TECHNICAL NOTE:

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

Running head: long-term changes in environmental data

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Abstract

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

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

INTRODUCTION

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

Here, we explore two approaches that quantify and visualize changes in the shape of empirical distributions of continuous environmental variables using thermal regimes of streams as an illustrative example. First, applying frequency analysis, we examine patterns of variability and long-term shifts in the shape of stream temperature empirical distributions using higher statistical moments (skewness and kurtosis) by season across decades. Second, we combine non-metric multidimensional scale ordination technique (N-MDS) and highest density regions (HDR) plots to detect anomalous years. To exemplify the utility of these approaches, we employ them to contrast predictions and questions about long-term responses of thermal regimes of streams to changing terrestrial climates and other human-related water uses (Fig. 1). Our main goal is to identify temporal changes in empirical distributions of environmental regimes not captured by lower statistical moments. This is particularly relevant in streams because (1) global environmental change may affect empirical distributions of water quality beyond the traditional lower statistical moments, and (2) ecosystems and organisms have been shown to be sensitive to such distributional changes (e.g., Thompson et al., 2013; Vasseur et al., 2014).

Thermal regime of streams as an illustrative example

Temperature is a fundamental driver of ecosystem processes in freshwaters (Shelford, 1931; Fry, 1947; Magnuson *et al*., 1979; Vannote & Sweeney, 1980). Short-term (daily/weekly/monthly) descriptors of mean and maximum temperatures during summertime are frequently used for characterizations of thermal habitat availability and quality (McCullough *et al*., 2009), definitions of regulatory thresholds (Groom *et al.*, 2011), and predictions about possible influences of climate change on streams (Mohseni *et al*., 2003; Mantua *et al*., 2010; Arismendi *et al.*, 2013a,b). These simple descriptors can serve as useful first approximations, but do not capture the full range of thermal conditions that the aquatic biota experience at daily, seasonal, or annual intervals (see Poole & Berman, 2001; Webb *et al.*, 2008). Both human impacts and climate change have been shown to affect thermal regimes of streams at a variety of temporal scales (e.g., Steel & Lange, 2007; Arismendi *et al.*, 2012; 2013a,b). For example, the recent warming climate could lead to different responses of streams that may not be well described using average or maximum temperature values (Arismendi *et al.*, 2012). Daily minimum stream temperatures in winter are showing more warming than daily maximum values during summer (Arismendi *et al.*, 2013a; for air temperatures see Donat & Alexander, 2012). In human modified streams, seasonal shifts in stream temperatures and earlier warmer temperatures have been recorded following removal of riparian vegetation (Johnson & Jones, 2000). However, simple threshold descriptors of central tendency or location cannot characterize these shifts.

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

MATERIAL AND METHODS

Study sites and time series

We selected long-term gage stations (US Geological Survey and US Forest Service) that monitored year-round daily stream temperature in Oregon, California, and Idaho (*n* = 10; Table 1). The sites were selected based on (1) availability of continuous daily records for at least 31 years (January 1st 1979 to December 31st 2009) and (2) complete information for time series of daily minimum (min), mean (mean), and maximum (max) stream temperature for at least 93% of the period of record. Half of the sites (n = 5) were located in unregulated streams (sites 1-5) and the other half were in regulated streams (sites 6-10). Regulated streams were those with reservoirs constructed before 1978. Time series were carefully inspected and for the outlier analysis only (see below) we interpolated missing data following Arismendi *et al.* (2013a). The percentage of daily missing records of each time series was less than 7%. To ensure enough observations to adequately represent the tails of the respective distributions at a seasonal scale for analyses of higher statistical moments (i.e., winter: December-February; spring: March-May; summer: June-August; fall: September-November), we grouped and compared daily stream temperature data at each site among the three decades 1980-1989, 1990-1999, and 2000-2009.

Higher statistical moments

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

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

where ST_i was the standardized temperature at day i, T_i was the actual temperature value at day i (°C), μ was the mean and σ was the standard deviation of the respective time series considering the entire time period.

