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Title page

Modeling future changes to the hydrological and thermal regime

Modeling future changes to the hydrological and thermal regime of unaltered streams using projected changes in climate to support planning for sensitive species management

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Abstract

Climate change will alter stream habitats through precipitation and air temperature changes and potentially threaten species that rely on contemporary streamflow and stream temperature regimes. Habitat projections are therefore critical to inform management decisions. Past and ongoing research has improved streamflow and temperature modeling in ungauged regions, but no studies merge these advancements with climate modeling for regional streamflow and stream temperatures predictions that describe stream habitat change. Here, we predict change in streamflow and stream temperature at the reach scale using projections from downscaled global climate models (GCMs) and the “business as usual” carbon emission scenario. We focus on unaltered streams in six southern California watersheds using data from baseline (1982-2014) and projected end-of-century (2082-2100). Stream temperature is projected to increase regionally, with high elevation stream reaches increasing most rapidly. There is less consistency in the streamflow projections, but a spatial and temporal homogenization of stream flow characteristics was predicted, i.e. flows become more similar across the region with less inter-annual variation. Additionally, there is a regional trend toward larger high flow magnitudes and more storm events. Despite the increased frequency and magnitude of storm events, high elevation streams are predicted to become drier for a greater portion of the year. Conversely, low elevation streams are predicted to have longer hydroperiods. Mapping future streamflow and stream temperatures at the reach scale can direct conservation efforts to streams that remain suitable, restoration to areas that decrease in suitability for target species, and support water policies that consider future stream condition.

Keywords

Climate change, riparian habitat, stream temperature, hydrologic modeling, CMIP5, conservation planning, random forest

Introduction

While climate change will no doubt alter streamflow and stream temperature leading to additional ecological impact in already threatened habitats, informative regional predictions that include both critical variables are lacking. Habitat conservation programs would be enhanced by considering these projected impacts of climate change (Jones et al., 2016; Foden et al., 2019; Wilson et al., 2020) and future projections of streamflow and stream temperature regimes may prompt management intervention such as species monitoring or strategically placing connectivity projects in regions projected to remain suitable. For example, while managers are committed to restoring the steelhead migration to southern California, streamflow and stream temperature may not be suitable for spawning in future streams. Predicting habitat suitability under climate change can therefore direct connectivity projects to the appropriate tributaries. Important characteristics of a streamflow regime include flow variability, the timing, magnitude, frequency, and duration of events (Poff et al., 1997). Ecohydrological relationships have been described for many species such as fish (Poff & Allan, 1995; Patterson et al., 2017), birds (Sidle et al., 1992), amphibians (Kupferberg, 1995), and vegetation (Mahoney & Rood, 1998; Stromberg et al., 2007). Stream temperature also drives habitat selection and survival. For example, rainbow trout have been observed to select pools with water below 21°C in the summertime (Matthews & Berg, 1997) and decline precipitously at 30°C (Sloat & Osterback, 2013). Critical thermal

65 maxima have been identified for many riverine fishes, such as an endangered species of
66 stickleback had a critical thermal maximum starting around 30°C, depending on acclimation
67 temperature (Feldmeth & Baskin, 1976). Regional projections of streamflow and stream
68 temperature regimes could direct conservation initiatives, but few studies have evaluated both
69 variables within the same region (but see Mantua et al., 2010).

70 Streamflow and stream temperature are master variables that drive riparian ecology (Cech
71 et al., 1990; Poff et al., 1997, 2002; Myrick & Cech, 2000; Bunn & Arthington, 2002; Sloat &
72 Osterback, 2013; Patterson et al., 2017) and are expected to change substantially due to climate
73 change through new precipitation and air temperature patterns (Christensen, Niklas et al., 2004;
74 Nelson & Palmer, 2007; Chang & Jung, 2010; Ficklin et al., 2013). While Mantua et al., (2010)
75 assessed changes in both variables in a gauged region, to attain a regional view of how we expect
76 stream habitat to change, we need similar analyses in ungauged regions because many streams
77 that support sensitive species lack monitoring. Analyses that predict changes in streamflow and
78 stream temperature in ungauged watersheds to produce an overall prediction of climate change
79 impacts in riparian systems have not occurred to our knowledge, yet are critically important for
80 biological management planning.

81 The challenge of evaluating potential hydrologic impacts of climate change due to the
82 lack of stream gauges is intensified by the difficulty of developing hydrologic models for
83 hundreds of stream reaches when a regional scale analysis is required. Hydrological modeling
84 typically occurs in regions with gauged flow that is used to calibrate the model and assess the
85 model performance. This poses problems for conducting ecohydrological analyses in ungauged
86 watersheds, like the upper tributaries in southern California. To address these challenges,

significant progress has been made to improve regional modeling of streamflow in ungauged watersheds and to evaluate streamflow patterns for biological purposes (Vogel et al., 1999; Sanborn & Bledsoe, 2006; Parajka et al., 2013; Sengupta et al., 2018). For example, hydrologic models can rely on transferable parameters from similar watersheds that have gauges to support model calibration and validation, or statistical relationships identified between streamflow and watershed characteristics that can be applied to ungauged streams. Sengupta et al. (2018) developed a novel technique to model flow in ungauged watersheds by using parameterized results from similar watersheds identified with random forest modeling. The authors successfully developed current and historical flow regimes and flow metrics for over 500 sites in southern California, demonstrating model transferability and applicability to ungauged watersheds for a wide geographic region. These new approaches allow for ecohydrological metric estimation in ungauged streams that can be applied to biological endpoints in regions with sparse monitoring.

Much like streamflow modeling, stream temperature models are typically developed in regions with historical monitoring data for use in calibration and validation for a single reach or watershed (Hawkins et al., 2010). However, the value of regional stream temperature modeling in ungauged streams for biological study has been recognized and many advances have been made (Hill et al., 2013). In regional models, watershed characteristics are often used to build statistical relationships with stream temperature by using monitoring from multiple sites, which can then be applied elsewhere. Unlike physical models, statistical relationships can be applied to new sites for use in ecological studies. The simplest statistical models use only air temperature as a predictor, which may perform well for a single site, but cannot be extrapolated to other sites as the other stream temperature drivers will vary (Stefan & Preud'homme, 1993). Other natural

variables found to impact stream temperature include watershed elevation and area (Kelleher et al., 2012), shading (Kelleher et al., 2012; Garner et al., 2014; Wondzell et al., 2018), water velocity (Garner et al., 2017), channel orientation (Garner et al., 2017), and streamflow (Letcher et al., 2016).

In this study we model streamflow and stream temperature metrics in a largely ungauged study area in southern California in baseline and forecasted end-of-century climate scenarios. We use a stream reach scale analysis because in topographically complex regions, like southern California, microclimates exist within close proximity, and predictions at the stream reach scale are critical to capturing spatial variability (Ficklin et al., 2013). We model streamflow by applying parameters from precalibrated and validated physical watershed models in the region with similar watershed characteristics (Sengupta et al., 2018). We calculate streamflow metrics in the modeled watersheds and use random forest to estimate metrics across the stream reaches within the study area. We model stream temperature metrics with statistical methods that use 19 stream temperature datasets monitored from three agencies, and air temperature data from two sources. We then predict stream temperature metrics regionally in the future climate scenarios. These methods inform conservation planning by forecasting regional streamflow and stream temperature attributes.

Methods

Overview

We predict the changes in stream temperature and streamflow patterns for the end-of-century by modeling the hydrologic and thermal regimes of streams in southern California using

downscaled global climate model (GCM) precipitation and air temperature (Figure 1). Using downscaled precipitation data for baseline water years, 1982-2014, we conducted hydrologic modeling in a selection of sub-watersheds. We calculated flow metrics from the streamflow time series data and developed a random forest model (Breiman, 2001) to estimate the flow metrics at the remaining stream reaches in the region for three baseline periods selected based on precipitation magnitude - a wet, moderate, and dry period. We then used future precipitation projections, averaged from three Coupled Model Intercomparison Project 5 (CMIP5) GCMs, and the “business as usual” carbon emission scenario Representative Concentration Pathway (RCP) 8.5 to predict the flow metrics in three end-of-century periods (a projected wet, moderate, and dry period). We developed a multivariate linear regression model for stream temperature and used the model to predict weekly stream temperature at all stream reaches within the region for three time periods (baseline, mid-century, and end-of-century) using air temperature projections from the same GCMs and carbon emission scenario. Ultimately, we evaluate change in streamflow and stream temperature metrics.

