



Thermal Regimes of Perennial Rivers and Streams in the Western United States

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Research Impact Statement: Thermal regimes in rivers and streams are parsimoniously described and classified using newly available, extensive annual monitoring records for the western U.S.

ABSTRACT: Thermal regimes of rivers and streams profoundly affect aquatic ecosystems, but are poorly described and classified in many areas due to the limited availability of annual datasets from extensive and representative monitoring networks. By mining a new temperature database composed of >23,000 site records that spans the western United States (U.S.), we extract annual monitoring records at 578 sites on perennial streams to describe regimes in this diverse region. Records were summarized using 34 metrics that described regime aspects related to magnitude, variation, frequency, duration, and timing. The metrics were used in a multivariate cluster analysis to classify streams into seven distinct regime types and in a principal components analysis (PCA) to examine patterns of redundancy among metrics. The PCA indicated that 2–5 orthogonal PC axes accounted for 74%–89% of the variation in thermal regimes at the monitoring sites. Most of the variation in PC scores that defined the two dominant axes was in turn predictable from a suite of geospatial covariates in multiple linear regressions that included elevation, latitude, riparian canopy density, reach slope, precipitation, lake prevalence, and dam height. Our results have parallels to previous flow regime analyses that describe the utility of small numbers of PCs or allied metrics in regime characterization, and can be used to better understand and parsimoniously represent thermal regimes in the western U.S.

(KEYWORDS: regime; temperature sensor; thermal metrics; western United States; rivers; streams.)

INTRODUCTION

Stream scientists, regulators, and aquatic ecologists have long recognized the importance of temperature (Ide 1935; Brett 1952; Himmelblau 1960) and recent decades of work have continued to elucidate linkages with stream metabolism (Demars et al. 2011; Bernhardt et al. 2018), water chemistry (Beaulieu et al. 2011; Comer-Warner et al. 2018), food-web structure (Kishi et al. 2005; Woodward et al. 2010), and species distributions and abundance (Hill and Hawkins 2014; Isaak et al. 2017b; Kärcher et al. 2019). Moreover, the importance of temperature will

only increase this century as climate change progresses and effects on lotic systems and communities comprised of ectothermic organisms are realized (Heino et al. 2009; Whitney et al. 2016). In fact, it might be argued that thermal considerations are of secondary importance only to the presence of flowing water as a physical characteristic defining streams and rivers. Previous description of spatiotemporal variation in flow regimes based on suites of descriptive metrics was key to uncovering fundamental insights about aquatic ecosystems and regime analysis now serves as a basis for the subdiscipline of ecological flows (Poff et al. 1997, 2010). Those contributions would have been impossible without

Paper No. JAWRA-19-0089-P of the *Journal of the American Water Resources Association* (JAWRA). Received June 13, 2019; accepted May 11, 2020. © Published 2020. This article is a U.S. Government work and is in the public domain in the USA. **Discussions are open until six months from issue publication.**

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Citation: Isaak, D.J., C.H. Luce, D.L. Horan, G.L., Chandler, S.P. Wollrab, W.B. Dubois, and D.E. Nagel. 2020. "Thermal Regimes of Perennial Rivers and Streams in the Western United States." *Journal of the American Water Resources Association* 1–26. <https://doi.org/10.1111/1752-1688.12864>.

data from discharge gauge monitoring networks and the availability of flow records to the research community. Comparable knowledge about thermal regimes is needed, but has lagged because temperature data are not recorded at most flow gauges and datasets of annual records have been difficult to obtain from more than a few sites or watersheds (Orr et al. 2015; Isaak et al. 2018b). In recent years, data limitations have begun to ease with the advent of inexpensive, reliable temperature sensors and grass-roots monitoring efforts are becoming common throughout much of Europe and North America (e.g., Hilderbrand et al. 2014; Trumbo et al. 2014; Nusslé et al. 2015; Daigle et al. 2016; Jackson et al. 2016; Mauger et al. 2016).

Previous data limitations have not constrained the number of studies that address temperatures in lotic systems, which is a popular topic with reviews common in both the physical science (Webb et al. 2008; Gallice et al. 2015; Dugdale et al. 2017) and ecological literatures (Ward 1985; Poole and Berman 2001; Caissie 2006; Olden and Naiman 2010; Steel et al. 2017). By necessity, however, a primary focus has often been the description and modeling of thermal characteristics at a small number of sites or across areas of limited geographic extent. Comparatively little is known about broader regime characteristics and how these may relate to regional physiographic controls, although previous studies do provide insights that are useful for setting expectations. For example, temperature dynamics at a stream site covary with changes in air temperature, discharge, and solar radiation conditions that affect stream heat budgets through multiple mechanisms (Stefan and Preud'homme 1993; Isaak and Hubert 2001; van Vliet et al. 2010). Thermal regimes, therefore, should generally reflect annual cycles in those conditions, with distinctions potentially emerging between streams flowing at different elevations, draining watersheds that are mesic or arid, or flowing through coastal areas vs. those more continental with greater climatic extremes, to name a few possibilities. Additional thermal nuances may arise in association with network topology because watershed conditions sometimes change dramatically at confluences (Benda et al. 2004; O'Sullivan et al. 2019), or due to the physical properties of water, such as its high specific heat value that dampens variability in larger rivers and the 0°C lower temperature bound in streams exposed to subzero air temperatures. Local factors may also affect thermal regimes and override macroscale effects, as when riparian vegetation conditions change abruptly or where geologic formations with high water yields create spring streams with relatively stable flow and temperature conditions (O'Driscoll and DeWalle 2006; Kelleher et al. 2012).

Similarly, dams and reservoirs may create abrupt serial discontinuities in thermal conditions depending on the size of reservoirs and depth of water intakes or local water management policies (Olden and Naiman 2010; Maheu et al. 2016; Isaak et al. 2018b).

In recent years, several studies have developed thermal regime classifications that condense the range of observed variability into a set of categories based on similar characteristics. For example, Rivers-Moore et al. (2013) used principal components analysis (PCA) and clustering techniques with temperature records from 82 sites in South African streams to summarize regimes into 11 categories based on descriptive metrics. Chu et al. (2010) and Daigle et al. (2019) summarized stream temperature records from glaciated terrain in eastern Canada and used multivariate techniques to describe associations with landscape and physicochemical conditions. At a much broader scale, Maheu et al. (2015) used temperature records from 135 gauging stations across the United States (U.S.) to classify streams into six categories based three parameters (magnitude, amplitude, and timing) derived from a Fourier analysis of annual temperature cycles. However, attempts at classification have yet to be made that use large, spatially extensive temperature datasets drawn from geographically and climatically diverse areas, to not only characterize thermal regimes at discrete monitoring sites, but also to extend those efforts with predictive models applied throughout networks. Regime mapping is a common and useful practice within the more mature flow regime literature (Snelder et al. 2009; Olden et al. 2012) and would be useful for rendering thermal regime domains and the environments available to aquatic organisms or that drive ecosystem processes in river networks.

Aiding predictive mapping efforts and coincident with the recent increase in temperature monitoring efforts, has been a proliferation of complimentary datasets and geospatial resources for organizing and attributing stream observations to conduct synthetic analyses (*sensu* Poisot et al. 2016). These consist of two primary components, first of which are nationally consistent geospatial frameworks that provide vector or raster streamline representations of drainage networks with unique reach identifiers for use in geographic information system environments (Cooter et al. 2010; Stein et al. 2014). Tiered to those networks are a number of covariate databases that describe reach attributes (e.g., length, elevation, slope) or those of the associated watersheds (e.g., contributing area, proportion of land cover types, geologic composition; Domisch et al. 2015; Hill et al. 2016; McManamay and DeRolph 2019), which provide a convenient and powerful means of attributing stream observations. Reach and watershed descriptors can also be used as

covariates in analyses and to visualize or map results, thus providing an important bridge for scaling from local observations to network patterns that may provide additional insights.

One place opportunities exist to advance thermal regime research is the western U.S. (hereafter, the “West”) where a convergence of factors related to aquatic species of concern, climate change, and water temperature standards has motivated considerable efforts to monitor temperature in recent years (Nehlsen et al. 1991; USEPA 2003; USGCRP 2018). Moreover, the region is large and physiographically diverse, which suggests that the thermal signatures of its flowing waters will be equally diverse and perhaps inclusive of conditions in other geographic areas. Enabling this research is the NorWeST temperature database, which is a compilation of temperature records from >23,000 stream and river sites that were collected by professional biologists and hydrologists employed by state, federal, tribal, and private resource agencies in the West (Isaak et al. 2017a). Here, we mine the database to extract a representative set of annual records that were taken contemporaneously over a multiyear period, summarize the records using a set of descriptive metrics, and then use multivariate analyses to describe metric commonalities and discern those that convey the most information about thermal regimes. Predictive models of key regime elements are developed using climatic, geomorphic, landscape, and hydrologic covariates and used to map thermal regimes throughout the network of perennial streams and rivers in the West. Results are discussed with regards to the thermal patterns that are observed, factors contributing to these patterns, implications for thermal ecology, and future directions in regime research given rapid growth in the availability of temperature data and geospatial resources for streams.

STUDY AREA

The West as circumscribed in this study encompasses 2,584,000 km², most or all of eleven states from the Pacific Ocean to the Great Plains in the central U.S., and is drained by an extensive network of rivers, streams, and intermittent channels (Benke and Cushing 2005; Palmer and Vileisis 2016; Figures 1 and 2). Major river drainages within the West include the Columbia-Snake River drainage and upper Missouri River of the northwest, the Colorado River and Rio Grande River drainages of the southwest, and Sacramento-San Joaquin River drainage of California. The area is topographically complex, with broad basins and numerous 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 southwest where summer monsoons are important (Mock 1996). Precipitation accumulates as snow at high elevations and northern latitudes during the winter 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- 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. Dams built for flood control, irrigation, and hydro-electrical production are not uncommon, but mostly occur on larger rivers, so free-flowing streams and rivers occur throughout major portions of the regional network. A diverse ichthyofauna inhabits the West, but cold-water fishes such as salmon, trout, and charr often dominate societal interests and conservation investments (Nehlsen et al. 1991; Isaak et al. 2018b). Exceptions occur, however, in warmer, drier areas such as California, the Great Basin, and desert portions of the southwest where numerous mussel species, amphibians, and nonsalmonid fishes are also of conservation concern (Minckley and Deacon 1968; Hershler et al. 2014; Howard et al. 2015).

