preud'homme, 1993). However, regression methods are not sufficient predictors of stream temperature because they do not account for hydrologic component inputs to the stream such as snowmelt, groundwater, and surface runoff (Constantz et al., 1994;Constantz, 1998;Pekarova et al., 2008;Ficklin et al., 2012;MacDonald et al., 2014). Neglecting these components severely limits the ability of regression-based models to accurately predict spatial variability in stream temperature changes, since the contributions of different sources to streamflow will be modified in a changing climate. Ignoring the distinct characteristics of different sources to streamflow therefore negatively impacts the assessment of the effects of climate change on aquatic biodiversity at landscape (and larger) scales.

To adequately capture the role of changing hydrology from a changing climate on stream temperature, numerical (Isaak et al., 2010; Kim and Chapra, 1997;Sinokrot and Stefan, 1994) and analytical (Null et al., 2013;Tang and Keen, 2009;Edinger et al., 1974) stream temperature models, in conjuction with hydrologic models, have been applied with success. These models allow stream temperature assessments at the local or regional level. For example, our prevous work in the Sierra Nevada mountain range in California found subbasin-scale stream temperature differences from region-to-region largely from localized changes in hydrology from changes in climate. Additionally, Null et al. (2013) found increasing stream tempreatures with increasing elevation due to the transition from snow- to rain-dominated, an effect opposite what would be predicted by a model based solely on air temperature

The primary objectives of this work are to [1] predict changes in stream temperature over the coming century across the Columbia River Basin at the ecological province level, [2] identify the contribution of specific hydrological components (such as snowmelt, surface water runoff, etc.) to the overall heat and water budget across the watershed, and [3] add to the literature regarding the role of changing hydrology on changes in stream temperature. Specifically, we aim to demonstrate the extent to which future changes in hydrology—streamflow, surface runoff, snowmelt, groundwater inflow, and lateral soil flow as simulated using global climate projections at the subbasin scale— could critically affect changes in localized stream temperatures, which are of high importance for aquatic species. The Columbia River Basin is a snowmelt-dominated region, where projected increases in global air temperatures are expected to result in early snowmelt runoff. These changes lead to reduced late spring and summer water discharges that change the thermal content of stream flow. Moreover, previous stream temperature assessments indicate that the Columbia River Basin is sensitive to changes in climate (Mantua et al., 2010;Chang and Psaris, 2013; Luce et al., 2014); these sensitivities vary spatially and are governed in part by the land use, hydroclimate and topographic variables of the local region (Chang and Psaris, 2013).

We use a landscape-scale hydrological model—the Soil and Water Assessment Tool (SWAT; Arnold et al. (1998))— combined with a stream temperature model that simulates stream temperature based on the effects of subbasin air temperature and hydrology.(Ficklin et al., 2012). The SWAT model efficiently represents snowmelt and runoff processes, and also incorporates a full range of water quality processes (Gassman et al., 2007). SWAT has been found to accurately simulate streamflow in regions where snowmelt dominates the hydrology (Wang and Melesse, 2005; Watson and Putz, 2012; Zang et al., 2012). Downscaled output from seven General Circulation Models (or Global Climate Models, GCMs) using one representative concentration pathway (RCP) associated with a trajectory of future greenhouse gas accumulation in the atmosphere for the late-21st century was used to drive the calibrated SWAT model at the subbasin-scale. For all Columbia River Basin ecological provinces, we spatially and temporally explore the changes in stream temperature, and interpret these changes with respect to changes in the hydrologic system.

2. Materials and Methods

2. 1 Study area

The CRB encompasses portions of seven states in the western United States and the Canadian province of British Columbia. The CRB for this study is defined as the area that flows into the The Dalles, Oregon (Figure 1) and has a surface area of 613,634 km^2. The water resources in the CRB have been extensively developed in the past 70 years for hydroelectric power, agricultural irrigation, and urban use. The CRB study area has been extensively discussed in Hatcher and Jones (2013), Mantua et al. (2010), and Payne et al. (2004).

Subbasins were aggregated into ecological provinces according to designations Northwwest Habitat Institute (N.H.I., 2008). Ecological provinces are delineated based on species composition within the region and environmental conditions. Because the ecological provinces do not expand into Canada, we extrapolated the boundaries based on watershed delineations. The ecoprovince areas (Figure 1) for this study average 68,000 km^2 and range from 300 km^2 (Columbia Gorge) to 145,000 km^2 (Mountain Columbia). For descriptive purposes, we further characterize ecological provinces as either ‘warmwater’ (Centrarchidae – bass, bluegill, crappie; Percidae – perch, walleye), ‘coldwater migratory’ (Salmonidae – salmon, steelhead, trout], and ‘coldwater non-migratory’ (Salmonidae – trout, whitefish) (Table 2), based on predominant focal fish species (N.H.I., 2008).

2.2 Modeling stream flow and water quality using SWAT

We used the SWAT model coupled with a stream temperature model to predict streamflow and stream temperature throughout the Columbia River Basin at an average spatial resolution of 250 km^2. SWAT is an integrative, mechanistic model that utilizes inputs of daily weather, topography, land use, and soil type to simulate the spatial and temporal dynamics of climate, hydrology, plant growth, and erosion (Arnold et al., 1998). Within SWAT, surface runoff and soil water infiltration were simulated using the modified Curve Number method (Neitsch et al., 2005). The Penman-Monteith method was used to estimate potential evapotranspiration. Stream temperature was simulated using the Ficklin et al. (2012) SWAT stream temperature model that uses local air temperature and hydrology for stream temperature estimation:

$$T_{w,local} = \frac{(0.1 \cdot sub\_snow) + (T_{gw} \cdot sub\_gw) + \lambda(T_{air,lag} \cdot (sub\_surq + sub\_latq))}{sub\_wyld} \qquad [1]$$

where *sub_snow* is the snowmelt contribution to streamflow within the subbasin (m^3), *sub_gw* is the groundwater contribution to streamflow within the subbasin (m^3), *sub_surq* is the surface water runoff contribution to streamflow within the subbasin (m^3), *sub_latq* is the soil water lateral flow contribution to streamflow within the subbasin (m^3), *sub_wyld* is the total water yield (all contributing hydrologic components) contribution to streamflow within in the subbasin (m^3), T_{gw} is the groundwater temperature (°C; annual average input by user), and $T_{air,lag}$ is the average daily air temperature with a lag (°C), and λ is a calibration coefficient relating to the relative contribution of the surface water runoff and lateral soil water flow to the local water temperature and is included to aid in calibration in case of improper hydrologic model calibration. The lag (days) is incorporated to allow the effects of delayed surface runoff and soil water flow into the stream. The 0.1 in Equation [1] represents the assumed temperature of snowmelt (0.1 °C).

After stream temperature of the local contributing water is determined, the stream temperature before the effects of air temperature is determined by:

$$Twater_{intial} = \frac{T_{w,upstream} * (Q_{outlet} - sub\_wyld) + (T_{w,local} * sub\_wyld)}{Q_{outlet}}$$

[2]

where $T_{w,upstream}$ is the temperature of the streamflow entering the subbasin (°C) and Q_{outlet} is the streamflow discharge at the outlet of the subbasin.