Higher statistical moments of skewness and kurtosis are often considered problematic in parametric statistics, where data is often assumed to be normal. In reality, however, these moments can be useful to describe changes in the shape of the distribution of environmental variables over long-term periods (see Shen *et al.*, 2011; Donat & Alexander, 2012). Skewness addresses the question of whether or not a certain variable is symmetrically distributed around its mean value. With respect to temperature, positive skewness of the distribution or skewed right indicates colder conditions are more common (Fig. 1a) whereas negative skewness or skewed left represents increasing prevalence of warmer conditions (Fig. 1b). Therefore, increases in the skewness over time could occur with increases in warm conditions, decreases in cold conditions, or both. Kurtosis describes the structure of the distribution between the center and the tails representing the dispersion around its 'shoulders'. In other words, as the probability mass decreases around its shoulders it may increase in either the center, or the tails, or both resulting in a rise in the peakedness, the tailweight, or both and thus, the dispersion of the distribution around its shoulders increases. The reference standard is zero, a normal distribution with excess kurtosis equal to kurtosis minus three (mesokurtic). A sharp peak in a distribution that is more extreme than a normal distribution (excess kurtosis exceeding zero) represented less dispersion in the observations over the tails (leptokurtic). Distributions with higher kurtosis tend to have "tails" that are more accentuated. Therefore, observations are spread more evenly throughout the tails. A distribution with tails more flattened than the normal distribution (excess kurtosis below zero) described higher frequencies spread across the tails (platykurtic). With respect to temperature, a leptokurtic distribution may indicate that average conditions are much more frequent and there is a lower proportion of both extreme cold and warm values (Fig. 1a). A platykurtic distribution represents a more evenly distributed distribution across all values with a higher proportion of both extreme cold and warm values (Fig. 1b). Therefore, increases in the kurtosis over time would occur with decreases in extreme conditions, increases of average conditions, or both.

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

$$Skewness = \frac{n}{(n-1)(n-2)} \sum_{i=1}^{n} \left(\frac{T_i - \mu}{\sigma} \right)^3$$

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

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

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

Outlier detection procedure

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

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

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

RESULTS AND DISCUSSION

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

Changes in the shape of empirical distributions among seasons over decades were not immediately evident, but the values of skewness or types of kurtosis captured these decadal changes in cases when lower statistical moments (average and standard deviation) did not show marked differences (e.g., unregulated site1 during fall and spring in Fig. 3; Table 2 and 3; see also differences among decades at site 1 during summer in Supplement). The utility of combining skewness and kurtosis to detect changes in distributional shapes over time is illustrated by unregulated site2 during winter and spring (Tables 2 and 3; Supplement). At this site, there was a shift across decades from symmetric towards a negatively skewed distribution in winter and from symmetric towards positively skewed in spring, as well as from mesokurtic towards a leptokurtic distribution in both winter and spring. Overall, in most unregulated sites, kurtosis changed type with recent increases during winter, summer, and spring (Table 3; Supplement). Winter and summer mostly had negatively skewed distributions whereas spring generally had positively skewed distributions or those with little change across decades, except for site 3 (Table 2; Supplement). Decadal changes in both skewness and kurtosis during winter and summer observed at unregulated sites suggest the probability mass moved from its shoulders into warmer values at its center, but maintained the tail-weight of the extreme colder conditions (Fig. 3; Tables 2 and 3; Supplement). However, in spring the probability mass diminished around its shoulders apparently due to decreases in the frequency of extreme colder conditions. Hence, higher statistical moments may help in describing the complexity of temporal changes in stream temperature among seasons and highlight how shifts may occur at different portions of the distribution (e.g., extreme cold, average, or warm conditions) or among streams.

In regulated sites, we observed shifts toward colder temperatures (e.g., sites 6 and 9 during summer and fall in Fig. 3; Supplement) suggesting local influences of water regulation may mask the impacts from recent warming climate. This illustrated the mixed patterns of skewness and kurtosis due to climate and water regulation, especially during spring, winter, and summer (Tables 2 and 3; Fig. 3; Supplement). In particular, in spring, patterns of skewness were similar to unregulated sites whereas patterns of kurtosis were in opposite directions (more platykurtic in regulated sites). This can be explained by the water discharged from reservoirs in spring that was a mix of the cool inflows to the reservoir, the cold water stored in the reservoir itself from the winter, and yet the surface of the reservoir warmed because of increasing solar radiation. Patterns of skewness and kurtosis seen in regulated sites also highlights the influences of site-dependent water management coupled with climatic influences. This is exemplified by the skewness of sites 7 and 8 compared to sites 9 and 10 in fall, winter, and spring (Table 2) and the high variability of the value of skewness among sites in summer.