METHODS

River Network and Temperature Dataset

Rivers and streams within the study area were delineated using the medium resolution 1:100,000-scale National Hydrography Dataset-Plus (NHD-Plus;

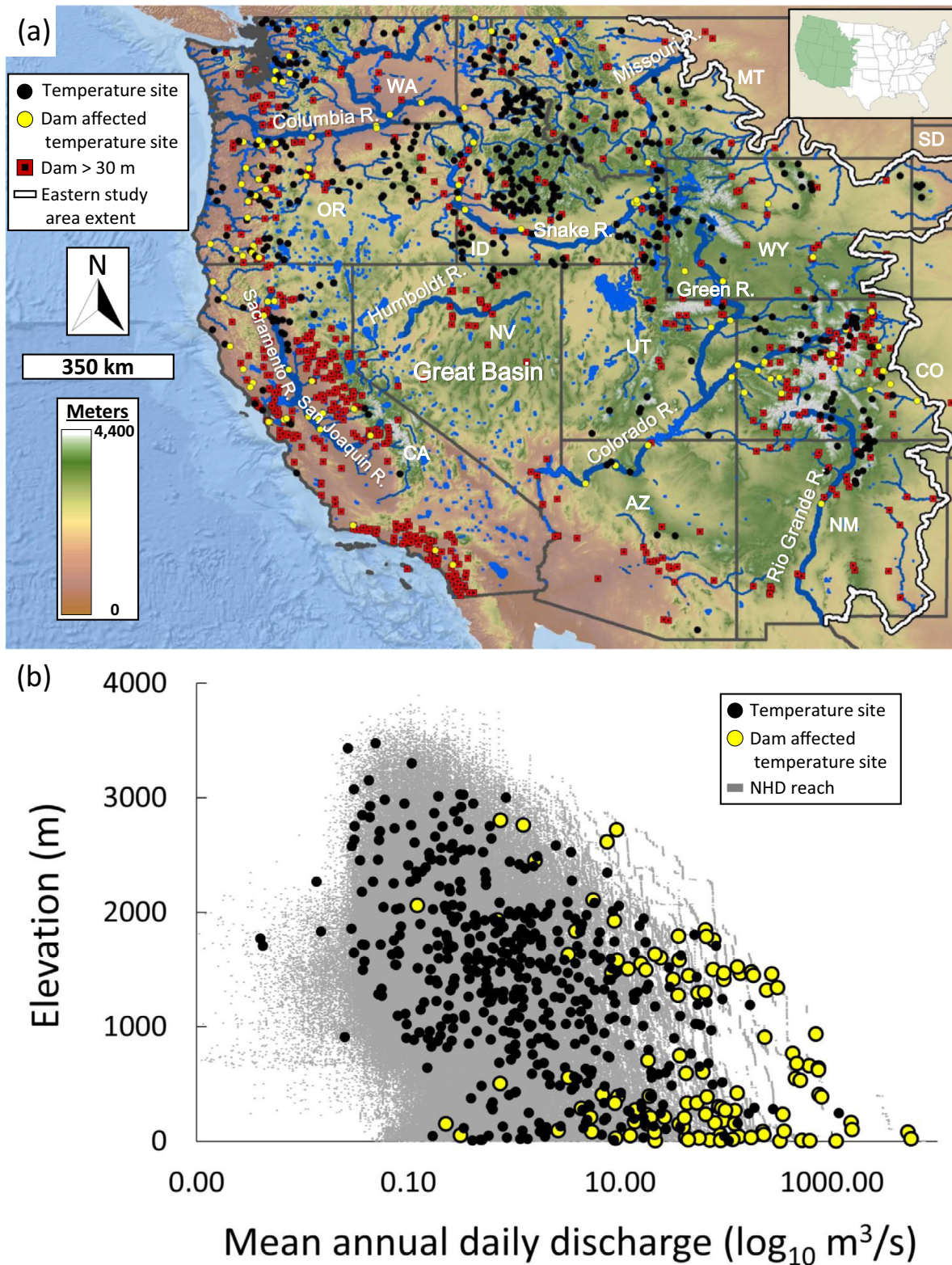


FIGURE 1. Study area map showing 578 river and stream temperature monitoring sites, locations of dams that exceed 30 m in height, and rivers with mean annual daily discharge $>6 \text{ m}^3/\text{s}$ in the western United States (U.S.) (a; thick blue lines denote major regional rivers). (b) Temperature monitoring sites relative to the mean annual daily discharge and elevation of all reaches in the 343,000 km perennial network. Supporting Information includes a high-resolution map showing this information in more detail. NHD, National Hydrography Dataset.

<http://www.horizon-systems.com/NHDPlus/index.php>) to take advantage of the extensive geospatial datasets that are available to describe reach attributes (e.g.,

McKay et al. 2012; Hill et al. 2016; Isaak et al. 2017a). However, the full NHD-Plus network contains many reaches that are unlikely to support aquatic species



FIGURE 2. The western U.S. hosts a diversity of flowing waters that include high-elevation mountain streams and rivers like the South Fork of the Payette River in central Idaho (a, photo credit: Dan Isaak), spring streams like Tilson Creek associated with karst geology in the Black Hills of South Dakota (b, photo credit: Steve Hirtzel), impounded rivers like the Colorado River downstream of Glen Canyon Dam in northern Arizona (c, photo credit: U.S. Bureau of Reclamation), low elevation coastal streams like Plaskett Creek that drain into the Pacific Ocean (d, photo credit: David Smith), mid-elevation streams flowing through rangelands and steppe like the Bruneau River in southern Idaho (e, photo credit: Dan Isaak), and desert streams like the Rio Chama in New Mexico (f, photo credit: Charles Burgess).

due to either topographic steepness in mountainous areas or flow intermittency in arid regions that are common across much of the West. To highlight the perennial subset of the network that was most ecologically relevant, therefore, reaches coded as intermittent in the NHD-Plus network (Fcode = 46003) were deleted, as were those with mean annual flows $<0.03 \text{ m}^3/\text{s}$, or reaches with channel slopes $>15\%$. The flow values were obtained from the Western U.S. Stream Flow Metrics website (http://www.fs.fed.us/rm/boise/AWAE/projects/modeled_stream_flow_metrics.shtml) and were previously validated by Wenger et al. (2010), whereas the slope and intermittency information were integral to the NHD-Plus stream dataset. These filtering criteria were based on our observations during extensive field research in the West and patterns of fish and amphibian species occurrence at thousands of stream survey sites that have previously been linked to the NHD-Plus network (Wenger et al. 2011; Isaak et al. 2017b). Filtering reduced the original network extent from 1,632,000 to 343,000 km within the study area, with remaining streams flowing at elevations of 0 m along the Pacific Ocean coast to 3,900 m at the highest elevations in the Rocky Mountains of Colorado (a high-resolution map of the study network and regional topography is provided in the Supporting Information).

The NorWeST database consists of $>300,000,000$ hourly temperature recordings at more than 23,000 unique stream and river sites that were provided by numerous natural resource agencies, checked for quality assurance, and georeferenced accurately to the NHD-Plus network (Isaak et al. 2017a). The large majority of site records in the database span only 1–3 years during summer months, so the database had to be queried to extract a subset of annual records useful for regime analysis. To do that, we intersected the filtered perennial NHD network with the NorWeST database of daily temperature summaries (Chandler et al. 2016) and extracted data for sites that had values on at least 70% of the days during the five-year period of December 1, 2010 to November 30, 2015. In portions of the network where site monitoring records were clustered and particularly dense, they were rarified by eliminating sites that occurred within 10 km of other sites to obtain a better spatial balance of samples and to reduce the possibility of spatial autocorrelation that often occurs in stream temperatures at short network distances (Isaak et al. 2010; Zimmerman and Ver Hoef 2017). Site deletions within a cluster were performed randomly until only one site remained with a 10 km radius. We also excluded temperature records that were located <1 km downstream from the base of dams as these were more indicative of the upstream reservoir temperatures than thermal conditions in flowing waters.

By requiring a minimum of 70% record completion, our database query also ensured that the records included considerable amounts of data representing conditions during the annual thermal cycle, which is necessary to characterize several important regime aspects (Maheu et al. 2015; Isaak et al. 2018a). Furthermore, targeting a consistent five-year period ensured that monitoring sites experienced similar intra and interannual variation in hydroclimatic conditions. Although a longer recording period would be desirable and has been recommended in thermal regime research (Jones and Schmidt 2018), broad installation of monitoring sites to record annual data rather than summer-only data is a relatively recent phenomenon in the West and the number of long-term annual records is very limited (Isaak et al. 2012, 2018b). Thus, our dataset struck a balance between accurately representing individual sites, providing consistency among sites, and spanning a broad geography to encompass a range of thermal conditions.

Similar to our previous regime work (Isaak et al. 2018a), we defined the thermal year as starting on December 1 because temperatures usually reach their annual lows by this date and the three-month period thereafter constitutes a logical winter season (i.e., December, January, February) that matches the convention used in the climatology literature (e.g., Abatzoglou et al. 2014). Subsequent three-month periods were considered to be spring (March, April, May), summer (June, July, August), and fall seasons (September, October, November). Because temperature records often consisted of recordings at different subdaily intervals, they were standardized by summarization to mean daily temperatures. Data were collected using different sensor models, which had measurement accuracies of $\pm 0.2^\circ\text{C}$ to $\pm 0.5^\circ\text{C}$ and resolutions of 0.02°C to 0.14°C (Stamp et al. 2014). All temperature records were subject to standard quality assurance-quality control measures as described elsewhere (Chandler et al. 2016) and have been used extensively in previous research that subjected them to additional scrutiny (e.g., Luce et al. 2014; Isaak et al. 2016, 2017a, 2018a, b).

The final stream temperature dataset consisted of records from 578 sites distributed throughout the perennial network of western streams and rivers (Figure 1). Although we set the minimum threshold for record completeness at 70% during the five-year period, the average completeness of records was higher at 86%. Missing daily values were imputed using the MissMDA package (Missing Values with Multivariate Data Analysis; Josse and Husson 2016) in R (R Development Core Team 2014) because temporal covariation among proximate stream temperature sites is usually strong. That was confirmed in our dataset by the high correlations between observed mean daily temperatures and predictions from the imputation

TABLE 1. Temperature metrics used to describe thermal regimes of perennial rivers and streams in the western U.S.

