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Using watershed characteristics to inform cost-effective stream temperature monitoring

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Abstract Water temperature is a key driver of aquatic processes. Monitoring stream water temperature is key to understanding current species distributions and future climate change impacts on freshwater ecosystems. However, a very small fraction of streams are continuously monitored for water temperature throughout North America, due to prohibitive logistical costs. We develop a framework that aids in developing cost-effective stream temperature monitoring by using stream habitat features to inform strategic site selection of temperature monitoring sites. We test this framework using sockeye salmon spawning streams as a model, which included 19 streams in the northern-most watershed of the Fraser River Basin, British Columbia, Canada. The objective of this framework is to evaluate the trade-off between cost (i.e., the number of streams monitored) and the effectiveness of monitoring scenarios at meeting different monitoring objectives. We compared monitoring scenarios that were informed by well-established relationships between variables and that are commonly collected or available as part of other monitoring activities (stream length, magnitude, order, gradient, wetted width, and spot temperatures) and water temperature metrics (maximum, mean, and variance during August) derived from continuously monitored streams to monitoring scenarios where streams were randomly selected. Informed scenarios included streams that were selected in order of watershed level and stream habitat characteristics (e.g., longest to shortest); ordering was based on the relationship between each habitat variable and temperature metrics. Informed monitoring scenarios were then compared to random selection of monitoring sites with regard to how well monitoring scenarios met two management objectives during the critical salmon spawning period: (1) identifying streams that exceed a temperature threshold and (2) identifying streams that represent the temperature regime of a complex of streams (e.g., mean and variance of streams within an aggregate of streams). Management objectives were met by monitoring fewer streams using the informed monitoring scenarios rather than the average of the random scenarios. This highlights how common inexpensive watershed level variables that relate to stream temperature can inform the strategic selection of sites and lead to more cost-effective stream temperature monitoring.

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Introduction

Water temperature plays a critical role in the biology and ecology of aquatic organisms (Ward and Stanford 1982; Magnuson 1991). Temperature drives key biological processes such as metabolic and developmental rates (Clarke and Johnston 1999), which can shape growth and size (Selong et al. 2001), behavior (Kovach et al. 2012), reproduction (Fleming and Gross 1990), and ultimately fitness (Becker and Genoway 1979). The well-demonstrated importance of water temperature for aquatic species highlights the need for water temperature monitoring, which can be used to understand how changes in temperature, such as through climate change, can impact aquatic systems and inform management.

Information on stream temperature is important for the management of freshwater ecosystems. For example, stream temperature is a key factor in determining habitat suitability for range of taxa (e.g., macroinvertebrates (Reynoldson et al. 2006) and fish (Eaton and Scheller 1996)). Long-term datasets of freshwater temperatures have also been used to identify high-temperature streams (Nelitz et al. 2007) and future climate change impacts on freshwater temperatures (Isaak et al. 2011; Mayer 2012; Luce et al. 2014). However, this extensive level of monitoring effort is concentrated in only a few watersheds (i.e., collecting hourly data on large number of sites annually) because of time and financial constraints. This forces managers to make difficult decisions about how much monitoring is enough for a given level of uncertainty for unmonitored or sparsely monitored systems. This decision is particularly challenging when little-to-no information about the trade-off between cost and effectiveness of stream temperature monitoring for assessing habitat status is available. Effectiveness can be thought of as how well a monitoring scenario (e.g., number and location of monitoring sites) meets an a priori objective. For example, this could be the certainty with which one designates habitat suitability or status. Costs are often thought of as primarily financial and will increase with monitoring effort. Although these general relationships provide a starting point, it is necessary to know their exact form. Understanding the form of the trade-off between cost and effectiveness for different levels of monitoring effort and what level of monitoring effort will meet management objectives will help guide the development of sustainable monitoring programs (Braun and Reynolds 2012; Whitfield 2012).

Strategic site or stream selection can also be important for cost-effective monitoring. There are many drivers of stream temperature such as atmospheric conditions, topography, streambed, and stream discharge (reviewed in Caissie 2006) that could aid in stream selection; however, many require expensive field monitoring. Relationships between these variables and stream temperature may be complex with seasonally (Hrachowitz et al. 2010) and regionally (Ward 1985) specific relationships. In contrast, steam order shows a general pattern whereby higher-order streams have higher mean daily temperature (Caissie 2006). Moore et al. (2015) showed that streams that integrate larger catchment areas had lower temperature variability between June and August. Streams that drain a larger area at lower elevations have the highest temperatures (Moore 2006; Nelitz et al. 2007). A large study of the US Pacific Northwest showed that a summer baseflow index and stream channel slope were strongly related to summer stream temperatures (Mayer 2012). It has also been shown that watershed geomorphology can largely explain water temperature during salmon spawning in Alaska (Lisi et al. 2013). Stream characteristics that can describe temperature could be used to select streams for temperature monitoring. For example, if the objective was to identify high-temperature streams (i.e., streams with temperatures that exceed some biologically relevant temperature), selecting the largest watersheds for monitoring would be the most cost effective. Knowing the relationships between watershed characteristics and water temperatures could be used to select subsets of streams for monitoring that maximize relevant information, which are likely to be more informative than randomly selecting streams. An application of watershed–temperature relationships would be to use them to design cost-effective temperature monitoring programs.

Relationships between measured values and their surrogates (e.g., relationships between water temperature and watershed characteristics) are particularly useful when the surrogate is less expensive to monitor

than the variable of interest. Watershed metrics, such as metrics of stream size, are inexpensive to collect for the individual researcher, since many can be derived from online sources, are being collected as part of another program, and are available for most watersheds. Continuous water temperature monitoring requires expensive fieldwork and temperature loggers and is not often feasible for all potential sites. The use of surrogates to select streams for monitoring can both reduce costs and expand the spatial extent of monitoring leading to more comprehensive programs.

Sockeye salmon spawning streams are a good model system to test a cost-effective monitoring framework because of the established links between water temperature and survival, and the increased use of temperature monitoring for salmon management. Recent studies have demonstrated particularly dramatic effects of high freshwater temperatures on salmonids (Richter and Kolmes 2005; Martins et al. 2012). Effects of high water temperatures include decreasing swimming performance (Lee et al. 2003), increasing disease prevalence (Bradford et al. 2010), decreasing juvenile size (Braun et al. 2013), and decreasing survival (Crozier et al. 2008; Martins et al. 2011). The importance of freshwater temperatures to salmonids has led to the development of predictive models of water temperatures for key life stages that are used to support adaptive management actions. For example, physical deterministic (Morrison and Quick 2002) and statistical (Hague and Patterson 2014) models have been developed to predict water temperatures during upstream migrations for Fraser River sockeye salmon populations. Water temperature predictions from both these models and associated risk of mortality are currently being used to make in-season management decisions about fisheries (Macdonald et al. 2010). Furthermore, water temperature is a key indicator of habitat status for salmon streams that are used for migrating, spawning, and juvenile rearing (Strategy 2, Wild Salmon Policy) (Stalberg et al. 2009). In addition, stream temperature monitoring can be used in future climate change scenarios that will allow for adaptive management of species and populations at risk (Crozier et al. 2008; Hague et al. 2011; Reed et al. 2011; Breau and Caissie 2013). Despite the importance of temperature measurements for salmon ecology and management in western Canada, the lack of publicly available data limits the current use of temperature data to inform management.