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

The outlier detection technique used here was able to incorporate all daily data to represent a complete and realistic comparison of environmental regimes across years. We were able to characterize whole year responses and identify where regional climatic or hydrologic trends dominated versus where local influences distinctively influenced stream temperature. For example, Year 1992 was identified as anomalous at three unregulated sites (or four at 90% CI) and at two regulated sites (or four at 90% CI), and identified that across the region, the majority of stream temperatures were being influenced. Stream temperatures in Years 1987 and 2008 were less synchronous across the region, but regulated and unregulated sites located in the same watershed (sites 2, 7, and 8 in Table 1; Figs. 4 and 5; Supplement) shared similar anomalous years. We also observed inconsistent anomalous years across sites, suggesting that more local conditions of watersheds influenced stream temperature (e.g., Arismendi et al., 2012). Indeed, sites spatially located close to one another (unregulated sites 3 and 4 in Table 1; Fig. 4; Supplement) did not necessarily share all anomalous years suggesting that local drivers were more influential than regional climate forces during those years. Hence, the outlier-detection method used here may be useful to evaluate and contrast the vulnerability of streams to regional or local climate changes by characterizing years with extreme conditions or those when seasonal shifts occurred (e.g., Brock & Carpenter 2012).

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

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

SUMMARY AND CONCLUSIONS

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

In conclusion, our two approaches complement traditional summary statistics by helping to characterize long-term continuous environmental variable behaviors for seasons and years. We illustrate this using temperature of streams in unregulated and regulated sites as an example. Although we did not include a broad range of stream types, they were sufficiently different to demonstrate the utility of the two approaches. The two approaches are transferable to other types of continuous environmental variable measurements and regions to examining seasonal and annual responses, and climate or human-related influences (e.g., for streamflow see Chebana *et al.*, 2012; for air temperature see Shen *et al.*, 2011). These analyses will be useful to characterize how regimes of continuous phenomena have changed in the past, may respond in the future, or to identify the type and timing of their resilience.

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SUPPORTING INFORMATION

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

Table 1. Location and characteristics of unregulated (*n* = 5) and regulated (*n* = 5) streams at the gaging sites. Percent of gaps in the 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 (km^2)	% 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%

[a] Regulation at times

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

		season/time period											
site type	**site ID**	**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(-)	

Table 3. Types of kurtosis of probability distributions of daily minimum stream temperature by season and decade at unregulated and regulated sites. ↔↔ = platykurtic; ↔ = moderately platykurtic; ↕ ↕ = leptokurtic, and ↕ = moderately leptokurtic. Mesokurtic distributions are not shown (see Supplement for more details).

		season/time period											
site type	**site**	**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			↔	↕	↕	↕	↕↕					
	site 2			↔			↕	↕↕				↔	↕
	site 3	↔	↔	↔			↕↕			↕	↔		
	site 4			↔				↕↕		↕↕			↕
	site 5	↔	↔	↔	↔				↕	↕	↕↕		↕
regulated (6-10)	site 6	↔	↔	↔								↔	↕
	site 7	↔		↔				↕↕					
	site 8	↕		↔	↕		↕		↔			↕	↕↕
	site 9			↔	↕			↔	↔	↔	↔	↔	
	site 10	↔↔	↔↔	↔↔	↔	↕↕		↔↔	↔	↔	↕↕	↕	↕

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 ± 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.

