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Key Points:

- The NorWeST stream temperature database was developed from data contributed by >100 agencies in the western U.S.
- Scenarios created from the database for 343,000 km of streams and rivers indicate a warming trend of 0.17° C/decade occurred during 1976–2015
- The geospatial stream analysis tools developed for the NorWeST project have broad utility for many types of stream data throughout the U.S.

Supporting Information:

- Supporting Information S1

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The NorWeST Summer Stream Temperature Model and Scenarios for the Western U.S.: A Crowd-Sourced Database and New Geospatial Tools Foster a User Community and Predict Broad Climate Warming of Rivers and Streams

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Abstract Thermal regimes are fundamental determinants of aquatic ecosystems, which makes description and prediction of temperatures critical during a period of rapid global change. The advent of inexpensive temperature sensors dramatically increased monitoring in recent decades, and although most monitoring is done by individuals for agency-specific purposes, collectively these efforts constitute a massive distributed sensing array that generates an untapped wealth of data. Using the framework provided by the National Hydrography Dataset, we organized temperature records from dozens of agencies in the western U.S. to create the NorWeST database that hosts >220,000,000 temperature recordings from >22,700 stream and river sites. Spatial-stream-network models were fit to a subset of those data that described mean August water temperatures (AugTw) during 63,641 monitoring site-years to develop accurate temperature models ($r^2 = 0.91$; RMSPE = 1.10°C; MAPE = 0.72°C), assess covariate effects, and make predictions at 1 km intervals to create summer climate scenarios. AugTw averaged 14.2°C (SD = 4.0°C) during the baseline period of 1993–2011 in 343,000 km of western perennial streams but trend reconstructions also indicated warming had occurred at the rate of 0.17°C/decade (SD = 0.067°C/decade) during the 40 year period of 1976–2015. Future scenarios suggest continued warming, although variation will occur within and among river networks due to differences in local climate forcing and stream responsiveness. NorWeST scenarios and data are available online in user-friendly digital formats and are widely used to coordinate monitoring efforts among agencies, for new research, and for conservation planning.

1. Introduction

The importance of temperature in defining aquatic environments is arguably second only to the presence of water. Often referred to as a "master variable," temperature dictates metabolic rates, physiological processes, and life history events across taxa (Angilletta, 2009; Kingsolver, 2009), constrains the distribution and abundance of ectothermic species that constitute most aquatic communities (Isaak et al., 2017a; Pörtner, 2001), is used to measure habitat impairment (Nusslé et al., 2015; Olden & Naiman, 2010; Rivers-Moore et al., 2013), and serves as the basis for regulatory actions (Todd et al., 2008; U.S. Environmental Protection Agency, 2003). That water temperature varies over time—from day to night, from summer to winter—is obvious, but at landscape to regional extents, temporal covariation among sites is strong, so spatial variation among sites often constitutes the largest proportion of total variation (Hari et al., 2006; Poole et al., 2004). That spatial component, which we refer to as a thermalscape to designate a spatially continuous temperature surface, is inextricably linked to patterns of species' habitat suitability and conservation strategies based on spatial prioritization of investments (Isaak et al., 2015; Peterson et al., 2013). Thermalscape characterization of river segments has advanced significantly in recent decades through innovations in remote sensing (Dugdale et al., 2015; Torgersen et al., 2001), but these technologies are best suited to riverine environments where the water surface is exposed to airborne sensors (Fullerton et al., 2015; Handcock et al., 2012). Alternative approaches are needed to characterize thermalscapes throughout networks where extents encompass hundreds or thousands of linear kilometers, small streams constitute the bulk of the network, and ungauged basins are common (Bishop et al., 2008; Gallice et al., 2015; Hrachowitz et al., 2013).

Sensor technologies for measuring stream temperatures have proliferated in recent decades (Dugdale, 2016; Ebersole et al., 2003; Quilty & Moore, 2007; Selker et al., 2006; Torgersen et al., 2012; Vaccaro & Maloy, 2006) but the most popular have been inexpensive sensors that record measurements at user-specified intervals and create time series of recordings (Angilletta & Krochmal, 2003; Dunham et al., 2005; Stamp et al., 2014). Inexpensive sensors democratized the collection of temperature data beginning in the early 1990s, which resulted in extensive, albeit largely uncoordinated, monitoring efforts throughout North America and Europe (Daigle et al., 2016; DeWeber & Wagner, 2014; Dunham et al., 2003; Hannah & Garner, 2015; Hilderbrand et al., 2014; Isaak et al., 2010; Isaak & Hubert, 2001; Jackson et al., 2016; Johnson & Wilby, 2015; Mauger et al., 2016; McKenna et al., 2010; Molinero et al., 2016; Moore et al., 2013; Trumbo et al., 2014; Wehrly et al., 2009). Sensors deployed in those efforts sometimes record data only for short periods (e.g., 1–3 months or years) but viewed collectively, constitute a massive distributed monitoring array that provides measurements from thousands of sites. The growth in temperature monitoring is a harbinger of similar trends in monitoring of other water quality constituents (Pellerin et al., 2016; Read et al., 2017), stream discharge (Stamp et al., 2014), and biological sampling using environmental DNA (Goldberg et al., 2015; McKelvey et al., 2016) as new technologies bring the era of big data to aquatic environments (Hampton et al., 2013; Isaak et al., 2017a; Porter et al., 2012).

The rate at which temperature data have been generated has exceeded efforts to organize and curate it in databases, a necessary task for realizing data's current and future potential. Well organized databases, if shared by many agencies and institutions, could also make future data collection efforts more efficient by reducing redundancies and spreading costs among users. Fundamental to organizing stream data sets in the U.S. is the National Hydrography Dataset (NHD), which provides a consistent geospatial framework in which all stream reaches are delineated, assigned unique identifiers within networks, attributed with topological information, and georeferenced in a cartographic projection system (Cooter et al., 2010; Moore & Dewald, 2016). NHD is available in several resolutions but of particular value is the medium-resolution (1:100,000 scale) NHD because of the many reach descriptor variables (e.g., elevation, slope, and watershed area) that have been developed and incorporated to create NHDPlus (McKay et al., 2012; Hill et al., 2016). Once temperature observations are linked to NHD reaches, those descriptors can be used to attribute the observations, serve as covariates in predictive models, visualize results within geographic information systems (GIS), and perform custom queries based on network characteristics.

Many stream data applications are enabled by NHDPlus, but particularly relevant for temperature is the potential to develop network thermalscapes that depict historical or future climatic conditions. Those scenarios are rare for lotic environments despite their obvious importance for stream ecology and conservation planning. Because temperature records are collected at discrete sampling locations, however, models are needed to estimate covariate parameters and make predictions at unsampled locations within networks. Many types of models are fit to stream temperature data sets (Benyahya et al., 2007; Webb et al., 2008) including network applications (DeWeber & Wagner, 2014; McKenna et al., 2010; Wehrly et al., 2009) but most are not optimized for broad spatial extents and use with large data sets where spatial autocorrelation is common and may bias parameter estimates (Isaak et al., 2014; Rushworth et al., 2015). Recently developed spatial-stream-network (SSN) models (Peterson & Ver Hoef, 2010; Ver Hoef et al., 2006; Ver Hoef & Peterson, 2010) overcome those limitations by relying on assumptions about the stochastic processes that generate observable data (Schabenberger & Gotway, 2005) and facilitate valid inference from spatially correlated samples (Rushworth et al., 2015; Som et al., 2014). Moreover, SSNs accommodate covariates to describe relationships with response variables and can be implemented with classical geostatistical kriging techniques (Cressie, 1993) to make predictions throughout river networks with spatially explicit uncertainty estimates (Isaak et al., 2017b; Ver Hoef et al., 2006). Like other spatial statistical models (Beale et al., 2010; Temesgen & Ver Hoef, 2015; Ver Hoef, 2002), SSNs also consistently improve predictive performance relative to nonspatial models when applied to correlated data sets (Brennan et al., 2016; Filipe et al., 2017; Isaak et al., 2010; Turschwell et al., 2016).

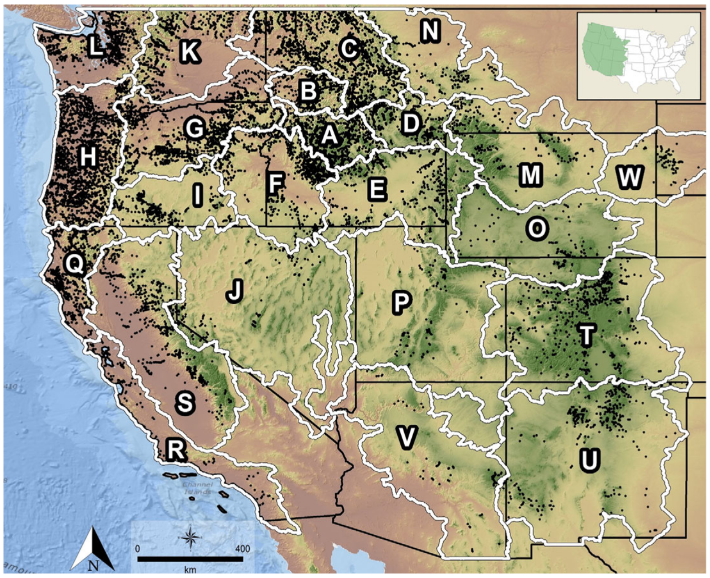

Figure 1. Locations of stream temperature data that were used to develop temperature models and scenarios in the western U.S. Letters and white boundaries denote 23 processing units used to partition the data and fit individual models.

In this paper, we use the NHDPlus framework to organize the comprehensive Northwest Stream Temperature (NorWeST) database that combines existing agency databases with thousands of new records collected by hundreds of professionals from dozens of natural resource agencies across the western U.S. (Figure 1 and supporting information S1). Temperature monitoring within the region has been extensive because of concerns about socioeconomically important cold-water fishes like salmon and trout and other aquatic species that are federally protected under the Endangered Species Act (McClure et al., 2013; Nehlsen et al., 1991). Concerns have grown in recent years as the effects of climate change increasingly manifest through air temperature trends (Barnett et al., 2008; Walsh et al., 2014), seasonal patterns of snow accumulation and stream runoff (Kormos et al., 2016; Luce et al., 2013; Mote et al., 2005; Stewart et al., 2005), and increasing wildfires (Littell et al., 2016; Westerling et al., 2006). We use a subset of the NorWeST database with SSN models and covariates derived from NHD and other national sources to parameterize a series of temperature models for subregions in the western U.S., assess their predictive performance, and then extend predictions to all river and stream reaches to create historical and future summer temperature scenarios. The models are also used to reconstruct historical stream-temperature trends during the 40 year period of 1976–2015 and in attribution analyses to understand the relative importance of covariates for explaining spatial and temporal variation in stream temperatures within and among river networks. Results are discussed with regards to factors affecting thermal heterogeneity in western landscapes, ecological responses to thermal trends, use of NorWeST information for conservation planning, and the broader utility of geospatial analysis tools for many types of stream data.

2. Methods

2.1. Study Site

The western U.S. as circumscribed here encompasses 2,584,000 km^2, most or all of eleven states from the Pacific Ocean to the Great Plains, and is drained by an extensive network of rivers, streams, and intermittent channels (Benke & Cushing, 2005; Palmer & Vileisis, 2016). The area is topographically complex, with broad basins and multiple mountain ranges, the latter dominated by the Cascade Range and Sierra Nevada near the coast and the Rocky Mountains further inland with peak elevations exceeding 4,400 m. Climate is characterized by seasonally variable temperatures with annual air temperatures that are approximately 10°C warmer at the southern border with Mexico than at the northern Canadian border. Much of the region is arid although coastal areas and higher elevations are relatively mesic. Most precipitation occurs during fall and winter months, except in the southwestern U.S. where summer monsoons are important (Mock, 1996). Precipitation accumulates as snow at high elevations and northern latitudes during cool seasons and meltwater runoff the following spring creates pronounced hydrologic peaks in most streams. The exceptions are lower elevation coastal streams, where peak runoff usually occurs in association with winter rains, and low-elevation southwestern streams where flashy peak flows sometimes occur during monsoons.

Vegetation types are diverse, track local climatic conditions, and include alpine tundra, forests, shrublands, grassland steppe, and deserts. Human populations are large in coastal areas but small throughout most of the interior except for scattered urban centers. Agricultural development occurs primarily in river valleys at the lowest elevations to take advantage of consistent summer water supplies and fertile floodplains. Most mid-elevation to high-elevation lands are publically owned and federally administered by the U.S. Forest Service, U.S. Bureau of Land Management, and National Park Service for a variety of land use, recreational, and conservation purposes. A diverse fauna inhabits western streams and rivers, but cold-water fishes dominate societal interests and conservation investments.

2.2. NorWeST Database

Stream temperature records were downloaded from online agency databases and were solicited from professional biologists and hydrologists employed by state, federal, tribal, private, county, and municipal natural resource groups (supporting information S1). Data sets contributed by individuals consisted of digital records with multiple daily recordings, file formats that became common in the early 1990s with the widespread adoption and use of data logging temperature sensors. Organizing the large amount of data in the western U.S. required geographic and sequential prioritization, so at project initiation in 2011, we divided the area into 23 discrete processing units based on NHD unit boundaries, anticipated data densities, and physiographic similarity (Figure 1). Data within each unit were processed using a standard set of data screening and quality assurance techniques before being summarized into daily minima, maxima, and means that are available from the NorWeST website (www.fs.fed.us/rm/boise/AWAE/projects/NorWeST.html). Individuals from more than 100 resource groups contributed data to build the NorWeST database, which consisted of >220,000,000 temperature recordings at >22,700 stream and river sites, numbers that continue to increase with periodic database additions. Additional details regarding data processing along with metadata descriptions are provided at the website and in Chandler et al. (2016).

To develop a data set for creating a consistent set of climate scenarios, data were queried from the NorWeST database for all years at sites where August temperatures had been recorded multiple times daily during at least 90% of the month's days and these recordings were averaged to create a mean AugTw metric. We focused on AugTw because the summer is critical for growth and survival of many aquatic species in the western U.S. and this metric is strongly correlated with other commonly used summer temperature metrics (Dunham et al., 2005; Isaak & Hubert, 2001). Data were also available for the largest number of stream sites during the month of August (supporting information S1), which maximized the empirical support for the SSN temperature models and scenarios.

2.3. Stream Network and Model Covariates

Mean AugTw values were linked to reaches in the National Stream Internet (NSI) network (Isaak et al., 2013a; Nagel et al., 2015), which is a derivative of the 1:100,000-scale NHDPlusV2 that has been topologically adjusted to facilitate SSN analysis by applying the Spatial Tools for the Analysis of River Systems (STARS; Peterson & Ver Hoef, 2014) custom ArcGIS toolset (available at the SSN/STARS website: www.fs.fed.us/rm/boise/AWAE/projects/SpatialStreamNetworks.shtml). Adjustments consisted of removing braided stream reaches, which created redundant flow paths for ~3% of the network, shifting the locations of a small proportion of tributary confluences by 50 m to avoid double confluences, and ensuring that network topology was consistent so that hydrologic distances and spatial weights required in SSN analyses could be calculated. Nagel et al. (2015) provide additional details on the technical procedures used to create the NSI network, which has been developed for all streams in the conterminous U.S. and is available for download from the NSI website (www.fs.fed.us/rm/boise/AWAE/projects/NationalStreamInternet.html). Reaches in the NSI are easily matched to their counterparts in NHDPlusV2 so that reach descriptors can be used as covariates in SSN models.

Covariates used in the NorWeST model fits were selected based on a review of the literature, a plausible mechanism that could cause a temperature effect, and whether the covariates could be summarized from nationally available data sets. Table 1 summarizes the rationales for the covariates we chose, supporting studies, and source information for the data sets. The covariates were of two types, spatial and temporal, similar to our previous SSN temperature model for a river network in Idaho (Isaak et al., 2010). Spatial covariates were treated as time-invariant properties of the network, calculated at 1 km intervals, and consisted of elevation (ELE), reach slope (SL), percentage of the upstream watershed area composed of lakes (LK), percentage of the upstream watershed area composed of glaciers (GLA), annual precipitation (AP), northing coordinate (NOR), base-flow index (BFI), cumulative drainage area (DA), and percentage riparian canopy coverage (RC). We did not adjust RC values for wildfires that may alter local canopy conditions and cause stream warming because of the amount of GIS work it requires (Isaak et al., 2010) and because revegetation occurs a few years to decades after fires to ameliorate temperature increases (Dunham et al., 2007; Holsinger et al., 2014; Mahlum et al., 2011). Of greater concern were persistent local temperature anomalies that are created in cold tailwaters (TW) by hypolimnetic water releases from deep reservoirs upstream of dams in some rivers (Dibble et al., 2015). The occurrence and extent of cold TWs was determined by examining temperature records and interviews with local professionals familiar with dam sites. Those reaches

Table 1
Covariates Used in Models to Predict Mean August Temperatures in Rivers and Streams of the Western U.S.