The final stream temperature is calculated by adding a change to the initial stream temperature in the subbasin from differences between stream and air temperature and travel time of water through the subbasin. Depending on T_{air}, the final stream temperature is estimated as*:*

$$T_{water} = Twater_{intial} + (T_{air} - Twater_{intial}) * K * (TT) \quad if\ T_{air} > 0 \qquad [3]$$

$$T_{water} = Twater_{intial} + ((T_{air} + \varepsilon) - Twater_{intial}) * K * (TT) \quad if\ T_{air} < 0 \qquad [4]$$

where T_{air} is the average daily air temperature (°C), K is a calibration conductivity parameter, TT is the travel time of water through the subbasin (hour) and is calculated from the SWAT simulations, and ε is an air temperature addition coefficient (°C), which was included to account for water temperature pulses when T_{air} is below 0°C. For the case when the effects of Tair and the hydrologic contributions are such that the final is T_{water} < 0°C, the stream temperature model sets T_{water} to 0.1 °C. T_{water} is also assumed to be the temperature of water discharge to downstream subbasin, and is further routed along the stream network. The calibration parameter, K, acts as a proxy for reach-specific adjustment of the radiative forcing, such as shading due to a vegetation canopy or geomorphic changes resulting in differing geometry. Additional details regarding the stream temperature model can be found in Ficklin et al. (2012).

2.3 Input Data

SWAT input parameter values for topography, land cover, and soils data were compiled from freely-available federal and state databases. A 30-meter Digital Elevation Model (USGS) formed the basis for watershed and sub-basin delineation. Soil properties were obtained from the STATSGO soil dataset. The 2001 National Land Cover Database was used for land cover/land use. Meteorological data (air temperature, precipitation, and wind speed) were extracted from Maurer et al. (2002) and relative humidity and solar radiation were generated within SWAT (Neitsch et al., 2005).The Columbia River Basin natural flow data that were used for streamflow calibration were obtained from output from a calibrated Variable Infiltration Capacity Model (VIC) model (from http://cses.washington.edu/) and the United States Geological Survey Hydro-Climatic Data Network (HCDN; Slack et al. (1993)). These data represent streamflow that would occur if no reservoirs or streamflow diversions were present within the basin. The HCDN is a hydrologic dataset developed to study surface water conditions throughout the United States that only fluctuate with changes in local climatic conditions and is therefore apt for use in climate change studies (Slack et al., 1993). SWAT was run at the monthly time step.

Climatic projections from seven GCMs (Table 1) and one RCP (8.5) were input into the calibrated SWAT model. Daily downscaled output from the seven GCMs (RCP 8.5) were obtained from the Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections archive (Maurer et al., 2013). RCP 8.5 represents the highest increase in radiative forcing of the Coupled Model Intercomparison Project – phase 5 (CMIP5; Taylor et al. (2011)) projections, and is based on an increased radiative forcing of 8.5 Wm^{-2} (relative to pre-industrial values) at the end of the 21st century. Downscaling was achieved using the daily bias-corrected and constructed analogs (BCCA) method (Maurer et al., 2010). In summary, the BCCA procedure consists of two steps. The first step is a bias correction using a quantile mapping technique which is applied to raw GCM output. Quantile mapping bias correction has been widely and successfully used in climate model downscaling (Wood et al., 2004). The bias correction step is followed by spatial downscaling using a constructed analogues approach for each day using a linear combination of days drawn from the historic record (Hidalgo et al., 2008). Maurer et al. (2010) found that the BCCA method consistently outperformed the Bias-Correction/Spatial-Downscaling method (BCSD) and the Constructed Analogues (CA) approach in capturing the daily large-scale skill and translating it to simulated streamflows that accurately reproduced historical streamflows.

2.4 SWAT streamflow calibration

The program Sequential Uncertainty Fitting Version 2 (SUFI-2; Abbaspour et al. (2007)) was used to automatically-calibrate SWAT streamflow at 104 sites in the Columbia River Basin (Figure 1). Initial and default SWAT model parameters were varied simultaneously until an optimal solution was met. Three statistics were used to evaluate model efficiency: [1] the Nash-Sutcliffe coefficient (Nash and Sutcliffe, 1970), [2] the coefficient of determination (R^2), and [3] a modified efficiency criterion (Φ). Φ is the result of the coefficient of determination, R^2, multiplied by the regression line slope, m (Krause et al., 2005). This statistic captures the discrepancy in the magnitude of the observed and simulated streamflow (captured by m) as well as the dynamics (captured by R^2). For all previously-mentioned statistics, a perfect simulation is represented by a value of 1. A split-sample approach was used for calibration and validation, and the calibration and validation periods differed at each streamflow gauge depending on streamflow data availability.

2. 5 SWAT stream temperature calibration

Monthly stream temperatures were predicted using the SWAT stream temperature model of Ficklin et al. (2012). This model includes the effects of hydrologic component inputs (e.g., snowmelt, groundwater, and surface runoff) on stream temperature. Previous studies have demonstrated that this stream temperature model performs better than linear regressions that use air temperature alone (Ficklin et al., 2013;Barnhart et al., 2014). The model requires four calibration parameters for each subbasin in the SWAT setup. Since the model is not incorporated into the previously mentioned SWAT-CUP software, we utilized the steady-state S-metric evolutionary multi-objective optimization algorithm (SMS-EMOA) to calibrate the stream temperature parameters after hydrologic calibration was performed (Emmerich et al., 2005;Beume et al., 2007). SMS-EMOA is an efficient and effective Pareto optimization evolutionary algorithm for finding solutions to multi-objective optimization problems. The algorithm seeks optimal solutions that maximize the hypervolume (S-metric)—which can be thought of as the volume of dominated space—and has been theoretically proven to converge to the Pareto set (Fleischer, 2003;Emmerich et al., 2005;Beume et al., 2007). For a recent application, see Stagge and Moglen (2014).

For this study, SMS-EMOA was used to seek the optimal set of calibration parameters to reduce the differences between simulated stream temperatures from SWAT and observed values. Observed stream temperatures were obtained from 50 sites within the Columbia River Basin between 1970-1992. Four calibration parameters for each subbasin were adjusted using the algorithm, and three objectives were specified including the RMSE values for the January-April, May-August, and September-December time periods to match the stream temperature rising limb, peak, and falling limb. Further objective functions were intentionally omitted to simplify the analysis. This decision is justified by the limited range of stream temperatures matched by the algorithm. Conversely, hydrological calibration attempts to match flows that vary over orders of magnitude and therefore require additional objectives to match all portions of the hydrograph. Convergence of the stream temperature calibration algorithm was assumed to be met when the S-metric did not vary more than 1% between 3 generations. The final set of solutions exhibited trade-offs between the three objective functions; therefore, a single solution—more specifically, a single set of calibration parameters—was then chosen from this set to be used in the calibrated SWAT simulation.

2. 6 Statistical analyses

The impacts of potential climate change on streamflow and hydrologic components were evaluated by comparing historical time period (1961-1990) simulations to those using the GCMs in Table 1 for the late-21st century (2080s; 2081-2099). When describing the ensemble average (or standard deviation) of a time period (i.e., late-21st century), this value is the average (or standard deviation) of the seven CMIP5 GCMs for this time period. Months are lumped into seasons for temporal analysis and are defined as spring (April-June), summer (July-September), fall (October and November), and winter (December-March). These seasons are defined to capture the snowmelt and dry/low flow seasons. Pearson correlations using a bootstrap method were used to measure the relationship between annual and seasonal changes in stream temperature and individual hydroclimatological components. A total of 10,000 bootstrap correlation iterations were run. Statistical significance was determined at the $\alpha = 0.05$ level. For statistical significance, the 5th and 95th percentiles of the bootstrap correlation iterations must agree on the correlation sign (+ or -). If the lower (higher) end of our confidence interval is above (below) zero, we can conclude that the correlation between stream temperature and hydroclimatological component change is significant at the $\alpha = 0.05$ level (two-tailed). Additionally, with changes in climate, it can be expected that drying of streams will occur.

