DEVELOPMENT OF FIELD-BASED MODELS OF SUITABLE THERMAL REGIMES FOR INTERIOR COLUMBIA BASIN SALMONIDS

FINAL REPORT

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This report describes results of research sponsored through an interagency agreement between the U.S. Forest Service Rocky Mountain Research Station and U.S. Environmental Protection Agency (Interagency Agreement #00-IA-11222014-521). The primary objectives of this research included 1) develop models relating occurrence of two threatened inland salmonid fishes to stream temperature regimes; 2) develop a comprehensive protocol for sampling stream temperatures using digital data loggers. The two species of interest were bull trout (*Salvelinus confluentus*) and Lahontan cutthroat trout (*Oncorhynchus clarki henshawi*). The distribution of each species in relation to stream temperature regimes was modeled using a variety of approaches. The results of this work were related to thermal responses of each species in the laboratory. Together, these lines of evidence form a more rigorous basis for evaluating the biological requirements of each species, and for determining appropriate temperature criteria for water quality management. Given that water temperature is a critical concern in streams in the western United States, it is also important to provide guidance for monitoring stream temperatures. The recent widespread availability and use of digital temperature data loggers has resulted in a proliferation of data on stream temperatures. In many cases, our ability to carefully assure and document the quality and utility of the data has not tracked our capacity to collect temperature data.

We anticipate three published products from this research. Two papers will focus on the relationships between the distribution of bull trout and Lahontan cutthroat trout in relation to different measures of maximum annual temperatures. A third paper will be a protocol for measuring and sampling stream temperatures using digital data loggers. The first two papers will be submitted to peer-reviewed journals, and the third will be published electronically as a Forest Service/Environmental Protection Agency report. Each section of this final report corresponds to these papers. These should be considered as early drafts of papers to be submitted for publication in the near future.

Predicting the distribution of stream-living Lahontan cutthroat trout in relation to air and water temperatures

Introduction

Temperature plays a key role in determining the distribution of many aquatic organisms (Magnuson et al. 1979). Temperature has been a particular focus for salmonid fishes, due to their requirement for relatively cold water (Elliott 1981). Past research has linked salmonid distributions to several indicators of temperature, including elevation gradients associated with climate (Fausch et al. 1994; Flebbe 1994), modeled air temperatures (Keleher and Rahel 1996; Rieman et al. 1997), measured (Nakano et al. 1996) or modeled (Meisner 1990) groundwater temperatures, and measured surface water temperatures (Eaton et al. 1995; Torgerson et al. 1999). While the latter most directly affect fish, detailed information on surface water temperatures is often limited or expensive to obtain, so alternative indicators (e.g., air temperature) may be more useful (e.g., Stoneman and Jones 1996). The utility of a particular indicator may also depend on the scale of inference. For example, distribution of fish within a small area may be related to small gradients in surface water temperatures (e.g., Nielsen et al. 1994; Peterson and Rabeni 1996; Ebersole et al. 2001), but distributions on a larger scale may be indicated by broad-scale climatic gradients (e.g., Fausch et al. 1994; Rieman et al. 1997; Dunham et al. 1999).

Our primary objective in this study was to examine the distribution of stream-living trout (Lahontan cutthroat trout; *Oncorhynchus clarki henshawi*) in relation to temperature. Studies of thermal tolerance in the laboratory (Vigg and Koch 1980; Dickerson and Vinyard 1999; Meeuwig 2000) suggest that surface water temperatures can potentially limit the distribution of Lahontan cutthroat trout in the field. Previous field studies (Dunham et al. 1999) indicate the distribution of Lahontan cutthroat trout in streams can be predicted by large-scale elevation and climatic (summer air temperature) gradients. However, this work did not provide any direct evidence to link fish distributions in the field to air or surface water temperature gradients at a local scale. To better understand

thermal habitat relationships on a local scale, we modeled the distribution of Lahontan cutthroat trout at sites within streams in relation to surface water temperatures.

Results of this study allowed us to assess the utility of surface water temperatures as indicators of the distribution of cutthroat trout within streams. We contrasted these results with our previous work relating cutthroat trout distributions to temperature at larger spatial scales (e.g., Dunham et al. 1999) to better understand the scale-dependent relationship between salmonid fish distributions and different indicators of temperature. We also compared our results to studies in different systems (e.g., Stoneman and Jones 1996) to better understand variability in the utility of air versus water temperatures as indicators of salmonid distributions. Finally, patterns of thermal habitat use in the field were compared to results of laboratory studies of responses of Lahontan cutthroat trout to temperature (Vigg and Koch 1980; Dickerson and Vinyard 1999; Meeuwig 2000).

Methods

Study system

Lahontan cutthroat trout is endemic to the Lahontan basin of northeast California, southeast Oregon, and northern Nevada. The Lahontan basin is part of the Great Basin desert, which is characterized by hot summers and cool winters, with most precipitation falling as snow at higher elevations in the winter (Peterson 1994). Topography in this region is characterized as "basin-and-range," with north-south trending mountain ranges and intervening alluvial valleys (Morris and Stubben 1994). Under current conditions, streams draining these mountain ranges often lose surface flow in the summer as they flow onto alluvial valley floors. Stream habitats occupied by Lahontan cutthroat trout are typically small in size, with summer low-flow wetted widths of less than 6 m (Jones et al. 1998; Dunham et al., in press).

Study streams were dispersed throughout the eastern half of the Lahontan basin, including the Coyote Lake, Quinn River, and Humboldt River basins (Figure 1). The

broad geographic distribution of study streams was chosen to capture a wide range of conditions. Populations in two streams (Edwards and Sherman Creeks, Nevada) were derived from undocumented transplants of Lahontan cutthroat trout (M. Sevon, Nevada Division of Wildlife, personal communication). Edwards Creek lies just outside of the native range of the species (Figure 1).

Sampling of water and air temperatures

We used a standardized protocol to sample temperatures using digital temperature data loggers. The model of data logger we used (Hobo Temp®; Onset Computer Corporation, Pocasset, MA) measures temperature to within ± 0.7 °C, and records temperatures within a range of 0-43 °C. We conducted pre- and/or post-calibrations following manufacturer specifications to correct for instrument bias in temperature readings.

Our interest was in characterizing general surface water temperatures of streams, as opposed to groundwater or thermal refugia (Nielsen et al. 1994, Torgerson et al. 1999; Ebersole et al. 2001). We placed data loggers at sample sites within the well-mixed portion of the main flow (thalweg) of the active stream channel, and out of contact with direct solar radiation. Air temperature data loggers were suspended from streamside trees or shrubs, and out of contact with direct solar radiation. Local water temperatures at sites were checked with hand-held thermometers before data loggers were deployed. In each stream, at least one air temperature data logger was deployed to provide a reference for water temperature readings. In 1998, air temperature loggers were placed at every water temperature sampling location. In 1999, a single air temperature logger was placed at the midpoint (up-downstream direction) of sampling within each stream. Data loggers were programmed to record temperature every 30 min.

Data loggers were placed in a longitudinal (up-downstream) array of sites within streams to bracket the known or suspected distribution limits of Lahontan cutthroat trout. This focused sampling at or near areas where thermal regimes were expected to exceed the tolerance of this subspecies. Within each stream, we sampled 4-10 sites, depending on

access, time, and physical constraints (e.g., lack of surface flow). Sites were generally spaced 600 meters apart, but spacing varied occasionally due to loss or failure of the data logger.

Water temperatures were sampled from 15 July to 15 September in 1998, and from 01 July to 15 September in 1999. We assumed that maximum water temperatures occurred within this temporal window. Prior to the study, we examined long-term climate records from monitoring stations throughout the region (e.g., Figure 2) to confirm that maximum air temperatures were likely to be observed at this time of year. Long-term water temperature data are not widely available, but we assumed the coincidence of high levels of solar radiation and long photoperiods, coupled with declining stream flows in the latter part of the summer should lead to maximum water temperatures during this time period (Figure 2).

Fish sampling

Fish sampling followed procedures described by Dunham et al. (1999). We used backpack electrofishers to survey for occurrence of cutthroat trout within ± 150 m of each temperature sampling site. If fish were found within this 300 m reach, then cutthroat trout were scored as "present." In 1998, fish distributions were determined once during the summer season (15 July-15 September). In 1999, streams were sampled several (≥3) times during the summer to confirm that fish distributions were constant (i.e., fish presence or absence remained the same within ± 150 m of sites sampled for temperature) over the summer season. Previous work on redband trout (*Oncorhynchus mykiss*) in the region also found that fish distribution limits in streams were constant over the summer season (Zoellick 1999).

Data screening and analysis

Temperature data were screened visually for unusual "spikes," or large fluctuations associated with instrument malfunction or stream desiccation. When necessary,

screening involved comparison with local air temperatures. Several different quantitative summaries of the thermal regime (temperature "metrics") were calculated (Table 1). Our choice of metrics attempted to capture the range of biological effects that temperature may have on cutthroat trout. Effects of temperature may range from chronic to acute exposure of fish to unsuitably warm temperatures (e.g., Sprague 1990). For example, temperature metrics based on average temperatures or longer (e.g., weekly) exposure periods should reflect the influences of prolonged or chronic exposure, while metrics based on thermal maxima or cumulative exposure over shorter time periods may represent acute exposure. Metrics describing cumulative exposure were calculated only for water temperature. The range of values for cumulative exposure metrics represents the range of lethal and sublethal effects that temperature may have on cutthroat trout (Vigg and Koch 1980; Dickerson and Vinyard 1999; Meeuwig 2000).

Because there are so many ways to describe temperature, we first examined correlations among all sets of metrics for both air and water. Previous analyses using multiple temperature metrics have used principal components analysis to deal with these intercorrelated summaries of temperature (Haas 2001). We considered this approach as well, in addition to modeling the effects of individual metrics. Our choice of individual metrics was guided primarily by the degree of correlation between metrics for each medium. For groups of metrics that were strongly correlated, we used only a single representative. Using more than one metric in such circumstances could lead to problems with multicollinearity (Phillipi 1994), and would presumably not add much new information, given the strong correlation among variables. We also examined correlations between air and water temperatures to compare to previous related work (e.g., Stoneman and Jones 1996).

Occurrence of cutthroat trout was modeled at all sites in both years in relation to predictors describing surface water temperature regimes. Data analyses used logistic regression (SAS, Allison 1999) to relate surface water temperature metrics to occurrence (presence or absence) of cutthroat trout. We also tested for variation among years and streams using a "stream-year" categorical variable (Dunham and Vinyard 1997). This

analysis tested for differences in the slopes or intercepts of the model parameter estimates among different streams or streams sampled in different years. The analysis of stream-year variability only used streams with multiple (>6) sites sampled within each stream. Therefore, we excluded data collected in 1998 from Sherman Creek and Dixie Creeks, where only four sites were sampled. To provide an alternative to classical null hypothesis testing (Anderson et al. 2000), we also evaluated the relative likelihood of the two alternative models (temperature only and temperature + stream-year effects) using model selection procedures described by Burnham and Anderson (1998; see also Thompson and Lee 2000).

Results

Mean dates for maximum daily water temperatures in streams were 5 August and 29 July in 1998 and 1999, respectively. Because we did not begin monitoring temperatures in 1998 until 15 July, there is some possibility the maximum temperatures could have occurred prior to that date. In 1998, the earliest date for which the maximum daily temperature was observed in a stream was 18 July, only three days after sampling was initiated. In 1999, water temperature monitoring was initiated by 1 July. Maximum water temperatures were generally observed after 15 July, but there were exceptions in some streams (Figure 2). In Frazer Creek, maximum water temperatures in sites occupied by Lahontan cutthroat trout occurred on 12 July and after 15 July 1999. Maximum water temperatures in unoccupied sites were also observed on 12 July in Frazer Creek in 1999. We also found maximum air and water temperatures did not occur at the same times in the streams we studied. For these reasons, we did not further pursue analyses of air temperature regimes in relation to fish distributions.

Water temperatures varied substantially among sites over the summers of 1998-1999 (Table 2). All temperature metrics were linearly correlated (all P-values < 0.0001). Nonparametric Spearman rank correlation coefficients ranged from 0.74 to 0.99 for the six water temperature metrics examined. Because all water temperature metrics were strongly correlated, we selected only one metric for use in relating water temperature to

occurrence of cutthroat trout. We selected maximum daily temperature because it is an easily understood metric with strong biological implications for acute exposure (e.g., Meeuwig 2000). We also attempted to use principal components analysis to create indices that incorporate information on several intercorrelated temperature metrics. In spite of attempts at data transformations, we could not produce normally distributed data, thus violating a basic assumption for principal components analysis (McGarigal et al. 2000). Accordingly, we abandoned principal components and modeled the response of cutthroat trout in relation to maximum daily water temperature.

Cutthroat trout were found to occur in sites with maximum daily temperatures ranging up to 28.5 ^{o}C, and were found to be absent in sites with summer maximum temperatures as cold as 18.9 ^{o}C (Figure 3). Occurrence of cutthroat trout in the site with the highest temperature (28.5 ^{o}C) was confirmed on the day when the maximum temperature was observed (A. Talabere, Oregon State University, personal communication). Overlap in water temperatures between occupied and unoccupied habitats was due to occurrence of cutthroat trout in two sites with relatively cool maximum daily temperatures (18.9-20.2 ^{o}C). For streams sampled in 1998 and 1999, the difference in maximum daily temperature associated with occurrence of cutthroat trout ranged from 0.2 to 1.1 ^{o}C (Figure 3).

Conventional analyses using logistic regression indicated highly significant (P<0.001) relationships between occurrence of Lahontan cutthroat trout and temperature, but stream-year effects were not significant (P=0.17) when analyzed together with temperature. A likelihood-based assessment of these alternative models suggested that stream-year effects were important, in spite of the large number of added parameters (Table 3). This finding was concordant with the wide range of maximum temperatures we found to be associated with distribution limits of Lahontan cutthroat trout in different streams (Figure 3).

Discussion

Correspondence between thermal responses observed in the field and laboratory

Based on responses of cutthroat trout to temperature in the laboratory, we expected distributions of fish within streams to correspond to stream temperature gradients. Streams in the Lahontan basin often heat to temperatures known to cause physiological stress for salmonids (e.g., Elliot 1981). Within most streams we studied, cutthroat trout occurred in sites with temperatures observed to cause sublethal stress (>22 ^{o}C; Dickerson and Vinyard 1999; Meeuwig 2000) or mortality (>24 ^{o}C; Dickerson and Vinyard 1999) in the laboratory under relatively optimal conditions (e.g., unlimited food, dissolved oxygen saturation, low ammonia levels). In a few sites, occurrence of cutthroat trout was associated with maximum daily temperatures (>26 ^{o}C) that could be lethal with very short-term (< 1d) exposure (Dickerson and Vinyard 1999).

Modeling fish distributions in relation to temperature

Spatial variation in the response of cutthroat trout distributions to temperature was evident among streams. In two streams, maximum temperatures associated with occurrence of cutthroat trout were relatively cool (≤ 20 ^{o}C). In both of these two streams, the influence of temperature may have been modified by extreme declines in surface flows in late summer (JBD, personal observations). Loss of surface flow is common in streams of the Great Basin desert as they flow from mountain slopes onto alluvial valleys with finer-textured sediments. As flows decline, fish are often trapped in intermittent pools, and may be vulnerable to other stressors (e.g., predators, changes in water quality) that could independently or interactively modify their response to temperature gradients.

We found logistic regression to be useful for assessing the relative strength of relationships between fish occurrence and water temperatures, but model predictions (Figure 4) did not accurately reflect the known biology of Lahontan cutthroat trout. In particular, the model for maximum daily temperature predicted occurrence of cutthroat

trout in water temperatures that should cause immediate mortality (>30 ^{o}C; Dickerson and Vinyard 1999). Simple summaries of maximum temperatures observed in association with cutthroat trout occurrence (Figure 3) provided a more biologically plausible representation of thermal habitat use.

