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

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38 **Abstract**
39
40 Water temperature is a primary physical factor regulating the persistence and distribution

41 of aquatic taxa. Considering projected increases in air temperature and changes in

42 precipitation in the coming century, accurate assessment of suitable thermal habitat in

43 freshwater systems is critical for predicting aquatic species responses to changes in climate

44 and for guiding adaptation strategies. We use a hydrologic model coupled with a stream

45 temperature model and downscaled General Circulation Model outputs to explore the

46 spatially and temporally varying changes in stream temperature for the late 21st century at

47 the subbasin and ecological province scale for the Columbia River Basin. On average,

48 stream temperatures are projected to increase 3.5 °C for the spring, 5.2 °C for the summer,

49 2.7 °C for the fall, and 1.6 °C for the winter. While results indicate changes in stream

50 temperature are correlated with changes in air temperature, our results also capture the

51 important, and often ignored, influence of hydrological processes on changes in stream

52 temperature. Decreases in future snowcover will result in increased thermal sensitivity

53 within regions that were previously buffered by the cooling effect of flow originating as

54 snowmelt. Other hydrological components, such as precipitation, surface runoff, lateral soil

55 water flow, and groundwater inflow, are negatively correlated to increases in stream

56 temperature depending on the ecological province and season. At the ecological province

57 scale, the largest increase in annual stream temperature was within the Mountain Snake

58 ecological province, which is characterized by non-migratory coldwater fish species.

59 Stream temperature changes varied seasonally with the largest projected stream

60 temperature increases occurring during the spring and summer for all ecological provinces.

61 Our results indicate that stream temperatures are driven by local processes and ultimately

62   require a physically-explicit modeling approach to accurately characterize the habitat

63   regulating the distribution and diversity of aquatic taxa.

64   **1. Introduction**

65   The temporal and spatial variability of stream temperature is a primary regulator of

66   the life-history, behavior, ecological interactions, and distribution of most aquatic species

67   (Peterson and Kwak, 1999). For example, metabolic processes in ectothermic freshwater

68   organisms (e.g., fishes, amphibians, invertebrates) are directly regulated by water

69   temperature (Angilletta, 2009), and thus the persistence of populations and the rate of

70   energy flow through aquatic ecosystems is dependent on the thermal characteristics of a

71   local habitat (Woodward et al., 2010). Moreover, much like terrestrial species, the timing

72   of important life-history traits such as reproduction and migration is heavily dependent on

73   seasonal thermal regimes (Johnson et al., 2009; Woodward et al., 2010). Additionally,

74   stream temperature plays a large role in chemical kinetic rates and is important for

75   governing stream management for recreation as well as urban and industrial water supplies.

76   Therefore, to better understand hydrologic systems and to better manage water resources

77   in a changing environment, it is critical to predict the potential effects of climate variability

78   and change on stream temperature, and to characterize how these changes affect the

79   distribution and diversity of freshwater taxa.

80   Potential impacts of climate change on stream temperatures have been widely

81   estimated using field investigations and modeling studies (Webb and Nobilis,

82   1994;Mohseni et al., 2003;Caissie, 2006;Hari et al., 2006;Nelson and Palmer, 2007;Webb

83   et al., 2008;Isaak et al., 2010;van Vliet et al., 2011;Null et al., 2013;Ficklin et al., 2013).

84   At larger spatial scales, regional regression models have been used to predict the impacts

85 of climate change on stream temperatures (Mohseni et al., 1998;Mohseni and Stefan,

86 1999;Mohseni et al., 1999;Erickson and Stefan, 2000;Bogan et al., 2003;Webb et al.,

87 2003;Stefan and Preud'homme, 1993). However, regression methods are not sufficient

88 predictors of stream temperature because they do not account for hydrologic component

89 inputs to the stream such as snowmelt, groundwater, and surface runoff (Constantz et al.,

90 1994;Constantz, 1998;Pekarova et al., 2008;Ficklin et al., 2012;MacDonald et al., 2014).

91 Neglecting these components severely limits the ability of regression-based models to

92 accurately predict spatial variability in stream temperature changes, since the contributions

93 of different sources to streamflow will be modified in a changing climate. Ignoring the

94 distinct characteristics of different sources to streamflow therefore negatively impacts the

95 assessment of the effects of climate change on aquatic biodiversity at landscape (and larger)

96 scales.

97   To adequately capture the role of changing hydrology from a changing climate on

98 stream temperature, numerical (Isaak et al., 2010; Kim and Chapra, 1997;Sinokrot and

99 Stefan, 1994) and analytical (Null et al., 2013;Tang and Keen, 2009;Edinger et al., 1974)

100 stream temperature models, in conjuction with hydrologic models, have been applied with

101 success. These models allow stream temperature assessments at the local or regional level.

102 For example, our prevous work in the Sierra Nevada mountain range in California found

103 subbasin-scale stream temperature differences from region-to-region largely from

104 localized changes in hydrology from changes in climate. Additionally, Null et al. (2013)

105 found increasing stream tempreatures with increasing elevation due to the transition from

106 snow- to rain-dominated, an effect opposite what would be predicted by a model based

107 solely on air temperature

4

108   The primary objectives of this work are to [1] predict changes in stream temperature

109   over the coming century across the Columbia River Basin at the ecological province level,

110   [2] identify the contribution of specific hydrological components (such as snowmelt,

111   surface water runoff, etc.) to the overall heat and water budget across the watershed, and

112   [3] add to the literature regarding the role of changing hydrology on changes in stream

113   temperature. Specifically, we aim to demonstrate the extent to which future changes in

114   hydrology—streamflow, surface runoff, snowmelt, groundwater inflow, and lateral soil

115   flow as simulated using global climate projections at the subbasin scale— could critically

116   affect changes in localized stream temperatures, which are of high importance for aquatic

117   species. The Columbia River Basin is a snowmelt-dominated region, where projected

118   increases in global air temperatures are expected to result in early snowmelt runoff. These

119   changes lead to reduced late spring and summer water discharges that change the thermal

120   content of stream flow. Moreover, previous stream temperature assessments indicate that

121   the Columbia River Basin is sensitive to changes in climate (Mantua et al., 2010;Chang

122   and Psaris, 2013; Luce et al., 2014); these sensitivities vary spatially and are governed in

123   part by the land use, hydroclimate and topographic variables of the local region (Chang

124   and Psaris, 2013).

125   We use a landscape-scale hydrological model—the Soil and Water Assessment

126   Tool (SWAT; Arnold et al. (1998))— combined with a stream temperature model that

127   simulates stream temperature based on the effects of subbasin air temperature and

128   hydrology.(Ficklin et al., 2012). The SWAT model efficiently represents snowmelt and

129   runoff processes, and also incorporates a full range of water quality processes (Gassman et

130   al., 2007). SWAT has been found to accurately simulate streamflow in regions where

131   snowmelt dominates the hydrology (Wang and Melesse, 2005; Watson and Putz, 2012;

132   Zang et al., 2012). Downscaled output from seven General Circulation Models (or Global

133   Climate Models, GCMs) using one representative concentration pathway (RCP) associated

134   with a trajectory of future greenhouse gas accumulation in the atmosphere for the late-21st

135   century was used to drive the calibrated SWAT model at the subbasin-scale. For all

136   Columbia River Basin ecological provinces, we spatially and temporally explore the

137   changes in stream temperature, and interpret these changes with respect to changes in the

138   hydrologic system.

139   **2. Materials and Methods**

140   **2. 1 Study area**

141   The CRB encompasses portions of seven states in the western United States and

142   the Canadian province of British Columbia. The CRB for this study is defined as the area

143   that flows into the The Dalles, Oregon (Figure 1) and has a surface area of 613,634 km^2.