Covariate	Definition and rationale	References	Data source[a]
Elevation (ELE)	Elevation at the AugTw sensor site. Cooler air temperatures and greater snow and precipitation accumulations (cooler ground water inputs) at higher elevations should cool stream temperatures.	Smith and Lavis (1975), Isaak and Hubert (2001), and Sloat et al. (2005)	Digital elevation models (30 m resolution) associated with NHDPlus, downloaded from http://www.horizon-systems.com/NHDPlus/NHDPlusV2_home.php
Slope (SL)	Slope of the stream reach at a sensor site. Steeper slopes should cool stream temperatures by increasing flow velocities and decreasing equilibration with warmer microclimatic conditions at lower elevations.	Sloat et al. (2005), Webb et al. (2008), and Isaak et al. (2010)	NHDPlus Value Added Attribute = SLOPE, downloaded from http://www.horizon-systems.com/NHDPlus/NHDPlusV2_home.php
Lake (LK)	Percentage of watershed upstream of a sensor composed of lake or reservoir surfaces. Lakes absorb heat, slow water transit times through watersheds, and should increase downstream temperatures.	Dripps and Granger (2013) and Maheu et al. (2016)	NHDPlus Value Added Attribute = NLCD11PC, downloaded from http://www.horizon-systems.com/NHDPlus/NHDPlusV2_home.php
Glacier (GLA)	Proportion of watershed upstream of a sensor composed of glacial ice surfaces. Glacial meltwater during the summer should cool streams.	Hari et al. (2006) and Brown et al. (2007)	Data downloaded from Glaciers of the western U.S. website: http://glaciers.research.pdx.edu/Downloads and calculated using flow accumulation script in GIS.
Annual precipitation (AP)	Mean annual precipitation in watershed upstream of sensor site. Wetter landscapes have higher water yields and more groundwater that should cool streams.	Isaak and Hubert (2001)	NHDPlus Value Added Attribute = PrecipV, downloaded from http://www.horizon-systems.com/NHDPlus/NHDPlusV2_home.php
Northing coordinate (NOR)	Albers Equal Area Northing coordinate at the sensor site. Air and groundwater temperatures are cooler further north and should cool streams.	Ward (1985) and Meisner et al. (1988)	Projected coordinates were generated for sensor locations using GIS software.
Base-flow index (BFI)	Base-flow index values at sensor sites calculated as the ratio of base flow to total flow and expressed as a percentage. Sites with larger base flows relative to peak flows have larger groundwater contributions that should cool streams.	Mayer (2012) and Kelleher et al. (2012)	Data developed by Wolock (2003) and downloaded from http://ks.water.usgs.gov/pubs/abstracts/of.03-263.htm
Drainage area (DA)	Drainage area of watershed upstream of sensor that is a surrogate for stream size. Larger streams are insolated over a greater length and are less shaded by riparian vegetation, which should result in warmer temperatures.	Ward (1985), Moore et al. (2005), and Garner et al. (2013)	NHDPlus Value Added Attribute = TotDASqKM, downloaded from http://www.horizon-systems.com/NHDPlus/NHDPlusV2_home.php
Riparian canopy (RC)	Canopy value associated with the 1 km stream reach that encompasses a sensor site. Higher canopy values are associated with more shade and cooler streams.	Moore et al. (2005), Cristea and Burges (2010), Garner et al. (2014), and Nusslé et al. (2015)	Percent canopy derived from the NLCD 2011 USFS Tree Canopy Cartographic layer averaged over 1 km stream reaches. Downloaded from https://www.mrlc.gov/nlcd11_data.php
Air temperature (AT)	Mean August air temperature assigned to AugTw records measured during the same year. Years with warmer air temperatures are associated with warmer stream temperatures.	Webb and Zhang (1997), Mohseni and Stefan (1999), Isaak et al. (2012), and Garner et al. (2013)	Gridded (15 km^2 resolution) air temperature data sets from RegCM3 climate model runs for a NCEP historical reanalysis. Data were downloaded from the USGS Regional Climate Downscaling website (http://regclim.coas.oregonstate.edu/index.html; Hostetler et al., 2011).

10.1002/2017WR020969

Table 1. *(continued)*

Covariate	Definition and rationale	References	Data source[a]
Discharge (Q)	Mean August stream discharge assigned to AugTw records measured during the same year. Years with higher discharge are associated with cooler stream temperatures.	Hockey et al. (1982), Gu et al. (1998), Isaak et al. (2012), and Elmore et al. (2016)	Discharge records from flow gages without upstream regulation, minimal water abstraction, and the longest records since 1952 were downloaded from NWIS (http://waterdata.usgs.gov/nwis/rt).
Tailwater (TW)	Occurrence of sensor in tailwater downstream from large dam with anomalously cold hypolimnetic water release.	Lehmkuhl (1972), Preece and Jones (2002), and Olden and Naiman (2010)	Examination of temperature records and consultation with local professionals.

[a]Additional details are in metadata documents downloadable from the NorWeST website: https://www.fs.fed.us/rm/boise/AWAE/projects/NorWeST.html.

were coded "1" in a binary scheme and TW was included as a categorical covariate when SSN models were fit in processing units that contained one or more TWs. In total, 2,352 km of rivers (~0.1% of the full network extent) were coded TW downstream of 58 dams. Cold TW lengths varied depending the size of dams and reservoirs from relatively short 10 km reaches to a long 150 km reach downstream of Lake Powell on the Colorado River. Smaller reservoirs produce minor temperature effects or cause downstream warming similar to natural lakes (Maheu et al., 2016), so they were considered functional equivalents and represented by the LK covariate. Values for each spatial covariate were assigned to all 1 km reaches in the NSI network, and mean AugTw values were referenced to the covariate values within their respective reaches.

Two temporal covariates, mean August air temperature (AT) and stream discharge (Q), were used to represent interannual climate variability that affects AugTw. We focused on an interannual time step because it negates the intraannual mediation of airstream temperature relationships that are caused by changing solar angles (Isaak et al., 2012; Luce et al., 2014) and yields AT and Q parameters useful for creating scenarios of historical and future conditions. For each temporal covariate, processing-unit average values were developed to represent time series of mean August conditions from 1976 through 2015, and these values were assigned to the AugTw samples recorded in the same year. August AT data were obtained from 15 km gridded data sets that were generated for a NCEP RegCM3 reanalysis and were downloaded from the U.S. Geological Survey Regional Climate Downscaling website (http://regclim.coas.oregonstate.edu/index.html; Hostetler et al., 2011). August Q data from flow gages in each processing unit were downloaded from the National Water Information System website (http://waterdata.usgs.gov/nwis/rt) and screened to extract the longest station records where upstream water abstraction was minimal and storage reservoirs did not occur. August Q from 3 to 17 gages that met those criteria within each processing unit were averaged to create the Q time series (station numbers are listed in S2 and Table S2).

2.4. NorWeST SSN Model

After covariates and AugTw data sets were prepared, the topological, spatial, and attribute information needed to fit SSN models were generated for the data sets using the STARS toolset (Peterson & Ver Hoef, 2014). That information was imported into R (R Development Core Team, 2014) and the SSN package (Ver Hoef et al., 2014; Version 1.1.7) was used to fit the temperature models (processed data sets and R scripts to replicate all analyses are available at the NorWeST website). A SSN model was fit to each processing-unit data set that included all covariates regardless of their final statistical significance (although GLA and TW were not included when absent from a unit). Retention of all covariates was a luxury afforded by our large sample sizes, but it also enabled consistent comparisons among the 23 processing units. The computation time required to fit SSN models (up to 7 days on a 16-core workstation for the largest data sets) also made minimizing the number of model fits a practical necessity. The SSN model was a linear mixed model of the form,

$$\boldsymbol{y}=\mathbf{X}\boldsymbol{\beta}+\mathbf{L}\gamma+\mathbf{R}\boldsymbol{\eta}+\mathbf{z}_{\mathrm{TU}}+\mathbf{z}_{\mathrm{TD}}+\mathbf{z}_{\mathrm{EUC}}+\varepsilon, \tag{1}$$

where $\boldsymbol{y}$ is a vector of AugTws, $\mathbf{X}$ is a design matrix of covariate values, $\boldsymbol{\beta}$ is a vector of regression coefficients, $\mathbf{L}$ is a random-effects design matrix for location, γ is a vector of zero-mean, normally distributed random effects for location, $\mathbf{R}$ is a random-effects design matrix for year, $\boldsymbol{\eta}$ is a vector of zero-mean, normally distributed random effects for year, and ε is a vector of independent and normally distributed random errors. The model specification included random effects for year and location to account for repeat measurements at sites across years or at many sites within years. Spatial structure in residual errors was modeled using vectors of zero-mean random effects ($\mathbf{z}_{TU}$, $\mathbf{z}_{TD}$, and $\mathbf{z}_{EUC}$) with an autocorrelation structure based on exponential Euclidean (EUC) and exponential tail-down (TD) covariance functions, as well as an exponential tail-up (TU) function with a spatial weighting scheme based on watershed area (Peterson & Ver Hoef, 2010; Ver Hoef & Peterson, 2010). We included a mixture of spatial-autocorrelation functions (TU, TD, and EUC) because each class represents spatial relationships in a different way (e.g., patterns created by passive downstream drift or upstream and downstream movement processes) and previous research suggests that mixed spatial-autocorrelation constructions perform better than single autocorrelation functions to characterize spatial patterns in stream networks (Frieden et al., 2014; Isaak et al., 2017b).

The covariance matrix for $\mathbf{y} \sim \mathrm{N}(\mathbf{X}\boldsymbol{\beta}, \Sigma)$ in (1) was

$$\Sigma = \sigma_\gamma^2 \mathbf{L}\mathbf{L}' + \sigma_\eta^2 \mathbf{R}\mathbf{R}' + \sigma_{TU}^2 \mathbf{C}_{TU} + \sigma_{TD}^2 \mathbf{C}_{TD} + \sigma_{EUC}^2 \mathbf{C}_{EUC} + \sigma_\varepsilon^2 \mathbf{I}, \tag{2}$$

where $\sigma_\gamma^2, \sigma_\eta^2, \sigma_{TU}^2, \sigma_{TD}^2, \sigma_{EUC}^2$, and σ_ε^2 were variances for γ, $\boldsymbol{\eta}$, $\mathbf{z}_{TU}$, $\mathbf{z}_{TD}$, $\mathbf{z}_{EUC}$, and ε, respectively, and $\mathbf{C}_{TU}$, $\mathbf{C}_{TD}$, and $\mathbf{C}_{EUC}$ were autocorrelation matrices for $\mathbf{z}_{TU}$, $\mathbf{z}_{TD}$, and $\mathbf{z}_{EUC}$, respectively, where each $\mathbf{C}$-matrix has an additional parameter that controls the spatial range of autocorrelation for that model. For an in-depth discussion of stream covariance functions, readers may wish to consult previous work (Frieden et al., 2014; Peterson & Ver Hoef, 2010; Ver Hoef & Peterson, 2010).

Prior to fitting each SSN model, potential issues with multicollinearity were assessed by calculating variance inflation factors (VIF; Helsel & Hirsch, 1992) using the covariates in a nonspatial multiple linear regression model. Except in rare cases, VIFs were low (i.e., <5) and not at levels problematic to parameter estimation or interpretation. After SSN models were fit, the relative importance of covariates within and among processing units was determined based on the magnitude of raw and standardized parameter estimates and their statistical significance. Predictive performance of the SSN models was described in three ways. First, we calculated the mean absolute prediction error (MAPE) between the observed and leave-one-out cross-validation (LOOCV) predicted AugTw values. Second, we computed a predictive r^2 based on the squared correlation of observations and the LOOCV predictions. Third, we computed the root mean square prediction error as

$$\mathrm{RMSPE} = \sqrt{\frac{\sum_{i=1}^{n} [\hat{y}(s_i) - y(s_i)]^2}{n}}, \tag{3}$$

where $y(s_i)$ is an observation at a unique location and time, $\hat{y}(s_i)$ is the LOOCV prediction value for s_i, and n is the total number of observed data values.

2.5 Historical Trend Description

Increasing air temperatures and decreasing summer flows associated with climate change are well documented across the western U.S. (Clow, 2010; Luce & Holden, 2009; Mote et al., 2005; Stewart et al., 2005) and these trends are expected to warm streams by increasing long-wave radiation and warming groundwater inputs (Kurylyk et al., 2015a; Webb et al., 2008). Previous stream-temperature trend estimates, however, are available only from a small number of sites with long-term monitoring records that sometimes provide inconsistent results due to variable record lengths (Arismendi et al., 2012; Isaak et al., 2012). To estimate historical trends consistently, we multiplied the AT and Q parameters from each SSN model fit by the amount of change observed in mean AT and Q for 1976–2015 and then summed the stream temperature changes as in previous work (Isaak et al., 2010, 2012). This approach obscured site-level variation in warming rates but yielded accurate estimates at the processing-unit scale while also providing a description of the relative contributions of long-term trends in AT and Q to stream temperature changes. Trend reconstructions were possible for any recent historical period, but 1976–2015 was a useful focus because the start date largely coincides with the globally coherent warming signal that emerged in recent decades (Foster & Rahmstorf, 2011; Intergovernmental Panel on Climate Change [IPCC], 2013). It was also long enough to temper the effects of short-term climate cycles like the El-Nino Southern Oscillation and Pacific Decadal Oscillation that are important in the western U.S. (Easterling & Wehner, 2009; Mote et al., 2003).

2.6. Stream Temperature Scenarios

The SSN model fits and universal kriging (Cressie, 1993) were used to predict stream temperatures at 1 km intervals and create scenarios for the networks within processing units. The kriging equations have two parts, predictions based on the linear regression model and adjustments based on local spatial autocorrelation,

$$\hat{\mathbf{y}}(s_0)=\mathbf{x}(s_0)'\hat{\boldsymbol{\beta}}+\mathbf{c}(s_0)'\Sigma^{-1}\left(\boldsymbol{y}-\boldsymbol{X}\hat{\boldsymbol{\beta}}\right), \tag{4}$$

where $\mathbf{x}(s_0)$ is a vector containing the covariate values at prediction location s_0 and the vector $\hat{\boldsymbol{\beta}}$ contains the estimated regression coefficients, so that $\mathbf{x}(s_0)'\hat{\boldsymbol{\beta}}$ forms the linear regression prediction. The remaining portion of equation (4) is an adjustment for spatial autocorrelation, where $\mathbf{c}(s_0)$ is a vector of covariances between observed data and the prediction site, and $\boldsymbol{\Sigma}$ is the covariance matrix among observed data (equation (2)). Prediction variances (Ver Hoef, 2008) are given by

$$\hat{\mathrm{var}}[\hat{\mathbf{y}}(s_0)]=\sigma_0^2-\mathbf{c}(s_0)'\Sigma^{-1}\mathbf{c}(s_0)+\mathbf{d}'\left(\boldsymbol{X}'\Sigma^{-1}\boldsymbol{X}\right)^{-1}\mathbf{d}, \tag{5}$$

where $\sigma_0^2=\mathrm{var}[\mathbf{y}(s_0)]$ (including all of the variance components) and $\mathbf{d}=\mathbf{x}(s_0)-\boldsymbol{X}'\Sigma^{-1}\mathbf{c}(s_0)$.

Thirty-six scenarios were created for each processing unit (supporting information S2 and supporting information Table S2). Two baseline scenarios representing composite periods when most of the temperature data were collected (Scenario 1: 1993–2011 and Scenario 2: 2002–2011) were developed based on the average AT and Q values for these periods. Additional historical scenarios were created for each year from 1993 through 2015 (Scenarios 3–21 and 33–36) based on the AT and Q values observed in individual years. Scenario 22 provides local prediction variances from equation (5) at 1 km intervals (e.g., Figure S3 in supporting information S2), which are useful for mapping spatial uncertainty and could be used to direct subsequent temperature monitoring efforts. Ten future scenarios (Scenarios 23–32) were developed by adding stream temperature deltas to the Scenario 1 baseline. Stream delta values were of three types: (1) simple integer values (+1.0, +2.0, and +3.0°C); (2) values obtained by multiplying global climate model (GCM) projected changes in August AT and Q (described below) by the parameters for these covariates in the SSN models, and (3) values based on the integers and GCM projections in 1 and 2, but which were also adjusted to account for differential sensitivity among streams within processing units (i.e., some streams warming more than others in response to the same climate forcing). Differences in stream sensitivity were incorporated into five of the future scenarios (Scenarios 24, 26, 28, 30, and 32) by adjusting projected AugTw increases based on unit-specific sensitivity parameters estimated from observed patterns of interannual variation (calculations and parameters are in supporting information S3). Those patterns usually showed that the coldest streams were less responsive to interannual climate variation than warmer streams as has previously been documented in the western U.S. (Luce et al., 2014; Isaak et al., 2016a) and other mountainous regions (Hari et al., 2006; Lisi et al., 2015). As a result, future scenarios with sensitivity adjustments project that temperature increases in cold streams will be smaller than in warm streams.