Comparison to related field studies

Recent work in an adjacent area to the north of our study system reported similar temperatures associated with the distribution of redband trout (*Oncorhynchus* mykiss; Zoellick 1999). In the four streams studied by Zoellick (1999), redband trout distributions were associated with maximum daily temperatures ranging from 22.5-29.0 ^{o}C. To our knowledge, there is only one published study of occurrence of cutthroat trout in relation to stream temperatures in the field. Eaton et al. (1995) reported the 95th percentile of average weekly mean temperatures (MWAT) associated with occurrence of cutthroat trout to be 23.2 ^{o}C. This temperature is closely associated with the induction of sublethal stress under chronic exposure (e.g., cessation of growth and feeding; Meeuwig 2000) for Lahontan cutthroat trout. Our sample size was limited (n < 100), but temperatures associated with distribution limits of Lahontan cutthroat trout were much colder. Mean weekly average temperatures associated with distribution limits averaged 17.5 ^{o}C, with a maximum of 20.9 ^{o}C.

The discrepancy between our results and those reported by Eaton et al. (1995) can be attributed to several potential causes. The approach used by Eaton et al. (1995) required a minimum of 1000 observations matching fish occurrences with stream temperatures. Our sample size was much smaller, so it was unlikely that we would have observed extremely high temperatures associated with occurrence of cutthroat trout, because the frequency of such observations should be very low. Our sample size was small, but matching between records of fish occurrence and temperature was more precise. Records of fish occurrence used by Eaton et al. (1995) were matched to temperature records located within 7 km, whereas our study matched fish occurrence to temperature records

within 0.3 km. Thus, it is possible that Eaton et al. (1995) could have overestimated actual temperatures associated with occurrence of cutthroat trout.

Air versus water temperatures as indicators

In the systems we studied, it was clear that maximum summer air and water temperatures did not occur within the same time frame. We anticipate the utility of maximum summer air temperatures for discriminating fish distributions in our study system is probably limited by lack of association between air and water temperatures, and limited variability in air temperatures in comparison to water temperatures within streams (unpublished results). Air temperature gradients appear to reliably discriminate salmonid distributions on smaller spatial scales in other regions (Stoneman and Jones 1996). Regional differences in the relationship between fish distributions and water or air temperatures likely reflect the degree of correlation between the latter. In areas with strong air-water temperature correlations, either measure may prove useful for delineating suitable habitats. In the western United States, air temperatures have been shown to be useful for modeling salmonid distributions at larger spatial scales, where variability in temperature should be larger and more informative. Examples include the distribution of cutthroat trout among streams across the eastern Lahontan basin (Dunham et al. 1999), and the distribution of bull trout in the interior Columbia River basin (Rieman et al. 1997).

Conclusions and management implications

The importance of temperature to Lahontan cutthroat trout has been demonstrated at several spatial scales and levels of biological organization. Studies in the laboratory (Vigg and Koch 1980; Dickerson and Vinyard 1999; Meeuwig 2000) have examined growth, survival, and behavior of individual fish exposed to different thermal regimes. In the field, fish distributions likely represent population-level responses to temperature. Within streams with perennial surface flow, summer maximum temperatures play a dominant role in determining the distribution of fish. Among streams within the region, distribution limits are tied strongly to elevation and climatic (air temperature) gradients

(Dunham et al. 1999). Within the eastern Lahontan basin, the amount of suitable thermal habitat, as indexed by watershed area upstream of distribution limits, is a strong predictor of the occurrence of local populations of cutthroat trout (Dunham et al. 2001). Watersheds with larger areas of potentially suitable thermal habitat are more likely to support extant populations of Lahontan cutthroat trout. Protection and restoration efforts to benefit habitat for Lahontan cutthroat trout should therefore focus on temperature as a primary limiting factor. Management should focus on changes in the distribution of suitable thermal habitat caused by contemporary human influences (Poole and Berman 2001) in the context of potential future scenarios, should climate change (Keleher and Rahel 1996) lead to increased fragmentation of suitable habitats.

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Table 1. Definition of statistical summaries of temperature or temperature "metrics."

Metric	Definition
Maximum average daily temperature	Mean daily temperature observed on the warmest day of the year
Maximum daily temperature	Maximum of maximum daily temperature observed within a year
Maximum weekly average temperature	Average of daily average temperatures observed on the warmest week within a year
Maximum weekly maximum temperature	Average of daily maximum temperatures observed on the warmest week within a year
Number of observations exceeding 18^{o}C	Self-explanatory: observations recorded at 30 min intervals
Number of observations exceeding 22^{o}C	Self-explanatory: observations recorded at 30 min intervals
Number of observations exceeding 26^{o}C	Self-explanatory: observations recorded at 30 min intervals

Table 2. Summary of observed water temperatures.

Metric	Units	N	Mean	Minimum	Maximum
Maximum daily temperature	^{o}C	87	23.5	15.2	32.5
Maximum weekly average temperature	^{o}C	87	16.8	12.13	23.0
Maximum weekly maximum temperature	^{o}C	87	22.7	14.9	30.4
Number of observations exceeding 18^{o}C	Time[1]	87	20.3	0	48
Number of observations exceeding 22^{o}C	Time	87	9.3	0	33
Number of observations exceeding 26^{o}C	Time	87	4.0	0	20

[1]Time units correspond to the number of 30-minute sampling intervals, for which a given temperature was observed or exceeded.

Table 3. Candidate models and relative likelihoods, as indicated by Akaike's information criterion (AIC). Larger $\Delta QAIC_c$ weights (*Wi*) indicate likely models. See Burnham and Anderson (1998).

Model	Parameters	$QAIC_c$	$\Delta QAIC_c$	*Wi*
Temperature and "stream-year"	10	78.06	0	0.60
Temperature only	2	78.85	0.80	0.40

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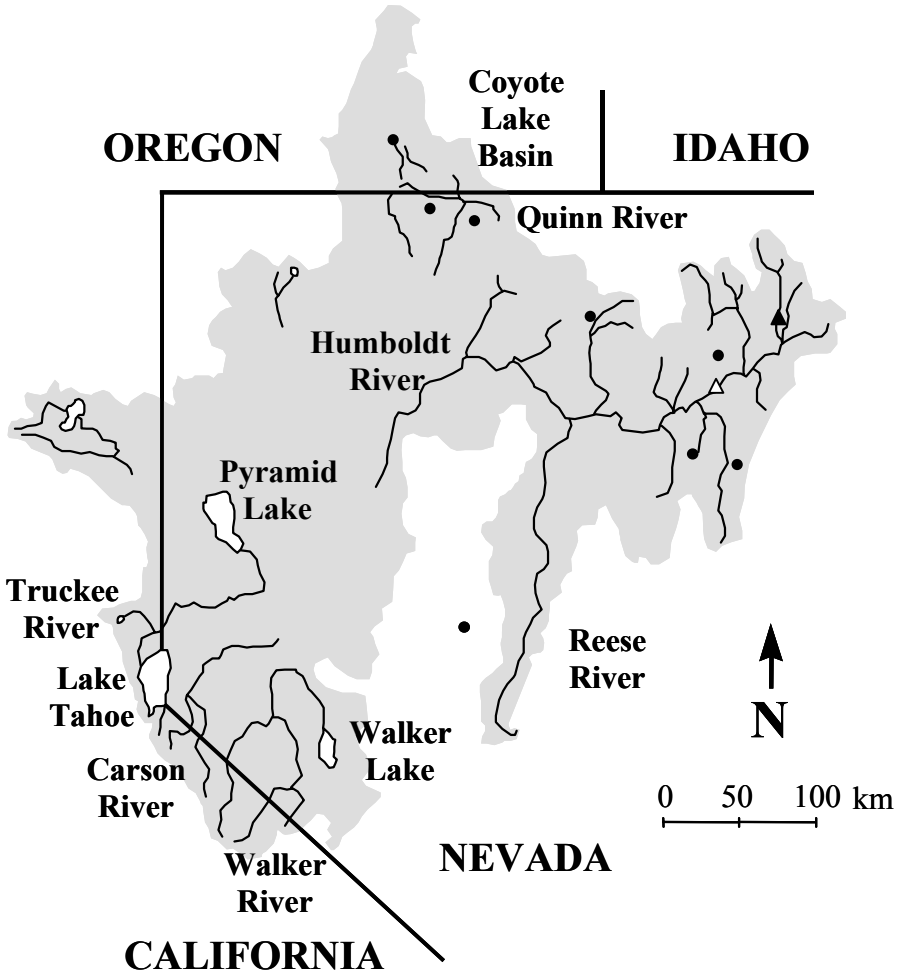
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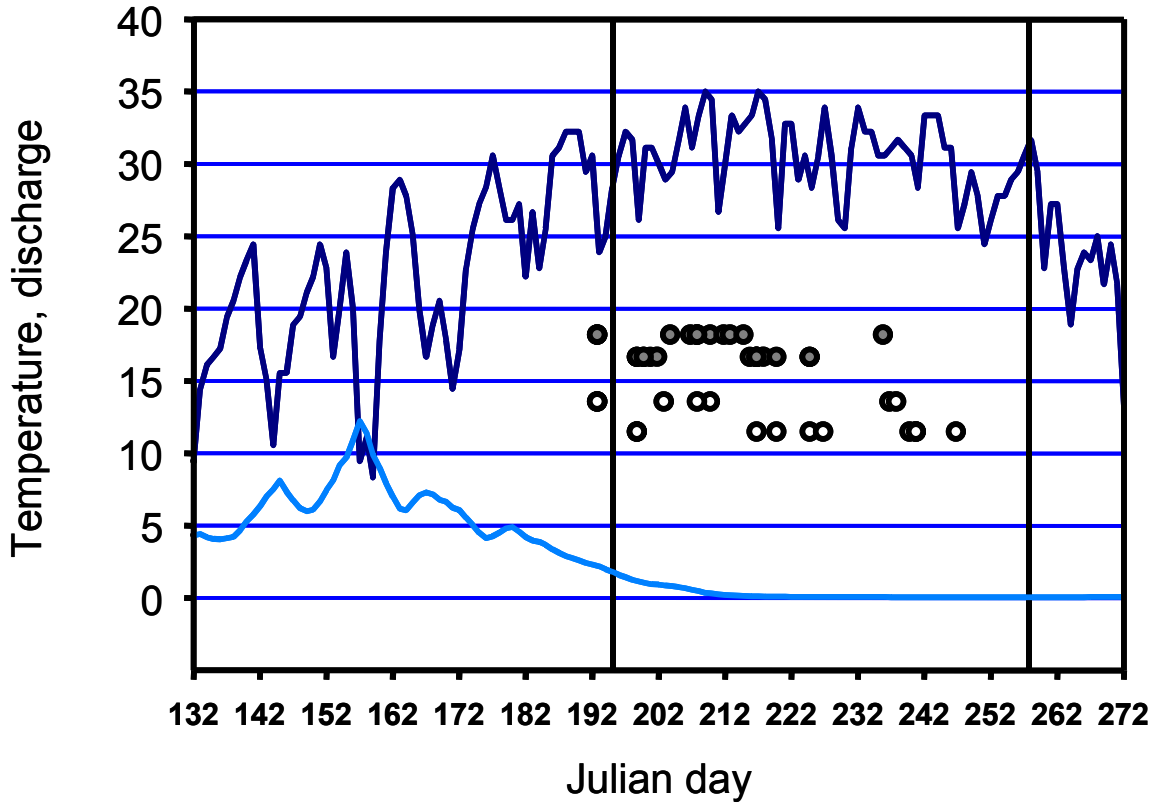
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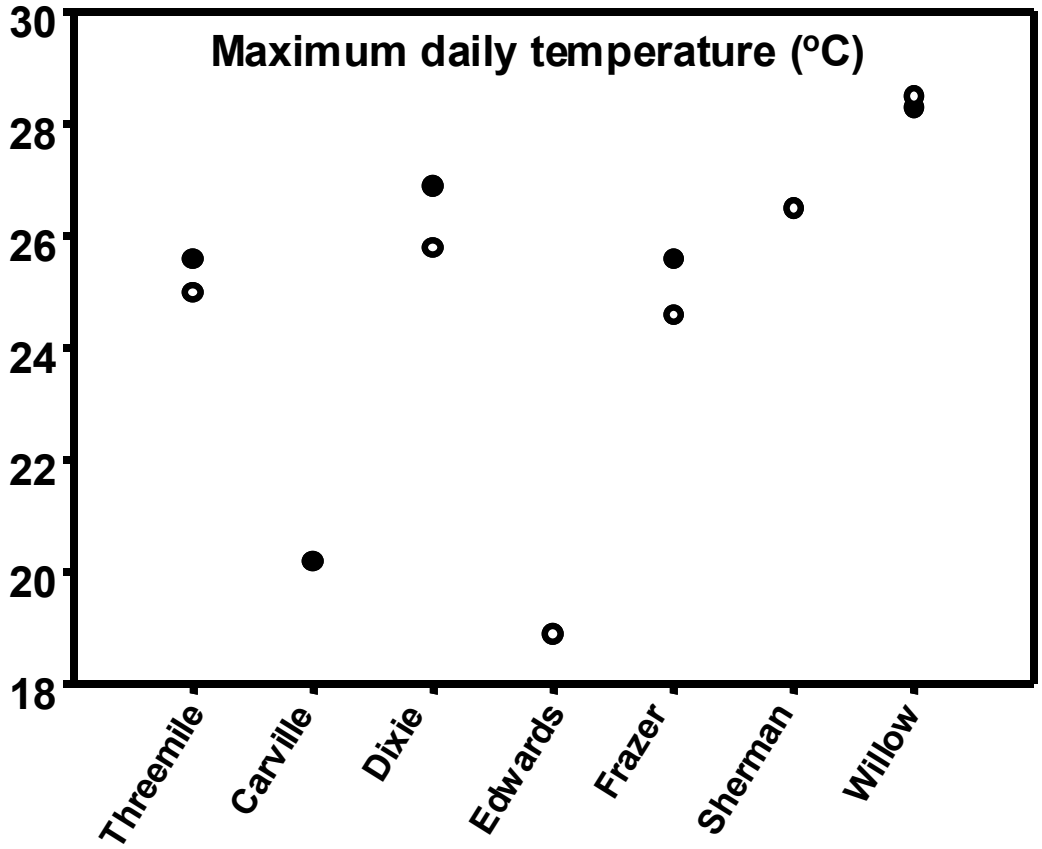
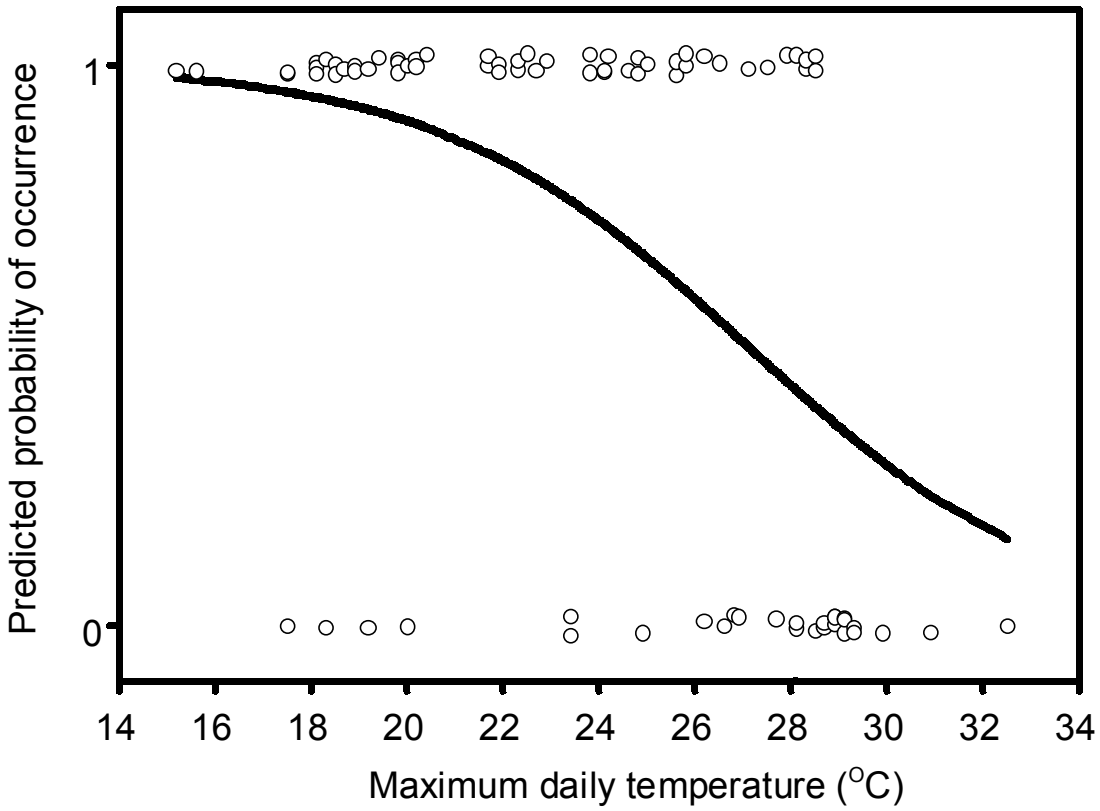
Julian day


Maximum daily temperature (ºC)
30
28
26
24
22
20
18
Threemile
Carville
Dixie
Edwards
Frazer
Sherman
Willow


Predicted probability of occurrence
1
0
14
16
18
20
22
24
26
28
30
32
34
Maximum daily temperature (°C)

Stream temperatures and the distribution of bull trout at the southern margin of its range

Introduction

Temperature is one of the fundamental elements that define suitable habitat for fishes (Magnuson et al. 1979). Temperature directly influences individual fish through physiological processes (e.g., growth, metabolism; Elliott 1981) and behavioral thermoregulation (Berman and Quinn 1991). Indirect effects of temperature include effects on biotic interactions (Reeves et al. 1987; Taniguchi et al. 1998; Taniguchi and Nakano 2000) and responses of individual fish to other physiological stressors, such as dissolved oxygen or ammonia (Dockray et al. 1998). These influences on individuals may be related to the distributions of local populations in landscapes (Dunham et al. 2001a,b), or be manifested as the geographic limits to species distributions (Shuter and Post 1990; Adams 1999).