Study region

The focus of this study is on natural and semi-natural streams in six major watersheds in Los Angeles and Ventura counties in southern California, southwestern United States (Figure 2). The region has a Mediterranean climate and the average annual precipitation is around 400 mm. Urbanization and flood control measures dominate the lower regions in the study area; consequently, factors such as wastewater discharge or dam operation exert greater influence on stream habitat than climate change effects. Therefore, we limited our focus to mainly unaltered

streams, where changes in climate will drive alterations in streamflow and temperature, and ultimately, impact the riparian fauna.

To determine which streams were considered urbanized (for *exclusion* in our study), we hierarchically clustered stream reaches using the National Hydrography Dataset (NHD) stream reach designation as our spatial unit (<https://www.usgs.gov/core-science-systems/ngp/national-hydrography>) and the ‘hclust’ function in R (R Core Team, 2018). Clustering was based on watershed and catchment data for each stream reach from the United States Environmental Protection Agency (U.S. EPA) StreamCat data set (<https://www.epa.gov/national-aquatic-resource-surveys/streamcat>, Hill et al., 2016) (Appendix S-1). We cut the dendrogram at the point where we identified major divisions between NHD stream reaches and produced five clusters. There was one cluster that represented minimally altered stream reaches (low or no dams, low impervious surface area, low urban space of any kind, and low road density), which we included in our study. To further ensure that these watersheds were not hydrologically altered, we excluded watersheds with major dams that store water in reservoirs. We did not remove other dams, like silt dams or small recreational dams, because of the lack of data and their lessor impact on hydrology. Many of the streams included in this study are mountainous because the streams in the lowlands have been impacted by urbanization.

Climate scenarios

The three GCMs used in this analysis were CanESM2, CCSM4, and MIROC5, from CMIP5 (Taylor et al., 2012, Appendix S-2). While these three models do not represent the entire range of outcomes projected from climate models, they capture a large amount of variation

172 among future climate projections (Berg & Hall, 2015; Walton et al., 2015). They performed well
173 in modeling atmospheric rivers impacting California (Goldenson, 2018) and were among the ten
174 selected for climate change planning in California based on historical performance (DWR,
175 2015). We averaged the stream temperature and streamflow modeling results across the three
176 GCMs to focus on the changes in stream habitat, and not the differences in climate models.
177 Maurer & Duffy (2005) reported that despite differences in GCM projections of precipitation and
178 air temperature, hydrological trends tended to be similar across models. For a comparison of the
179 separate models not using averaged results, see (Taylor et al., 2019).

180 In Mediterranean climates, the majority of annual precipitation occurs in just a few severe
181 storms, and the amount of precipitation varies annually (Gasith & Resh, 1999). In these
182 environments, in addition to predicting changes from decadal averages in streamflow, we
183 decided it may be important to predict changes in flow during particularly dry and wet periods.
184 We modeled streamflow conditions for three short-term temporally specific baseline and end-of-
185 century periods, selected based on the precipitation magnitude during a three-year period. In the
186 baseline period, 1990 - 1993 (0.90) was selected as a wet period, 2007 - 2010 (0.32) as a
187 moderate period, and 2011 - 2014 (0.03) as a dry period (parentheses denote the total
188 precipitation percentile of each three-year period). In the future years, 2092 - 2095 (1.0) was
189 selected as a wet period, 2097 - 2100 (0.38) as a moderate period, and 2087 - 2090 (0.06) as a
190 dry period. To evaluate change in streamflow, we compared each period between the baseline
191 and end-of-century years. For example, the period ending in 1993 is compared to the period
192 ending in 2095 to describe changes in wet period streamflow. To determine how the short-term

period analysis differs from an otherwise long-term analysis, we also modeled streamflow metric change using the entire duration of the baseline and end-of-century data.

We modeled stream temperature conditions annually for the baseline (1982-2014), mid-century (2022-2061), and end-of-century (2082-2101) time periods. To evaluate change for stream temperature, we compared summertime stream temperatures averaged over the baseline years and averaged over the end-of-century years. Because air temperatures do not vary to the same extent that precipitation varies in this region, we did not evaluate short-term changes for stream temperature, and instead, modeled annual conditions.

Hydrologic modeling

We utilized the hydrologic modeling framework developed by Sengupta et al. (2018) to represent the watersheds for our study area, briefly summarized herein. The framework was developed for ecohydrological studies in southern California streams that have long-term biology data, but no long-term streamflow data and uses an ensemble model approach to estimate flow regionally across ungauged systems. Sengupta et al.'s (2018) regional 26 model ensemble was calibrated and validated with United States Geological Survey (USGS) flow gages and national, state, and local precipitation data. Validation was performed to verify model transferability - or the ability of the model to be used for flow modeling at different sites. Each model was validated with 10 years of testing data independent from the calibration data set. We selected 68 sub-watersheds (Figure 2) to represent our study region and applied the U.S. Army Corps of Engineers Hydrologic Engineering Center Hydrologic Modeling System (HEC-HMS) rainfall-runoff model. Using the random forest method developed by Sengupta et al., (2018), each of the

68 ungauged watersheds in our study region were paired to one of the 26 models from the ensemble to estimate the flows based on similarities in land cover and soil criteria: mean imperviousness, road density, National Land Cover Database (NLCD) urban, agricultural, and developed open space land use, and soil erodibility.

Once assigned to one of the 26 gauged watersheds, additional watershed-specific parameters were defined: rainfall, watershed area, time of concentration (T_c), storage coefficient, and percent impervious area. Watershed area, length, and slope were derived from digital elevation models (DEMs). Travel time parameters, lag time (calculated as $0.6T_c$) and time of concentration (calculated with the Kirpich equation (Maidment, 1993): $T_c = 0.0071^{0.77} S^{-0.385}$), were computed for each watershed and are a function of length and slope. Percent impervious area was derived from the NLCD 2011 Percent Developed Imperviousness data. The NLCD 2001 to 2006 and NLCD 2006 to 2011 Percent Developed Imperviousness Change data sets were referenced to confirm that developed land area had remained relatively consistent through the portion of study period for which NLCD data is available (Homer et al., 2004, 2015; Fry et al., 2011).

Precipitation time series for each model were derived from a 90-meter, gridded precipitation data set, which consisted of a continuous, 3-hourly time series spanning water years 1982-2014 for the entire study region (Berg et al., 2015; downscaled by Huang & Hall, 2018). This is a modeled data set that was validated against three observational data sets. The average R^2 value between the modeled precipitation and the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center (CPC) $0.25^\circ \times 0.25^\circ$ daily U.S. unified precipitation was 0.82. Gridded precipitation values were averaged over each watershed. The

resulting precipitation time series were used as input into the HEC-HMS models. Each HEC-HMS model was run at a 3-hourly time-step, consistent with development of the ensemble models. The 3-hourly streamflow time series were averaged into daily average flow values in post-processing, resulting in a daily streamflow time series spanning water years 1982-2014 for each watershed at its downstream terminus.

Regional streamflow metric model

At each of the 68 HEC-HMS modeled watersheds we calculated five flow metrics from the model-derived streamflow time series (Table 1) for the wet, dry, and moderate periods. We also calculated the same five flow metrics using the entire duration of the modeled flow time series, which we call the ‘all-year’. These metrics were selected based on their descriptive power for hydrological patterns and their biological importance for supporting the native species in southern California. Relationships of these metrics and multiple riparian species are explored in Rogers et al., (2020).

With data from the 68 watersheds, we used random forest in R (Liaw & Wiener, 2002) to predict streamflow metrics for all NHD reaches in the study for the wet, dry and moderate periods. Two types of variables were included in the random forest: static predictors (Appendix S-3), which included watershed characteristics, such as elevation and area, and variable predictors that change over time, which included precipitation metrics. Static predictor variables were derived from the EPA StreamCat database (Hill et al., 2016) and we used the ‘nearZeroVar’ function from the Caret package (Kuhn et al., 2018) in R to exclude variables that showed no variation across the stream reaches in our study region. The variable predictors were

257 derived from the baseline precipitation data and we calculated a series of precipitation metrics,
258 such as ‘number of storm events’.