The GCM projections of AT changes were the mean values from a ten-climate model ensemble (Hamlet et al., 2013) that was used to simulate the A1B emissions scenario for the 2040s (2030–2059) and 2080s (2070–2099; Intergovernmental Panel on Climate Change, 2007). The same GCM ensemble and A1B scenario were used with the Variable Infiltration Capacity (VIC) hydrologic model to obtain projections of August Q changes at the gaging stations used to develop historical time series for each processing unit (supporting information S2 and supporting information Table S4). The VIC Q deltas were obtained from the Climate Impacts Group Hydrologic Climate Change website (http://warm.atmos.washington.edu/2860/) for the gages in Idaho, Oregon, and Washington processing units or were derived using similar techniques for gages in other western states based on the flow routing and accumulation procedures described in Wenger et al. (2010). Although the A1B emissions scenario was originally run for the third phase of the Coupled Model Intercomparison Project (CMIP3) and has been superseded by Representative Concentration Pathways (RCP) in CMIP5, there is a strong similarity between A1B and RCP 6.0 (Wright et al., 2015).

The 36 stream temperature scenarios were developed for the full extent of the NHDPlusV2 network within the 23 processing units that included 1,632,000 km of streams in the western U.S. Scenarios are downloadable as ArcGIS shapefiles (Environmental Systems Research Institute, 2015) from the NorWeST website and Isaak et al. (2016b) provide additional technical details. The full NHDPlus network, however, contains many reaches that are

Table 2
Descriptive Statistics for Covariates Associated With Mean August Stream Temperature Observations in the Data Set Used to Develop Temperature Models and Scenarios for Rivers and Streams in the Western U.S.

Variable	*n*	Mean	Median	Standard deviation	Minimum	Maximum
ELE (m)	22,751	964	891	723	0	3,576
SL (m/m)	22,751	0.0330	0.0197	0.0393	0	0.485
LK (%)	22,751	0.303	0	1.08	0	50
GLA (km^2/km^2)	22,751	0.000314	0	0.00624	0	0.5
AP (mm)	22,751	990	859	643	21.8	5,710
NOR (m)	22,751	1,566,658	1,622,016	329,347	177,326	2,329,746
BFI (%)	22,751	61.2	65.0	13.3	1	89
DA (km^2)	22,751	3,008	51.0	27,902	0	620,000
RC (%)	22,751	45.6	48.0	29.2	0	97.3
AT (°C)	13–23[a]	17.1	16.9	2.27	10.9	26.1
Q (m^3/s)	13–23	8.25	3.50	9.58	0.0354	58.0
AugTw (°C)	63,641	14.5	14.2	3.74	3.69	38.4

Note. Refer to Table 1 for definitions of variable acronyms. Summaries for individual processing units are in supporting information S4.
[a]Number of years varies from 13 to 23 in association with the availability of stream temperature data in the processing units.

unlikely to support aquatic species due to either topographic steepness or flow intermittency that is common in portions of the arid western U.S. Therefore, we filtered the network to represent perennial stream habitats by deleting reaches with slope >15%, with VIC summer flows <0.028 m^3/s, and those coded as intermittent (Fcode = 46003) to 343,000 km of streams and rivers that served as the basis of our result summaries.

3. Results

3.1. Temperature Data Set

The database query to extract AugTw records for modeling and scenario development yielded 63,641 years of data from 22,751 sites. Monitoring densities were highest in mesic areas like the Pacific Northwest and Rocky Mountains and lower in drier portions of the region like the Great Basin and Southwest (Figure 1). Descriptive statistics for AugTw and the covariate values at those sites are provided in Table 2 (summaries for individual processing units are in supporting information S4). Spatial variation in the data set was large with temperature monitoring sites spanning more than 2,000 km from north to south, occurring at elevations from 0 to 3,580 m, and in streams that drained headwater basins as small as 0.1 km^2 to the Columbia River with a basin size of 620,000 km^2 and mean annual discharge of 7,500 m^3/s. Interannual variation in AT and Q during the 13–23 years with AugTw measurements in the processing units was also large, with the

Table 3
Correlations Among Covariates and Mean August Stream Temperature Observations in the Data Set Used to Develop Temperature Models and Scenarios for Rivers and Streams in the Western U.S.

	ELE	SL	LK	GLA	AP	NOR	BFI	DA	RC	AT	Q
SL	0.19	1									
LK	−0.03	−0.11	1								
GLA	−0.02	0.02	0.00	1							
AP	−0.42	0.13	−0.07	0.08	1						
NOR	−0.17	0.03	−0.04	0.05	0.19	1					
BFI	0.55	0.12	0.04	0.02	−0.39	0.40	1				
DA	−0.09	−0.08	0.06	0.00	−0.05	0.02	−0.02	1			
RC	−0.16	0.29	−0.11	0.02	0.46	0.16	−0.10	−0.15	1		
AT	0.01	−0.04	0.06	−0.02	−0.18	−0.64	−0.29	0.02	−0.14	1	
Q	0.22	0.12	−0.04	0.00	−0.08	0.38	0.37	−0.04	0.02	−0.58	1
AugTw	−0.45	−0.38	0.15	−0.06	−0.12	−0.29	−0.44	0.18	−0.37	0.32	−0.32

Note. Summaries for individual processing units are in supporting information S4.

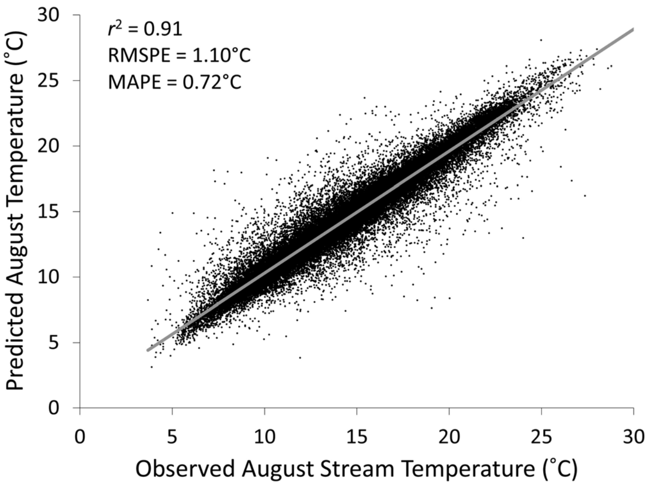

Figure 2. Comparison of 63,641 mean August stream temperature observations and leave-one-out cross-validation predictions from temperature models in the 23 processing units.

range of AT variation spanning 3–6°C and Q varying by threefold to tenfold (supporting information S2 and supporting information Table S1). Observed AugTw values averaged 14.5°C across all site-years of data and ranged from 3.7 to 38.4°C although temperatures <7°C or >21°C were infrequent (Table 2). Correlations among the covariates and AugTw are summarized in Table 3. AugTw was most strongly correlated with ELE (−0.45) followed by BFI (−0.44), SL (−0.38), and RC (−0.37; summaries for individual processing units are in supporting information S4).

3.2. Model Estimates and Historical Trends

The SSN models accurately predicted AugTw within the 23 processing units and had an average predictive r^2 of 0.91, RMSPE of 1.10°C, and MAPE of 0.72°C (Figure 2 and Table 4). The AugTw sample sizes used in the model fits ranged from 143 to 9,521 and model performance was good regardless of sample size. However, there were significant negative relationships between sample size and RMSPE ($r = -0.58$; $p < 0.01$) and MAPE ($r = -0.68$; $p < 0.01$) because predictions in units with higher sample densities could more often leverage information from neighboring samples through the spatial-autocorrelation function. Covariate relationships with AugTw met a priori expectations described in Table 1. Cooling effects were associated with ELE, SL, GLA, AP, NOR,

Table 4
Summary of Temperature Model Performance and Covariate Relationships With Mean August Stream Temperature for 23 Processing Units in the Western U.S.

					Covariates											
NorWeST unit	AugTw *n*	r2[a]	RMSPE[b]	MAPE[c]	ELE	SL	LK	GLA	AP	NOR	BFI	DA	RC	AT	Q	TW
A. Salmon	4,007	0.89	0.86	0.55	−, 1	−, 5	+, 2	na[d]	−, 4			+, 6	−, 8	+, 3	−, 7	na
B. Clearwater	4,487	0.91	0.96	0.60	−, 1	−, 5	+, 9	na	−, 7	−, 4	−, 6	+, 2	−, 8	+, 3		−
C. SpoKoot	5,482	0.90	0.97	0.62	−, 1	−, 8	+, 2	na	−, 7	−, 3		+, 4	−, 5	+, 6	−, 9	−
D. MissHW	1,145	0.91	1.17	0.75	−, 1	−, 8	+, 2	na	−, 3		−, 5	+, 4	−, 6	+, 7	−, 9	na
E. SnakeBear	1,173	0.86	1.46	0.92	−, 1	−, 2		na					−, 5	+, 3	−, 4	−
F. Mid-Snake	3,384	0.92	1.06	0.62	−, 1	−, 7	+, 3	na	−, 9	−, 2	−, 4		−, 5	+, 6	−, 8	−
G. Mid-Col	9,521	0.94	0.91	0.60	−, 1	−, 8	+, 2	na	−, 3		−, 4	+, 7	−, 5	+, 6		−
H. OR Coast	9,128	0.90	0.92	0.57	−, 1	−, 7	+, 8	−, 9	−, 4	−, 2		+, 6	−, 3	+, 5		−
I. OR South	1,676	0.93	0.95	0.63	−, 1	−, 6		na	−, 3	−, 4	−, 2	+, 5	−, 8	+, 7	−, 9	na
J. Lahontan	576	0.86	1.24	0.88	−, 1	−, 3	+, 8	na	−, 6	−, 5	−, 9	+, 4	−, 2	+, 10	−, 7	na
K. WA East	2,609	0.91	0.97	0.64	−, 1	−, 6	+, 2		−, 4		−, 5		−, 7	+, 8	−, 3	na
L. WA West	3,668	0.88	0.86	0.55	−, 1		+, 2	−, 5					−, 4	+, 3		na
M. Yellowst	513	0.89	1.34	0.91	−, 1	−, 7		na	−, 5		−, 2		−, 4	+, 3	−, 6	na
N. Miss-Marias	300	0.87	1.34	0.89	−, 1		+, 3	na				+, 4	−, 2	+, 5	−, 6	na
O. Wyoming	464	0.92	1.10	0.73	−, 1	−, 2		na		−, 3			−, 4	+, 5		−
P. Utah	248	0.95	1.07	0.74	−, 1			na			−, 2			+, 3		na
Q. CA North	8,118	0.91	0.96	0.60	−, 1	−, 4		na				+, 3	−, 2		−, 5	−
R. CA coastal	447	0.89	1.26	0.87		−, 2		na		−, 1						−
S. CA central	2,865	0.90	1.41	0.92	−, 1	−, 6		na	−, 3			−, 4	−, 2	+, 7	−, 5	−
T. Colorado	2,681	0.95	1.05	0.68	−, 1	−, 8	+, 7	na	−, 2		−, 3	+, 5	−, 4	+, 6	−, 9	−
U. New Mex	755	0.94	1.03	0.75	−, 1	−, 2		na	−, 4		−, 3			+, 5		na
V. Arizona	251	0.93	1.06	0.74	−, 1	−, 3		na			−, 2					na
W. Black Hills	143	0.94	1.41	0.87	−, 1			na						+, 2		−
Tot or ave =	63,641	0.91	1.10	0.72	22/23	19/23	12/23	2/3	14/23	8/23	12/23	12/23	18/23	20/23	13/23	12/12

Note. Significant positive covariate relationships ($\alpha \leq 0.05$) are indicated with +'s, significant negative relationships with −'s, and blank cells indicate nonsignificant relationships. Numbers adjacent to significant relationships indicate the rank importance of the covariate within the model for a processing unit based on standardized parameter estimates (supporting information S4 contains detailed results for each unit).
[a]Squared correlation between AugTw observations and leave-one-out cross-validation (LOOCV) predictions.
[b]Root-mean-square prediction error (°C).
[c]Mean absolute error between AugTw observations and the LOOCV predictions.
[d]Not applicable if a covariate did not occur in a processing unit.

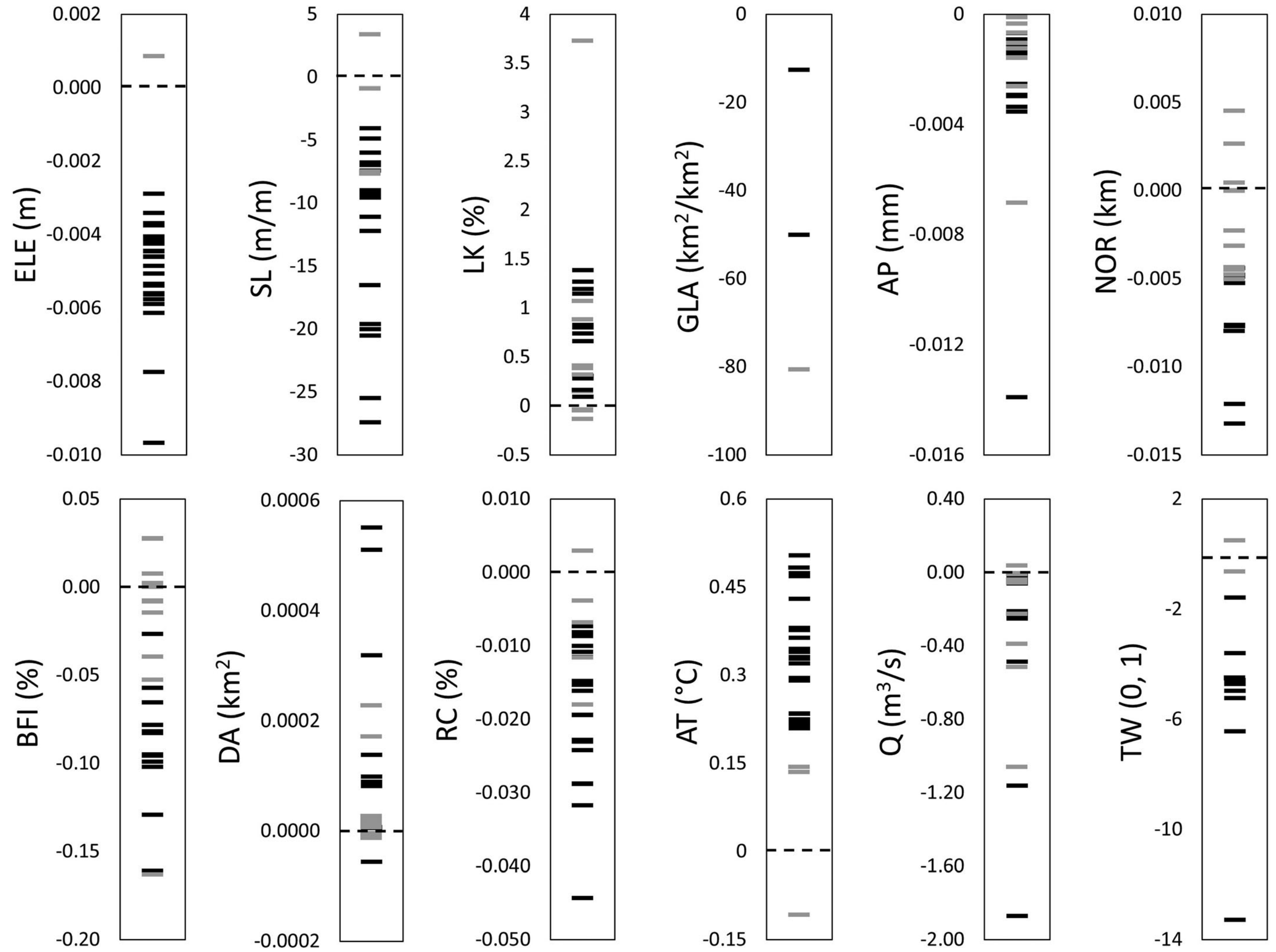

Figure 3. Covariate parameter estimates in original units for temperature model fits to 23 processing units. Black symbols indicate estimates that were statistically significant ($\alpha < 0.05$) in their respective units whereas grey symbols were not significant. Dashed lines indicate the location of zero values. Supporting information S4 provides additional details for individual processing units.