Patterns of temperature and fish distributions in the field may provide an important context for understanding thermal responses of individual fish in the laboratory. Laboratory conditions provide an excellent environment for controlled experimental studies, but it is impossible to duplicate the complex environments that individual fish experience in the field. Accordingly, thermal responses observed in the laboratory may have little ecological relevance. To address this issue, Eaton et al. (1995) attempted to relate results of laboratory-derived upper thermal tolerance limits for a variety of fishes to maximum water temperatures associated with records of species occurrence in the field. Maximum temperatures associated with species distributions in the field were often lower than upper thermal tolerance limits observed in the laboratory. For example, among the salmonid species studied, maximum water temperatures associated with fish distributions in the field were 1-4 ^{o}C cooler than upper thermal tolerance limits indicated by laboratory studies. The fact that fish distributions in the field corresponded to cooler temperatures suggests sublethal effects of temperature, such as growth limitation and disease

resistance, may be important. Alternatively, there may be conditions in the field, such as food limitation or interactions with other stressful conditions that reduce the thermal tolerance of individual fish. In any case, our understanding of the thermal requirements of fishes is greatly improved by considering lines of evidence from both field and laboratory studies.

Patterns of fish distribution in relation to temperature also have potentially important implications for the persistence of local populations. For example, recent studies suggest that persistence of local populations of stream-living salmonids can be tied strongly to the amount and distribution of suitable habitats on natural landscapes (Rieman and Dunham 2000; Dunham et al. 2001a). If fish distributions are limited by temperature, then large-scale patterns of thermal habitat availability may have strong effects on population persistence. The amount and distribution of thermally suitable habitat for fish is a major concern for regulation of water use and land management because temperature is sensitive to past and present human influences (Poole and Berman 2001) that may be exacerbated by future climate change (Keleher and Rahel 1996).

Species with a narrow thermal "niche" (Magnuson et al. 1979) are most likely to be affected by alterations in water temperature regimes. In particular, species tied to coldwater habitats may be especially vulnerable to increases in temperature that commonly result from human influences on water temperature regimes (Poole and Berman 2001). In western North America, bull trout (*Salvelinus confluentus*) is believed to be among the most thermally sensitive species in coldwater habitats (Rieman and McIntyre 1993; Buchanan and Gregory 1997; Haas 2001; Selong et al. 2001). Bull trout is listed as threatened under the U.S. Endangered Species Act, and occupies a broad range across the western United States (Rieman et al. 1997). Accordingly, issues regarding the sensitivity of bull trout to temperature, and in turn, the sensitivity of temperature to human influences, are of great interest to land management and species recovery efforts.

Information on the thermal tolerance of bull trout has come from a variety of indirect lines of evidence and localized case studies in the field (e.g., Pratt 1992; Rieman and McIntyre 1993, 1995; Bonneau and Scarnecchia 1996; Buchanan and Gregory 1997; Dunham and Rieman 1999; Zurstadt 2000; Haas 2001) and laboratory (Selong et al. 2001). These studies have provided key insights into the thermal requirements of bull trout, but with the exception of analyses of climatic gradients (Rieman et al. 1997), a comprehensive analysis of thermal habitat associations of bull trout in the field has not been conducted throughout the species' range. Of particular interest should be the southern margin of the species' range (e.g., Flebbe 1994), where temperature should be most important. Because bull trout are known to be sensitive to warm water temperatures (Buchanan and Gregory 1997; Selong et al. 2001), temperature metrics that reflect annual maximum temperatures should be suitable indicators of habitat use. Our primary objectives in this study were to 1) collect information on the distribution of bull trout and water temperatures throughout the southern margin of its range; 2) determine if temperature can predict the distribution of bull trout; 3) examine the generality of model predictions from different locations; and 4) relate results of associations between bull trout and temperature in the field to the results of previous field and laboratory studies.

We modeled the distribution of bull trout in relation to temperature in the field throughout the southern margin of its range in the United States. Our focus was on the distribution of small bull trout (<150 mm). Areas where small bull trout occur represent key spawning and rearing habitats, and are thus an essential component of bull trout habitat (Rieman and Dunham 2000). Small bull trout represent resident (non-migratory) individuals, or juveniles that have yet to emigrate. Juveniles rear in their natal streams for at least one year (Rieman and McIntyre 1993). Accordingly, small bull trout are present through at least one entire annual thermal regime within a stream. Larger fish often undertake extensive migrations (Bjornn and Mallet 1964; Swanberg 1997), it is therefore much more difficult to match their distribution with thermal regimes at a given time or location.

We used two data sets to model the distribution of bull trout in relation to water temperature. A model developed from a regional data set covering observations over a large portion of the range of bull trout within the United States (Rieman and Chandler 1999) was compared to a model developed from data collected on temperature and occurrence of bull trout in Washington State in 2000 (Dunham and Chandler 2001). Models developed using each data set were used to predict observations in the other. This cross validation with different data sets was used to determine if patterns in each were similar. The data sets were derived using different sampling methods, so differences between models generated with each could result from this influence, or from different responses of bull trout to temperature. Similarity in predictions from each model would suggest these potential influences are not important.

Methods

Data acquisition

Regional data set. We assembled a database of thermograph records throughout the current range of bull trout in the United States using data from our own surveys of bull trout and stream temperatures, and data received from other biologists in the region (Rieman and Chandler 1999). Temperature records for analysis of bull trout distributions in relation to maximum summer temperatures spanned from July 15-August 31. This period was selected to symmetrically bound the period for which maximum water temperatures were observed. Minimum requirements for temperature measurements were uniform sampling intervals of at least 4 instantaneous observations per day. Information on occurrence of bull trout within 500 m of the site (unknown was a potential response) was also required for all records. Records were classified for presence of small (<150 mm) bull trout. Only records with definite presence or absence of small bull trout were used in this analysis. This resulted in a total of 175 streams and 643 sites distributed throughout the western United States (Figure 1), representing data reported in Rieman and Chandler (1999), and subsequent data acquisition (1999-2001).

Washington State data set. To ensure broad coverage of stream habitat conditions experienced by bull trout in Washington State, we sampled streams over a broad geographic area. We selected streams from three broad regions, west of the Cascade Mountains, east of the Cascade Mountains, and Blue Mountains (southeast Washington). Final selection of study streams was based on workshops and consultation with over 100 local biologists familiar with each region. Streams sampled for bull trout occurrence and temperature included the South Fork Skokomish River, Twisp River, Chiwawa River, Ahtanum Creek, and Tucannon River (Figure 1).

Locations of sampling sites attempted to bracket the downstream distribution limits of small bull trout in each stream. Within each stream, 100 m sites were spaced 2 km apart in an up-downstream array. Site spacing varied occasionally, due to logistical difficulties encountered in the field. The purpose for 2 km spacing of sites was to provide enough distance between sites to sample changing thermal conditions as a function of downstream changes in stream characteristics.

All fish sampling was conducted using single-pass night snorkeling (see Thurow 1994), which is among the most efficient methods for sampling bull trout (Peterson et al. 2001). All bull trout were counted, and bull trout less than 150 mm in total length were specifically noted. Whenever possible, block nets were installed at the upper and lower unit boundaries to prevent fish movement into or out of the site during sampling. In some cases, it was not possible to hold block nets. This was common in larger (>5 m wetted width) streams, and streams with strong discharge. All sampling was conducted in late summer to early fall (15 July-15 September 2000), to capture observations of fish distributions during the warmest time of year.

We sampled water temperatures at all sites with "Tidbit" temperature data loggers manufactured by Onset Computer Corporation, Inc. (www.onset.com). These data loggers are waterproof, but were placed in protective PVC casings to protect them from potential physical damage while in the streams. Data loggers were programmed and

calibrated following manufacturer's instructions. Placement of data loggers within sites followed methods outlined by Dunham (1999) and Zaroban (1999).

Data Analysis

Data analyses used logistic regression (Allison 1999) to relate occurrence of small bull trout to maximum daily summer (15 July-15 September) temperatures in both data sets. Patterns of occurrence in each data set were analyzed separately. Cross validations were performed both within and between the data sets to evaluate model predictions. Within both data sets, a "leave one out" cross validation was performed. This was accomplished by sequentially omitting a single observation from the dataset, fitting a model with the remaining observations, and using the model to predict occurrence for the omitted observation. Using this method of cross-validation allows the entire data set to be used as independent observations to evaluate out-of-sample model performance.

Between data sets, we applied predictions from models developed with one data set (e.g., regional, or Washington State) to the other. In other words, we asked "How well do models developed from the regional data set predict observations in the Washington State data set, and vice versa?" Model predictions were classified as "present" when predicted probabilities of occurrence equaled or exceeded 0.50. Predictions of 0.49 or less were treated as predicted "absence." The frequency of correctly classified presence and absences, and overall (presence + absence) classification rates were summarized to evaluate model predictions.

We were also interested in the spatial stability of model predictions within each data set. Because the regional data set was not collected with a statistically based sampling design, we were only able to quantitatively test for spatial variability within the Washington State data set. Data collected in Washington State in 2000 were from sites nested within streams, so it was possible to test for the influence of spatial variability on the model results. Spatial variation included variation among sites within streams and variation among streams. Because sites within streams might not be truly independent, each

observation may not contribute a single degree of freedom to the analysis. The spatial autocorrelation of these sites may result in overestimation of degrees of freedom for hypothesis testing and underestimation of the precision of model parameter estimates and predictions (Legendre 1993). Spatial variability among streams (Dunham and Vinyard 1997; Dunham et al., in press) may also affect model parameter (slopes, intercepts, and interaction terms) estimates.

To look at both "site" and "stream" influences on the results, we analyzed a subset of data collected at sites along continuous lengths of major streams sampled in each study basin (see Dunham and Chandler 2001). We ordered sites in an upstream-downstream array to test for the effects of spatial autocorrelation among sites within streams. Variability among streams was analyzed by coding "stream" as a categorical or "group" variable in the analysis (Allison 1999).

Results

Maximum temperature consistently predicted occurrence of young small bull trout in all datasets and analyses. Logistic regression model parameter estimates for the Washington State data set were similar to parameter estimates from the similar analysis of the larger database (Table 1). Analysis of a spatially ordered subset of data from Washington State indicated significant autocorrelation among sites within streams, but "stream" effects were not significant, indicating that among-stream differences in the relationship between temperature and bull trout occurrence were not detectable. The main effect of accounting for autocorrelation was wider confidence bounds for parameter estimates (Table 1).

Overall error rates for cross validations within and between models and datasets were similar (68-72%), but error rates for absence and presence were not consistent (Table 2). Most notably, the regional model predicted presence very well for the Washington data set, but poorly for absence of bull trout. For other cross validations classification rates for presence and absence were similar, ranging from 64-77% (Table 2).

Discussion

Results of this and related studies (Rieman and Chandler 1999; Dunham and Chandler 2001) suggest that temperature is a useful predictor of the occurrence of small bull trout throughout the southern margin of the species' range in the conterminous United States. Concordance in parameter estimates and cross-validation both within and between a regional and a more "local" (Washington State) model provide evidence for a robust relationship between occurrence of bull trout and maximum stream temperatures.

Model predictions for the regional data set indicated slightly higher predicted probabilities of occurrence for bull trout at warmer (>12°C) maximum temperatures (Figure 2). This may be due to the larger sample size for the regional data set (n = 643) in relation to the Washington data set (n = 109). With a larger sample size, it should be more likely to observe bull trout in habitats with a low probability of use. Bull trout were never observed at temperatures exceeding 17.5°C in the smaller Washington data set, whereas the highest maximum temperature associated with occurrence of bull trout in the regional data set was 26.2°C. Accordingly, the regional model predicted a higher probability of occurrence for bull trout at warmer maximum temperatures.

Cross validations between the regional and Washington models reflected these differences as well (Table 2). For example, the regional model was good at predicting presence of bull trout in the Washington data set, but relatively poor at predicting absence of bull trout. Most of the incorrect classifications of absence were for maximum temperatures ranging from 13-17°C, where differences in predicted probabilities of occurrence between the models were greatest (Figure 2). This pattern reflects the greater uncertainty that should be expected in general for occurrence of bull trout at "intermediate" temperatures. At colder (<12°C) and warmer (>25°C) maximum temperatures, the probability of occurrence of bull trout predicted by both models is very similar (Figure 2).

Maximum temperatures associated with occurrence of bull trout in the field were consistent with the results of laboratory studies of thermal tolerance. Under laboratory conditions, mortality of bull trout occurs in less than 24 hours when fish are exposed to temperatures greater than or equal to 26°C (Selong et al. 2001). Our models (Figure 2) similarly indicate that occurrence of bull trout is very unlikely at these temperatures. Bull trout can survive chronic exposure to constant temperatures of up to 20°C for long periods of time, however. Selong et al. (2001) reported ultimate upper incipient lethal temperatures (UUILT) for bull trout ranging from 20.9°C and 23.5°C for 60 and 7-day exposures, respectively.

Model predictions from distributions in the field (Figure 2) imply that bull trout may be present at potentially lethal temperatures, but that probability of occurrence is relatively low (e.g., <0.50) until maximum daily temperatures decline to approximately 14-16°C. Probability of occurrence is not high (e.g., >0.75) until maximum daily temperatures decline to approximately 11-12°C. These patterns could reflect sublethal influences of temperature. For example, Selong et al. (2001) found that growth of bull trout on unlimited rations in the laboratory was maximized at 13.2°C. If rations are limited, the temperature at which maximum growth is realized can be shifted to lower temperatures (T. McMahon, Montana State University, personal communication). More detailed field investigations of growth, behavior, and other responses are needed to better understand the sublethal responses of bull trout to temperature.

