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PRIMARY RESEARCH PAPER

Summer stream temperature metrics for predicting brook trout (*Salvelinus fontinalis*) distribution in streams

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Abstract We developed a methodology to predict brook trout (*Salvelinus fontinalis*) distribution using summer temperature metrics as predictor variables. Our analysis used long-term fish and hourly water temperature data from the Dog River, Vermont (USA). Commonly used metrics (e.g., mean, maximum, maximum 7-day maximum) tend to smooth the data so information on temperature variation is lost. Therefore, we developed a new set of metrics (called event metrics) to capture temperature variation by describing the frequency, area, duration, and magnitude of events that exceeded a user-defined temperature threshold. We used 16, 18, 20, and 22°C. We built linear discriminant models and tested and compared the event metrics against the commonly used metrics. Correct classification of the observations was 66% with event metrics and 87% with commonly used metrics. However, combined event and commonly used metrics correctly classified 92%. Of the four individual temperature thresholds, it was difficult to assess which threshold had the "best" accuracy. The 16°C threshold had slightly fewer misclassifications; however, the 20°C threshold had the fewest extreme misclassifications. Our method leveraged the volumes of existing long-term data and provided a simple, systematic, and adaptable framework for monitoring changes in fish distribution, specifically in the case of irregular, extreme temperature events.

Keywords Stream temperature · Climate change · *Salvelinus fontinalis* · Event metrics

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Introduction

Climate-induced changes in Vermont are detectable at a decadal time scale and indicate a trend toward higher temperatures (Stager & Thill, 2010). A warmer climate poses threats to coldwater fish, such as brook trout (*Salvelinus fontinalis*), which are particularly affected by warm water temperatures. Long-term stream temperature monitoring is useful for detecting changes in fish distributions, as well as identifying the potential loss of suitable fish habitat from climate change (Kaushal et al., 2010). Specifically for brook trout, knowing what temperatures are stressful is important in tracking past and future changes in their distribution (Stranko et al., 2008). Fisheries managers can collect temperature data at a lower cost and higher frequency than conducting biological surveys; thus, using temperature is appealing as a first-cut metric for monitoring fish populations from a human resources and cost perspective during this time of climate change.

Fish such as native and introduced salmonids, which have restrictive thermal tolerance, compete via exploitation or interference (Fausch, 1988). However, temperature is important to species interactions and likely mediates competition (Taniguchi et al., 1998). Brook trout research in Tennessee revealed no net loss in brook trout distribution in the presence of exotic rainbow trout (Strange & Habera, 1998) and in a controlled environment; brook trout were dominant over rainbow trout at both 13 and 18°C (Magoulick & Wilzbach, 1998). Brook trout outside of their native range are predicted to decline with increasing temperatures, which favors native salmonids (Wenger et al., 2011). Thus, there is support in the literature that warmer temperatures can take precedence over species interactions in determining brook trout distributions.

Extremely warm temperatures become deadly to cold water fish. Lethal temperatures have been identified for many species using the critical thermal maximum (Lutterschmidt & Hutchison, 1997) and incipient lethal temperature (Fry et al., 1946) methods. Fish may recover from short exposures to high temperatures (Bevelhimer & Bennett, 2000), and may be adapted to the thermal regime of a particular river (Gamperl & Farrell, 2004). Two field-based studies, identified 7-day maximum mean temperatures of 22.5°C (Eaton et al., 1995) and 23.3°C (Wehrly et al., 2007), suggesting that prolonged exposure to temperatures >22°C is deleterious to brook trout. Unfortunately, field measurement of stress is difficult to attribute to a single factor. However, heat-shock proteins (hsp) have been identified as bioindicators of temperature stress (Iwama et al., 1998); specifically, hsp 70 becomes activated primarily from increased temperature exposure and not from other stressors (Lund et al., 2002; Feldhaus et al., 2008). Brook trout have significant increases in hsp 70 at 22°C, indicating temperatures >22°C are limiting (Lund et al., 2003).