144   The water resources in the CRB have been extensively developed in the past 70 years for

145   hydroelectric power, agricultural irrigation, and urban use. The CRB study area has been

146   extensively discussed in Hatcher and Jones (2013), Mantua et al. (2010), and Payne et al.

147   (2004).

148   Subbasins were aggregated into ecological provinces according to designations

149   Northwwest Habitat Institute (N.H.I., 2008). Ecological provinces are delineated based on

150   species composition within the region and environmental conditions. Because the

151   ecological provinces do not expand into Canada, we extrapolated the boundaries based on

152   watershed delineations. The ecoprovince areas (Figure 1) for this study average 68,000 km^2

153   and range from 300 km^2 (Columbia Gorge) to 145,000 km^2 (Mountain Columbia). For

154   descriptive purposes, we further characterize ecological provinces as either 'warmwater'

155   (Centrarchidae – bass, bluegill, crappie; Percidae – perch, walleye), 'coldwater migratory'

156   (Salmonidae – salmon, steelhead, trout], and 'coldwater non-migratory' (Salmonidae –

157   trout, whitefish) (Table 2), based on predominant focal fish species (N.H.I., 2008).

158

159   **2.2 Modeling stream flow and water quality using SWAT**

160   We used the SWAT model coupled with a stream temperature model to predict

161   streamflow and stream temperature throughout the Columbia River Basin at an average

162   spatial resolution of 250 km^2. SWAT is an integrative, mechanistic model that utilizes

163   inputs of daily weather, topography, land use, and soil type to simulate the spatial and

164   temporal dynamics of climate, hydrology, plant growth, and erosion (Arnold et al., 1998).

165   Within SWAT, surface runoff and soil water infiltration were simulated using the modified

166   Curve Number method (Neitsch et al., 2005). The Penman-Monteith method was used to

167   estimate potential evapotranspiration. Stream temperature was simulated using the Ficklin

168   et al. (2012) SWAT stream temperature model that uses local air temperature and

169   hydrology for stream temperature estimation:

170

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

172

173   [1]

174   where *sub_snow* is the snowmelt contribution to streamflow within the subbasin (m^3),

175   *sub_gw* is the groundwater contribution to streamflow within the subbasin (m^3), *sub_surq*

176   is the surface water runoff contribution to streamflow within the subbasin (m^3), *sub_latq*

177   is the soil water lateral flow contribution to streamflow within the subbasin (m^3), *sub_wyld*

178   is the total water yield (all contributing hydrologic components) contribution to streamflow

179   within in the subbasin (m^3), T_{gw} is the groundwater temperature (°C; annual average input

180   by user), and $T_{air,lag}$ is the average daily air temperature with a lag (°C), and λ is a

181   calibration coefficient relating to the relative contribution of the surface water runoff and

182   lateral soil water flow to the local water temperature and is included to aid in calibration in

183   case of improper hydrologic model calibration. The lag (days) is incorporated to allow the

184   effects of delayed surface runoff and soil water flow into the stream. The 0.1 in Equation

185   [1] represents the assumed temperature of snowmelt (0.1 °C).

186   After stream temperature of the local contributing water is determined, the stream

187   temperature before the effects of air temperature is determined by:

188
$$Twater_{intial} = \frac{T_{w,upstream} * (Q_{outlet} - sub\_wyld) + (T_{w,local} * sub\_wyld)}{Q_{outlet}}$$

189   [2]

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

191   is the streamflow discharge at the outlet of the subbasin.

192   The final stream temperature is calculated by adding a change to the initial stream

193   temperature in the subbasin from differences between stream and air temperature and travel

194   time of water through the subbasin. Depending on $T_{air,}$ the final stream temperature is

195   estimated as*:*

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

197 $$T_{water} = Twater_{intial} + ((T_{air} + \varepsilon) - Twater_{intial}) * K * (TT) \quad if \; T_{air} < 0 \qquad [4]$$

198   where T_{air} is the average daily air temperature (°C), K is a calibration conductivity

199   parameter, TT is the travel time of water through the subbasin (hour) and is calculated from

200   the SWAT simulations, and ε is an air temperature addition coefficient (°C), which was

201   included to account for water temperature pulses when T_{air} is below 0°C. For the case when

202   the effects of Tair and the hydrologic contributions are such that the final is $T_{water} < 0$°C,

203   the stream temperature model sets T_{water} to 0.1 °C. T_{water} is also assumed to be the

204   temperature of water discharge to downstream subbasin, and is further routed along the

205   stream network. The calibration parameter, K, acts as a proxy for reach-specific adjustment

206   of the radiative forcing, such as shading due to a vegetation canopy or geomorphic changes

207   resulting in differing geometry. Additional details regarding the stream temperature model

208   can be found in Ficklin et al. (2012).

209   Based on our previous work throughout the western United States (Ficklin et al.,

210   2012), the stream temperature model is highly sensitive to changes in λ (the calibration

211   coefficient for the surface runoff and lateral soil water flow contributions to streamflow)

212   and K (calibration conductivity parameter between air and stream temperature). Previous

213   work also indicates that simulated stream temperatures are sensitive to changes in

214   hydrologic components from increases in air temperature. For example, shifting snowmelt

215   earlier into the winter buffered the effects of increasing air temperature, resulting in only a

216   minor increase in stream temperature. Stream temperature in the late spring, early summer,

217   however, decreased from increases in snowmelt. Increasing groundwater streamflow

218   inputs decreased stream temperatures from the increase in cool water from groundwater.

219   These results are contingent on the volume and timing of the various hydrologic

220   components. For example, the larger the increase in groundwater flow volume to

221   streamflow, the larger the decrease in stream temperature. Further discussion on the stream

222   temperature model sensitivity can be found in Ficklin et al. (2012).

223   **2.3 Input Data**

224   SWAT input parameter values for topography, land cover, and soils data were

225   compiled from freely-available federal and state databases. A 30-meter Digital Elevation

226   Model (USGS) formed the basis for watershed and sub-basin delineation. Soil properties

227   were obtained from the STATSGO soil dataset. The 2001 National Land Cover Database

228   was used for land cover/land use. Meteorological data (air temperature, precipitation, and

229   wind speed) were extracted from Maurer et al. (2002) and relative humidity and solar

230   radiation were generated within SWAT (Neitsch et al., 2005).The Columbia River Basin

231   natural flow data that were used for streamflow calibration were obtained from output from

232   a   calibrated   Variable   Infiltration   Capacity   Model   (VIC)   model   (from

233   http://cses.washington.edu/) and the United States Geological Survey Hydro-Climatic Data

234   Network (HCDN; Slack et al. (1993)). These data represent streamflow that would occur

235   if no reservoirs or streamflow diversions were present within the basin. The HCDN is a

236   hydrologic dataset developed to study surface water conditions throughout the United

237   States that only fluctuate with changes in local climatic conditions and is therefore apt for

238   use in climate change studies (Slack et al., 1993). SWAT was run at the monthly time step.

239   Climatic projections from seven GCMs (Table 1) and one RCP (8.5) were input

240   into the calibrated SWAT model. Daily downscaled output from the seven GCMs (RCP

241   8.5) were obtained from the Downscaled CMIP3 and CMIP5 Climate and Hydrology

242   Projections archive (Maurer et al., 2013). RCP 8.5 represents the highest increase in

243   radiative forcing of the Coupled Model Intercomparison Project – phase 5 (CMIP5; Taylor

244   et al. (2011)) projections, and is based on an increased radiative forcing of 8.5 Wm^{-2}

245   (relative to pre-industrial values) at the end of the 21st century. Downscaling was achieved

246   using the daily bias-corrected and constructed analogs (BCCA) method (Maurer et al.,

247   2010). In summary, the BCCA procedure consists of two steps. The first step is a bias

248   correction using a quantile mapping technique which is applied to raw GCM output.