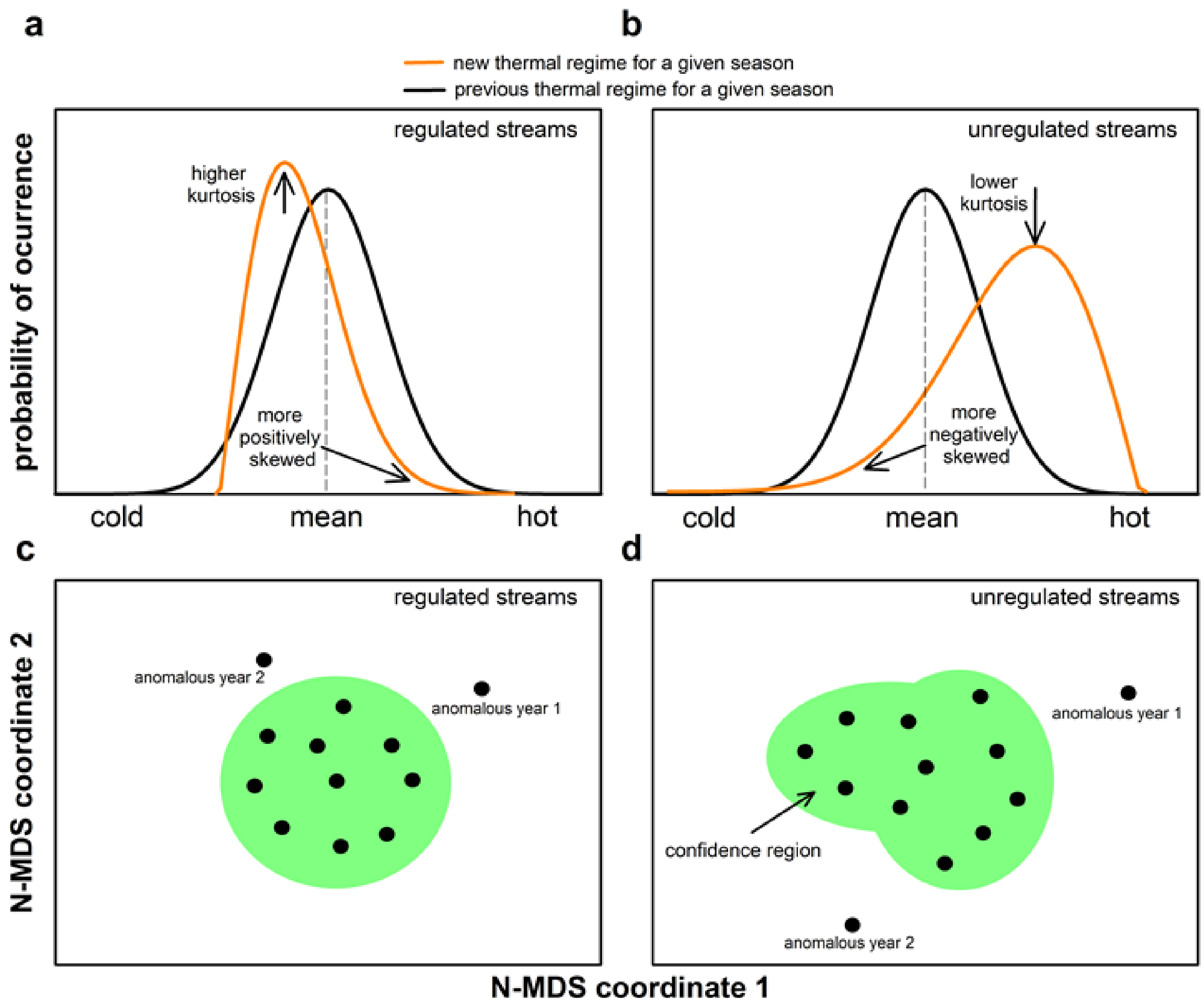
a
b
new thermal regime for a given season
previous thermal regime for a given season
regulated streams
higher kurtosis
more positively skewed
unregulated streams
lower kurtosis
more negatively skewed
probability of ocurrence
cold
mean
hot
cold
mean
hot
c
d
regulated streams
anomalous year 2
anomalous year 1
unregulated streams
anomalous year 1
confidence region
anomalous year 2
N-MDS coordinate 2
N-MDS coordinate 1