Management implications

Results of this work provide an answer to the question of "how cold?" water needs to be to consistently support small bull trout. The answer to this question is not a single number, but rather a continuum of values associated with the expected probability of occurrence for bull trout. Risk-averse strategies to protect this threatened species may adopt a more or less conservative approach to choosing an acceptable temperature for management purposes. For example, a very conservative approach would be to protect a

full range of habitats that bull trout could use (e.g., <26°C; Figure 2). Another approach would be to target restoration of water temperatures that likely to support bull trout (e.g., ≤12°C; Figure 2).

It is important to realize that maximum daily temperature is but one of a variety of different summary measures or "metrics" (e.g., maximum or mean temperatures summarized on daily, weekly, or seasonal intervals) that could be associated with occurrence of bull trout or used for management criteria. We used maximum daily temperature because it is relatively easy to interpret, and because it provides relatively fine-scale information on thermal exposure. Summary of temperatures in terms of means or multi-day summaries could mask important information at finer scales (e.g., Dunham 1999). Detailed information on the biological importance of different kinds of thermal exposure (e.g., sublethal versus lethal; chronic versus acute) is lacking. Finally, it is important to note that most measures of maximum temperatures in streams supporting bull trout are highly correlated, and are therefore statistically redundant, in terms of predicting fish distributions.

The question of "how cold?" is obviously critical, but an even more pressing question, in terms of the population-level significance of temperature is "how much?" (Dunham et al. 2001b). Research on bull trout and other salmonids has clearly linked patterns of occurrence to the amount and distribution of potentially suitable thermal habitat on landscapes (e.g., Rieman and McIntyre 1995; Dunham and Rieman 1999; Dunham et al. 2001a; Poole et al. 2001). Useful models to predict stream temperatures on landscapes are needed to provide a better view of large-scale habitat structuring that likely has important effects on population persistence for bull trout and associated species. Bull trout occupies a vast range in the western United States, and current models to predict the distribution of suitable habitat are very simplistic and limited in spatial extent (e.g., only the upper Boise River basin; Rieman and McIntyre 1995; Dunham and Rieman 1999). Future work should seek to provide useful landscape models for predicting stream temperatures throughout the range of bull trout.

With the models reported herein, we can now predict the distribution of potentially suitable habitats for small bull trout, given that stream temperature patterns are known (e.g., from direct measurement or landscape models). With these distribution models, it should be possible to develop maps of suitable habitats, and "patch-based" models of occurrence (Dunham et al., in press) to predict patterns of occurrence at larger scales (e.g., among basins, as opposed to within streams). One premise behind this kind of modeling is that some, but not all, potentially suitable habitat is occupied by bull trout (e.g., Rieman and McIntyre 1995; Dunham and Rieman 1999; Rieman and Dunham 2000). In the absence of information on larger-scale suitability of habitat (e.g., "how much?"), managers may opt to conservatively protect any habitat with water cold enough to potentially support bull trout. Application of larger-scale models, in conjunction with new sampling protocols (Peterson et al. 2001; Peterson and Dunham, in review), would be needed to provide increased resolution for land management classifications to protect bull trout populations and key habitats.

Acknowledgements

Critical support for this project was provided by dozens of individuals representing a diversity federal, state, tribal, private organizations and interests located throughout the western United States. Though too numerous to mention here, we are grateful to all who have provided data, key information on field sampling sites, and thoughtful discussions of the issues regarding bull trout and temperature.

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Table 1. Logistic regression parameter estimates and confidence intervals for three models of bull trout occurrence in relation to summer maximum temperature. The "Washington-All" dataset includes all fish-habitat data collected in 2000. The "Regional" dataset is an extended version of the dataset described by Rieman and Chandler (1999). The "Washington-Spatial" dataset (Dunham and Chandler 2001) includes data from a spatially ordered sample of sites sampled in 2000. Parameter estimates for all datasets are similar.

Dataset	Parameter	Estimated Coefficient	95% Confidence interval
Washington-All	Intercept	5.47	2.87, 8.58
	Temperature	-0.38	-0.58, -0.21
Regional	Intercept	4.64	3.81, 5.83
	Temperature	-0.28	-0.34, -0.23
Washington-Spatial	Intercept	7.91	0.52, 15.31
	Temperature	-0.52	-0.98, -0.07

Table 2. Results of cross validations using the "Washington-All" (WA) and "regional" (REG) models (Table 1). Cross validations within a model (i.e., WA→WA and REG→REG) were conducted by sequentially removing each observation from the dataset, fitting the model with the remaining observations, and predicting the omitted observation (e.g., a "leave one out" cross-validation). Cross validations between models (i.e., WA→REG and REG→WA) were conducted by using a model developed using one data set (e.g., WA or REG) to predict observations in the other.

		Presence			**Absence**		
Model	Overall Correct	Correct	Error	Percent correct	Correct	Error	Percent correct
WA→WA	0.70	30	17	63.8	46	16	74.2
WA→REG	0.67	208	145	58.9	223	67	76.9
REG→WA	0.68	42	4	91.3	32	31	50.8
REG→REG	0.72	290	120	70.7	170	63	73.0

Figure 1. Locations of sites sampled for occurrence of small bull trout and stream temperatures in the western United States. Circles represent sites within the "regional" data set, and triangles represent sites sampled in Washington State in 2000.

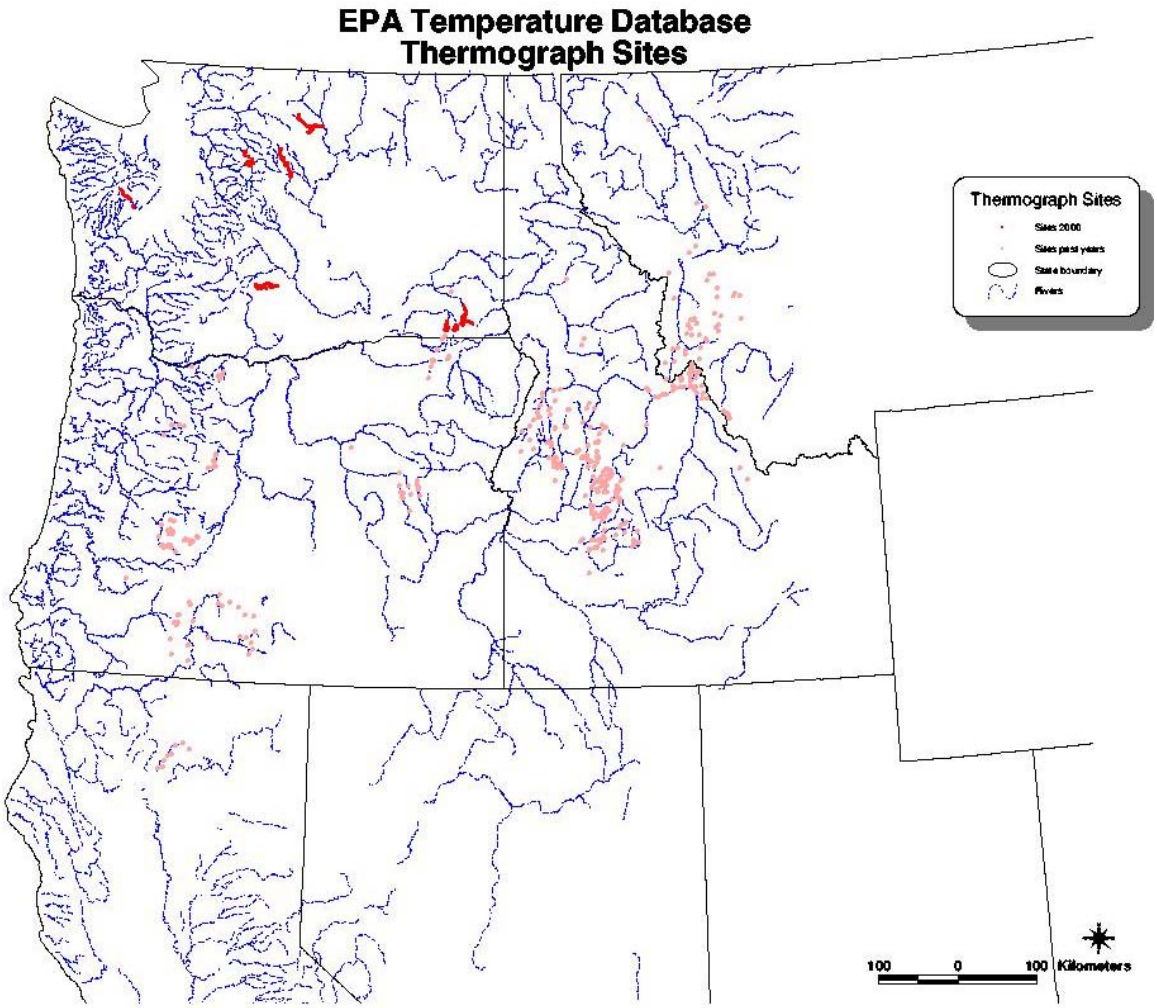
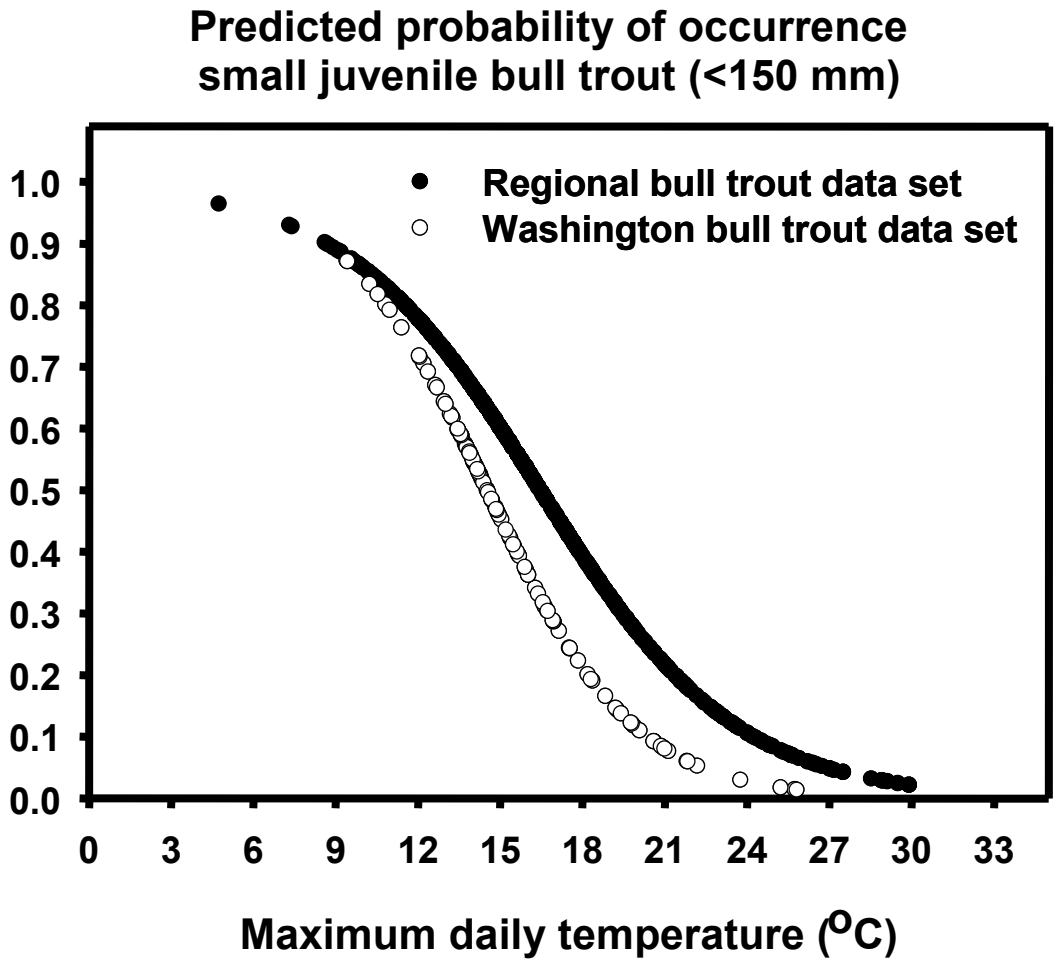


Figure 2. Predicted probability of presence (occurrence) for small bull trout in relation to maximum daily temperature for the regional and Washington 2000 data sets.



Measuring Stream Temperature with Digital Thermographs: A User's Guide

Introduction

Digital temperature data loggers (or thermographs) are among the most widespread instruments in use for monitoring physical conditions in aquatic ecosystems. Most temperature data loggers are relatively inexpensive (<$200 US), simple to deploy, and capable of collecting large amounts of data (>32 kb). Temperature is a variable of widespread interest in aquatic ecosystems because it is an important component of water quality (e.g., Poole et al. 2001a), and it is affected by many different natural and human-related influences (e.g., Webb and Zhang 1997; Poole and Berman 2001). Due in part to the dramatic increase in the use of temperature data loggers and other new technologies (e.g., Torgerson et al. 2001), the quantity of data on water temperature data has increased dramatically. The rapid accumulation of new data has perhaps surpassed our data processing ability, and it is not always clear that information from temperature data loggers is reliable, accurate, or useful. This problem is not new or unique in water quality monitoring, and has been termed the "data-rich, information-poor" syndrome by Ward et al. (1986). This protocol is an attempt to provide guidance to improve the quality and utility of water temperature data collected with digital temperature dataloggers.

What this protocol covers

In this protocol, we explore a range of issues associated with the use of temperature data loggers for water temperature monitoring. Our intent is to provide a comprehensive synthesis and analysis of the issues that must be addressed to ensure that data from temperature data loggers serve the objectives for which they were collected (Table 1). In addition to carefully considering the objectives for a monitoring effort, there are several other potentially important issues (Table 2). Several protocols (e.g., Dunham 1999; Lewis et al. 1999; Zaroban 1999) have summarized information on field sampling methods. We review much of the information in these protocols here for the sake of completeness, but we encourage users to refer to them as well. In this protocol, we cover these issues and several others, including measurement interval, data screening, correlations among various metrics, and development of a relational database for distribution. Users must be cognizant of these issues during all phases (e.g., planning, implementation, analysis, interpretation) of a monitoring effort. We do not wish to give readers of this protocol the impression that sampling of water temperatures with digital data loggers should be excessively complex or difficult. Rather, we wish to provide useful and relatively simple guidance that will substantially improve the quality and utility of temperature data.

Table 1. A list of common objectives for sampling of water temperatures (see also NRCS 1996).

Objective	**Examples**
Baseline monitoring	Monitoring of pre- and post-treatment water temperature regimes Monitoring to determine spatial and temporal temperature patterns Monitoring to provide information on temperature in previously unsurveyed habitats
Water quality compliance	Monitoring of temperatures to determine if beneficial uses (e.g., fish) are supported Monitoring of temperatures in relation to point source influences (e.g., warm or cold water discharges) Monitoring of temperature patterns to validate or parameterize water temperature models (e.g., Bartholow 2000)
Research	Monitoring of water temperatures to model responses of aquatic biota (e.g., Eaton et al. 1995) Monitoring of water temperatures to determine appropriate spatio-temporal sampling designs for a given sampling frame (e.g., water body or watershed of interest)

Table 2. List of temperature sampling issues covered in this document.

