

1 **Higher statistical moments and an outlier detection technique as two alternative methods**
2 **that capture long-term changes in continuous environmental data**

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Running head: long-term changes in environmental data

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Ivan Arismendi^{1*}, Sherri L. Johnson² & Jason B. Dunham³

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17 ¹Department of Fisheries and Wildlife, Oregon State University, Corvallis, Oregon 97331, USA.

18 ²US Forest Service, Pacific Northwest Research Station, Corvallis, Oregon 97331, USA.

19 ³US Geological Survey, Forest and Rangeland Ecosystem Science Center, Corvallis, Oregon
20 97331, USA.

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22 *Corresponding author: Ivan.Arismendi@oregonstate.edu; Phone: (1) 541-750-7443; Fax: (1)
23 541-758-7760;

24 **Abstract**

25 Central tendency statistics may not capture relevant or desired characteristics about the variation
26 of continuous phenomena and thus, they may not completely track temporal patterns of change.
27 Here, we present two methodological approaches to identify long-term changes in environmental
28 regimes. First, we use higher statistical moments (skewness and kurtosis) to examine potential
29 changes of empirical distributions at decadal scale. Second, we adapt an outlier detection
30 procedure combining a non-metric multidimensional scaling technique and higher density region
31 plots to detect anomalous years. We illustrate the use of these approaches by examining long-
32 term stream temperature data from minimally and highly human-influenced streams. In
33 particular, we contrast predictions about thermal regime responses to changing climates and
34 human-related water uses. Using these methods, we effectively diagnose years with unusual
35 thermal variability, patterns in variability through time, and spatial variability linked to regional
36 and local factors that influence stream temperature. Our findings highlight the complexity of
37 responses of thermal regimes of streams and reveal a differentiated vulnerability to both the
38 climate warming and human-related water uses. The two approaches presented here can be
39 applied with a variety of other continuous phenomena to address historical changes, extreme
40 events, and their associated ecological responses.

41

42 **Keywords:** frequency analyses, probability distributions, kurtosis, skew, global warming, stream
43 ecosystems, hydrology, thermal regimes

44

45 INTRODUCTION

46 Environmental fluctuation is a fundamental feature that shapes ecological and evolutionary
47 processes. Although empirical distributions of environmental data can be characterized in terms
48 of the central tendency (or location), variability, and shape, most traditional statistical
49 approaches are based on detecting changes in location and tend to oversimplify assumptions
50 about temporal variation. This issue is particularly troublesome for understanding the stationarity
51 of temporally continuous phenomena and thus, the detection of potential shifts in distributional
52 properties beyond the location. For instance, descriptors of location, such as mean, median or
53 mode, may not be the most informative when extreme hydrological events are of primary
54 attention (e.g., Chebana et al., 2012). In many regions, the future climate is expected to be
55 characterized by increasing the frequency of extreme events (e.g., Jentsch et al., 2007; IPCC
56 2012). Hence, the detection of changes in the shape of empirical distributions appears to be more
57 informative than only using traditional descriptors of central tendency (e.g., Shen et al., 2011;
58 Donat & Alexander, 2012). More importantly, factors associated with changes in the shape of
59 empirical distributions may have greater effects on species and ecosystems than do simple
60 changes in location (e.g., Colwell, 1974; Gaines & Denny, 1993; Thompson et al., 2013; Vasseur
61 et al., 2014).

62 Here, we explore two approaches that quantify and visualize changes in the shape of
63 empirical distributions of continuous environmental variables using thermal regimes of streams
64 as an illustrative example. First, applying frequency analysis, we examine patterns of variability
65 and long-term shifts in the shape of stream temperature empirical distributions using higher
66 statistical moments (skewness and kurtosis) by season across decades. Second, we combine non-
67 metric multidimensional scale ordination technique (N-MDS) and highest density regions (HDR)

68 plots to detect anomalous years. To exemplify the utility of these approaches, we employ them to
69 contrast predictions and questions about long-term responses of thermal regimes of streams to
70 changing terrestrial climates and other human-related water uses (Fig. 1). Our main goal is to
71 identify temporal changes in empirical distributions of environmental regimes not captured by
72 lower statistical moments. This is particularly relevant in streams because (1) global
73 environmental change may affect empirical distributions of water quality beyond the traditional
74 lower statistical moments, and (2) ecosystems and organisms have been shown to be sensitive to
75 such distributional changes (e.g., Thompson *et al.*, 2013; Vasseur *et al.*, 2014).

76

77 **Thermal regime of streams as an illustrative example**

78 Temperature is a fundamental driver of ecosystem processes in freshwaters (Shelford, 1931; Fry,
79 1947; Magnuson *et al.*, 1979; Vannote & Sweeney, 1980). Short-term (daily/weekly/monthly)
80 descriptors of mean and maximum temperatures during summertime are frequently used for
81 characterizations of thermal habitat availability and quality (McCullough *et al.*, 2009),
82 definitions of regulatory thresholds (Groom *et al.*, 2011), and predictions about possible
83 influences of climate change on streams (Mohseni *et al.*, 2003; Mantua *et al.*, 2010; Arismendi *et*
84 *al.*, 2013a,b). These simple descriptors can serve as useful first approximations, but do not
85 capture the full range of thermal conditions that the aquatic biota experience at daily, seasonal, or
86 annual intervals (see Poole & Berman, 2001; Webb *et al.*, 2008). Both human impacts and
87 climate change have been shown to affect thermal regimes of streams at a variety of temporal
88 scales (e.g., Steel & Lange, 2007; Arismendi *et al.*, 2012; 2013a,b). For example, the recent
89 warming climate could lead to different responses of streams that may not be well described
90 using average or maximum temperature values (Arismendi *et al.*, 2012). Daily minimum stream

91 temperatures in winter are showing more warming than daily maximum values during summer
92 (Arismendi *et al.*, 2013a; for air temperatures see Donat & Alexander, 2012). In human modified
93 streams, seasonal shifts in stream temperatures and earlier warmer temperatures have been
94 recorded following removal of riparian vegetation (Johnson & Jones, 2000). However, simple
95 threshold descriptors of central tendency or location cannot characterize these shifts.

96 Using higher statistical moments, we examine the question of whether a recent warming
97 climate has led a shift in the shape of the stream temperature distribution or if stream
98 temperatures have all warmed and simply moved entirely to the right without any change in
99 shape. In addition, we compare these potential shifts in the distribution of stream temperature
100 between streams with unregulated and human-regulated flows. Using outlier detection
101 technique), we address the question of whether anomalous years are repeatedly detected across
102 streams types (regulated and unregulated) and examine if those anomalous years represent a
103 regional influence of the climate or alternatively highlight the importance of local factors.
104 Previous studies have shown that detecting long-term changes of thermal regimes of streams is
105 complex and the use of only traditional statistical approaches may oversimplify characterization
106 of a variety of responses of ecological relevance (Arismendi *et al.*, 2013a,b).

107

108 **MATERIAL AND METHODS**

109 **Study sites and time series**

110 We selected long-term gage stations (US Geological Survey and US Forest Service) that
111 monitored year-round daily stream temperature in Oregon, California, and Idaho ($n = 10$; Table
112 1). The sites were selected based on (1) availability of continuous daily records for at least 31
113 years (January 1st 1979 to December 31st 2009) and (2) complete information for time series of

114 daily minimum (min), mean (mean), and maximum (max) stream temperature for at least 93% of
 115 the period of record. Half of the sites ($n = 5$) were located in unregulated streams (sites 1-5) and
 116 the other half were in regulated streams (sites 6-10). Regulated streams were those with
 117 reservoirs constructed before 1978. Time series were carefully inspected and for the outlier
 118 analysis only (see below) we interpolated missing data following Arismendi *et al.* (2013a). The
 119 percentage of daily missing records of each time series was less than 7%. To ensure enough
 120 observations to adequately represent the tails of the respective distributions at a seasonal scale
 121 for analyses of higher statistical moments (i.e., winter: December-February; spring: March-May;
 122 summer: June-August; fall: September-November), we grouped and compared daily stream
 123 temperature data at each site among the three decades 1980-1989, 1990-1999, and 2000-2009.

124

125 *Higher statistical moments*

126 To visualize and use a similar scale of stream temperatures across sites, we standardized time
 127 series of daily temperature values using a Z-transformation as follows:

128

$$ST_i = \frac{T_i - \mu}{\sigma}$$

129

130 where ST_i was the standardized temperature at day i , T_i was the actual temperature value at day i
 131 ($^{\circ}\text{C}$), μ was the mean and σ was the standard deviation of the respective time series considering
 132 the entire time period.