Category	Thermal metric	Definition
Magnitude	M1. Mean annual temperature	Average of mean daily temperatures during a year
	M2. Mean winter temperature	Average of mean daily temperatures during December, January, and February
	M3. Mean spring temperature	Average of mean daily temperatures during March, April, and May
	M4. Mean summer temperature	Average of mean daily temperatures during June, July, and August
	M5. Mean August temperature	Average of mean daily temperatures during August
	M6. Mean fall temperature	Average of mean daily temperatures during September, October, and November
	M7. Minimum daily temperature	Lowest mean daily temperature during a year
	M8. Minimum weekly average temperature	Lowest seven-day running average of mean daily temperature during a year
	M9. Maximum daily temperature	Highest mean daily temperature during a year
	M10. Maximum weekly average temperature	Highest seven-day running average of mean daily temperature during a year
	M11. Annual degree days	Cumulative total of degree days during a year (1°C for 24 h = 1 degree day)
Variability	V1. Annual standard deviation	Standard deviation of mean daily temperature during a year
	V2. Winter standard deviation	Standard deviation of mean daily temperature during winter months
	V3. Spring standard deviation	Standard deviation of mean daily temperature during spring months
	V4. Summer standard deviation	Standard deviation of mean daily temperature during summer months
	V5. August standard deviation	Standard deviation of mean daily temperature during the month of August
	V6. Fall standard deviation	Standard deviation of mean daily temperature during fall months
	V7. Range in extreme daily temperatures	Difference between minimum and maximum mean daily temperatures during a year (M9 minus M7)
	V8. Range in extreme weekly temperatures	Difference between minimum and maximum weekly average temperatures during a year (M10 minus M8)
	V9. Interannual standard deviation of mean annual	Interannual standard deviation in mean annual temperature
	V10. Interannual standard deviation of minimum weekly	Interannual standard deviation in minimum weekly average temperature
	V11. Interannual standard deviation of maximum weekly	Interannual standard deviation in maximum weekly average temperature
	V12. Interannual standard deviation of 5% degree days	Interannual standard deviation in date of 5% of degree days
	V13. Interannual standard deviation of 50% degree days	Interannual standard deviation in date of 50% of degree days
Frequency	F1. Frequency of hot days	Number of days with mean daily temperatures >20°C
	F2. Frequency of cold days	Number of days with mean daily temperatures <2°C
Timing	T1. Date of 5% degree days	Number of days from December 1 until 5% of degree days are accumulated
	T2. Date of 25% degree days	Number of days from December 1 until 25% of degree days are accumulated
	T3. Date of 50% degree days	Number of days from December 1 until 50% of degree days are accumulated
	T4. Date of 75% degree days	Number of days from December 1 until 75% of degree days are accumulated
	T5. Date of 95% degree days	Number of days from December 1 until 95% of degree days are accumulated
Duration	D1. Growing season length	Number of days between the 95% and 5% of degree days (T5 minus T1)
	D2. Duration of hot days	Longest number of consecutive days with mean daily temperatures >20°C
	D3. Duration of cold days	Longest number of consecutive days with mean daily temperatures <2°C

technique, which ranged from $r = 0.85$ to $r = 1.0$, but averaged $r = 0.98$. After the imputation process, all temperature records at the 578 sites were complete and consisted of 1,825 mean daily temperatures from December 1, 2010 to November 30, 2015.

To describe the temperature records, 34 summary metrics were calculated in association with five categories related to magnitude, variability, frequency, timing, and duration (Table 1). Twenty-eight of the metrics were identical to those used previously in a smaller-scale thermal regime study of mountain streams (Isaak et al. 2018a) and were calculated after the five-year records of 1,825 daily temperatures at each site had been averaged to create representative values for one year of 365 days. Five additional

metrics were calculated using the full five-year records to describe interannual variability in a subset of thermal characteristics (metrics V9–V13, Table 1). We also calculated a metric to describe the variability in temperatures during August (V5) because it is a critical low-flow period during the warmest portion of the year when discharge in regulated reaches is often actively managed for ecological purposes (Keefer and Caudill 2015; Isaak et al. 2018b).

Data Analysis

Thermal metric values were normalized to zero means and unit standard deviations to accommodate

the different measurement scales among the metrics and agglomerative hierarchical cluster analysis was used to classify the 578 sites. The analysis was done using the Cluster Procedure in SAS (SAS Institute Inc 2015) based on Euclidean distances and a group average joining method wherein the distance between groups was defined as the average of all the dissimilarities between all possible pairs of points such that one of each pair was in each group. To determine the number of groups, the pseudo- T^2 criterion was used (SAS/STAT 14.3 User's Manual Proc CLUSTER) and group membership results were also mapped to judge their geographic interpretability. Next, a PCA was done to describe and summarize relationships among the metrics (Pearson 1901; Sergeant et al. 2016) using the Princomp Procedure in SAS (SAS Institute Inc 2015). The first principal component (PC) axis accounted for the largest possible variance in the metric dataset and succeeding components accounted for the largest portions of the remaining variance along axes that were orthogonal (i.e., uncorrelated) to the preceding component axes. PCA axes were not rotated to maintain their orthogonality because the dominant axes were generally interpretable (Richman 1986). PC scores were used to create an ordination plot in which temperature sites were displayed by their group membership from the cluster analysis following Rivers-Moore et al. (2013). Correlations, or loadings, between each metric and the PCs were also calculated and summarized in a biplot to aid interpretation of the PCs.

To understand the aspects of landscapes, networks, and meteorology that affected thermal regime characteristics, PCA scores from the first two component axes were used as response variables in multiple linear regressions as is common practice (Richman 1986; Luce et al. 2014). Most covariates used in the regressions described spatial variation in characteristics among reaches and were derived from nationally available geospatial datasets that were used previously in the NorWeST project to develop climate change scenarios of mean August stream temperatures (Isaak et al. 2017a). Those covariates were elevation, latitude, longitude, reach slope, riparian canopy density, baseflow index, average annual precipitation, the prevalence of lakes (both natural lakes and reservoirs), and watershed drainage area. Because our previous research indicated that stream temperature magnitude often conveys information about thermal variability (Luce et al. 2014; Isaak et al. 2016), we used mean August stream temperature from a NorWeST scenario representing a baseline climate period as a covariate if a PC response metric was indicative of variability rather than magnitude. We also considered three covariates that described time-averaged, spatial variation among

reaches in flow regime characteristics during the same baseline climate period, which were mean annual daily flow (a measure of stream size), the number of days with high flows during the winter (a measure of flashiness), and the date at which the center of annual flow mass occurred (a measure of runoff timing) as defined in Wenger et al. (2010). Descriptive attributes of these spatial covariates at the 578 temperature sites are summarized in Appendix A, and additional details regarding hypothesized effects on water temperatures and the data sources used to quantify covariates are summarized in Appendix B.

To compliment the spatial covariates described above, covariates were also developed to describe the temporal variability in air temperatures and discharge that occurred during the monitoring period because these factors correlate with variability in water temperatures (Chen et al. 2016; Laizé et al. 2017). The same set of variability metrics described previously (V1–V13) was calculated from time series of mean daily air temperature and discharge that were obtained at or near the 578 water temperature sites for the five-year period from December 1, 2010 to November 30, 2015. Mean daily air temperature data were downloaded as contiguous 4-km² raster grids that spanned the West from the PRISM climate website (Parameter–Elevation Regressions on Independent Slopes Model; <http://prism.oregonstate.edu/>), whereas daily discharge data were downloaded from the National Water Information System database (NWIS; <https://waterdata.usgs.gov/usa/nwis/nwis>) for all western gauges that were active during the study period. Because water temperature sites and flow gauges were rarely co-located, discharge variability metrics were assigned to temperature sites from the nearest gauge. An exception occurred if a water temperature site on a free-flowing reach was closest to a gauge on a regulated reach downstream from a dam. In that instance, discharge variability metric values were instead assigned from the nearest gauge on an unregulated stream.

Water releases from dams and reservoirs have well documented effects on thermal regimes (Langford 1990; Olden and Naiman 2010), so each of the 578 temperature sites was classified based on their occurrence downstream of dams at least 30 m in height. The U.S. Army Corp of Engineers National Inventory of Dams database (USACOE 2016; (http://nid.usace.army.mil/cm_apex/f?p=838:1:0::NO::APP_ORGANIZATION_TYPE,P12_ORGANIZATION:8)) was used to provide the locations and heights of dams. Dam height was used as an index to reservoir depth that was included in the multiple linear regressions as a covariate. Because many shallow reservoirs often act as natural lakes to warm downstream rivers (Maheu et al. 2016) while especially deep reservoirs with cold

hypolimnions cause cooling (Olden and Naiman 2010; Rivers-Moore et al. 2013), this differential effect was assessed using a quadratic dam height term in the regression models. Some evidence supporting this characterization was also apparent in our dataset from examination of time-series plots of paired monitoring sites immediately upstream and downstream of eight dam sites (Supporting Information). In addition to the dam height covariate, the lake covariate provided an additional measure of potential dam effects on thermal regimes because reservoirs are treated as lakes in the geospatial covariate descriptors available for NHD-Plus (Appendix B).

After attributing the temperature sites and all reaches in the perennial network with covariate values, the stepwise option in the Reg Procedure of SAS was used to fit a series of models in which covariates were added one by one, but remained in the model only if their statistical probability was <0.15 . After the addition of a new covariate, the procedure performed subsequent checks to delete covariates that were no longer significant before another new covariate was considered. The stepwise process ended when none of the variables outside the model had statistical significance in the model and every variable in it did. To avoid problems that multicollinearity could cause regarding parameter estimate interpretability, covariates that were strongly correlated with another covariate (i.e., $r > 0.7$; Dormann et al. 2013) were not included in the same model. Models from the stepwise option were ranked and final models selected based on Akaike information criterion (AIC) scores (Anderson and Burnham 2004). Akaike weights and their ratios were calculated to indicate the plausibility of the best-fitting models compared to other models. The robustness of the final models was assessed by five-fold cross-validation involving 1,000 model fits to 80% of the data and average r^2 values were calculated from relationships between PC scores predicted at 20% of the withheld sites and observed values. The final regression models were used to visualize thermal regime characteristics by predicting PC1 and PC2 scores throughout the perennial stream network by multiplying the covariate values for each reach by the regression model parameter estimates.

RESULTS

The 578 water temperature monitoring sites were not distributed randomly, but spanned a wide geographic range and set of environmental conditions and probably represented most stream and river types in the West (Figure 1; Appendix A). A plot of

site locations relative to elevation and mean annual daily discharge for the reaches within the perennial network suggested good coverage along these important gradients (Figure 1b). Few temperature records occurred in the Great Basin and the driest portions of the southwestern U.S., but these areas also have few perennial streams. Of the 578 temperature records, 101 occurred in reaches downstream of dams at least 30 m in height. Summaries of thermal conditions represented by the 34 metrics are provided in Appendix C. Highlighting the variability in the dataset, mean annual water temperatures ranged by almost an order of magnitude from 2.19°C to 19.1°C, annual standard deviations of mean daily temperatures varied from 0.023°C to 8.48°C, and growing season lengths ranged from 98 to 333 days. Plots of the five-year temperature site monitoring records also revealed large amounts of intra and interannual variability associated with meteorological variation (see Supporting Information).