We developed a general approach to guide the selection of monitoring sites with regard to the number and location of sites. We use sockeye salmon spawning streams to illustrate the general principles of this approach. The basic approach is outlined in Fig. 1. We used two monitoring objectives: (1) identify spawning streams with high temperatures (i.e., >15 °C) and (2) identify subsets of spawning streams that are most representative of the thermal regime of a complex or aggregate of streams. For both objectives, we aimed to minimize the number of streams required to achieve either minimal cost (i.e., fewest number of streams) for a desired level of uncertainty or maximal effectiveness for a fixed cost (i.e., fixed number of streams). Relationships between stream thermal characteristics (derived from continuous temperature monitoring) and watershed characteristics (including spot temperature measurements) for 19 streams were explored to inform selection of streams in the absence of continuous temperature monitoring. We show how well sampling designs informed by existing watershed and temperature data perform relative to uninformed designs (random selection of streams). Uninformed monitoring scenarios, based on random stream selection, are used to illustrate the uncertainty in either identifying high-temperature streams or appropriately characterizing temperature status of an aggregate of streams. We show how this uncertainty varies over a range of streams sampled and that a few inexpensive stream variables can inform sampling designs to reduce uncertainty and lead to more cost-effective temperature monitoring.

Materials and methods

Study system

We studied 19 tributaries of the Stuart watershed, which is the northern-most watershed in the Fraser River Basin, British Columbia. These tributaries are home to spawning populations of sockeye salmon (*Oncorhynchus nerka*) known as the Early Stuart sockeye complex. These fish enter the Fraser River in early July and migrate upstream to spawn in August. Their spawn timing overlaps with the warmest water temperatures in their spawning streams (Braun—unpublished data). Resident fish species include rainbow trout (*Oncorhynchus mykiss*), bull trout (*Salvelinus confluentus*),

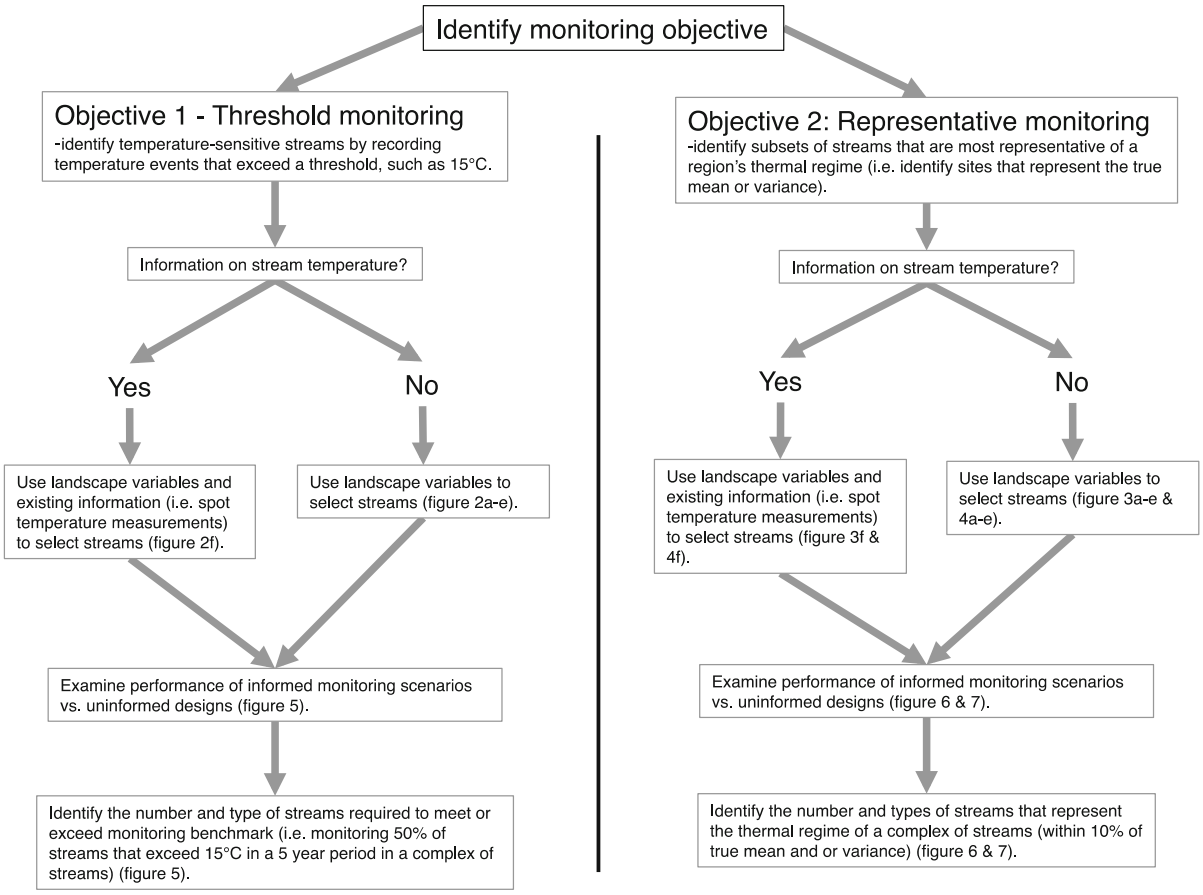

Fig. 1 Flow diagram of the framework for examining cost-effective monitoring scenarios

prickly sculpin (*Cottus asper*), mountain whitefish (*Prosopium williamsoni*) and burbot (*Lota lota*). All streams in this study have a stream order between 2 and 4 and bankfull width of <30 m.

Exploratory analyses

Watershed characteristics

We measured 6 watershed characteristics from field surveys (Braun and Reynolds 2011) and from online mapping programs (Table 1). Details for how data were collected during field surveys can be found in Braun and Reynolds (2011) but briefly, stream characteristics were measured in stream reaches that have historically had the highest sockeye salmon spawning densities. Reach length was defined as 30 times the bankfull width. Wetted width measured at 16 transects were used to calculate the mean wetted width. Stream gradient is the average slope of the reach and was measured using a 5X Abney hand meter. Spot temperature measurements are single temperature measurements using a handheld multimeter. Our spot measurements were replicated 3–5 times between June to August, and our values are averages for each stream. Spot temperatures were measured between 8:00 and 18:00. Spot temperature collections are standard practice for salmon enumeration programs during visual spawning surveys (e.g., every 3–7 days re-visit each creek) (Schubert and Fanos 1997), as such they represent a common source of inexpensive data for large number of streams.