In this study, streams that have no flow for an extended time period of the year (and thus have no stream temperature) are removed from the stream temperature analyses, but since drying streams are an important barrier for aquatic species migration, they will be discussed.

3. Results

3.1 Hydrologic model calibration

NS, R^2 and Φ average and standard deviation values for the calibration and validation time periods are shown in Table 2. Overall, the model efficiency statistics show that the SWAT model adequately simulated streamflow compared to observations. The average NS coefficient for the calibration and validation period was 0.69 and 0.64, respectively, with a standard deviation of 0.13 for the calibration period and 0.13 for the validation period. This indicates that a large portion of the NS values for both time periods varied only 0.13 around their respective means, which is still within acceptable NS limits (Moriasi et al., 2007). The other model efficiency statistics, R^2 and Φ, indicate similar model performance.

3. 2 Stream temperature model calibration

After SWAT was calibrated for discharge, the model was used within the SMS-EMOA algorithm to calibrate the stream temperature model. RMSE values between observed and simulated daily stream temperatures range from 2-5 °C for the majority of observation sites. The resulting monthly RMSE values for each site are shown in Figure 2. No distinct spatial distributions of the magnitude of errors are present. Errors distinguished by month of year were also quantified (Figure 3). Errors are largest during the summer months of July through September. Lowest RMSE values were present between December and February. Also, the model gives highly unrealistic (RMSE >15 °C) results for a moderate number of points, especially during summer months. This is due to low values of discharge within reaches during the summer months. Stream temperature is strongly inversely dependent on streamflow, and very small values of discharge cause the model to produce uncharacteristically high stream temperature simulation values. The calibrated stream temperature model parameters can be found in the supplemental information.

3.3 Temperature and precipitation projections

Ensemble average projections of maximum and minimum air temperature and precipitation, as compared to the historical time period, are shown in Figure 4. Overall, the maximum and minimum air temperatures vary spatially throughout the CRB, with an average ensemble increase of 5.5 °C for maximum air temperature and 5.4 °C for minimum air temperature. All GCMs agreed that air temperature is expected to increase by the end of the 21st century. Precipitation projections, on the other hand, varied between downscaled GCM projections, with an overall average of a 14.4% increase compared to the historical time period.

3.4 Stream temperature projections

Figures 5 and 6 display the spring/summer and fall/winter historical and projected stream temperatures for the CRB. Simulated stream temperatures are projected to increase throughout the CRB, with largest increases occurring in the east-central portion of the CRB. On average, stream temperatures are projected to increase 3.5 °C for the spring, 5.2

°C for the summer, 2.7 °C for the fall, and 1.6 °C for the winter. It is important to note that a large number of subbasins were removed from this analysis due to no-flow conditions (i.e., running completely dry or icing-up) from changes in climate (hatched areas in Figures 5 and 6). Of these, winter had the largest number of subbasins removed from the analysis (31%), followed by fall (18%), summer (16%), and spring (15%). The average period of subbasins with no-flow conditions is projected to 34%, or 81 months out of the 240 months for the 2080s time period. We consider these subbasins to not be reliable refugia for aquatic species.

Simulated stream temperature changes also vary at the ecological province scale (Table 3). At the annual time scale, the largest stream temperature increases (4.3 °C) occurred within the Mountain Snake ecological province, which is characterized by cold-water migratory fish species. The largest inter-annual variation around the mean occurred in the Upper Snake ecological province, which is characterized by non-migratory coldwater species, with a +/- 3.8 °C standard deviation. Important differences between ecological provinces occurred at the seasonal time scale. Overall, the largest spring increase in stream temperature occurred in the Mountain Snake (5.0 °C) and Upper Snake (4.3 °C), both containing coldwater species. The largest summer temperature increase compared to the historical time period was for the Mountain Snake ecological province with a 7 °C increase in average monthly stream temperature, followed by Upper Snake (6 °C), Blue Mountain (5.3 °C), Intermountain (5.0 °C), and Mountain Columbia (5.0 °C), indicating that ecological provinces with coldwater species will experience some of the largest increases in stream temperature in the basin. These large increases are expected during the summer because air temperature is at its highest and streamflow is at its lowest.

Fall and winter had the smallest increases in stream temperature including a CRB average of 2.9 °C for fall and 1.6 °C for winter. This was expected because this is when air temperatures are the lowest, and cold precipitation recharge and streamflow are highest, resisting stream temperature increases. The basins with the highest stream temperature increases for the fall and winter time period were the Mountain Snake and Blue Mountain (4.0/2.1 °C).

3.5 Sensitivities of stream temperature changes to air temperature

We define TS_{max} and TS_{min} as the thermal sensitivity or stream temperature change per 1 °C of maximum or minimum air temperature change. For the entire CRB and the water year annual time scale, the value for the average TS_{max} is 0.6 and that for TS_{min} is 0.86, demonstrating that, on average, the increases in stream temperature seen by the 2080s are to a larger degree tied to future changes in minimum air temperatures (Table 4). On the seasonal time scale, stream temperature changes during the summer were the most sensitive to changes in maximum air temperature with TS_{max} equal to 0.8, followed by spring (0.7), fall (0.5), and winter (0.3). For minimum air temperature sensitivities, however, spring values of TS_{min} were the highest of all seasons, equal to 0.9, followed by summer (0.8), fall (0.5), and winter (0.3). Air temperature sensitivities varied by ecological province as well as by season. At the annual and seasonal time scales the Intermountain, Middle Snake, and Mountain Snake ecological provinces exhibited the highest values of TS_{max}.

For minimum air temperatures, the ecological provinces that were the most sensitive were Columbia Cascade, Mountain Snake, and Upper Snake. Summer once again had the highest overall TS_{min} values. However, the largest TS_{min} values were found in the winter and spring seasons, with the Columbia Cascades in the winter (1.4) and the Mountain Snake and Upper snake exhibiting TS_{min} values of 1.1 and 1.2 in the spring. Overall, it can be seen that spring has higher TS_{min} values than TS_{max}, a possible artifact of snowmelt (see Discussion).

3.6 Sensitivities of stream temperature to changes in hydroclimatological components

3.6.1 Correlations at the Columbia River Basin scale

At the CRB scale, all stream temperature changes were significantly correlated to all hydroclimatic components during the spring and fall seasons for the 2080s (Table 5), suggesting that during these seasons stream temperatures are highly sensitive to changing environments. For summer, groundwater inflow change was the only variable not significantly correlated to stream temperature changes. For winter, streamflow and groundwater inflow changes were the only variables not significantly correlated to stream temperature changes (see Discussion).

3.6.2 Correlations at the ecological province scale

Correlations between stream temperature and hydroclimatological components at the seasonal time scale and ecological province spatial scale for the 2080s suggest that multiple hydroclimatological components affect stream temperatures (Figure 7). As expected, maximum and minimum air temperatures were significantly positively correlated to changes in stream temperatures for all seasons and nearly all ecological provinces. The only two ecological provinces where no significant correlations were found between air and stream temperature were the Blue Mountain and Upper Snake provinces (see

Discussion), which are characterized by migratory salmonids and non-migratory salmonids, respectively. Additionally, precipitation changes were negatively correlated to stream temperature changes for all seasons and nearly all ecological provinces.

