United States
Department
of Agriculture

Forest Service

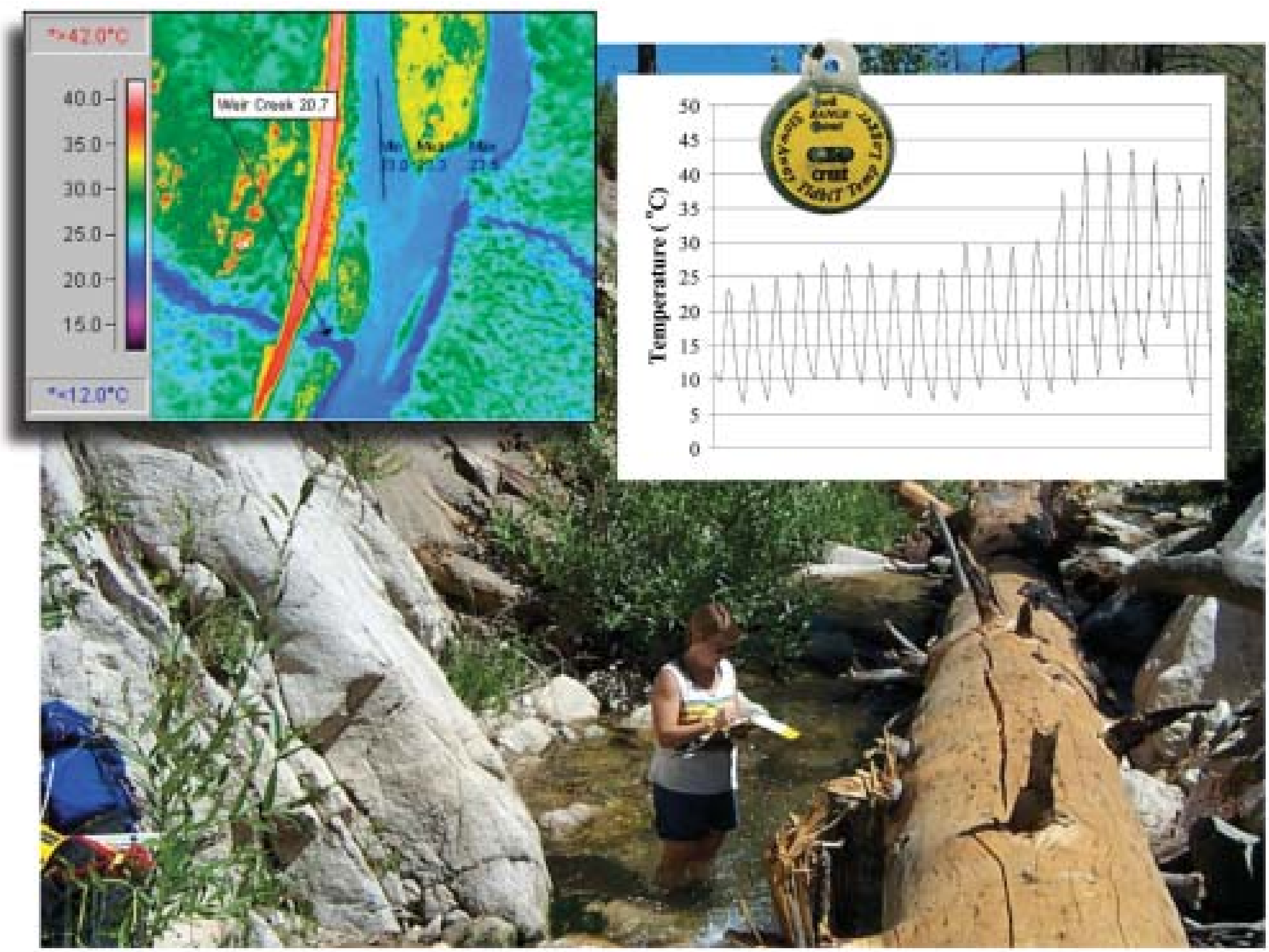
**Rocky Mountain
Research Station**

General Technical
Report RMRS-GTR-150WWW

March 2005

Measuring Stream Temperature with Digital Data Loggers: A User's Guide

Jason Dunham
Gwynne Chandler
Bruce Rieman
Don Martin



Abstract

Dunham, Jason; Chandler, Gwynne; Rieman, Bruce; Martin, Don. 2005. **Measuring stream temperature with digital data loggers: a user's guide**. Gen. Tech. Rep. RMRS-GTR-150WWW. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 15 p.