Additional stream characteristics were obtained from Habitat Wizard (http://www.fishwizard.com/), an online map display tool that can be used to measure different watershed characteristics in British Columbia. These variables included stream magnitude, which is the sum of stream segments with a magnitude of one

Table 1 Summary of stream characteristics and temperature metrics

Creek	Online data (low cost)			Field data (high cost)			Continuous temperature metrics		
	Mainstem length (km)	Order	Magnitude	Spot temp (°C)	Gradient (%)	Wetted width (m)	Max daily temp (°C)	Mean daily temp (°C)	Temp variance (°C)
10 Mile	5.9	2	2	8.2	4.8	3.8	12.7	9.6	1.6
15 Mile	18.5	3	14	7.0	3.7	9.5	13.1	9.9	2.3
25 Mile	17.6	2	6	7.8	2.7	7.9	13.9	10.2	3.2
Ankwill	27.4	4	44	8.6	1.6	29.1	15.1	10.7	3.4
Blanchette	10.6	2	5	6.7	3.5	8.1	12.9	10.1	1.4
Crow	10.4	2	4	7.9	1.4	7.3	11.8	9.2	1.3
Die hard	7.8	2	4	6.1	5.8	7.2	12.1	9.5	1.8
Forfar	15.4	3	13	9.0	1.4	6.5	14.2	10.4	2.7
Forsythe	25.7	4	36	8.8	1.2	9.0	16.6	11.7	4.3
French	23.5	3	25	9.7	1.3	6.8	16.1	11.8	4.1
Frypan	26.9	4	59	9.2	0.8	11.6	17.2	11.9	5.1
Gluskie	18.5	3	13	7.7	1.2	8.3	14.2	10.7	2.0
Hooker	6.6	2	2	7.3	4.2	3.1	11.2	8.5	1.2
Hudson Bay	18.4	3	11	8.9	1.4	7.9	14.4	10.7	3.1
Leo	20.8	3	14	12.0	0.8	7.7	16.7	13.7	2.9
Maclaing	22.3	3	10	9.6	2.1	7.2	15.9	11.7	3.8
Narrows	19.7	2	6	11.0	1.2	12.3	15.2	11.9	2.6

Online and field data were collected in 2007. Field data were collected between June and July. Continuous temperature metrics were calculated using temperature data collected during sockeye salmon spawning season (August) in 2010. Field data and temperature were collected in the lower reach of >1.5 km from lake confluence

(Bridge 2003) and stream length, which is the total length of the mainstem of the stream. We also identified stream order (Strahler 1957). A first-order stream is a stream that has no tributaries, whereas a second-order stream has two tributaries that are both first order. The order of a stream segment is equal to 1 plus the *n*th order of the two joining stream segments (Platts 1979).

Stream temperature

Temperature metrics were derived from temperature loggers placed in 19 sockeye spawning streams. Three temperature loggers were vertically stratified at one location per stream. A 3-foot piece of rebar was hammered into the streambed, and loggers were fixed to the rebar. The bottom logger was positioned 15 cm in the substrate, the middle one on the substrate surface, and the top logger was 15 cm above the substrate surface. Within streams, loggers were located in habitats where sockeye salmon typically spawn (e.g., glide and run habitats). Loggers began recording on the same hour and at 2-h intervals from August 2010 to August 2011. Comparisons among streams were made with temperatures derived from all loggers when possible, though in some cases data from a single logger were used due to logger failure. The mean was taken when there were data for more than one logger at each 2-h interval. There was little variation among loggers within a stream (mean difference <0.55 °C and standard deviation <0.91 °C).

In this study, we focused on the spawning period for sockeye salmon, which typically begins the last week of July and peaks between the first and second week of August. This period coincides with the warmest temperatures experienced by spawners and their incubating eggs. Specifically, we calculated three temperature metrics using the continuous temperature loggers for a 25-day period from August 7–31, 2010: (1) Maximum temperature recorded in a stream during the sampling period; (2) daily mean temperature in a stream over the entire sampling period; and (3) variance of the daily mean temperatures of a stream over the entire

sampling period. There were strong correlations between these temperature metrics across the 19 streams (maximum vs. mean $r = 0.92$; maximum vs. variance $r = 0.88$; mean vs. variance $r = 0.68$).

Monitoring objectives and approaches

We assessed how different monitoring scenarios, which varied in the number and location of monitoring sites, would meet two monitoring objectives. We used the number of monitoring sites as our cost metric rather than specific dollar amounts because our aim was to provide a general illustration of our framework.

Objective 1—threshold monitoring

Our first objective was to identify high-temperature streams (Fig. 1), which is important to understanding the distributions (Beer and Anderson 2013; Lisi et al. 2013) and survival of salmonids (Elliott 1991; Mcmahon et al. 2007). We define high-temperature streams as streams that are likely to exceed some biologically relevant threshold. For example, it has been suggested that temperatures >15 °C can have negative impacts on spawning, incubation (Whitney et al. 2013) and rearing salmonids (Stalberg et al. 2009). We applied our framework using 15 °C but any temperature could be used to accommodate differences in thermal thresholds among species and populations; this could also include minimum temperature thresholds. Identifying high-temperature streams can help identify salmonid populations at risk of high (or low) temperature events, leading to harvest reductions to compensate for higher mortality from temperature stress (e.g., Macdonald et al. 2010) or to prioritize habitat restoration efforts.

We evaluated how well different subsets (i.e., monitoring scenarios) of streams captured high-temperature streams by calculating the percentage of temperature events >15 °C. Temperature events are defined as the number of days when the temperature recorded by the loggers exceeded the threshold. The number of temperature events was summed for each stream. The total number of events for sampling scenarios was calculated as:

$$T_i = \frac{\sum_{j=1}^{n_i} t_j}{\sum_{j=1}^{n} t_j} \times 100 \qquad (1)$$

where T is the percentage of temperature events for monitoring scenario with a sample size of i, n is the total number of streams for sample size i, and t are the number of temperature events for each stream j that make up the monitoring scenario i. The numerator represents the total number of temperature events detected for monitoring scenario of sample size i, and the denominator represents the total number of temperature events detected when all streams are monitored (i.e., $n = 19$).

Objective 2—representative monitoring

Assessing habitat status for a Conservation Unit (Canada) (Canada 2005) or Evolutionarily Significant Unit (USA) (Good et al. 2007) is a key goal for salmon management. To know the true temperature status of all salmon streams in the geographic region of the Conservation Unit, all streams need to be monitored; however, approximations of status could be made using subsets of streams if they provided good representations of the others.