For spring, nearly all hydroclimatological components were significantly correlated to stream temperature changes for each ecological province. Streamflow changes were not correlated to stream temperature changes within the Blue Mountain, Intermountain, and Upper Snake ecological provinces, which are characterized by warmwater species, migratory coldwater salmonids, and non-migratory coldwater salmonids, respectively. We also found that snowmelt changes within the Blue Mountain ecological province were not correlated to stream temperature changes. However, within the Blue Mountain ecological province we find that snowmelt is not a large portion of the hydrological cycle during this season.

For the summer season, no relationships were found for streamflow, snowmelt, surface runoff, and groundwater inflows within multiple ecological provinces. Overall, streamflow was found to be significantly correlated with stream temperature within the Columbia Cascades and Middle Snake, which are characterized by coldwater migratory salmonids, and Mountain Columbia, which is characterized by non-migratory coldwater salmonids, ecological provinces. Within the Columbia Plateau, Intermountain, and Mountain Columbia ecological provinces, we find snowmelt to still be a large portion of the hydrological cycle, thus any reductions of snowmelt do not significantly affect stream temperature. Lastly, surface runoff and groundwater inflows were not significantly correlated to the stream temperature changes in the Mountain Columbia and Upper Snake ecological provinces and the Mountain Snake ecological province, respectively. Within these regions we did not find large changes in surface runoff or groundwater inflows.

For the fall season, we find that changes in stream temperature within the Blue Mountain ecological province, which is characterized by migratory coldwater salmonids, is only positively correlated to changes in maximum and minimum air temperature, and thus loses its ties to the other hydrology-related components. Note also that during the fall season groundwater inflow changes become a non-significant factor in stream temperature changes for five out of the eight ecological provinces. The only ecological provinces where groundwater inflow changes were significantly correlated to stream temperature changes were the Columbia Plateau, Intermountain, characterized by warmwater species, and the Middle Snake, which is characterized by coldwater migratory species. These are regions where groundwater inflows increased and therefore contributed cooling effects during this time period.

During the winter season, changes in multiple hydroclimatological components within multiple ecological provinces are not significantly correlated to changes in stream temperature. Generally, changes in maximum air temperature, minimum air temperature, precipitation, snowmelt, and surface runoff are still significantly correlated to changes in stream temperature. These relationships make sense because during the winter season, increases in maximum and minimum air temperatures in conjunction with changes in precipitation will have the largest effects on two hydrological components: snowmelt and surface runoff. This is the season where snowmelt-dominated regions with large snowmelt components may perhaps become rain-dominated regions with large surface runoff components.

4. Discussion and Conclusions

The importance of stream temperature to aquatic species distributions, interactions, behavior, and persistence is well documented (Matthews, 1998), particularly for coldwater-adapted taxa such as trout and salmon (Milner et al., 2003;McCullough, 1999). Considering predicted increases in air temperature in the coming century, accurate assessment of suitable thermal habitat is critical for predicting species responses to changes in climate. Accordingly, recent research has investigated the potential impacts of climate change on aquatic taxa by explicitly incorporating regression-based stream temperature predictions into ecological models (Britton et al., 2010;Al-Chokhachy et al., 2013). While simplified regression studies may boast low RMSE values between simulated and observed stream temperatures, the relatively broad spatial scale of many of these studies (Mohseni et al., 2003), neglects the variety of local hydrological systems that are differentially driven by the array of inputs to each system (e.g., snowmelt, groundwater, runoff). The resulting stream temperature model inaccuracies from this approach, clustered in particular regions can be particularly problematic when investigating local population responses and range shifts at the edge of species' distributions. Our results highlight this issue by characterizing the varied relative contributions of different hydrological component inputs among ecological provinces and suggest the complex system-level regulation of stream temperature

As with any modeling study, modeling errors originate from multiple sources. Wilby and Harris (2006) discuss these aforementioned uncertainties in detail and ranked their importance in decreasing order as follows: differences in GCM output, downscaling methods, hydrological model structure, hydrological model parameters, and then greenhouse gas emission scenario. While their work was performed for a hydrological model, the results still hold true for our stream temperature model. Particular to this study, in order to quantify the differences between errors due to parameter uncertainty and GCM (or projection) uncertainty, much more work needs to be done and is well beyond the scope of this work.

However, we do note that our simulations for stream temperature demonstrated higher errors during the summer months. This is due to low and fluctuating discharge values that ultimately affect stream temperature. Also, it is likely due to the fact that hydrologic components may influence stream temperature differently during different seasons. For this study, we used annual calibration parameters and allowed them to vary for each subbasin. An alternative approach would be to utilize seasonally varying calibration parameters, and to analyze the dynamic (i.e., seasonal) influence of hydrologic components on stream temperature. This may better capture the stream temperature fluctuations in the summer months. Nonetheless, our spatially resolved methodology using a mechanistic model, SWAT, better characterizes the complex processes of stream temperature throughout the CRB by accounting for the hydrologic components contributing to stream temperature and its variation.

Within the CRB, Wenger et al. (2013) used air temperature as a surrogate for stream temperature to predict the response of Bull trout (Salmonidae: *Salvelinus confluentus*) to predicted changes in climate, while Beer and Anderson (2013) used air temperature-stream temperature relationships to predict the impacts of climate change on salmonid life-histories. These approaches are common (Britton et al., 2010;Tisseuil et al., 2012;Al-Chokhachy et al., 2013), yet overlook important differences in the inputs influencing stream temperature across the basin. For example, our results suggest that hydrologic contributions from snowmelt are relatively important drivers of stream temperature within ecological provinces with primarily non-migratory coldwater focal fish species. The influence of snowmelt tends to buffer stream temperatures against increases in air temperature during the year relative to other areas in the watershed. In this case, a regression-based approach to estimating stream temperature or the use of air temperature as a surrogate for stream temperature will tend to overestimate stream temperature, and thus underestimate the amount of suitable thermal habitat for coldwater species. In addition, decreases in snowcover (and snowmelt) in the future will result in increased thermal sensitivity within these formerly buffered regions. For example, current stream temperatures in the Mountain Snake ecological province are buffered by relatively high levels of snowmelt, yet decreases in future snowcover are predicted to result in this province experiencing the greatest seasonal and annual increases in stream temperature in the coming century.

Some of the relationships between stream temperature and hydroclimatic changes at the CRB scale were expected, such as increases in maximum air temperature and minimum air temperature resulting in increases in stream temperature, which were significant for all seasons for the entire CRB. This relationship is well-established and many models have been developed solely based on air-stream temperature relationships (Stefan and Preud'homme, 1993;Mohseni and Stefan, 1999). Also, a decrease in precipitation led to an increase in stream temperature, largely because greater runoff and infiltration leads to larger volumes of water in the stream channel, and thus increases the amount of energy needed to heat the water. Precipitation changes had the largest negative correlations during the spring and summer seasons, followed by fall and winter. Both surface runoff and lateral soil flow changes follow the same correlation patterns as precipitation, as both are inherently tied to the amount of incoming precipitation. Additionally, streamflow is tied to all hydrological components within the subbasin and the incoming streamflow that is entering the streamflow reach. Since streamflow is a mix of incoming hydrologic components, it is difficult to determine correlations. However, much research has assumed that streamflow and stream temperature changes are inversely correlated (van Vliet et al., 2011). The correlations within this study were significant and positively correlated for the spring, summer, and fall seasons; however, all correlations were below 0.10, which suggests the correlations were relatively minor, especially compared to other components.

