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Principle components of thermal regimes in mountain river networks

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Abstract. Description of thermal regimes in flowing waters is key to understanding physical processes, enhancing predictive abilities, and improving bioassessments. Spatially and temporally sparse datasets, especially in logistically challenging mountain environments, have limited studies on thermal regimes but inexpensive sensors coupled with crowd-sourced data collection efforts provide efficient means of developing large datasets for robust analyses. Here, thermal regimes are assessed using annual monitoring records spanning a five-year period (2011–2015) at 226 sites across several contiguous montane river networks in the northwestern U.S. Regimes were summarized with 28 metrics and principle components analysis (PCA) was used to determine those metrics which best explained thermal variation on a reduced set of orthogonal axes. Four principle components (PC) accounted for 93.4% of the variation in the temperature metrics, with the first PC (49% of variance) associated with metrics that represented magnitude and variability and the second PC (29% of variance) associated with metrics representing the length and intensity of the winter season. Another variant of PCA, T-mode analysis, was applied to daily temperature values and revealed two distinct phases of spatial variance—a homogeneous phase during winter when daily temperatures at all sites were < 3 °C and a heterogeneous phase throughout the year's remainder when variation among sites was more pronounced. Phase transitions occurred in March and November, and coincided with the abatement and onset of subzero air temperatures across the study area. S-mode PCA was conducted on the same matrix of daily temperature values after transposition and indicated that two PCs accounted for 98% of the temporal variation among sites. The first S-mode PC was responsible for 96.7% of that variance and correlated with air temperature variation (r = 0.92) whereas the second PC accounted for 1.3% of residual variance and was correlated with discharge (r = 0.84). Thermal regimes in these mountain river networks were relatively simple and responded coherently to external forcing factors, so sparse monitoring arrays and small sets of summary metrics may be adequate for many aspects of their description. PCA provides a computationally efficient means of extracting key information elements from large temperature datasets and could be applied broadly to facilitate comparisons among more diverse stream types and develop classification schemes for thermal regimes.

1 Introduction

Temperatures of flowing waters control many physicochemical processes (Likens and Likens, 1977; Gordon et al., 1991; Ducharne, 2007) and affect the ecology of aquatic organisms and communities (Isaak et al., 2017a; Neuheimer and Taggart, 2007; Woodward et al., 2010). The annual sequence of temperatures characteristic to specific locations within a river network constitutes the local thermal regime (Caissie, 2006), of which knowledge is key to understanding natural conditions and diagnosing anthropogenic impairments. Seminal work by Poff and colleagues (Poff and Ward, 1989; Poff et al., 1997) created a robust framework for describing flow regimes based on metric descriptions of magnitude, frequency, timing, duration, and variability that are largely transferrable to thermal regimes (Poole et al., 2004; Olden and Naiman, 2010). Recent studies have contributed useful derivations of temperature metrics (Arismendi et al., 2013; Chu et al., 2010; Rivers-Moore et al., 2013; Steel et al., 2016) or classification schemes based on a small number of pre-selected metrics (Maheu et al., 2016) but the limited availability of annual temperature records (Orr et al., 2015; Isaak et al., 2018) has slowed broad development and adoption of thermal regime concepts. Data inadequacies are often compounded for montane riverscapes that are difficult to sample (Brown and Hannah, 2008; Isaak et al., 2013), a shortfall that needs to be overcome given the importance of these areas as climate refugia for cold-water biodiversity (Brown et al., 2009; Isaak et al., 2016) and as the focus of costly regional conservation strategies (Roni et al., 2002; Rieman et al., 2015).

Despite existing limitations, the importance of temperature to stream biota is well recognized and inculcated to regulatory standards based on metrics used within threshold-based approaches (Poole et al., 2004; Todd et al., 2008). Most often, those metrics represent some aspect of conditions during warm summer months when temperature sensitive species or life stages are thought to be most vulnerable (Ice et al., 2004; McCullough, 2010), which may contribute to the preponderance of short monitoring records that span only these months (Isaak et al., 2017b). However, thermally mediated ecological processes occur throughout the year (Neuheimer and Taggart, 2007; Olden and Naiman, 2010), so adequate understanding requires broader characterization of thermal conditions from annual datasets. That may bring additional complexity but most warm season metrics are strongly correlated and therefore redundant (Isaak and Hubert, 2001; Dunham et al., 2005; Steel et al,. 2016). If redundancy is also the norm among a broader array of annual temperature metrics, then multivariate data reduction techniques might be useful for identifying a few key aspects of thermal regimes.

Supporting that idea, Rivers-Moore et al. (2013) used Principle Components Analysis (PCA) to describe covariation among 39 temperature metrics calculated for 82 South African stream sites and found that two PCs accounted for 75% of the total variation among metrics. Similarly in the field of hydrology, Olden and Poff (2003) examined 171 flow metrics calculated from 420 gage sites across the U.S. and found that two to four PCs accounted for 76–97% of variation in the dataset. In addition to metric-based PCA that is commonly used in hydrological sciences, several other PCA

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variants are standard analytical tools in the field of climatology and may be relevant for characterizing thermal regimes (Richman, 1986; Demsar et al., 2013). Most notably, PCA can be done on repeated measurements of a single variable to identify common spatial or temporal behavior among monitoring stations. In the climatology literature, empirical orthogonal function analysis (S-mode PCA in the taxonomy of Richman (1986)) is used to determine which sites covary temporally as a means of developing regionalization schemes for precipitation, air temperatures, or wind speeds (Piechota et al., 2001; Jimenez et al., 2008; Martins et al., 2012). If common temporal patterns are identified, it suggests potential redundancy in the monitoring network and the information can be used to refine future sampling designs. The closely allied T-mode PCA identifies dominant spatial patterns in datasets and the times when these phases occur (Richman, 1986; Gallacher et al., 2016). A single dominant spatial pattern suggests the spatial distribution of a variable is temporally consistent whereas more than one spatial phase suggests change points and alternate states.

The advent of inexpensive sensors, combined with regulatory requirements and concerns about climate change, have led to a recent expansion in lotic temperature monitoring networks (Rivers-Moore et al., 2013; Hilderbrand et al., 2014; Luce et al., 2014; Trumbo et al., 2014; Hannah and Garner, 2015; Isaak et al., 2017b; Jackson et al., 2016; Molinero et al., 2015; Daigle et al., 2016; Mauger et al., 2016; Steele et al., 2016). What was once a data dearth is becoming a deluge and opportunities exist to study thermal regimes with robust datasets. Here, we use annual temperature records compiled from several natural resource agencies for 226 monitoring sites in a mountainous landscape to conduct an initial assessment of thermal regimes. We limit the geographic scope of our effort to several adjacent river basins in the northwestern U.S. that are geologically and topographically similar but which have particularly dense monitoring networks to maximize analytical flexibility. Our objectives were to: 1) provide a basic description of the annual thermal characteristics in mountain rivers and streams because these are rare within the literature, 2) develop metrics to describe thermal regime characteristics based on magnitude, frequency, timing, duration, and variability, and 3) explore redundancy and patterns of spatiotemporal covariance among those metrics and monitoring sites to determine the principle components of thermal regimes in montane river networks. Findings are discussed with regards to the implications for temperature monitoring and modeling, thermal ecology, and as an initial step towards broader regional classification efforts.

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2 Study area

The study area encompasses 79,500 km^2 of mountainous, topographically complex terrain that spans a broad elevation range of 200–3,600 m (Figure 1). Climate is characterized by cold, wet winters with moderate to heavy snow accumulations at high elevations and hot, dry summers. Hydrographs are typical of snowmelt runoff systems, with high flows during spring and early summer and low flows during late summer, fall, and winter (Figure 2). Vegetation is dominated by conifer forests except at low elevations and south facing aspects where grasses and shrubs predominate. Wildfires are common within the landscape and burned 8% of the area from 2011 to 2015 (Morgan et al., 2014). Parent geology consists mostly of resistant granites of the Idaho Batholith and a smaller easterly portion of intrusive volcanics (Bond and Wood, 1978; Meyer et al., 2001). Both geologies are heavily dissected and stream valleys are V-shaped except for some alpine valleys at the highest elevations that were once glaciated. Human population densities are low except along wider segments of river valleys where fertile floodplains and easy access to water accommodate small amounts of agriculture and ranching. Most of the study area is publically owned (81%) and federally administered by the National Forest Service and Bureau of Land Management for a variety of land-use, recreational, and conservation purposes. Unpaved road networks have been developed in some drainages for timber harvest but many drainages are protected in large wilderness areas with minimal anthropogenic effects or roads (Swanson, 2015).