Issue	Examples
Instrument error	Accuracy and precision, range of measurement, lag time in temperature recording
Calibration	Post and pre-use calibration of data loggers, "drifting" of temperature readings, reliability of calibration conditions
Measurement interval	Effects of temperature measurement interval on probability of detecting important maximum and minimum temperatures
Field sampling	Locating representative sampling sites to make inferences about temperatures of interest (e.g., surface versus benthic temperatures), effects of data logger housings on temperature readings
Error screening	Numerical filters for detecting outlier and erroneous observations, visual inspection of thermal patterns to detect possible errors
Data summaries	Choice of statistical summaries of temperature, correlations among different temperature metrics, methods for defining "exceptional" conditions

Important issues not covered

Our focus in this protocol is on sampling temperatures at specific localities or sites. We do not provide extensive guidance on different sampling designs for making inferences about larger-scale spatial patterns of stream temperatures (e.g., Poole et al. 2001b). Another topic that is worthy of consideration, but not considered in detail here, is documentation and archiving of temperature data in a format that is readily accessible by a wide range of users. As water temperature data accumulate at an accelerating pace and scale, the need to organize this information in a useable format will increase accordingly. Although we have developed a relational database for the temperature data used herein, we did not wish to duplicate existing efforts to archive water quality information. There are several noteworthy existing efforts related to this need, including StreamNet (http://www.streamnet.org), the U.S. Environmental Protection Agency (e.g., STORET; http://www.epa.gov/storet/) the USDA Forest Service National Resource Information System (http://www.fs.fed.us/emc/nris/), and the U.S. Geological Survey National Water Quality Assessment (http://water.usgs.gov/nawqa/).

Outline of the protocol

This protocol is organized into four major sections that correspond to the series of steps that users must take in using temperature data loggers. These steps include 1) study design and planning, 2) field sampling, 3) data processing, and 4) data storage and archiving.

Step 1. Study design and planning

Study objectives – Who will use the data, and why?

There are a variety of objectives for measuring or monitoring water temperature (Table 1, NRCS 1996). In our experience, most uses of temperature data loggers are linked to a specific objective. It is also common, however, to find several independent water temperature monitoring efforts occurring in the same water body at the same time. Often data loggers from different investigators are located in the same reach of stream, for example. Coordination among investigators would help to minimize duplication of effort, and allow opportunities for multiple uses of information from a single data collection effort.

Choosing a data logger

There are many manufacturers and models of data loggers to choose from (Table 3). Prices for data loggers at the time this protocol was written started at approximately $50.00 (US). Important features to consider when choosing a logger include accuracy, precision, memory capacity, durability, and programmability.

Accuracy and precision

Most data loggers, when properly functioning, are very accurate and capable of relatively precise (± 1^{o}C or less) temperature readings. Most manufacturers provide relatively detailed information on the accuracy and precision of their instruments, some of which is summarized in Table 3.

Table 3. Examples with websites of some of the data loggers that are currently available.

Manufacturer		Logger Type	Submersible	Memory Capacity	Temperature Range	Accuracy	Resolution	Battery Type	Web Site
Onset		HOBO H8	No	7943	-20 – 70	0.7	0.4	1 year replaceable	Onsetcomp.com
		HOBO Pro Temp	No	65291	-30 – 50	0.2	0.02	3 year replaceable	Onsetcomp.com
		StowAway Tidbit	Yes	32520	-4 – 37	0.2	0.16	5 year non-replaceable	Onsetcomp.com
		Optic StowAway	Yes	32520	-4 – 37	0.2	0.16	10 year replaceable	Onsetcomp.com
Veriteq		Spectrum 1000	Yes	32520	-40 – 85	0.15	0.05	10 year non-replaceable	Veriteq.com
Gemini		Tinytag Ultra	No	7943	-40 – 85	0.2	0.4	2 year replaceable	Geminidataloggers.com
		TinyTag Plus	No	10836	-40 – 85	0.2	0.4	2 year replaceable	Geminidataloggers.com
Ryan		RL 100	Yes	1800	-39 – 87	0.5	0.1		Ryaninst.com
Vemco		Minilog	Yes	10836	-5 – 40	0.1	0.015	Replaceable	Vemco.com

Memory capacity

Memory capacity is more important if temperatures are to be recorded for long periods of time (e.g., >1 year) or short sampling intervals (e.g., <30 min). Most data loggers manufactured today have a minimum of 8k of memory, which allows deployment of 165 days at 30-minute intervals (7920 observations).

Durability

Durability is important when deploying data loggers in many water bodies. While some models are quite durable, there are a wide variety of field conditions that can lead to damage or loss of data loggers. For this reason, we recommend using data logger housings in situations where there is any possibility of damage or loss. For example, data loggers in streams could be damaged or lost during high flows, bed scour, and associated transport of sediment and wood. Trampling from humans or animals could be important in some locations.

Types of data logger housings. Many data loggers are not submersible and must be deployed within sealed waterproof housings. Data loggers within waterproof housings are not in direct contact with the water, and are actually recording air temperatures within the sealed housing. Heat transfer between the air within the housing and the surrounding water is not immediate, but air temperatures within the housing should track surrounding water temperatures. There is a short time lag (~15 min) required for the air within the housing to equilibrate with the surrounding water temperature. Thus, temperatures recorded from data loggers within housings may not precisely track water temperatures on very short (> 15 min) time scales. This is not usually a problem, except for applications that require very precise tracking of water temperatures over short time intervals.

In situations where temperatures must be measured precisely, it may be more advisable to use data loggers with sensors that are in direct contact with water. For example, we placed paired data loggers in two different streams for the summer months. Data loggers in each pair were submersible but one was placed in a sealed, waterproof housing and the second was placed in a flow through housing. Differences in temperature measurements between the two setups (sealed and flow through housings) in a stream with moderate diel fluctuation (6 ^{o}C) were within the reported accuracy of the instruments (Figures 1 and 2). Measurements from the paired data loggers in a stream with more diel fluctuation (10 ^{o}C) differed between setups. Temperatures recorded in the sealed housing were cooler during the day and warmer at night (Figures 1 and 2). It seems likely that air within the sealed housings does not closely track the actual variability in ambient water temperatures, leading to an underestimation of the maximum temperatures and overestimation of the minimum temperatures. This problem appears to be most important for streams with large daily fluctuations in temperature in this example, but further study is needed to identify the range of conditions that could be important.

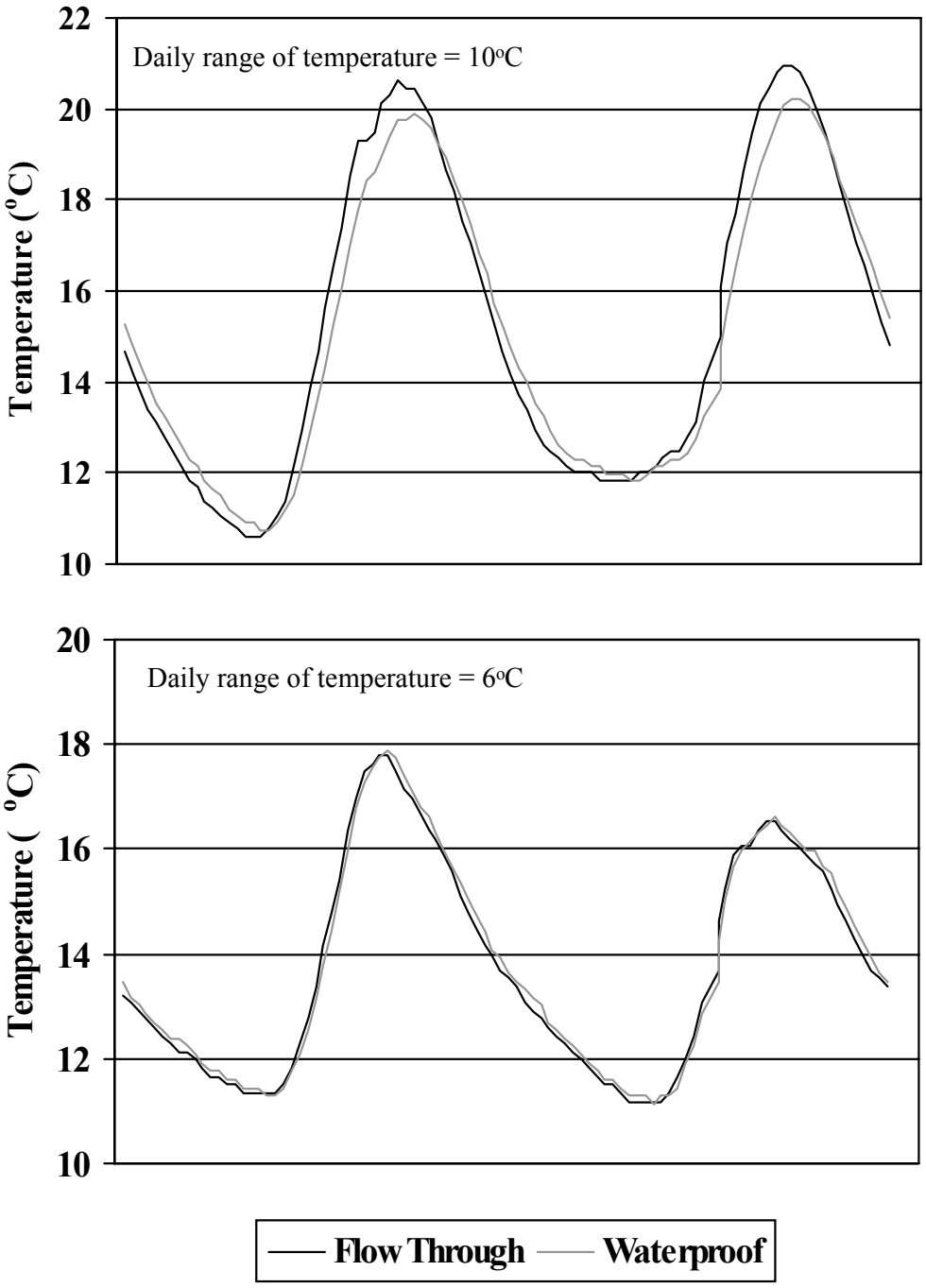


Figure 1. Comparison of 2 days of recorded temperatures for data loggers placed in two streams. Each stream had a data logger placed in a flow through housing and a data logger placed in a sealed (waterproof) housing.

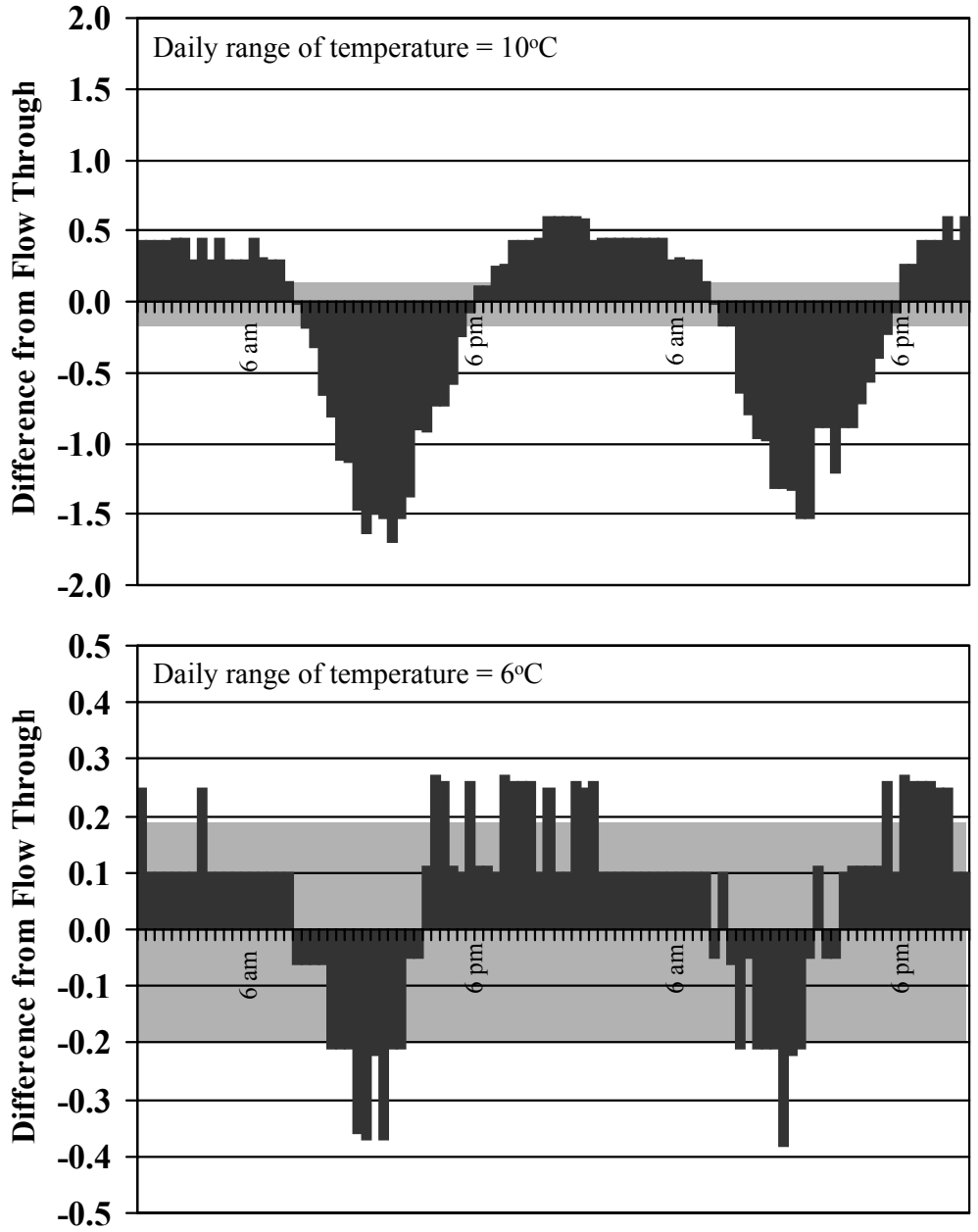


Figure 2. Comparison of the differences in temperature recorded from paired data loggers in two streams. The difference is the recorded temperature of the sealed (waterproof) minus the flow through housing. Grey shading indicates the range of accuracy for the instruments (± 0.2 °C).

Data loggers that are submersible should be placed in flow-through, durable housings (e.g., heavy duty, UV-resistant PVC pipe) to protect from physical impact or abrasions and direct solar radiation. Investigators must consider local conditions when designing data logger housings. For example, housings with fine screens or small flow-through holes could be easily fouled in eutrophic systems with abundant periphyton or algal growth. Housings placed in areas with abundant sediment deposition could be buried or filled with fine sediment.

One important function of the data logger housing is to protect the sensor from direct solar radiation. If the housing itself absorbs solar radiation, it may conduct heat to the data logger's sensor and bias temperature readings. For example, we tested temperatures recorded by data loggers placed in waterproof housings of three different colors: white, metallic, and transparent. Maximum water temperatures measured by loggers in clear housings were up to 5^{o}C warmer than temperatures measured by loggers in reflective white or metallic colored housings. Thus, clear data logger housings may have acted like miniature greenhouses that trapped solar radiation, causing erroneously warm water temperature measurements. Black data logger housings may also bias temperature measurements because they can absorb and re-radiate significant amounts of heat.

Programmability. Most temperature data loggers allow the user to program a starting time (delayed deployment) and sampling interval. Delayed deployment is particularly useful when using several data loggers within a single system. This assures that temperatures are taken at the exact same times for all data loggers. Some data loggers have a variable sampling interval option. This can be useful in a variety of situations. For example, if memory is limited and temperatures must be sampled for the entire year. Measurements can be programmed for longer sampling intervals in winter months when the daily range of temperatures is smaller and shorter intervals during the summer when daily variability in temperature is highest.

Calibration of data loggers

Regardless of the type of data logger used, it is good practice to make sure it is functioning properly. Calibration is a relatively simple process, and well worth the time, given the consequences of lost or misleading data. A simple and effective procedure for calibrating data loggers is the "ice bucket" method (see also http://www.onsetcomp.com/Newsletters/Honest_Observer/HO.2.1.html). The procedure involves the following steps:

1. Deploy the data loggers at a short sampling interval (for example, 1 minute).

2. Submerge data loggers in an insulated, well-mixed water bath with a generous amount of melting ice (e.g., a large cooler with ice water). Be sure to use fresh water (dissolved materials may alter the thermal properties of water).

3. If possible, record water temperatures using a NIST (National Institute of Standards and Technology, http://www.nist.gov/) thermometer to ensure the temperature of the water bath is 0^{o}C.