Cluster analysis of the 34 temperature metrics suggested that the monitoring records could be grouped into seven distinct thermal classes (Table 2). Mapping those categories at the monitoring sites revealed geographic differences between coastal and inland areas, as well as northern and southern areas. There was also a mix of classes in some areas, probably due to local gradients in elevation and other factors that strongly affect thermal dynamics over short distances in complex terrain (Figure 3a). Stream sites in the coastal regime class occurred at low elevations along the Pacific Ocean and were characterized by warm winters, early spring onsets, and moderate summer temperatures (Figure 3b). Often in close proximity were streams with mid-elevation mountain regimes, which occurred in the Cascade Mountain range of Oregon and Washington and were scattered in parts of the Rocky Mountains. These streams had cold temperatures during both the winter and summer and a limited annual range. High mountain thermal regimes were common throughout the Rocky Mountain region and characterized by streams with winter temperatures near 0°C for prolonged periods, cold summers, and spring onset that was one to three months later than other classes. Streams with continental regimes were also common in the Rocky Mountain region, but occurred at lower elevations and had warmer summer temperatures and larger annual temperature ranges. Sites with spring thermal regimes were rare in our sample and had temperature profiles that were distinct from the other regime types by their near constant temperatures (Figure 3b). Most spring streams were cold with mean annual temperatures of $\sim 7^\circ\text{C}$, but one stream was comparatively warm with a mean temperature of 15.1°C and may have been geothermally influenced.

Another uncommon regime type was the river-reservoir class, which had cold winters, warm summers, peak temperatures that occurred relatively late in the year, and little short-term variability despite the presence of seasonal cycles similar to most other classes. Sites in this class were limited to run-of-the-river reservoirs along the Columbia and Snake Rivers, which are the two largest rivers by discharge in the West (mean annual discharge $>1,550 \text{ m}^3/\text{s}$). Hot streams comprised the last thermal class and were mostly confined to the southwestern portion of the West and inland parts of southern California.

PCA of the temperature metrics indicated that five PCs had eigenvalues greater than one and accounted for 89.1% of the variation in the 34 metrics (Table 3). The first PC explained 46.1% of the variation and correlated strongly with most of the metrics that represented magnitude, frequency, duration, and timing (Figure 4). The second PC accounted for 27.9% of variation and was primarily associated with variability metrics for seasonal and annual time periods. Variation explained by the remaining three PCs was much smaller and their interpretability decreased by the lack of metrics with strong loadings. Metrics designed to represent interannual variability (i.e., V9–V13) did not load consistently or especially strongly on any PC. An ordination plot of the PC1 and PC2 scores at the 578 sites revealed a continuous data cloud with stream sites in the high mountains and hot categories representing the extreme conditions along the first axis (Figure 4). Large values on the PC2 axis indicated greater variability, which is where streams with continental regimes plotted opposite spring streams that showed little variability. The 101 sites downstream of large dams were also highlighted in the ordination plot, although except for the river reservoir category, they did not create distinct clusters and were instead scattered throughout the hot, continental, and coastal regime types.

Multiple linear regressions predicted most of the variation in PC1 scores (Table 4 and Appendix D), with two covariates, elevation and latitude, accounting for 79% of the variation in PC1 scores. The best model explained 87% of PC1 score variation and included seven variables (in decreasing order of effect size): elevation, latitude, riparian canopy, reach slope, annual precipitation, lake prevalence, and a quadratic effect for dam height. That model was 6.3 AIC points lower and almost 23 times more plausible than the second ranked model, while also having an Akaike weight of 0.93 in the regression set. The best regression model for PC2 accounted for 63% of the variation in PC2 scores and included eight covariates. The three dominant variables in the PC2 model were mean August water temperature, elevation, and latitude. Smaller effects were associated with the

standard deviation of August air temperatures, riparian canopy, drainage area, lake prevalence, and a linear effect for dam height. Both final regression models also appeared to be robust, with five-fold cross-validation r^2 values of 0.86 for PC1 and 0.63 for PC2 that showed little or no decrease relative to the model fits based on the full dataset (Table 4).

A map of PC1 scores predicted by the multiple linear regression model showed considerable heterogeneity across the West, with high scores indicative of warm streams, early spring onsets, long growing seasons, and few cold days common at low elevations in California, coastal Oregon, and the southwest (Figure 5a). Streams with low PC1 scores and contrasting regime characteristics were prevalent in mountainous areas and adjacent foothills throughout the Sierra Nevada Range of eastern California, the interior Rocky Mountain region, and the Cascade Range of western Oregon and Washington. The PC2 map of thermal variability (Figure 5b) showed broadly similar spatial patterns as the PC1 map in that stream thermal regimes throughout coastal areas were generally distinct from streams in the Rocky Mountain region. However, streams with particularly low PC2 scores and variability were most common in coastal and mountain areas of Oregon, Washington, and northern California, whereas low variability streams inland occurred only at the highest elevations in the central Rocky Mountains and portions of northern Idaho and northwest Montana. The highest PC2 scores occurred in the western interior and foothill areas that bordered mountains, as well as moderate elevation steppe and range landscapes throughout the region.

DISCUSSION

Thermal Regimes in the West

Our results highlight the diversity and key attributes of thermal regimes in perennial rivers and streams across the West, as well as many of the environmental factors that broadly shape these regimes. Despite this diversity, much of the information in temperature records could be summarized by a few PCs, indicating that distinct regime components were limited in number and that the underlying regime structure was relatively simple. The first PC represented many metrics associated with magnitude, duration, timing, and frequency, whereas most of the variability metrics loaded heavily on PC2. Metrics describing interannual variation were not prominent in defining either of the dominant PCs, which suggests that relatively short time series of annual

TABLE 2. Mean and variance (standard deviation) of selected temperature metrics associated with seven thermal regime classes.

Thermal regime class (n)	M2. Mean winter temperature (°C) ¹	M4. Mean summer temperature (°C)	T1. Date of 5% degree days ²	General comments
1. Coastal (82)	7.26 (1.95)	16.9 (2.32)	30.7 (7.16)	Streams and rivers along the Pacific Ocean coast, but with extensions into the southwest. Warm winters, early spring onset, and moderate annual temperature range
2. Mid-elevation mountain (76)	3.71 (1.24)	11.2 (2.03)	37.5 (10.7)	Streams in mid-elevation mountainous basins near coast with some extensions inland. Cold temperatures, early spring onset, and small annual temperature range
3. High mountain (281)	0.61 (0.51)	11.3 (2.58)	118 (29.2)	Streams in high-elevation inland mountain basins. Cold temperatures, often extended winter periods at 0°C, late spring onset, and moderate annual temperature range
4. Continental (105)	2.15 (1.43)	18.5 (2.53)	87.5 (26.4)	Streams and rivers located inland in rangeland and steppe environments. Cold winters, warm summers, late spring onset, and large annual temperature range
5. Spring (7)	7.59 (3.57)	8.60 (3.62)	18.7 (7.6)	Uncommon and restricted to geologies with high local water yields. Little temperature variation. Depending on water source, temperatures may be warm or cold
6. River reservoir (7)	4.43 (0.50)	18.9 (0.66)	41.3 (9.36)	Uncommon and restricted to run-of-the-river reservoirs on largest rivers like the Columbia and Snake Rivers. Cold winters and warm summers
7. Hot (20)	9.68 (2.28)	23.2 (1.41)	32.7 (6.04)	Streams and rivers in southwest and portions of inland California. Warm summer and winter temperatures, early spring onset, and large annual temperature range

¹Column headers match the thermal metrics described in Table 1.

²Days from December 1, which was considered the beginning of a thermal year.

records (e.g., 1–3 years) may be adequate in some cases, at least for initial regime characterizations. Interestingly, Rivers-Moore et al. (2013) documented a similar split between the types of metrics that represented PC1 and PC2 in an analysis of temperature records from a broad set of South African streams. That is encouraging because it suggests a basic set of attributes which transcend physiographic boundaries and regions may be operable and broadly definitive of thermal regimes. Confirming that possibility and reaching a general consensus, however, will require consideration of additional datasets from a breadth of regions to facilitate comparisons. Because many thermal metrics loaded heavily on a few PCs, our results also indicate that considerable redundancy exists among them and that careful selection and use of a few metrics could represent most of the information about thermal regimes in many ecological or physical science applications. Such screening would also help minimize problems associated with multicollinearity that may arise when multiple, highly correlated temperature metrics are used as covariates in statistical models (Dormann et al. 2013).

Use of a few key thermal metrics served as the basis of the regime classification system developed by Maheu et al. (2015) for the contiguous U.S. Our results support that simplified approach, and we note that some of the regime categories proposed by

Maheu (i.e., variable cold and cool, stable cold and cool) in the West have analogues in a subset of our categories (i.e., coastal, continental, and mountain). Our use of a larger, denser sample of monitoring site records, however, helped identify rarer regime types (e.g., spring and river reservoir regimes) and better resolved the geographic domains where thermal regimes occurred. That resolution was enhanced by using PC score summaries, which provided continuous, information-rich variables that were easily modeled and predictively mapped to provide a network context for the patterns observed at the 578 temperature sites. The spatial patterns and covariate relationships associated with the PC1 map and model met our expectations given the concordance of this PC with summer magnitude metrics, the considerable amount of research that has focused on modeling these metrics (e.g., Rivers-Moore et al. 2013; Detenbeck et al. 2016; Isaak et al. 2017a), and the dominant effects of elevation and latitude throughout the region. The PC2 variability map is a more novel contribution, but the predictive skill of the underlying model was somewhat weaker. Elevation and latitude were again important factors in the model, as was mean August stream temperature, which was expected based on patterns observed in previous research (Luce et al. 2014; Isaak et al. 2016). However, the contributions of additional covariates were