249   Quantile mapping bias correction has been widely and successfully used in climate model

250   downscaling (Wood et al., 2004). The bias correction step is followed by spatial

251   downscaling using a constructed analogues approach for each day using a linear

252   combination of days drawn from the historic record (Hidalgo et al., 2008). Maurer et al.

253   (2010) found that the BCCA method consistently outperformed the Bias-

254   Correction/Spatial-Downscaling method (BCSD) and the Constructed Analogues (CA)

255   approach in capturing the daily large-scale skill and translating it to simulated streamflows

256   that accurately reproduced historical streamflows.

257

258   **2.4 SWAT streamflow calibration**

259   The program Sequential Uncertainty Fitting Version 2 (SUFI-2; Abbaspour et al.

260   (2007)) was used to automatically-calibrate SWAT streamflow at 104 sites in the Columbia

261   River Basin (Figure 1). Initial and default SWAT model parameters were varied

262   simultaneously until an optimal solution was met. Three statistics were used to evaluate

263   model efficiency: [1] the Nash-Sutcliffe coefficient (Nash and Sutcliffe, 1970), [2] the

264   coefficient of determination (R^2), and [3] a modified efficiency criterion (Φ). Φ is the result

265   of the coefficient of determination, R^2, multiplied by the regression line slope, m (Krause

266   et al., 2005). This statistic captures the discrepancy in the magnitude of the observed and

267   simulated streamflow (captured by *m*) as well as the dynamics (captured by R^2). For all

268   previously-mentioned statistics, a perfect simulation is represented by a value of 1. A split-

269   sample approach was used for calibration and validation, and the calibration and validation

270   periods differed at each streamflow gauge depending on streamflow data availability.

271

272   **2. 5 SWAT stream temperature calibration**

273   Monthly stream temperatures were predicted using the SWAT stream temperature

274   model of Ficklin et al. (2012). This model includes the effects of hydrologic component

275   inputs (e.g., snowmelt, groundwater, and surface runoff) on stream temperature. Previous

276   studies have demonstrated that this stream temperature model performs better than linear

277   regressions that use air temperature alone (Ficklin et al., 2013;Barnhart et al., 2014). The

278   model requires four calibration parameters for each subbasin in the SWAT setup. Since the

279   model is not incorporated into the previously mentioned SWAT-CUP software, we utilized

280   the steady-state S-metric evolutionary multi-objective optimization algorithm (SMS-

281   EMOA) to calibrate the stream temperature parameters after hydrologic calibration was

282   performed (Emmerich et al., 2005;Beume et al., 2007). SMS-EMOA is an efficient and

283   effective Pareto optimization evolutionary algorithm for finding solutions to multi-

284   objective optimization problems. The algorithm seeks optimal solutions that maximize the

285   hypervolume (S-metric)—which can be thought of as the volume of dominated space—

286   and has been theoretically proven to converge to the Pareto set (Fleischer, 2003;Emmerich

287   et al., 2005;Beume et al., 2007). For a recent application, see Stagge and Moglen (2014).

288   For this study, SMS-EMOA was used to seek the optimal set of calibration

289   parameters to reduce the differences between simulated stream temperatures from SWAT

290   and observed values. Observed stream temperatures were obtained from 50 sites within the

291   Columbia River Basin between 1970-1992. Four calibration parameters for each subbasin

292   were adjusted using the algorithm, and three objectives were specified including the RMSE

293   values for the January-April, May-August, and September-December time periods to

294   match the stream temperature rising limb, peak, and falling limb. Further objective

295   functions were intentionally omitted to simplify the analysis. This decision is justified by

296   the limited range of stream temperatures matched by the algorithm. Conversely,

297   hydrological calibration attempts to match flows that vary over orders of magnitude and

298   therefore require additional objectives to match all portions of the hydrograph.

299   Convergence of the stream temperature calibration algorithm was assumed to be met when

300   the S-metric did not vary more than 1% between 3 generations. The final set of solutions

301   exhibited trade-offs between the three objective functions; therefore, a single solution—

302   more specifically, a single set of calibration parameters—was then chosen from this set to

303   be used in the calibrated SWAT simulation.

304

305   **2. 6 Statistical analyses**

306   The impacts of potential climate change on streamflow and hydrologic components

307   were evaluated by comparing historical time period (1961-1990) simulations to those using

308   the GCMs in Table 1 for the late-21st century (2080s; 2081-2099). When describing the

309   ensemble average (or standard deviation) of a time period (i.e., late-21st century), this value

310   is the average (or standard deviation) of the seven CMIP5 GCMs for this time period.

311   Months are lumped into seasons for temporal analysis and are defined as spring (April-

312   June), summer (July-September), fall (October and November), and winter (December-

313   March). These seasons are defined to capture the snowmelt and dry/low flow seasons.

314   Pearson correlations using a bootstrap method were used to measure the relationship

315   between annual and seasonal changes in stream temperature and individual

316   hydroclimatological components. A total of 10,000 bootstrap correlation iterations were

317   run. Statistical significance was determined at the α = 0.05 level. For statistical

318   significance, the 5th and 95th percentiles of the bootstrap correlation iterations must agree

319   on the correlation sign (+ or -). If the lower (higher) end of our confidence interval is above

320   (below) zero, we can conclude that the correlation between stream temperature and

321   hydroclimatological component change is significant at the α = 0.05 level (two-tailed).

322   Additionally, with changes in climate, it can be expected that drying of streams will occur.

323   In this study, streams that have no flow for an extended time period of the year (and thus

324   have no stream temperature) are removed from the stream temperature analyses, but since

325   drying streams are an important barrier for aquatic species migration, they will be

326   discussed.

327   **3. Results**

328   **3.1 Hydrologic model calibration**

329   NS, R^2 and Φ average and standard deviation values for the calibration and

330   validation time periods are shown in Table 2. Overall, the model efficiency statistics show

331   that the SWAT model adequately simulated streamflow compared to observations. The

332   average NS coefficient for the calibration and validation period was 0.69 and 0.64,

333   respectively, with a standard deviation of 0.13 for the calibration period and 0.13 for the

334   validation period. This indicates that a large portion of the NS values for both time periods

335   varied only 0.13 around their respective means, which is still within acceptable NS limits

336   (Moriasi et al., 2007). The other model efficiency statistics, R^2 and Φ, indicate similar

337   model performance.

338

339   3. 2 Stream temperature model calibration

340   After SWAT was calibrated for discharge, the model was used within the SMS-

341   EMOA algorithm to calibrate the stream temperature model. RMSE values between

342   observed and simulated daily stream temperatures range from 2-5 °C for the majority of

343   observation sites. The resulting monthly RMSE values for each site are shown in Figure 2.

344   No distinct spatial distributions of the magnitude of errors are present. Errors distinguished

345   by month of year were also quantified (Figure 3). Errors are largest during the summer

346   months of July through September. Lowest RMSE values were present between December

347   and February. Also, the model gives highly unrealistic (RMSE >15 °C) results for a

348   moderate number of points, especially during summer months. This is due to low values

349   of discharge within reaches during the summer months. Stream temperature is strongly

350   inversely dependent on streamflow, and very small values of discharge cause the model to

351   produce uncharacteristically high stream temperature simulation values. The calibrated

352   stream temperature model parameters can be found in the supplemental information.