BFI, RC, Q, and TW, and warming effects were associated with LK, DA, and AT (Table 4). Of the 245 covariate significance tests in the SSN model fits, 164 were statistically significant ($\alpha < 0.05$) and only one was counterintuitive (cooling effect of DA in central California unit S; Table 4). ELE was the dominant factor in 22 of 23 models, lacking significance in the coastal California unit where only SL and NOR covariates had significant effects. The covariates SL, RC, and AT also had significant effects in most processing units although their relative importance varied among units as did the size of raw parameter estimates. For example, significant SL (m/m) parameters ranged from -4.03 to -27.4, RC (%) parameters ranged from -0.0073 to -0.0443, AT (°C) parameters ranged from 0.21 to 0.50, and ELE (m) parameters ranged from -0.00289 to -0.00967 (Figure 3; additional details regarding model fits for each processing unit are in supporting information S4).

August AT warming trends (average = 0.43°C/decade) and Q declines (average = -6.1%/decade) were common to most of the processing units during 1976–2015 (Figure 4 and supporting information S2 and supporting information Table S1). The product of those trends and the SSN parameter estimates for AT and Q yielded the estimated AugTw trends for that same period as summarized in Figure 5. Variation occurred among the units, but 22 of 23 showed warming trends and the average trend across all units was 0.17°C/decade (SD = 0.067°C/decade). Notably, the four coastal units (H, L, Q, and R; Figure 1) showed smaller rates

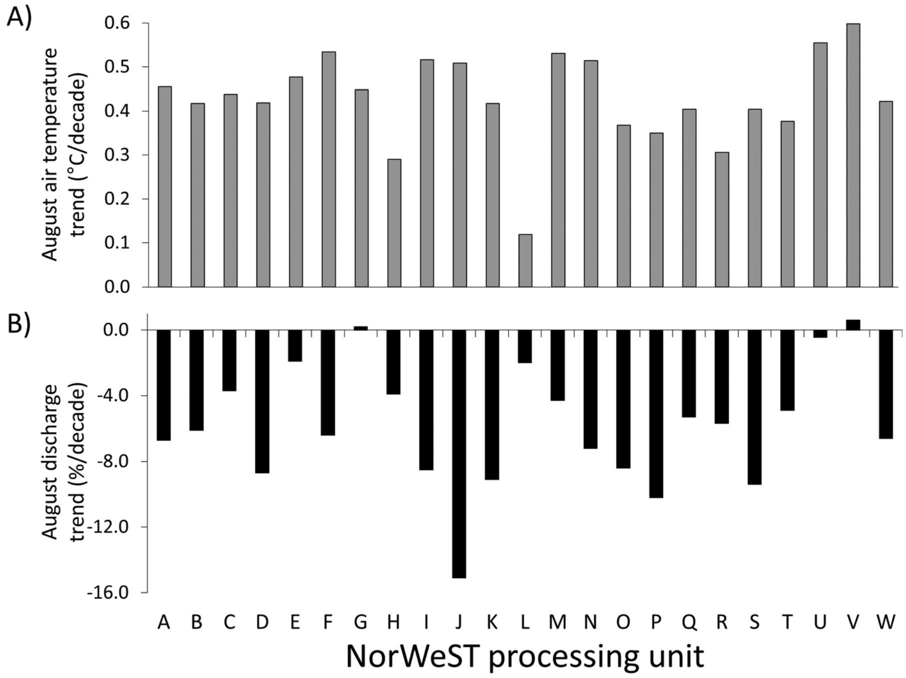

Figure 4. Trends in mean August (a) air temperatures and (b) stream discharge for 1976–2015 in the 23 processing units. Letters correspond to processing units as defined in Figure 1 and Table 5.

of warming (average = 0.07°C/decade) due to either weak AT and Q trends (units H and L) or small AT and Q parameters (units Q and R). Most of the AugTw trend for 1976–2015 (83%) was attributable to AT trends although Q declines played important roles in some units (Figure 5b).

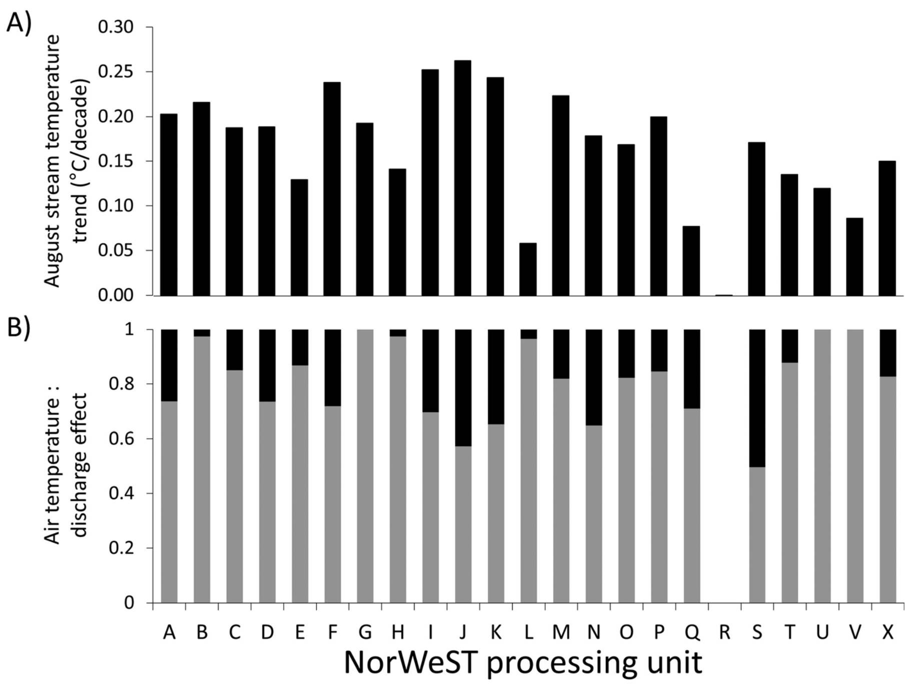

Figure 5. Reconstructed historical trends in mean August (a) stream temperatures for 1976–2015 and the proportional contributions of trends in (b) air temperature (grey bars) and stream discharge (black bars) during the same period. Letters correspond to processing units as defined in Figure 1 and Table 5.

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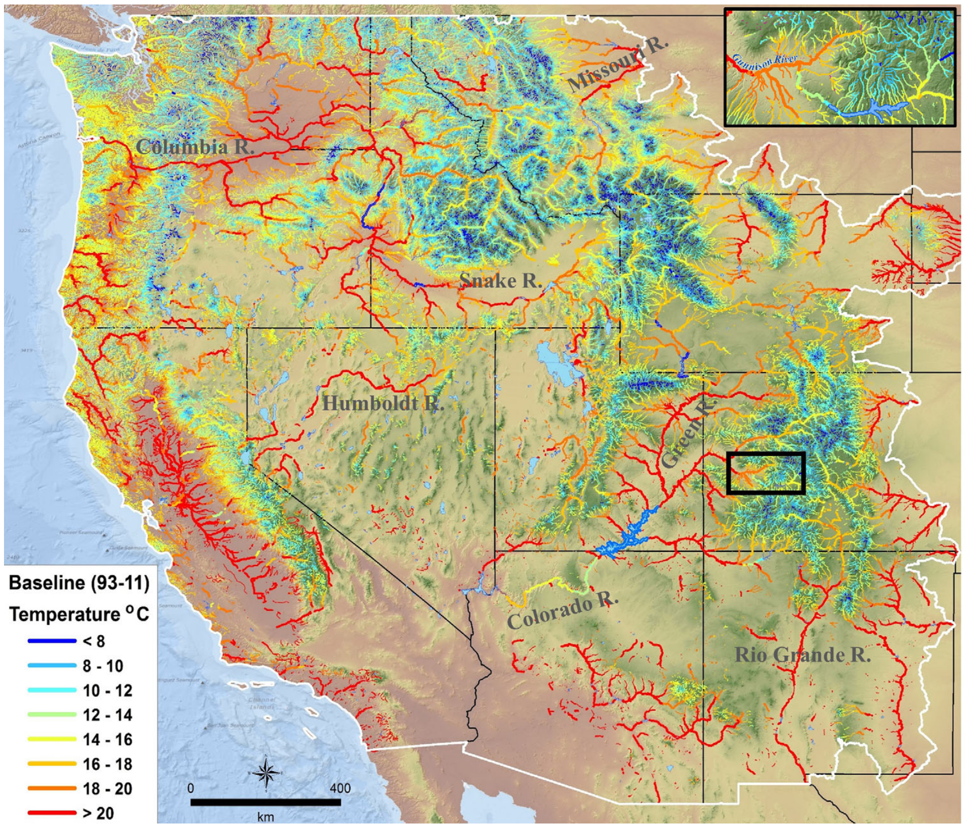

Figure 6. Mean August stream temperature thermalscape for Scenario 1 baseline period of 1993–2011 mapped to the 343,000 km of perennial streams in the western U.S. Map inset shows details within the black box.

3.3. Stream Temperature Scenarios

AugTw in the Scenario 1 baseline period of 1993–2011 averaged 14.2°C (SD = 4.0°C) and this thermalscape is shown in Figure 6 for the 343,000 km perennial stream network (detailed maps for each processing unit are provided in supporting information S4). Significant heterogeneity is apparent across the region with the coldest streams and rivers occurring in mountainous environments and warmer streams flowing through intermountain basins, deserts, and grassland steppes. Also apparent are the large differences in densities of perennial streams between mesic areas and drier subregions. Under the A1B emissions scenario, AugTw was predicted to increase an average of 0.73 and 1.42°C by 2040 and 2080, respectively, relative to the Scenario 1 baseline (Figure 7). As with the historical trends, substantial variation in warming is predicted among

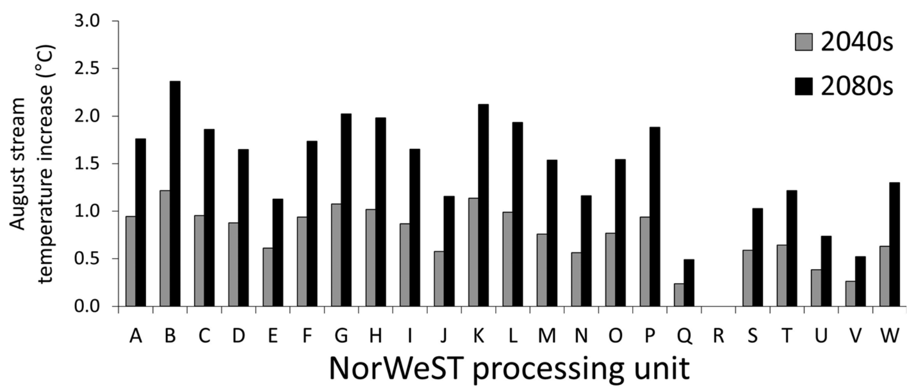

Figure 7. Mean August stream temperature increases predicted for the A1B emissions trajectory by the 2040s and 2080s relative to the Scenario 1 baseline period of 1993–2011.

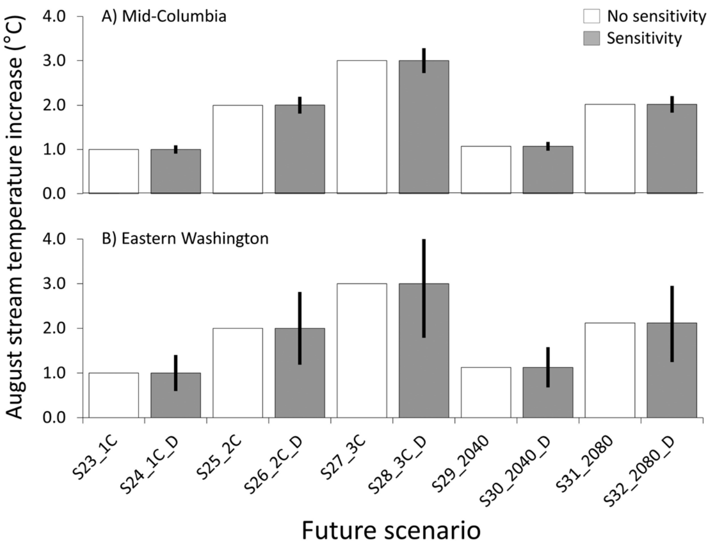

Figure 8. Mean August stream temperature increases relative to the Scenario 1 baseline period of 1993–2011 for two processing units with and without sensitivity adjustments. (a) Scenarios for a processing unit with a small sensitivity parameter, compared to (b) a unit with a large sensitivity parameter. Error bars associated with the sensitivity scenarios are ±2 standard deviations.

the units although the magnitude of future changes often mimic historical trends (i.e., smaller future changes are predicted where historical trends are small).

The full set of 10 future scenarios, including those based on +1.0, +2.0, and +3.0°C deltas, are summarized for two processing units in Figure 8. In that example, the +1.0 and +2.0°C scenarios are nearly identical to the 2040 and 2080 scenarios but the +3.0°C scenario exceeds the others and generally provides a more aggressive alternative scenario for all the processing units. Figure 8 also highlights differences between scenarios with and without the differential sensitivity adjustment, the latter scenarios denoted by standard deviation error bars that describe variation among predicted changes in the population of 1 km reaches within a processing unit. Also noteworthy is that in scenarios with the sensitivity adjustment, the unit-averaged delta is the same as that of the paired scenario without the adjustment. The practical implications of the sensitivity adjustment are shown in Figure 9, which maps future stream deltas for a small set of streams in the Eastern Washington unit. Temperature increases are a uniform 2°C without the adjustment in Scenario 25 (Figure 9b) but range from 1.6 to 2.6°C with the adjustment in Scenario 26 because cold streams at higher elevations warm less than those at lower elevations (Figure 9c).

4. Discussion

4.1. Stream-Temperature Trends and Projections

Combining a stream temperature database of unprecedented size with new geospatial analysis tools proved useful for describing the thermal heterogeneity of streams and rivers throughout the western U.S. Both observed and predicted AugTw values spanned an order of magnitude, with large differences sometimes occurring in portions of networks that were separated by short geographic distances due to the region's topographic diversity and strong environmental gradients from mountain headwaters to lowland rivers. For that reason, the spatial covariates representing those gradients (ELE, SL, DA, and RC) dominated our temperature models. Other spatial covariates representing more localized effects (LK, GLA, and BFI) were important where specific geologies enhanced groundwater contributions or in landscapes that were glaciated and contain many lakes. Given the amount of variation associated with spatial covariates, the comparatively small effects of temporal covariates, AT and Q, were not unexpected. Combined with multidecadal trends in AT and Q, however, those effects are noteworthy because they indicate a broad warming trend in rivers and streams during recent decades. To the extent that AT and Q trends are now attributed to anthropogenic climate change (Barnett et al., 2008; National Climate Assessment, 2014), the same attribution appears warranted for warming of the region's lotic environments. Moreover, because historical stream-temperature trends were more strongly associated with trends in AT than Q, the likelihood of continued warming this century is high because nearly all GCMs predict future AT increases (IPCC, 2013). Greater uncertainty exists regarding future precipitation and Q trends but there is a general expectation for lower summer flows as regional snowpacks continue to decline (Barnett et al., 2005; Gergel et al., 2017; Kormos et al., 2016), which may exacerbate stream-temperature trends in many places.