Digital data loggers (thermographs) are among the most widespread instruments in use for monitoring physical conditions in aquatic ecosystems. The intent of this protocol is to provide guidelines for selecting and programming data loggers, sampling water temperatures in the field, data screening and analysis, and data archiving.

Key words: temperature measurement, temperature sampling, thermographs, temperature dataloggers, water temperature, aquatic monitoring, monitoring protocol, data quality control

The Authors

Jason Dunham is a Research Fisheries Scientist with the Rocky Mountain Research Station at the Forestry Sciences Laboratory in Boise, ID. He completed a B.S. degree in zoology at Oregon State University, an M.S. degree in zoology at Arizona State University, and a Ph.D. degree at the University of Nevada – Reno.

Gwynne Chandler is a Fisheries Biologist with the Rocky Mountain Research Station at the Forestry Sciences Laboratory in Boise, ID. She completed a B.S. degree in water resources at the University of Wisconsin—Stevens Point, and an M.S. degree in fisheries management from the University of Idaho.

Bruce Rieman is a Research Fisheries Scientist and Project Leader with the Rocky Mountain Research Station at the Forestry Sciences Laboratory in Boise, ID. He completed a B.S. degree in zoology at the University of Idaho, an M.S. degree in fisheries management at the University of Idaho, and a Ph.D. degree in forestry, wildlife and range sciences at the University of Idaho.

Don Martin is an Aquatic Ecologist with the U.S. Environmental Protection Agency, Region 10 and is based in Coeur d'Alene, ID. He completed a B.A. degree in zoology at Humboldt State College and an M.A. degree in biology at Humboldt State University.

Acknowledgments

Data used in this protocol were assembled with the help of numerous individuals, including K. Benkert, J. Delavergne, H. Gearns, S. Kanouse, D. Lantz, D. Low, J. Polos, J. Schultz, J. Shellberg, S. Spalding, M. Weber, W. Bowers, N. Bruener, P. Coffin, B. Dickerson, C. Drake, C. Evans, J. Fredrick, B. Hammon, M. Holford, O. Kulkoyluoglu, B. Lay, M. Meeuwig, M. Peacock, K. Ramsey, R. Schroeter, M. Sevon, A. Talabere, D. Tracy, L. Weber, G. Vinyard, D. Anderson, S. Bachman, T. Burton, C. Clancy, B. Connors, L. Dominquez, D. Garcia, B. Gardner, S. Gerdes, T. Herron, D. Myers, R. Nelson, M. Northrop, S. Rosquist, B. Sanchez, T. Smith, N. Swanson, D. Horan and R. Thurow. Thanks to Dan Isaak and Amanda Rosenberger for comments on an early draft of this protocol, and Matt Dare, Dona Horan, and Rudy King for comments on a later draft.

Measuring Stream Temperature with Digital Data Loggers: A User's Guide

Jason Dunham
Gwynne Chandler
Bruce Rieman
Don Martin

Introduction

Temperature is a variable of widespread interest in aquatic ecosystems because it is an important component of water quality (for example, Poole and others 2001a), and temperature is affected by many different natural and human-related influences (for example, Poole and Berman 2001; Webb and Zhang 1997). 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 (less than $200 US), simple to deploy, and capable of collecting large amounts of data (more than 32 kb).

Due in part to the dramatic increase in the use of temperature data loggers and other new technologies (for example, Torgerson and others 2001), the quantity of data on water temperature has increased dramatically. The rapid accumulation of new data has perhaps surpassed our processing ability, and it is not always clear that information from temperature data loggers is reliable, accurate, or useful. This problem, which is not new or unique in water quality monitoring, has been termed the "data-rich, information-poor" syndrome (Ward and others 1986).