259 For each flow metric, two models were created with 80% of the data for training. The
260 first used *all* static and variable predictors and the second used only the top ten most important
261 predictors from the first model (based on cumulative changes in model error after excluding each
262 variable). The final model for each metric was based on overall performance on a validation data
263 set that was a random selection of 20% of the observations from the complete data set. Overall
264 performance was assessed using root mean squared errors and R^2 values comparing the observed
265 flow metrics and those predicted from each model for the validation data set. Flow metrics were
266 then predicted at all stream reaches using the best performing model for each metric.

267 To predict the flow metrics for the end-of-century time period, the random forest model
268 was applied with the same static predictors, but with the end-of-century precipitation data for the
269 wet, dry, and moderate periods. Some static variables like land cover change can impact stream
270 habitat (Maloney et al., 2020); however, because our region includes only the unaltered
271 watersheds predominantly in mountainous areas, many of which are protected, we do not
272 anticipate substantial urbanization in future years. All processing for the streamflow metrics was
273 completed in R (R Core Team, 2018).

274 **Water temperature modeling**

275 We used an empirical stream temperature model with data from multiple sites (Hawkins
276 et al., 2010) to predict stream temperature metrics in our study region. Summertime data (May
277 through September) from 19 unaltered sites in southern California with continuous stream

temperature records (Appendix S-4) were combined to develop a statistical model using air temperature, watershed elevation and area, riparian herbaceous and woody cover, and baseflow index to predict maximum, minimum, and mean weekly stream temperature. Stream gauges used in model calibration proportionally represent stream elevations in the study area, (first quartile: 418m, 489m; median: 624m, 871m; and third quartile: 1045m, 1227m for the set of gauges and all the study area stream reaches, respectively). Catchment area of the gauges also proportionally represent the catchment area of all the stream reaches (first quartile: 0.9km², 0.61 km²; median: 1.56 km², 1.28 km²; and third quartile: 3.18km², 2.28 km² for the set of gauges and all the stream reaches, respectively). If only minimum and maximum water temperature were reported, we calculated the mid-range in lieu of the mean. In the sites that reported the mean, the mid-range and mean values were similar ($R^2=0.99$), but at high stream temperatures the mid-range value exceeds the mean value and the variance around the mean value increases (Appendix S-5). When possible, we used the mean temperature as it was reported, or calculated the mean from sub-daily measurements that were reported. Maximum and minimum stream temperatures were either reported directly or calculated from sub-daily reporting.

Two gridded air temperature data sets were used; a grid of modeled air temperature (Walton et al., 2015, the Walton data set) and a statewide grid of observed air temperature with interpolated values (Livneh et al., 2015, <https://cal-adapt.org/data/>, the Livneh data set). Both data sets were needed to align with all the stream temperature loggers either spatially or temporally (see Appendix S-6 for comparison between the two data sets). The Walton dataset was validated against 24 station measurements and a previous version of the Livneh data set (Livneh et al., 2013), and in both cases, performed well spatially and temporally. It performed

particularly well in the summer months when compared to station measurements, with an R^2 value of 0.93. The data set consists of modeled daily mean air temperature, at 90m resolution, from water years 1982-2014 (averaged from a modeled timeseries with 3-hourly increments). The Livneh data set consists of observed daily maximum and minimum air temperatures from 1950 -2013 with interpolated values at approximately 6km pixels. We averaged the maximum and minimum temperatures over the 6km scale, to get daily mid-range air temperature.

For every day of the stream temperature record, daily air temperature was extracted from the appropriate air temperature data set at the correct date and location. Stream temperature was summarized as running 7-day average, minimum, and maximum temperatures, which have a more linear relationship with air temperature than daily data (Stefan & Preud'homme, 1993; Kelleher et al., 2012). The air temperature data, which consists of a time series of daily mean air temperature, we calculated the 7-day running maximum-mean, mean-mean, and minimum-mean values. The three stream temperature metrics were modeled using the air temperature metrics, watershed area (km^2), watershed elevation (m), woody or herbaceous riparian cover (%), and Baseflow Index (%) as predictor variables in a multiple linear model using 75% of the data and saving 25% for validation (Figure 3). Baseflow index represents the percentage of total streamflow that is from ground-water discharge into streams. We used woody and herbaceous riparian cover as a proxy for stream shading. The additional predictor variables were included in the stream temperature prediction model because they have been identified as parameters that influence stream temperature in the literature (for example, see Stefan & Preud'homme, 1993; Kelleher et al., 2012; Garner et al., 2014; Wondzell et al., 2018) and because they have been previously quantified for every stream reach in our region and are available from the StreamCat

dataset (Hill et al., 2016). We applied a $\log(x+1)$ transformation to the woody and herbaceous riparian cover and a log transformation to the watershed area to reduce the skewness of the data. These models were used to calculate the mean, minimum, and maximum 7-day stream temperature for every stream reach during water years 1982-2014. Six stream temperature metrics were calculated from the predicted values (Table 2). Like the streamflow metrics, these metrics were selected for their importance in identifying suitable habitat (for example, Welsh et al., (2001) and to describe different aspects of the stream temperature regime. Relationships of the stream temperature metrics and multiple riparian species are also discussed in (Rogers et al., 2020). Future stream temperature metrics were calculated from averaged air temperature predictions across the three GCMs using the same regression models (Walton et al., 2015), assuming the other predictor variables stay constant.

Results

Stream temperatures are projected to increase; more for maximum and average temperatures compared to minimum temperatures, and more in high elevation streams compared to low elevation streams. End-of-century predictions for streamflow showed an increase in the number of storms, and larger high flows for high and low elevation streams, and for all water year types. Hydroperiod is projected to increase in low elevation streams but decrease in high elevation streams. Storm flows are predicted to recede more rapidly in high elevations, but more slowly in low elevations. We observed a general trend toward spatial and temporal homogenization of streams for all flow metrics. This means we predict a decrease in the range of streamflow metrics that are observed across the region (spatially) and between water year types (temporally).

344 **Model performance**

345 **Stream temperature**

346 The linear models that predicted rolling seven-day averages, minimums, and maximums
347 had root mean square errors (RMSE) approximately 10% of the range of the values (Table 3).
348 The model for average and minimum temperatures performed substantially better than the
349 maximum temperature. Residuals of each model were sufficiently normal to suggest the linear
350 regression was appropriate (Figure 3). The predictor variables were all highly significant except
351 the herbaceous wetland vegetation percent cover for the running seven-day mean ($P=0.04$) and
352 maximum ($P=0.66$) stream temperature models (Table 4).

353 **Streamflow random forest**

354 The random forest models performed well for each flow metric, with R^2 values mostly
355 above 0.8 (Table 5). The random forest models for each flow metric generally performed better
356 with the entire suite of predictor variables (rather than the top ten). For each variable, the
357 prediction R^2 was better for the all-year timeframe than the 3-year, however both were very
358 good. This suggests that while predicting flow characteristics over a long period is more
359 accurate - not surprising given that in the region annual streamflow can fluctuate widely - short-
360 term prediction is possible.

361 We report the top three predictor variables for each flow metric (Table 5). While we
362 initially expected the variable predictors, based on precipitation, to be the most important in
363 driving streamflow metrics, we found that in many cases the static variables were more
364 important. This is likely because our study region is relatively small and storms tend to impact

365 the entire region, so watershed characteristics are what really drive regional differences in
366 streamflow metrics.

367 **Stream temperature projections**

368 End-of-century mean stream temperatures are projected to increase at a faster rate,
369 followed by maximum temperatures, and finally minimum temperatures (Figure 4). Averaging
370 all the stream reaches together across the study region, there is a maximum 7-day average
371 increase of 2.29°C (1.99°C, 2.54°C), a maximum 7-day maximum increase of 2.05°C (1.78°C,
372 2.29°C), and a minimum 7-day minimum increase of 1.67°C (1.42°C, 1.82°C). Parentheses
373 show 5th and 95th percentiles. The greater increase of maximum temperature compared to
374 minimum temperatures leads to a larger 7-day temperature range of mean 0.18°C. Finally, there
375 is an average increase in 13 (0, 75) days where temperatures surpass 30°C, a biologically
376 important threshold for Steelhead where mortality increases rapidly (Sloat & Osterback, 2013).