133 Higher statistical moments of skewness and kurtosis are often considered problematic in
 134 parametric statistics, where data is often assumed to be normal. In reality, however, these
 135 moments can be useful to describe changes in the shape of the distribution of environmental
 136 variables over long-term periods (see Shen *et al.*, 2011; Donat & Alexander, 2012). Skewness

137 addresses the question of whether or not a certain variable is symmetrically distributed around its
138 mean value. With respect to temperature, positive skewness of the distribution or skewed right
139 indicates colder conditions are more common (Fig. 1a) whereas negative skewness or skewed
140 left represents increasing prevalence of warmer conditions (Fig. 1b). Therefore, increases in the
141 skewness over time could occur with increases in warm conditions, decreases in cold conditions,
142 or both. Kurtosis describes the structure of the distribution between the center and the tails
143 representing the dispersion around its 'shoulders'. In other words, as the probability mass
144 decreases around its shoulders it may increase in either the center, or the tails, or both resulting
145 in a rise in the peakedness, the tailweight, or both and thus, the dispersion of the distribution
146 around its shoulders increases. The reference standard is zero, a normal distribution with excess
147 kurtosis equal to kurtosis minus three (mesokurtic). A sharp peak in a distribution that is more
148 extreme than a normal distribution (excess kurtosis exceeding zero) represented less dispersion
149 in the observations over the tails (leptokurtic). Distributions with higher kurtosis tend to have
150 "tails" that are more accentuated. Therefore, observations are spread more evenly throughout the
151 tails. A distribution with tails more flattened than the normal distribution (excess kurtosis below
152 zero) described higher frequencies spread across the tails (platykurtic). With respect to
153 temperature, a leptokurtic distribution may indicate that average conditions are much more
154 frequent and there is a lower proportion of both extreme cold and warm values (Fig. 1a). A
155 platykurtic distribution represents a more evenly distributed distribution across all values with a
156 higher proportion of both extreme cold and warm values (Fig. 1b). Therefore, increases in the
157 kurtosis over time would occur with decreases in extreme conditions, increases of average
158 conditions, or both.

159 Although time series of environmental data may include large datasets often they are
 160 incomplete due to missing values and errors. To account for a potential bias inherent to
 161 incomplete time series or in cases of small samples sizes, we used the sample skewness (adjusted
 162 Fisher-Pearson standardized moment coefficient) and the sample excess kurtosis (Joanes and Gill
 163 1998). The sample skewness and sample excess kurtosis are dimensionless and were estimated as
 164 follows:

$$\begin{aligned}
 \text{Skewness} &= \frac{n}{(n-1)(n-2)} \sum_{i=1}^n \left(\frac{T_i - \mu}{\sigma} \right)^3 \\
 \text{Kurtosis} &= \left[\frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum_{i=1}^n \left(\frac{T_i - \mu}{\sigma} \right)^4 \right] - \frac{3(n-1)^2}{(n-2)(n-3)}
 \end{aligned}$$

169
 170 where n represented the number of records of the time series, T_i was the temperature of the day i ,
 171 μ and σ the mean and standard deviation of the time series.

172 To define the status of the skewness for the stream temperature distribution in a particular
 173 season and decade, we followed Bulmer (1979) defining three categories as follows “highly
 174 skewed” (if skewness was < -1 or > 1), “moderately skewed” (if skewness was between -1 and $-$
 175 0.5 or between 0.5 and 1), and “symmetric” (if skewness was between -0.5 and 0.5). We used
 176 similar procedures to define the status of excess kurtosis. We defined five categories that
 177 included “negative kurtosis or platykurtic” (if kurtosis was < -1), “moderately platykurtic” (if
 178 kurtosis was between -0.5 and -1), “positive kurtosis or leptokurtic” (if kurtosis was > 1),
 179 “moderately leptokurtic” (if kurtosis was between 0.5 and 1). Finally, if kurtosis was between $-$
 180 0.5 and 0.5 , we considered the distribution as “mesokurtic”.

181

182 ***Outlier detection procedure***

183 We considered an entire year as one finite-dimensional observation (365 days of daily minimum
184 stream temperature). Using a non-metric multidimensional scaling (N-MDS) unconstrained
185 ordination technique (Kruskal, 1964), we compared the similarity among years of the Euclidean
186 distance of standardized temperatures for each day within a year across all years. The N-MDS
187 analysis places each year in a multivariate space in the most parsimonious arrangement (relative
188 to each other) with no a priori hypotheses. Based on an iterative optimization procedure (999
189 random starts) we minimize a measure of disagreement or stress between their distances in 2-D
190 (Kruskal, 1964). The Kruskal's stress value is estimated as the square root of the ratio of the
191 squared differences between the calculated distances and the plotted distances, and the sum of
192 the plotted distances squared (Kruskal 1964). A rule of thumb (Clarke 1993) suggests the
193 following benchmarks: stress <0.05 – excellent ordination; stress <0.1 - good ordination; stress
194 <0.2 acceptable ordination; stress >0.2 – poor ordination. The resulting coordinates 1 and 2 from
195 the resulted optimized 2-D plot provided a collective index of how unique a given year was (Fig.
196 1c,d). In N-MDS the order of the axes was arbitrary and the coordinates represented no
197 meaningful absolute scales for the axis. Fundamental to this method was the relative distances
198 apart of points with a higher proximity indicating a higher degree of similarity, whereas more
199 dissimilar points were positioned further apart. We performed the N-MDS analyses using the
200 software Primer ver. 6.1.15 (Clarke, 1993; Clarke & Gorley, 2006).

201 Using the two coordinates of each point (year) from the 2-D plot originated in the N-MDS
202 ordination procedure, we created a bivariate high dimensional region (HDR) box-plot
203 (Hyndman, 1996). The HDR plot has been typically produced using the two main principal
204 component scores from a traditional principal component analysis (PCA) (Hyndman, 1996;

205 Chebana *et al.*, 2012). However, in this study, we modified this procedure taking the advantage
206 of the higher flexibility and lack of assumptions of the N-MDS analysis (Everitt, 1978; Kenkel &
207 Orloci, 1986) to provide the two coordinates needed to create the HDR plot. In the HDR box-
208 plot, there are regions defined based on a probability coverage (e.g., 50%; 90%; or 95%) where
209 all points (years) within the probability coverage region have higher density estimates than any
210 of the points outside the region (Fig. 1c,d). The outer-region of the probability coverage region is
211 bounded by points representing anomalous years (in Fig. 1c,d). We created the HDR plots using
212 the package ‘hdrcde’ (Hyndman *et al.*, 2012) in R ver. 2.15.1 (R Development Core Team,
213 2012).

214

215 **RESULTS AND DISCUSSION**

216 Empirical distributions of stream temperature were distinctive among seasons, and seasons were
217 relatively similar across sites (Fig. 2). Temperature distributions during winter had high overlap
218 with those during spring. Winter had the narrowest range and the highest frequency of
219 observations occurred at colder standardized temperature categories (-1.3, -0.7). The second
220 highest proportion of observations in the year were also colder values occurring during spring in
221 unregulated streams and during summer at four of the five regulated sites. This shift of frequency
222 was likely due to release of warmer water from the reservoir management upstream. Fall
223 distributions showed broadest range, with a similar proportion for a number temperature values.

224 Changes in the shape of empirical distributions among seasons over decades were not
225 immediately evident, but the values of skewness or types of kurtosis captured these decadal
226 changes in cases when lower statistical moments (average and standard deviation) did not show
227 marked differences (e.g., unregulated site1 during fall and spring in Fig. 3; Table 2 and 3; see

228 also differences among decades at site 1 during summer in Supplement). The utility of
229 combining skewness and kurtosis to detect changes in distributional shapes over time is
230 illustrated by unregulated site2 during winter and spring (Tables 2 and 3; Supplement). At this
231 site, there was a shift across decades from symmetric towards a negatively skewed distribution in
232 winter and from symmetric towards positively skewed in spring, as well as from mesokurtic
233 towards a leptokurtic distribution in both winter and spring. Overall, in most unregulated sites,
234 kurtosis changed type with recent increases during winter, summer, and spring (Table 3;
235 Supplement). Winter and summer mostly had negatively skewed distributions whereas spring
236 generally had positively skewed distributions or those with little change across decades, except
237 for site 3 (Table 2; Supplement). Decadal changes in both skewness and kurtosis during winter
238 and summer observed at unregulated sites suggest the probability mass moved from its shoulders
239 into warmer values at its center, but maintained the tail-weight of the extreme colder conditions
240 (Fig. 3; Tables 2 and 3; Supplement). However, in spring the probability mass diminished around
241 its shoulders apparently due to decreases in the frequency of extreme colder conditions. Hence,
242 higher statistical moments may help in describing the complexity of temporal changes in stream
243 temperature among seasons and highlight how shifts may occur at different portions of the
244 distribution (e.g., extreme cold, average, or warm conditions) or among streams.

245 In regulated sites, we observed shifts toward colder temperatures (e.g., sites 6 and 9 during
246 summer and fall in Fig. 3; Supplement) suggesting local influences of water regulation may
247 mask the impacts from recent warming climate. This illustrated the mixed patterns of skewness
248 and kurtosis due to climate and water regulation, especially during spring, winter, and summer
249 (Tables 2 and 3; Fig. 3; Supplement). In particular, in spring, patterns of skewness were similar
250 to unregulated sites whereas patterns of kurtosis were in opposite directions (more platykurtic in

251 regulated sites). This can be explained by the water discharged from reservoirs in spring that was
252 a mix of the cool inflows to the reservoir, the cold water stored in the reservoir itself from the
253 winter, and yet the surface of the reservoir warmed because of increasing solar radiation. Patterns
254 of skewness and kurtosis seen in regulated sites also highlights the influences of site-dependent
255 water management coupled with climatic influences. This is exemplified by the skewness of sites
256 7 and 8 compared to sites 9 and 10 in fall, winter, and spring (Table 2) and the high variability of
257 the value of skewness among sites in summer.