353

354   3.3 Temperature and precipitation projections

355   Ensemble average projections of maximum and minimum air temperature and

356   precipitation, as compared to the historical time period, are shown in Figure 4. Overall, the

357   maximum and minimum air temperatures vary spatially throughout the CRB, with an

358   average ensemble increase of 5.5 °C for maximum air temperature and 5.4 °C for minimum

359   air temperature. All GCMs agreed that air temperature is expected to increase by the end

360   of the 21st century. Precipitation projections, on the other hand, varied between downscaled

361   GCM projections, with an overall average of a 14.4% increase compared to the historical

362   time period.

363

364   **3.4 Stream temperature projections**

365   Figures 5 and 6 display the spring/summer and fall/winter historical and projected

366   stream temperatures for the CRB. Simulated stream temperatures are projected to increase

367   throughout the CRB, with largest increases occurring in the east-central portion of the

368   CRB. On average, stream temperatures are projected to increase 3.5 °C for the spring, 5.2

369   °C for the summer, 2.7 °C for the fall, and 1.6 °C for the winter. It is important to note that

370   a large number of subbasins were removed from this analysis due to no-flow conditions

371   (i.e., running completely dry or icing-up) from changes in climate (hatched areas in Figures

372   5 and 6). Of these, winter had the largest number of subbasins removed from the analysis

373   (31%), followed by fall (18%), summer (16%), and spring (15%). The average period of

374   subbasins with no-flow conditions is projected to 34%, or 81 months out of the 240 months

375   for the 2080s time period. We consider these subbasins to not be reliable refugia for aquatic

376   species.

377   Simulated stream temperature changes also vary at the ecological province scale

378   (Table 3). At the annual time scale, the largest stream temperature increases (4.3 °C)

379   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

403 0.86, demonstrating that, on average, the increases in stream temperature seen by the 2080s

404 are to a larger degree tied to future changes in minimum air temperatures (Table 4). On the

405 seasonal time scale, stream temperature changes during the summer were the most sensitive

406 to changes in maximum air temperature with TS_{max} equal to 0.8, followed by spring (0.7),

407 fall (0.5), and winter (0.3). For minimum air temperature sensitivities, however, spring

408 values of TS_{min} were the highest of all seasons, equal to 0.9, followed by summer (0.8), fall

409 (0.5), and winter (0.3). Air temperature sensitivities varied by ecological province as well

410 as by season. At the annual and seasonal time scales the Intermountain, Middle Snake, and

411 Mountain Snake ecological provinces exhibited the highest values of TS_{max}.

412 For minimum air temperatures, the ecological provinces that were the most

413 sensitive were Columbia Cascade, Mountain Snake, and Upper Snake. Summer once again

414 had the highest overall TS_{min} values. However, the largest TS_{min} values were found in the

415 winter and spring seasons, with the Columbia Cascades in the winter (1.4) and the

416 Mountain Snake and Upper snake exhibiting TS_{min} values of 1.1 and 1.2 in the spring.

417 Overall, it can be seen that spring has higher TS_{min} values than TS_{max}, a possible artifact of

418 snowmelt (see Discussion).

419

420 **3.6 Sensitivities of stream temperature to changes in hydroclimatological components**

421 **3.6.1 Correlations at the Columbia River Basin scale**

422 At the CRB scale, all stream temperature changes were significantly correlated to

423 all hydroclimatic components during the spring and fall seasons for the 2080s (Table 5),

424 suggesting that during these seasons stream temperatures are highly sensitive to changing

425 environments. For summer, groundwater inflow change was the only variable not

426 significantly correlated to stream temperature changes. For winter, streamflow and

427 groundwater inflow changes were the only variables not significantly correlated to stream

428 temperature changes (see Discussion).

429

430 **3.6.2 Correlations at the ecological province scale**

431   Correlations between stream temperature and hydroclimatological components at

432 the seasonal time scale and ecological province spatial scale for the 2080s suggest that

433 multiple hydroclimatological components affect stream temperatures (Figure 7). As

434 expected, maximum and minimum air temperatures were significantly positively correlated

435 to changes in stream temperatures for all seasons and nearly all ecological provinces. The

436 only two ecological provinces where no significant correlations were found between air

437 and stream temperature were the Blue Mountain and Upper Snake provinces (see

438 Discussion), which are characterized by migratory salmonids and non-migratory

439 salmonids, respectively. Additionally, precipitation changes were negatively correlated to

440 stream temperature changes for all seasons and nearly all ecological provinces.

441   For spring, nearly all hydroclimatological components were significantly correlated

442 to stream temperature changes for each ecological province. Streamflow changes were not

443 correlated to stream temperature changes within the Blue Mountain, Intermountain, and

444 Upper Snake ecological provinces, which are characterized by warmwater species,

445 migratory coldwater salmonids, and non-migratory coldwater salmonids, respectively. We

446 also found that snowmelt changes within the Blue Mountain ecological province were not

447 correlated to stream temperature changes. However, within the Blue Mountain ecological

448 province we find that snowmelt is not a large portion of the hydrological cycle during this

449 season.

450   For the summer season, no relationships were found for streamflow, snowmelt,

451 surface runoff, and groundwater inflows within multiple ecological provinces. Overall,

452 streamflow was found to be significantly correlated with stream temperature within the

453 Columbia Cascades and Middle Snake, which are characterized by coldwater migratory

454 salmonids, and Mountain Columbia, which is characterized by non-migratory coldwater

455 salmonids, ecological provinces. Within the Columbia Plateau, Intermountain, and

456 Mountain Columbia ecological provinces, we find snowmelt to still be a large portion of

457 the hydrological cycle, thus any reductions of snowmelt do not significantly affect stream

458 temperature. Lastly, surface runoff and groundwater inflows were not significantly

459 correlated to the stream temperature changes in the Mountain Columbia and Upper Snake

460 ecological provinces and the Mountain Snake ecological province, respectively. Within

461 these regions we did not find large changes in surface runoff or groundwater inflows.

462   For the fall season, we find that changes in stream temperature within the Blue

463 Mountain ecological province, which is characterized by migratory coldwater salmonids,

464 is only positively correlated to changes in maximum and minimum air temperature, and

465 thus loses its ties to the other hydrology-related components. Note also that during the fall

466 season groundwater inflow changes become a non-significant factor in stream temperature

467 changes for five out of the eight ecological provinces. The only ecological provinces where

468 groundwater inflow changes were significantly correlated to stream temperature changes

469 were the Columbia Plateau, Intermountain, characterized by warmwater species, and the

470 Middle Snake, which is characterized by coldwater migratory species. These are regions

471   where groundwater inflows increased and therefore contributed cooling effects during this

472   time period.

473   During the winter season, changes in multiple hydroclimatological components

474   within multiple ecological provinces are not significantly correlated to changes in stream

475   temperature. Generally, changes in maximum air temperature, minimum air temperature,

476   precipitation, snowmelt, and surface runoff are still significantly correlated to changes in

477   stream temperature. These relationships make sense because during the winter season,

478   increases in maximum and minimum air temperatures in conjunction with changes in

479   precipitation will have the largest effects on two hydrological components: snowmelt and

480   surface runoff. This is the season where snowmelt-dominated regions with large snowmelt

481   components may perhaps become rain-dominated regions with large surface runoff

482   components.

483

484   **4. Discussion and Conclusions**

485   The importance of stream temperature to aquatic species distributions, interactions,

486   behavior, and persistence is well documented (Matthews, 1998), particularly for coldwater-

487   adapted taxa such as trout and salmon (Milner et al., 2003;McCullough, 1999).