Brook trout sensitivity to warm temperatures (i.e., any above ~12°C affects growth rates (Xu et al., 2010)) indicates the usefulness of identifying temperature metrics that capture temperature variation for monitoring species distributions. However, research on the thermal tolerance of coldwater stream fish is complicated by daily temperature variations that occur in the wild. Given that commonly used temperature metrics smooth variations in seasonal temperature, we developed new metrics that preserved temperature fluctuations. We were interested in temperatures that exceeded some user-specified threshold (for demonstration purposes, 16, 18, 20, and 22°C in this study) to better monitor potential threats to brook trout. Our analysis used long-term fish population and stream temperature data from the Dog River, Vermont (USA) to explore the relationship of these new metrics alone, and in combination with commonly used metrics, to the spatial distribution of brook trout. We used these seasonal temperature metrics (i.e., our new metrics in combination with commonly used temperature metrics, such as mean, maximum, maximum 7-day mean, and maximum 7-day maximum) as predictor variables to improve classified predictions of brook trout distribution. We chose our model set to answer the following questions: (1) Are the new metrics better predictors than the commonly used metrics? (2) Do the new metrics add value when used in combination with commonly used metrics? (3) Do the metrics that describe duration and magnitude of temperature exposure perform better than integrated (i.e., area under the curve) metrics of exposure? (4) Are median temperature metrics better predictors than more extreme, 90th quantile metrics? Our method leveraged the existing volumes of long-term data and provided a simple, systematic, and adaptable framework for monitoring temperature changes related to fish distribution.

Methods

Study area

Vermont is located in the northeastern United States (Fig. 1) and is characterized by forested highlands and

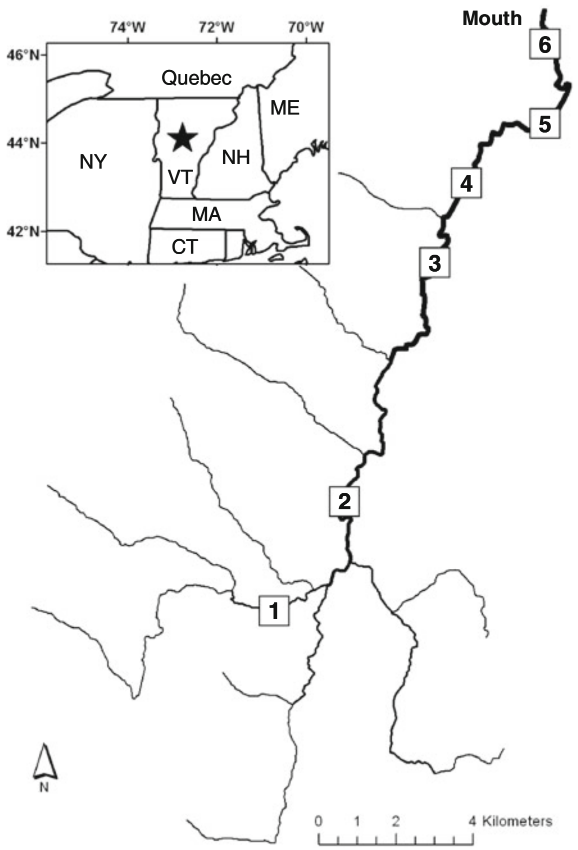

Fig. 1 Locations of six long-term fish and temperature sampling sites on the Dog River in Vermont, USA. Each site is a 150- to 200-m stream reach

agricultural valleys. Rivers are typically freestone (i.e., water source is precipitation) with occasional inputs from groundwater springs. Vermont rivers are subject to low base flows and warmer temperatures in mid- to late-summer. Brook trout are a highly valued native sport fish in Vermont and have thriving populations in the headwaters of most watersheds, although reduction in the native range has been recognized by research-based conservation and policy initiatives (e.g., Eastern Brook Trout Joint Venture). In addition to native brook trout, the salmonid fish assemblage is comprised of naturalized brown (*Salmo trutta*) and rainbow trout (*Oncorhynchus mykiss*) introduced throughout Vermont in the 1800s (MacMartin, 1962); in some areas, Atlantic salmon (*Salmo salar*) were reintroduced beginning in the 1980s (McMenemy, 1995).

Located in central Vermont near Montpelier, the Dog River is a 33-km long third-order river (Fig. 1). The watershed drains 240 km^2, ranges in elevation from 150 to 460 m, and has a natural (unregulated) flow regime. The majority of the watershed is forested (72%), although the river is crossed by roads and railroad bridges and flows through some agricultural lands and small communities. The Dog River is an ideal system to investigate brook trout distribution because it has the longest annual fish survey and temperature data in Vermont and self-sustaining populations of brook, brown, and rainbow trout have thrived without stocking since 1991.