377 While we predicted an increase in temperature for all stream reaches in the study region,
378 stream reaches in higher elevations (375m and higher) generally increase by a larger magnitude
379 than those in lower elevations (Figure 5). Seven-day maximum, average, and minimum
380 temperatures increased by an average of 2.08°C, 2.32°C, and 1.70°C in high elevation
381 watersheds, compared to 1.89°C, 2.13°C, 1.50°C in low elevation watersheds. Differences
382 between high and low elevation were significant at the $\alpha = 0.05$ level for all three variables ($P <$
383 0.001 for all). Temperature change distributions were unimodal in low elevation stream reaches,
384 whereas they are more variable in high elevation streams. The different modes in the data
385 distributions of high elevation stream reaches (as shown in Figure 5, panels F, H, and I)
386 correspond to different mountain ranges in the region. This suggests that although stream

temperature in high elevations are generally projected to increase more than those in low elevation, the temperature increase is not constant across high elevation streams. Despite the increased warming of high elevation streams, temperatures are projected to remain below 30°C, which suggests they may continue to be important ecological refuges for cold water fishes.

Streamflow projections

Three trends were identified by comparing projected end-of-century streamflow metrics to baseline years: a magnitude shift of each flow metric, lower variability of flow metrics regionally in end-of-century compared to baseline (lower spatial variability), and a reduction in the difference between water year types for each flow metric in end-of-century compared to baseline (lower temporal variability).

The clearest trend identified in comparing projected end-of-century streamflow metrics to baseline years is a magnitude shift of some variables. This is most evident in the increase in storm flow frequency and storm flow magnitude (Figure 6 panels A and B). Both storm flow metrics change more in dry periods, when there is a mean increase in storm flow events of 1.53 (0.88, 2.09), 0.86 (-0.05, 1.3), and 0.8 (-0.7, 1.43) in dry, moderate and wet periods, respectively (5% and 95% percentile shown in parentheses). There is a mean increase in storm flow magnitudes of 2.22 cms (0.57, 6.46), 1.48 cms (0.52, 4.04), and 0.74 cms (-0.73, 1.81) for dry, moderate and wet periods, respectively. The duration of low flows is projected to change differently in future years depending on year types (Figure 6 panel C), of -85 days (-279, 78), 59 days (-147, 279), and 119 days (-53, 289) for dry, moderate, and wet periods, respectively. Hydroperiod does not show a strong positive or negative trend for each period (Figure 6 panel D). Storm flow recession is predicted to be more rapid in future years for all water year types -

409 0.06 (-0.16, 0.07), -0.07 (-0.24, 0.1), and -0.03 (-0.16, 0.11) dry, moderate, and wet,
410 respectively, however there is spread across zero for all periods showing some streams recede
411 more slowly (Figure 6 panel E).

412 We predict an overall reduction in the range of streamflow metrics across the region in
413 the end-of-century time period compared to the baseline time period, i.e. the streams across the
414 region become more similar. The range of values for the number of storm events across stream
415 reaches in the end-of-century time period was 78% of the baseline range. Similarly, the end-of-
416 century duration of low flow range was 33% of the baseline range, end-of-century hydroperiod
417 range was 72% of the baseline range, and end-of-century storm flow recession range was 81% of
418 the baseline range. Maximum flow was the only metric to increase in range and was 1.20 times
419 the range in the baseline. This suggests that except for high flow magnitudes, there will be less
420 spatial variability of flow across the study region in the end-of-century time period.

421 In addition to reduction in spatial variability, we observed less interannual variability in
422 streamflow between year types in the predictions for each flow metric (i.e. dry, moderate, and
423 wet periods). In the baseline years, there was a greater difference between wet, moderate, and
424 dry periods across stream reaches for all flow metrics compared to end-of-century years (Table
425 6). This is most evident for duration of low flows, where the end-of-century dry period has
426 shorter dry spells and wet years have longer dry spells, making them more similar than baseline
427 years.

428 Stream elevation (high elevation is >375m) did not impact the direction of change from
429 baseline for frequency of storm events, high flow magnitude, or the duration of low flows (Table
430 7). However, the direction of change in hydroperiod and storm flow recession did differ between

431 high and low elevations (Figure 7). While both had large variation surrounding the mean, storm
432 flow recession decreased in the high elevation watersheds and increased in the low elevation
433 watersheds (see Table 4 for mean change, all water year types had $P < 0.01$ in a paired t-test).
434 Hydroperiod decreased in the high elevation streams but increased in the low elevation streams
435 (see Table 4 for mean change, all high elevation year types and low elevation dry and moderate
436 year types had $P < 0.01$. Low elevation wet year had $P = 0.10$). Therefore, streams in high
437 elevations may be drier for more of the year, despite the increase in storms and storm flows,
438 while streams in low elevations may retain flow for longer.

439 **Timeframe comparison**

440 We evaluated the importance of quantifying future change in streamflow metrics during
441 periods that experience comparable precipitation magnitudes (for example three year periods in
442 the baseline and future with low precipitation), versus quantifying change in long-term
443 conditions. We find that the end-of-century change calculated for time periods with comparable
444 conditions does differ from change calculated between long-term conditions in the baseline and
445 future years (Figure 8). Most interesting is that change from baseline to end-of-century using the
446 entire timeseries (i.e. approximately a 30 year baseline and a 16 year end-of-century) produces
447 very little overall change in the 5 metrics, whereas the short-term three year periods that differ in
448 precipitation magnitude show greater deviation from baseline.

Discussion

Comparisons to other studies and modeling performance

The major hydrologic trend we projected is an increase in storm flow magnitude and frequency, and an overall homogenization of stream flow metrics between water year types and across the region. High elevation streams are predicted to recede faster following storms and have shorter hydroperiods, whereas the opposite is predicted for low elevation streams. Other studies also predict an increase in the magnitude of very large flood events toward the end of the century (Das et al., 2013; Knowles et al., 2018). Studies also project the timing of flows to shift earlier in the year, creating wetter winters and drier springs and summers (Stewart et al., 2004; Knowles et al., 2018), something that our study did not investigate, but could help explain why high elevation streams have shorter hydroperiods and faster recessions.

We had good performance for minimum and mean weekly stream temperature predictions. The maximum weekly stream temperature model performed substantially worse. This could be explained by evaporative cooling at high air temperatures and a flattening of the linear relationship, i.e. an increase in air temperature leads to less of an increase in stream temperature (Mohseni & Stefan, 1999). The ‘flattening’ has been observed at approximately 20°C (Kelleher et al., 2012) and 25°C (Erickson & Stefan, 2000). Despite that phenomena, our residuals were reasonably normal, but it is important to acknowledge that many of the stream temperatures we predicted are above this threshold suggesting our predictions may be high.

468 **Considerations and assumptions**

469 The southern California mountains, which surround the urban areas in Los Angeles,
470 receive snow in the wintertime. Changes in projected streamflow could be exacerbated if more
471 winter precipitation falls as rain and if snow melts earlier in the year (Stewart et al., 2004;
472 Knowles et al., 2018). The models we used in this analysis were trained with contemporaneous
473 data, meaning the rain to snow fraction is implicit in the model. End of century snow fall is
474 predicted to be less than 50% of baseline snow fall at low elevations, less than 70% of snowfall
475 at mid-elevations, and little change to the highest elevations (Sun et al., 2016). This suggests
476 higher flows in the winter and lower flows earlier in the spring than our model projections, i.e.
477 lower hydroperiod. Similarly, summer flows could decrease as evaporation increases due to
478 higher temperatures, and result in even lower hydroperiods. These additional considerations
479 would likely not change the direction of our projections, just increase the magnitude of projected
480 change from the baseline.