488   Considering predicted increases in air temperature in the coming century, accurate

489   assessment of suitable thermal habitat is critical for predicting species responses to changes

490   in climate. Accordingly, recent research has investigated the potential impacts of climate

491   change on aquatic taxa by explicitly incorporating regression-based stream temperature

492   predictions into ecological models (Britton et al., 2010;Al-Chokhachy et al., 2013). While

493   simplified regression studies may boast low RMSE values between simulated and observed

494   stream temperatures, the relatively broad spatial scale of many of these studies (Mohseni

495   et al., 2003), neglects the variety of local hydrological systems that are differentially driven

496   by the array of inputs to each system (e.g., snowmelt, groundwater, runoff). The resulting

497   stream temperature model inaccuracies from this approach, clustered in particular regions

498   can be particularly problematic when investigating local population responses and range

499   shifts at the edge of species' distributions. Our results highlight this issue by characterizing

500   the varied relative contributions of different hydrological component inputs among

501   ecological provinces and suggest the complex system-level regulation of stream

502   temperature

503   As with any modeling study, modeling errors originate from multiple sources.

504   Wilby and Harris (2006) discuss these aforementioned uncertainties in detail and ranked

505   their importance in decreasing order as follows: differences in GCM output, downscaling

506   methods, hydrological model structure, hydrological model parameters, and then

507   greenhouse gas emission scenario. While their work was performed for a hydrological

508   model, the results still hold true for our stream temperature model. Particular to this study,

509   in order to quantify the differences between errors due to parameter uncertainty and GCM

510   (or projection) uncertainty, much more work needs to be done and is well beyond the scope

511   of this work.

512   However, we do note that our simulations for stream temperature demonstrated

513   higher errors during the summer months. This is due to low and fluctuating discharge

514   values that ultimately affect stream temperature. Also, it is likely due to the fact that

515   hydrologic components may influence stream temperature differently during different

516   seasons. For this study, we used annual calibration parameters and allowed them to vary

517   for each subbasin. An alternative approach would be to utilize seasonally varying

518   calibration parameters, and to analyze the dynamic (i.e., seasonal) influence of hydrologic

519   components on stream temperature. This may better capture the stream temperature

520   fluctuations in the summer months. Nonetheless, our spatially resolved methodology using

521   a mechanistic model, SWAT, better characterizes the complex processes of stream

522   temperature throughout the CRB by accounting for the hydrologic components

523   contributing to stream temperature and its variation.

524   Within the CRB, Wenger et al. (2013) used air temperature as a surrogate for

525   stream temperature to predict the response of Bull trout (Salmonidae: *Salvelinus*

526   *confluentus*) to predicted changes in climate, while Beer and Anderson (2013) used air

527   temperature-stream temperature relationships to predict the impacts of climate change on

528   salmonid life-histories. These approaches are common (Britton et al., 2010;Tisseuil et al.,

529   2012;Al-Chokhachy et al., 2013), yet overlook important differences in the inputs

530   influencing stream temperature across the basin. For example, our results suggest that

531   hydrologic contributions from snowmelt are relatively important drivers of stream

532   temperature within ecological provinces with primarily non-migratory coldwater focal fish

533   species. The influence of snowmelt tends to buffer stream temperatures against increases

534   in air temperature during the year relative to other areas in the watershed. In this case, a

535   regression-based approach to estimating stream temperature or the use of air temperature

536   as a surrogate for stream temperature will tend to overestimate stream temperature, and

537   thus underestimate the amount of suitable thermal habitat for coldwater species. In

538   addition, decreases in snowcover (and snowmelt) in the future will result in increased

539   thermal sensitivity within these formerly buffered regions. For example, current stream

540 temperatures in the Mountain Snake ecological province are buffered by relatively high

541 levels of snowmelt, yet decreases in future snowcover are predicted to result in this

542 province experiencing the greatest seasonal and annual increases in stream temperature in

543 the coming century.

544   Some of the relationships between stream temperature and hydroclimatic changes

545 at the CRB scale were expected, such as increases in maximum air temperature and

546 minimum air temperature resulting in increases in stream temperature, which were

547 significant for all seasons for the entire CRB. This relationship is well-established and

548 many models have been developed solely based on air-stream temperature relationships

549 (Stefan and Preud'homme, 1993;Mohseni and Stefan, 1999). Also, a decrease in

550 precipitation led to an increase in stream temperature, largely because greater runoff and

551 infiltration leads to larger volumes of water in the stream channel, and thus increases the

552 amount of energy needed to heat the water. Precipitation changes had the largest negative

553 correlations during the spring and summer seasons, followed by fall and winter. Both

554 surface runoff and lateral soil flow changes follow the same correlation patterns as

555 precipitation, as both are inherently tied to the amount of incoming precipitation.

556 Additionally, streamflow is tied to all hydrological components within the subbasin and

557 the incoming streamflow that is entering the streamflow reach. Since streamflow is a mix

558 of incoming hydrologic components, it is difficult to determine correlations. However,

559 much research has assumed that streamflow and stream temperature changes are inversely

560 correlated (van Vliet et al., 2011). The correlations within this study were significant and

561 positively correlated for the spring, summer, and fall seasons; however, all correlations

562 were below 0.10, which suggests the correlations were relatively minor, especially

563 compared to other components.

564   Snowmelt changes were negatively correlated during the spring, fall, and winter

565 seasons, and positively correlated during the summer season. A decrease in snowmelt will

566 lead to an increase in stream temperature because the cooling effect that snowmelt has on

567 stream temperature is no longer present. In summer, snowmelt and stream temperature

568 were positively correlated (albeit not significant), suggesting the counterintuitive notion

569 that an increase in snowmelt led to an increase in stream temperature. This can be explained

570 largely because snowmelt changes did not occur at all in 975 (60% of the subbasins with

571 streamflow) of the CRB subbasins, while for spring, fall, and winter, these values were 89

572 (5%), 50 (3%) and 48 (3%), respectively. These observations suggest that snowmelt is still

573 a component of the hydrologic cycle during the summer season.

574   Lastly, groundwater inflow changes to the stream channel were negatively

575 correlated to stream temperature change at the CRB scale for the spring and fall seasons.

576 This also makes sense, as groundwater temperature is generally cooler than the stream

577 temperature of the water already within the channel. Quite often, stream temperature

578 variations of cool water are used for tracer studies to determine where surface and

579 groundwater flows are exchanging water (Anderson, 2005;Constantz et al., 2003).

580 However, no significant correlation was found during the summer, when groundwater is a

581 large source of stream flow. This is likely because groundwater is the main source of water

582 for this season, any climate-induced changes in groundwater will not have a major effect

583 on stream temperature because the main water source for streamflow is still groundwater.

584 For example, if 85% of the streamflow comes from groundwater, and is then decreased to

585 75%, the change in stream temperature isn't likely to significantly change. Additionally,

586 no groundwater inflow change correlations were found for the winter season.

587 Species' responses to stream temperature occur within populations and are based

588 on local environmental conditions. Consequently, accurate assessment of local variation

589 in stream temperature is critical and only possible when local system drivers are accurately

590 represented in stream temperature models. While stream temperature is primarily

591 influenced by air temperature, this study emphasized the important effects of other

592 contributors (e.g., runoff, groundwater, snowmelt) that are differentially represented across

593 the CRB. Also, we have characterized the ecological provinces by warmwater and

594 coldwater focal fish species, which was done for qualitative biological assessments and not

595 as a predictive approach. However, these groupings have provided important information

596 regarding factors driving differential variation in stream temperatures across seasons in the

597 context of the biological groups experiencing particular stream temperature changes. River

598 basins encompass a spatially heterogeneous array of biological communities and these

599 communities are regulated by a spatially heterogeneous array of environmental conditions.

600 These environmental conditions are driven by local processes and require a systems-based

601 approach to accurately characterize the habitat regulating the distribution and diversity of

602 aquatic taxa.