2.1 River networks and temperature dataset

Rivers and streams within the study area were delineated using the 1:100,000-scale National Hydrography Dataset (NHD; http://www.horizon-systems.com/NHDPlus/index.php; McKay et al., 2012), which was attributed with mean annual flow values from data at the Western U.S. Stream Flow Metrics website (http://www.fs.fed.us/rm/boise/AWAE/projects/modeled_stream_flow_metrics.shtml; Wenger et al., 2010). To highlight the perennial subset of the network where temperature monitoring occurred, reaches with annual flows less than 0.03 m^3/s were removed from the network, as were reaches with channel slopes >15%, and those coded as intermittent in the NHD (Fcode = 46003). Filtering reduced the original network extent from 58,000 km to 29,600 km with streams flowing at elevations of 200–2,600 m. To visualize thermal heterogeneity in the network, a scenario representing mean August temperatures for a baseline climate period of 1993–2011 was downloaded from the Northwestern Stream Temperature website (NorWeST:

https://www.fs.fed.us/rm/boise/AWAE/projects/NorWeST.html; Isaak et al., 2017b) and linked to the NHD river reaches. Several large rivers drain the area in a generally westerly direction, the largest of which is the Salmon River with a mean annual discharge of 315 m^3/s and a basin that comprises 44% of the study area. Six large dams and reservoirs occur in downstream portions of the network (three in the Boise River basin, two in the Payette River basin, and one in the Clearwater River basin) but these affect thermal conditions in less than 300 km of river and no temperature data were used from these sections.

To obtain a temperature dataset for analysis, we intersected the filtered network with the NorWeST database of daily temperature summaries (Chandler et al., 2016) and extracted data for sites that had mean daily temperature values on at least 70% of the days from December 1, 2010 to November 30, 2015. We started the thermal year on December 1 because temperatures usually reach their annual lows by this date and the 3-month period thereafter constituted a logical winter season (i.e., December, January, February). Subsequent three-month periods were considered to be spring (March, April, May), summer (June, July, August), and fall seasons (September, October, November). NorWeST temperature records were supplemented with additional data solicited from hydrologists and fisheries biologists employed by the Idaho Department of Fish and Game and the U.S. Forest Service, and we also downloaded data from online databases maintained by the Columbia Habitat Monitoring Program (https://www.champmonitoring.org/Home/Index) and the NOAA Northwest Fisheries Science Center (https://www.webapps.nwfsc.noaa.gov/WaterQuality/). Geographic gaps in monitoring were identified using geospatial analysis (e.g., Jackson et al., 2016) and additional sensors were strategically deployed where needed (Isaak et al., 2010; 2013). Data from the different sources were often recorded at different sub-daily intervals, so records were summarized to mean daily temperatures for standardization. Data were collected using different sensor models (TidbiT, Stowaway, and Pendant models from Onset Computer Corporation, Pocasset, Massachusetts, USA; Temp101a model from MadgeTech, Warner, New Hampshire, USA), which had measurement accuracies of +/-0.2°C to +/-0.5°C and resolutions of 0.02°C to 0.14°C based on manufacturer specifications and calibration tests we performed. Sensors were deployed using underwater epoxy or steel cables for connection to large boulders and other immobile channel structures and were shielded from direct sunlight (Isaak et al., 2013; Stamp et al., 2014). Temperature records were subject to standard quality assurance-quality control measures as described elsewhere (Chandler et al., 2016).

The stream temperature dataset consisted of records from 226 sites across a range of elevations, stream sizes, and reach slopes (Figure 1; Table 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 88%. Missing values in records were imputed using the MissMDA package (Missing Values with Multivariate Data Analysis; Josse and Husson, 2016) in R (R 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 daily temperatures and predictions from the imputation technique, which ranged from r = 0.98 to 0.99. All temperature records at the 226 sites were complete after imputation and consisted of 1,826 mean daily temperatures from December 1, 2010 to November 30, 2015. Climatological variation during the same period was described using discharge data downloaded from the National Water Information System database (https://waterdata.usgs.gov/usa/nwis/nwis) for a high-elevation gage site at 1,850 m and a low-elevation gage site at 294 m and air temperature data from monitoring stations in the Cooperative Observer Network (https://www.ncdc.noaa.gov/data-access) that were near each gage (Figure 1).

3 Data analysis

3.1 PCA of thermal metrics

Prior to calculating metrics for thermal characteristics, mean daily temperatures for 365 days were calculated from the five-years of data at each site to provide representative values for each day. Twenty-eight temperature metrics were then calculated to describe aspects of that annual record based on five categories associated with magnitude, variability, frequency, timing, and duration (Table 2). Metrics were similar to those used in previous studies of thermal regimes (Arismendi et al., 2013; Chu et al., 2010; Rivers-Moore et al., 2013; Steel et al., 2016) and in studies assessing the effects of peak summer temperatures on the distribution and abundance of aquatic organisms (Dunham et al., 2003; Huff et al., 2005; Isaak et al., 2017a). Relationships among the thermal metrics were described by conducting PCA on a data matrix in which columns represented the 28 metrics and rows were the 226 monitoring sites. Linear combinations of the data were estimated with coefficients equal to the eigenvectors of their correlation matrix, which were the principal components (PCs; Pearson, 1901; Sergeant et al., 2016). The first principal component accounted for the largest possible variance in the dataset and succeeding components accounted for the largest portions of the remaining variance while being orthogonal (i.e., uncorrelated) to the preceding components. Correlations, or loadings, between each metric and the PCs were also calculated to assist in subsequent interpretations. The Princomp procedure was used to conduct the PCA (SAS Institute, 2015). To understand geographical relationships, PC scores were mapped to the 226 temperature sites and bivariate correlations were calculated with descriptors of major environmental gradients such as elevation, reach slope, and discharge.

3.2 PCA of daily water temperatures

To assess the consistency of spatial temperature patterns among monitoring sites, a T-mode PCA (Richman, 1986) was done on a data matrix of mean daily temperatures in which the columns were the 365 days starting on December 1 and the rows were the 226 monitoring sites. In this analysis, the number of principle components explaining significant variation indicates the number of distinct spatial phases that occur throughout the year (Gallacher et al., 2016). Eigenvector loadings on the dominant PCs were plotted for each day of the year to describe when each phase occurred, and mean daily temperatures were mapped during these periods for visualization.

To assess temporal covariance among sites, a S-mode PCA (Richman, 1986) was done by transposing the T-mode data matrix so that monitoring sites were columns and the time ordered daily mean temperatures were rows. Because hydroclimatic conditions among years could have affected the results, the S-mode PCA was done not only for the five-year averages of daily water temperatures but also on the disaggregated time series of 1,826 daily values at the 226 monitoring sites. Concordance between the S-mode PC scores, air temperature, and discharge were examined posthoc by plotting standardized time-series and calculating bivariate correlations.

4. Results

Water temperatures within the study area network exhibited spatial and temporal variation reflective of the local topography, drainage basin characteristics, and annual hydroclimatic cycles. The annual temperature cycle is illustrated in Figure 2 by the slopes of linear regressions between mean monthly temperatures and elevation at the 226 monitoring sites throughout the course of one year in 2013. No trend occurred relative to elevation during cold winter months (0˚C / m) when many sites had water temperatures at or near 0˚C and were often exposed to subzero air temperatures. As temperatures warmed during the spring a small elevation trend appeared, which became most

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pronounced (approximately -0.0037˚C / m) when peak temperatures occurred during the months of July and August. Examples of inter-annual variation are shown in Figure 3, which contrasts the extreme conditions observed in 2011 and 2015. The former year was relatively cool with a large winter snow accumulation and subsequent spring runoff, whereas 2015 had below average snowfall, low runoff, and particularly warm early summer air temperatures. As a result, the median discharge date occurred 1–2 months earlier in 2015 than in 2011 and peak water temperatures were 4–5 °C warmer.

Four PCs accounted for 93.4% of the variation in the 28 temperature metrics (Table 4). The first PC explained 49% of the variation and was strongly correlated with metrics that represented magnitude and variability during most seasonal periods. Correlations between PC1 scores and elevation (r = -0.59) and mean flow (r = 0.58) suggested gradients in these environmental factors were important controls on this component of thermal regimes (Table 5). PC2 explained 29% of thermal variation and represented the length and intensity of the winter period, with strong loadings for mean winter temperature, minimum temperature, and timing metrics that determine growing season length based on degree day accumulations. PC3 accounted for 9.8% of total variation and was associated with summer temperature variability and two timing metrics, whereas PC4 accounted for 5.6% of thermal variance. An ordination plot of scores from the two dominant PCs showed a symmetrical distribution except for several sites with large positive scores on the first axis that were from large rivers at low elevations and had the warmest temperatures (Figure 4). A map of PC1 scores indicated that the spatial pattern in magnitude and variability (Figure 4b) was congruent with the network scenario of mean August temperatures as would be expected (Figure 1). In fact, the correlation between PC1 scores and the August scenario predictions at the 226 monitoring sites was strong at r = 0.86. The PC2 map showed several clusters of stream sites with high scores scattered throughout the study area. Those sites tended to occur in higher elevation basins where reach slopes were low (Table 5).