Snowmelt changes were negatively correlated during the spring, fall, and winter seasons, and positively correlated during the summer season. A decrease in snowmelt will lead to an increase in stream temperature because the cooling effect that snowmelt has on stream temperature is no longer present. In summer, snowmelt and stream temperature were positively correlated (albeit not significant), suggesting the counterintuitive notion that an increase in snowmelt led to an increase in stream temperature. This can be explained largely because snowmelt changes did not occur at all in 975 (60% of the subbasins with streamflow) of the CRB subbasins, while for spring, fall, and winter, these values were 89 (5%), 50 (3%) and 48 (3%), respectively. These observations suggest that snowmelt is still a component of the hydrologic cycle during the summer season.

Lastly, groundwater inflow changes to the stream channel were negatively correlated to stream temperature change at the CRB scale for the spring and fall seasons. This also makes sense, as groundwater temperature is generally cooler than the stream temperature of the water already within the channel. Quite often, stream temperature variations of cool water are used for tracer studies to determine where surface and groundwater flows are exchanging water (Anderson, 2005;Constantz et al., 2003). However, no significant correlation was found during the summer, when groundwater is a large source of stream flow. This is likely because groundwater is the main source of water for this season, any climate-induced changes in groundwater will not have a major effect on stream temperature because the main water source for streamflow is still groundwater. For example, if 85% of the streamflow comes from groundwater, and is then decreased to 75%, the change in stream temperature isn't likely to significantly change. Additionally, no groundwater inflow change correlations were found for the winter season.

Species' responses to stream temperature occur within populations and are based on local environmental conditions. Consequently, accurate assessment of local variation in stream temperature is critical and only possible when local system drivers are accurately represented in stream temperature models. While stream temperature is primarily influenced by air temperature, this study emphasized the important effects of other contributors (e.g., runoff, groundwater, snowmelt) that are differentially represented across the CRB. Also, we have characterized the ecological provinces by warmwater and coldwater focal fish species, which was done for qualitative biological assessments and not as a predictive approach. However, these groupings have provided important information regarding factors driving differential variation in stream temperatures across seasons in the context of the biological groups experiencing particular stream temperature changes. River basins encompass a spatially heterogeneous array of biological communities and these communities are regulated by a spatially heterogeneous array of environmental conditions. These environmental conditions are driven by local processes and require a systems-based approach to accurately characterize the habitat regulating the distribution and diversity of aquatic taxa.

Acknowledgements

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Table 1. Coupled Model Intercomparison Project – phase 5 General Circulation Models used in this study

Modeling Group	**CMIP5 Model**
Canadian Centre for Climate Modeling & Analysis	canesm2
Météo-France / Centre National de Recherches Météorologiques, France	cnrm-cm5
Geophysical Fluid Dynamics Laboratory, USA	gfdl-cm3
Institut Pierre Simon Laplace, France	ipsl-cm5a-mr
Center for Climate System Research (The University of Tokyo), National Institute for Environmental Studies, and Frontier Research Center for Global Change (JAMSTEC), Japan	miroc5
Max Planck Institute for Meteorology, Germany	mpi-esm-lr
Meteorological Research Institute, Japan	mri-cgcm3

Table 2. Summary of streamflow calibration statistics.

	Calibration		Validation	
	Average	Std. Dev.	Average	Std. Dev.
NS	0.69	0.13	0.64	0.13
R^2	0.75	0.10	0.75	0.08
Φ	0.62	0.15	0.65	0.13

*NS: Nash-Sutcliffe coefficient

*R^2: coefficient of determination

* Φ: coefficient of determination multiplied by slope of regression line, b

Table 3. Stream temperature changes and focal fish species groups for the Columbia River Basin ecological provinces during the 2080s.

Ecological province	**Spring (°C)**	**Summer (°C)**	**Fall (°C)**	**Winter (°C)**	**Annual (°C)**	**Focal Fish Species**
Blue Mountain	3.7	5.3	3.2	2.1	3.5	coldwater migratory
Columbia Cascades	2.6	4.1	2.0	1.2	2.4	coldwater migratory
Columbia Plateau	2.0	3.8	2.0	1.5	2.2	warmwater
Intermountain	3.3	5.0	2.7	1.5	3.0	warmwater
Middle Snake	2.4	3.7	2.3	1.4	2.2	coldwater migratory
Mountain Columbia	3.6	5.0	2.4	1.5	3.1	coldwater non-migratory
Mountain Snake	5.0	7.0	4.0	2.1	4.3	coldwater migratory
Upper Snake	4.3	6.0	3.3	1.6	3.6	coldwater non-migratory

Table 4. Sensitivities of stream temperature changes to changes in maximum and minimum air temperatures for the Columbia River Basin during the 2080s

Maximum air temperature

Ecological province	**Spring (°C/°C)**	**Summer (°C/°C)**	**Fall (°C/°C)**	**Winter (°C/°C)**	**Annual (°C/°C)**
Blue Mountain	0.7	0.5	0.8	0.4	0.6
Columbia Cascades	0.5	0.7	0.7	0.3	0.6
Columbia Plateau	0.5	0.4	0.7	0.0	0.4
Intermountain	0.7	0.8	1.1	0.6	0.8
Middle Snake	0.5	0.5	0.8	0.9	0.7
Mountain Columbia	0.4	0.7	0.7	0.3	0.5
Mountain Snake	0.7	1.0	1.0	0.0	0.7
Upper Snake	0.6	0.7	0.8	0.3	0.6

Minimum air temperature

Ecological province	**Spring (°C/°C)**	**Summer (°C/°C)**	**Fall (°C/°C)**	**Winter (°C/°C)**	**Annual (°C/°C)**
Blue Mountain	0.7	0.7	0.9	0.0	0.6
Columbia Cascades	0.2	0.7	0.8	1.4	0.7
Columbia Plateau	0.2	0.6	0.8	0.4	0.5
Intermountain	0.7	0.9	0.8	0.0	0.6
Middle Snake	0.8	0.9	1.0	0.5	0.6
Mountain Columbia	0.3	0.9	0.6	0.2	0.5
Mountain Snake	0.7	1.1	1.0	0.5	0.8
Upper Snake	0.8	1.2	0.9	0.5	0.9

Table 5. Pearson correlations between stream temperature and individual hydroclimatological changes for the entire Columbia River Basin during the 2080s.

Hydroclimatological Component	Spring	Summer	Fall	Winter
Maximum air temperature	0.67	0.61	0.49	0.36
Minimum air temperature	0.65	0.61	0.47	0.34
Precipitation	-0.51	-0.50	-0.36	-0.20
Streamflow	0.08	0.07	-0.10	-0.02*
Snowmelt	-0.36	0.10	-0.31	-0.26
Surface runoff	-0.39	-0.08	-0.30	-0.28
Groundwater inflow	-0.24	-0.04*	-0.12	0.00*
Lateral soil flow	-0.42	-0.32	-0.36	-0.07

* indicates there was no significant correlation at $p = 0.05$

Figures

Figure 1. Columbia River Basin study area ecological provinces with streamflow and stream temperature gauges for calibration.