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829 Table 1. Coupled Model Intercomparison Project – phase 5 General Circulation Models
830 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

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844   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

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846   *NS: Nash-Sutcliffe coefficient

847   *R^2: coefficient of determination

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

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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

1 Table 4. Sensitivities of stream temperature changes to changes in maximum and minimum air
2 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

3   Table 5. Pearson correlations between stream temperature and individual hydroclimatological
4   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

5   * indicates there was <u>no</u> significant correlation at p =0.05

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Figures

Figure 1. Columbia River Basin study area ecological provinces with streamflow and stream

temperature gauges for calibration.
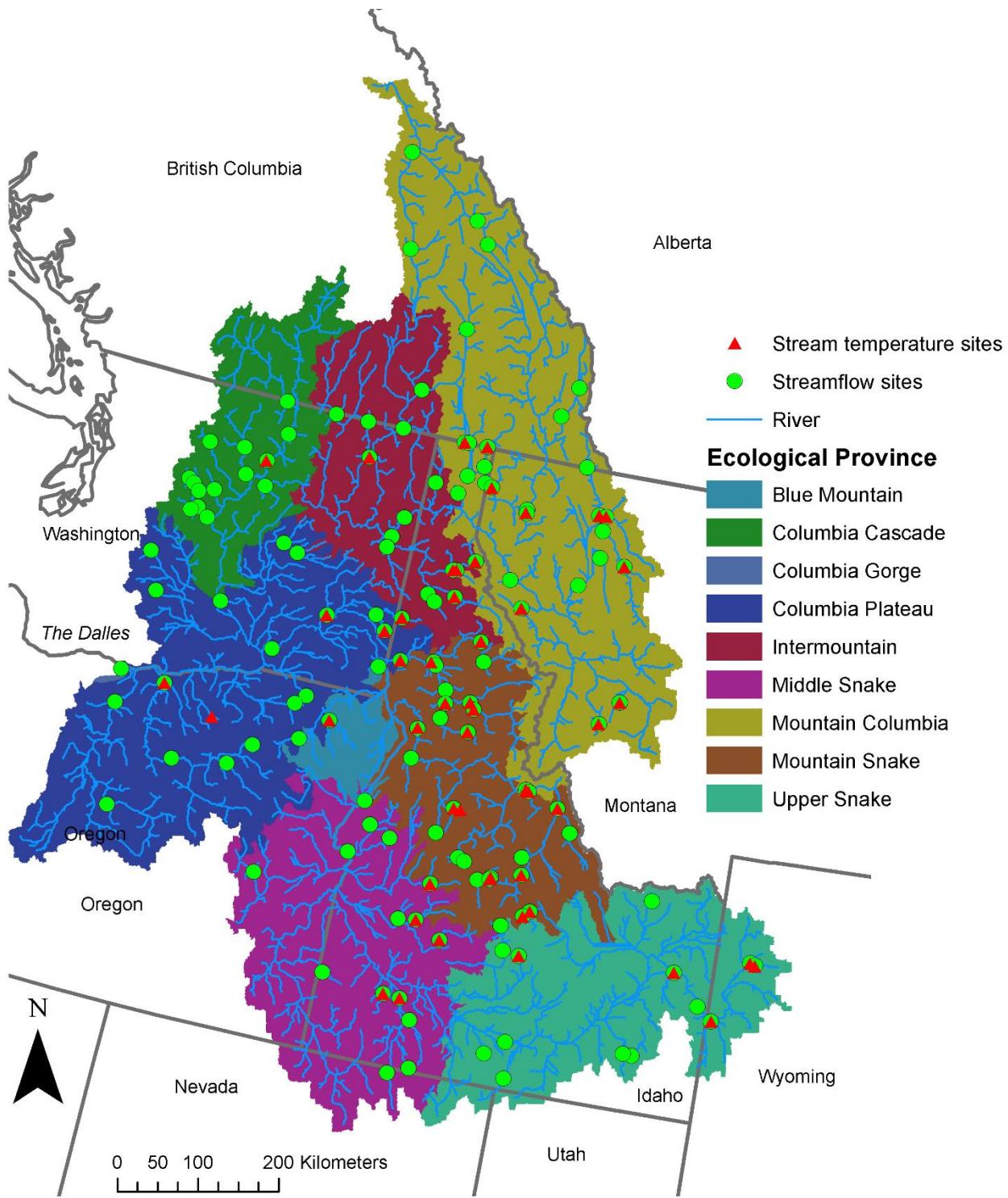
23   Figure 2. Root mean square errors of the simulated and observed stream temperatures

Stream temp. model RMSE (celsius)

2.1 - 3.0   3.1 - 4.0   4.1 - 5.0   5.1 - 6.0   > 6.1
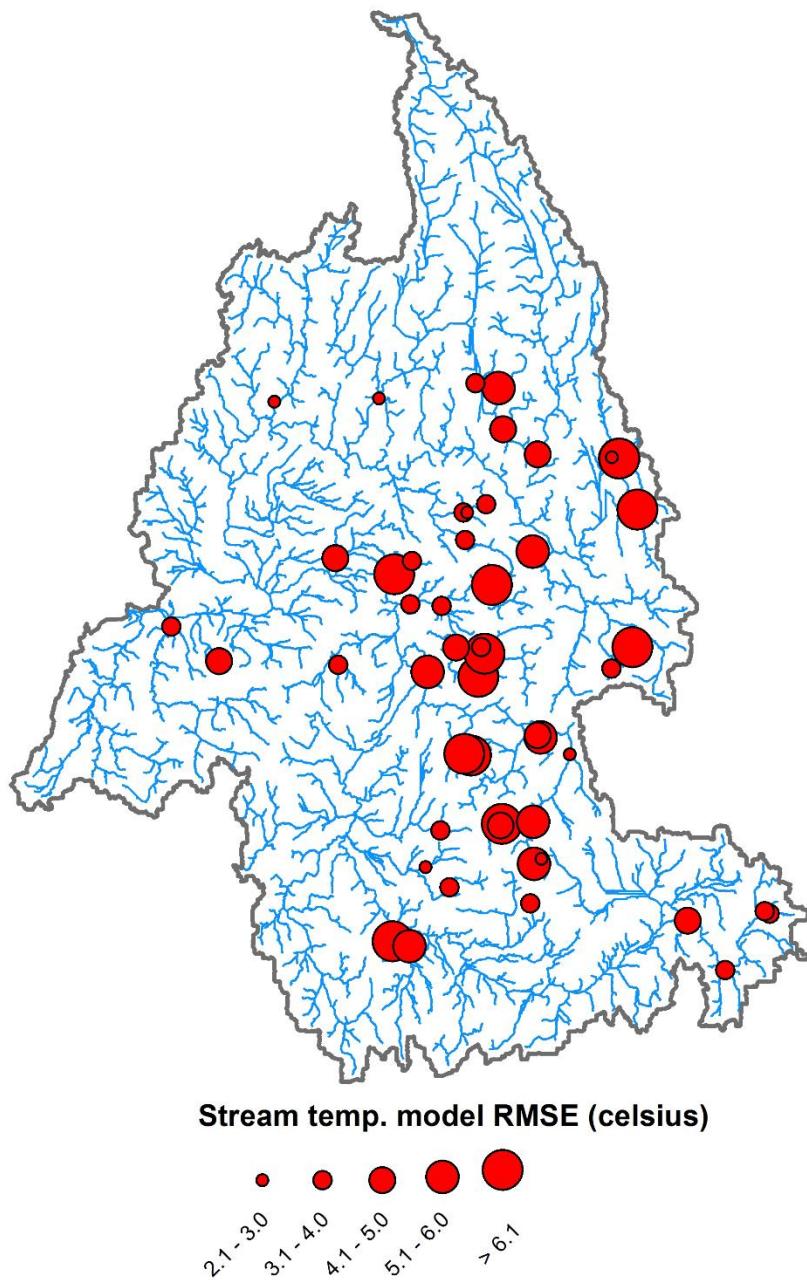
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29   Figure 3. Monthly stream temperature error distributions for all stream temperature gauges.