We compared the means and variances for subsets of streams to the mean and variance of all the streams in a Conservation Unit. This evaluates how well a monitoring scenario represents the true status of a group of streams, such as a region, Conservation Unit or Evolutionary Significant Unit. While this approach assesses the relative performance of monitoring scenarios, managers need to decide what constitutes acceptable levels of performance/uncertainty. For the purpose of illustration in this paper, subsets are deemed representative if they are within ±5 % of the mean for all streams sampled, which we refer to as the aggregate's mean herein.

Comparing random versus informed monitoring scenarios

To inform selection of sampling locations (i.e., streams), we used watershed characteristics and spot temperatures. For threshold monitoring, streams were drawn in order according to their values that corresponded to warmer streams. For example, longer streams tend to be warmer; therefore, streams were selected in descending order of length (longest to shortest). This was repeated separately for each of the six stream characteristics.

To evaluate the performance of monitoring scenarios whereby subsets of streams are chosen in an attempt to represent the entire group of streams, we ranked streams in ascending order from most similar to the aggregate mean (mean of all streams from continuous temperature loggers) or aggregate variance (variance of all streams from continuous temperature loggers) of the entire set of streams, based on a single stream characteristic.

To illustrate the uncertainty at different levels of monitoring costs (i.e., cost increases with the number of streams monitored) and to provide a comparison for informed scenarios, random monitoring scenarios were generated by randomly selected subsets of streams across the range of potential costs (i.e., from 1 to 19 streams). For each sample size, we drew 100 random combinations of our 19 sites and calculated the performance metrics for each scenario. This provided a null expectation in the absence of information on stream characteristics that could be compared with our informed sampling designs.

We also compared the efficiency (percent events/number of streams) of each of the informed designs along with the average of the random design at 4, 8, 12, 16 sites sampled for the threshold monitoring. In addition, the number of sites required to detect >25, >50, >75, and >100 % of the temperature threshold events was compared.

Results

There was a large range in temperatures among streams during the critical spawning period (Table 1). Maximum spawning temperatures among streams ranged from 11.2 to 17.2 °C, and mean spawning temperatures among streams ranged from 8.5 to 13.7 °C. Streams with higher mean and maximum temperatures also had higher variance in temperature during the spawning period.

Watershed characteristics and temperature metrics

The single variable that best explained maximum temperature was mainstem length ($R^2 = 0.82$, $p < 0.01$). Maximum stream temperature was positively correlated with mainstem length, magnitude, order, spot temperature and negatively correlated with gradient (Fig. 2). Mean stream temperature was best explained by spot temperature ($R^2 = 0.71$, $p < 0.01$; Fig. 3). Longer streams with higher magnitude and order also had higher mean temperatures (Fig. 3). Gradient was negatively related to mean water temperature. The variable that best explained temperature variance was stream length ($R^2 = 0.79$, $p < 0.01$) (Fig. 4). Streams that were longer, with higher magnitude and larger wetted widths had higher variance in temperature (Fig. 4). Higher gradient streams had less variance in temperature. While spot temperature explained a large proportion of variation in both maximum and mean temperatures, it had only a weak relationship with temperature variance ($R^2 = 0.28$, $p < 0.05$).

Informed versus random site allocation

Threshold monitoring

The random sampling design resulted in a linear increase in the detection of temperatures >15 °C with the number of streams monitored (Fig. 5). There was large variation in the percent of total events detected within sample sizes. For example, a random selection of 5 streams could detect from 0 to over 55 % of the total events.

The informed sampling design was more effective than random at every sample size tested (Fig. 5) (Tables 2, 3). All of the stream metrics performed better than the average random design, even when they had little relationship with temperature (e.g., wetted width). Thus, sampling streams in descending order of length, magnitude, order, wetted width, and spot temperature values result in much more effective sampling designs than the average random sampling design. In fact, many of the informed designs achieved a detection rate of 50 % with half as many samples as the average random design (e.g., length, gradient, and spot temperature). Although all informed designs were better than random, some stream characteristics were more informative than others. For example, stream length and spot temperature were consistently in the top two of metrics across levels of detection (Table 2) and sample sizes (Table 3).

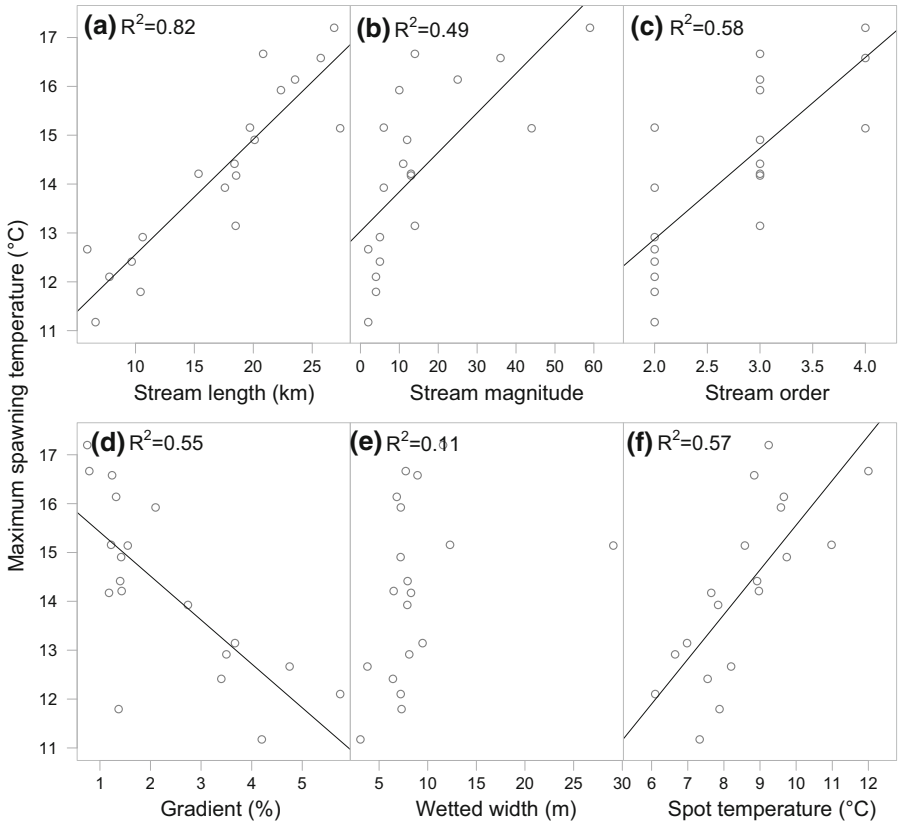

Fig. 2 Maximum spawning temperature versus **a** stream length, **b** stream magnitude, **c** stream order, **d** gradient, **e** wetted width, and **f** spot temperature. Maximum spawning temperature between August 7 and 31 also corresponds to the single highest value recorded in 2010 (2-h sampling interval)

Representative monitoring: mean temperature and variance

Informed scenarios out-performed random sampling approaches 63 % of the time for achieving a mean representative monitoring objective. When the number of streams monitored was five, informed sampling out-performed random sampling 88 % of the time (Fig. 6). For sample sizes less than five the only sampling design that performed poorer than random was informed by wetted width (Fig. 6). All informed sampling provided mean temperatures within 5 % of the aggregate's mean after sampling only four streams (Fig. 6). However, at larger sample sizes, the only metrics that were consistently within 5 % of the aggregate's mean were spot temperature and wetted width.