4. After at least an hour, remove the data loggers and download the data. If the data loggers are calibrated correctly, the temperature readings should level out at 0^{o}C (Figure 3).

5. It is good practice to check calibration both before and after data loggers are deployed and retrieved. It is also advisable to use a NIST thermometer to test the accuracy of data loggers at temperatures other than 0^{o}C.

6. Calibration to determine the accuracy of time recorded by data logger may also be necessary if temperature measurements are to be synchronized among different data loggers, or measured on a short time interval (e.g., < 30 min).

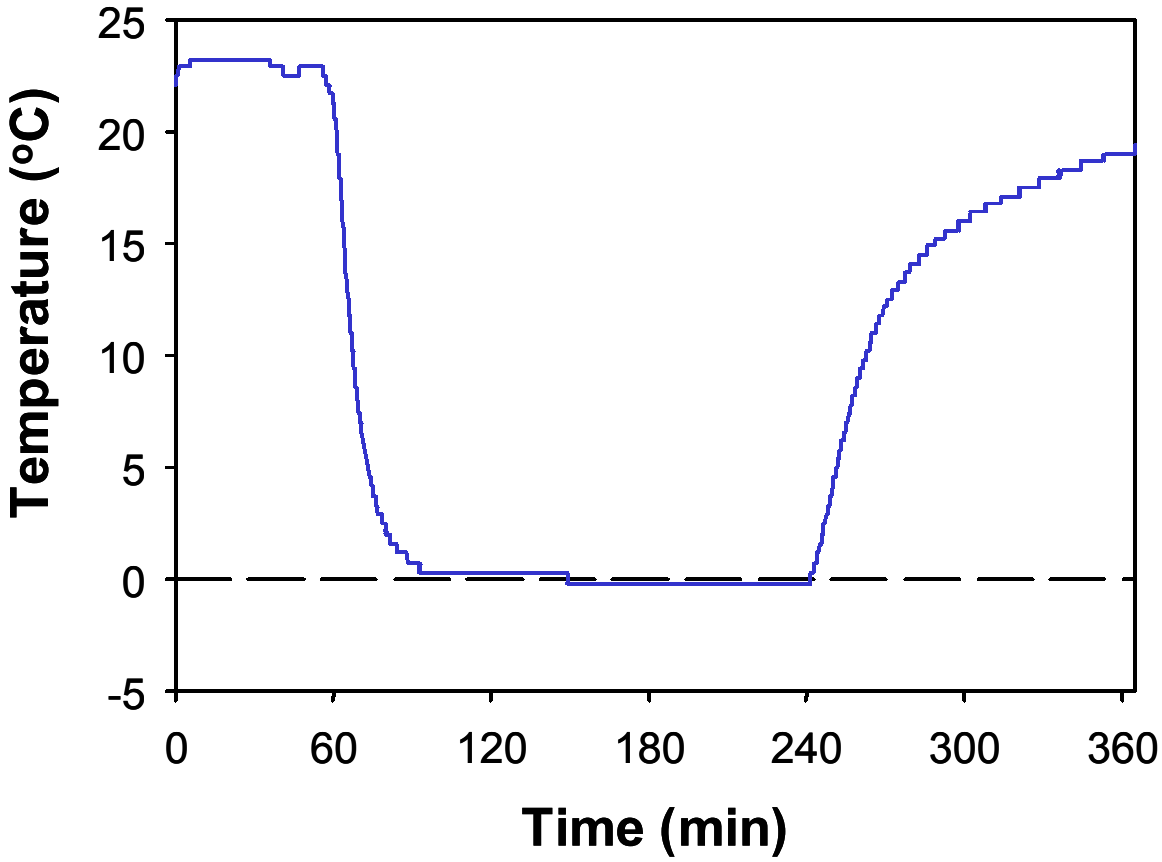


Figure 3. Illustration of data logger calibration using the "ice bucket" method.

Choosing a sampling interval

Most data loggers can be programmed to measure and record temperatures at a variety of time intervals. Obviously, longer time intervals will result in lower resolution and greater potential for bias. For some measures of temperature, such as the daily maximum, it may be necessary to sample with high frequency (short time intervals) if the variability or range in temperatures over the course of a day is large. In other words, infrequent sampling (e.g., >2 hour sampling intervals) in systems with a large amount of daily variation in temperature may not adequately describe the true thermal regime at a site. This may be particularly true of important instantaneous measures of temperature, such as the daily maximum temperature. For a given daily range of variation in temperatures, it should be possible to prescribe sampling intervals that ensure temperature regimes are adequately described.

To quantitatively address the issue of temperature sampling frequency or sampling interval, we used temperature data from data loggers deployed at 1252 sites sampled in the Pacific Northwest and Rocky Mountain regions (Dunham 1999; Rieman and Chandler 1999; Dunham and Chandler 2001; Figure 3). Sampling intervals at these sites

ranged from as few as 5 observations per day (every 4.8 hours) to 96 observations per day (every 15 minutes). These samples represent sites exhibiting a large range of variability in daily water temperatures and the variability is highly correlated to the daily range of temperature (Figure 5). The maximum range in daily temperature for the entire data set was 17.8°C.

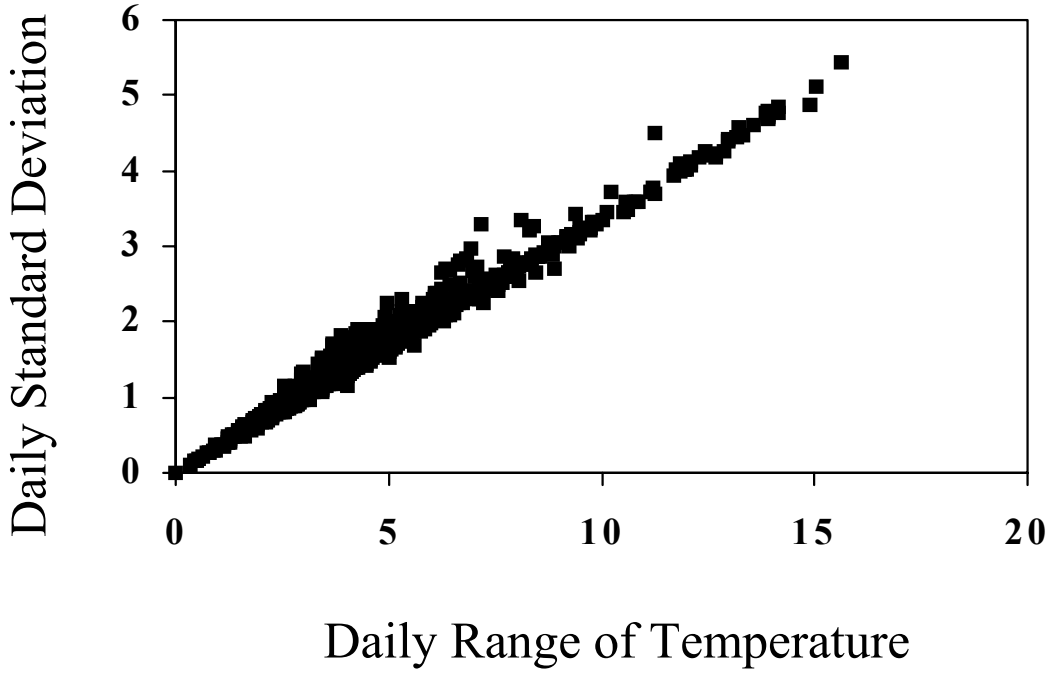


Figure 5. Linear correlation of mean daily range of temperature with mean daily standard deviation (square root of variance) for each site in the data set (r=0.98).

We focused our analyses on the influence of sampling interval on the observed maximum daily temperature. Maximum daily temperature should be the most sensitive to sampling interval for several reasons. First, it is a relatively instantaneous measure of temperature, and could easily be missed by sampling at longer intervals. Second, maximum daily temperatures and the range or variability in temperatures are strongly correlated (Dunham 1999). Therefore, higher maximum daily temperatures may be more difficult to detect with a given sampling interval.

To evaluate the potential for bias related to temperature sampling intervals, we needed a baseline or reference representing the "true" thermal regime. The "true" thermal regime within a day is the theoretical distribution of temperatures observed by sampling at infinitely small intervals. In the data set we used, the shortest sampling interval for which there were sufficient data to analyze was 30 min. This included a total of 211 "baseline" samples out of the 1252 for which we had information.

To compare maximum daily temperatures observed in the baseline data samples to those observed with sampling at >30 min intervals, we sub-sampled observations from the baseline data sets to simulate sampling at one, two, three and four hour intervals. For these simulated sampling intervals, we predicted the probability of missing the maximum daily temperature by more than 1°C from the baseline samples. The obvious consequence of "missing" the maximum temperature during sampling is underestimating the warmest temperatures that occurred at a given site. Probabilities of missing the true maximum temperature were predicted using logistic regression (Allison 1999, also see Dunham 1999).

As expected, sites with larger diel fluctuations (larger daily range in temperature) have a greater probability of missing the true maximum than those with smaller diel fluctuations (Figure 5). A daily range of 8°C would have an error rate of 4.5% and 8.5% for 3 and 4-hour sampling intervals, respectively.

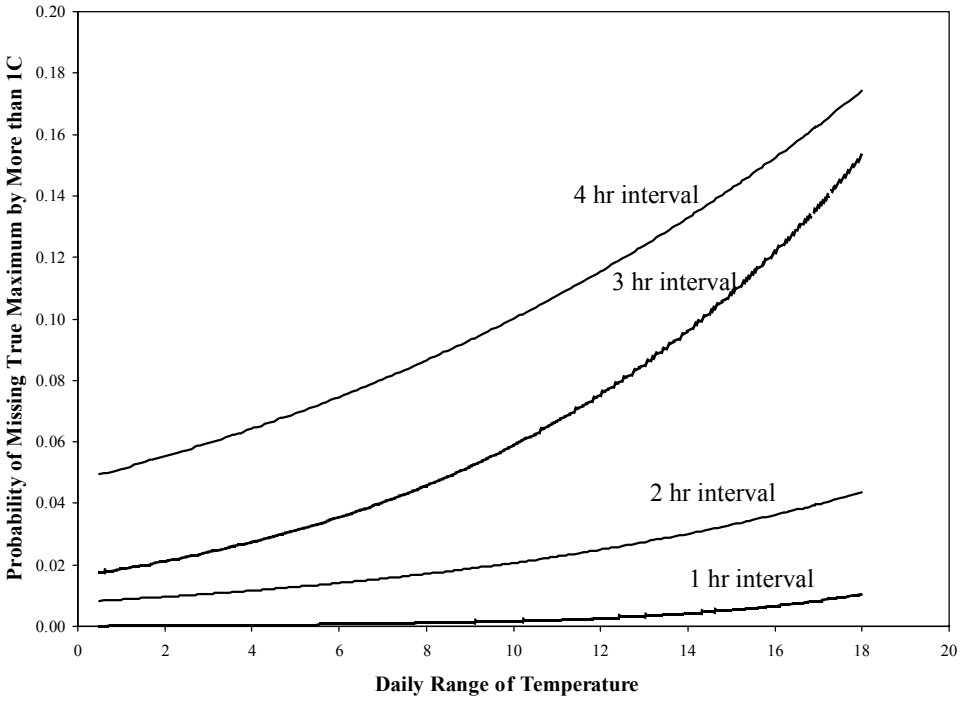


Figure 5. Probability of missing the maximum daily temperature by 1 °C in relation to daily range of temperature and sampling interval.

Step 2. Field procedures

Spatial thermal variation and sample site selection

Spatial patterns of thermal variability are common in water bodies of all types. Spatial differences in water temperature may be obvious at a variety of scales. In lakes and reservoirs, larger-scale (e.g., > 1 m) patterns of vertical stratification are commonly associated with thermal differences in the density of water. Patterns of stratification may vary on a seasonal or irregular basis (Wetzel 1975). Smaller-scale (<10 m) variability in the temperature of lakes and reservoirs can be caused by groundwater (e.g., springs) and tributary inflow. Small-scale thermal heterogeneity is similarly common in streams. Within a short segment of stream, localized variation in temperature can occur in a lateral, horizontal, or vertical direction (Figure 6)

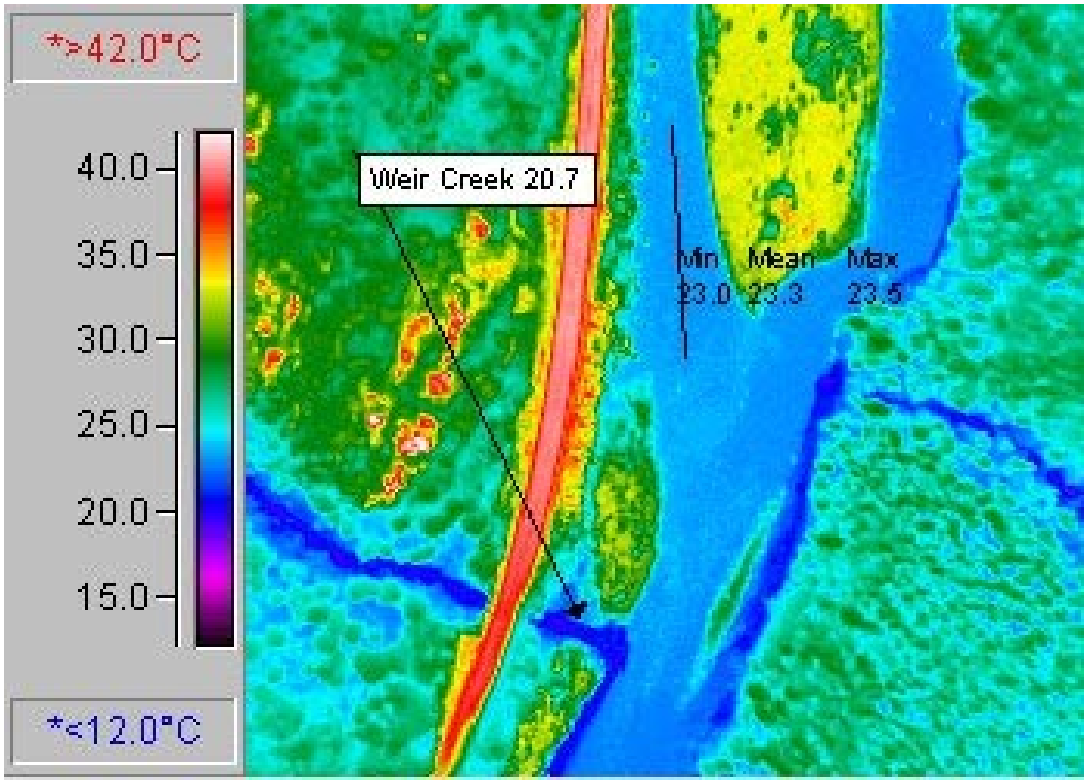


Figure 6. An illustration of spatial variation in temperature in the Lochsa River, Idaho. Note the influence of tributary inflow. The image was generated using infrared aerial videography (Torgerson et al. 2001; image provided by Don Essig, Idaho Department of Environmental Quality).

If the objective is to characterize the well-mixed or "thalweg" temperature in a stream, then small-scale variability in temperature must be carefully considered in selection of sites for temperature measurements. For example, stream temperatures near tributary junctions where flows are incompletely mixed are not representative of thalweg temperatures (Figure 6).

Information on thermal variability at a small spatial scale is best obtained by probing with a hand-held thermometer. Spatial variation in dissolved gases (e.g., dissolved oxygen) or conductivity may also indicate sources of thermal variation. These alternatives may be useful when potential thermal variability is not measurable at the time of data logger deployment. This may be important during high spring flows, seasonal turnover periods in lakes and still pools, and time periods when groundwater and surface water temperatures are not distinguishable. At larger spatial scales, information from infrared aerial videography can be useful for designing sampling programs for water temperatures, particularly in streams (Torgerson et al. 2001).