481 Stationarity of air to water temperature relationships may not hold in the future
482 (Arismendi et al., 2014). This is because water temperature is not controlled by air temperature
483 alone, and many of the other drivers may change in future years. For example, the impact of
484 shading from riparian vegetation has been found to substantially impact stream temperature
485 (Garner et al., 2014, 2017; Wondzell et al., 2018), and vegetation change is possible through new
486 climate regimes and invasive species (Ikeda et al., 2014). Therefore, a major assumption of our
487 model predictions is that streamside vegetation and baseflow index remains constant (watershed
488 area and elevation will likely remain constant unless a major earthquake or storm event changes
489 stream routing). Most of the reaches we include are in protected land either at the state or federal

490 level so major land use change is not likely to occur. The major invasive riparian plant species
491 in the region are Giant reed (*Arundo donax*) and salt cedar (*Tamarix* spp.) and a transition to
492 more mesic riparian plants due to lower hydroperiods would favor lower canopy cover
493 (Stromberg et al., 2010). In either case, we would expect a transition to lower shade cover which
494 would make our stream temperature estimates conservative and any predicted trends would be
495 exacerbated.

496 Streamflow and stream temperature are related (see review: Webb, 1996), thus one
497 potential limitation of our study was the separate analysis of each variable. For example, one
498 study found that as streamflow increased, there was a diminishing impact of air temperature on
499 stream temperature (Letcher et al., 2016). Another study showed that decreasing streamflow
500 resulted in lower minimum temperatures in the winter and higher maximum temperatures in the
501 summer due to the smaller thermal capacity, which increases sensitivity to air temperature (Van
502 Vliet et al., 2012). By modeling the streamflow and stream temperature separately there is
503 potential to under or overestimate the changes in the two variables. For example, warmer stream
504 temperatures at high elevations could lead to greater evaporation and therefore a smaller
505 streamflow than what we predict. Lower hydroperiods and greater duration of days with low
506 flow during wet years could lead to higher maximum summertime stream temperatures due to
507 less water in the stream and the associated greater sensitivity to air temperature, leading to even
508 more evaporation, creating a feedback loop. Thus, future studies, should consider integrating
509 streamflow and temperature to acknowledge the relationship of the two variables in model
510 simulations. However, we do not think that this would affect the overall conclusions of our study

or the directions of change that we predict – instead, considering the interaction of the two variables may make our stated predictions conservative.

Ecological and management implications

In this study we described substantial changes predicted for stream hydrology and stream temperatures in the Los Angeles region. Summer stream temperatures are projected to increase regionally, with the largest increases occurring in the mountains. Thermal stress can impair food consumption and growth in southern California rainbow trout (Myrick & Cech, 2000), particularly if there is no cooler water refugia available. Additionally, warmer water facilitates invasion by warm water fishes that predate and compete with the native species (Rahel & Olden, 2008), which already are widespread in the lowland portions of these watersheds. In the northern part of their range, rainbow trout have a thermal threshold of 25°C (Cech et al., 1990). However, in our study area, which is the southern part of their range, they occur in temperatures approaching 30°C (Sloat & Osterback, 2013). Our results project many streams to have maximum temperatures exceeding 30°C, however many of the high elevation mountain tributaries are projected to continue to maintain stream temperatures below this temperature.

Streamflow changes are also predicted. Traditionally, steelhead downstream migration might only occur in wet years in southern California, when tributaries connect to the main channels. Booth, (forthcoming) found that smoltification did not occur before the first storm flow of the season, which shows the importance of storms in this region dominated by intermittent streams. Therefore, the ecological implication of a predicted flow change may differ depending on the recent precipitation trend. For example, a further decrease in hydroperiod in high elevation streams during dry and moderate periods would harm the resident rainbow trout and

533 the non-migrating steelhead by substantially reducing available habitat (Dagit et al., 2017).

534 Alternatively, an increase in storms during dry years could provide additional opportunity for

535 smolts to migrate downstream.

536 Planning channel modifications to support steelhead migration and access to spawning

537 grounds will be most effective if changing conditions caused by climate change are considered

538 when making decisions about where to focus efforts. There may be a tradeoff between

539 streamflow and temperature that managers will need to consider when planning refuge habitats.

540 We project stream temperature to increase regionally, in many locations above thermal limits of

541 steelhead, but many high elevation streams are projected to maintain maximum temperatures at

542 levels that they can endure (if only for a short time). However, we project the regional

543 hydrology to become drier in high elevation streams, despite more frequent storms. Managers

544 can look at the regional variations in projections to determine which spawning grounds are

545 projected to maintain the highest qualities and focus connectivity efforts on the channels that lead

546 to those streams.

547 **Author Contributions**

548 JR and ES designed the study. JR, MB, and KF completed different portions of the

549 analysis. JR, RA, AK, MB, and ES discussed implications of findings. JR wrote the manuscript

550 with contributions and critical edits from all authors. MB designed the interactive website.

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557 The data produced by this analysis, spatially explicit hydrologic and stream temperature metrics,
558 are available for viewing and download at <https://sccwrp.shinyapps.io/flowecology/>. Scripts
559 used in this analysis are archived with Zenodo here:
560 <https://zenodo.org/badge/latestdoi/253941508>.

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Reference List

- Arismendi, I., M. Safeeq, J. B. Dunham, & S. L. Johnson, 2014. Can air temperature be used to project influences of climate change on stream temperature?. *Environmental Research Letters* IOP Publishing 9:.
- Berg, N., & A. Hall, 2015. Increased interannual precipitation extremes over California under climate change. *Journal of Climate* 28: 6324–6334.
- Berg, N., A. Hall, F. Sun, S. Capps, D. Walton, B. Langenbrunner, & D. Neelin, 2015. Twenty-first-century precipitation changes over the Los Angeles region. *Journal of Climate* 28: 401–421.
- Booth, M. T., (n.d.). Patterns and Potential Drivers of Steelhead Smolt Migration in Southern California. .
- Breiman, L., 2001. Random forests. *Machine Learning* 45: 5–32.
- Bunn, S. E., & A. H. Arthington, 2002. Basic principles and ecological consequences of altered flow regimes for aquatic biodiversity. *Environmental Management* 30: 492–507.
- Cech, J. J., S. J. Mitchell, D. T. Castleberry, & M. McEnroe, 1990. Distribution of California stream fishes: influence of environmental temperature and hypoxia. *Environmental Biology of Fishes* 29: 95–105.
- Chang, H., & I. W. Jung, 2010. Spatial and temporal changes in runoff caused by climate change in a complex large river basin in Oregon. *Journal of Hydrology Elsevier B.V.* 388: 186–207, <http://dx.doi.org/10.1016/j.jhydrol.2010.04.040>.

582 Christensen, Niklas, S. ., W. . Wood, Andrew, V. Nathalie, P. Lettenmaier, Dennis, & N.
 583 Palmer, Richard, 2004. The Effects of Climate Change on the Hydrology and Water Resources
 584 of the Colorado River Basin. *Climatic Change* 62: 337.

585 Dagit, R., E. Bell, K. Adamek, & J. Mongolo, 2017. The effects of a prolonged drought
 586 on southern Steelhead Trout (*Oncorhynchus mykiss*) in a coastal creek , Los Angeles County,
 587 California. *Bulletin of the Southern California Academy of Sciences* 116: 162–173.

588 Das, T., E. P. Maurer, D. W. Pierce, M. D. Dettinger, & D. R. Cayan, 2013. Increases in
 589 flood magnitudes in California under warming climates. *Journal of Hydology Elsevier B.V.* 501:
 590 101–110.

591 DWR, 2015. Perspectives and Guidance for Climate Change Analysis. .

592 Erickson, T. R., & H. G. Stefan, 2000. Linear Air/Water Temperature Correlations for
 593 Streams During Open Water Periods. *Journal of Hydrological Engineering* 317–321.

594 Feldmeth, C. R., & J. N. Baskin, 1976. Thermal and respiratory studies with reference to
 595 temperature and oxygen tolerance for the unarmored stickleback *GASTEROSTEUS*
 596 *ACULEATUS WILLIAMSONI* hubbs. *Southern California Acadamy of Sciences* 75:.

597 Ficklin, D. L., I. T. Stewart, & E. P. Maurer, 2013. Effects of climate change on stream
 598 temperature, dissolved oxygen, and sediment concentration in the Sierra Nevada in California.
 599 *Water Resources Research* 49: 2765–2782.

600 Foden, W. B., D. Bickford, B. E. Young, B. A. Stein, J. A. Carr, H. R. Akçakaya, & C.
 601 D. Thomas, 2019. Climate change vulnerability assessment of species. *Wiley Interdisciplinary*
 602 *Reviews: Climate Change* 10:e551: 1–36.