Informed scenarios for variance were more effective than random sampling approaches 76 % of the time. Informed designs out-performed random sampling designs 100 % of the time at sample sizes of five or less, with the exception of gradient (Fig. 7). While informed sampling was consistently more effective than random sampling many metrics failed to produce variance estimates within 5 % of the aggregate's variance (Fig. 7). The exception to this was spot temperature, which produced estimates within the 5 % benchmark for 84 % of the sample sizes.

Discussion

Monitoring scenarios that exploit the relationships between readily available watershed metrics and stream temperature were up to 3 times more cost-effective than average random monitoring scenarios. These informed scenarios were more effective for a given number of streams in predicting all of the different management objectives we tested, high threshold temperatures, mean temperatures, and variance. Moreover, single variables such as stream length, spot temperature, and stream order were sufficient to explain large variation in all three temperature metrics. The ability to use a minimum

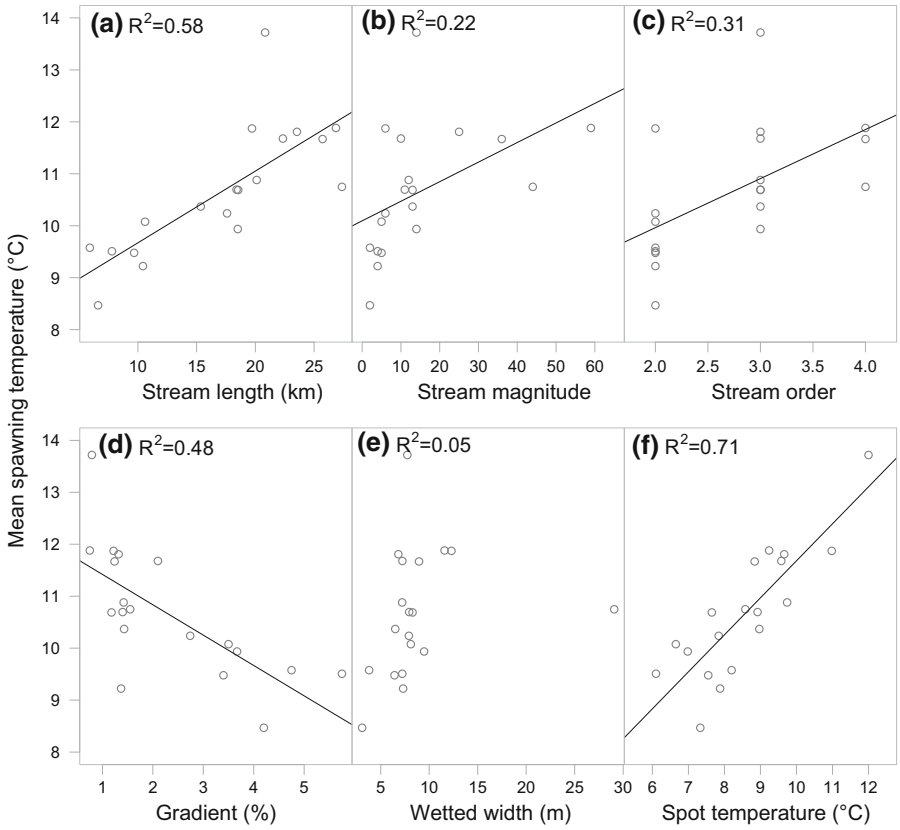

Fig. 3 Mean spawning temperature versus **a** stream length, **b** stream magnitude, **c** stream order, **d** gradient, **e** wetted width, and **f** spot temperature. Mean spawning temperature is calculated using all recorded values between August 7 and 31 in 2010 (2-h sampling interval)

of explanatory watershed characteristics highlights the utility of applying this type of framework to different stream temperature monitoring scenarios with large number of streams and variable management objectives.

Many of the watershed characteristics we examined showed strong relationships with the three temperature metrics we chose, consistent with previous work on larger watersheds (Nelitz et al. 2007; Mayer 2012). For example, stream length was consistently the first- or second-ranked explanatory variable (with regard to R^2 value; Figs. 2, 3 and 4) and informing site selection for monitoring (Tables 2, 3). Longer streams were warmer and more variable in temperatures than smaller streams (Luce et al. 2014). The result that longer streams are warmer parallels the findings of Nelitz et al. (2007), who showed that larger watersheds have higher maximum weekly average temperature (MWAT) than smaller watersheds. Other size metrics such as stream order and magnitude did not perform as well as stream length, probably because they are coarser measures of watershed size. Gradient also influenced temperatures whereby lower gradient streams are warmer. Mayer et al. (2012) also found that streams with lower channel slopes were warmer in the Pacific Northwest of the US. Taken together, these relationships probably represent how the size and structure of watersheds influences water residency time and discharge, which influences temperatures through exposure to warm air temperatures during summer months (Poole and Berman 2001; Caissie 2006; Mayer 2012).

Perhaps the most promising surrogate for our temperature metrics derived from continuous data was spot temperature, which was strongly correlated with our maximum and mean temperature metrics and overall was the most informative variable in selecting monitoring sites. Moore (2006) also found spot temperature to be a good surrogate of water temperature across a large geographic region. Furthermore, his study only included watersheds with drainages >100 km^2, whereas the watersheds in this study are typically smaller than that, suggesting that spot temperature could be used across a wide range of