This current general technical report presents a protocol that is an attempt to provide guidance to improve the quality and utility of water temperature data collected with digital temperature data loggers.

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 synthesis and analysis of the issues that must be addressed to ensure that data collected from temperature data loggers serve the objectives for which they were collected (table 1). In addition to carefully considering

Table 1—Common objectives for sampling of water temperatures (see also NRCS 1997).

Objective	Examples
Baseline monitoring	Monitoring of pre- and posttreatment 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 (for example, fish) are supported. Monitoring of temperatures in relation to point source influences (for example, warm or cold water discharges). Monitoring of temperature patterns to validate or parameterize water temperature models (for example, Bartholow 2000).
Research	Monitoring of water temperatures to model responses of aquatic biota (for example, Eaton and others 1995). Monitoring of water temperatures to determine appropriate spatio-temporal sampling designs for a given sampling frame (for example, water body or watershed of interest).

the objectives for a monitoring effort, there are several other potentially important issues affecting the quality and utility of temperature data (table 2). Several protocols (for example, Dunham 1999; Lewis and others 2000; 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 sampling issues (table 2) and several related considerations, including selection of measurement intervals, data screening, correlations among various temperature metrics, and development of a relational database. Users must be cognizant of these issues during all phases (for example, planning, implementation, analysis, interpretation) of a monitoring effort. We do not wish to give readers 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 can substantially improve the quality and utility of temperature data.

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 (for example, Poole and others 2001b). Another topic that is worthy of consideration but is 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.

Several noteworthy efforts related to this need include StreamNet (http://www.streamnet.org), the U.S. Environmental Protection Agency (for example, 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 planning, (2) field sampling, (3) data processing, and (4) data storage and archiving.

Table 2—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 preuse 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 (for example, 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

Step 1. Study Planning

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

A variety of objectives exist for measuring or monitoring water temperature (table 1). 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. Data loggers from different investigators are often 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. Readers are referred to the National Handbook of Water Quality Monitoring (NRCS 1996) for additional details on defining objectives.

Choosing a data logger

There are many manufacturers and models of data loggers from which to choose (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: When properly functioning, most data loggers are accurate and capable of relatively precise (±1 °C or less) temperature readings. Most manufacturers provide relatively detailed information on the accuracy and precision of their instruments (table 3).

Memory capacity: Memory capacity is more important if temperatures are to be recorded for long periods (for example, more than 1 year) or short sampling intervals (for example, less than 30 minutes). Most data loggers manufactured today have a minimum of 8kb of memory, which allows deployment of 165 days with data recorded at 30-minute intervals (7,920 observations; table 3).

Durability: While some data loggers are quite durable, a wide variety of field conditions might lead to damage or loss. 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.

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. A short time lag (approximately15 minutes) is required for the air within the housing to equilibrate with the surrounding water temperature. Thus, temperatures recorded from data loggers within housings may not track water temperatures precisely on very short (less than 15 minutes) time scales.

Table 3—Types of data loggers among those 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
	OpticStow Away	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	Geminidata loggers.com
	TinyTag Plus	No	10836	–40—85	0.2	0.4	2 year replaceable	Geminidata loggers.com
Vemco	Minilog	Yes	10836	–5—40	0.1	0.015	Replaceable	Vemco.com

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. To consider this issue, we placed two paired data loggers in two 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 in a stream with moderate diel fluctuation (6 °C) were within the reported accuracy of the instruments (fig. 1 and 2). However, measurements from the paired data loggers in a stream with more diel fluctuation (10 °C) differed by more than 1.5 °C. Temperatures recorded in the sealed housing were cooler during the day and warmer at night (fig. 1 and 2). It seems likely that air temperature within the sealed housings lagged behind 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, but further study is needed to identify the range of conditions that could be important.

Data loggers that are submersible should be placed in flow-through, durable housings (for example, heavy duty, UV-resistant PVC pipe) to protect them 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. It is important to maintain an exchange of water through the housing to minimize bias in temperature readings.