Data collection and preparation

We used 17 years (1991–2007) of electrofishing data from the annual salmonid population surveys conducted on the Dog River by Vermont Fish and Wildlife (VTFW) biologists. Sampling occurred during late-summer or early fall at six index sites, each 150–200 m long (Fig. 1). Population sizes were estimated using the multiple pass depletion method (Carle & Strub, 1978). Estimated numbers of brook, brown, and rainbow trout per kilometer were used to calculate the average yearly proportion of brook trout of the total trout present at each sampling site. We categorized fish sampling sites in terms of the proportion of brook trout: Dominant ($\geq$0.33), Reduced (<0.33), and Absent (0).

Hourly temperature data were recorded between early June and mid-September with HOBO® water temperature loggers (Onset Computer Corp., Bourne, Massachusetts, USA) in years 2000–2007 at all six sites. Loggers were located directly upstream or downstream of each Dog River fish survey site. In addition, site-specific, fine-scaled (both spatial and temporal) temperature data were collected using 6–12 small, inexpensive temperature loggers (Thermochron iButton®, Dallas Semiconductor Corp., Dallas, USA) within each site. Spatial and temporal details can be found in Butryn (2010). The spatial variation of recorded temperatures at individual sites was less than the error tolerance of the iButton®, verifying that the temperature data collected by each site-specific VTFW temperature logger were representative of the entire site (Butryn, 2010).

We calculated six commonly used temperature metrics (mean, maximum, minimum, mean daily maximum; maximum 7-day mean (MEANT); and maximum 7-day maximum (MAXT)) over the summer time period (15 June–15 September). The 7-day metrics were calculated as a moving window average. These metrics are often compared to laboratory-derived upper incipient lethal temperature (UILT) for brook trout (McCormick et al., 1972) and field-derived maximum 7-day daily mean and maximum 7-day daily maximum limits (Wehrly et al., 2007).

In addition to the commonly used metrics, we developed four new temperature metrics, referred to in this study as *event metrics*, that described the frequency, area, duration, and magnitude over which temperatures exceeded a user-defined threshold. An event was defined as the period of time during which a specified threshold was exceeded (Fig. 2). *Event frequency* is defined as the total number of events occurring during the seasonal monitoring (i.e., 15 June to 15 September). *Event area* has the units of °C·hour and is the summed difference of the threshold from the recorded temperature for each hour interval in the event and represented the area under each event's curve. *Event duration* was defined as the length of time (in hours) that temperature remained above the given threshold. *Event average magnitude,* expressed in °C, was the average hourly difference between the recorded temperature and the threshold in the event.

Statistical analysis

We provide a methodology for selecting temperature metrics to "best" explain brook trout distribution categories in the Dog River demonstrated using four temperature thresholds (16, 18, 20, or 22°C). Although temperature data are measured hourly throughout the summer, our dependent variable (i.e., brook trout abundance) is only measured at the end of the summer field season. This results in a single, real-valued number for each stream site for each year of monitoring. To assume these single snapshot-in-time, real-valued numbers are precise representations of total brook trout in given reaches over the entire field season is overkill from a statistical point of view; and classifying abundance into categories of brook trout distribution (i.e., dominant, reduced, and absent) was more practical from a management perspective. We performed an analysis of variance (ANOVA) to test for statistical differences in classified proportion of brook trout and their relationship to differences in temperature metrics among Dog River sites. All statistical tests were considered significant at $\alpha = 0.05$. We tested for normality within groups (Kolmogorov–Smirnov test) and equal variance between groups (Levene's test; Sokal & Rohlf,