Warming rates will vary within and among streams due to differences in climate forcing and stream responsiveness. At a subregional scale, a distinction appears to exist between interior and coastal areas with the latter showing small or nonexistent warming trends. That pattern could result from a combination of AT trend moderation by the ocean (Jain et al., 1999) and fog persisting in or near ocean areas despite warming (e.g., Dettinger, 2013; Luce et al., 2014). Interior streams may warm more rapidly, but still relatively slowly because their average trend rates are usually less than half that of AT trends. The low responsiveness of streams in the Rocky Mountain region has been noted previously (Mohseni et al., 1999) and broadly attributed to cold mountain environments, winter snow accumulations, and large groundwater reservoirs that

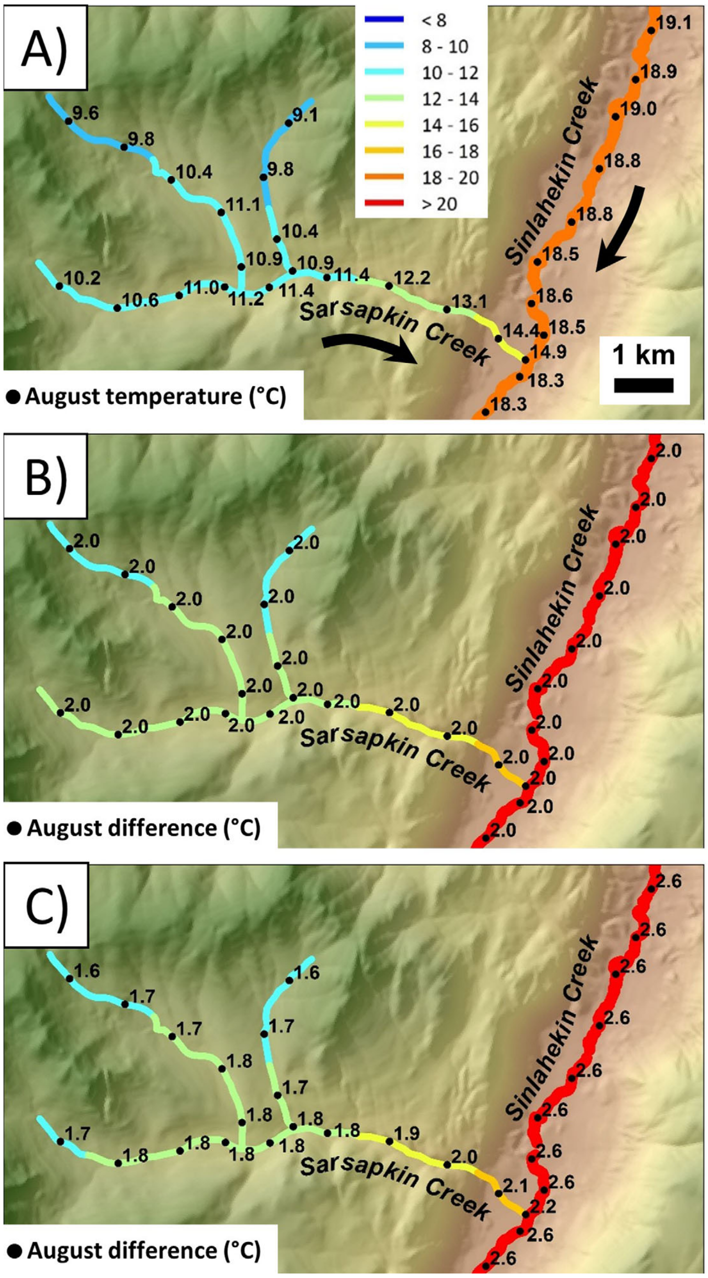

Figure 9. Mean August (a) stream temperatures for the Scenario 1 baseline and future deltas based on (b) Scenario 25 (+2°C) with no sensitivity adjustment and (c) Scenario 26 with a sensitivity adjustment. Note that in Scenario 26, the temperature deltas in the warmest reaches in the low-elevation streams are larger than those in the coldest reaches at higher elevations. In all figures, the line segments are color coded by the August stream temperatures associated with the scenario predictions and the color categories shown in the legend.

provide abundant cold-water influxes during the summer (Luce et al., 2014; Mayer, 2012; Tague et al., 2007). Those buffering sources are unlikely to disappear entirely from the many high-elevation mountain ranges scattered throughout the region and should continue to moderate stream temperature increases for the foreseeable future.

Concerns have been expressed about the stability of statistical models in a changing climate, and consequently, whether model predictions of future conditions are useful for planning (Arismendi et al., 2014; Li et al., 2012; Peel & Blöschl, 2011). However, we think it unlikely that NorWeST projections will be significantly compromised by instability for two primary reasons. First, the representation of the Tw-AT relationship in the NorWeST model has a sounder physical basis for making projections than many previous statistical models. In this regard, the time step of the regression model is important and an interannual basis is preferred over an intraannual basis because AT effects in the latter are confounded with changing sun angles and the amount of daily solar radiation (Luce et al., 2014). Models based on interannual changes, as NorWeST uses, are not similarly confounded and better represent the effect of AT, which is an important determinant of the downwelling long-wave radiation balance that is changing with climate change (IPCC, 2013). Second, the calibration data used to fit the NorWeST model span a large proportion of expected future changes. Interannual variability in AT was 3–6°C and Q varied threefold to tenfold within the processing units and captured high and low flow years, warm and cold years, and many combinations thereof. As a result, projected future deltas in AT and Q generally do not result in conditions outside the range of observed data until the latter half of the century. That far into the future, uncertainties associated with future greenhouse gas emissions and GCM projections (Cox & Stephenson, 2007) are much greater than those associated with the NorWeST model.

However warming of western rivers and streams manifests, it will profoundly affect their ecology. At a fundamental level, net primary productivity, nutrient processing capacity, and food webs will be altered as the region's relatively cold streams become less so (Davis et al., 2013; Woodward et al., 2010). Distributions of macroinvertebrates, stream-dwelling amphibians, and fish species will have to shift in space and time to track thermal niches that strongly constrain ectothermic organisms (Harper & Peckarsky, 2006; Isaak et al., 2017a). Evidence of distribution shifts already exists for headwater trout populations (Al-Chokhachy et al., 2016; Eby et al., 2014) and some salmon species have altered their migration dates to minimize exposure to thermally stressful summer temperatures (Crozier et al., 2008, 2011). For headwater species, local topographic relief and pronounced spatial temperature gradients create slow climate velocities and cold-water refuges are often available upstream (Isaak et al., 2016a; Uno & Power, 2015). Those factors, however, do not buffer species in larger rivers where warming rates are larger and thermal refuges are sparse (Fullerton et al., 2015; Torgersen et al., 1999). Cold-water fish populations in many western rivers already show evidence of heat-related stress during warm summers that sometimes leads to fishing season closures, migration delays, and mortality events (Cooke et al., 2004; Keefer et al., 2009; Lynch & Risley, 2003). As heat phenomena become more common in the future, their context dependency is also likely to become more apparent. Near warm-edge or cold-edge boundaries of thermal niches, large biological changes may occur with small temperature increases whereas little or no change is observed across most of the species' range (Isaak et al., 2017a). Similarly, if temperature increases further constrain already small populations, risks of extirpation may increase dramatically whereas that risk may change inconsequentially for populations occupying large habitats (Isaak et al., 2015). The spatial resolution and extent of NorWeST scenarios can be used to assess those risks and discern where critical thermal limitations occur for most aquatic species in the western U.S. with populations that occupy habitat extents $>$1 km.

Habitat restoration could partially offset future warming and biological effects, especially in small-sized to medium-sized streams and rivers where degradation is severe, if investments are made strategically. Improving minimum flows during the summer where water abstraction is common can help cool streams (Elmore et al., 2016), as would maximizing shade from riparian vegetation because of solar radiation's dominance in stream heat budgets (Diabat et al., 2013; Johnson & Wilby, 2015; Webb & Zhang, 1997). Reconnecting streams to floodplains and facilitating greater lateral and hyporheic flow exchanges have been proposed as cooling strategies (Beechie et al., 2013; Caissie & Luce, 2017; Kurylyk et al., 2015b) although their efficacy at broad spatial scales remains untested. Unfortunately, the NorWeST model in its current form yields few insights about where thermal regimes are impaired by anthropogenic factors because the covariates we used from national data sets do not represent those factors. This limitation has been recognized previously (Moore et al., 2013; Wehrly et al., 2009) and once more detailed covariates are developed, they could be included in temperature model revisions to test for additional effects, identify effect locations through residual sensitivity analysis, and improve predictive accuracy (see Scown et al., 2017 for a relevant SSN example with stream nutrients). Useful covariates might include inventories of channel realignments, water diversions, or detailed measures of riparian canopy conditions. Promising in the latter category are new remote-sensing applications for describing riparian vegetation and site-potential shade (Dauwalter et al., 2015; MacFarlane et al., 2016; Wawrzyniak et al., 2016), although these tasks are made more challenging by the prospect that climate change may also alter future riparian communities (Catford et al., 2013).

4.2. SSN Temperature Model

The rich literature that exists concerning stream temperatures was a valuable guide for choosing covariates and our results largely confirm a priori notions about warming or cooling effects and the mechanisms previously described by numerous authors. The magnitude and statistical significance of those effects differed among processing units, but that was expected because each unit is a unique landscape with a slightly different covariance structure that may or may not have been well represented by the nonrandom samples in the NorWeST database. More remarkable we thought, was that the SSN models consistently predicted $\sim$90% of the observed variation in AugTw across diverse landscape and climatic conditions using readily available covariates. That was probably due to the pronounced spatial gradients associated with temperature samples in topographically complex regions but also from the spatial configuration of samples in NorWeST data sets that was conducive to SSN analysis. Data sets built from numerous sources provided samples spread broadly across those gradients that were useful for estimating covariate effects, as well as clustered samples that helped represent local autocorrelation modeled by the spatial correlation function (Ver Hoef et al., 2006). That autocorrelation is associated with environmental variation not represented by the covariates, so developing better or more comprehensive sets of covariates could provide additional resolution.

Regarding the $\sim$10% of variation that the SSN models did not predict, a portion was due to processes occurring at sampling grains less than the 1 km interval at which our covariates were calculated as well as measurement errors associated with sensor imprecision and data screening, but the majority probably resulted from inadequate representation of temporal changes at sensor sites. Most notably, riparian canopy and local solar radiation levels at some sensor sites changed during the course of monitoring due to wildfires and natural disturbances but our RC covariate values were static. In an earlier SSN model implementation (Isaak et al., 2010), we coupled Thematic Mapper satellite imagery and field hemispherical photography estimates of solar radiation prefire and postfire to document the local importance of riparian canopy changes but the labor intensity of the approach made it intractable at the scale of the western U.S. Additional variation was associated with the use of unit-scale averages based on 15 km resolution AT grids and sparse networks of Q gaging stations to represent interannual changes at sensor sites. Subunit scale variation in interannual cloud cover, weather patterns, and precipitation storm tracks (Nakamura et al., 2002), interacting with processes like topographically influenced cold-air pooling in complex terrain (Daly et al., 2010; Minder et al., 2010) would expose individual stream temperature sensors to different amounts of AT and Q variation. In the case of Q, the number of gaging stations with long-term records not subject to dam regulation was often limited, and many of the unregulated gages were affected to varying degrees by upstream water withdrawals for agricultural or municipal purposes (Falcone et al., 2010). Imprecise representation of the Q covariate, therefore, could have degraded the temperature model's estimation of this effect, although results here are consistent with a previous analysis of long-term stream temperature records in this region that showed small Q effects at sites colocated with gaging stations (Isaak et al., 2012). Regardless, more precise local representations of both AT and Q covariates would be beneficial and could be derived from high-resolution models parameterized using dense networks of inexpensive AT and Q sensors (Holden et al., 2013; Stamp et al., 2014). Those types of AT microclimate models (Ashcroft & Gollan, 2012; Holden et al., 2016) can provide empirically supported interpolations at subkilometer scales but are not yet broadly available and we are unaware of comparable efforts to develop high-resolution Q models from dense monitoring networks. It may also be possible to reduce unexplained variation in future large-scale stream temperature models by using covariates that are more representative of the mechanistic processes in stream heat budgets. Measurements of those processes are typically costly and limited in spatial extent, but suitable proxies might be found in the increasing array of satellite-based remote sensing data products (Dauwalter et al., 2017), some of which have already been used to accurately predict stream temperatures (McNyset et al., 2015).

4.3. Spatial Analysis Tools for Streams

Achieving NorWeST would have been impossible without the technical and analytical advances provided by NHD and SSN models during the last decade. NHD has long been available at several spatial resolutions but the release of NHDPlus in 2006 with reach descriptors (McKay et al., 2012; Moore & DeWald, 2016) immediately created synergies with the spatially explicit SSN models. The SSNs could then be used with preexisting sets of descriptors to fit models with covariate parameters and make predictions at unsampled locations throughout river networks. This removed a large constraint on our previous SSN temperature model (Isaak et al., 2010), which was implemented using a raster-based synthetic network and required laborious calculation of custom covariates that limited the geographic scope to a single river basin and 2,500 km stream network. Developing custom covariates is now more convenient with ArcGIS toolsets (Peterson et al., 2011; Peterson & Pearse, 2017) and may be essential for some applications but many modeling needs can be met with the dozens of reach descriptors that already exist for NHDPlus (Hill et al., 2016; McKay et al., 2012).

Equally essential to NorWeST were SSNs, which are only one type of recently developed statistical model for stream network data as this field of statistics grows (Cressie et al., 2006; O'Donnell et al., 2014; Skøien et al., 2005). Common to the new generation of models is explicit recognition of an underlying network topology and these models generally offer performance comparable to, or better than, techniques like random forests or neural networks that are frequently applied to network data sets (Jackson et al., 2017; Rizo-Decelis et al., 2017; Turschwell et al., 2016). Of the network models, however, the SSNs possessed several attributes that suited them to the NorWeST project. These included flexible mixed-model spatial-autocorrelation structures, estimation of covariate effects, and prediction using both covariates and spatial autocorrelation so that interpolated scenarios were accurate in regions with sparse data (Peterson & Ver Hoef, 2010; Ver Hoef et al., 2006; Ver Hoef & Peterson, 2010). Moreover, the SSN software enables data simulations on stream networks, can be used to explore sampling design optimization (Falk et al., 2014; Som et al., 2014), and fits not only normally distributed data sets but also Poisson (e.g., count) and binomial (e.g., occurrence) distributions (Ver Hoef et al., 2014). Drawbacks of SSNs relative to other network models are greater technical complexity because data sets require preprocessing with GIS software, minimum sample sizes of 50–100 to support the number of parameters that are estimated, and computational requirements that grow at n^3 (Isaak et al., 2014; Rushworth et al., 2015). When especially large data sets are modeled and computational efficiency is at a premium, therefore, the spline approach employed by O'Donnell et al. (2014) may be a better alternative (Rushworth et al., 2015).

To streamline the application of SSN models, we developed the NSI network by reconditioning the NHDPlusV2 data set for the conterminous U.S. (Nagel et al., 2015). Compatibility among those components now provides a flexible system that can be used broadly for geostatistical analyses of stream data sets. In addition to many local applications, NorWeST-scale efforts could be undertaken with large data sets for water quality parameters (Olson & Hawkins, 2012; Read et al., 2017; Stoddard et al., 2016), discharge (Falcone et al., 2010), species distribution and abundance (Loftus & Beard, 2009; Wenger et al., 2011), habitat quality (Kershner & Roper, 2010; U.S. Environmental Protection Agency, 2016), or stream temperature data outside the western U.S. (DeWeber & Wagner, 2014; McKenna et al., 2010). Those data sets represent significant investments and contain large amounts of untapped information that could be developed by research teams with technical proficiency in spatial stream analyses. An integrated NSI-SSN-NHDPlus system also incentivizes data aggregation because of its efficiency at creating information from nonrandom samples and could be used to systematically address ungaged basins. For example, as comprehensive databases are developed, inexpensive sensors or biological sampling efforts could be targeted at basins without data and preexisting models simply refit with samples from the new locations, where the predictive accuracy is enhanced by leveraging information about patterns of spatial autocorrelation from the larger database. As computational power increases and database formats are standardized, many analytical steps to perform those calculations could be scripted for automation of model runs and rapid visualization of results (Bush et al., 2017).

4.4. NorWeST User Community

Given the amount of stream temperature data that had been collected at the onset of the NorWeST project in 2011, a robust but informal user community already existed. However, the process of organizing disparate data sets into an openly accessible central database fostered and strengthened that community by increasing communication, facilitating data sharing, and making new monitoring efforts more efficient. Evidence supporting that claim is the amount of traffic through the NorWeST website, which receives ~12,000 annual visits during which time hundreds of temperature data sets, scenarios, and related products are downloaded each year. Database development highlighted important limitations and redundancies within existing data sets, which are now being systematically addressed. Those limitations included the need for more annual and long-term monitoring records rather than those based on summer-only monitoring, so new sensor installation protocols were developed (Isaak et al., 2013b; Stamp et al., 2014) as was an online mapping tool to share information about the locations of annual monitoring sites (https://www.fs.fed.us/rm/boise/AWAE/projects/stream_temp/maps.html). In parts of the western U.S. with sparse data sets, we have partnered with Trout Unlimited, National Forests, Bureau of Land Management, and other resource agencies to coordinate new monitoring efforts (Williams et al., 2016) and SSN models will be refit to denser data sets to provide NorWeST scenario revisions in the future. Database summaries have also been instrumental for highlighting the subset of sites with the best long-term monitoring records and communication of that information to local biologists and hydrologists. Most of those sites were established and maintained through grassroots efforts and the long-term perseverance of individuals rather than formalized institutional support, so their recognition may encourage continued monitoring and perhaps help garner that support in the future.

NorWeST scenarios and data sets have been broadly adopted by local decision makers for conservation planning because of their accuracy, ubiquity to all western streams, availability in convenient digital formats, and development from data sets collected by the user community. Planning efforts routinely involve National Environmental Policy Act and Endangered Species Act consultations, National Forest Plan revisions, and climate vulnerability assessments for many species. Several western states are either developing or refining regulatory temperature criteria and NorWeST data sets figure prominently in those discussions. NorWeST scenarios have also been used in a variety of studies to describe realized thermal niches for fish and amphibian species (Al-Chokhachy et al., 2016; Isaak et al., 2017a), delineate climate refuges for trout and char (Isaak et al., 2015, 2016a), describe temperature effects on salmon migrations (Westley et al., 2015), and estimate fish abundance and genetic patterns along temperature gradients (Dauwalter et al., 2015; Isaak et al., 2017b; Young et al., 2016). The data sets used to create the NorWeST scenarios are large but ultimately compose a small portion of the overall database, which makes it a valuable resource to fuel additional temperature research. During this time of rapid global change, particularly important is research on thermal regimes (Maheu et al., 2015; Steel et al., 2017), description of minimally sufficient metric sets for describing those regimes (Olden & Poff, 2003), biological validation of metric relevance (Garcia et al., 2014), and development of climate scenarios for all seasons.