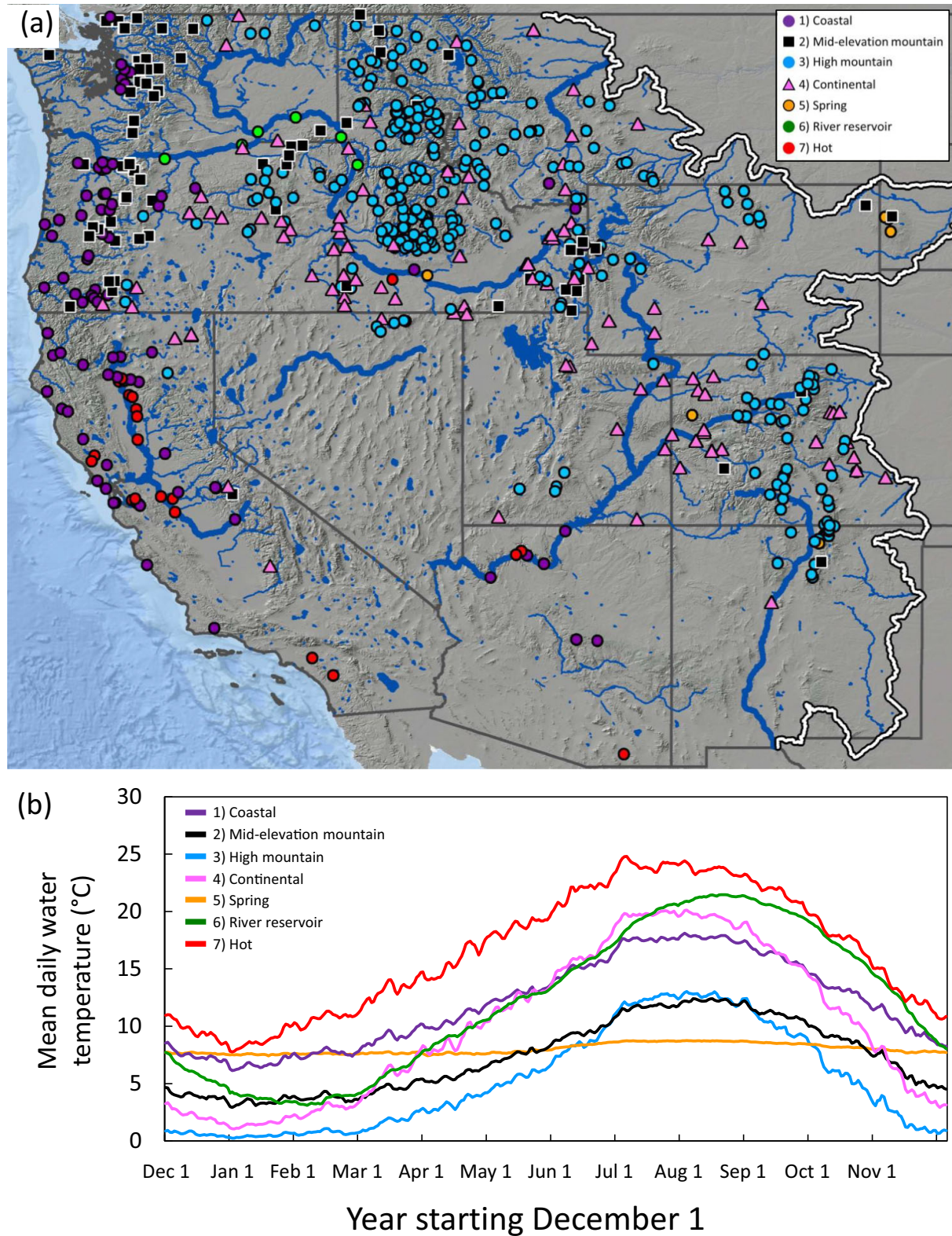


FIGURE 3. Regime classes from an agglomerative hierarchical cluster analysis mapped for 578 river and stream temperature monitoring sites in the western U.S. (a). Blue lines denote rivers with mean annual daily discharge $>6 \text{ m}^3/\text{s}$; thick white line denotes the eastern extent of the study area. Archtypical annual thermographs for the regime classes derived by averaging mean daily temperature values across sites within the stream records in each class (b).

TABLE 3. Loadings of temperature metrics on the first five PCs in a PCA of annual temperature records from perennial streams and rivers in the western U.S. Values in bold indicate the highest correlation between a metric and individual PC.

Temperature metric	PC1	PC2	PC3	PC4	PC5
M1. Mean annual temperature	0.98	0.10	-0.04	-0.02	0.08
M2. Mean winter temperature	0.85	-0.45	0.02	-0.09	0.20
M3. Mean spring temperature	0.97	0.06	-0.13	-0.07	0.06
M4. Mean summer temperature	0.84	0.53	-0.07	-0.04	0.01
M5. Mean August temperature	0.81	0.57	0.05	0.05	0.03
M6. Mean fall temperature	0.97	0.03	0.06	0.11	0.05
M7. Minimum daily temperature	0.77	-0.53	0.01	-0.14	0.23
M8. Minimum weekly average temperature	0.78	-0.53	0.02	-0.14	0.22
M9. Maximum daily temperature	0.79	0.60	0.02	-0.02	0.02
M10. Maximum weekly average temperature	0.79	0.60	0.02	-0.01	0.02
M11. Annual degree days	0.98	0.10	-0.04	-0.02	0.08
V1. Annual SD	0.24	0.95	-0.03	0.06	-0.13
V2. Winter SD	0.82	0.19	0.05	0.26	-0.06
V3. Spring SD	0.36	0.76	-0.27	-0.15	-0.27
V4. Summer SD	-0.29	0.55	0.54	0.29	0.10
V5. August SD	0.06	0.71	0.15	-0.43	-0.12
V6. Fall SD	0.10	0.96	-0.01	0.10	-0.08
V7. Range in extreme daily temperatures	0.34	0.92	0.02	0.06	-0.13
V8. Range in extreme weekly temperatures	0.33	0.93	0.02	0.07	-0.12
V9. Interannual SD of mean annual temperature	0.46	0.21	0.74	-0.18	0.05
V10. Interannual SD of minimum weekly temperature	0.71	-0.34	0.18	-0.06	-0.00
V11. Interannual SD of maximum weekly temperature	0.16	0.34	0.45	-0.56	-0.11
V12. Interannual SD of 5% degree days	-0.34	0.26	0.42	0.01	0.07
V13. Interannual SD of 50% degree days	-0.12	-0.19	0.75	-0.30	0.23
F1. Frequency of hot days	0.66	0.43	-0.14	0.20	0.45
F2. Frequency of cold days	-0.87	0.32	-0.06	-0.06	0.31
T1. Date of 5% degree days	-0.75	0.56	-0.11	-0.09	0.19
T2. Date of 25% degree days	-0.80	0.53	0.11	0.15	0.08
T3. Date of 50% degree days	-0.75	0.41	0.31	0.35	0.02
T4. Date of 75% degree days	0.13	-0.38	0.52	0.63	-0.11
T5. Date of 95% degree days	0.76	-0.53	0.17	0.18	-0.20

(continued)

TABLE 3. (continued)

Temperature metric	PC1	PC2	PC3	PC4	PC5
D1. Growing season length	0.76	-0.56	0.12	0.10	-0.20
D2. Duration of hot days	0.65	0.40	-0.14	0.21	0.48
D3. Duration of cold days	-0.85	0.32	-0.07	-0.07	0.33
Variance explained (%)	46.1	27.9	7.1	4.6	3.4
Cumulative variance (%)	46.1	74.0	81.1	85.7	89.1
Eigenvalue	15.7	9.49	2.42	1.58	1.16

minor and more than a third of the total variation in PC2 scores was not predicted. This contrasts with statistical stream temperature models built for individual monitoring sites that commonly account for 80%–90% of water temperature variability using air temperature and discharge covariates (Van Vliet et al. 2010; Chen et al. 2016). We speculate that condensing the five-year stream temperature records into coarser summary metrics for the analysis may have contributed to that loss of predictive performance, as could the imprecisions which arose from using air temperature and discharge datasets that were not based on sensors co-located with the water temperature sensors. Both factors were undesirable, but compromises necessary to conduct a regime analysis across a broad area.

The effects of dams and reservoirs on thermal regimes are important given their abundance in many areas, as well as current trends to decommission or build new dams in different parts of the world (Zarfl et al. 2015; Bellmore et al. 2017). Both dam height and lake prevalence, which included reservoir extent, had discernable effects on thermal regimes across the western U.S. that were usually indicative of warming and dampened variability, except downstream of especially tall dams where cooling trends occurred. That these effects were detectable across such a large and diverse region is noteworthy, and indicative of broader cumulative effects on thermal regimes that are not yet well studied or understood. Nonetheless, when stream and river sites affected by large dams were viewed within the ordination plot of PC scores, the sites largely fell within the observed ranges of unregulated sites and rarely were distinct regime categories created. The river reservoir class could be viewed as an exception, but this category was limited to a small number of sites that occurred within the largest regional rivers and was also closely bracketed by regime categories which exhibited similar thermal dynamics. This contrasts with classification results from a warmer region like South Africa where cold dam tail-waters created a regime cluster that was strongly differentiated from all other