In the T-mode analysis, the first two PCs explained 88% of the total variation in mean daily temperatures. A plot of the daily eigenvector loadings indicated that one distinct spatial phase occurred in the winter and a second phase spanned the year's remainder (Figure 5). Phase transitions occurred around days 100 and 350, which closely aligned with the abatement and onset of subzero air temperatures in the study area (Figure 2). Figure 6 illustrates the spatial patterns characteristic of the two phases by mapping mean daily water temperatures at the monitoring sites on days 50 and 250, which occurred in mid-January and late July, respectively. Temperatures during the winter phase were spatially homogenous and exhibited a narrow range from 0 °C to 2.5 °C whereas the non-winter phase was heterogeneous and had a broader temperature range from 7.6 °C to 23.4 °C.

In the S-mode analysis, the first PC accounted for 98% of the variation when applied to the average year of 365 daily temperatures at the 226 monitoring sites. Nearly an identical result was obtained when the analysis was repeated on the disaggregated time-series of 1,826 daily temperatures, as PC1 then explained 96.7% of total variation (Figure 7a). The correlation between PC1 scores and mean daily air temperatures in the disaggregated series was strong (r = 0.94), suggesting that water temperatures responded in a coherent manner to temporal variation in air temperatures at the two monitoring stations. A second PC accounted for 1.3% of water temperature variation in the disaggregated series and was strongly correlated with mean daily discharge at the two flow gages (r = 0.83). Plots of the PC scores revealed nonlinearities in the air-water temperature relationship likely caused by subzero air temperatures during portions of the year and hysteresis wherein discharge levels mediated water temperature responses to air temperature variation (Figure 7c, d, e, f). In the latter case, water temperatures were less sensitive to air temperature variation on the ascending limb of the hydrograph than on the descending limb.

5 Discussion

5.1. Thermal regime characteristics

Thermal regimes in the mountain river networks we studied were relatively simple and responded coherently to climatic conditions and runoff patterns. Little evidence existed for subdomains or regionalization within the study area, probably because streams drained similar geologies and sample sites spanned a limited spatial extent relative to the scales at which heterogeneity in weather patterns occurred. Moreover, strong seasonal climate cycles and annual pulses of snowmelt runoff are dominant temporal factors that also served to synchronize temporal variation in water temperatures across this landscape. At larger spatial extents, a greater range of hydroclimates and geological conditions should increase stream diversity and distinctive thermal behaviors would be expected to emerge that are characteristic of regionalization. In a continental-scale assessment, Maheu et al. (2016) concluded that streams in the northwestern U.S. exhibit at least four types of thermal regimes but the density of sampling locations supporting that claim was relatively sparse and opens the possibility that additional types may exist.

Similar to previous studies that have assessed multiple thermal metrics (Isaak and Hubert, 2001; Dunham et al., 2005; Steele et al., 2016), we observed strong correlations and redundancies among metrics. The metric-based PCA suggested that 2–3 metrics were adequate for describing the main components of thermal regimes in the study networks. The first component could be represented by any of several non-winter magnitude metrics that loaded strongly on PC1 (e.g., mean annual temperature, annual degree days, mean spring, summer, or fall temperatures, short-term maximums); whereas PC2 could be represented by metrics for winter magnitude or growing season length. The relative simplicity of thermal regimes in this mountain landscape was similar to that observed by Rivers-Moore et al. (2013) in a comparable PCA for South African streams. The metrics assessed in each study differed slightly and our mountain streams had a distinct homogenous winter phase characterized by near zero temperatures but in both instances, PC1 accounted for ~50% of variation and PC2 accounted for ~30% of variation.

5.2. Implications for monitoring and bioassessments

Within mountain landscapes characterized by uniform geohydroclimates, the coherent behavior we observed among sites suggests that a limited number of monitoring stations can represent temporal dynamics in thermal regimes. Those sites would need to be spread geographically and along major environmental gradients and replicated to mitigate against sensor losses, but 10–30 stations might prove sufficient at scales comparable to our study area. Given low costs, the availability of standard protocols (Isaak et al., 2013; Stamp et al., 2014), and growing interest in temperature monitoring (Daigle et al., 2016; Isaak et al., 2017b), monitoring arrays could also be crowd-sourced effectively if site locations were coordinated and chosen strategically using geospatial analyses to describe and stratify networks for sample allocation (Jackson et al., 2016). Monitoring networks might also be supplemented by incorporating sites established for other factors such as documenting thermal responses to habitat restoration efforts (Nichols and Ketcheson, 2013) or disturbances associated with land management, wildfires, or livestock grazing (Mahlum et al., 2011; Nussel et al., 2015). In fact, those factors motivated collection of many of the datasets compiled for this analysis, although supplementation with additional sites was needed to ensure representative coverage. If one monitoring goal is to develop accurate prediction maps showing spatial variation in one or more thermal metrics (e.g., Isaak et al., 2017b), sites may also need to be more densely sampled than the above considerations otherwise suggest. Spatial autocorrelation in temperature metric values is minimal beyond network distances of 10–100 km (Isaak et al., 2010), so similar sensor spacing is required to generate the most accurate maps. Given the extent of most river networks, that would often translate to a large number of sites but most of these could be monitored for short periods while temporal dynamics were represented by a subset of long-term sites since temporal covariance among sites would be strong.

Water temperature is often monitored because of its importance to aquatic organism phenology (Neuheimer and Taggart, 2007), distributions, and abundance (Isaak et al., 2017a). The majority of previous assessments, however, focus on biothermal relationships associated with magnitude metrics, which has prompted calls to “move beyond the mean” and consider thermal regimes more broadly (Steel et al., 2012; Dillon et al., 2016). PCA is a useful tool for pursuing that goal, in that it enables identification and selection of meaningful metrics that are distinct from mean conditions while also providing eigenvector loadings that describe orthogonal axes which could be used to replace summary metrics with uncorrelated synthetic temperature variables. In either instance, the relevance of thermal regime components should be more readily ascertained in biological models (Garcia et al., 2014), the potential for multicollinearity and model bias reduced, and confusion caused by the proliferation and use of redundant thermal metrics partially stemmed (Roberts et al., 2013; DeWeber and Wagner, 2018). New challenges will emerge regarding the need to measure or predict relevant thermal metrics in concert with biological phenomena but growing temperature databases and ongoing advances in network scale stream-temperature models may soon provide those capabilities (Gallice et al., 2015; Isaak et al., 2017b; Jackson et al., 2017).

5.3. Conclusion

Our analysis of thermal regimes follows previous work that has proven fundamental to advancing the understanding of hydrologic regimes (Poff et al., 1997; Olden and Poff, 2003) but also adds novel applications of T-mode and S-mode PCA from the field of climatology that hold utility for stream temperature research and monitoring design. Thermal conditions in the mountain river networks studied here were strongly coherent through time, exhibited two distinct spatial phases, and were adequately described by a few principle components or allied metrics. A logical next step is application of PCA tools to larger stream and river temperature datasets that span regional, continental, or intercontinental scales to discern distinct regime aspects and the geographic domains where they are operable. Results from such undertakings would support the broad framework already outlined by Maheu et al. (2016) but if accomplished with spatially dense datasets, might also provide information relevant to local prescriptions concerning biological or habitat impairments (Rivers-Moore et al., 2013). As research on the topic of thermal regimes matures, syntheses with flow regime concepts and datasets could also be sought to more fully describe the hydroclimatic conditions of flowing waters.

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) whereas the full data set that includes air temperature and discharge data are available at the lead author's ResearchGate profile entry for this study (https://www.researchgate.net/profile/Daniel_Isaak).

Competing interests. The authors declare that they have no conflict of interest.

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References (Format these for HESS)

Arismendi, I., Johnson, S.L., Dunham, J.B., and Haggerty, R.: Descriptors of natural thermal regimes in streams and their responsiveness to change in the Pacific Northwest of North America, Freshwater Biology, 58, 880-894, 2013.

Bond, J.G. and Wood, C.H.: Geologic map of Idaho, 1:500 000 scale. Idaho Department of Lands, Bureau of Mines and Geology, Moscow, Idaho, 1978.

Brown, L.E., Cereghino, R., and Compin, A.: Endemic freshwater invertebrates from southern France: diversity, distribution and conservation implications, Biological Conservation, 142, 2613–2619, 2009.

Brown, L.E. and Hannah, D.M.: Spatial heterogeneity of water temperature across an alpine river basin, Hydrological Processes, 22, 954-967, 2008.

Caissie, D.: The thermal regime of rivers: a review, Freshwater Biology, 51, 1389–1406, 2006.

Carlisle, D.M., Grantham, T.E., Eng, K., and Wolock, D.M.: Biological relevance of streamflow metrics: regional and national perspectives, Freshwater Science, 36, 927-940, 2017.