258 Collectively, increased understanding of the shape of empirical distributions by season or
259 year will help researchers and resource managers evaluate potential impacts of shifting
260 environmental regimes on organisms and processes across a range of disturbance types.
261 Empirical distributions were a simple, but comprehensive way to examine high frequency
262 measurements that included the full range of values. Higher statistical moments provided useful
263 information to characterize and compare environmental regimes showing which season were
264 most responsive to disturbances. Use of higher moment metrics could help improve predictive
265 models of climate change impacts in streams by incorporating site-specific characteristics and
266 full environmental regimes into scenarios rather than only the inclusion of summer conditions.

267 The outlier detection technique used here was able to incorporate all daily data to represent a
268 complete and realistic comparison of environmental regimes across years. We were able to
269 characterize whole year responses and identify where regional climatic or hydrologic trends
270 dominated versus where local influences distinctively influenced stream temperature. For
271 example, Year 1992 was identified as anomalous at three unregulated sites (or four at 90% CI)
272 and at two regulated sites (or four at 90% CI), and identified that across the region, the majority
273 of stream temperatures were being influenced. Stream temperatures in Years 1987 and 2008

274 were less synchronous across the region, but regulated and unregulated sites located in the same
275 watershed (sites 2, 7, and 8 in Table 1; Figs. 4 and 5; Supplement) shared similar anomalous
276 years. We also observed inconsistent anomalous years across sites, suggesting that more local
277 conditions of watersheds influenced stream temperature (e.g., Arismendi et al., 2012). Indeed,
278 sites spatially located close to one another (unregulated sites 3 and 4 in Table 1; Fig. 4;
279 Supplement) did not necessarily share all anomalous years suggesting that local drivers were
280 more influential than regional climate forces during those years. Hence, the outlier-detection
281 method used here may be useful to evaluate and contrast the vulnerability of streams to regional
282 or local climate changes by characterizing years with extreme conditions or those when seasonal
283 shifts occurred (e.g., Brock & Carpenter 2012).

284 The outlier-detection method identified years with anomalies in either magnitude or timing of
285 events (Figs. 4 and 5) and mapped these differences within the ordination plot. For example, year
286 1992 and 1987 were anomalous likely due to magnitude of warming throughout year. At other
287 sites, such as unregulated sites 3, 4 and 5 (Fig. 4), the anomalous years were most likely due to
288 increased temperatures in seasons other than summertime, and not related to higher summertime
289 temperatures. Years 1992 and 2008 plotted at the opposite extremes of the ordination plot for
290 sites 1, 2 and 7 (Figs. 4 and 5); see also Years 1982-1983 and 1986-1987 for site3. These years
291 represented warm and cold conditions respectively and likely they influenced the shape of the
292 confidence region (Figs. 4 and 5; Supplement). Interestingly, we observed that the confidence
293 region for unregulated sites (Fig. 4) appeared to be more irregularly shaped than regulated sites
294 (Fig. 5). Collectively, this suggests that stream regulation may tightly cluster and homogenize
295 temperature values across years (e.g., Fig. 1c, d) and, in some cases, mask the influence of
296 extreme climate conditions on these sites. Further attention on the interpretation of the geometry

297 of confidence region may be useful to contrast purely climatic from human influences on
298 streams.

299 When using these proposed approaches, there are some caveats inherent to time series
300 analyses of environmental data that should be considered. First, error terms for nearby time
301 periods may lead to serial correlation affecting the independence of data. For hypothesis testing,
302 when serial correlation occurs, the goodness of fit is inflated and the estimated standard error is
303 smaller than the true standard error. Serial correlation often occurs on short-term scales (hourly,
304 daily, weekly) in analyses of environmental water quality (Helsel & Hirsch, 1992). In this study,
305 we reduced the potential for serial correlation by using longer time periods that allowed for a
306 contrast among decades. Second, it is important to note that temporal changes in skewness and
307 kurtosis could lead to misleading interpretations if they are only attributed to the change of any
308 single high-moment ratio. Because skewness and kurtosis are ratios based on lower-order
309 moments their temporal changes may be the result of changes in only the lower-order moments,
310 changes in the higher-order moments or both. Thus, we recommend the use of higher-moment
311 ratios in conjunction to the lower-order moments of central tendency and dispersion. Further, the
312 outlier-detection technique used here identified years outside a confidence region, in other
313 words, those years that fall in the tails of the distribution. Because the confidence region
314 represented an overall pattern extracted from the available data, it was constrained by the length
315 of the time series. Thus, anomalous years located outside of the confidence region may not
316 necessarily represent true outliers. In addition, when the level of “stress” in the ordination of
317 years is acceptable ($\text{stress} < 0.2$) interpreting the regularity/irregularity of the geometry of the
318 confidence region may provide interesting outcomes. For example, in our illustrative example,
319 the regularity of the confidence region seen for regulated streams, when contrasted to

320 unregulated sites, could be interpreted as the reservoir effect buffering the inter-annual
321 variability of hydroclimatic conditions.

322

323 **SUMMARY AND CONCLUSIONS**

324 Here we show the utility of using higher statistical moments and outlier detection as
325 complementary approaches to capture long-term changes in empirical distributions of
326 environmental regimes and evaluate whether these changes are consistent across site types.
327 Stream ecosystems are exposed to multiple climatic and non-climatic forces which may
328 differentially affect their hydrological regimes (e.g., temperature and streamflow). In particular,
329 we show that potential timing and magnitude of responses of stream temperature to both the
330 recent warming climate and other human-related impacts may vary among seasons, years, and
331 across sites. Central tendency statistics may or may not distinguish between thermal regimes or
332 characterize changes to thermal regimes which could be relevant to infer their ecological and
333 management implications. In addition, when only single metrics are used to describe
334 environmental regimes, they have to be selected carefully. Often selection means simplification
335 resulting in the compression or loss of information (e.g., Arismendi et al., 2013a). By examining
336 the whole empirical distributions, we can provide a better characterization of shifts over time or
337 following disturbances than simple thresholds or descriptors.

338 In conclusion, our two approaches complement traditional summary statistics by helping to
339 characterize long-term continuous environmental variable behaviors for seasons and years. We
340 illustrate this using temperature of streams in unregulated and regulated sites as an example.
341 Although we did not include a broad range of stream types, they were sufficiently different to
342 demonstrate the utility of the two approaches. The two approaches are transferable to other types

343 of continuous environmental variable measurements and regions to examining seasonal and
344 annual responses, and climate or human-related influences (e.g., for streamflow see Chebana *et*
345 *al.*, 2012; for air temperature see Shen *et al.*, 2011). These analyses will be useful to characterize
346 how regimes of continuous phenomena have changed in the past, may respond in the future, or to
347 identify the type and timing of their resilience.

348

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359

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440

441 **SUPPORTING INFORMATION**

442 **Supplement** Supplementary results of skewness, kurtosis, and outlier's detection

443 **Table 1.** Location and characteristics of unregulated ($n = 5$) and regulated ($n = 5$) streams at the gaging sites. Percent of gaps in the
 444 stream temperature time series from Jan-1979 to Dec-2009 used in this study.

River	Start of water regulation	gage ID	ID	Lat N	Long W	elevation (m)	watershed area (km²)	% of daily gaps
Fir Creek, OR	unregulated	14138870	site1	45.48	122.02	439	14.1	2.8%
SF Bull Run River, OR	unregulated	14139800	site2	45.45	122.11	302	39.9	2.0%
McRae Creek, OR	unregulated	TSMCRA	site3	44.26	122.17	840	5.9	3.5%
Lookout Creek, OR	unregulated	TSLOOK	site4	44.23	122.12	998	4.9	2.6%
Elk Creek, OR	unregulated	14338000	site5	42.68	122.74	455	334.1	5.2%
Clearwater River, ID	1971	13341050	site6	46.50	116.39	283	20,658	4.0%
Bull Run River near Multnomah Falls, OR	1915 ^a	14138850	site7	45.50	122.01	329	124.1	5.3%
NF Bull Run River, OR	1958	14138900	site8	45.49	122.04	323	21.6	2.6%
Rogue River near McLeod, OR	1977	14337600	site9	42.66	122.71	454	2,429	3.7%
Martis Creek near Truckee, CA	1971	10339400	site10	39.33	120.12	1747	103.4	6.5%

445 ^a Regulation at times

446 **Table 2.** Magnitude and direction of the value of skewness in probability distributions of daily minimum stream temperature by
 447 season and decade at unregulated (sites 1-5) and regulated (sites 6-10) streams. Symmetric distributions are not shown. m =
 448 moderately skewed; h = highly skewed; (-) = negatively skewed; (+) = positively skewed (see Supplement for more details).

site type	site ID	season/time period											
		fall			winter			Spring			summer		
		80-89	90-99	00-09	80-89	90-99	00-09	80-89	90-99	00-09	80-89	90-99	00-09
unregulated (1-5)	site1				m(-)	m(-)	m(-)	m(+)	m(+)	m(+)			
	site2					m(-)	m(-)	m(+)	m(+)	m(+)	m(-)		m(-)
	site3						m(-)		m(+)	h(+)			m(-)
	site4							h(+)	m(+)	h(+)	m(-)	m(-)	m(-)
	site5							m(+)	h(+)	m(+)	m(-)	m(-)	m(-)
regulated (6-10)	site6							m(+)					m(+)
	site7						m(-)	m(+)	m(+)	m(+)			m(-)
	site8	m(-)	m(-)					m(+)		m(+)			h(-)
	site9	m(+)	m(+)	m(+)	m(+)	m(+)							m(+)
	site10					m(+)					h(-)	m(-)	