603 Fry, J. A., G. Xian, S. Jin, J. A. Dewitz, C. G. Homer, L. Yang, C. A. Barnes, N. D.
604 Herold, & J. D. Wickham, 2011. Completion of the 2006 National Land Cover Database Update
605 for the conterminous United States. *Photogrammetric Engineering and Remote Sensing* 77: 858–
606 864.

607 Garner, G., I. A. Malcolm, J. P. Sadler, & D. M. Hannah, 2014. What causes cooling
608 water temperature gradients in a forested stream reach?. *Hydrology and Earth System Sciences*
609 18: 5361–5376.

610 Garner, G., I. A. Malcolm, J. P. Sadler, & D. M. Hannah, 2017. The role of riparian
611 vegetation density, channel orientation and water velocity in determining river temperature
612 dynamics. *Journal of Hydrology* 553: 471–485, <http://dx.doi.org/10.1016/j.jhydrol.2017.03.024>.

613 Gasith, A., & V. H. Resh, 1999. Streams in mediterranean climate regions: Abiotic
614 influences and biotic responses to predictable seasonal events. *Annual Review of Ecology,*
615 *Evolution, and Systematics* 30: 51–81.

616 Goldenson, N., 2018. Evaluating Global Climate Model Performance in Simulating U.S.
617 West Coast Atmospheric Rivers. .

618 Hawkins, A., P. Charles, R. John, A. Ryan, C. P. Hawkins, J. R. Olson, & R. A. Hill,
619 2010. The reference condition : predicting benchmarks for ecological and water-quality
620 assessments water-quality assessments. *J. N. Am. Benthol. Soc.* 29: 312–343.

621 Hill, R. A., C. P. Hawkins, & D. M. Carlisle, 2013. Predicting thermal reference
622 conditions for USA streams and rivers. *Freshwater Science* 32: 39–55,
623 <http://www.journals.uchicago.edu/doi/10.1899/12-009.1>.

624 Hill, R. A., M. H. Weber, S. G. Leibowitz, A. R. Olsen, & D. J. Thornbrugh, 2016. The
 625 Stream-Catchment (StreamCat) Dataset: A Database of Watershed Metrics for the Conterminous
 626 United States. *Journal of the American Water Resources Association (JAWRA)* 52: 120–128.

627 Homer, C., J. Dewitz, L. Yang, S. Jin, P. Danielson, G. Xian, J. Coulston, N. Herold, J.
 628 Wickham, & K. Megown, 2015. Completion of the 2011 National Land Cover Database for the
 629 Conterminous United States – Representing a Decade of Land Cover Change Information.
 630 *Photogrammetric Engineering and Remote Sensing* 81: 345–354.

631 Homer, C., C. Huang, L. Yang, B. Wylie, & C. Michael, 2004. Development of a 2001
 632 National Land-Cover Database for the United States. *Photogrammetric Engineering & Remote*
 633 *Sensing* 70: 829–840.

634 Huang, H.-Y., & A. Hall, 2018. Downscaling climate data for the Los Angeles and
 635 Ventura Region. .

636 Ikeda, D. H., K. C. Grady, S. M. Shuster, & T. G. Whitham, 2014. Incorporating Climate
 637 Change and Exotic Species into Forecasts of Riparian Forest Distribution. *PLOS one* 9:.

638 Jones, K. R., J. E. . Watson, H. P. Possingham, & C. J. Klein, 2016. Incorporating climate
 639 change into spatial conservation prioritisation: A review. *Biological Conservation* 194: 121–130,
 640 <http://dx.doi.org/10.1016/j.biocon.2015.12.008>.

641 Kelleher, C., T. Wagener, M. Gooseff, B. McGlynn, K. McGuire, & L. Marshall, 2012.
 642 Investigating controls on the thermal sensitivity of Pennsylvania streams. *Hydrological Processes*
 643 26: 771–785.

644 Knowles, N., C. Cronkite-Ratcliff, D. W. Pierce, & D. R. Cayan, 2018. Responses of

645 Unimpaired Flows, Storage, and Managed Flows to Scenarios of Climate Change in the San
 646 Francisco Bay-Delta Watershed. *Water Resources Research* 54: 7631–7650.

647 Kuhn, M., J. Wing, S. Weston, A. Williams, C. Keefer, A. Engelhardt, T. Cooper, Z.
 648 Mayer, Y. Kenkel, R Core Team, & M. Benesty, 2018. caret: Classification and Regression
 649 Training. R package version 6.0-80. , <https://cran.r-project.org/package=caret>.

650 Kupferberg, S. J., 1995. Hydrologic and Geomorphic Factors Affecting Conservation of a
 651 River- Breeding Frog (RANA BOYLII). *Ecological Applications* 6: 1332–1344.

652 Letcher, B. H., D. J. Hocking, K. O’Neil, A. R. Whiteley, K. H. Nislow, & M. J.
 653 O’Donnell, 2016. A hierarchical model of daily stream temperature using air-water temperature
 654 synchronization, autocorrelation, and time lags. *PeerJ* 4: e1727, <https://peerj.com/articles/1727>.

655 Liaw, A., & M. Wiener, 2002. Classification and Regression by randomForest. *R News* 2:
 656 18–22.

657 Livneh, B., T. J. Bohn, D. W. Pierce, F. Munoz-arriola, B. Nijssen, R. Vose, D. R. Cayan,
 658 & L. Brekke, 2015. A spatially comprehensive , hydrometeorological data set for Mexico , the
 659 U . S . , and Southern Canada 1950 – 2013. *Scientific Data* 5: 1–12.

660 Livneh, B., E. A. Rosenberg, C. Lin, B. Nijssen, V. Mishra, K. M. Andreadis, E. P.
 661 Maurer, & D. P. Lettenmaier, 2013. A long-term hydrologically based dataset of land surface
 662 fluxes and states for the conterminous United States: Update and extensions. *Journal of Climate*
 663 26: 9384–9392.

664 Mahoney, J. M., & S. B. Rood, 1998. Streamflow Requirements for Cottonwood Seedling
 665 Recruitment~an Integrative Model. *Wetlands* 18: 634–645.

666 Maidment, D. R., 1993. Handbook of hydrology. McGraw-Hill, Inc., New York, NY.

667 Maloney, K. O., K. P. Krause, C. Buchanan, L. E. Hay, G. J. McCabe, Z. M. Smith, T. L.

668 Sohl, & J. A. Young, 2020. Disentangling the potential effects of land-use and climate change on

669 stream conditions. *Global Change Biology* 1–19.

670 Mantua, N., I. Tohver, & A. Hamlet, 2010. Climate change impacts on streamflow

671 extremes and summertime stream temperature and their possible consequences for freshwater

672 salmon habitat in Washington State. *Climatic Change* 102: 187–223.

673 Matthews, K. R., & N. H. Berg, 1997. Rainbow trout responses to water temperature and

674 dissolved oxygen stress in two southern California stream pools. *Journal of Fish Biology* 50: 50–

675 67.

676 Maurer, E. P., & P. B. Duffy, 2005. Uncertainty in projections of streamflow changes due

677 to climate change in California. *Geophysical Research Letters* 32: 1–5.

678 Mohseni, O., & H. G. Stefan, 1999. Stream temperature / air temperature relationship: a

679 physical interpretation. *Journal of Hydology* 218: 128–141.

680 Myrick, C. A., & J. J. Cech, 2000. Temperature influences on California rainbow trout

681 physiological performance. *Fish Physiology and Biochemistry* 22: 245–254.

682 Nelson, K., & M. A. Palmer, 2007. Stream Temperature Surges Under Urbanization and

683 climate change: Data, Models, and Responses. *Journal of the Water Resources Association* 43:

684 440–452.

685 Parajka, J., A. Viglione, M. Rogger, J. L. Salinas, M. Sivapalan, & G. Blöschl, 2013.

686 Comparative assessment of predictions in ungauged basins – Part 1 : Runoff-hydrograph studies.
687 Hydrological Sciences Journal 17: 1783–1795.

688 Patterson, L., J. Phelan, C. Goudreau, & R. Dykes, 2017. Flow-Biology Relationships
689 Based on Fish Habitat Guilds in North Carolina. Journal of the American Water Resources
690 Association 53: 56–66.

691 Poff, N. L., & J. D. Allan, 1995. Functional Organization of stream Fish Assesmlages in
692 relation to hydrological variability. Ecology 72: 606–627.