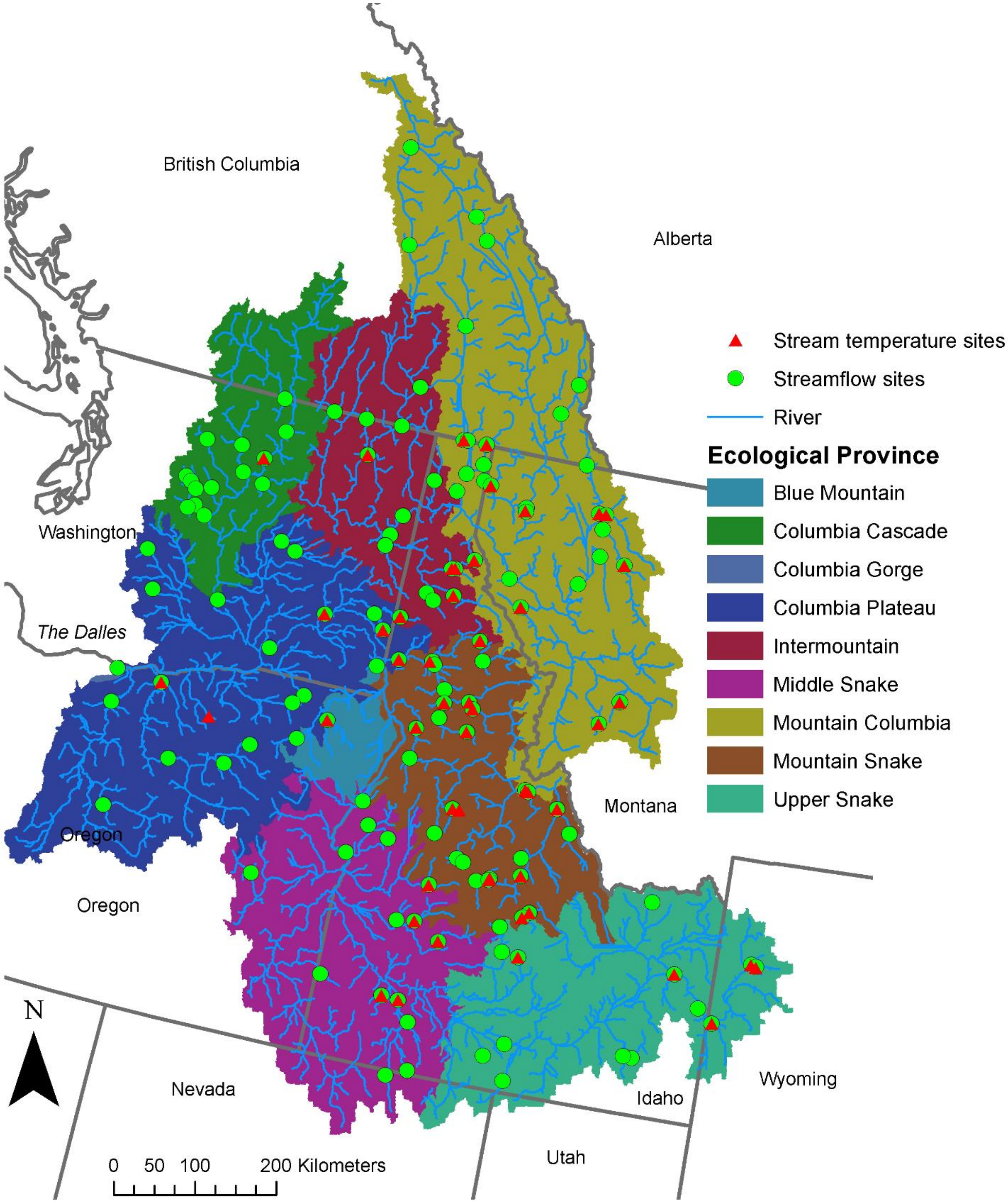

Figure 2. Root mean square errors of the simulated and observed stream temperatures

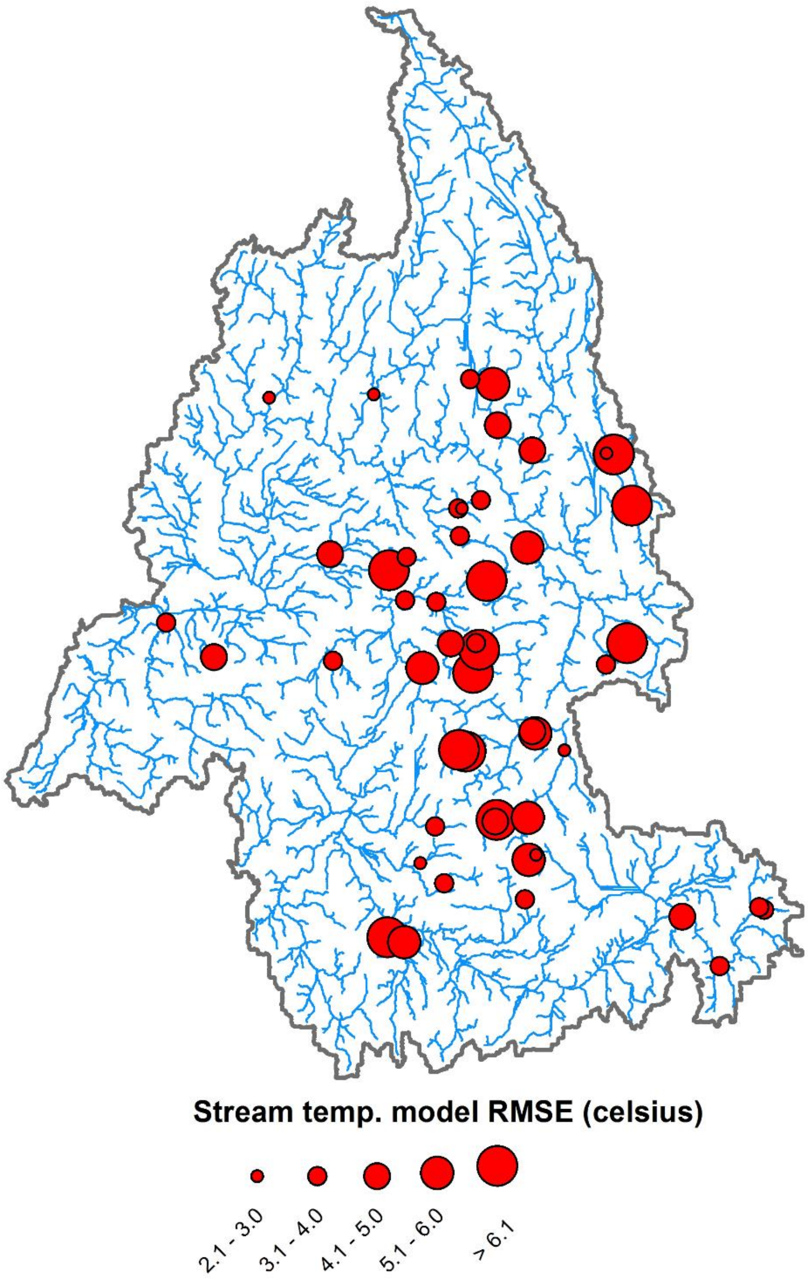

Figure 3. Monthly stream temperature error distributions for all stream temperature gauges.