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453 **Table 3.** Types of kurtosis of probability distributions of daily minimum stream temperature by season and decade at unregulated and
 454 regulated sites. $\leftrightarrow\leftrightarrow$ = platykurtic; \leftrightarrow = moderately platykurtic; $\uparrow\downarrow$ = leptokurtic, and \uparrow = moderately leptokurtic. Mesokurtic
 455 distributions are not shown (see Supplement for more details).

site type	site	season/time period											
		fall			winter			Spring			summer		
		80-89	90-99	00-09	80-89	90-99	00-09	80-89	90-99	00-09	80-89	90-99	00-09
unregulated (1-5)	site 1			\leftrightarrow	\uparrow	\uparrow	\uparrow	$\uparrow\downarrow$					
	site 2			\leftrightarrow			\downarrow	$\uparrow\downarrow$				\leftrightarrow	\uparrow
	site 3	\leftrightarrow	\leftrightarrow	\leftrightarrow			$\uparrow\downarrow$			\uparrow	\leftrightarrow		
	site 4			\leftrightarrow				$\uparrow\downarrow$		$\uparrow\downarrow$			\uparrow
	site 5	\leftrightarrow	\leftrightarrow	\leftrightarrow	\leftrightarrow				\uparrow	\uparrow	$\uparrow\downarrow$		\uparrow
	site 6	\leftrightarrow	\leftrightarrow	\leftrightarrow								\leftrightarrow	\uparrow
regulated (6-10)	site 7	\leftrightarrow		\leftrightarrow				$\uparrow\downarrow$					
	site 8	\uparrow		\leftrightarrow	\uparrow		\uparrow		\leftrightarrow			\uparrow	$\uparrow\downarrow$
	site 9			\leftrightarrow	\uparrow			\leftrightarrow	\leftrightarrow	\leftrightarrow	\leftrightarrow	\leftrightarrow	
	site 10	$\leftrightarrow\leftrightarrow$	$\leftrightarrow\leftrightarrow$	$\leftrightarrow\leftrightarrow$	\leftrightarrow	$\uparrow\downarrow$		$\leftrightarrow\leftrightarrow$	\leftrightarrow	\leftrightarrow	$\uparrow\downarrow$	\uparrow	\uparrow

FIGURE LEGENDS

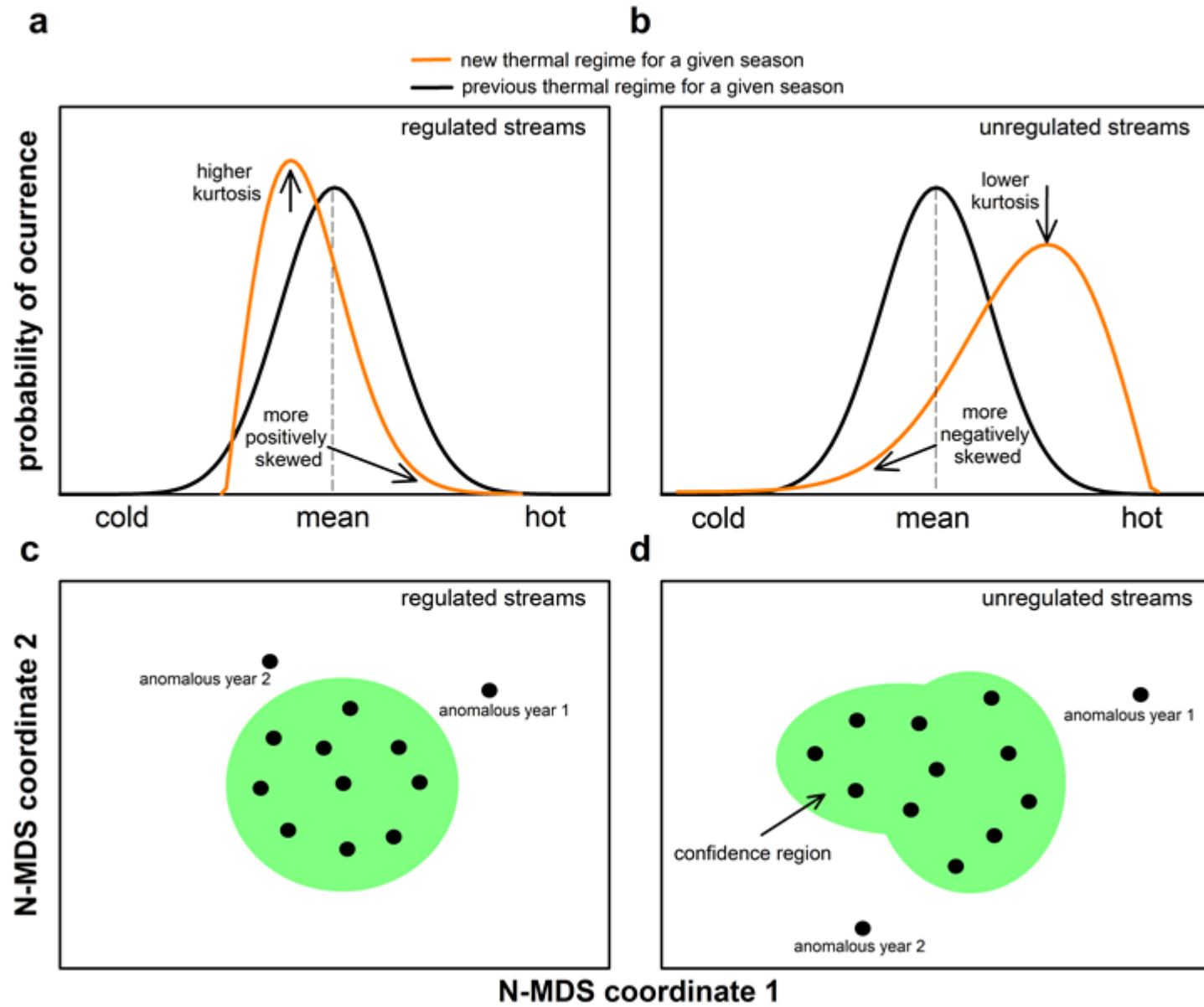
Fig. 1. Conceptual diagram showing hypothesized long-term responses of water temperature at both seasonal (upper panel) and annual (lower panel) scales in regulated (left panel) and unregulated (right panel) streams. In the upper panel we showed examples of changes in skewness and kurtosis for temperature distributions affected by stream regulation and a warming climate in a given season. For instance, in regulated streams the influence of the reservoir may reduce both extreme cold and warm temperatures confounding the effect from the climate (a) whereas less cold temperatures and an overall shift toward warming values may occur in unregulated streams (b). In the lower panel we illustrate the use of N-MDS and HDR plots for detecting anomalous years in regulated and unregulated streams (the shaded area represent a given coverage probability). Points located in the outer or the confidence region represent anomalous years. For instance, in regulated streams individual years are more clustered due to the reservoir may homogenize temperatures across years whereas (c) whereas in unregulated streams individual years are less clustered due to more heterogeneous responses to the warming climate (b).

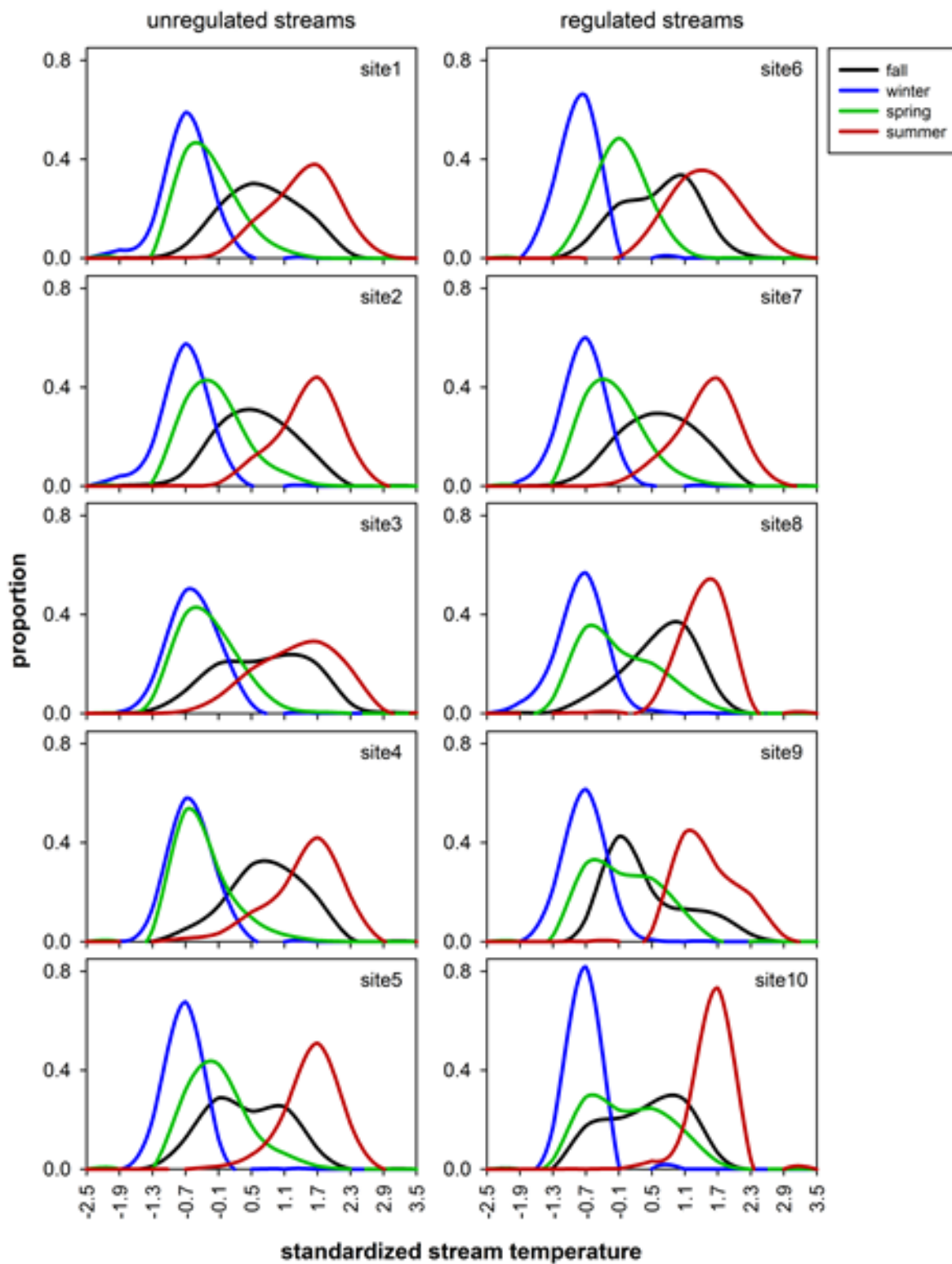
Fig. 2. Density plots of standardized temperatures (1979-2009) by season (winter – blue line; spring – green line; summer – red line; fall – black line) in unregulated (left panel) and regulated (right panel) streams using time series of daily minimum.