693 Poff, N. L., J. D. Allan, M. B. Bain, J. R. Karr, K. L. Prestegard, B. D. Richter, R. E.
694 Sparks, & J. C. Stromberg, 1997. A paradigm for river conservation and restoration. BioScience
695 47: 769–784.

696 Poff, N. L., M. M. Brinson, & J. W. Day, 2002. Aquatic ecosystems & Global climate
697 change: Potential Impacts on Inland Freshwater and Coastal Wetland Ecosystems in the United
698 States. Pew Center on Global Climate Change. .

699 R Core Team, 2018. R: A language and environment for statistical computing. R
700 Foundation for Statistical Computing, Vienna, Austria, <https://www.r-project.org/>.

701 Rahel, F. J., & J. D. Olden, 2008. Assessing the effects of climate change on aquatic
702 invasive species. Conservation Biology 22: 521–533.

703 Rogers, J. B., E. D. Stein, M. W. Beck, & R. F. Ambrose, 2020. The impact of climate
704 change induced alterations of streamflow and stream temperature on the distribution of riparian
705 species. PLOS one 15: 1–23, <http://dx.doi.org/10.1371/journal.pone.0242682>.

706 Sanborn, S. C., & B. P. Bledsoe, 2006. Predicting streamflow regime metrics for
 707 ungauged streams in Colorado , Washington , and Oregon. *Journal of Hydology* 325: 241–261.

708 Sengupta, A., S. K. Adams, B. P. Bledsoe, E. D. Stein, K. S. McCune, & R. D. Mazor,
 709 2018. Tools for managing hydrologic alteration on a regional scale: Estimating changes in flow
 710 characteristics at ungauged sites. *Freshwater Biology* 63: 769–785.

711 Sidle, J. G., D. E. Carlson, E. M. Kirsch, & J. J. Dinan, 1992. Flooding: Mortality and
 712 Habitat Renewal for Least Terns and Piping Plovers. *Colonial Waterbirds* 15: 132–136.

713 Sloat, M. R., & A. K. Osterback, 2013. Maximum stream temperature and the
 714 occurrence, abundance, and behavior of steelhead trout (*Oncorhynchus mykiss*) in a southern
 715 California stream. *Canadian Journal of Fisheries and Aquatic Sciences* 70: 64–73.

716 Stefan, H. G., & E. B. Preud'homme, 1993. Stream temperature estimation from air
 717 temperature. *Water Resources Bulletin* 29: 27–45.

718 Stewart, I., D. Cayan, & M. Dettinger, 2004. Changes in snowmelt runoff timing in
 719 western North America under “business as usual” climate change scenario. *Climatic Change* 62:
 720 217–232.

721 Stromberg, J. C., V. B. Beauchamp, M. D. Dixon, S. J. Lite, & C. Paradzick, 2007.
 722 Importance of low-flow and high-flow characteristics to restoration of riparian vegetation along
 723 rivers in arid south-western United States. *Freshwater Biology* 52: 651–679.

724 Stromberg, J. C., S. J. Lite, & M. D. Dixon, 2010. Effects of stream flow patterns on
 725 riparian vegetation of a semiarid river: Implications for a changing climate. *River Research and*
 726 *Applications* 26: 712–729.

727 Sun, F., A. Hall, M. Schwartz, D. B. Walton, & N. Berg, 2016. Twenty-First-Century
 728 Snowfall and Snowpack Changes over the Southern California Mountains. *Journal of Climate*
 729 29: 91–110.

730 Taylor, J. B., E. D. Stein, M. Beck, K. Flint, & A. Kinoshita, 2019. Vulnerability of
 731 Stream Biological Communities in Los Angeles and Ventura Counties to Climate Change
 732 Induced Alterations of Flow and Temperature. .

733 Taylor, K. E., R. J. Stouffer, & G. A. Meehl, 2012. An overview of CMIP5 and the
 734 experiment design. *Bulletin of the American Meteorological Society* 93: 485–498.

735 Van Vliet, M. T. H., J. R. Yearsley, W. H. P. Franssen, F. Ludwig, I. Haddeland, D. P.
 736 Lettenmaier, & P. Kabat, 2012. Coupled daily streamflow and water temperature modelling in
 737 large river basins. *Hydrology and Earth System Sciences* 16: 4303–4321.

738 Vogel, R. M., I. Wilson, & C. Daly, 1999. Regional Regression Models of Annual
 739 Streamflow for the United States. *Journal of irrigation and drainage engineering* 125: 148–157.

740 Walton, D. B., F. Sun, A. Hall, & S. Capps, 2015. A Hybrid Dynamical – Statistical
 741 Downscaling Technique. Part I: Development and Validation of the Technique. *Journal of*
 742 *Climate* 28: 4597–4617.

743 Webb, B. W., 1996. Trends in Stream and River Temperature. *Hydrological Processes*
 744 10: 205–226.

745 Welsh, H. H. J., G. R. Hodgson, B. C. Harvey, & M. F. Roche, 2001. Distribution of
 746 Juvenile Coho Salmon in Relation to Water Temperatures in Tributaries of the Mattole River ,
 747 California. *North American Journal of Fisheries Management* 21: 464–470.

748 Wilson, K. L., D. P. Tittensor, B. Worm, & H. K. Lotze, 2020. Incorporating climate
749 change adaptation into marine protected area planning. *Global Change Biology* 1–17.

750 Wondzell, S. M., M. Diabat, & R. Haggerty, 2018. What Matters Most: Are Future
751 Stream Temperatures More Sensitive to Changing Air Temperatures, Discharge, or Riparian
752 Vegetation?. *Journal of the American Water Resources Association* 1–17.

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Figure Captions

Figure 1: Study design delineated with a flow chart. Key data sets are listed in the bullets. Top grey box shows the temperature modeling design and the lower dark box shows the hydrological modeling design.

Figure 2: Map showing the study region's major watersheds (light grey outline) and the sub-watersheds (black outline) that were modeled with HEC-HMS. National Hydrography Dataset (NHD) flowlines show the streams included in the analysis after removing those with alterations like dams. Red points show the 19 temperature gauges used in the stream temperature model. Blue dots show the 26 models that comprise the ensemble modeled used from Sengupta et al., (2018).

Figure 3: Stream temperature modeling performance. The top row shows the residuals calculated as observed minus predicted during model calibration with 80% of the data used in training. The second row shows the predicted stream temperature metric using the remaining 20% of the data saved for testing. Red dotted line shows $y=x$. Red solid line shows the linear model.

Figure 4: Annual stream temperature from 1980 through 2100. Values are averaged across all the stream reaches and across the three GCMs to show the annual mean stream temperature (dark black line). The trend line and R^2 values are shown. The upper and lower light grey lines show the annual 5th and 95th percentiles of the annual stream temperature. The gaps in the data, are years we lacked projections for air temperature.

Figure 5: The distribution of the change in stream temperature metrics for each stream reach, averaged across the three GCMs. A-E: Change is calculated by averaging the values in the end-of-century time period and subtracting the values averaged from the baseline time period, for each stream reach. A darker color represents a greater change. F-J: The distribution of stream temperature changes from baseline to end-of-century shown for high (>375m) and low (<375m) elevation. The outer violin plot shows the distribution of streams, represented by the width of the violin. The inner box plot shows the median, the 25th and 75th percentiles, and 1.5*the inter-quartile range at the upper and lower end. Points beyond the ‘whiskers’ represent outliers.

Figure 6: The boxplots show the distributions of values for each flow metric at the stream reaches in the study region by water year type and by time period. The light-colored boxplots show the baseline values and the dark grey boxplots show the end-of-century values. Boxplots show the 25th and 75th percentiles, and 1.5*the inter-quartile range at the upper and lower end. Points beyond the ‘whiskers’ represent outliers.

Figure 7: The boxplots show the distributions of stream reach values for the two flow metrics that showed different trends in high and low elevation streams, by water year type and time period. The facets show high and low elevation streams (> 375m marks high elevation streams). The light-colored boxplots show the baseline values and the dark grey boxplots show the end-of-century values. Boxplots show the 25th and 75th percentiles, and 1.5*the inter-quartile range at the upper and lower end. Points beyond the ‘whiskers’ represent outliers.