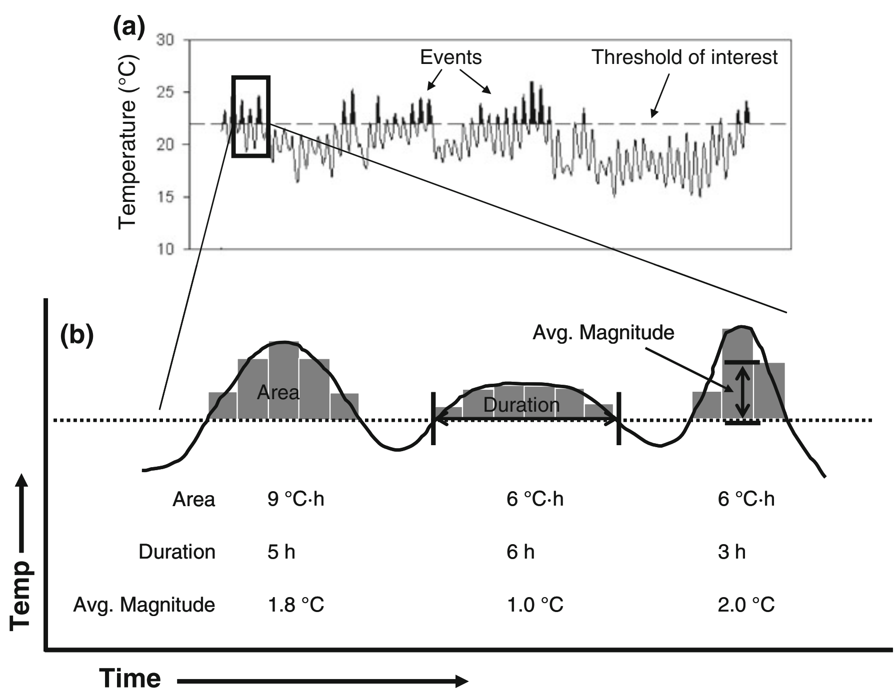

Fig. 2 **a** An example of hourly summer temperature data collected at a site. *Dashed line* at 22°C represents threshold at which an event starts and stops. **b** Close up of theoretic thermograph showing the dimensions that each event metric represents. *Note*: events of similar area can have different magnitudes

1995). When these assumptions were met, an ANOVA was performed with Student–Newman–Keuls (SNK) multiple comparison test; when assumptions were not met, a Kruskal–Wallis (K–W) one-way ANOVA on ranks and Dunn's Method (Hollander & Wolfe, 1979) were used for all pair-wise comparisons (SigmaPlot 11, Systat Software, Inc., Chicago, Illinois, USA). Temperature metrics with significant differences among sites were hypothesized to be associated with changes in the distribution of brook trout and were, therefore, included in subsequent discriminant models to predict trout distribution categories (JMP 9, SAS Institute, Inc., Cary, North Carolina, USA).

To test the temperature thresholds and event metrics most indicative of brook trout distribution (classified into one of three categories: Dominant, Reduced, and Absent) in the Dog River, we performed a set of linear discriminant classification models. Possible explanatory variables included all temperature metrics identified as significant by the ANOVA at all sites and all years, where events occurred ($n = 40$). In addition, we performed a discriminant analysis on the six commonly used temperature metrics for comparison purposes. Discriminant analysis is designed to classify samples into one of two or more alternative groups (or populations) on the basis of a set of measurements.

We identified the "best" temperature threshold and classification model using two measures of model fit (i.e., Wilks' λ (Sokal & Rohlf, 1995)) and the -2 Log likelihood) and two measures of classification performance (i.e., the overall misclassification rate and *extreme* misclassifications). We defined *extreme* misclassifications as those for which the discriminant model predicted a site as having the brook trout distribution category Dominant when in fact field measurements classified the site as Absent (and vice versa). A 30-year air temperature and stream discharge dataset for the Dog River was also used to help further explain other model misclassifications (Butryn, 2010).

Results

Each of the six Dog River sites were assigned to one of three brook trout distribution categories (Dominant, Reduced, and Absent). Sites 1 and 2 had brook trout proportions of 0.44 and 0.36, respectively, placing them in the category Dominant. Sites 3 and 5 had brook trout proportions of 0.13 and 0.001, which classified these sites as Reduced. On average, sites 4 and 6 did not have brook trout; so they were assigned to the category Absent. In terms of overall salmonid abundance (numbers of trout per kilometer $\pm$ SE) during the study period, sites 4 and 5 were estimated to contain (3024 ± 414) and (1396 ± 189), respectively, followed by Site 1 (610 ± 116), Site 6 (243 ± 67), Site 3 (226 ± 75), and Site 2 (226 ± 75).

In general, the event temperature metrics had skewed distributions with many short, less intense events and fewer extreme events; therefore, median and quantile statistics were appropriate descriptors. Each of the six sites had events that exceeded the 16 and 18°C thresholds every year (Table 1). Five sites had events that exceeded 20°C every year. The exception was Site 1, located in the headwaters, where the 20°C threshold was exceeded in three of six years. Events over 22°C did not occur every year at most sites, except for Site 2 where the threshold was exceeded every year. The relationship between temperature threshold and the number of events that occurred at a site seemed counterintuitive; however, it is important to keep in mind that fewer events occurred at the lower thresholds simply because those thresholds were exceeded for longer time periods. The other event metrics (area, duration, and average magnitude) exhibited the expected pattern of smaller median values for higher temperature thresholds (Table 1).