Chandler, G.L., Wollrab, S., Horan, D., Nagel, D., Parkes, S., Isaak, D.J., Wenger, S.J., Peterson, E.E., Ver Hoef, J. M., Hostetler, S., Luce, C.H., Dunham, J.B., Kershner, J., and Roper, B.B.: NorWeST stream temperature data summaries for the western U.S. U.S. Forest Service, Rocky Mountain Research Station Research Data Archive, Fort Collins, CO, https://doi.org/10.2737/RDS-2016-0032, 2016.

Chu, C., Jones, N.E., and Allin, L.: Linking the thermal regimes of streams in the Great Lakes Basin, Ontario, to landscape and climate variables, River Research and Applications, 26, 221-241, 2010.

Daigle, A., Caudron, A., Vigier, L., and Pella, H.: Optimization methodology for a river temperature monitoring network for the characterization of fish thermal habitat, Hydrological Sciences Journal, 62, 483-497, 2016.

Demsar, U., Harris, P., Brunsdon, C., Fotheringham, A.S., and McLoone, S.: Principle components analysis on spatial data: An overview, Annals of the Association of American Geographers, 103, 106-128, 2013.

DeWeber, J. and Wagner, T.: Probabilistic measures of climate change vulnerability, adaptation action benefits, and related uncertainty from maximum temperature metric selection, Global Change Biology, 2018.

Dillon, M.E., Woods, H.A., Wang, G., Fey, S.B., Vasseur, D.A., Telemeco, R.S., Marshall, K., and Pincebourde, S.: Life in the frequency domain: the biological impacts of changes in climate variability at multiple time scales, Integrative and Comparative Biology, 56, 14-30, 2016.

Ducharne, A.: Importance of stream temperature to climate change impact on water quality, Hydrology and Earth System Sciences Discussions, 4, 2425-2460, 2007.

Dunham, J.B., Chandler, G., Rieman, B.E., and Martin D.: Measuring stream temperature with digital dataloggers: A user's guide, General Technical Report RMRSGTR-150WWW. U.S. Forest Service, Rocky Mountain Research Station, Fort Collins, Colorado, USA, 2005.

Dunham, J., Rieman, B., and Chandler, G.: 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, 2003.

Fuhrman, A.E., Larsen, D.A., Steel, E.A., Young, G., and Beckman, B.R.: Chinook salmon emergence phenotypes: Describing the relationships between temperature, emergence timing and condition factor in a reaction norm framework, Ecology of Freshwater Fish, 27, 350-362, 2018.

Gallacher, K., Miller, C., Scott, E.M., Willows, R., Pope, L., and Douglass, J.: Flow-directed PCA for monitoring networks, Environmetrics, 28, e2434, 2017.

Gallice, A., Schaefli, B., Lehning, M., Parlange, M.B. and Huwald, H.: 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, 2015.

Garcia, R.A., Cabeza, M., Rahbek, C., and Araújo, M.B.: Multiple dimensions of climate change and their implications for biodiversity, Science, 344, 1247579, 2014.

Gordon, N.D., McMahon, T.A., and Finlayson, B.L.: Stream hydrology: an introduction for ecologists, Stream hydrology: an introduction for ecologists, John Wiley and Sons, Chichester, UK, 1991.

Hannah, D. and Garner, G.: 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, 2015.

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

Huff, D.D., Hubler, S.L., and Borisenko, A.N.: Using field data to estimate the realized thermal niche of aquatic vertebrates, North American Journal of Fisheries Management, 25, 346–360, 2005.

Ice, G.G., Light, J., and Reiter, M.: Use of natural temperature patterns to identify achievable stream temperature criteria for forest streams, West. J. Appl. For., 19, 252–259, 2004.

Isaak, D.J. and Hubert, W.A.: A hypothesis about factors that affect maximum summer stream temperatures across montane landscapes, Journal of the American Water Resources Association, 37, 351-366, 2001.

Isaak, D.J., Luce, C.H., Rieman, B.E., Nagel, D.E., Peterson, E.E., Horan, D.L., Parkes, S., and Chandler, G.L.: Effects of climate change and wildfire on stream temperatures and salmonid thermal habitat in a mountain river network, Ecol. Appl., 20, 1350–1371, 2010.

Isaak, D.J., Luce, C., Horan, D., Chandler, G., Wollrab, S., Nagel, D.: Global warming of salmon and trout rivers in the northwestern U.S.: Road to ruin or path through purgatory?, Transactions of the American Fisheries Society, DOI: 10.1002/tafs.10059, 2018.

Isaak, D.J., Horan, D.L., and Wollrab, S.P.: A simple protocol using underwater epoxy to install annual temperature monitoring sites in rivers and streams, U.S. Forest Service General Technical Report, Rocky Mountain Research Station, 314, Fort Collins, Colorado, USA, 2013.

Isaak, D.J., Young, M.K. Luce, C.H. Hostetler, S. Wenger, S. Peterson, E.E. Ver Hoef, J.M. Groce, M. Horan, D.L. and Nagel D.: Slow climate velocities of mountain streams portend their role as refugia for cold-water biodiversity, Proceedings of the National Academy of Sciences, 113, 4374-4379, 2016a.

Isaak, D.J., Wenger, S.J., and Young, M.K.: Big biology meets microclimatology: Defining thermal niches of aquatic ectotherms at landscape scales for conservation planning, Ecological Applications, 27, 977-990, 2017a.

Isaak, D.J., Wenger, S.J., Peterson, E.E., Ver Hoef, J.M., Nagel, D.E., Luce, C.H., Hostetler, S.W., Dunham, J.B., Roper, B.B., Wollrab, S., Chandler, G., Parkes, S., and Horan, D.: The NorWeST summer stream temperature model and scenarios: A crowd-sourced database and new geospatial tools foster a user community and predict broad climate warming of rivers and streams in the western U.S., Water Resources Research, 53, 9181-9205, 2017b.

Isaak, D.J., Wenger, S.J., Peterson, E.E., Ver Hoef, J.M., Nagel, D.E., Luce, C.H., Hostetler, S.W., Dunham, J.B., Roper, B.B., Wollrab, S., Chandler, G., Parkes, S., and Horan, D.: NorWeST modeled summer stream temperature scenarios for the western U.S. U.S. Forest Service, Rocky Mountain Research Station Research Data Archive, Fort Collins, CO, https://doi.org/10.2737/RDS-2016-0033. 2016b.

Jackson, F.L., Malcolm, I.A., and Hannah, D.M.: A novel approach for designing large-scale river temperature monitoring networks, Hydrology Research, 47, 569-590, 2016.

Jackson, F.L., Fryer, R.J., Hannah, D.M., Millar, C.P., and Malcolm, I.A.: A spatio-temporal statistical model of maximum daily river temperatures to inform the management of Scotland's Atlantic salmon rivers under climate change, Science of the Total Environment, 612, 1543-1558, 2018.

Jiménez, P.A., García-Bustamante, E., González-Rouco, J.F., Valero, F., Montávez, J.P., and Navarro, J.: Surface wind regionalization in complex terrain, Journal of Applied Meteorology and Climatology, 47, 308–325, 2008.

Josse, J. and Husson, F.: Handling missing values in exploratory multivariate data analysis methods, Journal of the Société Française de Statistique, 153, 79-99, 2012.

Josse, J. and Husson, F.: missMDA: a package for handling missing values in multivariate data analysis, Journal of Statistical Software, 70, 1-31, 2016.

Likens, G.E. and Likens, G.E.: Biogeochemistry of a forested ecosystem, Springer-Verlag, 1977.

Luce, C.H., Staab, B., Kramer, M., Wenger, S., Isaak, D., and McConnell, C.: Sensitivity of summer stream temperatures to climate variability in the Pacific Northwest, Water Resour Res, 50, 3428-3443, 2014.

Maheu, A., Poff, N.L., and St-Hilaire, A.: A classification of stream water temperature regimes in the conterminous USA, River Research and Applications, 32, 896-906, 2016.

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

Martins, D.S., Raziei, T., Paulo, A.A., and Pereira, L.S.: Spatial and temporal variability of precipitation and drought in Portugal, Nat. Hazards Earth Syst. Sci., 12, 1493–1501, 2012.

Mauger, S., Shaftel, R., Leppi, J.C., and Rinella, D.J.: 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, 2016.

McCullough, D.A.: Are coldwater fish populations of the United States actually being protected by temperature standards?, Freshwater Reviews, 3, 147-199, 2010.

McKay, L., Bondelid, T., Dewald, T., Johnston, J., Moore, R., and Reah, A.: NHDPlus Version 2: User Guide. ftp://ftp.horizon-systems.com/NHDPlus/NHDPlusV21/Documentation/NHDPlusV2_User_Guide.pdf, 2012.

Meyer, G.A., Pierce, J.L., Wood, S.H., and Jull, A.J.T.: Fire, storms, and erosional events in the Idaho batholith, Hydrol. Process., 15, 3025–3038, 2001.

Molinero, J., Larrañaga, A., Pérez, J., Martínez, A., and Pozo, J.: Stream temperature in the Basque Mountains during winter: thermal regimes and sensitivity to air warming, Climatic Change, 134, 593-604, 2016.