Figure 1

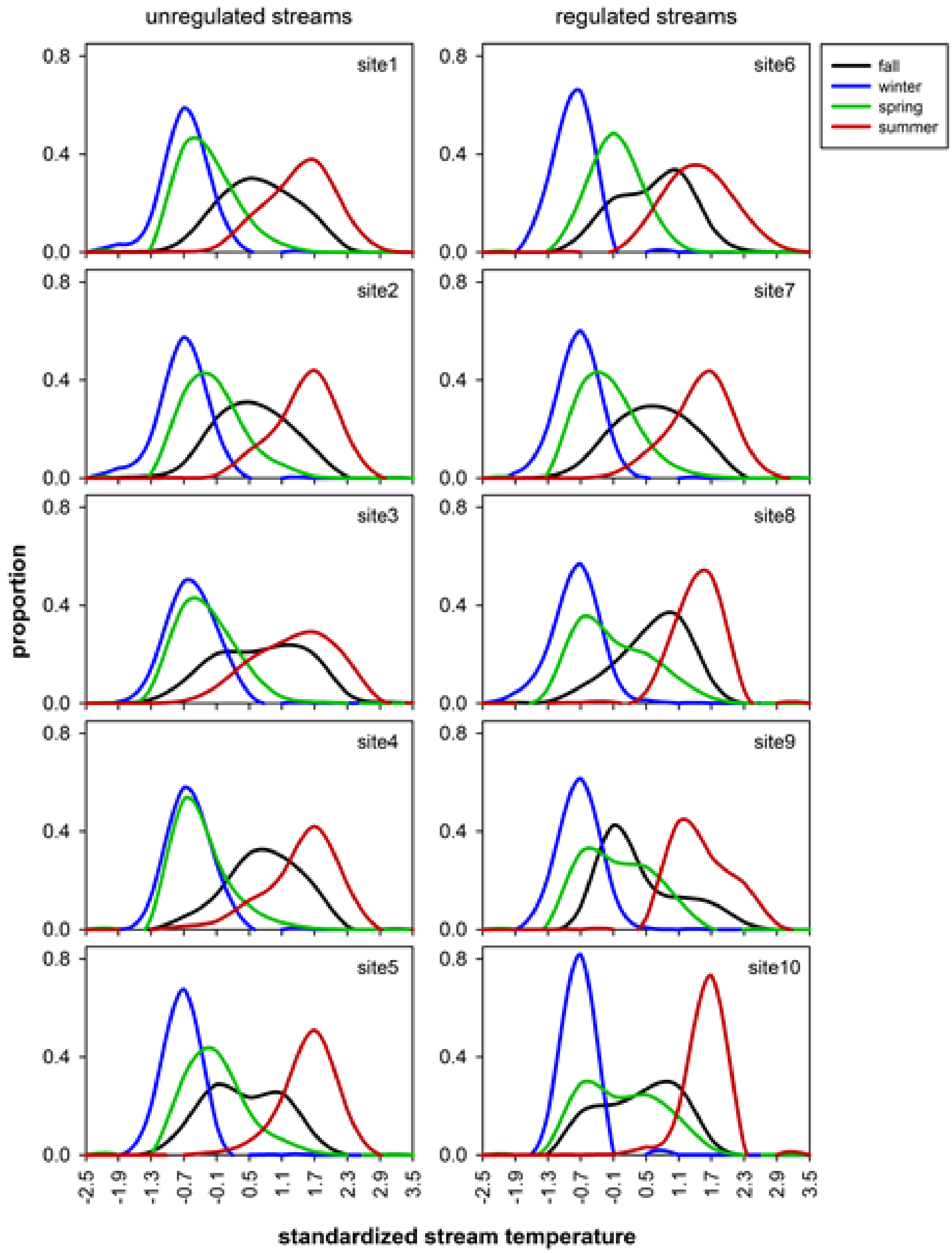
unregulated streams
regulated streams
site1
site2
site3
site4
site5
site6
site7
site8
site9
site10
fall
winter
spring
summer
proportion
0.0
0.4
0.8
-2.5
-1.9
-1.3
-0.7
-0.1
0.5
1.1
1.7
2.3
2.9
3.5
standardized stream temperature