Variables identified by ANOVA as statistically significant included three of our four event metrics, plus the 90th quantile temperature event, and were used in the discriminant classification models. The commonly used temperature metrics did not approach UILT or MEANT levels for brook trout at any of our Dog River sites (Fig. 3a). Brook trout distributions across sites 4, 5, and 6 were not different (Fig. 3a). Whereas, the event metrics helped to differentiate brook trout distributions across the three sites (Fig. 3b–d). Thus, commonly used metrics were not included in the discriminant analysis, but are shown for comparison purposes (Table 2).

Classification models

Discriminant classification models were constructed for every temperature metric, as well as all possible combinations that showed statistical significance

Table 1 Median temperature event metrics (frequency, area, duration, and average magnitude) during 2000–2007 for threshold temperatures from 16 to 22°C at each site on the Dog River

Site	Brook trout category	Threshold (°C)	Threshold Yr/#Yr	Event metrics			
				Frequency (#/yr)	Area (°C*h)	Duration (h)	Average magnitude (°C)
1	Dominant	16	6/6	52	9.78	10	0.94
		18	6/6	23	3.51	7	0.51
		20	3/6	2	2.27	4	0.48
		22	0/6	0	0.00	0	0.00
2	Dominant	16	5/5	58	19.57	13	1.50
		18	5/5	60	12.16	10	1.21
		20	5/5	33	3.94	6	0.66
		22	5/5	8	0.80	3	0.27
3	Reduced	16	7/7	37	17.53	15	1.10
		18	7/7	44	9.72	11	0.77
		20	7/7	27	4.99	8	0.54
		22	6/7	6	1.50	5	0.31
4	Absent	16	7/7	35	20.10	15	1.26
		18	7/7	51	10.80	11	0.98
		20	7/7	37	7.03	8	0.85
		22	6/7	13	3.25	5	0.64
5	Reduced	16	8/8	34	17.52	15	1.21
		18	8/8	46	12.64	12	1.00
		20	8/8	32	5.72	9	0.67
		22	6/8	8	2.97	7	0.46
6	Absent	16	7/7	29	23.66	16	1.44
		18	7/7	53	12.52	12	1.03
		20	7/7	42	9.20	9	0.97
		22	6/7	20	4.08	6	0.77

Threshold Yr/# Yr is the number of years each threshold was reached at least one time of the total number of years data were collected at each site

across sites using the ANOVA (Table 2). The model that most accurately predicted brook trout distribution categories (i.e., Dominant, Reduced, and Absent) was the commonly used temperature metrics. The linear discriminant model using these six metrics was significant (Wilks' $\lambda = 0.1361$; $P < 0.0001$) and correctly classified 87% of the Dog River observations (Table 2, Model #1).

The second best model used two event metrics (i.e., duration and average magnitude; Table 2, Model #3) and on average was significant (Wilks' $\lambda = 0.5056$; $P = 0.0015$) with 14 misclassified (34%) observations. However, when we combined event and commonly used metrics we correctly predicted 92% of the observations. The 16°C threshold had slightly fewer misclassifications; however, the 20°C threshold had the fewest extreme misclassifications.

Confusion matrices were used to assess error produced by the discriminant model (Table 3). The confusion matrices of our best-fit discriminant model (i.e., event temperature metrics—duration and average magnitude) showed both the correct (along the diagonal) and incorrect (on the off-diagonal) predictions for each of the four temperature thresholds. The matrices display the number of sites predicted to be in one of our three brook trout distribution categories (columns of Table 3) against measured reality (rows of Table 3). Misclassifications occurred for all categories; however, we were able to predict sites belonging to Dominant more accurately across all four temperature thresholds than Reduced or Absent. We defined the misclassifications in the off-diagonal corners of the matrix as *extreme* misclassifications (bold values). Predictions using the new event metrics