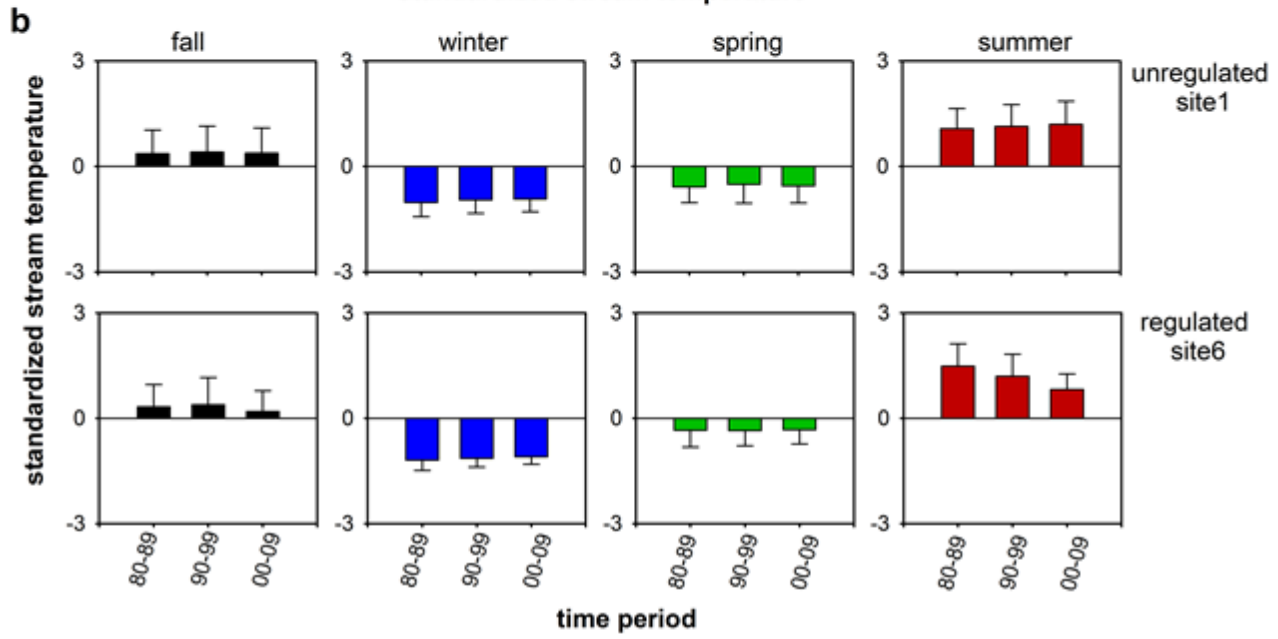
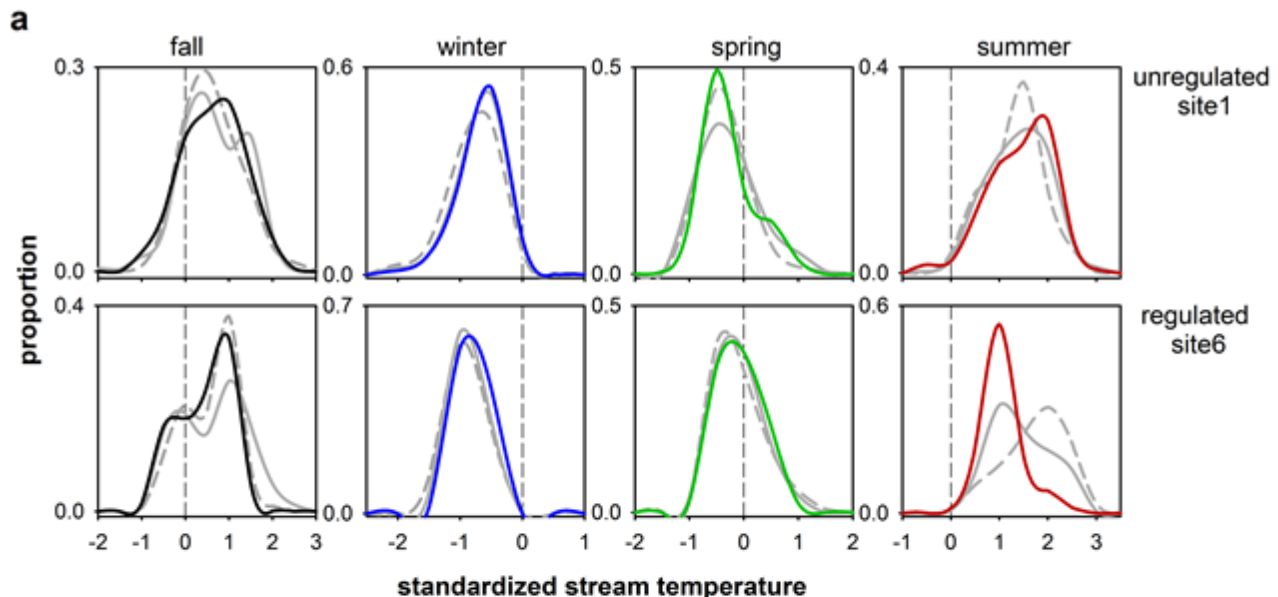
Fig. 3. Examples of (a) density plots of standardized temperatures by decade (period 80-89 dashed line; period 90-99 gray line; period 00-09 solid color line) and season using time series of daily minimum in an unregulated (site1) and a regulated (site6) stream. In the lower panel (b) central tendency statistics (average \pm SD) for each decade and season (winter – blue; spring – green; summer – red; fall – black) are also included. See results for all sites in the Supplement.