**Seasonal Distribution of
Stream Temperature Simulation Errors**

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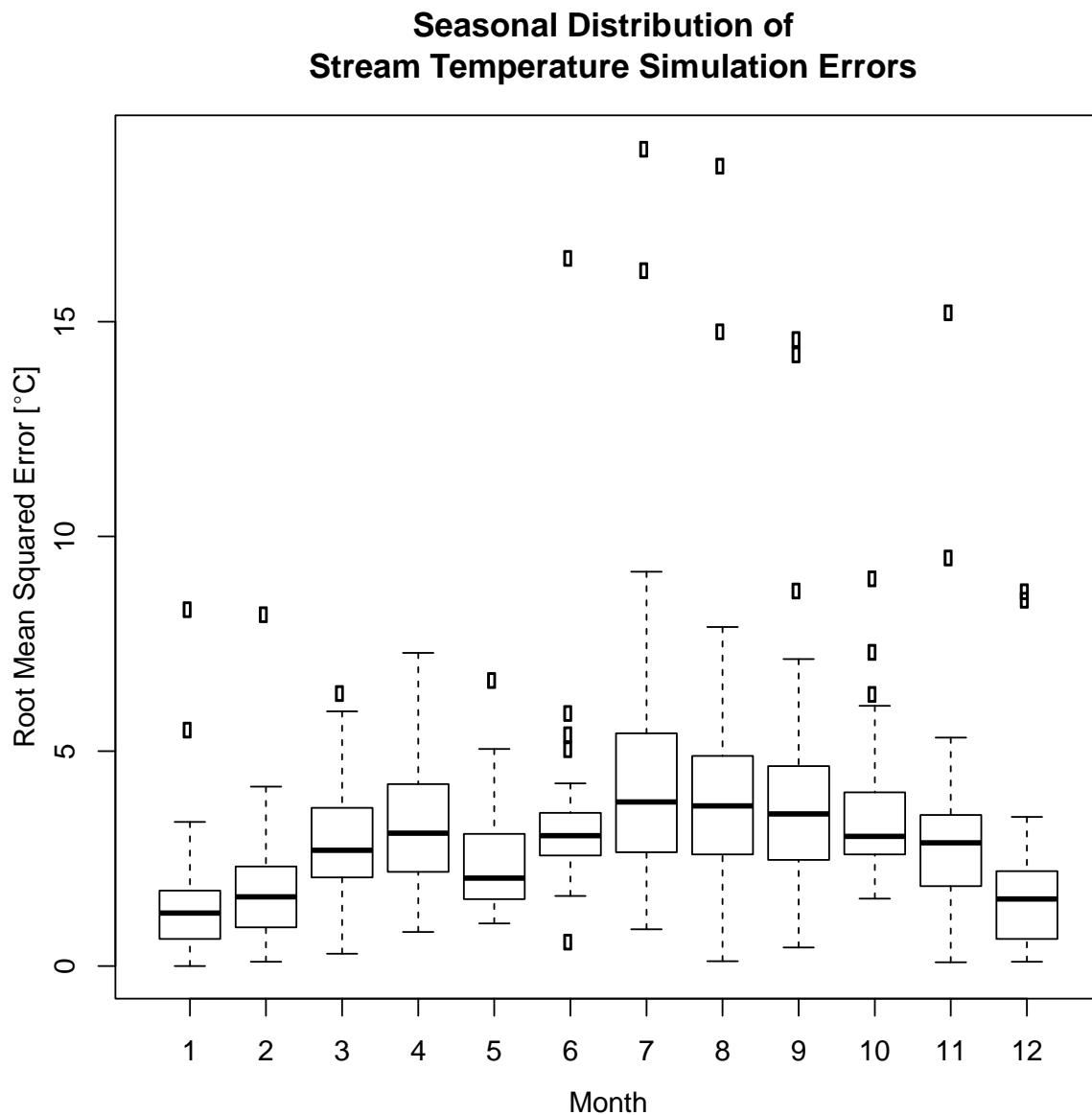
Figure 4. Changes in average precipitation and air temperature (maximum and minimum) for the

end of the 21st century as compared to the historical time period
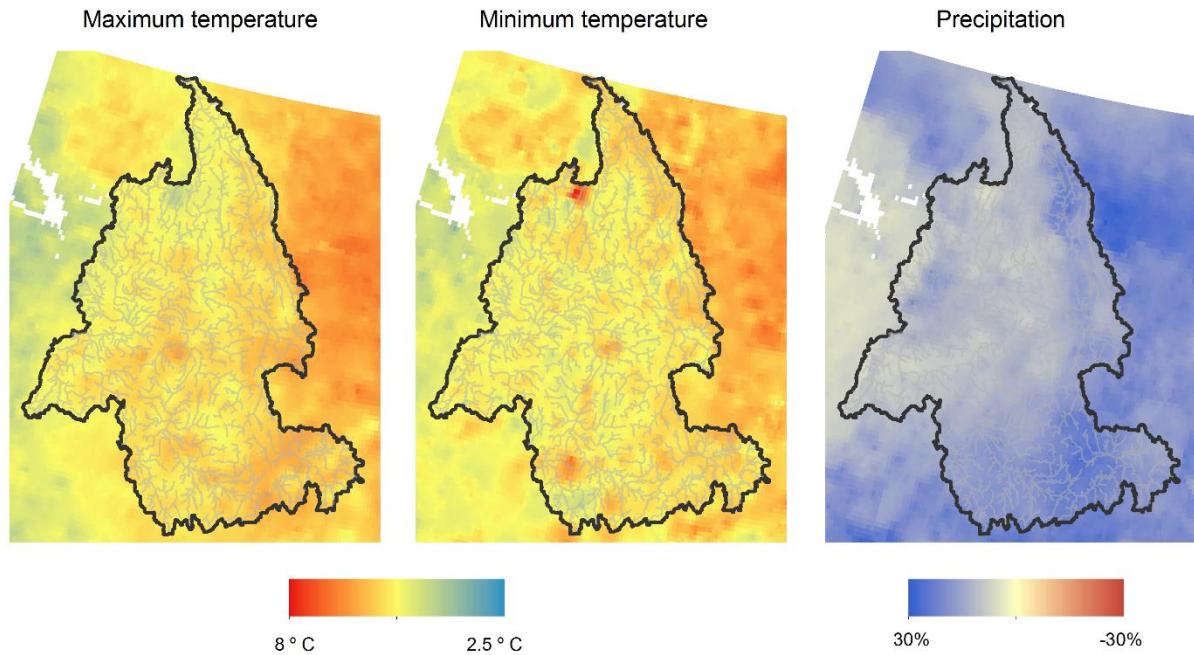
50   Figure 5. Spring and summer historical and projected stream temperatures at the subbasin-level.