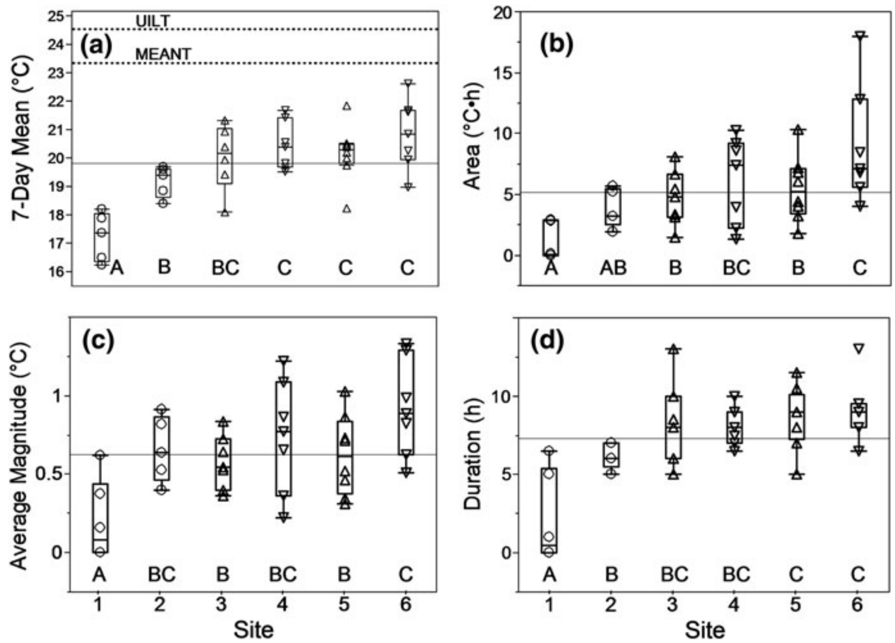

Fig. 3 *Box–whisker* plots (median ± interquartiles) for **a** maximum 7-day mean with *upper* incipient lethal temperature (UILT) and the maximum 7-day mean temperature limit (MEANT) *dotted lines* **b** area **c** average magnitude and **d** duration for the six Dog River sites. Symbols (*open circle* Dominant, *open up-pointing triangle* Reduced, *open down-pointing triangle* Absent) represent brook trout distribution categories. Sites with the same letter are not statistically different (SNK or K–W test). *Horizontal solid line* on each panel is the grand mean of the six sites

Table 2 A subset of discriminant models ($N = 5$) tested brook trout category classification by event metrics

Model # and inputs	Threshold (°C)	−2 Log likelihood	Misclassified # (%)	Extreme misclassified
(1) Commonly used metrics	NA	24.9	5 (13)	0
(2) Area	16	79.7	15 (38)	6
	18	82.6	24 (60)	10
	20	71.4	17 (42)	2
	22	78.3	22 (55)	5
(3) Duration, average magnitude	16	58.9	12 (30)	5
	18	52.0	16 (40)	11
	20	57.9	13 (32)	2
	22	73.2	14 (35)	5
(4) 90th quantile of (duration, average magnitude)	16	64.8	18 (45)	1
	18	63.2	20 (50)	15
	20	68.9	18 (45)	6
	22	77.6	19 (47)	5
(5) Duration, average magnitude, (combined with commonly used metrics)	16	23.9	7 (18)	0
	18	18.6	3 (8)	0
	20	21.5	2 (5)	0
	22	13.1	2 (5)	0

The −2 Log likelihood indicates model fit of the data. Misclassifications are those off by one category and extreme misclassifications are off by two categories. Models with best-fit and fewest misclassifications are considered the best

NA not applicable

were not as accurate as those with commonly used metrics, which we expected as most of the temperature data were below defined thresholds and were eliminated from the analyses. However, these new event metrics added value when variation in temperature increased (i.e., the discriminant analysis accuracy increased dramatically when event and commonly used metrics were combined). There were no extreme misclassifications for all four temperature thresholds when using the combined metrics and the number and percent misclassified were lower than those classified by commonly used metrics alone.