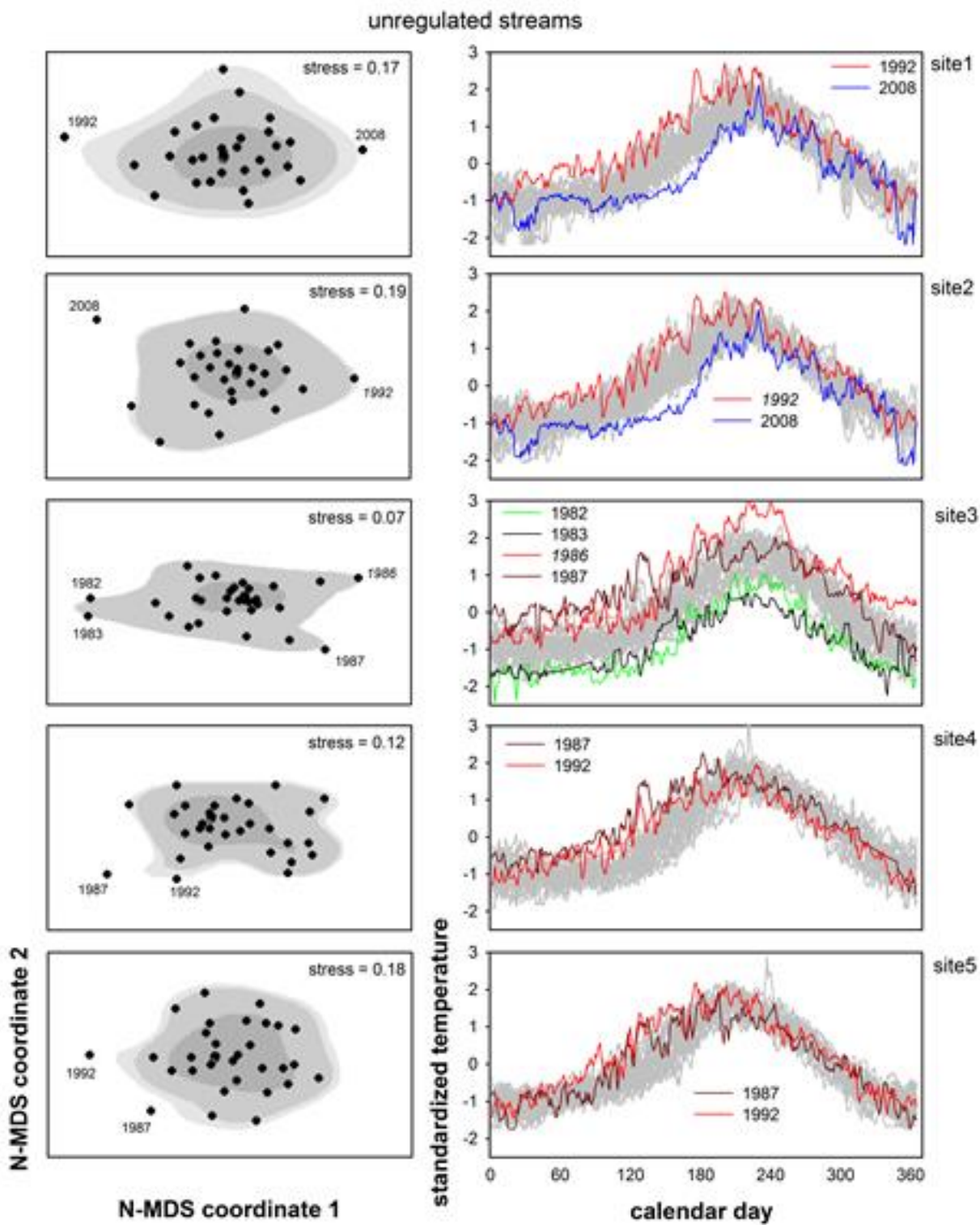
Fig. 4. Bivariate HDR boxplots (left panel) and standardized daily temperature distribution (right panel) in unregulated streams using annual time series of daily minimum. The dark and light grey regions show the 50%, 90%, 95% coverage probability. The symbols outside the grey regions and darker lines represent anomalous years. Examples of years between 90% and 95% of the coverage probability were italicized. See results for all sites in the Supplement.

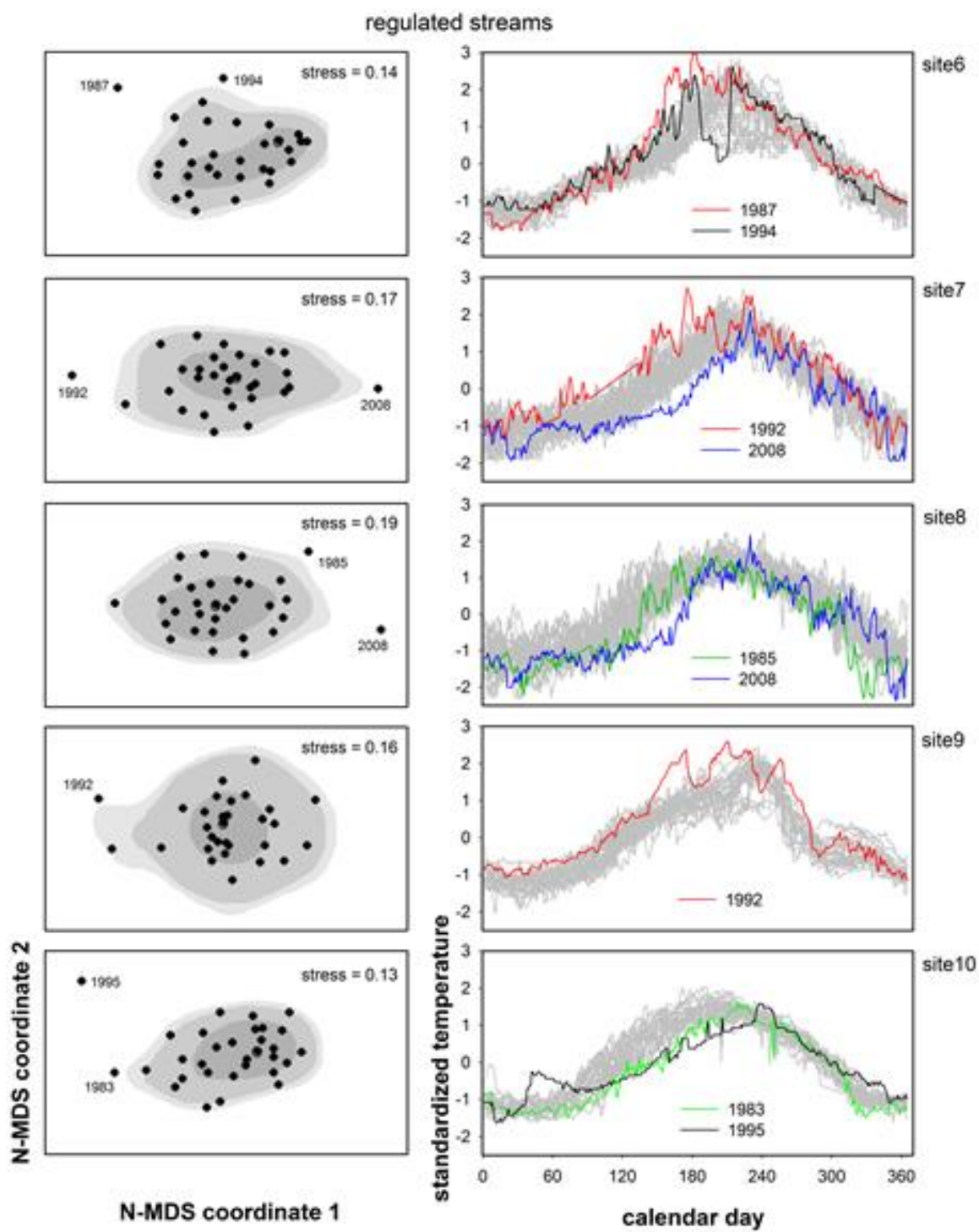
Fig. 5. Bivariate HDR boxplots (left panel) and standardized daily temperature distribution (right panel) in regulated streams using annual time series of daily minimum. The dark and light grey regions show the 50%, 90%, 95% coverage probability. The symbols outside the grey regions and darker lines represent anomalous years. Examples of years between 90% and 95% of the coverage probability were italicized. See results for all sites in the Supplement.











SUPPLEMENT

Table S1 Skewness in probability distributions of daily minimum stream temperature by season and decade at unregulated (sites 1-5) and regulated (sites 6-10) streams.

site ID	season/time period											
	fall			winter			Spring			summer		
	80-89	90-99	00-09	80-89	90-99	00-09	80-89	90-99	00-09	80-89	90-99	00-09
site 1	0.335	-0.225	-0.066	-0.543	-0.662	-0.631	0.865	0.747	0.789	-0.221	-0.142	-0.486
site 2	-0.170	-0.225	-0.115	-0.345	-0.538	-0.574	0.823	0.664	0.772	-0.522	-0.220	-0.764
site 3	0.064	-0.025	-0.142	0.152	0.103	-0.805	0.450	0.549	1.010	0.048	-0.204	-0.630
site 4	-0.355	-0.210	-0.185	0.210	0.138	-0.244	1.059	0.831	1.371	-0.859	-0.604	-0.999
site 5	0.109	-0.060	0.003	-0.074	-0.462	-0.206	0.716	1.044	0.963	-0.922	-0.743	-0.821
site 6	-0.300	0.067	-0.283	0.456	-0.005	-0.034	0.647	0.216	0.195	-0.422	0.153	0.744
site 7	0.031	-0.263	-0.177	-0.353	-0.581	-0.340	0.902	0.763	0.771	-0.421	-0.160	-0.606
site 8	-0.836	-0.529	-0.416	0.002	-0.363	-0.143	0.621	0.340	0.633	-0.361	-0.395	-1.335
site 9	0.853	0.877	0.711	0.781	0.562	0.397	0.444	0.277	0.017	0.414	0.329	0.519
site 10	-0.163	-0.137	-0.103	0.187	0.755	-0.118	0.134	0.138	0.200	-1.161	-0.835	-0.229

Table S2 Skewness in probability distributions of daily mean stream temperature by season and decade at unregulated (sites 1-5) and regulated (sites 6-10) streams.

site ID	season/time period											
	fall			winter			Spring			summer		
	80-89	90-99	00-09	80-89	90-99	00-09	80-89	90-99	00-09	80-89	90-99	00-09
site 1	0.364	-0.192	-0.022	-0.466	-0.579	-0.493	1.026	0.827	0.821	-0.292	-0.191	-0.533
site 2	-0.122	-0.182	-0.108	-0.322	-0.572	-0.557	0.902	0.711	0.713	-0.501	-0.192	-0.732
site 3	-0.001	-0.034	-0.156	0.214	0.072	-0.561	0.449	0.506	1.002	-0.079	-0.259	-0.674
site 4	-0.303	-0.218	-0.155	0.217	0.166	-0.060	1.000	0.778	1.335	-0.874	-0.562	-1.015
site 5	0.124	-0.005	0.084	-0.227	-0.607	-0.351	0.641	1.016	0.882	-1.056	-0.640	-0.934
site 6	-0.199	0.099	-0.252	0.484	0.187	-0.058	0.594	0.229	0.306	-0.468	0.218	0.777
site 7	0.027	-0.265	-0.180	-0.322	-0.622	-0.316	0.980	0.777	0.755	-0.518	-0.286	-0.674
site 8	-0.730	-0.465	-0.389	0.107	-0.286	-0.031	0.702	0.420	0.617	-0.402	-0.432	-1.251
site 9	0.806	0.906	0.626	0.795	0.675	0.416	0.418	0.302	0.024	0.394	0.299	0.437
site 10	-0.182	-0.145	-0.061	-0.012	0.609	-0.128	0.120	0.246	0.202	-1.280	-1.023	-0.872