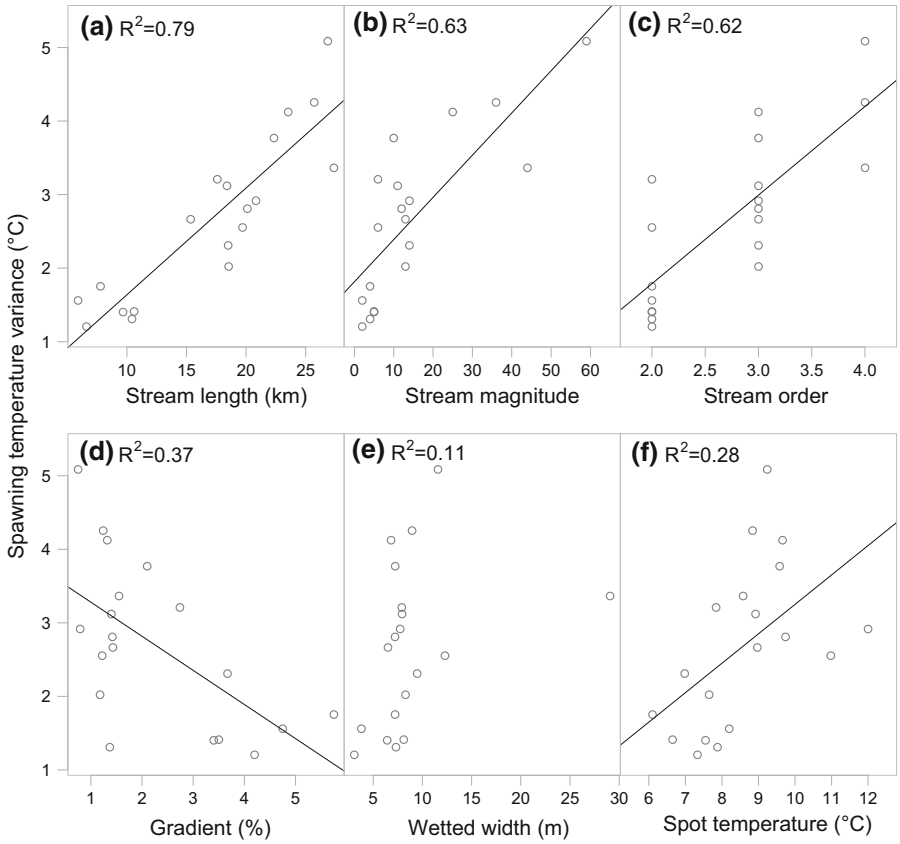

Fig. 4 Variance in spawning temperature versus **a** stream length, **b** stream magnitude, **c** stream order, **d** gradient, **e** wetted width, and **f** spot temperature. Temperature variance is calculated using all recorded values between August 7 and 31 in 2010 (2-h sampling interval)

watershed size (i.e., 10–100,000 km^2). A major benefit of using spot temperature as a surrogate is that it does not rely on deriving watershed–temperature relationships that may be region-specific. In addition, it is collected extensively across British Columbia by a number of monitoring agencies (Moore 2006), including salmon spawning surveys for stock assessment (Schubert and Fanos 1997). Therefore, the low cost of spot measurements (i.e., being available from other data sources), extensive coverage, and the generality of its relationship with other temperature metrics makes this a powerful metric for informing cost-effective temperature monitoring.

Determining which watershed metrics to use and how many streams to monitor can be difficult. Spot temperature (a field based metric) often outperformed online sourced watershed metrics but may require expensive "on the ground" monitoring if not part of another program unlike online sourced data (stream length, order, magnitude). This trade-off highlights the difficulty in determining which is the "best" watershed metrics to measure. One way to decide how many streams or what metrics to monitor is based on budgetary constraints. For example, if a budget for monitoring high-temperature streams could only afford to place temperature loggers in four streams, using Table 3, one would use either stream length or magnitude to select the most effective set of streams. These watershed metrics could be easily extracted from existing maps and provide a slight performance advantage over spot temperature. Furthermore, in our study, the four streams selected using these watershed metrics detected 50 % of all the temperature events. Following this approach will maximize the effectiveness of monitoring programs for a set cost. However, this approach may lead to an undesirable level of effectiveness. An alternative approach would be to determine the confidence required for making sound management decisions and then determine the lowest cost scenario to achieve this objective. For example, if one determines that a monitoring program should detect a minimum of 75 % high-temperature events,

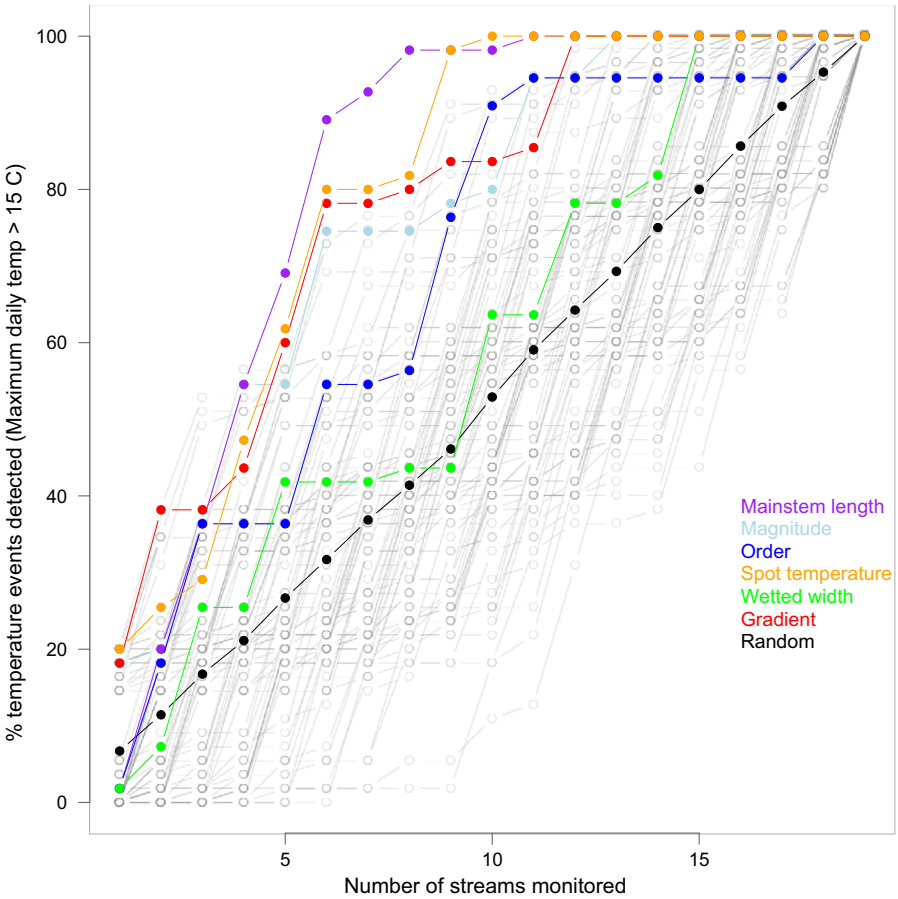

Fig. 5 Plot of the percent of temperature events that exceed 15 °C that are detected for random subsets of streams sampled (*gray*) and sampling designs based on stream characteristics (*color*). Individual random sampling iterations are in *gray*, and the average random sampling design is shown in *black*. The range in *gray* points for a given sample size represents the uncertainty in detecting temperature events using a random design. The total events are the number of events recorded for all 19 streams. *Colors* represent informed sampling designs based on stream characteristics (*purple* = length, *light blue* = magnitude, *blue* = order, *orange* = spot temperature, *green* = wetted width, *red* = gradient, *black* = average of random). (Color figure online)

according to Table 2 one would use length or spot temperature to select streams for monitoring. Given that length is a less expensive watershed metric to measure one would use length over spot temperature. In our study, using either metric would require only six streams to be monitored which is on average 150 % less monitoring effort to achieve the 75 % detection of high-temperature events than if streams were randomly selected. Regardless of whether outcome is primarily driven by cost or uncertainty, the framework described herein can accommodate these trade-offs.