Extreme misclassifications (i.e., brook trout distributions predicted as Dominant when observed as

Table 3 Actual versus predicted matrices of brook trout category from the discriminant model with the best-fit event (duration, average magnitude) and combined (event + commonly used) metrics for four temperature thresholds (16, 18, 20, and 22°C)

Threshold (°C)	Actual	Predicted (event metric)			Predicted (combined metrics)		
		Dominant	Reduced	Absent	Dominant	Reduced	Absent
16	Dominant	8	0	**3**	10	4	**0**
	Reduced	2	11	2	3	11	0
	Absent	**2**	3	9	**0**	0	10
18	Dominant	9	0	**2**	12	2	**0**
	Reduced	1	8	6	1	13	0
	Absent	**2**	5	7	**0**	0	10
20	Dominant	7	2	**2**	12	2	**0**
	Reduced	2	10	3	0	14	0
	Absent	**0**	4	10	**0**	0	10
22	Dominant	9	1	**1**	13	1	**0**
	Reduced	5	9	1	1	13	0
	Absent	**4**	2	8	**0**	0	10

Extreme misclassifications (bold) were those in which brook trout were Absent but predicted to be Dominant or Dominant but predicted to be Absent

Table 4 Extreme misclassifications (i.e., model predicted brook trout distributions as Dominant when observed as Absent (A–D) or predicted Absent when observed as Dominant (D–A)) by year from the discriminant model with the best-fit (duration, average magnitude) at four temperature thresholds (16, 18, 20, and 22°C)

Model threshold	Years							
	2000	2001	2002	2003	2004	2005	2006	2007
16°C								
Site 2			D–A	D–A		D–A		
Site 4				A–D	A–D			
18°C								
Site 2				D–A		D–A		
Site 4			A–D					A–D
20°C								
Site 2			D–A			D–A		
22°C								
Site 2						D–A		
Site 4							A–D	
Site 6	A–D		A–D				A–D	

Absent (A–D) or predicted as Absent when observed as Dominant (D–A)) only occurred at three of the six sites (Sites 2, 4, and 6); and the majority (13 out of 16) of these events occurred in 2002, 2003, 2005, and 2006 (Table 4). These years had four of the five warmest mean summer air temperatures in 30 years, based on the data recorded near the Dog River (Fig. 4).

Discussion

A majority of Vermont's rivers have temperatures that are intermittently unsuitable for brook trout, yet mean or maximum temperature metrics are not indicative of lower brook trout abundance. The Dog River contains a well-established wild trout assemblage; thus, brook trout distribution within the river is a naturally occurring pattern. Based on 7–17 years of data, brook trout abundance was stable, although reduced when occurring with other trout species. Therefore, we used average proportion of brook trout to define categories because proportion best represented states of distribution that may be expected despite interannual variability in density-dependent regulatory processes (Milner et al., 2003), year class strength, or sampling efficiency. The distribution of brook trout was limited despite having temperatures that remain below the laboratory and field-based estimates of lethal or

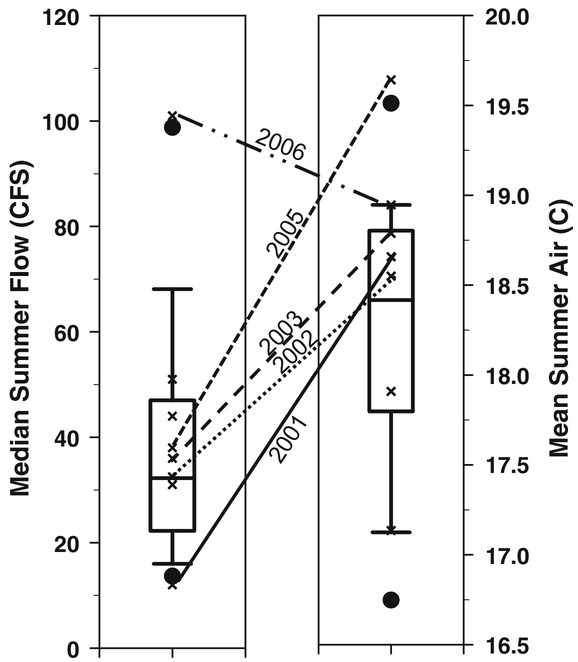

Fig. 4 *Box–whisker* (median ± interquartiles) plots of 30-year discharge and air temperature records in central Vermont. Discharge data were collected near Site 4 on the Dog River and air temperature data were recorded at an airport ∼5 km from the mouth of Dog River. The x's indicate the years for which we had data and years 2001, 2002, 2003, 2005, and 2006 are indicated on the *connecting lines*

limiting temperatures. In response to this, we developed new event-based metrics (area, duration, and magnitude) that better capture the variation associated with hourly temperature data and compare well with seasonal fish distribution data. We develop methodology that can be used with any temperature threshold and show proof of concept using four thresholds that are all greater than 12°C, the upper limit for growth in brook trout in Massachusetts (Xu et al., 2010). As research on temperature stress advances (Feldhaus et al., 2008; McCullough et al., 2009), we expect that more site- and species-specific temperature thresholds will be examined in combination with long-term monitoring of temperature.