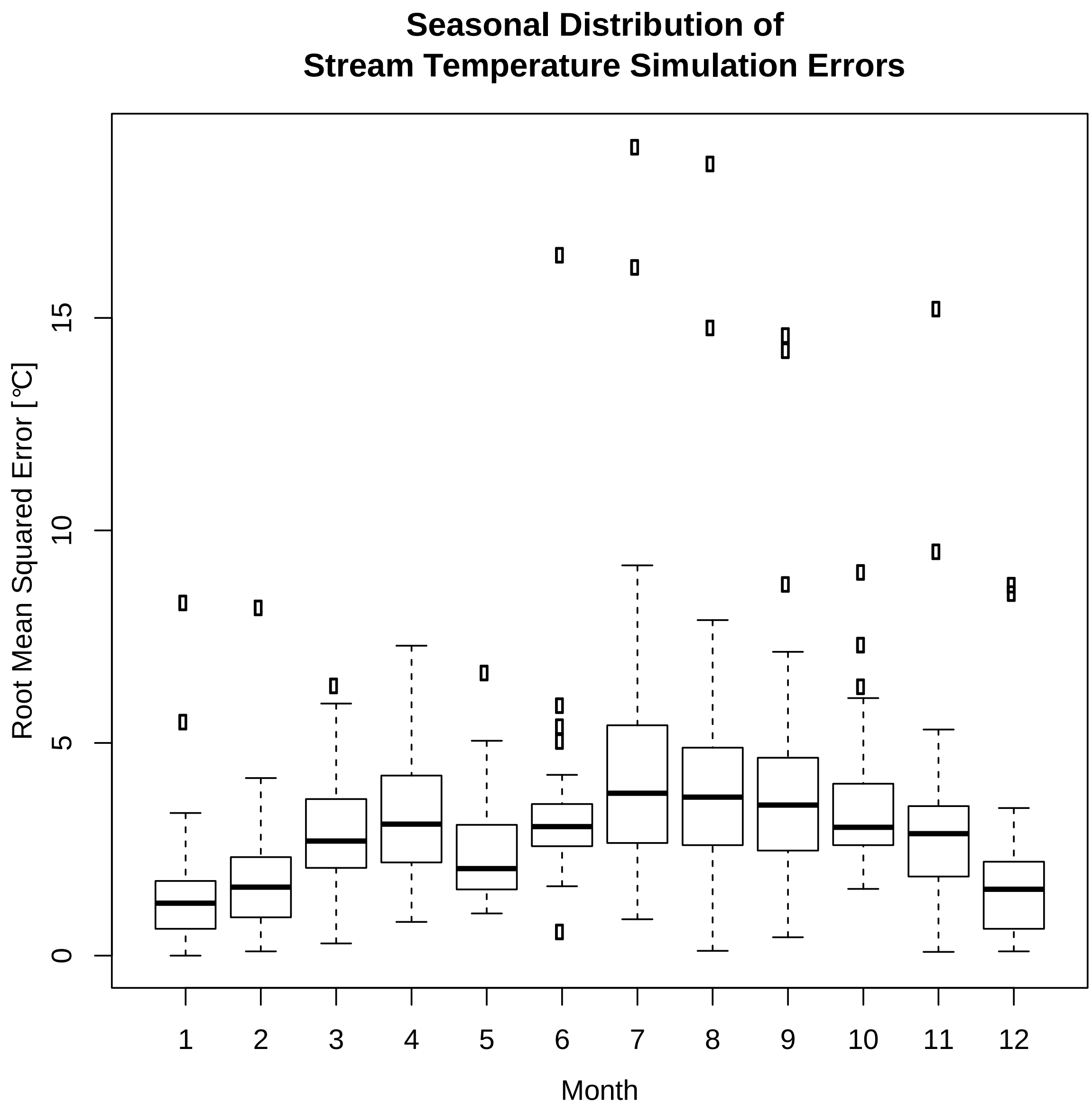

Figure 4. Changes in average precipitation and air temperature (maximum and minimum) for the end of the 21st century as compared to the historical time period

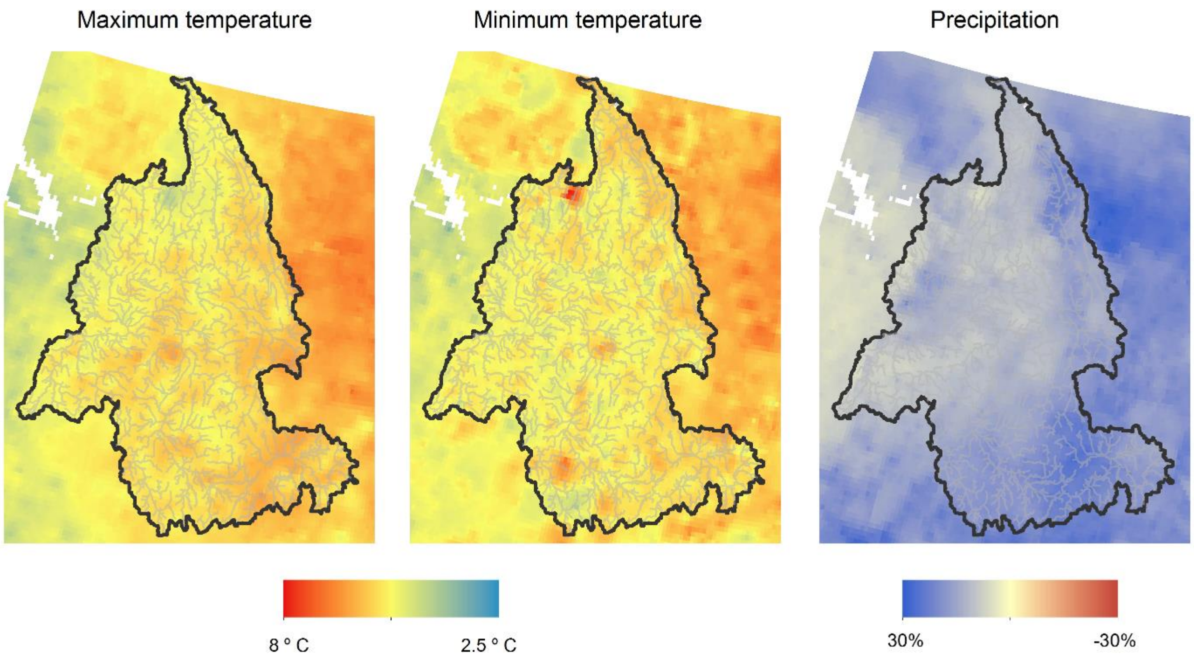

Figure 5. Spring and summer historical and projected stream temperatures at the subbasin-level. Hatched subbasins indicate that drying occurred under climate projections and were removed from analyses.