5. Conclusion

Significant concerns exist about climate change and the effects that temperature increases this century may have on the diverse and valuable aquatic ecosystems in the western U.S. Prior to the NorWeST project, the absence of basic information to describe spatial climate patterns and trends throughout the region's stream and river networks created uncertainties that magnified concerns. Addressing those information needs was the ultimate motivation for this work, which began with one small grant to build a temperature database and scenarios from existing data for a portion of the Northern Rocky Mountains. The value unlocked from those first data sets propelled the project's organic growth during the subsequent five years until it encompassed the western U.S. and had generated a database that would require 10–15 million US$ to replicate. Several factors combined fortuitously to enable the success, including the availability of new spatial tools, large data sets, a favorable funding climate, a scientific team with complementary skillsets, and the advent of digital social media that enabled inexpensive mass communication about the project. The simplest and most essential ingredients, however, were the willingness of people to share their data and a database team that focused exclusively on the social interactions necessary to transfer and organize those data sets while providing responsive customer service whenever questions arose. The human factor is often overlooked with the excitement and efficiencies that new technologies sometimes bring but interpersonal relationships and the trust built between the NorWeST team and hundreds of individuals scattered across a broad geography were ultimately the project's foundation. The resultant database and scenarios, coupled with an efficient analytical framework for stream data, now benefit everyone with a stake in the aquatic resources of the western U.S. as the community moves collectively through a century that will test those resources.

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References

Al-Chokhachy, R., Schmetterling, D. A., Clancy, C., Sael, P., Kovach, R. P., Nyce, L. G., . . . Pierce, R. (2016). Are brown trout replacing or displacing bull trout populations in a changing climate? *Canadian Journal of Fisheries and Aquatic Sciences*, *73*, 1395–1404.

Angilletta, M. J. (2009). *Thermal adaptation: A theoretical and empirical synthesis*. Oxford, NY: Oxford University Press.

Angilletta, M. J., & Krochmal, A. R. (2003). The Thermochron: A truly miniature and inexpensive temperature-logger. *Herpetological Review*, *34*, 31–32.

Arismendi, I., Johnson, S. L., Dunham, J. B., Haggerty, R., & Hockman-Wert, D. (2012). The paradox of cooling streams in a warming world: Regional climate trends do not parallel variable local trends in stream temperature in the Pacific continental United States. *Geophysical Research Letters*, *39*, L10401. https://doi.org/10.1029/2012GL051448

Arismendi, I., Safeeq, M., Dunham, J. B., & Johnson, S. L. (2014). Can air temperature be used to project influences of climate change on stream temperature? *Environmental Research Letters*, *9*, 084015.

Ashcroft, M. B., & Gollan, J. R. (2012). Fine-resolution (25 m) topoclimatic grids of near-surface (5 cm) extreme temperatures and humidities across various habitats in a large (200 × 300 km) and diverse region. *International Journal of Climatology*, *32*, 2134–2148.

Barnett, T. P., Adam, J. C., & Lettenmaier, D. P. (2005). Potential impacts of a warming climate on water availability in snow-dominated regions. *Nature*, *438*, 303–309.

Barnett, T. P., Pierce, D. W., Hidalgo, H. G., Bonfils, C., Santer, B. D., Das, T., . . . Cayan, D. R. (2008). Human-induced changes in the hydrology of the western United States. *Science*, *319*, 1080–1083.

Beale, C. M., Lennon, J. J., Yearsley, J. M., Brewer, M. J., & Elston, D. A. (2010). Regression analysis of spatial data. *Ecology Letters*, *13*, 246–264. https://doi.org/10.1111/j.1461-0248.2009.01422.x

Beechie, T., Imaki, H., Greene, J., Wade, A., Wu, H., Pess, G., . . . Mantua, N. (2013). Restoring salmon habitat for a changing climate. *River Research and Applications*, *29*, 939–960.

Benke, A. C., & Cushing, C. E. (2005). *Rivers of North America* (1168 pp.). New York, NY: Elsevier Academic Press.

Benyahya, L., Caissie, D., St-Hilaire, A., Ouarde, T., & Bobee, B. (2007). A review of statistical water temperature models. *Canadian Water Resources Journal*, *32*, 179–192.

Bishop, K., Buffam, I., Erlandsson, M., Fölster, J., Laudon, H., Seibert, J., & Temnerud, J. (2008). *Aqua Incognita*: The unknown headwaters. *Hydrological Processes*, *22*, 1239–1242. https://doi.org/10.1002/hyp.7049

Brennan, S. R., Torgersen, C. E., Hollenbeck, J. P., Fernandez, D. P., Jensen, C. K., & Schindler, D. E. (2016). Dendritic network models: Improving isoscapes and quantifying influence of landscape and in-stream processes on strontium isotopes in rivers. *Geophysical Research Letters*, *43*, 5043–5051. https://doi.org/10.1002/2016GL068904

Brown, L. E., Hannah, D. M., & Milner, A. M. (2007). Vulnerability of alpine stream biodiversity to shrinking glaciers and snowpacks. *Global Change Biology*, *13*, 958–966.

Bush, A., Sollmann, R., Wilting, A., Bohmann, K., Cole, B., Balzter, H., . . . Yu, D. W. (2017). Connecting Earth observation to high-throughput biodiversity data. *Nature: Ecology and Evolution*, *1*, 0176. https://doi.org/10.1038/s41559-017-0176

Caissie, D., & Luce, C. H. (2017). Quantifying streambed advection and conduction heat fluxes. *Water Resources Research*, *53*, 1595–1624. https://doi.org/10.1002/2016WR019813

Catford, J. A., Naiman, R. J., Chambers, L. E., Roberts, J., Douglas, M., & Davies, P. (2013). Predicting novel riparian ecosystems in a changing climate. *Ecosystems*, *16*, 382–400.

Chandler, G. L., Wollrab, S., Horan, D., Nagel, D., Parkes, S., Isaak, D. J., . . . Roper, B. B. (2016). NorWeST stream temperature data summaries for the western U.S. Fort Collins, CO: U.S. Forest Service, Rocky Mountain Research Station Research Data Archive. https://doi.org/10.2737/RDS-2016-0032

Clow, D. W. (2010). Changes in the timing of snowmelt and streamflow in Colorado: A response to recent warming. *Journal of Climate*, *23*, 2293–2306. https://doi.org/10.1175/2009JCLI2951.1

Cooke, S. J., Hinch, S. G., Farrell, A. P., Lapointe, M. F., Jones, S. R., Macdonald, J. S., . . . Van Der Kraak, G. (2004). Abnormal migration timing and high en route mortality of sockeye salmon in the Fraser River, British Columbia. *Fisheries*, *29*, 22–33.
Cooter, W., Rineer, J., & Bergenroth, B. (2010). A nationally consistent NHD-Plus framework for identifying interstate waters: Implications for integrated assessments and interjurisdictional TMDLs. *Environmental Management*, *46*, 510–524. https://doi.org/10.1007/s00267-010-9526-y
Cox, P., & Stephenson, D. (2007). A changing climate for prediction. *Science*, *317*, 207–208.
Cressie, N. (1993). *Statistics for spatial data* (Rev. ed.). New York, NY: John Wiley.
Cressie, N., Frey, J., Harch, B., & Smith, M. (2006). Spatial prediction on a river network. *Journal of Agricultural, Biological, and Environmental Statistics*, *11*, 127–150.
Cristea, N. C., & Burges, S. J. (2010). An assessment of the current and future thermal regimes of three streams located in the Wenatchee River basin, Washington State: Some implications for regional river basin systems. *Climatic Change*, *102*, 493–520.
Crozier, L. G., Hendry, A. P., Lawson, P. W., Quinn, T. P., Mantua, N. J., Battin, J., . . . Huey, R. B. (2008). Potential responses to climate change in organisms with complex life histories: Evolution and plasticity in Pacific salmon. *Evolutionary Applications*, *1*, 252–270.
Crozier, L. G., Scheuerell, M. D., & Zabel, R. W. (2011). Using time series analysis to characterize evolutionary and plastic responses to environmental change: A case study of a shift toward earlier migration date in sockeye salmon. *The American Naturalist*, *178*, 755–773.
Daigle, A., Caudron, A., Vigier, L., & Pella, H. (2016). Optimization methodology for a river temperature monitoring network for the characterization of fish thermal habitat. *Hydrological Sciences Journal*, *62*, 483–497. https://doi.org/10.1080/02626667.2016.1242869
Daly, C., Conklin, D. R., & Unsworth, M. H. (2010). Local atmospheric decoupling in complex topography alters climate change impacts. *International Journal of Climatology*, *30*, 1857–1864.
Dauwalter, D. C., Fesenmyer, K. A., & Bjork, R. (2015). Using aerial imagery to characterize redband trout habitat in a remote desert landscape. *Transactions of the American Fisheries Society*, *144*, 1322–1339.
Dauwalter, D. C., Fesenmyer, K. A., Leasure, D. R., & Wenger, S. J. (2017). Satellite and airborne remote sensing applications to freshwater fisheries. *Fisheries*, *42*, 510–521.
Davis, J. M., Baxter, C. V., Rosi-Marshall, E. J., Pierce, J. L., & Crosby, B. T. (2013). Anticipating stream ecosystem responses to climate change: Toward predictions that incorporate effects via land–water linkages. *Ecosystems*, *16*, 909–922.
Dettinger, M. D. (2013). Projections and downscaling of 21st century temperatures, precipitation, radiative fluxes and winds for the Southwestern US, with focus on Lake Tahoe. *Climatic Change*, *116*, 17–33.
DeWeber, J. T., & Wagner, T. (2014). A regional neural network ensemble for predicting mean daily river water temperature. *Journal of Hydrology*, *517*, 187–200.
Diabat, M., Haggerty, R., & Wondzell, S. M. (2013). Diurnal timing of warmer air under climate change affects magnitude, timing and duration of stream temperature change. *Hydrological Processes*, *27*, 2367–2378.
Dibble, K. L., Yackulic, C. B., Kennedy, T. A., & Budy, P. (2015). Flow management and fish density regulate salmonid recruitment and adult size in tailwaters across western North America. *Ecological Applications*, *25*, 2168–2179.
Dripps, W., & Granger, S. R. (2013). The impact of artificially impounded, residential headwater lakes on downstream water temperature. *Environmental Earth Sciences*, *68*, 2399–2407.
Dugdale, S. J. (2016). A practitioner's guide to thermal infrared remote sensing of rivers and streams: Recent advances, precautions and considerations. *Wiley Interdisciplinary Reviews: Water*, *3*, 251–268.
Dugdale, S. J., Bergeron, N. E., & St-Hilaire, A. (2015). Spatial distribution of thermal refuges analysed in relation to riverscape hydromorphology using airborne thermal infrared imagery. *Remote Sensing of Environment*, *160*, 43–55.
Dunham, J. B., Chandler, G., Rieman, B. E., & Martin, D. (2005). *Measuring stream temperature with digital dataloggers: A user's guide* (Gen. Tech. Rep. RMRSGTR-150WWW). Fort Collins, Colorado: U.S. Forest Service, Rocky Mountain Research Station.
Dunham, J. B., Rieman, B. E., & Chandler, G. (2003). Influences of temperature and environmental variables on the distribution of bull trout within streams at the southern margin of its range. *North American Journal of Fisheries Management*, *23*, 894–904.
Dunham, J. B., Rosenberger, A. E., Luce, C. H., & Rieman, B. E. (2007). Influences of wildfire and channel reorganization on spatial and temporal variation in stream temperature and the distribution of fish and amphibians. *Ecosystems*, *10*, 335–346.
Easterling, D. R., & Wehner, M. F. (2009). Is the climate warming or cooling? *Geophysical Research Letters*, *36*, L08706. https://doi.org/10.1029/2009GL037810
Ebersole, J. L., Liss, W. J., & Frissell, C. A. (2003). Cold water patches in warm streams: Physicochemical characteristics and the influence of shading. *Journal of the American Water Resources Association*, *39*, 355–368.
Eby, L. A., Helmy, O., Holsinger, L. M., & Young, M. K. (2014). Evidence of climate-induced range contractions in bull trout *Salvelinus confluentus* in a Rocky Mountain watershed, USA. *PLoS ONE*, *9*, e98812.
Elmore, L. R., Null, S. E., & Mouzon, N. R. (2016). Effects of environmental water transfers on stream temperatures. *River Research and Applications, River Research and Applications*, *32*, 1415–1427. https://doi.org/10.1002/rra.2994
Environmental Systems Research Institute. (2015). *ArcGIS desktop: Release 10.3.1*. Redlands, CA: Author.
Falcone, J. A., Carlisle, D. M., Wolock, D. M., & Meador, M. R. (2010). GAGES: A stream gage database for evaluating natural and altered flow conditions in the conterminous United States. *Ecology*, *91*, 621–621.
Falk, M. G., McGree, J. M., & Pettitt, A. N. (2014). Sampling designs on stream networks using the pseudo-Bayesian approach. *Environmental and Ecological Statistics*, *21*, 751–773. https://doi.org/10.1007/s10651-014-0279-2
Filipe, A., Quaglietta, L., Ferreira, M., Magalhaes, M., & Beja, P. (2017). Geostatistical distribution modelling of two invasive crayfish across dendritic stream networks. *Biological Invasions*, *19*, 2899–2912. https://doi.org/10.1007/s10530-017-1492-3
Foster, G., & Rahmstorf, S. (2011). Global temperature evolution 1979–2010. *Environmental Research Letters*, *6*, 044022. https://doi.org/10.1088/1748-9326/6/4/044022
Frieden, J. C., Peterson, E. E., Webb, J. A., & Negus, P. M. (2014). Improving the predictive power of spatial statistical models of stream macroinvertebrates using weighted autocovariance functions. *Environmental Modelling & Software*, *60*, 320–330. https://doi.org/10.1016/j.envsoft.2014.06.019
Fullerton, A. H., Torgersen, C. E., Lawler, J. J., Faux, R. N., Steel, E. A., Beechie, T. J., . . . Leibowitz, S. G. (2015). Rethinking the longitudinal stream temperature paradigm: Region-wide comparison of thermal infrared imagery reveals unexpected complexity of river temperatures. *Hydrological Processes*, *29*, 4719–4737.
Gallice, A., Schaefli, B., Lehning, M., Parlange, M. B., & Huwald, H. (2015). Stream temperature prediction in ungauged basins: Review of recent approaches and description of a new physics-derived statistical model. *Hydrology and Earth System Sciences*, *19*, 3727–3753.
Garcia, R. A., Cabeza, M., Rahbek, C., & Araújo, M. B. (2014). Multiple dimensions of climate change and their implications for biodiversity. *Science*, *344*, 1247579.

Garner, G., Hannah, D. M., Sadler, J. P., & Orr, H. G. (2013). River temperature regimes of England and Wales: Spatial patterns, inter-annual variability and climatic sensitivity. *Hydrological Processes*, *28*, 5583–5598. https://doi.org/10.1002/hyp.9992

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

Gergel, D. R., Nijssen, B., Abatzoglou, J. T., Lettenmaier, D. P., & Stumbaugh, M. R. (2017). Effects of climate change on snowpack and fire potential in the western United States. *Climatic Change*, *141*, 287–299.

Goldberg, C. S., Strickler, K. M., & Pilliod, D. S. (2015). Moving environmental DNA methods from concept to practice for monitoring aquatic macroorganisms. *Biological Conservation*, *183*, 1–3.

Gu, R., Montgomery, S., & Austin, T. A. (1998). Quantifying the effects of stream discharge on summer river temperature. *Hydrological Sciences Journal*, *43*, 885–904.

Hamlet, A. F., Elsner, M. M., Mauger, G. S., Lee, S.-Y., Tohver, I., & Norheim, R. A. (2013). An overview of the Columbia Basin climate change scenarios project: Approach, methods, and summary of key results. *Atmosphere-Ocean*, *51*, 392–415.

Hampton, S. E., Strasser, C. A., Tewksbury, J. J., Gram, W. K., Budden, A. E., Batcheller, A. L., . . . Porter, J. H. (2013). Big data and the future of ecology. *Frontiers in Ecology and the Environment*, *11*, 156–162.