Our analysis focuses on identifying temperature metrics to better predict brook trout distribution. Commonly used temperature metrics such as seasonal mean and maximum, and moving average metrics such as 7-day mean and maximum are useful descriptors of thermal regimes and often associate well with stream fish distribution patterns (Wehrly et al., 2003; Nelitz et al., 2007). We have confirmed that the commonly used metrics work well to predict proportion of brook trout in the Dog River. However, we also confirmed that the commonly used metrics are insufficient for detecting variation caused by irregular and extreme events.

Ideally, one might like to upscale finely resolved temperature data to a single seasonal value and to make easier comparisons of brook trout distribution routinely monitored on a seasonal time scale. On the Dog River, where we had 7–17 years of brook trout distribution data, our new metrics alone enabled correct classifications approximately 66% of the time. Misclassifications occurred most often for years when few temperature events were recorded. The combination of event duration and average magnitude provided the best predictions overall. Interestingly, we expected event area to be the best individual predictor because it combined both event duration and magnitude. However, this was not the case. Event magnitude was the best individual predictor, suggesting perhaps that the magnitude of temperature above a given threshold may be more relevant than the duration.

Our research indicates that Dog River brook trout occurred with brown and rainbow trout in equal or greater proportion when temperature events are short and mild. Longer events were associated with category Reduced and the longest and largest events were associated with category Absent. Our results follow patterns of duration used as a predictor of age 0 Atlantic salmon density (Mather et al. 2008) and laboratory experiments with rainbow trout that showed long exposure to moderately stressful temperature was more difficult to overcome than short exposure to highly stressful temperature (Bevelhimer & Bennett, 2000). Hopefully, the importance of event duration and magnitude can be addressed in future laboratory research with heat stress and tested on other rivers with well-established wild trout populations.

Median values for event metrics produced only a slightly better classification rate than 90th percentile values. Our justification for including the 90th percentile values as potential explanatory variables was that some sites with similar median event size might be prone to more extreme events. This was not tested or verified because our data were limited to sites spatially contiguous along a single river. However, this metric should be given further consideration if multiple rivers are used to build a model. Interestingly, 2001 was the lowest flow year of the 30-year record, but was not associated with high temperatures (Fig. 4). The 2001 pattern did not result in any extreme misclassifications, suggesting that temperature may be a more important factor than flow in the Dog River.

The addition of our new event metrics with commonly used metrics improved prediction accuracy. Event metrics better preserved the temperature variation in finely resolved stream temperature data than metrics that smooth and generalize temperature profiles. Clearly, climate change scenarios predict the occurrence of more extreme and irregular events, which indicates that using event metrics will be more important in the future. Event metrics may also be useful in a hydrological setting for measuring the influence of riparian shading and groundwater inputs. Although field data are typically limited, we believe that metrics capable of preserving the range and variation associated with finely resolved temperature data, as a first-cut, is useful in assisting researchers and managers interested in using temperature to predict species distributions now and even more so in the future.

Extending the Dog River model to other rivers would require considerations such as historical interactions between native brook trout and introduced salmonids. Rivers not managed as wild trout fisheries generally are stocked annually, which may lead to fish distributions that would not occur naturally. Rivers vary in trout species composition and different competitive pressures on brook trout from brown and rainbow trout have been observed (Weigel & Sorensen, 2001). Barriers to fish movement and accessibility to coldwater refuges (Baird & Krueger, 2003) may have positive or negative influence on brook trout proportion. These complexities would limit the performance of our predictive model in other regions and illustrate the need for long-term datasets. In addition, when extending our methodology to other river systems and larger datasets, modeling techniques in addition to discriminant analysis may be appropriate (e.g., neural network models (McKenna et al., 2010)).

Warm temperatures in addition to temperature variation are important determinates of brook trout success, but are difficult to quantify. The scale over which commonly used temperature metrics are averaged mask their ability to identify pertinent features/events (e.g., frequency, duration, and magnitude) that correlate to fish stress. Event metrics provide a vehicle to answer these questions and explore hourly temperature data in a biologically relevant manner. Our approach can be transferred to other species, datasets, and temperature thresholds as well as accommodate future research on temperature stress in fish.

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