Table S3 Skewness in probability distributions of daily maximum stream temperature by season and decade at unregulated (sites 1-5) and regulated (sites 6-10) streams.

site ID	season/time period											
	fall			winter			Spring			summer		
	80-89	90-99	00-09	80-89	90-99	00-09	80-89	90-99	00-09	80-89	90-99	00-09
site 1	0.382	-0.161	0.018	-0.396	-0.503	-0.369	1.132	0.889	0.857	-0.374	-0.264	-0.576
site 2	-0.066	-0.154	-0.101	-0.335	-0.608	-0.551	0.945	0.741	0.652	-0.477	-0.185	-0.705
site 3	-0.064	0.010	-0.159	0.265	0.082	-0.339	0.509	0.487	0.899	-0.178	-0.332	-0.766
site 4	-0.292	-0.226	-0.162	0.231	0.195	0.145	0.946	0.725	1.208	-0.840	-0.464	-0.874
site 5	0.147	0.069	0.194	-0.355	-0.697	-0.521	0.569	0.893	0.762	-0.960	-0.398	-0.828
site 6	-0.111	0.134	-0.191	0.461	0.300	-0.049	0.545	0.245	0.397	-0.448	0.291	0.794
site 7	0.032	-0.263	-0.185	-0.300	-0.681	-0.317	1.029	0.787	0.756	-0.550	-0.435	-0.775
site 8	-0.581	-0.380	-0.324	0.213	-0.205	0.077	0.772	0.507	0.618	-0.398	-0.459	-1.025
site 9	0.796	0.972	0.552	0.671	0.747	0.363	0.402	0.333	0.042	0.319	0.231	0.264
site 10	-0.147	-0.070	0.005	-0.111	0.477	-0.063	0.109	0.349	0.219	-0.821	-0.723	-0.551

Table S4 Type of excess kurtosis of probability distributions of daily minimum stream temperature by season and decade at unregulated (sites 1-5) and regulated (sites 6-10) streams.

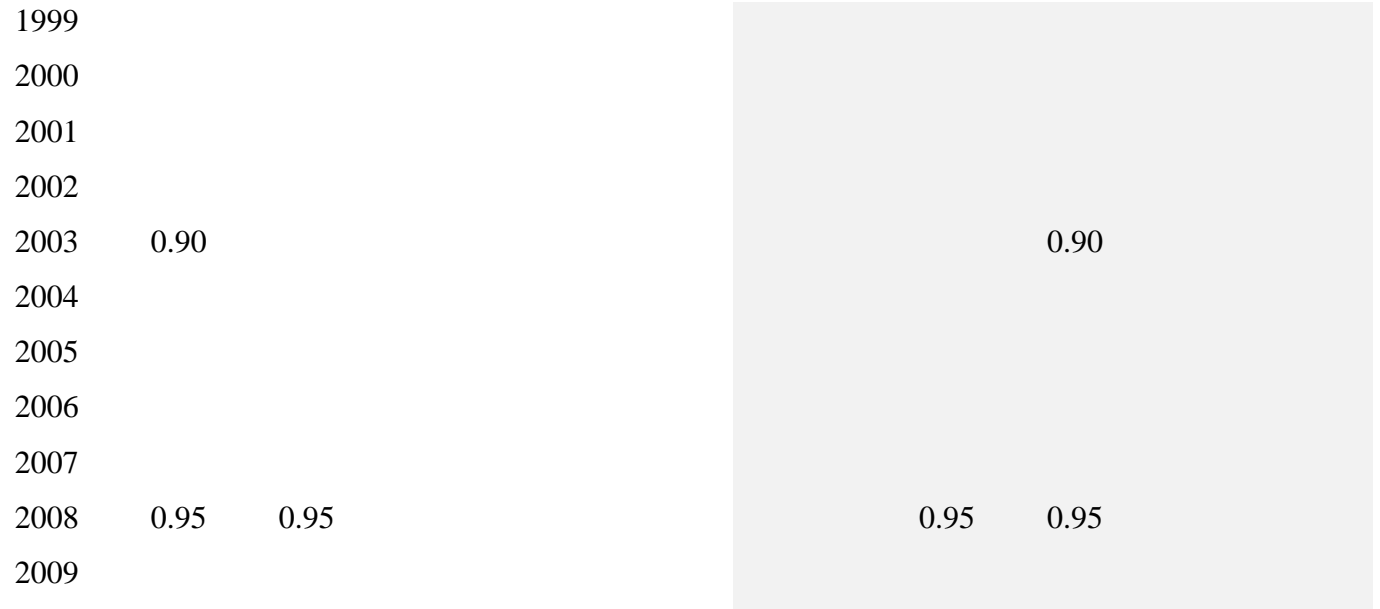
site ID	season/time period											
	fall			winter			spring			summer		
	80-89	90-99	00-09	80-89	90-99	00-09	80-89	90-99	00-09	80-89	90-99	00-09
site 1	-0.187	-0.268	-0.571	0.768	0.715	0.906	1.193	0.053	0.168	-0.396	-0.428	-0.021
site 2	0.220	-0.240	-0.592	0.119	-0.135	0.671	1.104	0.016	0.208	-0.347	-0.587	0.706
site 3	-0.770	-0.877	-0.806	-0.289	-0.093	1.223	-0.104	-0.269	0.893	-0.598	-0.479	-0.290
site 4	-0.366	-0.480	-0.667	-0.332	0.039	0.065	1.171	0.414	2.004	0.409	-0.046	0.953
site 5	-0.785	-0.983	-0.981	-0.513	-0.038	-0.398	0.172	0.737	0.702	1.288	0.200	0.910
site 6	-0.683	-0.792	-0.790	0.076	0.178	-0.168	0.453	-0.491	-0.052	-0.302	-0.687	0.664
site 7	-0.528	-0.466	-0.639	-0.219	-0.155	0.137	1.275	0.434	0.322	0.056	-0.192	-0.026
site 8	0.960	-0.178	-0.612	0.670	0.314	0.800	-0.140	-0.691	-0.375	0.342	0.660	4.217
site 9	0.037	-0.178	-0.852	0.613	0.314	0.215	-0.955	-0.993	-0.867	-0.896	-0.863	-0.125
site 10	-1.079	-1.066	-1.166	-0.513	2.350	-0.074	-1.052	-0.996	-0.940	2.440	0.958	0.570

Table S5 Type of excess kurtosis of probability distributions of daily mean stream temperature by season and decade at unregulated (sites 1-5) and regulated (sites 6-10) streams.

site ID	season/time period											
	fall			winter			spring			summer		
	80-89	90-99	00-09	80-89	90-99	00-09	80-89	90-99	00-09	80-89	90-99	00-09
site 1	-0.177	-0.340	-0.551	0.886	0.704	0.770	1.672	0.228	0.188	-0.284	-0.374	0.062
site 2	0.159	-0.301	-0.580	0.194	0.003	0.752	1.291	0.109	0.114	-0.250	-0.509	0.694
site 3	-0.759	-0.872	-0.744	-0.286	-0.006	1.026	-0.091	-0.419	0.582	-0.557	-0.529	-0.114
site 4	-0.370	-0.469	-0.720	-0.427	0.113	0.016	1.054	0.160	1.504	0.586	-0.059	1.251
site 5	-0.893	-1.133	-1.072	-0.319	0.315	-0.116	-0.151	0.750	0.445	1.536	-0.040	0.976
site 6	-0.774	-0.816	-0.828	0.084	-0.047	-0.203	0.214	-0.485	-0.107	-0.336	-0.717	0.704
site 7	-0.544	-0.457	-0.612	-0.095	0.042	0.243	1.463	0.374	0.320	0.239	-0.068	0.195
site 8	0.692	-0.320	-0.639	0.788	0.369	0.860	0.047	-0.591	-0.357	0.227	0.500	3.718
site 9	-0.069	-0.210	-1.000	0.598	0.297	0.403	-1.035	-0.962	-0.887	-0.861	-0.837	-0.345
site 10	-0.958	-1.244	-1.183	-0.501	2.208	-0.658	-1.029	-0.729	-0.921	1.999	1.166	1.753

Table S6 Type of excess kurtosis of probability distributions of daily maximum stream temperature by season and decade at unregulated (sites 1-5) and regulated (sites 6-10) streams.