Morgan, P., Heyerdahl, E., Miller, C., Wilson, A., and Gibson, C.: Northern Rockies pyrogeography: an example of fire atlas utility, Fire Ecology, 10, 14–30, 2014.

Neuheimer, A.B. and Taggart, C.T.: The growing degree-day and fish size-at-age: the overlooked metric, Canadian Journal of Fisheries and Aquatic Sciences, 64, 375-385, 2007.

Nichols, R.A., and Ketcheson, G.L.: A two-decade watershed approach to stream restoration log jam design and stream recovery monitoring: Finney Creek, Washington, Journal of the American Water Resources Association, 49, 1367-1384, 2013.

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

Olden, J.D. and Poff, N.L.: Redundancy and the choice of hydrologic indices for characterizing streamflow regimes, River Research and Applications, 19, 101-121, 2003.

Olden, J.D. and Naiman, R.J.: Incorporating thermal regimes into environmental flows assessments: modifying dam operations to restore freshwater ecosystem integrity, Freshwater Biology, 55, 86-107, 2010.

Orr, H.G., Johnson, M.F., Wilby, R.L., Hatton-Ellis, T., and Broadmeadow, S.: What else do managers need to know about warming rivers? A United Kingdom perspective, Wiley Interdisciplinary Reviews—Water, 2, 55-64, 2015.

Pearson, K.: On Lines and Planes of Closest Fit to Systems of Points in Space, Philosophical Magazine, 6, 559–572, 1901.

Piechota, T.C., Dracup, J.A., and Fovell, R.G.: Western US streamflow and atmospheric circulation patterns during El Nino-Southern Oscillation, Journal of Hydrology, 201, 249-271, 1997.

Poff, N.L. and Ward, J.V.: Implications of streamflow variability and predictability for lotic community structure: a regional analysis of streamflow patterns, Canadian Journal of Fisheries and Aquatic Sciences, 46, 1805–1818, 1989.

Poff, N.L., Allan, J.D., Bain, M.B., Karr, J.R., Prestegaard, K.L., Richter, B.D., Sparks, R.E., and Stromberg, J.C.: The natural flow regime, BioScience, 47, 769-784, 1997.

Poole, G.C., Dunham, J.B., Keenan, D.M., Sauter, S.T., McCullough, D.A., Mebane, C., Lockwood, J.C., Essig, D.A., Hicks, M.P., Sturdevant, D.J., and Materna, E.J.: The case for regime-based water quality standards, BioScience, 54, 155-161, 2004.

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

Richman, M.B.: Rotation of principal components, International Journal of Climatology, 6, 293-335, 1986.

Rieman, B.E., Smith, C.L., Naiman, R.J., Ruggeronee, G.T., Wood, C.C., Huntly, N., Merrill, E.N., Alldredge, J.R., Bisson, P.A., Congleton, J., Fausch, K.D., Levings, C., Pearcy, W., Scarnecchia, D., and Smouse, P.: A comprehensive approach for habitat restoration in the Columbia Basin, Fisheries, 40, 124-135, 2015.

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

Roberts, J.J., Fausch, K.D., Peterson, D.P., and Hooten, M.B.: Fragmentation and thermal risks from climate change interact to affect persistence of native trout in the Colorado River basin, Global Change Biology, 19, 1383-1398, 2013.

Roni, P., Beechie, T.J., Bilby, R.E., Leonetti, F.E., Pollock, M.M., and Pess, G.R.: A review of stream restoration techniques and a hierarchical strategy for prioritizing restoration in Pacific Northwest watersheds, North American Journal of Fisheries Management, 22, 1-20, 2002.

SAS Institute Inc. SAS/STAT 14.1 User's Guide Cary, NC, USA, 2015.

Sergeant, C.J., Starkey, E.N., Bartz, K.K., Wilson, M.H., and Mueter, F.J.: A practitioner's guide for exploring water quality patterns using principal components analysis and Procrustes, Environ Monit Assess, 188, 249, 2016.

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

Steel, E.A., Tillotson, A., Larsen, D.A., Fullerton, A.H., Denton, K.P., and Beckman, B.R.: Beyond the mean: the role of variability in predicting ecological effects of stream temperature on salmon, Ecosphere, 3, 1-11, 2012.

Steel, E.A., Beechie, T.J., Torgersen, C.E., and Fullerton, A.H.: Envisioning, quantifying, and managing thermal regimes on river networks, BioScience, 67, 506-522, 2017.

Steel, E.A., Sowder, C., and Peterson, E.E.: Spatial and temporal variation of water temperature regimes on the Snoqualmie River network, Journal of the American Water Resources Association, 52, 769-787, 2016.

Swanson, F.: Where roads will never reach: Wilderness and its visionaries in the Northern Rockies, University of Utah Press. Salt Lake City, Utah, 2015.

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

Wenger, S.J., Luce, C.H., Hamlet, A.F., Isaak, D.J., and Neville, H.M.: Macroscale hydrologic modeling of ecologically relevant flow metrics, Water Resources Research, 46:W09513, 2010.

Woodward, G., Perkins, D.M., and Brown, L.E.: Climate change and freshwater ecosystems: impacts across multiple levels of organization, Philosophical Transactions of the Royal Society B: Biological Sciences, 365, 2093-2106, 2010.

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Table 1. Descriptive statistics for spatial attributes of 226 monitoring sites with annual temperature data from mountain river networks in the northwestern U.S.

	Mean	Median	SD	Minimum	Maximum
Elevation (m)	1392	1407	464	280	2369
Drainage area (km^2)	687	47.3	3011	2.18	34865
Mean annual flow (m^3/s)	7.37	0.692	26.4	0.0253	281
Reach slope (%)	0.0389	0.0273	0.0403	0	0.206

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Table 2. Temperature metrics used to describe thermal regimes of mountain rivers and streams.

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 hours = 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. Fall standard deviation	Standard deviation of mean daily temperature during fall months
	V6. Range in extreme daily temperatures	Difference between minimum and maximum mean daily temperatures during a year (M9 minus M7)
	V7. Range in extreme weekly temperatures	Difference between minimum and maximum weekly average temperatures during a year (M10 minus M8)
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% of degree days	Number of days from December 1st until 5% of degree days are accumulated
	T2. Date of 25% of degree days	Number of days from December 1st until 25% of degree days are accumulated
	T3. Date of 50% of degree days	Number of days from December 1st until 50% of degree days are accumulated
	T4. Date of 75% of degree days	Number of days from December 1st until 75% of degree days are accumulated
	T5. Date of 95% of degree days	Number of days from December 1st 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

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Table 3. Descriptive statistics for temperature metrics used to describe thermal regimes at 226 monitoring sites in mountain river networks. Statistics were calculated from the imputed time-series and mean daily values for the period 2011–2015.

	Mean (°C)	Median (°C)	SD (°C)	Minimum (°C)	Maximum (°C)
M1. Mean annual temperature	5.36	5.10	1.44	3.10	10.34
M2. Mean winter temperature	0.75	0.63	0.60	-0.10	4.03
M3. Mean spring temperature	3.67	3.47	1.61	1.14	9.38
M4. Mean summer temperature	11.2	10.9	2.68	6.55	19.1
M5. Mean August temperature	12.5	12.1	2.78	7.78	22.5
M6. Mean fall temperature	5.71	5.50	1.53	3.04	11.5
M7. Minimum daily temperature	0.21	0.14	0.35	-0.45	2.18
M8. Minimum weekly average temperature	0.31	0.23	0.40	-0.42	2.69
M9. Maximum daily temperature	13.5	13.0	3.00	8.26	23.5
M10. Maximum weekly average temperature	13.2	12.7	2.99	7.96	23.2
M11. Annual degree days	1956	1863	527	1132	3775
V1. Annual standard deviation	4.43	4.27	1.05	2.51	7.40
V2. Winter standard deviation	0.30	0.29	0.16	0.00	0.87
V3. Spring standard deviation	1.62	1.57	0.72	0.33	5.36
V4. Summer standard deviation	1.99	1.88	0.61	0.61	4.45
V5. Fall standard deviation	3.43	3.34	0.73	2.13	6.05
V6. Range in extreme daily temperatures	13.3	12.8	3.06	7.50	23.3
V7. Range in extreme weekly temperatures	12.9	12.3	3.06	6.99	22.9
F1. Frequency of hot days	0.81	0	5.82	0	61
F2. Frequency of cold days	131	132	35.6	0	212
T1. Date of 5% of degree days	109	113	25.5	44	168
T2. Date of 25% of degree days	193	194	10.9	148	217
T3. Date of 50% of degree days	237	238	5.01	215	251
T4. Date of 75% of degree days	276	276	2.99	264	288
T5. Date of 95% of degree days	323	323	4.78	309	340
D1. Growing season length	214	210	29.7	141	296
D2. Duration of hot days	0.691	0	5.61	0	61
D3. Duration of cold days	124	124	39.0	0	207

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Table 4. Loadings of 28 temperature metrics on the first four principal components in a PCA of annual temperature records from mountain river networks in the northwestern U.S.