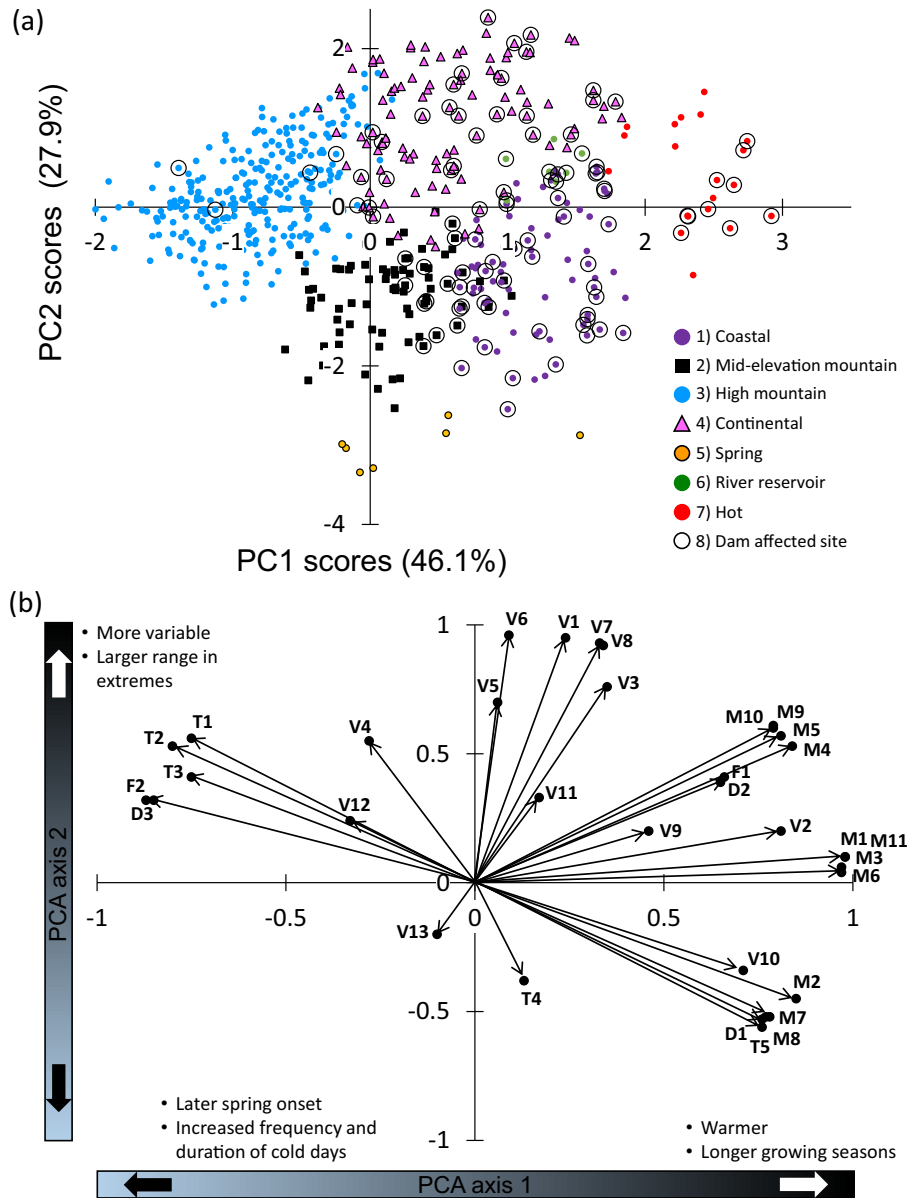


FIGURE 4. Ordination plot of principal component (PC) scores that summarize 34 water temperature metrics describing thermal records at 578 monitoring sites in the western U.S. (a). Sites were classified into seven regime types using hierarchical agglomerative cluster analysis and are symbolized accordingly. Sites downstream of dams >30 m in height are circled. Biplot that shows the loadings of the 34 water temperature metrics on the first two PC axes (b; monitoring sites are hidden for clarity). PCA, principal components analysis.

clusters describing the region's thermal landscapes (Rivers-Moore et al. 2013).

One of the rationales frequently offered for classification systems, especially in the study of hydrologic regimes which has a longer history, is as a means of diagnosing anthropogenic impairments. That basis, at least presently, however, does not seem compelling for thermal regime classifications at broad scales. A large anthropogenic effect associated with dams was detectable in our models, but it ranked as one of the smallest effects, and yet smaller effects would be expected for less dramatic and more diffuse sources

of thermal impairment that are common within landscapes such as land use and riparian alterations, or flow diversions (Moore et al. 2005; Elmore et al. 2015). Moreover, detailed local inventories of more subtle impairment factors have yet to be done systematically in a manner that would enable integration with classification schemes. Some progress is being made on these fronts, especially with regards to better characterization of riparian vegetation and shade potential from remote sensing and near-Earth sensing (Dauwalter et al. 2015; Wawrzyniak et al. 2017), but these efforts are nascent and often done

TABLE 4. Summaries of final multiple linear regression models selected to predict PCs of thermal regimes in the western U.S.

Model	Covariate	Parameter estimate (standard error)	<i>t</i> statistic	<i>p</i> value	<i>r</i> ²	<i>r</i> _{CV} ^{2 1}
PC1	Intercept	7.36 (0.23)	31.4	<0.01	0.87	0.86
	Elevation	−0.00104 (0.0000239)	−43.6	<0.01		
	Latitude	−0.129 (0.00528)	−24.5	<0.01		
	Riparian canopy	−0.00593 (0.000683)	−8.68	<0.01		
	Reach slope	−3.32 (0.584)	−5.69	<0.01		
	Annual precipitation	−0.000200 (0.0000385)	−5.20	<0.01		
	Lake	0.0671 (0.0153)	4.38	<0.01		
	Dam height	0.00213 (0.00114)	1.88	<0.01		
	Dam height ²	−0.0000203 (7.02 × 10 ^{−6})	−2.89	0.06		
PC2	Intercept	−11.1 (0.567)	−19.5	<0.01	0.63	0.63
	August mean stream temperature	0.276 (0.010)	27.6	<0.01		
	Elevation	0.00107 (0.0000518)	20.7	<0.01		
	Latitude	0.120 (0.0115)	10.4	<0.01		
	August SD of air temperature	0.381 (0.125)	3.04	<0.01		
	Riparian canopy	0.00275 (0.00117)	2.34	0.02		
	Drainage area	−1.24 × 10 ^{−6} (6.18 × 10 ^{−7})	−2.01	0.05		
	Lake	−0.0498 (0.0254)	−1.96	0.05		
	Dam height	−0.00124 (0.000837)	−1.48	0.14		

¹Based on 1,000 five-fold cross validation model fits.

for project specific purposes. Nonetheless, it is important to expand and improve efforts to better describe local thermal impairments given their prevalence in many landscapes, and because meaningful ecological restoration can often be achieved by their remediation (Nusslé et al. 2015; Null et al. 2017).

Ecological Implications of Thermal Regimes

Although no new ecological applications of thermal regimes were explored in this study, such efforts are a logical next step so the prediction maps of PC1 and PC2 have been formatted as geospatial datasets and are available at the NorWeST project website. Previous research in the West has used similar geospatial scenarios of mean August stream temperature, also developed from the NorWeST database and closely allied with PC1, to begin addressing at least some thermal ecology questions. These include predicting where in river networks species invasions, range contractions from climate warming, and hybridization zones may occur near thermally mediated boundaries (Al-Chokhachy et al. 2016; Young et al. 2016; Rubenson and Olden 2019); understanding phenological cues for aquatic insects (Anderson et al. 2019), developing accurate species distribution models to estimate the effect of temperature relative to other environmental covariates (Isaak et al. 2017b; Wilcox et al. 2018), assessments of migration success and interspecific competition (Westley et al. 2015; Myrvold and Kennedy 2017; Rinnan 2018); and precise identification of climate refuge streams throughout the ranges of species of conservation concern (Isaak et al. 2015; Palmer 2017; Young et al. 2018). None of these early

applications have relied on datasets derived from simultaneous collection of temperature and biological datasets, but instead as Hill and Hawkins (2014) also demonstrate, simply referenced existing biological survey information from separate sources against accurate stream temperature scenario maps. Although applications to date involve biological phenomena, maps of thermal regime characteristics might also be useful for deriving estimates of stream metabolism (Demars et al. 2011; Rodriguez-Castillo et al. 2019), solubility and concentrations of gases in water (Himmelblau 1960), and emission fluxes of greenhouse gases at scales broader than those traditionally considered (Beaulieu et al. 2011; Comer-Warner et al. 2018). Even if temperature and thermal effects are not the principal focuses of research, the use of temperature as a model covariate may often account for nuisance variation and lead to better estimates for factors of interest.

Previous considerations of temperature in stream ecology have relied heavily on summer magnitude metrics due to limited data availability for other seasons. Therefore, it was reassuring that many temperature metrics in different categories correlated strongly with summer magnitude metrics and represented a large portion of the information about thermal regimes. The obvious departures from that association were the variability metrics that largely defined PC2. It has been hypothesized that thermal variability is important to many ecological processes (Steel et al. 2012; Dillon et al. 2016), but empirical proofs for stream organisms are often limited to laboratory settings and scenarios that may be unlikely to occur in nature (e.g., Johnstone and Rahel 2003; Steel et al. 2012). Separation of variability

information as PC2 from other aspects of thermal regimes and the availability of this information as a geospatial dataset opens new possibilities for testing that hypothesis and understanding the role that

variability may play in lotic ecosystems of the West. The same is also true for evaluating other aspects of thermal regimes represented by additional PCs, or distinctive metrics that may not load heavily on

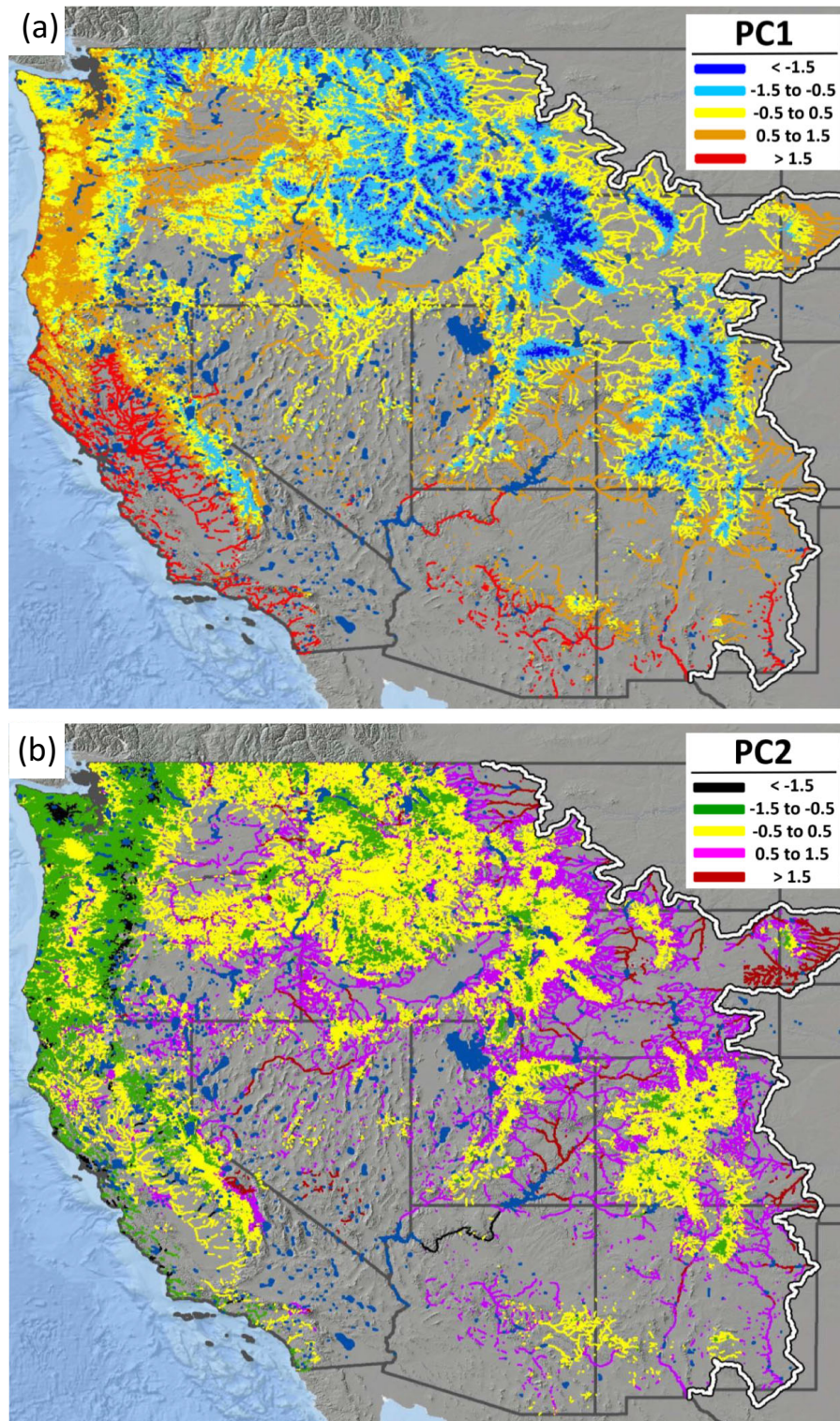


FIGURE 5. Maps of thermal regime PC scores (a: PC1; b: PC2) predicted by multiple linear regression models for the 343,000 km network of perennial streams and rivers in the western U.S.

individual PCs. A more nuanced understanding of thermal ecology should result that will be useful for ascertaining the various pathways by which phenomena such as climate change and habitat degradation affect ecological processes (Garcia et al. 2014).