Figure 2

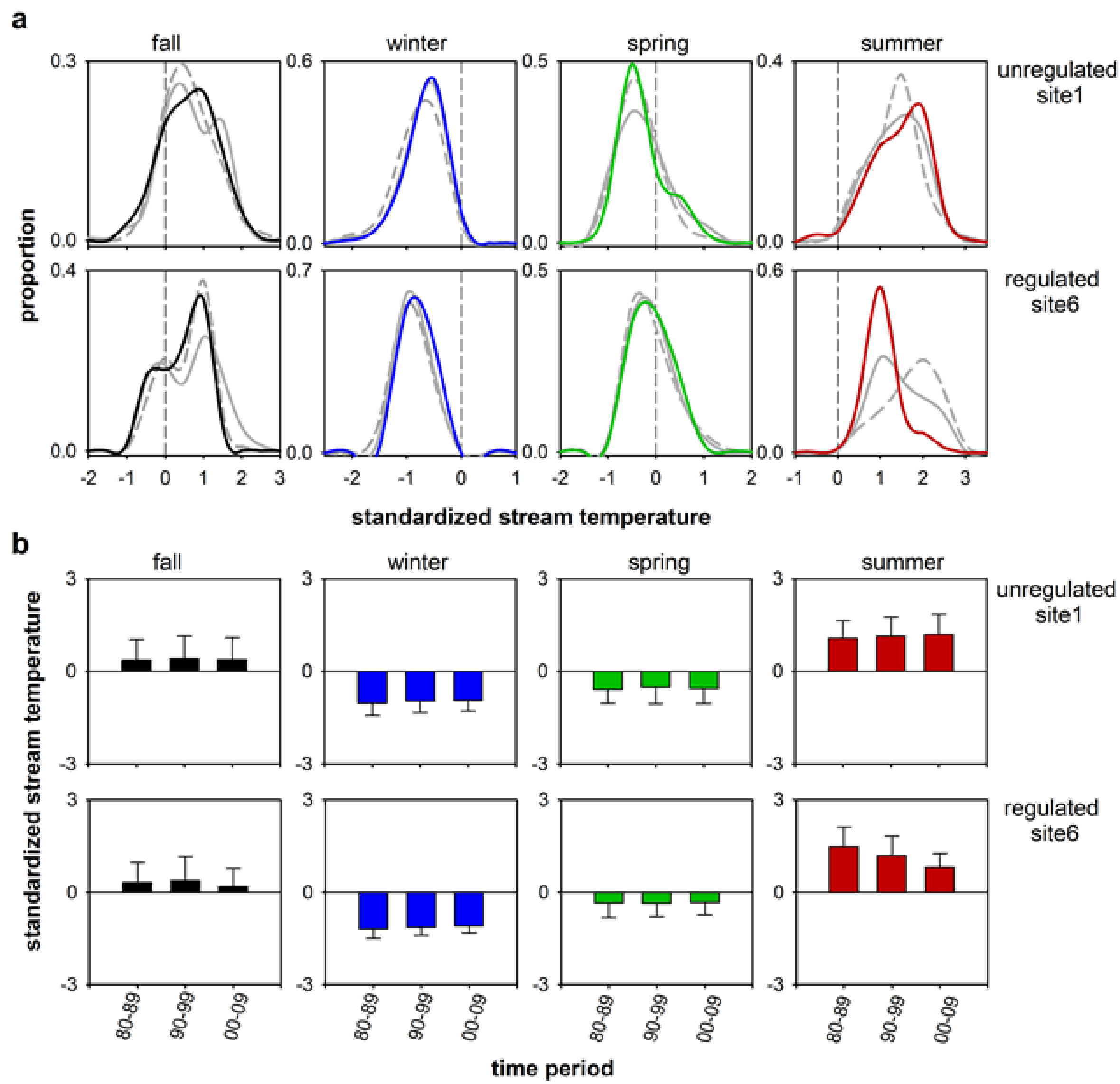
a
fall
winter
spring
summer
unregulated
site1
regulated
site6
proportion
standardized stream temperature
b
fall
winter
spring
summer
unregulated
site1
regulated
site6
standardized stream temperature
80-89
90-99
00-09
time period