Temperature metric	PC1	PC2	PC3	PC4
M1. Mean annual temperature	0.99	-0.07	-0.05	-0.03
M2. Mean winter temperature	0.26	-0.92	0.14	0.00
M3. Mean spring temperature	0.91	-0.19	-0.25	0.04
M4. Mean summer temperature	0.97	0.21	-0.06	-0.05
M5. Mean August temperature*	0.95	0.22	0.16	-0.10
M6. Mean fall temperature	0.96	-0.18	0.14	-0.08
M7. Minimum daily temperature	-0.02	-0.86	0.08	-0.02
M8. Minimum weekly average temperature	-0.03	-0.90	0.08	0.00
M9. Maximum daily temperature	0.95	0.26	0.09	-0.08
M10. Maximum weekly average temperature	0.95	0.25	0.09	-0.07
M11. Annual degree days	0.99	-0.07	-0.05	-0.03
V1. Annual standard deviation	0.90	0.41	0.01	-0.07
V2. Winter standard deviation	0.69	-0.54	0.16	0.00
V3. Spring standard deviation	0.71	0.30	-0.55	0.04
V4. Summer standard deviation	0.42	0.32	0.78	-0.14
V5. Fall standard deviation	0.87	0.39	0.19	-0.12
V6. Range in extreme daily temperatures	0.93	0.33	0.08	-0.07
V7. Range in extreme weekly temperatures	0.93	0.33	0.08	-0.07
F1. Frequency of hot days	0.47	-0.01	0.30	0.82
F2. Frequency of cold days	-0.70	0.61	0.09	0.11
T1. Date of 5% of degree days	0.02	0.96	-0.10	0.01
T2. Date of 25% of degree days	-0.43	0.74	0.46	-0.08
T3. Date of 50% of degree days	-0.45	0.37	0.79	-0.16
T4. Date of 75% of degree days	-0.19	-0.51	0.72	-0.19
T5. Date of 95% of degree days	0.30	-0.88	0.12	-0.09
D1. Growing season length	0.03	-0.97	0.11	-0.03
D2. Duration of hot days	0.44	-0.03	0.32	0.84
D3. Duration of cold days	-0.64	0.66	0.07	0.11
Variance explained (%):	49.0%	29.0%	9.8%	5.6%
Cumulative variance (%):	49.0%	78.0%	87.8%	93.4%
Eigenvalue:	13.73	8.12	2.74	1.56

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Table 5. Correlations among stream temperature principle components and spatial attributes of 226 monitoring sites with annual data from river networks in the northwestern U.S.

	Elevation	Mean flow	Reach slope	PC1	PC2	PC3	PC4
Elevation	1						
Mean flow	-0.34	1					
Reach slope	-0.10	-0.23	1				
PC1	-0.59	0.58	-0.34	1			
PC2	0.27	-0.06	-0.49	0.00	1		
PC3	-0.23	0.35	0.13	0.00	0.00	1	
PC4	0.12	0.54	-0.02	0.00	0.00	0.00	1

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Fig. 1. Locations of 226 monitoring sites overlaid on an August stream temperature scenario for the 29,600 km network in the study area. Stars denote where air temperature and stream discharge data were obtained from a low-elevation site (294 m, northern station) and a high-elevation site (1850 m, southern station).

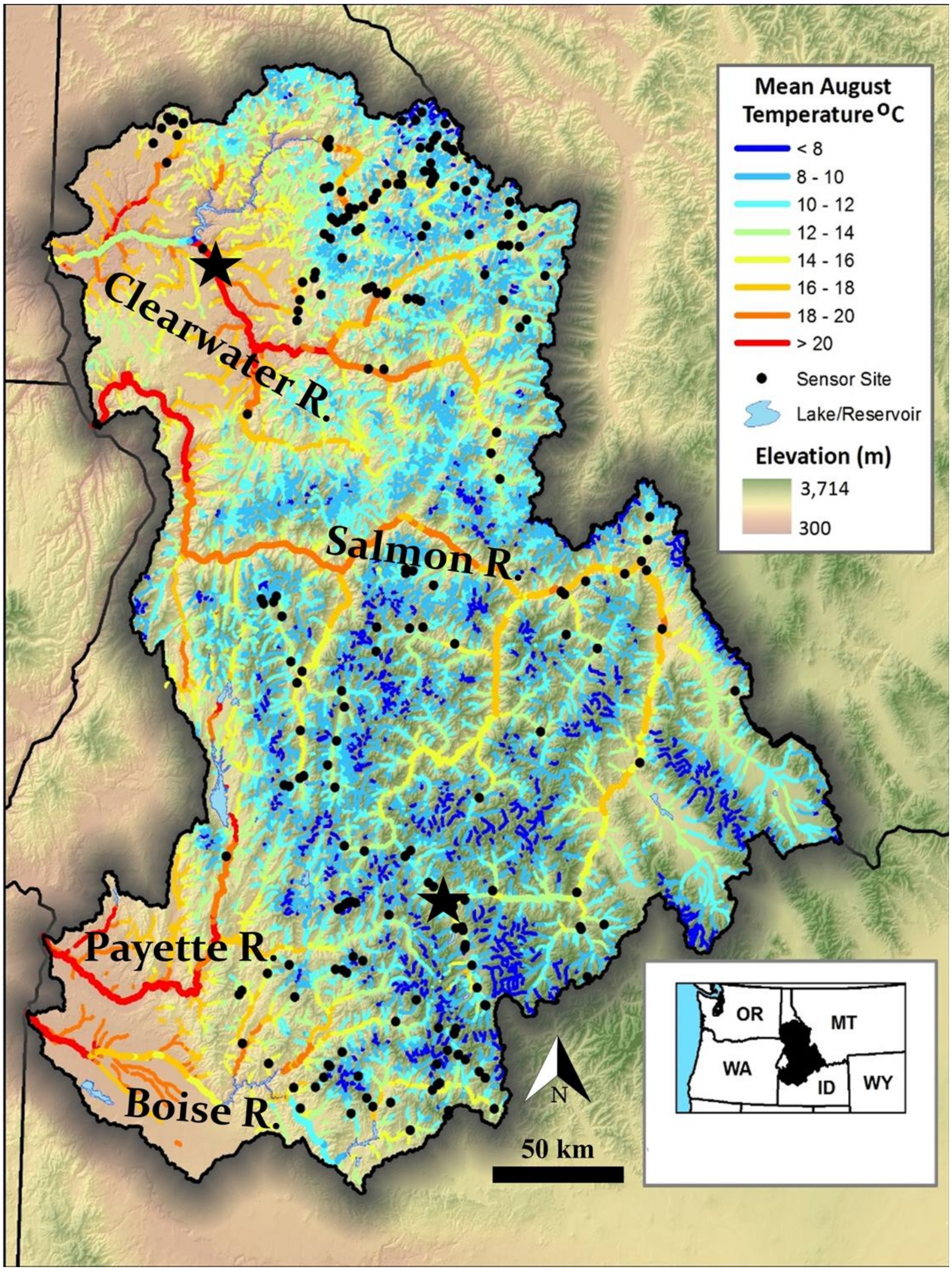
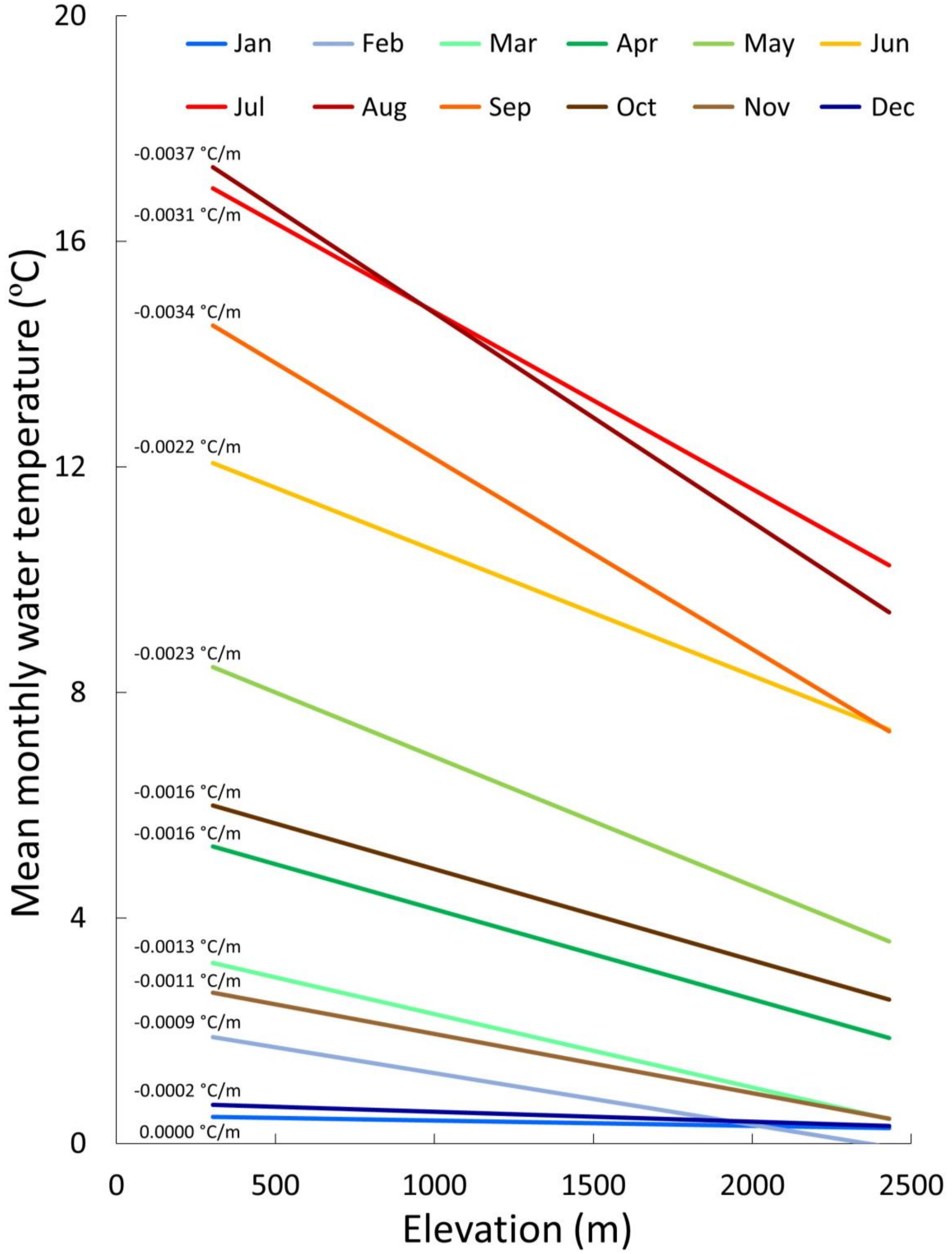