Temperature Databases and Geospatial Resources

As this research highlights, data from existing temperature datasets can be successfully repurposed and a regime analysis is just one of many ways that a spatiotemporally rich database can be queried and subset for new research when guided by useful questions. It is important that researchers have access to extensive temperature records because many important questions pertaining to thermal ecology have yet to be adequately addressed (McCullough et al. 2009; Dillon et al. 2016), and new types of temperature models and inference will be needed at a variety of scales. In the western U.S., the NorWeST database provides a valuable resource to assist in those endeavors because the 578 temperature site records used here were only a small subset of records from the >23,000 unique sites in the database (Chandler et al. 2016; Isaak et al. 2017a). Most of the database consists of short records taken during the summer in 1–3 years, but annual records and those of greater length are becoming more common as database updates are done periodically. Despite the recency of the database, it has already yielded datasets that enabled thermal research on differences among streams in sensitivity to climatic variation (Luce et al. 2014; Isaak et al. 2016), description of thermal regimes in mountain river networks (Isaak et al. 2018a), estimation of recent warming trends in rivers from climate change (Isaak et al. 2018b), and provided spatially dense datasets to develop high-resolution climate change scenarios and forecasts (Isaak et al. 2017a). Data repurposing is not a new concept for those working with flow regimes because discharge data have traditionally been obtained from sources like NWIS or other state-sanctioned monitoring programs and centralized databases. Different, however, is the grassroots nature of temperature databases, which are growing because declining sensor costs are democratizing data acquisition efforts. Temperature sensors with multi-year data logging capacities cost U.S. \$20–200, for example, are available from several manufacturers, and are easily deployed using standard protocols (Stamp et al. 2014), which has spawned an array of local monitoring networks by natural resource agencies and watershed councils in many countries (e.g., Trumbo et al. 2014; Daigle et al. 2016; Jackson et al. 2016; Mauger et al. 2016).

Geospatial representations of stream networks further enhance the value of temperature databases by

facilitating their organization and linkage to descriptive covariates. Although it is possible to create custom networks from digital elevation models, doing so requires specialized skills and is often labor intensive, so most stream ecologists will benefit from using existing networks like those that now exist for many individual countries (e.g., Cooter et al. 2010; Stein et al. 2014) or global representations (Lehner and Grill 2013; Yamazaki et al. 2015). Once observations are linked to reaches in the network, attribution with covariates is straightforward and facilitates model development and mapping of results. Often important in that regard is the proper contextualization and representation of results by network subsetting. In our western U.S. study area, for example, the NHD-Plus network spans more than 1,600,000 km, but most reaches are dry channels or are too steep and small to serve as habitat for most aquatic species. Thus, the network of primary concern had to be highlighted through application of simple network filters chosen based on previous field experience and empirical biological relationships (Wenger et al. 2011; Isaak et al. 2017b). Similar network queries, when coupled with observational databases, would also be useful for identifying gaps in monitoring network coverage for strategic supplementation with additional data collections (DeWeber et al. 2014). Similarly, the design and implementation of new monitoring networks or surveys can often be done efficiently by using geospatial queries to describe and stratify networks prior to sample allocation (Som et al. 2014; Jackson et al. 2016). Used collectively, the suite of increasing geospatial capabilities and expanding aquatic databases should prove useful for better resolving what Bishop et al. (2008) have referred to as *Aqua Incognita* and a persistent uncertainty regarding the extent and characteristics of flowing water networks.

CONCLUSION

As was the case two decades ago with the need for better flow regime information to understand ecological effects (Poff et al. 1997), the time is ripe and the needs are similar for improving our understanding of thermal regimes. Then, as now, the potential for advances was triggered in part by the availability of data. Rapidly growing databases are making new analyses possible, and where temperature data are lacking, can be developed relatively quickly using inexpensive sensors and broadly available geospatial tools to guide strategic monitoring. In the western U.S., our regime analysis benefitted from the pre-

existence of the NorWeST database that was easily mined to yield a set of annual records for perennial streams that were spatially extensive and representative. Several distinct regime types were identified that were predictably related to geomorphic, climatic, vegetative, and anthropogenic controls. This information could enable subsequent biophysical investigations to further highlight and elucidate the important role that thermal regimes play in western streams and rivers. We suspect that similar information about

thermal regimes will prove useful in many places given the mechanistic basis for temperature in biophysical processes, as well as the global reach of climate change and habitat degradation associated with growing human populations and land uses. As thermal regime research proliferates and matures, it should complement the corpus of knowledge surrounding flow regimes and broaden our understanding of hydroclimates and biophysical processes in flowing waters.

APPENDIX A

TABLE A1. Descriptive statistics for geospatial covariates at 578 river and stream temperature monitoring sites with annual records in the western U.S. Appendix B provides additional information about covariates including data sources.

Covariate	Mean	Median	SD	Minimum	Maximum
Latitude (decimal degrees)	43.23559	43.92683	3.42	31.62596	48.99712
Longitude (decimal degrees)	-115.134	-115.336	5.48	-124.059	-103.764
Elevation (m)	1,292	1,331	804	2.57	3,476
Annual precipitation (mm)	757	636	499	29.1	2,757
Reach slope (m/m)	0.0241	0.0128	0.0310	0	0.15
Riparian canopy (%)	35.5	33.0	27.8	0	91.4
Lake upstream (%)	0.415	0.061	1.04	0	14.8
Baseflow index (%)	64.1	67.0	12.7	2.0	88.0
Drainage area (km ²)	8,053	113	44,445	1.36	570,000
Mean annual daily flow (m ³ /s)	58.2	1.57	349	0.03	5,597
Days with winter high flows (days)	5.46	3.31	5.46	0	17.7
Median flow date (date)	188	194	25.4	127	244
Mean August water temperature (°C)	14.6	13.9	4.09	6.45	26.5
Dam height (m)	85.2	70	44.8	30	219

APPENDIX B

TABLE B1. Descriptions and sources of covariate data used to describe and model temperature regimes in rivers and streams of the western U.S.

Covariate	Definition and rationale	References	Data source
Elevation (Ele)	Elevation at the water temperature site. Cooler air temperatures and greater snow and precipitation accumulations (cooler groundwater inputs) at higher elevations should cool stream temperatures	Smith and Lavis (1975); Isaak and Hubert (2001); 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 water temperature 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); 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 temperature site composed of lake or reservoir surfaces. Lakes absorb heat, slow water transit times through watersheds, and should increase downstream temperatures while dampening variability	Dripps and Granger (2013); Maheu et al. (2016)	NHDPlus Value Added Attribute = NLCD11PC, downloaded from http://www.horizon-systems.com/NHDPlus/NHDPlusV2_home.php
Annual precipitation (AP)	Mean annual precipitation in watershed upstream of temperature site. Wetter landscapes have higher water yields and more groundwater that should cool streams and dampen their variability	Isaak and Hubert (2001)	NHDPlus Value Added Attribute = PrecipV, downloaded from http://www.horizon-systems.com/NHDPlus/NHDPlusV2_home.php
Longitude (Long)	Longitude coordinate at a water temperature site. Temperatures in coastal streams may be moderated by ocean proximity, whereas inland streams could exhibit greater variability from exposure to continental climates with larger temperature extremes	Driscoll and Yee Fong (1992); Shinker (2010)	Temperature site meta-data from the NorWeST website at https://www.fs.fed.us/rm/boise/AWAE/projects/NorWeST.html
Latitude (Lat)	Latitude coordinate at a water temperature site. Air and groundwater temperatures are cooler further north and should cool streams. At higher latitudes, variability may also be dampened during winter due to increased frequency of 0°C days when air temperatures are subzero	Ward (1985); Meisner et al. (1988)	Temperature site meta-data from the NorWeST website at https://www.fs.fed.us/rm/boise/AWAE/projects/NorWeST.html
Mean annual flow (MAF)	Mean annual daily discharge value a water temperature site. Larger streams are insulated over a greater length and are less shaded by riparian vegetation, which should result in warmer temperatures. Larger streams also have greater mass and thermal inertia, which may dampen variability	Ward (1985); Moore et al. (2005); Webb et al. (2008); Garner et al. (2013)	Shapefile attribute = MAF for NHDPlus reaches, downloaded from the Western U.S. Streamflow Metrics website at https://www.fs.fed.us/rm/boise/AWAE/projects/modeled_stream_flow_metrics.shtml
Center of flow mass (CFM)	The date on which the center of annual flow mass occurs at a water temperature site. Streams with different runoff dates may be differentially affected by seasonal air temperature variation	Wenger et al. 2010; Isaak et al. (2018a, b)	Shapefile attribute = CFM for NHDPlus reaches, downloaded from the Western U.S. Streamflow Metrics website at https://www.fs.fed.us/rm/boise/AWAE/projects/modeled_stream_flow_metrics.shtml
Winter high flow frequency (WHFF)	The number of days with high flows during the winter season at a water temperature site. A measure of hydrologic flashiness that differentiates between snowmelt and rainfall runoff regimes, which are the two primary hydrologic types in the western U.S. Streams with more winter discharge	Hockey et al. (1982); Gu et al. (1998); Elmore et al. (2016)	Shapefile attribute = W95 for NHDPlus reaches, downloaded from the Western U.S. Streamflow Metrics website at https://www.fs.fed.us/rm/boise/AWAE/projects/modeled_stream_flow_metrics.shtml