site ID	season/time period											
	fall			winter			spring			summer		
	80-89	90-99	00-09	80-89	90-99	00-09	80-89	90-99	00-09	80-89	90-99	00-09
site 1	-0.173	-0.398	-0.508	1.133	0.723	0.767	1.962	0.374	0.285	-0.209	-0.331	0.114
site 2	0.098	-0.319	-0.559	0.311	0.133	0.883	1.278	0.164	0.038	-0.148	-0.401	0.678
site 3	-0.771	-0.852	-0.708	-0.275	0.017	0.891	0.031	-0.412	0.281	-0.483	-0.617	0.148
site 4	-0.352	-0.453	-0.681	-0.462	0.159	0.126	0.802	-0.050	0.917	0.667	-0.035	1.544
site 5	-0.954	-1.191	-1.032	-0.052	0.745	0.290	-0.373	0.588	0.190	1.223	-0.249	0.700
site 6	-0.727	-0.822	-0.810	0.058	-0.108	-0.194	0.040	-0.466	-0.131	-0.435	-0.684	0.752
site 7	-0.504	-0.428	-0.572	0.165	0.355	0.473	1.374	0.292	0.289	0.142	-0.019	0.497
site 8	0.441	-0.416	-0.635	1.005	0.500	0.924	0.218	-0.430	-0.302	-0.090	0.150	2.325
site 9	-0.169	0.025	-1.105	0.282	0.371	0.359	-1.015	-0.871	-0.848	-0.797	-0.841	-0.524
site 10	-0.908	-1.235	-1.166	-0.425	1.627	-0.577	-1.011	-0.536	-0.871	0.757	0.493	1.068



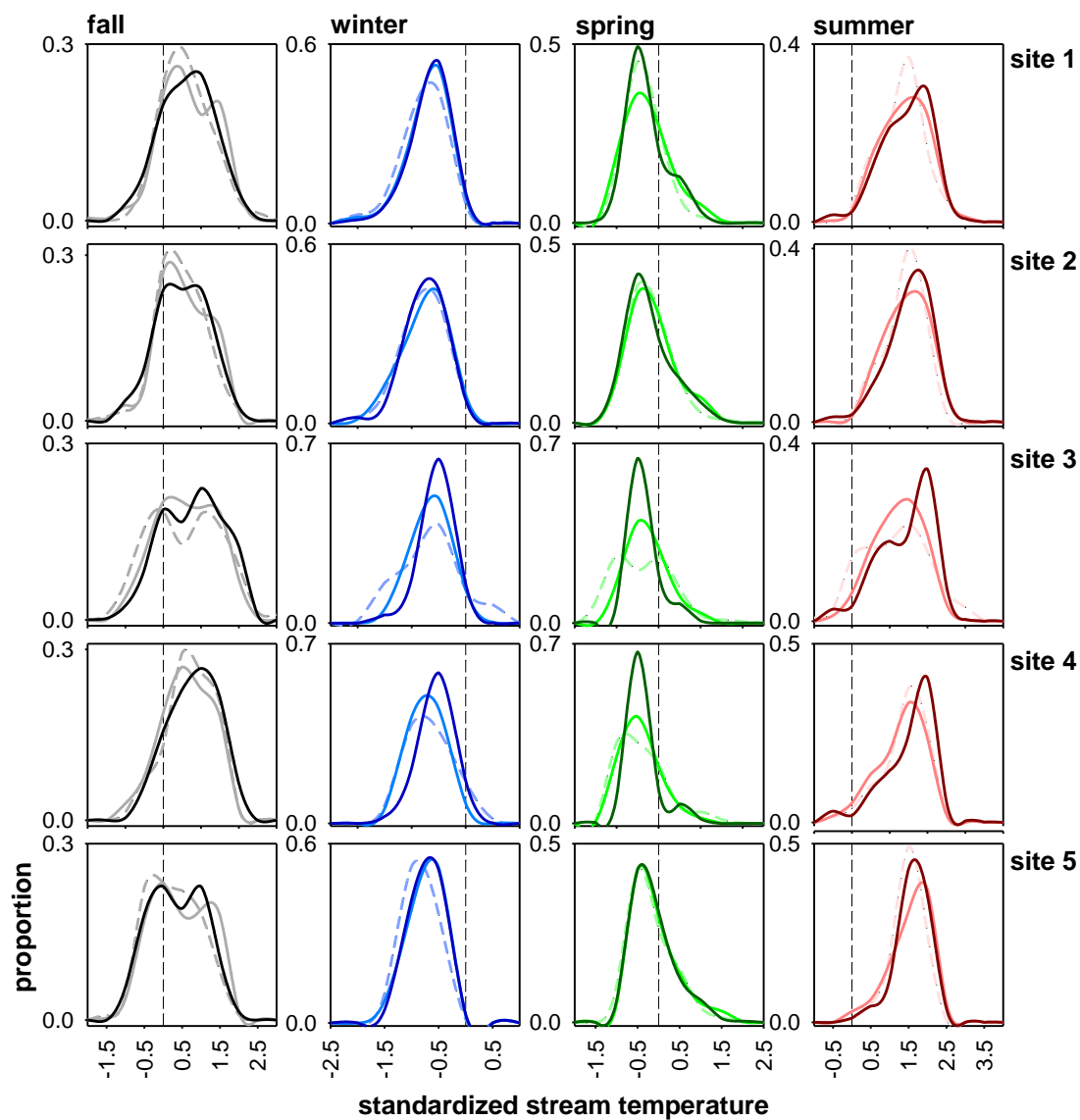


Fig. S1 Density plots of standardized temperatures by decade (period 80-89 dashed line; period 90-99 solid lighter color; period 00-09 dark color) and season (winter – blue line; spring – green line; summer – red line; fall – black line) using time series of daily minimum in unregulated streams.

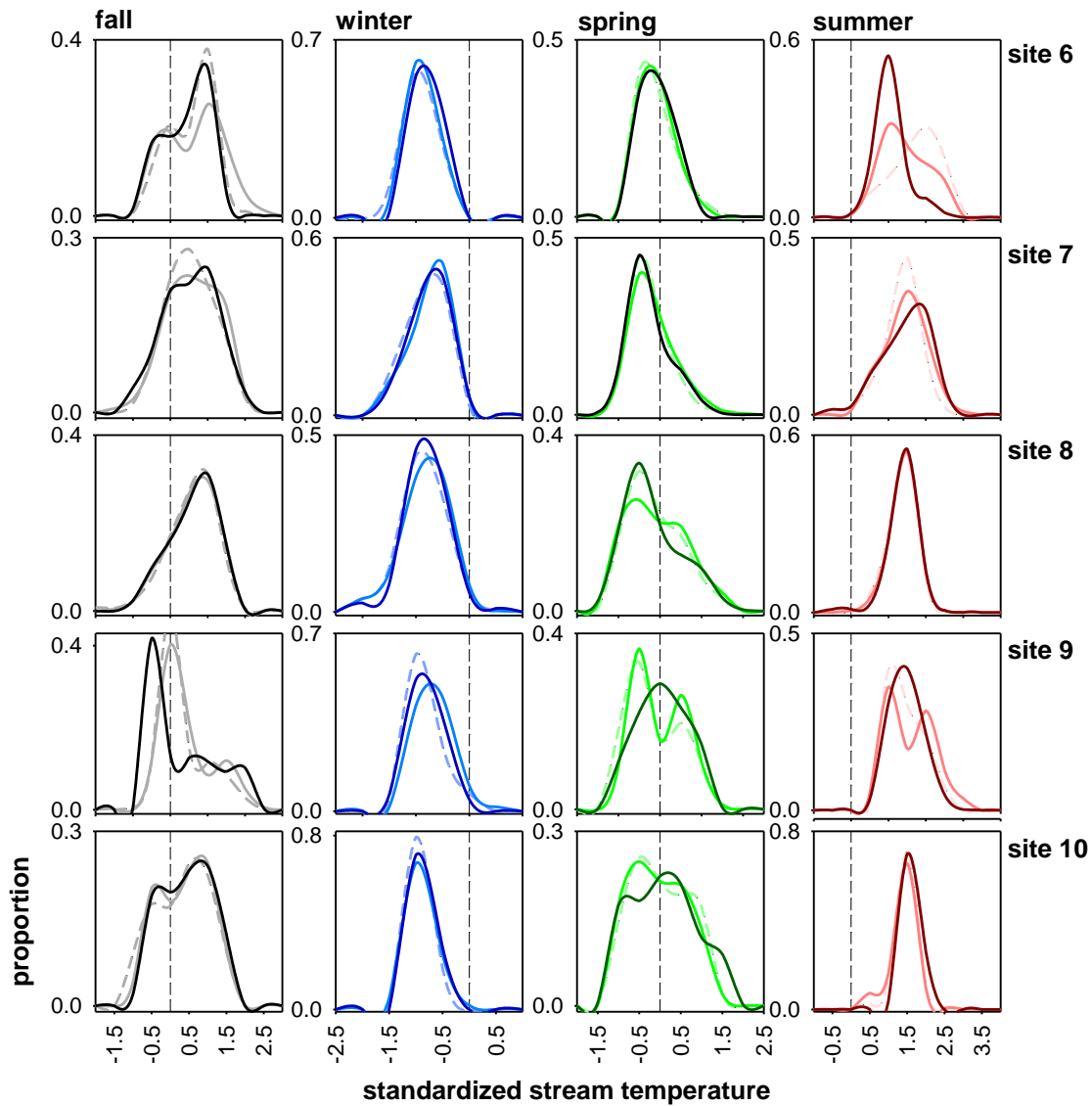


Fig. S2 Density plots of standardized temperatures by decade (period 80-89 dashed line; period 90-99 solid lighter color; period 00-09 dark color) and season (winter – blue line; spring – green line; summer – red line; fall – black line) using time series of daily minimum in regulated streams.