Each of our 19 streams flows directly into a single lake–river network independently of each other. This simple network is similar to coastal streams that drain directly into the ocean but differ from more complex stream networks that are spatially correlated due to convergence downstream (Peterson et al. 2013; Som et al. 2014). Therefore, temperature for a downstream site is a function of upstream tributaries in addition to watershed characteristics. This directional autocorrelation could be useful for informing the selection of cost-effective sites because downstream sites integrate upstream temperatures. Som et al. (2014) provide suggestions for the most effective sampling designs for monitoring stream networks. This framework could be easily modified to integrate the autocorrelation between connected sites and which may provide additional cost savings due to higher correlations

Table 2 The number of streams that would need to be monitored to detect various percentages of sampling events for informed sampling designs based on watershed characteristics

	25 (%)	50 (%)	75 (%)	100 (%)	R^2 with max temp
Percentage of events detected					
Length	3 (2)	**5 (1)**	**6 (1)**	11 (2)	**0.82**
Magnitude	3 (2)	6 (2)	10 (3)	13 (4)	0.49
Order	3 (2)	8 (3)	10 (3)	18 (6)	0.58
Gradient	**2 (1)**	**5 (1)**	8 (2)	12 (3)	0.55
Wetted width	3 (2)	10 (4)	12 (4)	15 (5)	0.11
Spot temperature	**2 (1)**	**5 (1)**	**6 (1)**	**10 (1)**	0.57
Random	6 (3)	10 (4)	15 (5)	19 (7)	–

For example, if streams are chosen for monitoring from the longest to the shortest, then 5 streams would be capable of detecting 50 % of the stream days where the 19 streams exceeded 15 °C over the 25-day sampling. The average random sampling design is also shown. Ranks for values in each sample size are in parentheses, and top values are in bold

Table 3 The percentage of sampling events detected for a given number of streams monitored for informed sampling designs based on watershed characteristics

Variable	4	8	12	16
Number of streams monitored				
Length	**50 (1)**	**97 (1)**	**100 (1)**	**100 (1)**
Magnitude	**50 (1)**	68 (4)	92 (2)	**100 (1)**
Order	34 (4)	53 (5)	92 (2)	92 (2)
Gradient	42 (3)	76 (3)	**100 (1)**	**100 (1)**
Wetted width	26 (5)	45 (6)	79 (3)	**100 (1)**
Spot temperature	47 (2)	82 (2)	**100 (1)**	**100 (1)**
Random	19 (6)	40 (7)	61 (4)	83 (3)

For example, if streams are chosen for monitoring from the longest to the shortest, then monitoring 4, 8, 12, and 16 streams would be capable of detecting 50, 97, 100, and 100 % of the stream days where the 19 streams exceeded 15 °C over the 25-day sampling. The average random sampling design is also shown. Ranks for values in each sample size are in parentheses, and top values are in bold

between streams within a network compared to non-linked streams; this topic should be investigated further.

Implementation

The general application of this framework depends largely on the relationships between watershed characteristics and temperature that we estimated for one basin, over 1 year, and for a limited time period (within one August). These relationships may be regionally (Ward 1985) or temporally specific. There is also inter-annual and seasonal variation in these relationships that our study did not capture (Hrachowitz et al. 2010). However, if the patterns we have shown are general then this could lead to substantial cost savings by using existing or online data sources, which would eliminate costly field work. We show that even weak relationships between watershed characteristics and temperature improve the cost and effectiveness of monitoring scenarios. In the absence of regional relationships between watershed characteristics and temperature, we propose testing whether expert knowledge and qualitative assessments to see if they are sufficient to inform sampling designs.

Access to field sites will be an important cost consideration when implementing this framework. For example, this study was conducted in a remote area of British Columbian and many sites could only be accessed by boat, while the others were accessed by truck. Monitoring boat-accessed sites cost substantially more than monitoring truck-accessed sites and were also logistically more challenging because of the additional skills, safety and weather requirements associated with operating a boat. We estimate that the average cost of deploying a temperature logger by boat is double the cost of deploying a logger by truck. This is an important consideration that could accompany our framework, especially given the high costs of field sampling in remote areas (e.g., cost for field work for this study was over $10,000 CND).

While our framework can inform site selection, it does not provide managers with guidelines as to acceptable levels of uncertainty around the metrics

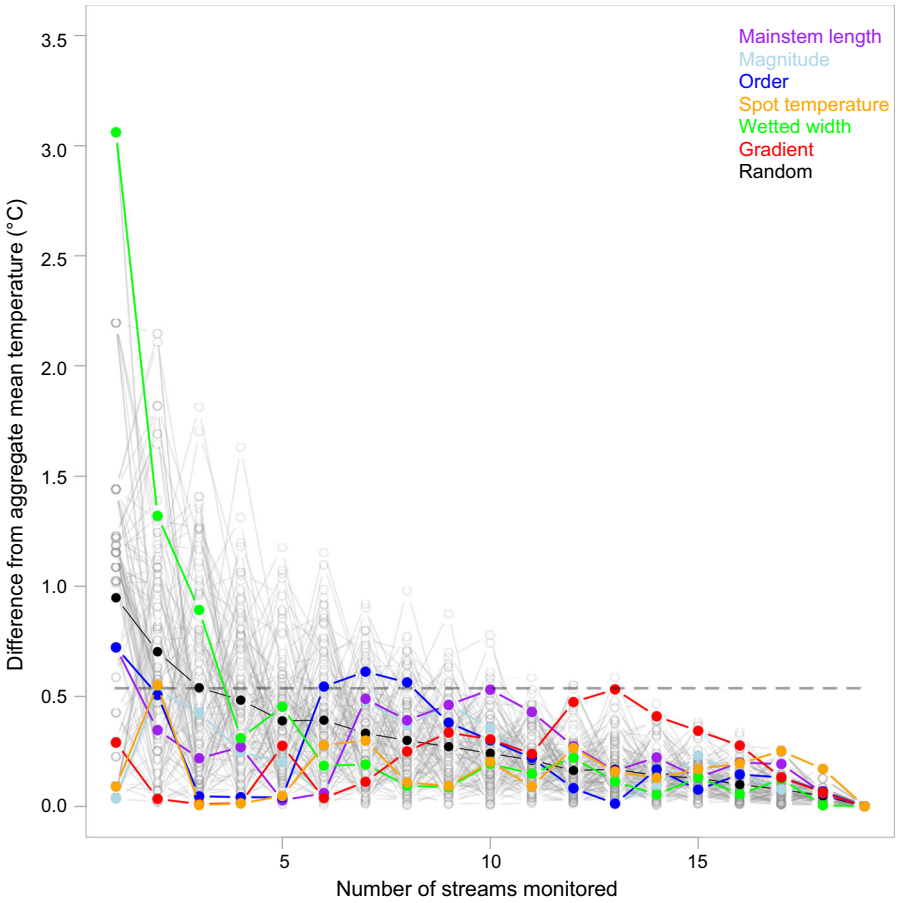

Fig. 6 Plot of the centered mean temperatures for random subsets of streams sampled (*gray*) and sampling designs based on stream characteristics (*color*). Data were centered by subtracting the aggregate's mean (i.e., 10.7 °C) and taking the absolute value. Individual random sampling iterations are in *gray*, and the average random sampling design is shown in *black*. The range in gray points for a given sample size represents the uncertainty in detecting the mean temperature using a random design. The mean temperature is calculated using all temperature values in a given subset. The light *dashed line* represents ±5 % of the aggregate mean temperature. *Colors* represent informed sampling designs based on stream characteristics (*purple* = length, *light blue* = magnitude, *blue* = order, *orange* = spot temperature, *green* = wetted width, *red* = gradient, *black* = average of random). (Color figure online)