Fig. 2. Linear regression trends between elevation and mean monthly temperatures at 226 river and stream sites during 2013. Data values are not shown for clarity; slope values next to the regression trend lines are °C / m elevation.



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581 **Fig. 3.** Annual cycle of mean daily water temperatures (a), air temperatures (b), and discharge (c) at
582 a high-elevation site and a low-elevation site during two contrasting climate years. Discharge values
583 at the high elevation site are multiplied by ten for better visibility.

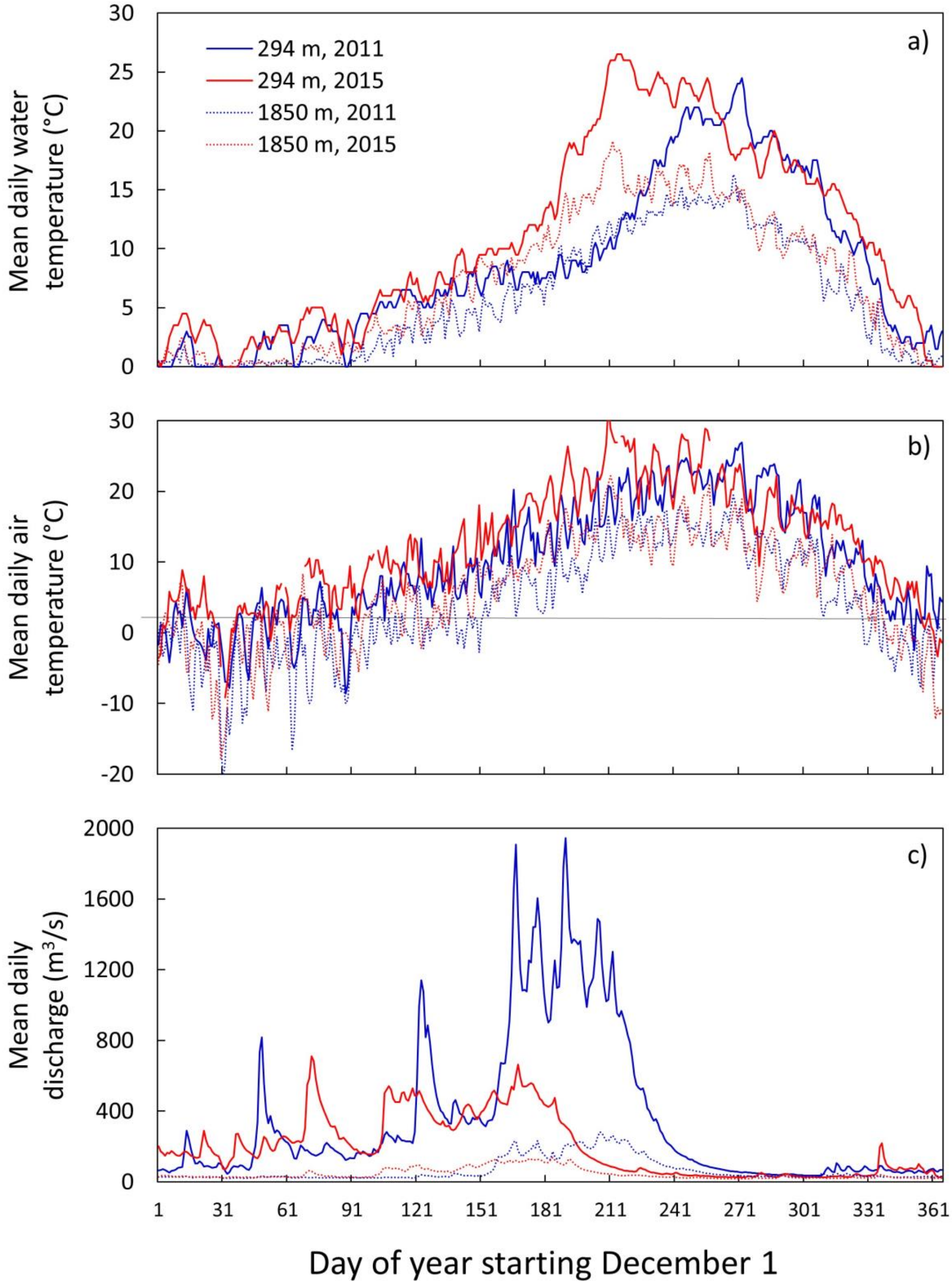

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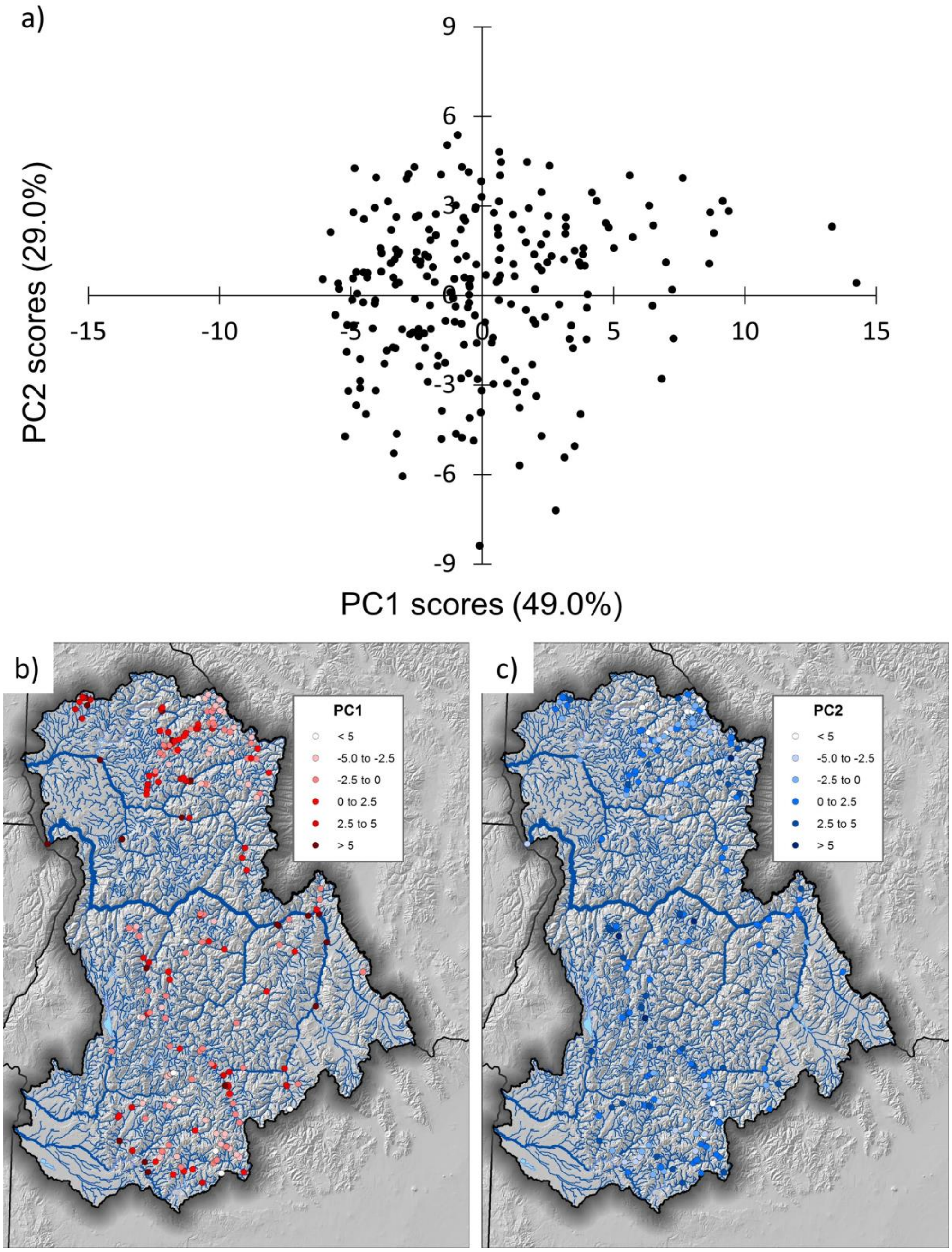
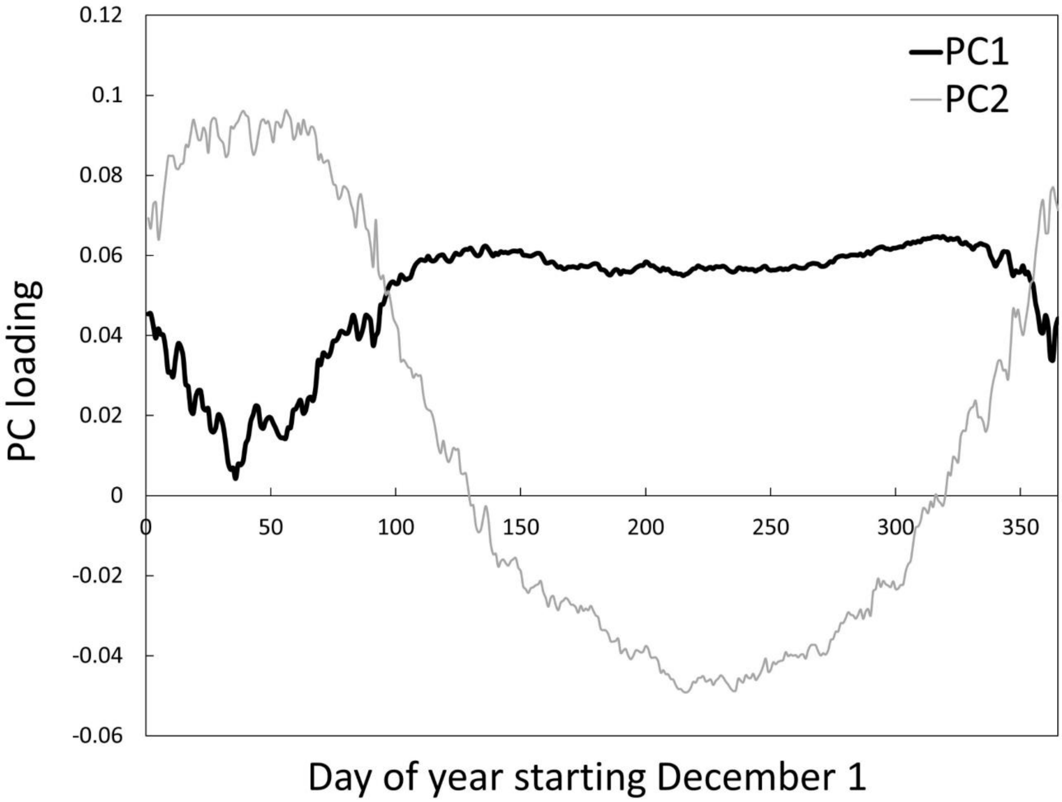
Fig. 4. PCA ordination plot of 226 stream sites based on 28 thermal metrics derived for annual data from mountain rivers and streams (a). Panels b and c show principle component scores mapped to network locations.



590 **Fig. 5.** T-mode PCA results showing the principle component eigenvector loadings throughout a