51   Hatched subbasins indicate that drying occurred under climate projections and were removed

52   from analyses.
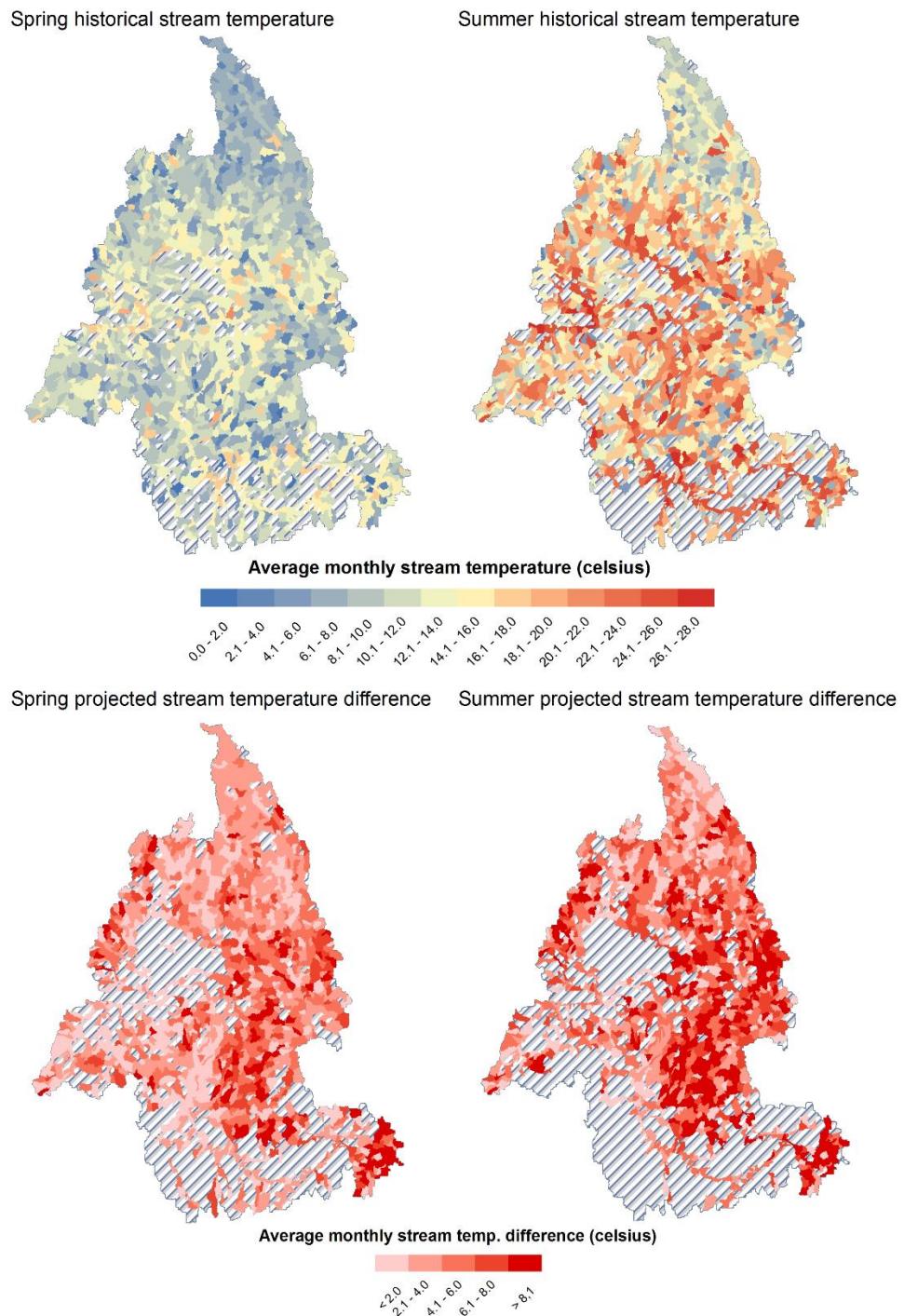
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54   Figure 6. Fall and winter historical and projected stream temperatures at the subbasin-level.
55   Hatched subbasins indicate that drying occurred under climate projections and were removed
56   from analyses.
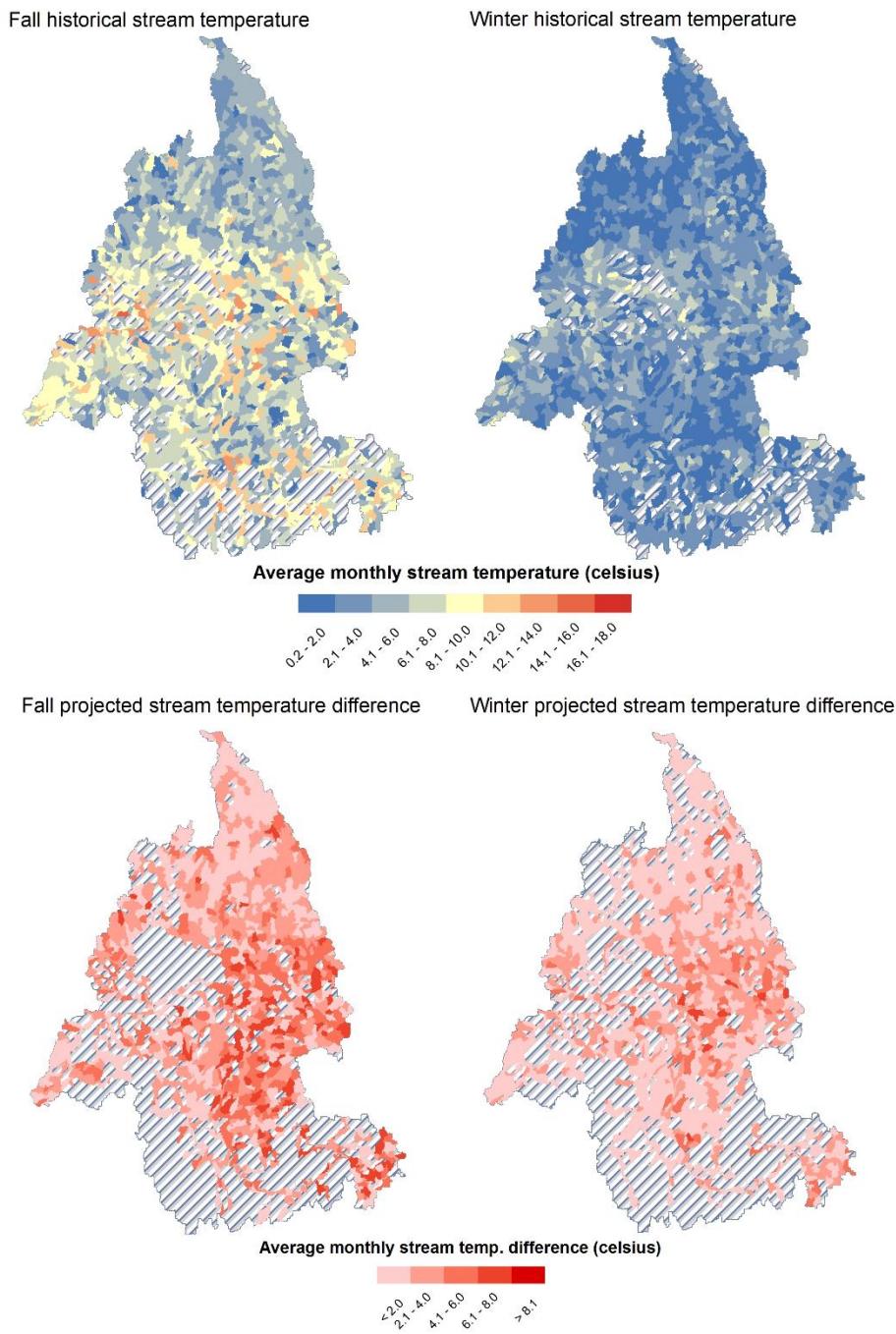
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60 Figure 7. Pearson correlations between changes in stream temperature and hydroclimatological
61 components for the Columbia River Basin ecological provinces. Tmax = maximum air
62 temperature; Tmin = minimum air temperature; Precip. = precipitation; Flow = streamflow;
63 Snomlt = snowmelt; SWQ = surface water runoff; GWQ = groundwater inflow; LatQ = lateral
64 soil flow. Asterisks represent <u>no</u> significant correlation at p =0.05

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