being monitored. In Figs. 6 and 7, we arbitrarily set the acceptable level of uncertainty to <±5 % of the mean and variance. This choice can dramatically change the level of monitoring effort. With the uncertainty set at <±5 % and using a random subset of sites, 16 sites would need to be monitored to obtain this level of uncertainty for variance. Increasing the level of uncertainty to ±15 % would reduce the number of sites from 16 to 9. An alternative approach would be to let the budget drive the number of sites and therefore the level of uncertainty. The motivation behind the decision about acceptable levels of uncertainty is an important consideration that should be tackled prior to monitoring and can be easily assessed using our framework.

Application of this protocol should consider all sources of potential uncertainty and how it may influence site selection and management outcomes. Uncertainty may be caused by temperature logger measurement error, the measurement of the watershed characteristics, and uncertainty in relationships between watershed characteristics and stream temperatures we have estimated. The measurement error associated with some watershed metrics, such as stream length, order, and magnitude, will have little-to-no measurement error. Field measured watershed

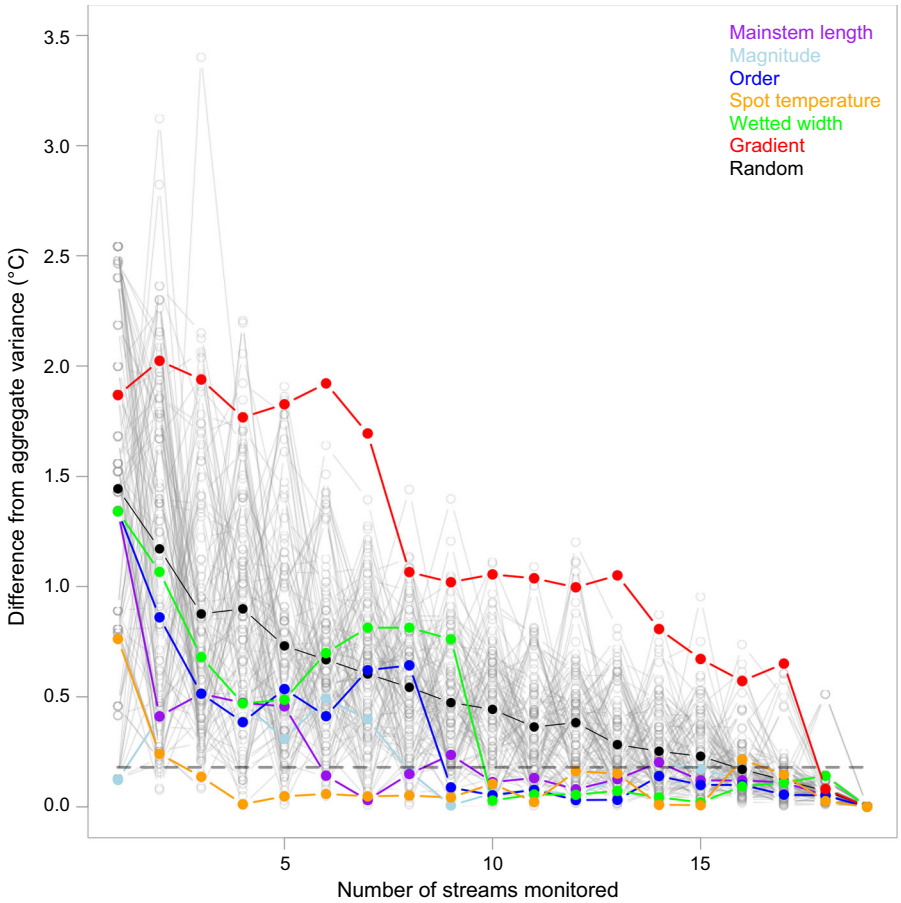

Fig. 7 Plot of the centered temperature variance for random subsets of streams sampled (*black and gray*) and sampling designs based on stream characteristics (*color*). Data were centered by subtracting the aggregate's variance (i.e., 3.5 °C) and taking the absolute value. Individual random sampling iterations are in gray, and the average random sampling design is shown in black. The range in *gray* points for a given sample size represents the uncertainty in detecting the true variance using a random design. Variance is calculated using all temperature values in a given subset. The light d*ashed line* represents ±5 % of the aggregate's temperature variance. *Colors* represent informed sampling designs based on stream characteristics (*purple* = length, *light blue* = magnitude, *blue* = order, *orange* = spot temperature, *green* = wetted width, *red* = gradient, *black* = average of random). (Color figure online)

metrics such as gradient and wetted width will have measurement error that could influence the outcome of the protocol. Temperature loggers have relatively low measurement error, for example ±0.5 °C for the loggers used in this study and can be as low as ±0.01 °C for more expensive temperature loggers. In contrast, spot temperatures are highly dependent on the time of day and potentially the location they are taken. One way to limit variance in spot temperature measurements due to sampling time would be to limit the time of day when the sample can be taken to a few hours around the peak temperature or sample at a consistent time of day. Inter-annual variation in the relationship between surrogates and stream temperature will also lead to additional variance. Although the slope and intercept of these relationships will vary from year-to-year, the important variance to consider for our protocol is how the order of sites varies when ordered by watershed variables.

Future work on this framework should include evaluating its application in different regions that exhibit different characteristics such as coastal streams that differ in their climate, ecology, geomorphology and hydrology. Regions that have substantial groundwater inputs should also be investigated and our framework could potentially be merged with groundwater classification protocols (Allen et al. 2010). In addition, this framework

could be further developed to include network autocorrelation associated with more complex stream networks.

In conclusion, our framework uses readily available watershed metrics to develop cost-effective stream temperature monitoring programs. Monitoring scenarios informed by surrogates of temperature were much more cost effective than alternative scenarios based on no information (i.e., random site selection) in describing high-temperature streams, mean water temperatures, and variance. This approach can aid managers in optimizing the limited resources to best match their temperature monitoring purposes.

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