Handcock, R. N., Torgersen, C. E., Cherkauer, K. A., Gillespie, A., Tockner, R. K., Faux, R. N., & Tan, J. (2012). Thermal infrared remote sensing of water temperature in riverine landscapes. In *Fluvial remote sensing for science and management*. Hoboken, NJ: Wiley.

Hannah, D., & Garner, G. (2015). River water temperature in the United Kingdom: Changes over the 20th century and possible changes over the 21st century. *Progress in Physical Geography*, *39*, 68–92.

Hari, R. E., Livingstone, D. M., Siber, R., Burkhardt-Holm, P., & Guttinger, H. (2006). Consequences of climatic change for water temperature and brown trout populations in Alpine rivers and streams. *Global Change Biology*, *12*, 10–26.

Harper, M. P., & Peckarsky, B. L. (2006). Emergence cues of a mayfly in a high-altitude stream ecosystem: Potential response to climate change. *Ecological Applications*, *16*, 612–621.

Helsel, D. R., & Hirsch, R. M. (1992). *Statistical methods in water resources*. New York, NY: Elsevier Science.

Hilderbrand, R. H., Kashiwagi, M. T., & Prochaska, A. P. (2014). Regional and local scale modeling of stream temperatures and spatio-temporal variation in thermal sensitivities. *Environmental Management*, *54*, 14–22.

Hill, R. A., Weber, M. H., Leibowitz, S. G., Olsen, A. R., & Thornbrugh, D. J. (2016). The stream-catchment (StreamCat) dataset: A database of watershed metrics for the conterminous United States. *Journal of the American Water Resources Association*, *52*, 120–128. https://doi.org/10.1111/1752-1688.12372

Hockey, J. B., Owens, I. F., & Tapper, N. J. (1982). Empirical and theoretical models to isolate the effect of discharge on summer water temperatures in the Hurunui River. *Journal of Hydrology (New Zealand)*, *21*, 1–12.

Holden, Z. A., Klene, A. E., F. Keefe, R., & G. Moisen, G. (2013). Design and evaluation of an inexpensive radiation shield for monitoring surface air temperatures. *Agricultural and Forest Meteorology*, *180*, 281–286.

Holden, Z. A., Swanson, A., Klene, A. E., Abatzoglou, J. T., Dobrowski, S. Z., Cushman, S. A., . . . Oyler, J. W. (2016). Development of high-resolution (250 m) historical daily gridded air temperature data using reanalysis and distributed sensor networks for the US Northern Rocky Mountains. *International Journal of Climatology*, *36*, 3620–3632. https://doi.org/10.1002/joc.4580

Holsinger, L., Keane, R. E., Isaak, D. J., Eby, L., & Young, M. K. (2014). Relative effects of climate change and wildfires on stream temperatures: A simulation modeling approach in a Rocky Mountain watershed. *Climatic Change*, *124*, 191–206.

Hostetler, S. W., Alder, J. R., & Allan, A. M. (2011). *Dynamically downscaled climate simulations over North America: Methods, evaluation, and supporting documentation for users* (Open File Rep. 2011-1238, 64 pp.). Menlo Park, CA: U.S. Geological Survey.

Hrachowitz, M., Savenije, H. H. G., Blöschl, G., McDonnell, J. J., Sivapalan, M., Pomeroy, J. W., . . . Fenicia, F. (2013). A decade of predictions in ungauged basins (PUB)—A review. *Hydrological Sciences Journal*, *58*, 1198–1255.

Intergovernmental Panel on Climate Change. (2007). *Climate change 2007: The physical science basis*. Retrieved from http://www.ipcc.ch/

Intergovernmental Panel on Climate Change (IPCC). (2013). *Climate change: The physical science basis*. Retrieved from http://www.ipcc.ch/

Isaak, D. J., & Hubert, W. A. (2001). A hypothesis about factors that affect maximum summer stream temperatures across montane landscapes. *Journal of the American Water Resources Association*, *37*, 351–366.

Isaak, D. J., Luce, C. H., Rieman, B. E., Nagel, D. E., Peterson, E. E., Horan, D. L., . . . Chandler, G. L. (2010). Effects of climate change and wildfire on stream temperatures and salmonid thermal habitat in a mountain river network. *Ecological Applications*, *20*, 1350–1371. https://doi.org/10.1890/09-0822.1

Isaak, D. J., Peterson, E. E., Nagel, D. E., Ver Hoef, J. M., & Kershner, J. (2013a). *A National Stream Internet to facilitate accurate, high-resolution status and trend assessments for water quality parameters and aquatic biotas*. U.S. Fish and Wildlife Service, National Landscape Conservation Cooperative grant. Retrieved from www.fs.fed.us/rm/boise/AWAE/projects/NationalStreamInternet.html

Isaak, D. J., Horan, D. L., & Wollrab, S. P. (2013b). *A simple protocol using underwater epoxy to install annual temperature monitoring sites in rivers and streams* (Gen. Tech. Rep. RMRS-GTR-314). Fort Collins, CO: U.S. Department of Agriculture, Forest Service.

Isaak, D. J., Peterson, E. E., Ver Hoef, J. M., Wenger, S. J., Falke, J., Torgersen, C. E., . . . Monestiez, P. (2014). Applications of spatial statistical network models to stream data. *Wires Interdisciplinary Reviews: Water*, *1*, 277–294. https://doi.org/10.1002/wat2.1023

Isaak, D. J., Ver Hoef, J. M., Peterson, E. E., Horan, D., & Nagel, D. (2017b). Scalable population estimates using spatial-stream-network (SSN) models, fish density surveys, and national geospatial database frameworks for streams. *Canadian Journal of Fisheries and Aquatic Sciences*, *74*, 147–156. https://doi.org/10.1139/cjfas-2016-0247

Isaak, D. J., Young, M., Luce, C., Hostetler, S., Wenger, S., Peterson, E., . . . Nagel, D. (2016a). Slow climate velocities of mountain streams portend their role as refugia for cold-water biodiversity. *Proceedings of the National Academy of Sciences of the United States of America*, *113*, 4374–4379.

Isaak, D. J., Young, M. K., Nagel, D. E., Horan, D. L., & Groce, M. C. (2015). The cold-water climate shield: Delineating refugia for preserving salmonid fishes through the 21st century. *Global Change Biology*, *21*, 2540–2553.

Isaak, D. J., Wenger, S. J., Peterson, E. E., Ver Hoef, J. M., Hostetler, S. W., Luce, C. H., . . . Horan, D. L. (2016b). *NorWeST modeled summer stream temperature scenarios for the western U.S.* Fort Collins, CO: U.S. Forest Service, Rocky Mountain Research Station Research Data Archive. https://doi.org/10.2737/RDS-2016-0033

Isaak, D. J., Wenger, S. J., & Young, M. K. (2017a). Big biology meets microclimatology: Defining thermal niches of aquatic ectotherms at landscape scales for conservation planning. *Ecological Applications*, *27*, 977–990. https://doi.org/10.1002/eap.1501

Isaak, D. J., Wollrab, S., Horan, D., & Chandler, G. (2012). Climate change effects on stream and river temperatures across the northwest U.S. from 1980–2009 and implications for salmonid fishes. *Climatic Change*, *113*, 499–524. https://doi.org/10.1007/s10584-011-0326-z

Jackson, F. L., Hannah, D. M., Fryer, R. J., Millar, C. P., & Malcolm, I. A. (2017). Development of spatial regression models for predicting summer river temperatures from landscape characteristics: Implications for land and fisheries management. *Hydrological Processes*, *31*, 1225–1238.

Jackson, F. L., Malcolm, I. A., & Hannah, D. M. (2016). A novel approach for designing large-scale river temperature monitoring networks. *Hydrology Research*, *47*, 569–590. https://doi.org/10.2166/nh.2015.106

Jain, S., Lall, U., & Mann, M. E. (1999). Seasonality and interannual variations of Northern Hemisphere temperature: Equator-to-pole gradient and ocean–land contrast. *Journal of Climate*, *12*, 1086–1100.

Johnson, M. F., & Wilby, R. L. (2015). Seeing the landscape for the trees: Metrics to guide riparian shade management in river catchments. *Water Resources Research*, *51*, 3754–3769. https://doi.org/10.1002/2014WR016802

Keefer, M. L., Peery, C. A., & High, B. (2009). Behavioral thermoregulation and associated mortality trade-offs in migrating adult steelhead (*Oncorhynchus mykiss*): Variability among sympatric populations. *Canadian Journal of Fisheries and Aquatic Sciences*, *66*, 1734–1747.

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

Kershner, J. L., & Roper, B. B. (2010). An evaluation of management objectives used to assess stream habitat conditions on Federal lands within the Interior Columbia Basin. *Fisheries*, *35*, 269–278.

Kingsolver, J. G. (2009). The well-temperatured biologist. *The American Naturalist*, *174*, 755–768.

Kormos, P., Luce, C., Wenger, S. J., & Berghuijs, W. R. (2016). Trends and sensitivities of low streamflow extremes to discharge timing and magnitude in Pacific Northwest mountain streams. *Water Resources Research*, *52*, 4990–5007. https://doi.org/10.1002/2015WR018125

Kurylyk, B. L., MacQuarrie, K. T., Caissie, D., & McKenzie, J. M. (2015a). Shallow groundwater thermal sensitivity to climate change and land cover disturbances: Derivation of analytical expressions and implications for stream temperature modeling. *Hydrology and Earth System Sciences*, *19*, 2469–2489.

Kurylyk, B. L., MacQuarrie, K. T., Linnansaari, T., Cunjak, R. A., & Curry, R. A. (2015b). Preserving, augmenting, and creating cold-water thermal refugia in rivers: Concepts derived from research on the Miramichi River, New Brunswick (Canada). *Ecohydrology*, *8*, 1095–1108.

Lehmkuhl, D. (1972). Change in thermal regime as a cause of reduction of benthic fauna downstream of a reservoir. *Journal of Fisheries Board Research of Canada*, *29*, 1329–1332.

Li, C. Z., Zhang, L., Wang, H., Zhang, Y. Q., Yu, F. L., & Yan, D. H. (2012). The transferability of hydrological models under nonstationary climatic conditions. *Hydrology and Earth System Sciences*, *16*, 1239–1254. https://doi.org/10.5194/hess-16-1239-2012

Lisi, P. J., Schindler, D. E., Cline, T. J., Scheuerell, M. D., & Walsh, P. B. (2015). Watershed geomorphology and snowmelt control stream thermal sensitivity to air temperature. *Geophysical Research Letters*, *42*, 3380–3388. https://doi.org/10.1002/2015GL064083

Littell, J. S., Peterson, D. L., Riley, K. L., Liu, Y., & Luce, C. H. (2016). A review of the relationships between drought and forest fire in the United States. *Global Change Biology*, *22*, 2353–2369. https://doi.org/10.1111/gcb.13275

Loftus, A. J., & Beard, T. D. (2009). The multistate aquatic resources information system (MARIS): Sharing data across agency boundaries. In S. A. Bonar, W. A. Hubert, & D. W. Willis (Eds.), *Standard methods for sampling North American freshwater fishes*. Bethesda, MD: American Fisheries Society.

Luce, C. H., Abatzoglou, J. T., & Holden, Z. A. (2013). The missing mountain water: Slower westerlies decrease orographic enhancement in the Pacific Northwest USA. *Science*, *342*, 1360–1364. https://doi.org/10.1126/science.1242335

Luce, C. H., & Holden, Z. A. (2009). Declining annual streamflow distributions in the Pacific Northwest United States, 1948–2006. *Geophysical Research Letters*, *36*, L16401. https://doi.org/10.1029/2009GL039407

Luce, C. H., Staab, B., Kramer, M., Wenger, S., Isaak, D., & McConnell, C. (2014). Sensitivity of summer stream temperatures to climate variability in the Pacific Northwest. *Water Resources Research*, *50*, 3428–3443. https://doi.org/10.1002/2013WR014329

Lynch, D. D., & Risley, J. C. (2003). *Klamath River Basin hydrologic conditions prior to the September 2002 die-off of salmon and steelhead* (Water Resour. Invest. Rep. 03–4099, 10 pp.). Portland, OR: U.S. Geological Survey.

MacFarlane, W. W., McGinty, C. M., Laub, B. G., & Gifford, S. J. (2016). High-resolution riparian vegetation mapping to prioritize conservation and restoration in an impaired desert river. *Restoration Ecology*, *25*, 333–341. https://doi.org/10.1111/rec.12425

Maheu, A., Poff, N. L., & St-Hilaire, A. (2015). A classification of stream water temperature regimes in the conterminous USA. *River Research and Applications*, *32*, 896–906.

Maheu, A., St-Hilaire, A., Caissie, D., & El-Jabi, N. (2016). Understanding the thermal regime of rivers influenced by small and medium size dams in eastern Canada. *River Research and Applications*, *32*, 2032–2044. https://doi.org/10.1002/rra.3046

Mahlum, S. K., Eby, L. A., Young, M. K., Clancy, C. G., & Jakober, M. (2011). Effects of wildfire on stream temperatures in the Bitterroot River Basin, Montana. *International Journal of Wildland Fire*, *20*, 240–247.

Mauger, S., Shaftel, R., Leppi, J. C., & Rinella, D. J. (2016). Summer temperature regimes in southcentral Alaska streams: Watershed drivers of variation and potential implications for Pacific salmon. *Canadian Journal of Fisheries and Aquatic Sciences*, *74*, 702–715. https://doi.org/10.1139/cjfas-2016-0076

Mayer, T. (2012). Controls of summer stream temperature in the Pacific Northwest. *Journal of Hydrology*, *475*, 323–335. https://doi.org/10.1016/j.jhydrol.2012.10.012

McClure, M. M., Alexander, M., Borggaard, D., Boughton, D., Crozier, L., Griffis, R., . . . Seney, E. E. (2013). Incorporating climate science in applications of the U.S. Endangered Species Act for aquatic species. *Conservation Biology*, *27*, 1222–1233.

McKay, L., Bondelid, T., Dewald, T., Johnston, J., Moore, R., & Rea, A. (2012). *NHDPlus version 2: User guide*. Retrieved from ftp://ftp.horizon-systems.com/NHDPlus/NHDPlusV21/Documentation/NHDPlusV2_User_Guide.pdf

McKelvey, K. S., Young, M. K., Knotek, W. L., Carim, K. J., Wilcox, T. M., Padgett-Stewart, T. M., & Schwartz, M. K. (2016). Sampling large geographic areas for rare species using environmental DNA: A study of bull trout *Salvelinus confluentus* occupancy in western Montana. *Journal of Fish Biology*, *88*, 1215–1222.

McKenna, J. E., Butryn, R. S., & McDonald, R. P. (2010). Summer stream water temperature models for Great Lakes streams: New York. *Transactions of the American Fisheries Society*, *139*, 1399–1414.

McNyset, K. M., Volk, C. J., & Jordan, C. E. (2015). Developing an effective model for predicting spatially and temporally continuous stream temperatures from remotely sensed land surface temperatures. *Water*, *7*, 6827–6846.

Meisner, J. D., Rosenfeld, J. S., & Regier, H. A. (1988). The role of groundwater in the impact of climate warming on stream salmonines. *Fisheries*, *13*, 2–8.

Minder, J. R., Mote, P. W., & Lundquist, J. D. (2010). Surface temperature lapse rates over complex terrain: Lessons from the Cascade Mountains. *Journal of Geophysical Research*, *115*, D14122. https://doi.org/10.1029/2009JD013493

Mock, C. J. (1996). Climatic controls and spatial variations of precipitation in the western United States. *Journal of Climate*, *9*, 1111–1125.

Mohseni, O., Erickson, T. R., & Stefan, H. G. (1999). Sensitivity of U.S. stream temperatures to air temperatures projected under a global warming scenario. *Water Resources Research*, *35*, 3723–3734.

Mohseni, O., & Stefan, H. G. (1999). Stream temperature/air temperature relationship: A physical interpretation. *Journal of Hydrology*, *218*, 128–141.

Molinero, J., Larrañaga, A., Pérez, J., Martínez, A., & Pozo, J. (2016). Stream temperature in the Basque Mountains during winter: Thermal regimes and sensitivity to air warming. *Climatic Change*, *134*, 593–604.

Moore, R. B., & Dewald, T. G. (2016). The road to NHDPlus—Advancements in digital stream networks and associated catchments. *Journal of the American Water Resources Association*, *52*, 890–900. https://doi.org/10.1111/1752-1688.12389

Moore, R. D., Nelitz, M., & Parkinson, E. (2013). Empirical modelling of maximum weekly average stream temperature in British Columbia, Canada, to support assessment of fish habitat suitability. *Canadian Water Resources Journal*, *38*, 135–147.

Moore, R. D., Spittlehouse, D. L., & Story, A. (2005). Riparian microclimate and stream temperature response to forest harvesting: A review. *Journal of the American Water Resources Association*, *41*, 813–834.