Figure 3

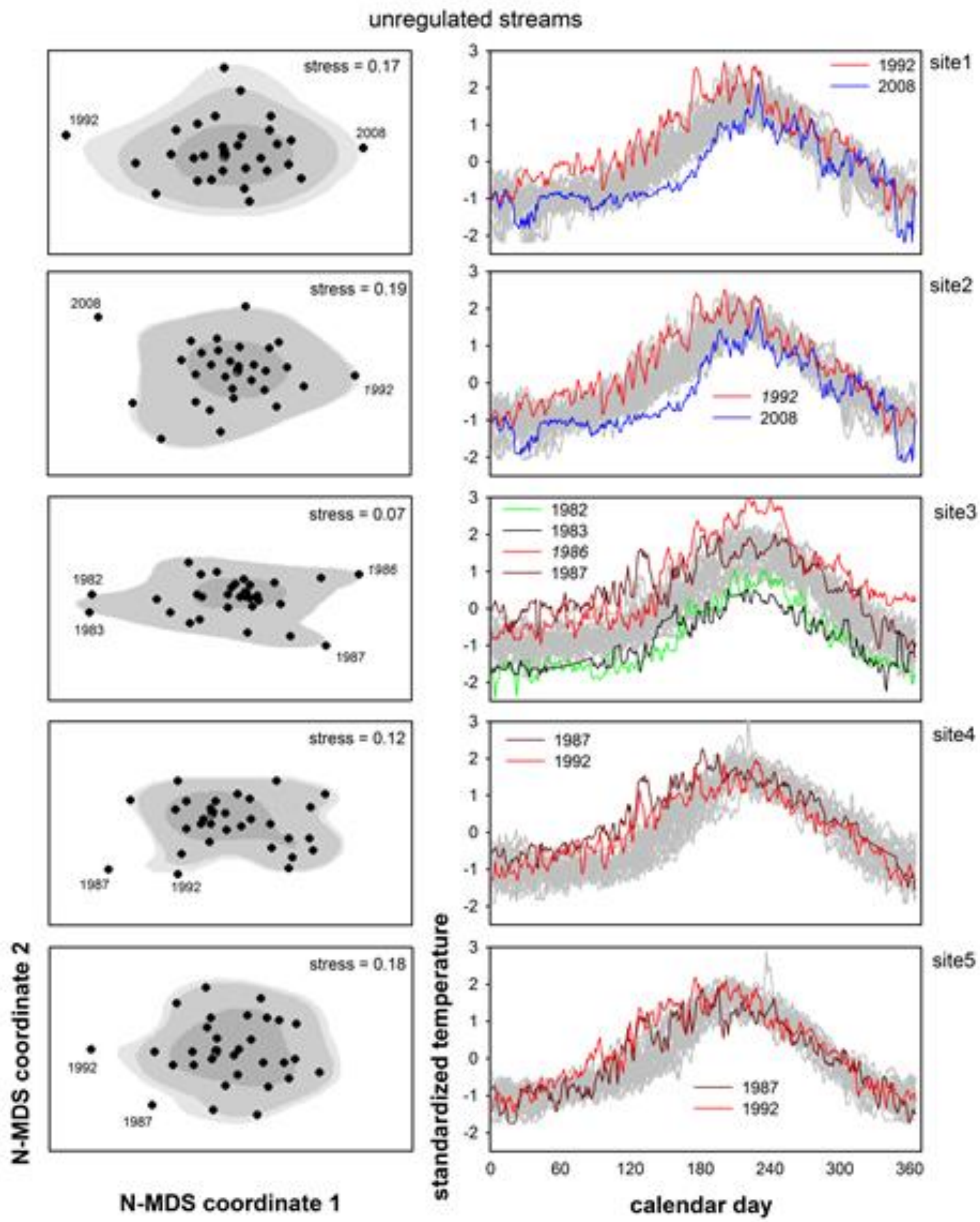
unregulated streams
stress = 0.17
1992
2008
stress = 0.19
2008
1992
stress = 0.07
1982
1983
1986
1987
stress = 0.12
1987
1992
stress = 0.18
1992
1987
N-MDS coordinate 2
N-MDS coordinate 1
site1
site2
site3
site4
site5
standardized temperature
calendar day
0
60
120
180
240
300
360