Protecting the data logger in the field

Once a suitable site is selected for temperature sampling, the data logger must be securely placed within the site. There are three common reasons for the loss or damage of data loggers: 1) failure to relocate the data logger after initial field deployment; 2) human tampering or vandalism; 3) natural disturbances, such as flooding, substrate movement, and animal influences (e.g., trampling by livestock or wildlife, beaver pond construction).

Failures to relocate data loggers can be minimized by attention to a few simple practices. Detailed hand-drawn maps and notes are usually necessary to re-locate temperature data loggers following initial field deployment. This is particularly important when different individuals are involved in different stages of field operations, as is often the case. Site descriptions should keep in mind potential changes in conditions that could affect a person's ability to relocate the data logger (e.g., changes in stream flow or reservoir level). Storing of geographic coordinates using a global positioning system (GPS) may be useful as well, but GPS coordinates are often insufficient by themselves.

Human tampering or vandalism can be a challenge. In many situations it is necessary to record temperatures in areas with high levels of human activity. The options for minimizing human interference include camouflage, secured storage, or use of back-up data loggers. The choice obviously depends on the situation. Camouflage is generally less expensive, but it may also make the data logger more difficult to relocate. Alternatively, data loggers can be secured in locked and signed housings may be relatively impervious to physical vandalism or disruption. A third option is to use two or more data loggers in a single location as back-ups in the case of human (or other) interference.

Human tampering can also result from unintentional interference. Some examples include damage to data loggers from construction or restoration efforts in the stream channel and electrofishing surveys. Active coordination with ongoing research, monitoring, or management in the study area is thus essential, not only to minimize

duplication of temperature sampling efforts, but also to minimize problems with unintentional interference.

Natural disturbances to data loggers are obviously impossible and perhaps undesirable to control entirely, but they can be anticipated in many situations. Stream environments pose the biggest problems, in terms of natural disturbance. The most common natural disturbance affecting data loggers is stream discharge, particularly during higher flows. Drag induced by higher water velocities and associated substrate movement and transport of debris can damage or dislodge data loggers. In our experience, the durability of housings provided by manufacturers or made by individual users is generally more than sufficient to protect data loggers under most natural disturbances.

The most common source of data logger loss is dislodging. Accordingly, it is important to properly anchor the data logger so it will not be lost. A variety of anchors can be used, including large rocks, concrete blocks, and metal stakes (see also http://www.onsetcomp.com/Newsletters/Honest_Observer/HO.2.1.html). A practical consideration is the effort involved in transporting the anchor to the field site. We have encountered a variety of weight-reducing alternatives. Lightweight and durable bags or containers that can be easily carried to the site and filled with rocks or sand are popular. Examples include sand bags (usually available from hardware stores) and rubber inner tubes from automobile tires. Chain, cable, or metal stakes are also popular, but they must be firmly anchored into the substrate. Chains or cables are often tethered to rocks or large wood in the stream, or anchored into the stream bed with a variety of devices (need picture of duckbill anchors, etc.).

Data loggers can also be buried under substrate, aquatic macrophytes, or accumulations of debris. Location of data loggers in such situations can be aided by use of a metal detector. Unfortunately, however, the ultimate solution is usually labor-intensive excavation. Users should also keep in mind that buried temperature data loggers are no longer recording surface water temperatures.

Finally, the issue of dealing with the effects of domestic or wild animals on data loggers may be important. Given that most data logger housings are relatively durable, we have encountered few problems with trampling from livestock or wildlife. In our experience, beaver activity has been more important. Data loggers can be buried under beaver dams or unsafe or difficult to retrieve in beaver ponds formed during sampling. Our only suggestion is to use more than one data logger in areas where beaver activity is expected to be important.

Step 3. Data processing

Error Screening

Once data loggers are retrieved from the field and their data is downloaded, it is important to verify the quality of the data, and check for potential errors. It is useful to visually inspect each time series to catch any obvious data logger malfunctions or dewatering of site (Figure 6). In many cases, there are tails of the data that need to be trimmed. For example, if the logger was recording temperatures in the office during or after deployment, these observations should obviously be removed before continuing with any analysis. Usually, these problems are immediately obvious from visual inspection of the data (Figure 7).

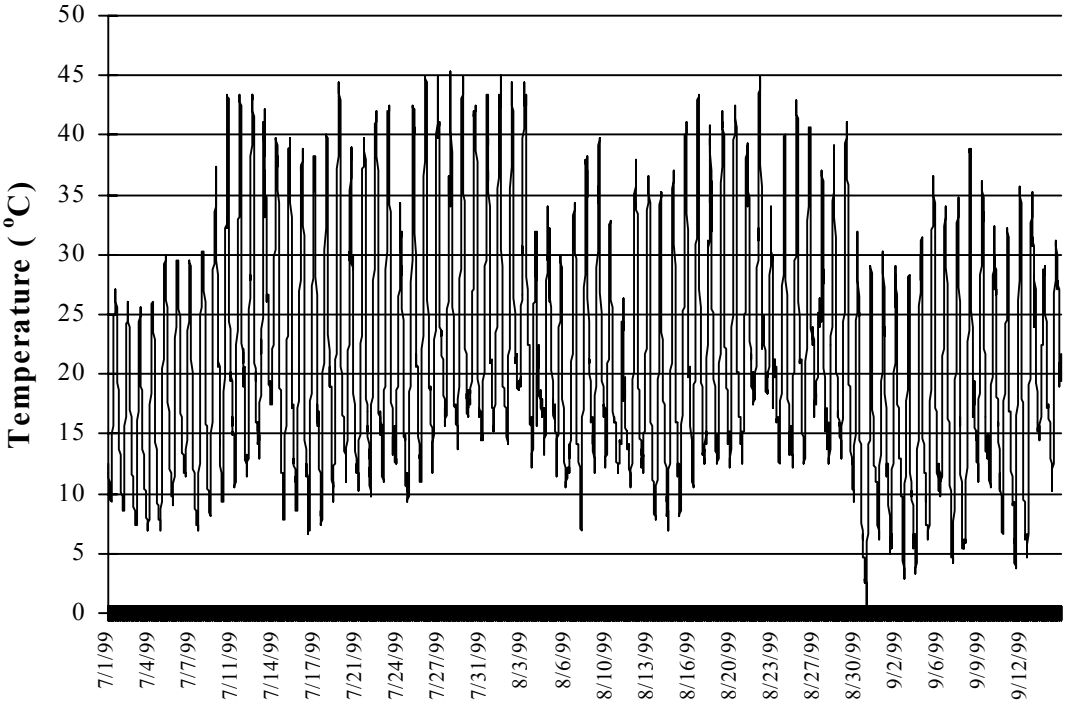


Figure 7. Example of temperature measurements from a site that was dewatered during the sampling period. Note the extreme (>30 ^{o}C) daily fluctuation in temperature, and extraordinarily warm (>40 ^{o}C) temperatures.

It is also useful to automatically flag any suspect observations. For example, Rieman and Chandler (1999) flagged all temperature observations that fell below –1^{o}C or above 30^{o}C. Observations were also flagged if there was a rate of change greater than 3^{o}C per hour or a daily mean change of greater than 3^{o}C between two successive days. The upper and lower 5th percentiles of the overall distribution of observed temperatures were also flagged. Flagged observations were not removed from the database. They were re-verified with personnel involved in data logger programming and field sampling. Flagged observations were only removed if obvious problems were noted. The reason for removal was noted in each case.

Statistical summaries of temperature data

There are a variety of statistical summaries or "metrics" to describe important elements of temperature regimes. Most often, the focus is on maximum temperatures, due to their regulatory importance. Water quality criteria for temperature commonly use one or more metrics to describe maximum temperatures. From a biological perspective, there are a number of different components of thermal regimes (e.g., minimum temperatures, seasonal patterns, timing and duration of different temperatures) that are biologically important, but we will focus our discussion here on temperature metrics that describe maximum temperatures.

Maximum temperatures are generally summarized within an annual time frame. Within a year, there are a variety of time frames over which maximum temperatures may be described. For water quality criteria, temperatures are most often summarized for the warmest day or week of the year. Summaries of mean and maximum temperatures are common, but it may also be useful to describe cumulative exposure to temperatures exceeding a critical threshold. For example, if important biological (e.g., lethal or sublethal) effects are known to occur above a certain temperature, then the time above that threshold may be important. We summarized the data set based upon the hottest day of the summer; hottest week of the summer; and cumulative exposure during the hottest week and throughout the summer. We used 15 July – 15 September to represent the summer. The metrics we summarized were:

1) Daily average on the hottest day (MN_DAY)
2) Overall summer maximum (hottest day – MX_SUM)
3) Maximum weekly average maximum temperature (hottest week – MX_WEEK)
4) Average weekly temperature during the hottest week (MOV_AVG)
5) Overall average summer temperature (MN_SUM)
6) Cumulative days maximum greater than 14^{o}C during hottest week (WEEK_14)
7) Cumulative days maximum greater than 18^{o}C during hottest week (WEEK_18)
8) Cumulative days maximum greater than 22^{o}C during hottest week (WEEK_22)
9) Cumulative days maximum greater than 14^{o}C during entire summer (SUM_14)
11) Cumulative days maximum greater than 18^{o}C during entire summer (SUM_18)
12) Cumulative days maximum greater than 22^{o}C during entire summer (SUM_22)

We categorized each site by average daily range and grouped the sites on 2^{o}C daily range intervals. Within these intervals we correlated the metrics and also computed differences among the metrics. Tables 4 – 10 summarize the correlations and conversion factors for each grouping.

Table 4a**.** Correlation matrix among temperature metrics (N=101) where the average daily range over the summer was 0 – 2°C. Numbers underlined and in italics were not significant correlations.

	MN_DAY	MX_SUM	MX_WEEK	MN_SUM	MOV_AVG	WEEK_14	WEEK_18	WEEK_22	SUM_14	SUM_18	SUM_22
MN_DAY	1.00	0.98	0.98	0.96	0.99	0.72	0.46	***0.21***	0.72	0.46	***0.21***
MX_SUM	0.98	1.00	0.98	0.96	0.98	0.73	0.47	0.24	0.73	0.47	0.24
MX_WEEK	0.98	0.98	1.00	0.97	0.99	0.73	0.46	***0.24***	0.73	0.46	***0.24***
MN_SUM	0.96	0.96	0.97	1.00	0.97	0.71	0.46	***0.22***	0.72	0.46	***0.22***
MOV_AVG	0.99	0.98	0.99	0.97	1.00	0.72	0.46	***0.23***	0.72	0.46	***0.23***
WEEK_14	0.72	0.73	0.73	0.71	0.72	1.00	0.58	0.28	0.99	0.58	0.28
WEEK_18	0.45	0.47	0.46	0.46	0.46	0.58	1.00	0.48	0.59	1.00	0.48
WEEK_22	***0.21***	0.24	***0.23***	***0.22***	***0.23***	0.28	0.48	1.00	0.29	0.49	1.00
SUM_14	0.72	0.73	0.73	0.72	0.72	0.99	0.59	0.29	1.00	0.59	0.29
SUM_18	0.46	0.47	0.46	0.46	0.46	0.58	1.00	0.49	0.59	1.00	0.49
SUM_22	***0.21***	0.24	***0.24***	***0.22***	***0.23***	0.28	0.48	1.00	0.29	0.49	1.00

Table 4b. Conversion factors for the continuous temperature metrics where the average daily range over the summer was 0 – 2°C. The conversion is row minus column (i.e. if maximum summer (mx_sum) was 12°C then the overall mean summer temperature (mn_sum) would be: 12.00-2.55=9.45 with bounds of 9.22 – 9.67.

		MN_SUM			MOV_AVG			MN_DAY			MX_WEEK	
	MEAN	LOWER	UPPER	MEAN	LOWER	UPPPER	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER
MX_SUM	2.55	2.33	2.78	1.49	1.34	1.64	1.17	0.97	1.38	0.55	0.44	0.67
MX_WEEK	2.00	1.84	2.15	0.93	0.87	0.99	0.62	0.49	0.75			
MN_DAY	1.38	1.22	1.54	0.31	0.21	0.41						
MOV_AVG	1.07	0.92	1.21									

Table 5a**.** Correlation matrix among temperature metrics (N=520) where the average daily range over the summer was 2 – 4°C. Numbers underlined and in italics were not significant correlations.

	MN_DAY	MX_SUM	MX_WEEK	MN_SUM	MOV_AVG	WEEK_14	WEEK_18	WEEK_22	SUM_14	SUM_18	SUM_22
MN_DAY	1.00	0.95	0.96	0.95	0.99	0.88	0.50	0.19	0.90	0.51	0.20
MX_SUM	0.95	1.00	0.98	0.93	0.95	0.91	0.52	0.22	0.93	0.53	0.24
MX_WEEK	0.96	0.98	1.00	0.95	0.97	0.91	0.51	0.19	0.93	0.51	0.20
MN_SUM	0.95	0.93	0.95	1.00	0.97	0.86	0.50	0.18	0.90	0.51	0.19
MOV_AVG	0.99	0.95	0.98	0.97	1.00	0.88	0.50	0.18	0.91	0.51	0.19
WEEK_14	0.87	0.91	0.91	0.86	0.88	1.00	0.43	0.15	0.96	0.44	0.17
WEEK_18	0.50	0.52	0.51	0.50	0.50	0.43	1.00	0.41	0.51	0.98	0.43
WEEK_22	0.19	0.22	0.19	0.18	0.18	0.15	0.41	1.00	0.18	0.41	0.95
SUM_14	0.90	0.93	0.93	0.90	0.91	0.96	0.51	0.18	1.00	0.52	0.19
SUM_18	0.51	0.53	0.51	0.51	0.51	0.44	0.98	0.41	0.52	1.00	0.43
SUM_22	0.20	0.24	0.20	0.19	0.19	0.17	0.43	0.95	0.19	0.43	1.00

Table 5b. Conversion factors for the continuous temperature metrics where the average daily range over the summer was 2 – 4°C. The conversion is row minus column (i.e. if maximum summer (mx_sum) was 12°C then the overall mean summer temperature (mn_sum) would be: 12.00-4.08=7.92 with bounds of 7.79 – 8.04.

		MN_SUM			MOV_AVG			MN_DAY			MX_WEEK	
	MEAN	LOWER	UPPER	MEAN	LOWER	UPPPER	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER
MX_SUM	4.08	3.96	4.21	2.76	2.67	2.86	2.28	2.18	2.37	0.80	0.71	0.88
MX_WEEK	3.29	3.22	3.36	1.96	1.92	2.01	1.48	1.43	1.53			
MN_DAY	1.81	1.74	1.88	0.49	0.45	0.52						
MOV_AVG	1.32	1.26	1.38									

Table 6a**.** Correlation matrix among temperature metrics (N=336) where the average daily range over the summer was 4 – 6^{o}C. Numbers underlined and in italics were not significant correlations.

	MN_DAY	MX_SUM	MX_WEEK	MN_SUM	MOV_AVG	WEEK_14	WEEK_18	WEEK_22	SUM_14	SUM_18	SUM_22
MN_DAY	1.00	0.94	0.96	0.95	0.98	0.82	0.79	0.39	0.90	0.79	0.39
MX_SUM	0.94	1.00	0.98	0.93	0.94	0.83	0.81	0.40	0.92	0.83	0.41
MX_WEEK	0.96	0.98	1.00	0.94	0.97	0.86	0.82	0.39	0.94	0.83	0.39
MN_SUM	0.95	0.93	0.95	1.00	0.97	0.83	0.77	0.37	0.93	0.78	0.38
MOV_AVG	0.98	0.94	0.97	0.97	1.00	0.84	0.79	0.38	0.92	0.79	0.38
WEEK_14	0.82	0.83	0.86	0.83	0.84	1.00	0.51	0.17	0.85	0.52	0.18
WEEK_18	0.79	0.81	0.82	0.77	0.79	0.51	1.00	0.43	0.74	0.98	0.43
WEEK_22	0.39	0.40	0.39	0.37	0.38	0.17	0.43	1.00	0.28	0.45	0.97
SUM_14	0.90	0.92	0.94	0.93	0.92	0.85	0.74	0.28	1.00	0.76	0.28
SUM_18	0.79	0.83	0.83	0.78	0.79	0.52	0.98	0.45	0.76	1.00	0.45
SUM_22	0.39	0.41	0.39	0.38	0.38	0.18	0.43	0.97	0.28	0.45	1.00

Table 6b. Conversion factors for the continuous temperature metrics where the average daily range over the summer was 4 – 6^{o}C. The conversion is row minus column (i.e. if maximum summer (mx_sum) was 14^{o}C then the overall mean summer temperature (mn_sum) would be: 14.00-5.60=8.40 with bounds of 8.22 – 8.57.