591 year to determine when dominant spatial phases occurred in water temperatures at 226 sites in
592 mountain rivers and streams in the northwestern U.S.



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594 **Figure 6.** Thermal patterns during two periods with distinct spatial phases based on T-mode PCA
595 results (a). Day 50 occurs in mid-January and was chosen to represent the homogenous winter
596 period (b) whereas day 250 occurs in late July and represents the heterogeneous period (c).

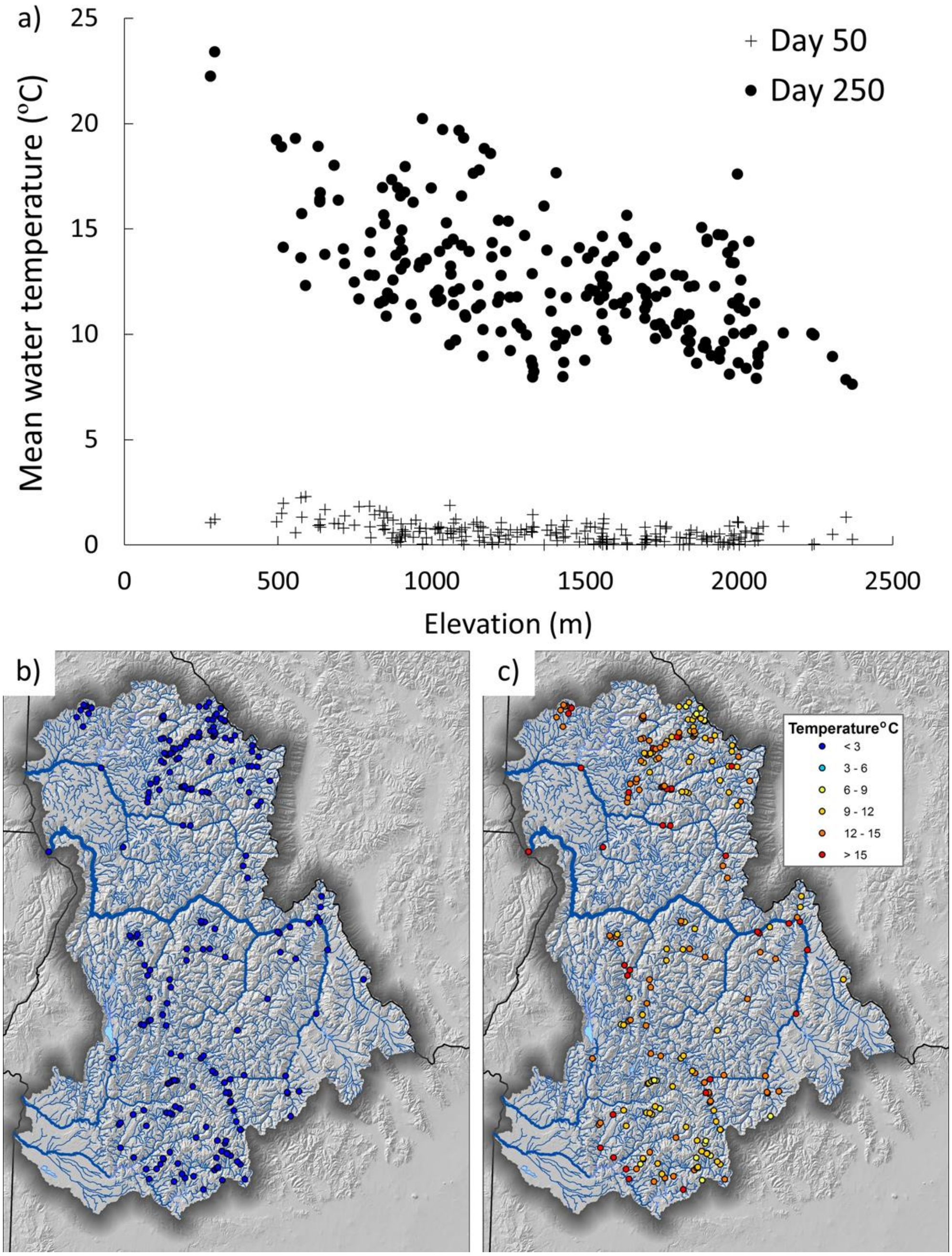

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Fig. 7. S-mode PCA results showing principle component scores to describe temporal patterns in mean daily water temperatures among 226 stream sites during five years (a and b). Daily air temperatures and discharge values from two monitoring stations are aligned with the PCs for comparative purposes. Graphs to the right show pairwise correlations among water temperature, air temperature, and discharge.