Figure 4

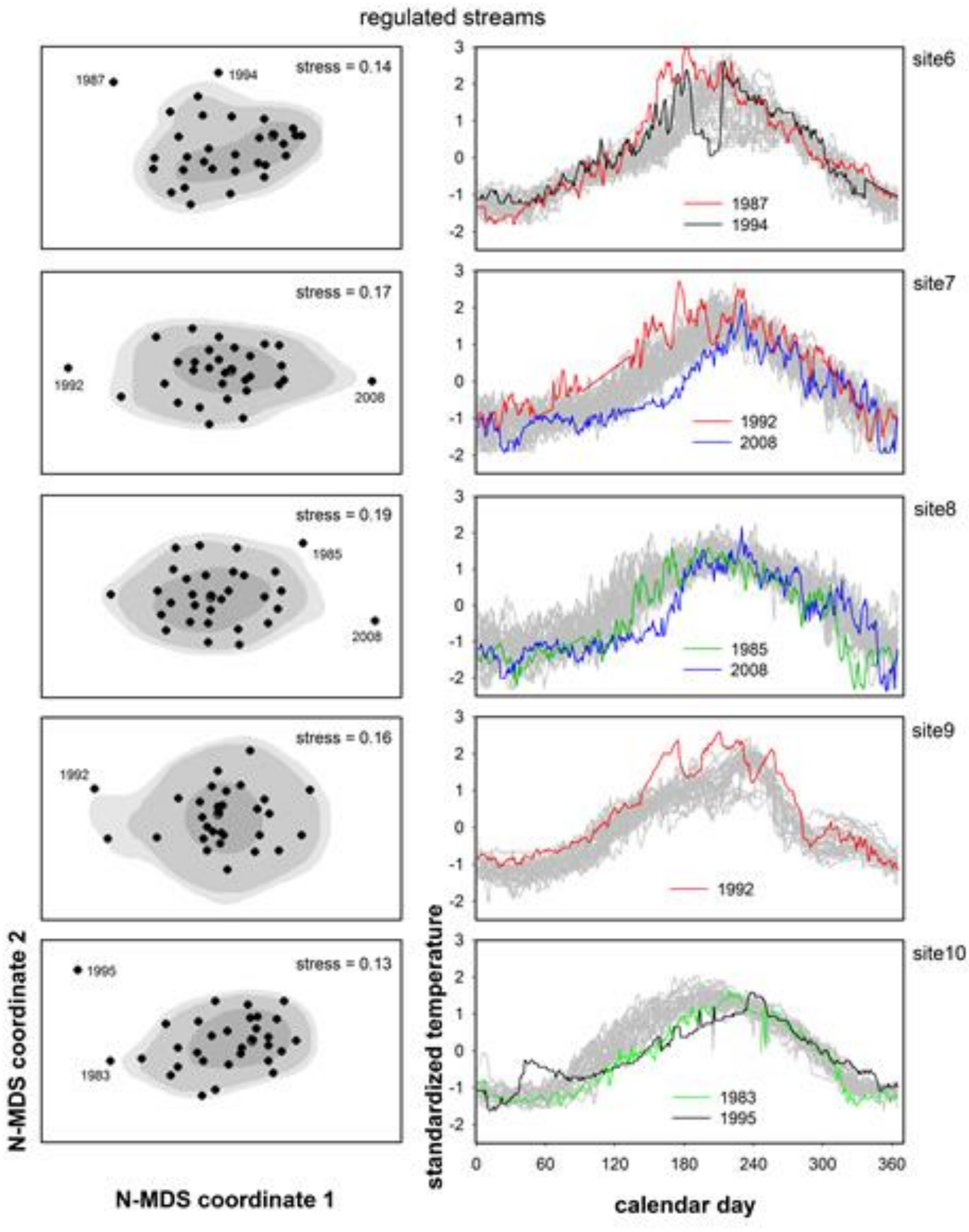
regulated streams
stress = 0.14
1987
1994
site6
1987
1994
stress = 0.17
1992
2008
site7
1992
2008
stress = 0.19
1985
2008
site8
1985
2008
stress = 0.16
1992
site9
1992
stress = 0.13
1995
1983
site10
1983
1995
N-MDS coordinate 2
N-MDS coordinate 1
standardized temperature
calendar day
0
60
120
180
240
300
360
3
2
1
0
-1
-2

Figure 5