Figure 8: The standardized change in each metric calculated as future minus baseline value. To standardize, we subtracted the mean and divided by the standard deviation using the

797 'scale' function in R. Standardizing allows for comparison across metrics to see which change
798 the most. The dotted line shows the zero change. Outliers were cut off for Q99 (full range -1.65
799 to 6.08) and duration of low flow (full range -5.80 to 0.82) to better show most of the data.

800 **Tables**

801 Table 1: Streamflow metrics. Script used for calculation and definition came from Konrad et al., 2008. Timeframe
 802 refers to the number of years of flow data used in the calculation, measured back in time, from the year of analysis.

Variable	Pattern	Definition [units]	Timeframe
HighNum	Frequency	[events/year] number of events > high flow threshold.	3, all
LowDur	Duration	[days/event]- longest consecutive days <= the low flow threshold	3, all
Hydroperiod	Duration	[% of years] - fraction of period of analysis with flow	3, all
SFR	Variability	[%/day] - Storm flow recession.	3, all
Q99	Magnitude	[m ³ /s] – 99 th percentile flow	3, all

803

804 Table 2: Stream temperature metric definitions. The months included in calculating these metrics are May through
805 September.

Temperature Pattern	Metric	Definition
Magnitude	Minimum 7-day minimum	[°C] The minimum value of a rolling 7-day minimum
	Maximum 7-day maximum	[°C] The maximum value of a rolling 7-day maximum
	Maximum 7-day average	[°C] The maximum value of a rolling 7-day average
Variability	Maximum 7-day range	[°C] The maximum difference between the rolling 7-day maximum and minimum. I.e. the largest temperature swing within a 7-day period.
	Mean 7-day range	[°C] The average difference between the rolling 7-day maximum and minimum. I.e. the average temperature swing within a 7-day period.
Frequency	Number of 7-day maximums > 30°C	[days] The number of 7-day rolling averages that are greater than 30°C

806

807 Table 3: Stream temperature model performance on the testing data.

Model	RMSE (°C)	NSC (unitless)	Data range (°C)
Average	1.79	0.80	11.00 – 30.18
Min	2.11	0.61	6.67 - 23.00
Max	3.17	0.73	13.30 - 42.05

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809

810 Table 4: Weekly stream temperature regression results.

Model	Variable	Coefficient	P-Value
Mean stream temperatur e	SevDayMeanAir	0.4502711	< 2e-16 ***
	ElevWs	-0.0041903	< 2e-16 ***
	Log(WsAreaSqKm)	1.2452106	< 2e-16 ***
	Log(PctHbWet2011WsRp100 + 1)	-0.5560131	0.0362 *
	Log(PctWdWet2011WsRp100 + 1)	-0.7454881	1.24e-11 ***
	BFIWs	-0.0441507	8.00e-08 ***
Maximum stream temperatur e	SevDayMaxAir	0.4039205	< 2e-16 ***
	ElevWs	-0.0074777	< 2e-16 ***
	Log(WsAreaSqKm)	1.5676793	< 2e-16 ***
	Log(PctHbWet2011WsRp100 + 1)	-0.2023614	0.658
	Log(PctWdWet2011WsRp100 + 1)	1.6692248	< 2e-16 ***
	BFIWs	-0.2473168	< 2e-16 ***
Minimum stream temperatur e	SevDayMinAir	0.3647440	< 2e-16 ***
	ElevWs	-0.0013293	< 2e-16 ***
	Log(WsAreaSqKm)	0.8775967	< 2e-16 ***
	Log(PctHbWet2011WsRp100 + 1)	1.1907832	9.13e-05 ***
	Log(PctWdWet2011WsRp100 + 1)	-2.3505446	< 2e-16 ***
	BFIWs	0.0985327	< 2e-16 ***

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812

813 Table 5: Flow metric random forest performance. Top three predictors (columns Predictor 1, Predictor 2, Predictor
814 3) for each of five flow metrics separated by time frame. The predictor type as static (S) or variable (V) is noted in
815 parentheses.

Flow Metric	Time Frame	Cal RMSE	Val RMSE	Cal R ²	Val R ²	Predictor 1	Predictor 2	Predictor 3
HighNum	3	0.02	0.02	0.96	0.95	PctUrbLo2011Cat.y (S)	PctUrbOp2011Ws (S)	PctImp2011Cat (S)
	all	0.00	0.01	1.00	1.00	PctUrbLo2011Cat.y (S)	PctUrbOp2011Ws (S)	PctImp2011Cat (S)
Hydroperiod	3	0.00	0.00	0.94	0.95	Tmax8110Ws (S)	ElevWs (S)	all_QmaxID R (V)
	all	0.00	0.00	1.00	1.00	Tmax8110Ws (S)	ElevWs (S)	all_QmaxID R (V)
SFR	3	0.00	0.00	0.93	0.93	all_QmaxID R (V)	PctUrbOp2011Ws (S)	PctUrbLo2011Ws (S)
	all	0.00	0.00	1.00	1.00	all_QmaxID R (V)	PctUrbOp2011Ws (S)	PctUrbLo2011Ws (S)
Q99	3	0.50	3.74	0.93	0.93	WsAreaSqKm (S)	Tmin8110Ws (S)	RunoffWs (S)
	all	0.06	0.12	1.00	1.00	WsAreaSqKm (S)	Tmin8110Ws (S)	RunoffWs (S)
LowDur	3	0.67	5.03	0.86	0.86	all_MaxMonthQ (V)	RunoffWs (S)	WsAreaSqKm (S)
	all	0.95	0.86	1.00	1.00	all_MaxMonthQ (V)	Precip8110Cat (S)	all_Qmax (V)

816

817

818 Table 6: The mean values of the flow metrics in the baseline and end-of-century year types $\pm$ one standard deviation.

	Baseline			End-of Century		
	dry	mod	wet	dry	mod	wet
Number of storms (#)	0.74 ± 1.4	1.6 ± 1.75	2.03 ± 1.77	2.26 ± 1.3	2.46 ± 1.41	2.82 ± 1.17
Q99 (cms)	0.59 ± 0.8	1.64 ± 2.28	3.22 ± 4.26	2.81 ± 3.01	3.12 ± 3.34	3.96 ± 4.02
Low duration (days)	540 ± 146	400 ± 167	283 ± 150	455 ± 63	459 ± 60	402 ± 52
Hydroperiod (%)	0.56 ± 0.32	0.6 ± 0.3	0.63 ± 0.25	0.55 ± 0.24	0.55 ± 0.23	0.58 ± 0.22
SFR (%/day)	-0.16 ± 0.2	-0.17 ± 0.21	-0.2 ± 0.19	-0.22 ± 0.16	-0.23 ± 0.17	-0.22 ± 0.15

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820

821 Table 7: The mean change in each flow metric (end-of-century minus baseline) for each year type and each
822 elevation. Numbers in parentheses show the 5th and 95th percentile. (In a paired t-test to determine if the change
823 between the future values is different from the baseline values, * P<0.001, NS = not significant)

elevation	Dry		Moderate		Wet	
	high	low	high	low	high	low
Number of storms (#)	1.59 (0.98,2.1) *	1.23 (0.5,1.8) *	0.95 (0.36,1.3) *	0.43 (-0.97,1.3) *	0.96 (0.04,1.45) *	0.02 (-1.71,1.2) NS
Low duration (days)	-81 (-279,88) *	-104 (-281,42) *	71 (-113,288) *	3 (-191,206) NS	133 (-10,299) *	56 (-138,223) *
Q99 (cms)	2.33 (0.59,6.75) *	1.7 (0.52,4.59) *	1.46 (0.52,4.08) *	1.58 (0.53,3.82) *	0.7 (-0.85,1.58) *	0.94 (-0.58,2.21) *
Hydroperiod (%)	-0.03 (-0.14,0.14) *	0.06 (-0.08,0.17) *	-0.07 (-0.16,0.09) *	0.03 (-0.12,0.16) *	-0.06 (-0.14,0.06) *	0.01 (-0.16,0.12) NS
SFR (%/day)	-0.07 (-0.17,0.01) *	0.01 (-0.09,0.13) *	-0.08 (-0.24,0.01) *	0.02 (-0.13,0.16) *	-0.04 (-0.17,0.04) *	0.05 (-0.05,0.18) *

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