		MN_SUM			MOV_AVG			MN_DAY			MX_WEEK	
	MEAN	LOWER	UPPER	MEAN	LOWER	UPPPER	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER
MX_SUM	5.60	5.43	5.78	4.13	3.99	4.28	3.55	3.42	3.68	0.95	0.85	1.05
MX_WEEK	4.64	4.53	4.77	3.18	3.10	3.27	2.60	2.51	2.69			
MN_DAY	2.05	1.94	2.15	0.58	0.53	0.63						
MOV_AVG	1.47	1.38	1.55									

Table 7a**.** Correlation matrix among temperature metrics (N=130) where the average daily range over the summer was 6 – 8^{o}C. Numbers underlined and in italics were not significant correlations.

	MN_DAY	MX_SUM	MX_WEEK	MN_SUM	MOV_AVG	WEEK_14	WEEK_18	WEEK_22	SUM_14	SUM_18	SUM_22
MN_DAY	1.00	0.93	0.94	0.93	0.98	0.43	0.86	0.75	0.74	0.91	0.76
MX_SUM	0.93	1.00	0.98	0.90	0.92	0.44	0.89	0.82	0.71	0.92	0.83
MX_WEEK	0.94	0.98	1.00	0.93	0.95	0.45	0.92	0.82	0.75	0.95	0.83
MN_SUM	0.93	0.90	0.93	1.00	0.95	0.45	0.83	0.75	0.74	0.92	0.77
MOV_AVG	0.98	0.93	0.95	0.95	1.00	0.44	0.87	0.77	0.77	0.93	0.78
WEEK_14	0.43	0.44	0.45	0.45	0.44	1.00	0.39	***0.20***	0.45	0.39	***0.20***
WEEK_18	0.86	0.89	0.92	0.83	0.87	0.39	1.00	0.65	0.69	0.92	0.66
WEEK_22	0.75	0.82	0.82	0.75	0.77	***0.20***	0.65	1.00	0.57	0.76	0.98
SUM_14	0.75	0.71	0.75	0.74	0.77	0.45	0.69	0.57	1.00	0.82	0.58
SUM_18	0.91	0.92	0.95	0.92	0.93	0.39	0.92	0.76	0.82	1.00	0.77
SUM_22	0.76	0.83	0.83	0.77	0.78	***0.20***	0.66	0.98	0.58	0.77	1.00

Table 7b. Conversion factors for the continuous temperature metrics where the average daily range over the summer was 6 – 8^{o}C. The conversion is row minus column (i.e. if maximum summer (mx_sum) was 14^{o}C then the overall mean summer temperature (mn_sum) would be: 14.00-7.27=6.73 with bounds of 6.48 – 6.98.

		MN_SUM			MOV_AVG			MN_DAY			MX_WEEK	
	MEAN	LOWER	UPPER	MEAN	LOWER	UPPPER	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER
MX_SUM	7.27	7.02	7.52	5.57	5.33	5.80	4.93	4.71	5.14	1.01	0.88	1.14
MX_WEEK	6.26	6.07	6.45	4.55	4.41	4.71	3.92	3.74	4.09			
MN_DAY	2.34	2.15	2.53	0.64	0.53	0.74						
MOV_AVG	1.70	1.54	1.86									

Table 8a**.** Correlation matrix among temperature metrics (N=61) where the average daily range over the summer was 8 – 10°C. Numbers underlined and in italics were not significant correlations.

	MN_DAY	MX_SUM	MX_WEEK	MN_SUM	MOV_AVG	WEEK_14	WEEK_18	WEEK_22	SUM_14	SUM_18	SUM_22
MN_DAY	1.00	0.82	0.84	0.92	0.97	--	0.70	0.80	0.39	0.82	0.84
MX_SUM	0.82	1.00	0.98	0.79	0.81	--	0.68	0.90	***0.12***	0.64	0.90
MX_WEEK	0.84	0.98	1.00	0.83	0.86	--	0.70	0.93	***0.17***	0.68	0.92
MN_SUM	0.92	0.79	0.83	1.00	0.94	--	0.70	0.78	***0.30***	0.80	0.85
MOV_AVG	0.97	0.81	0.86	0.94	1.00	--	0.71	0.82	0.37	0.84	0.87
WEEK_14	--	--	--	--	--	--	--	--	--	--	--
WEEK_18	0.70	0.68	0.70	0.70	0.71	--	1.00	0.54	0.39	0.69	0.53
WEEK_22	0.80	0.90	0.93	0.78	0.82	--	0.54	1.00	***0.14***	0.64	0.95
SUM_14	0.39	***0.12***	***0.17***	***0.30***	0.37	--	0.39	***0.14***	1.00	0.66	***0.18***
SUM_18	0.82	0.64	0.68	0.80	0.84	--	0.69	0.64	0.66	1.00	0.72
SUM_22	0.84	0.90	0.92	0.85	0.87	--	0.53	0.95	***0.18***	0.72	1.00

Table 8b. Conversion factors for the continuous temperature metrics where the average daily range over the summer was 8 – 10°C. The conversion is row minus column (i.e. if maximum summer (mx_sum) was 16°C then the overall mean summer temperature (mn_sum) would be: 16.00-8.79=7.21 with bounds of 6.77 – 7.66.

		MN_SUM			MOV_AVG			MN_DAY			MX_WEEK	
	MEAN	LOWER	UPPER	MEAN	LOWER	UPPPER	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER
MX_SUM	8.79	8.34	9.23	7.07	6.63	7.51	6.42	6.00	6.84	1.06	0.91	1.22
MX_WEEK	7.72	7.36	8.08	6.01	5.68	6.34	5.36	5.02	5.70			
MN_DAY	2.36	2.11	2.61	0.65	0.49	0.80						
MOV_AVG	1.72	1.50	1.93									

Table 9a**.** Correlation matrix among temperature metrics (N=26) where the average daily range over the summer was 10 – 12°C. Numbers underlined and in italics were not significant correlations.

	MN_DAY	MX_SUM	MX_WEEK	MN_SUM	MOV_AVG	WEEK_14	WEEK_18	WEEK_22	SUM_14	SUM_18	SUM_22
MN_DAY	1.00	0.83	0.92	0.89	0.95	--	***0.33***	0.61	***-0.05***	***0.19***	0.80
MX_SUM	0.83	1.00	0.93	0.83	0.92	--	***0.33***	0.61	***-0.10***	***0.08***	0.68
MX_WEEK	0.92	0.93	1.00	0.86	0.97	--	***0.33***	0.68	***-0.03***	***0.21***	0.78
MN_SUM	0.89	0.83	0.86	1.00	0.90	--	***0.33***	0.59	***-0.32***	***-0.02***	0.65
MOV_AVG	0.95	0.92	0.97	0.90	1.00	--	***0.33***	0.62	***-0.03***	***0.20***	0.80
WEEK_14	--	--	--	--	--	--	--	--	--	--	--
WEEK_18	***0.33***	***0.33***	***0.33***	***0.33***	***0.33***	--	1.00	***0.45***	***0.26***	***0.34***	***0.33***
WEEK_22	0.61	0.61	0.68	0.59	0.62	--	***0.45***	1.00	***0.01***	***0.34***	0.70
SUM_14	***-0.05***	***-0.10***	***-0.03***	***-0.32***	***-0.03***	--	***0.26***	***0.01***	1.00	0.85	***0.36***
SUM_18	***0.19***	***0.08***	***0.21***	***-0.03***	***0.19***	--	***0.34***	***0.34***	0.85	1.00	0.64
SUM_22	0.80	0.68	0.78	0.65	0.80	--	***0.33***	0.69	***0.36***	0.64	1.00

Table 9b. Conversion factors for the continuous temperature metrics where the average daily range over the summer was 10 – 12°C. The conversion is row minus column (i.e. if maximum summer (mx_sum) was 16°C then the overall mean summer temperature (mn_sum) would be: 16.00-10.37=5.67 with bounds of 5.13 – 6.13.

		MN_SUM			MOV_AVG			MN_DAY			MX_WEEK	
	MEAN	LOWER	UPPER	MEAN	LOWER	UPPPER	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER
MX_SUM	10.37	9.87	10.87	8.17	7.82	8.52	7.60	7.13	8.06	1.31	0.97	1.64
MX_WEEK	9.06	8.55	9.58	6.86	6.60	7.13	6.29	5.94	6.64			
MN_DAY	2.77	2.28	3.26	0.57	0.30	0.84						
MOV_AVG	2.20	1.79	2.61									

Table 10a**.** Correlation matrix among temperature metrics (N=25) where the average daily range over the summer was over 12°C. Numbers underlined and in italics were not significant correlations.

	MN_DAY	MX_SUM	MX_WEEK	MN_SUM	MOV_AVG	WEEK_14	WEEK_18	WEEK_22	SUM_14	SUM_18	SUM_22
MN_DAY	1.00	0.55	0.62	0.81	0.77	--	--	***0.43***	***-0.10***	***0.14***	0.53
MX_SUM	0.55	1.00	0.95	0.74	0.65	--	--	***0.47***	***-0.05***	***0.27***	0.59
MX_WEEK	0.62	0.95	1.00	0.81	0.72	--	--	***0.47***	***-0.08***	***0.28***	0.61
MN_SUM	0.81	0.74	0.81	1.00	0.93	--	--	***0.47***	***-0.11***	***0.25***	0.68
MOV_AVG	0.77	0.65	0.72	0.93	1.00	--	--	***0.47***	***0.03***	***0.36***	0.72
WEEK_14	--	--	--	--	--	--	--	--	--	--	--
WEEK_18	--	--	--	--	--	--	--	--	--	--	--
WEEK_22	***0.43***	***0.47***	***0.47***	***0.47***	***0.47***	--	--	1.00	***-0.30***	***-0.06***	***0.47***
SUM_14	***-0.10***	***-0.06***	***-0.09***	***-0.11***	***0.03***	--	--	***-0.30***	1.00	0.88	***0.40***
SUM_18	***0.14***	***0.27***	***0.28***	***0.25***	***0.36***	--	--	***-0.06***	0.87	1.00	0.72
SUM_22	0.53	0.58	0.61	0.68	0.72	--	--	***0.47***	***0.40***	0.72	1.00

Table 10b. Conversion factors for the continuous temperature metrics where the average daily range over the summer was over 12°C. The conversion is row minus column (i.e. if maximum summer (mx_sum) was 16°C then the overall mean summer temperature (mn_sum) would be: 16.00-11.82=4.18 with bounds of 3.55 – 4.81.

		MN_SUM			MOV_AVG			MN_DAY			MX_WEEK	
	MEAN	LOWER	UPPER	MEAN	LOWER	UPPPER	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER
MX_SUM	11.82	11.19	12.45	10.20	9.46	10.94	9.70	8.78	10.61	1.17	0.91	1.43
MX_WEEK	10.65	10.21	11.09	9.03	8.45	9.60	8.52	7.76	9.29			
MN_DAY	2.12	1.55	2.69	0.51	-0.04	1.05						
MOV_AVG	1.62	1.31	1.92									

Step 4. Data storage and archiving

Data storage and archiving is one of the most important steps in a temperature monitoring effort. A plan for data storage is especially important for large studies. The volume of information data loggers can collect warrants storage within a relational database system (i.e., Oracle, Sybase, Access, etc.). Spreadsheets have limitations with the number of observations each sheet can hold as well as ease of summarization of data. Relational databases, designed correctly, will have a very minimal (if any) amount of redundant information. Therefore, time needed to summarize and edit the data is greatly reduced. Relational database applications also have the advantage of using far less computer hard drive space.

There are three basic steps to collecting and storing temperature data. Since temperature data is generally collected as an objective of a much larger study, efficient storage and archiving of this data makes it easy to relate to the other objectives of the study. The three steps are:

1. Pre-deployment information gathering
2. Field deployment information
3. Post-deployment information

Pre-deployment information includes data and notes on field site characteristics and calibration of the data loggers. Minimal site data include: stream name, drainage and topographical map name. Minimal data logger information includes: logger type (model), logger serial number and pre-calibration factor (if calibration was performed).

Field deployment information includes site definition and time of deployment. Efficient data collection at this point will save numerous hours of work at the post deployment stage. Minimal data needed at this stage includes: stream name and site number (if appropriate), UTM coordinates or other location information to geo-reference the site, description of site, habitat type data logger was deployed in, date and time data logger was placed in stream, time interval of samples, data logger serial number (to relate back to pre-calibration information), wetted width at data logger, depth of logger and a picture of the site. An example of a field deployment datasheet is shown in Figure 8.

Post-deployment information is gathered in the field as well as in the office. Minimal field data includes: date and time of removal, wetted width at time of removal and any other relevant site information (e.g., “Did the site dry up during sampling?,” “Was there any evidence of tampering with the data logger?”) Once the data logger is retrieved and the data downloaded the logger should be calibrated again to note any differences in the pre and post calibration factors. We have found loggers that can drift (i.e., the pre and post calibration factors are not the same).

Temperature data has numerous levels or tables including site data, logger data, deployment data, removal data and temperature data. Setting this information up in a relational database system allows for efficient processing of the data (Table 11).

Table 11. Example of a relational database application for storage of temperature data collected using data loggers.

Table name	Field name	Description
Site	Site ID	Auto number assigning consecutive numbers to sites.
	Stream name	Name of stream sampled
	Site	Number of descriptor of site within stream
	Basin	River basin
	Quad	24K Quad name
	UTM X	UTM easting coordinate
	UTM Y	UTM northing coordinate
	UTM zone	UTM zone number
	Elevation	Elevation in meters of site
Logger	Logger ID	Unique ID or serial number of logger
	Type	Manufacturer and/or model of logger
	Year	Year of sample
	Pre calib	Pre calibration factor
	Post calib	Post calibration factor
Deployed	Site ID	Site ID of stream and site (relates back to Site table)
	Logger ID	Unique ID of logger deployed in the stream (relates back to Logger table)
	Date	Date logger placed in water
	Time	Time logger placed in water
	Interval	Time interval of samples
	Width	Wetted width of site at deployment
	Depth	Depth of logger
	Hab type	Habitat type where logger was placed
Removal	Site ID	Site ID of stream and site (relates back to Site table)
	Date	Date logger removed from water
	Time	Time logger removed from water
	Width	Wetted width at time of removal
	Comments	Any site differences from time of deployment to time of removal
Temperature	Site ID	Site ID of stream and site (relates back to Site table)
	Date	Date of sample
	Time	Time of sample
	Temperature	Temperature (in C or F) of sample

These are the minimal data required to store temperature data. Additional tables and/or fields to existing tables would be added depending upon the objectives of the study. The structure of any relational database application should allow for the easy expansion of the database.

Figure 8. An example of the data logger deployment field form.

Stream Information:

Stream Name:_____ Site:_____ Basin:_____

Quad Name:_____

UTM easting:_____ UTM northing:_____ UTM zone:_____

Site Description:_____

Data Logger Information:

Logger Type:_____ Serial Number:_____ Sampling interval:_____

Date placed in stream:_____ Time placed in stream:_____

Site Information:

Habitat type of placement:_____

Wetted width at logger (m):_____ Depth of logger (m): _____

Hand-held temperature at placement (°C):_____

Comments:_____
_____

Tethering method for logger:_____

Map of specific site of logger placement:

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