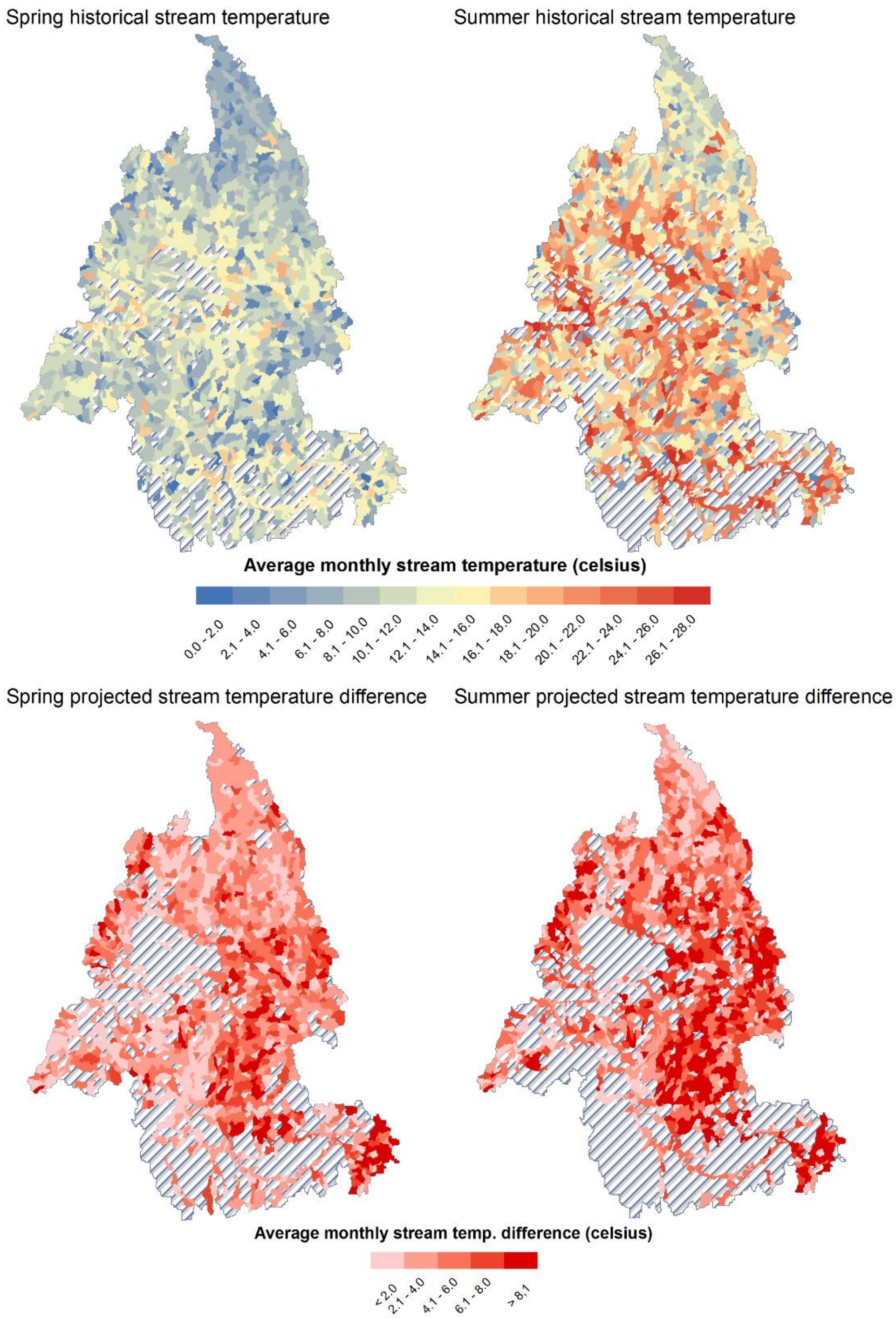

Figure 6. Fall and winter historical and projected stream temperatures at the subbasin-level. Hatched subbasins indicate that drying occurred under climate projections and were removed from analyses.

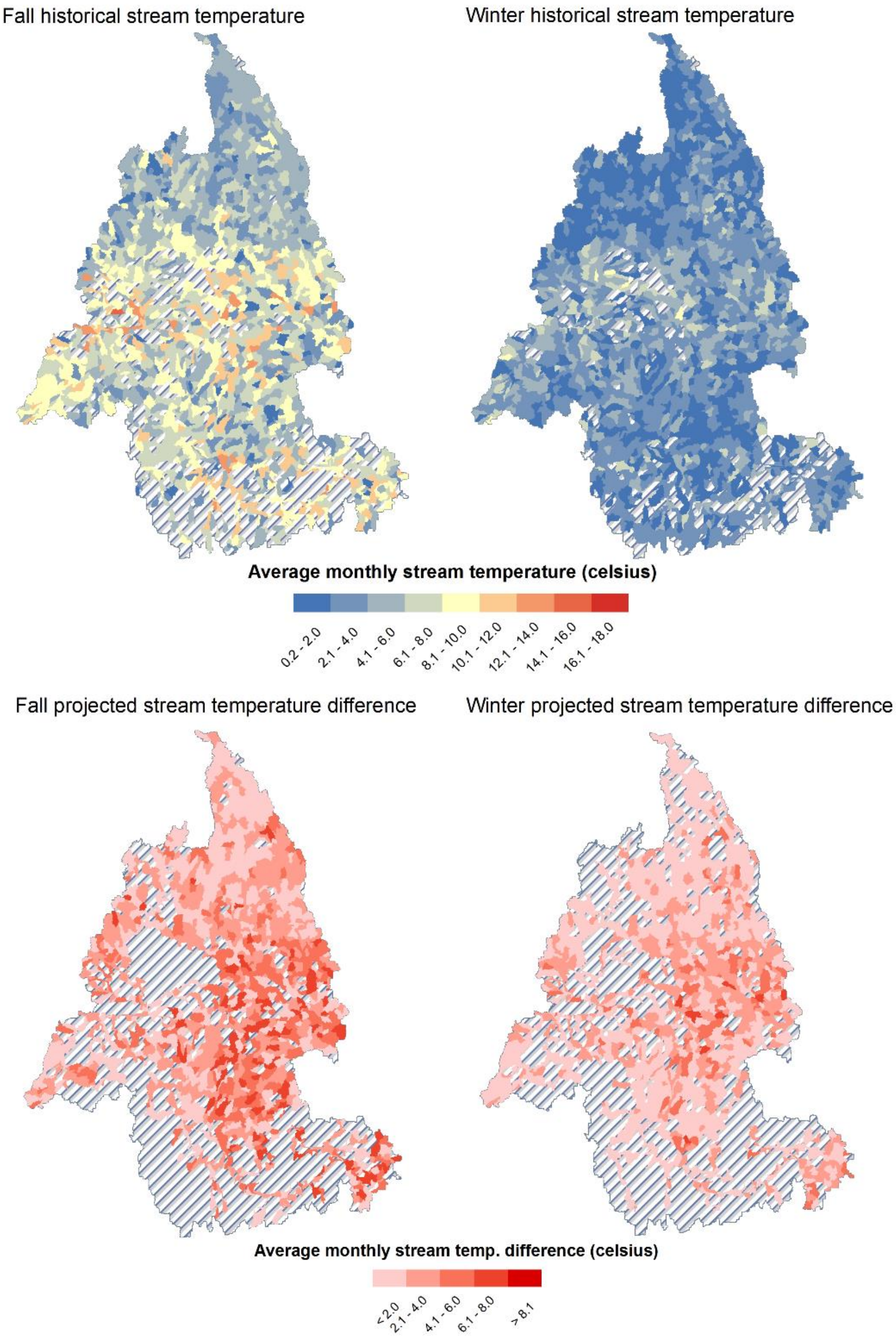

Figure 7. Pearson correlations between changes in stream temperature and hydroclimatological components for the Columbia River Basin ecological provinces. Tmax = maximum air temperature; Tmin = minimum air temperature; Precip. = precipitation; Flow = streamflow; Snomlt = snowmelt; SWQ = surface water runoff; GWQ = groundwater inflow; LatQ = lateral soil flow. Asterisks represent <u>no</u> significant correlation at p =0.05