Mote, P. W., Hamlet, A. F., Clark, M. P., & Lettenmaier, D. P. (2005). Declining mountain snowpack in western North America. *Bulletin of the American Meteorological Society*, *86*, 39–49.

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

Nagel, D., Peterson, E. E., Isaak, D. J., Ver Hoef, J. M., & Horan, D. L. (2015). *National Stream Internet protocol and user's guide* (technical report). Boise, ID: U.S. Forest Service. Retrieved from http://www.fs.fed.us/rm/boise/AWAE/projects/NationalStreamInternet/downloads/NationalStreamInternetProtocolandUserGuide.pdf

Nakamura, H., Izumi, T., & Sampe, T. (2002). Interannual and decadal modulations recently observed in the Pacific storm track activity and East Asian winter monsoon. *Journal of Climate*, *15*, 1855–1874.

National Climate Assessment. (2014). *Climate change impacts in the United States: The third national climate assessment* (841 pp.). U.S. Global Change Research Program. https://doi.org/10.7930/J0Z31WJ2

Nehlsen, W., Williams, J. E., & Lichatowich, J. A. (1991). Pacific salmon at the crossroads: Stocks at risk from California, Oregon, Idaho, and Washington. *Fisheries*, *16*, 4–20.

Nusslé, S., Matthews, K. R., & Carlson, S. M. (2015). Mediating water temperature increases due to livestock and global change in high elevation meadow streams of the Golden Trout Wilderness. *PLoS ONE*, *10*, e0142426.

O'Donnell, D., Rushworth, A., Bowman, A. W., Marian Scott, E., & Hallard, M. (2014). Flexible regression models over river networks. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, *63*, 47–63.

Olden, J. D., & Naiman, R. J. (2010). Incorporating thermal regimes into environmental flows assessments: Modifying dam operations to restore freshwater ecosystem integrity. *Freshwater Biology*, *55*, 86–107.

Olden, J. D., & Poff, N. L. (2003). Redundancy and the choice of hydrologic indices for characterizing streamflow regimes. *River Research and Applications*, *19*, 101–121.

Olson, J. R., & Hawkins, C. P. (2012). Predicting natural base-flow stream water chemistry in the western United States. *Water Resources Research*, *48*, W02504. https://doi.org/10.1029/2011WR011088

Palmer, T., & Vileisis, A. (2016). *Great rivers of the West* (report). Portland, OR: Western Rivers Conservancy. Retrieved from http://www.westernrivers.org/about/greatrivers/

Peel, M. C., & Blöschl, G. (2011). Hydrological modelling in a changing world. *Progress in Physical Geography*, *32*, 249–261. https://doi.org/10.1177/0309133311402550

Pellerin, B. A., Stauffer, B. A., Young, D. A., Sullivan, D. J., Bricker, S. B., Walbridge, M. R., . . . Shaw, D. M. (2016). Emerging tools for continuous nutrient monitoring networks: Sensors advancing science and water resources protection. *Journal of the American Water Resources Association*, *52*, 993–1008. https://doi.org/10.1111/1752-1688.12386

Peterson, D. P., Wenger, S. J., Rieman, B. E., & Isaak, D. J. (2013). Linking climate change and fish conservation efforts using spatially explicit decision support tools. *Fisheries*, *38*, 112–127.

Peterson, E. E., & Pearse, A. R. (2017). IDW-Plus: An ArcGIS toolset for calculating spatially explicit watershed attributes for survey sites. *Journal of the American Water Resources Association*, *53*, 1241–1249. https://doi.org/10.1111/1752-1688.12558

Peterson, E. E., Sheldon, F., Darnell, R., Bunn, S. E., & Harch, B. D. (2011). A comparison of spatially explicit landscape representation methods and their relationship to stream condition. *Freshwater Biology*, *56*, 590–610. https://doi.org/10.1111/j.1365-2427.2010.02507.x

Peterson, E. E., & Ver Hoef, J. M. (2010). A mixed-model moving-average approach to geostatistical modeling in stream networks. *Ecology*, *91*, 644–651. https://doi.org/10.1890/08-1668.1

Peterson, E. E., & Ver Hoef, J. M. (2014). STARS: An ArcGIS toolset used to calculate the spatial information needed to fit spatial statistical models to stream network data. *Journal of Statistical Software*, *56*(2), 1–17. https://doi.org/10.18637/jss.v056.i02

Poole, G. C., Dunham, J. B., Keenan, D. M., Sauter, S. T., McCullough, D. A., Mebane, C., . . . Materna, E. J. (2004). The case for regime-based water quality standards. *BioScience*, *54*, 155–161.

Porter, J. H., Hanson, P. C., & Lin, C. C. (2012). Staying afloat in the sensor data deluge. *Trends in Ecology and Evolution*, *27*, 121–129.

Pörtner, H. (2001). Climate change and temperature-dependent biogeography: Oxygen limitation of thermal tolerance in animals. *Naturwissenschaften*, *88*, 137–146.

Preece, R. M., & Jones, H. A. (2002). The effect of Keepit Dam on the temperature regime of the Namoi River, Australia. *River Research and Applications*, *18*, 397–414.

Quilty, E., & Moore, R. D. (2007). Measuring stream temperature. *Streamline Watershed Management Bulletin*, *10*(2), 25–30.

R Development Core Team. (2014). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing.

Read, E. K., Carr, L., De Cicco, L., Dugan, H. A., Hanson, P. C., Hart, J. A., . . . Winslow, L. A. (2017). Water quality data for national-scale aquatic research: The Water Quality Portal. *Water Resources Research*, *53*, 1735–1745. https://doi.org/10.1002/2016WR019993

Rizo-Decelis, L. D., Pardo-Igúzquiza, E., & Andreo, B. (2017). Spatial prediction of water quality variables along a main river channel in presence of pollution hotspots. *Hydrology and Earth System Sciences*, *10*, 277–287. https://doi.org/10.5194/hess-10-277-2006

Rivers-Moore, N. A., Dallas, H. F., & Morris, C. (2013). Towards setting environmental water temperature guidelines: A South African example. *Journal of Environmental Management*, *128*, 380–392.

Rushworth, A. M., Peterson, E. E., Ver Hoef, J. M., & Bowman, A. W. (2015). Validation and comparison of geostatistical and spline models for spatial stream networks. *Environmetrics*, *26*, 327–338. https://doi.org/10.1002/env.2340

Schabenberger, O., & Gotway, C. A. (2005). *Statistical methods for spatial data analysis*. Boca Raton, FL: Chapman and Hall.

Scown, M. W., McManus, M. G., Carson, J. H., & Nietch, C. T. (2017). Improving predictive models of in-stream phosphorus concentration based on nationally-available spatial data coverages. *Journal of the American Water Resources Association*, *53*, 944–960. https://doi.org/10.1111/1752-1688.12543

Selker, J., van DeGiesen, N., Westhoff, M., Luxemburg, W., & Parlange, M. B. (2006). Fiber optics opens window on stream dynamics. *Geophysical Research Letters*, *33*, L24401. https://doi.org/10.1029/2006GL027979

Skøien, J. O., Merz, R., & Blöschl, G. (2005). Top-kriging—Geostatistics on stream networks. *Hydrology and Earth System Sciences Discussions*, *2*, 2253–2286.

Sloat, M. R., Shepard, B. B., White, R. G., & Carson, S. (2005). Influence of stream temperature on the spatial distribution of westslope cutthroat trout growth potential within the Madison River basin, Montana. *North American Journal of Fisheries Management*, *25*, 225–237.

Smith, K., & Lavis, M. E. (1975). Environmental influences on the temperature of a small upland stream. *Oikos*, *26*, 228–236.

Som, N. A., Monestiez, P., Ver Hoef, J. M., Zimmerman, D. L., & Peterson, E. E. (2014). Spatial sampling on streams: Principles for inference on aquatic networks. *Environmetrics*, *25*, 306–323. https://doi.org/10.1002/env.2284

Stamp, J., Hamilton, A., Craddock, M., Parker, L., Roy, A., Isaak, D., . . . Bierwagen, B. (2014). *Best practices for continuous monitoring of temperature and flow in wadeable streams* (Rep. EPA/600/R-13/170F). Washington, DC: Global Change Research Program, National Center for Environmental Assessment.

Steel, E. A., Beechie, T. J., Torgersen, C. E., & Fullerton, A. H. (2017). Envisioning, quantifying, and managing thermal regimes on river networks. *BioScience*, *67*, 506–522. https://doi.org/10.1093/biosci/bix047

Stewart, I. T., Cayan, D. R., & Dettinger, M. D. (2005). Changes toward earlier streamflow timing across western North America. *Journal of Climate*, *18*, 1136–1155.

Stoddard, J. L., Van Sickle, J., Herlihy, A. T., Brahney, J., Paulsen, S., Peck, D. V., . . . Pollard, A. I. (2016). Continental-scale increase in lake and stream phosphorus: Are oligotrophic systems disappearing in the United States? *Environmental Science and Technology*, *50*, 3409–3415. https://doi.org/10.1021/acs.est.5b05950

Tague, C., Farrell, M., Grant, G., Lewis, S., & Rey, S. (2007). Hydrogeologic controls on summer stream temperatures in the McKenzie River Basin, Oregon. *Hydrologic Processes*, *21*, 3288–3300.

Temesgen, H., & Ver Hoef, J. M. (2015). Evaluation of the spatial linear model, random forest and gradient nearest-neighbor methods for imputing potential productivity and biomass of the Pacific Northwest forests. *Forestry*, *88*, 131–142. https://doi.org/10.1093/forestry/cpu036

Todd, A. S., Coleman, M. A., Konowal, A. M., May, M. K., Johnson, S., Vieira, N. K. M., & Saunders, J. F. (2008). Development of new water temperature criteria to protect Colorado's fisheries. *Fisheries*, *33*, 433–443.

Torgersen, C. E., Ebersole, J. E., & Keenan, D. M. (2012). *Primer for identifying cold-water refuges to protect and restore thermal diversity in riverine landscapes* (Rep. EPA 910-C-12-001). Seattle, WA: United States Environmental Protection Agency.

Torgersen, C. E., Faux, R. N., McIntosh, B. A., Poage, N. J., & Norton, D. J. (2001). Airborne thermal remote sensing for water temperature assessment in rivers and streams. *Remote Sensing of Environment*, *76*, 386–398.

Torgersen, C. E., Price, D. M., Li, H. W., & McIntosh, B. A. (1999). Multiscale thermal refugia and stream habitat associations of Chinook salmon in northeastern Oregon. *Ecological Applications*, *9*, 301–319.

Trumbo, B. A., Nislow, K. H., Stallings, J., Hudy, M., Smith, E. P., Kim, D. Y., . . . Dolloff, C. A. (2014). Ranking site vulnerability to increasing temperatures in southern Appalachian brook trout streams in Virginia: An exposure-sensitivity approach. *Transactions of the American Fisheries Society*, *143*, 173–187.

Turschwell, M. P., Peterson, E. E., Balcombe, S. R., & Sheldon, F. (2016). To aggregate or not? Capturing the spatio-temporal complexity of the thermal regime. *Ecological Indicators*, *67*, 39–48. https://doi.org/10.1016/j.ecolind.2016.02.014

Uno, H., & Power, M. E. (2015). Mainstem-tributary linkages by mayfly migration help sustain salmonids in a warming river network. *Ecology Letters*, *18*, 1012–1020.

U.S. Environmental Protection Agency. (2003). *EPA Region 10 guidance for Pacific Northwest state and tribal temperature water quality standards* (Rep. EPA 910-B-03-002, 49 pp.). Seattle, WA: EPA Office of Water. Retrieved from http://www.epa.gov/r10earth/temperature.htm

U.S. Environmental Protection Agency. (2016). *National Rivers and Streams Assessment 2008–2009: A Collaborative Survey* (Rep. EPA/841/R-16/007). Washington, DC: Office of Water and Office of Research and Development.

Vaccaro, J. J., & Maloy, K. J. (2006). *A thermal profile method to identify potential ground-water discharge areas and preferred salmonid habitats for long river reaches* (Sci. Invest. Rep. 2006–5136, 16 pp.). Washington, DC: U.S. Geological Survey.

Ver Hoef, J. M. (2002). Sampling and geostatistics for spatial data. *Ecoscience*, *9*, 152–161.

Ver Hoef, J. M. (2008). Spatial methods for plot-based sampling of wildlife populations. *Environmental and Ecological Statistics*, *15*, 3–13. https://doi.org/10.1007/s10651-007-0035-y

Ver Hoef, J. M., & Peterson, E. E. (2010). A moving average approach for spatial statistical models of stream networks. *Journal of the American Statistical Association*, *105*, 6–18. https://doi.org/10.1198/jasa.2009.ap08248

Ver Hoef, J. M., Peterson, E. E., Clifford, D., & Shah, R. (2014). SSN: An R package for spatial statistical modeling on stream networks. *Journal of Statistical Software*, *56*(3), 1–45. https://doi.org/10.18637/jss.v056.i03

Ver Hoef, J. M., Peterson, E. E., & Theobald, D. M. (2006). Spatial statistical models that use flow and stream distance. *Environmental and Ecological Statistics*, *13*, 449–464.

Walsh, J., Wuebbles, D., Hayhoe, K., Kossin, J., Kunkel, K., Stephens, G., . . . Somerville, R. (2014). Chapter 2: Our changing climate. Climate change impacts in the United States. In J. M. Melillo, Terese (T. C.) Richmond, & G. W. Yohe (Eds.), *The third national climate assessment* (pp. 19–67). Washington, DC: U.S. Global Change Research Program. https://doi.org/10.7930/J0KW5CXT

Ward, J. V. (1985). Thermal-characteristics of running waters. *Hydrobiologia*, *125*, 31–46.

Wawrzyniak, V., Allemand, P., Bailly, S., Lejot, J., & Piégay, H. (2016). Coupling LiDAR and thermal imagery to model the effects of riparian vegetation shade and groundwater inputs on summer river temperature. *Science of the Total Environment*, *592*, 616–626. https://doi.org/10.1016/j.scitotenv.2017.03.019

Webb, B. W., Hannah, D. M., Moore, R. D., Brown, L. E., & Nobilis, F. (2008). Recent advances in stream and river temperature research. *Hydrological Processes*, *22*, 902–918.

Webb, B. W., & Zhang, Y. (1997). Spatial and seasonal variability in the components of the river heat budget. *Hydrological Processes*, *11*, 79–101.

Wehrly, K. E., Brenden, T. O., & Wang, L. (2009). A comparison of statistical approaches for predicting stream temperatures across heterogeneous landscapes. *Journal of the American Water Resources Association*, *45*, 986–997.

Wenger, S. J., Isaak, D. J., Luce, C. H., Neville, H. M., Fausch, K. D., Dunham, J. B., . . . Hamlet, A. F. (2011). Flow regime, temperature, and biotic interactions drive differential declines of trout species under climate change. *Proceedings of the National Academy of Sciences of the United States of America*, *108*, 14175–14180.

Wenger, S. J., Luce, C. H., Hamlet, A. F., Isaak, D. J., & Neville, H. M. (2010). Macroscale hydrologic modeling of ecologically relevant flow metrics. *Water Resources Research*, *46*, W09513. https://doi.org/10.1029/2009WR008839

Westerling, A. L., Hidalgo, H. G., Cayan, D. R., & Swetnam, T. W. (2006). Warming and earlier spring increase western US forest wildfire activity. *Science*, *313*, 940–943.

Westley, P. A., Dittman, A. H., Ward, E. J., & Quinn, T. P. (2015). Signals of climate, conspecific density, and watershed features in patterns of homing and dispersal by Pacific salmon. *Ecology*, *96*, 2823–2833.
Williams, J. E., Rummel, S., Lemon, J., Barney, M., Smith, K., Fesenmyer, K., & Schoen, J. (2016). Engaging a community of interest in water quality protection: Anglers monitoring wadeable streams. *Journal of Soil and Water Conservation*, *71*, 114A–119A.
Wolock, D. M. (2003). *Base-flow index grid for the conterminous United States* (Open File Rep. 03–263). Lawrence, KS: U.S. Geological Survey.
Woodward, G., Perkins, D. M., & Brown, L. E. (2010). Climate change and freshwater ecosystems: Impacts across multiple levels of organization. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *365*, 2093–2106.
Wright, A. N., Schwartz, M. W., Hijmans, R. J., & Shaffer, H. B. (2015). Advances in climate models from CMIP3 to CMIP5 do not change predictions of future habitat suitability for California reptiles and amphibians. *Climatic Change*, *134*, 579–591.
Young, M. K., Isaak, D. J., McKelvey, K. S., Wilcox, T. M., Bingham, D. M., Pilgrim, . . . Schwartz, M. K. (2016). Climate, demography, and zoogeography predict introgression thresholds in salmonid hybrid zones in Rocky Mountain streams. *PLoS ONE*, *11*, e0163563.