(continued)

TABLE B1. (continued)

Covariate	Definition and rationale	References	Data source
Dam height (DH)	variability are expected to show more winter thermal variability Height of the nearest, tallest dam upstream from a water temperature site that is >30 m in height. Especially tall dams with deep reservoirs have cold hypolimnions that often cool downstream reaches and may dampen thermal variability. Smaller dams and reservoirs may act as heat sinks and effectively operate as natural lakes to increase temperatures and dampen thermal variability	Preece and Jones (2002); Olden and Naiman (2010); Maheu et al. (2016)	Dam heights and locations were obtained from the U.S. Army Corp of Engineers 2016 National Inventory of Dams database at http://nid.usace.army.mil/cm_apex/f?p=838:1:0::NO::APP_ORGANIZATION_TYPE,P12_ORGANIZATION:8
August water temperature (AWT)	Mean August temperature at water temperature site for a historical climate period that represents the average of condition from 1993 to 2011. Streams which are cold during the summer receive considerable groundwater contributions and exhibit dampened variability	Luce et al. (2014); Isaak et al. (2016)	Scenario S1 (1993–2011) shapefile attribute for NHDPlus reaches downloaded from the NorWeST website at https://www.fs.fed.us/rm/boise/AWAE/projects/NorWeST.html
Baseflow index (BFI)	Baseflow index values at water temperature site calculated as the ratio of baseflow to total flow and expressed as a percentage. Sites with larger baseflows relative to peak flows have larger groundwater contributions that should cool streams and dampen variability	Mayer (2012); 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 insulated over a greater length and are less shaded by riparian vegetation, which should result in warmer temperatures. Larger streams also have greater mass and thermal inertia, which may dampen variability	Ward (1985); Moore et al. (2005); Webb et al. (2008); 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, cooler streams, and dampened variability	Moore et al. (2005); Cristea and Burges (2010); Garner et al. (2014); 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 variability (ATV)	Air temperature variability at a water temperature site. The same set of 13 variability metrics that were calculated for water temperature (V1–V13 in Table 1) were also calculated for air temperature. Air temperature covaries with several factors that affect stream heat budgets, so more variable air temperatures often result in more variable river and stream temperatures	Webb and Zhang (1997); Mohseni et al. (1999); Isaak et al. (2018a, b); Garner et al. (2013)	Daily mean air temperature records were downloaded as 4 km ² resolution raster grids from the Parameter–Elevation Regressions on Independent Slopes Model website (http://prism.oregonstate.edu/)
Discharge variability (DV)	Flow discharge variability at a water temperature site. The same set of 13 variability metrics that were calculated for water temperature (V1–V13 in Table 1) were also calculated for discharge. Flow discharge covaries with several factors that affect stream heat budgets, so more variable discharge often results in more variable river and stream temperatures	Hockey et al. (1982); Gu et al. (1998); Isaak et al. (2018a, b); Elmore et al. (2016)	Daily discharge records were downloaded from the USGS National Water Information System (http://waterdata.usgs.gov/nwis/rt)

APPENDIX C

TABLE C1. Descriptive statistics for temperature metrics used to describe thermal regimes at 578 monitoring sites in perennial rivers and streams of the western U.S.

Temperature metric	Mean	Median	SD	Minimum	Maximum
M1. Mean annual temperature (°C)	7.87	7.13	3.43	2.19	19.10
M2. Mean winter temperature (°C)	2.71	1.37	3.00	−0.60	14.95
M3. Mean spring temperature (°C)	6.47	5.68	3.81	0.05	19.12
M4. Mean summer temperature (°C)	13.83	13.24	4.35	5.23	25.90
M5. Mean August temperature (°C)	14.84	14.30	4.24	5.89	26.05
M6. Mean fall temperature (°C)	8.36	7.38	3.68	2.48	21.38
M7. Minimum daily temperature (°C)	1.82	0.48	2.62	−0.96	13.99
M8. Minimum weekly average temperature (°C)	1.99	0.65	2.69	−0.94	14.16
M9. Maximum daily temperature (°C)	15.90	15.33	4.51	5.92	28.22
M10. Maximum weekly average temperature (°C)	15.60	14.98	4.48	5.92	27.60
M11. Annual degree days (DD)	2,873	2,604	1,250	800	6,972
V1. Annual SD (°C)	4.63	4.48	1.51	0.023	8.48
V2. Winter SD (°C)	0.49	0.42	0.35	0.005	1.96
V3. Spring SD (°C)	1.96	1.86	0.87	0.014	5.36
V4. Summer SD (°C)	1.66	1.62	0.68	0.014	4.45
V5. August SD (°C)	0.47	0.43	0.21	0.0062	1.62
V6. Fall SD (°C)	3.45	3.36	1.15	0.0061	6.44
V7. Range in extreme daily temperatures (°C)	14.1	13.5	4.44	0.078	25.8
V8. Range in extreme weekly temperatures (°C)	13.6	13.0	4.39	0.074	25.4
V9. Interannual SD of mean annual temperature (°C)	0.63	0.59	0.29	0.004	2.62
V10. Interannual SD of minimum weekly temperature (°C)	0.43	0.24	0.46	0.000	3.09
V11. Interannual SD of maximum weekly temperature (°C)	1.08	1.01	0.49	0.0065	4.04
V12. Interannual SD of 5% degree days (DD)	11.7	10.2	7.02	0.71	46.4
V13. Interannual SD of 50% degree days (DD)	5.09	5.03	1.85	0.84	19.1
F1. Frequency of hot days (days)	13.2	0	30.8	0	172
F2. Frequency of cold days (days)	78.9	88	70.1	0	246
T1. Date of 5% degree days (days)	84.4	87	44.8	16	202
T2. Date of 25% degree days (days)	173.8	180	27.5	90	235
T3. Date of 50% degree days (days)	229.3	232	11.8	182	261
T4. Date of 75% degree days (days)	276.7	276	4.72	264	295
T5. Date of 95% degree days (days)	328.9	328	9.95	300	349
D1. Growing season length (days)	244.5	241	54.3	98	333
D2. Duration of hot days (days)	11.8	0	29.3	0	167
D3. Duration of cold days (days)	73.5	66	69.0	0	246

APPENDIX D

TABLE D1. Stepwise model selection results for multiple linear regressions that predict scores of the first two PCs of thermal regimes at 578 stream and river sites. Models are ranked from most plausible ($\Delta AIC = 0$) to least plausible; p is the number of parameters. The ratio of Akaike weights (w_i/w_i) indicates the plausibility of the best-fitting model compared to other models. Models shown in bold font were selected to predict values of the PCs throughout the network of perennial streams in the western U.S.

PC	Covariates	p	ΔAIC	r^2	Akaike weight (w_i)	w_i/w_i
PC1	Ele, Lat, RC, SI, AP, Lk, DH, DH²	8	0	0.87	0.93	1.00
	Ele, Lat, RC, SI, AP, Lk, DH	7	6.3	0.87	0.04	22.7
	Ele, Lat, RC, SI, AP, Lk	6	7.2	0.87	0.03	34.7
	Ele, Lat, RC, SI, AP	5	26.8	0.86	0.00	6.13×10^5
	Ele, Lat, RC, SI	4	48.8	0.86	0.00	3.61×10^{10}
	Ele, Lat, RC	3	92.7	0.84	0.00	1.21×10^{20}
	Ele, Lat	2	250	0.79	0.00	1.81×10^{54}
	Ele	1	734	0.52	0.00	1.68×10^{159}
	AWT, Ele, Lat, ATV₅, DH, RC, DA, Lk	8	0	0.63	0.61	1.00
PC2	AWT, Ele, Lat, ATV ₅ , DH, RC, DA	7	1.8	0.63	0.25	2.39
	AWT, Ele, Lat, ATV ₅ , DH, RC	6	3.5	0.63	0.11	5.46
	AWT, Ele, Lat, ATV ₅ , DH	5	6.5	0.62	0.03	2.39×10^1
	AWT, Ele, Lat, ATV ₅	4	15	0.62	0.00	1.65×10^3
	AWT, Ele, Lat	3	26.2	0.61	0.00	4.40×10^5
	AWT, Ele	2	221.7	0.45	0.00	1.23×10^{48}
	AWT	1	402.5	0.25	0.00	2.23×10^{87}

Notes: DH², quadratic effect of dam height; ATV₅, standard deviation of mean August air temperature.

SUPPORTING INFORMATION

Additional supporting information may be found online under the Supporting Information tab for this article: (1) a high-resolution digital map showing 578 water temperature monitoring sites, locations of dams, and 343,000 km perennial stream and river network in the western U.S., (2) time-series plots of mean daily water temperatures at fifteen representative stream and river sites, and (3) time-series plots of mean daily water temperatures upstream and downstream of eight dams.

DATA AVAILABILITY

All water temperature data used in this study are available at the NorWeST website (<https://www.fs.fed.us/rm/boise/AWAE/projects/NorWeST.html>). An ArcGIS shapefile with values of PC1 and PC2 scores predicted by multiple linear regressions at 1-km resolution throughout the 343,000 km network of perennial streams in the western U.S. is also available at the NorWeST website. The data set used for analyses with covariates and water temperature metrics is available at the lead author's ResearchGate profile (https://www.researchgate.net/profile/Daniel_Isaak).

ACKNOWLEDGMENTS

We thank the many individual biologists that contributed their temperature data that were used to constitute the NorWeST database. Several supplementary data records used in this research were provided by Lee Mabey and Steve Hirtzel with the U.S. Forest Service, Dan Dauwalter and Kurt Fesenmeyer with Trout Unlimited, Rick Wilkison with Idaho Power, and Zach Herzfeld with EcoSystems Sciences. Comments from two anonymous reviewers improved the quality of the final manuscript. The authors were supported by the U.S. Forest Service, Rocky Mountain Research Station during preparation of this manuscript.

AUTHORS' CONTRIBUTIONS

Dan J. Isaak: Conceptualization; formal analysis; funding acquisition; investigation; methodology; project administration; visualization; writing-original draft; writing-review & editing. **Charles H. Luce:** Conceptualization; formal analysis; writing-original draft; writing-review & editing. **Dona L. Horan:** Data curation; visualization. **Gwynne L. Chandler:** Data curation; resources; visualization. **Sherry P. Wollrab:** Data curation; resources; validation. **William B. Dubois:** Data curation; resources. **David E. Nagel:** Resources; visualization.

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