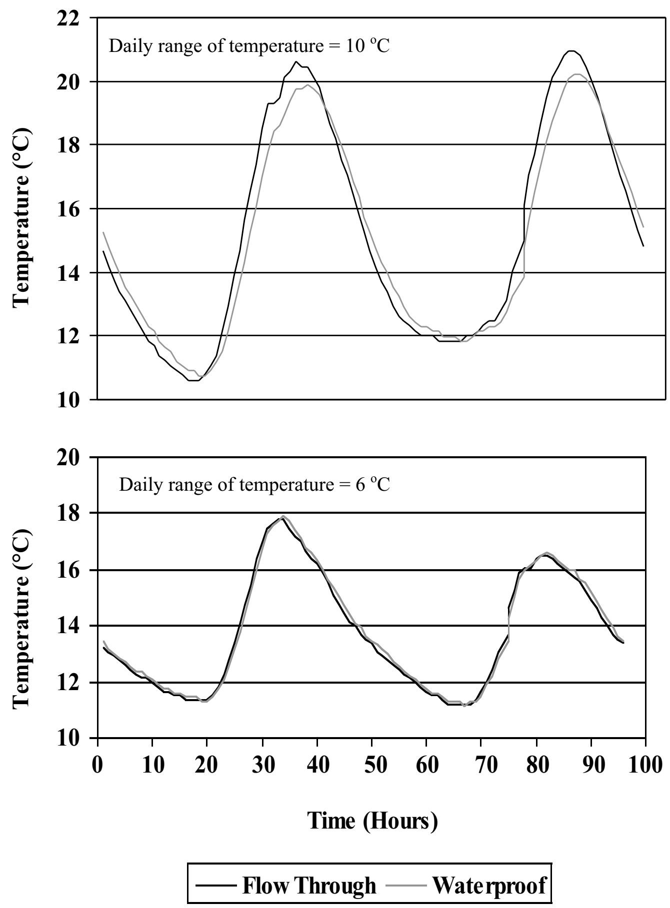


Figure 1—Comparison of 2 days of recorded temperatures for data loggers placed in two streams. Each stream had a data logger placed in a flow through housing and a data logger placed in a sealed (waterproof) housing.

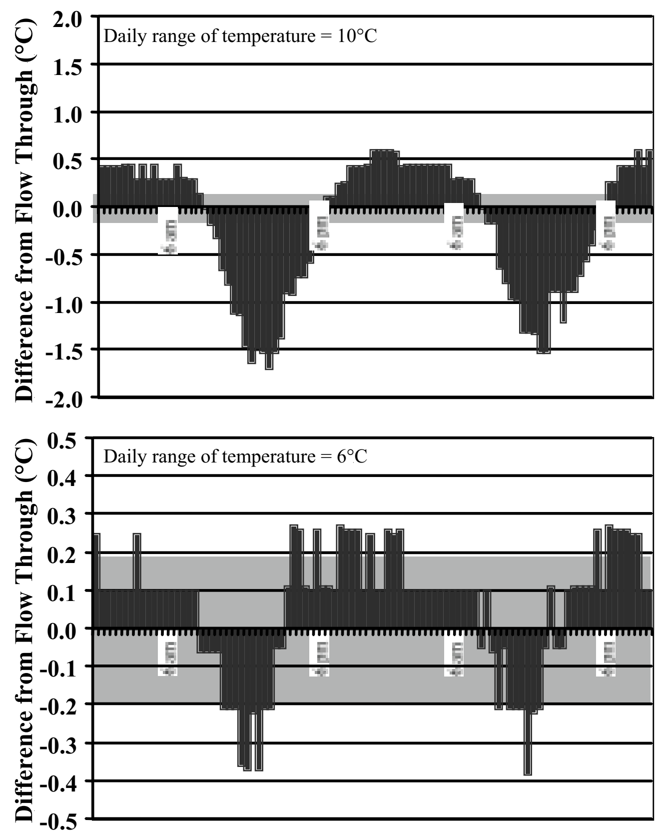


Figure 2—Comparison of the differences in temperature recorded from paired data loggers in two streams with different daily ranges. The difference is the recorded temperature of the sealed (waterproof) minus the flow through housing over a period of 48 hours (X axis) during July. Grey shading indicates the range of accuracy for the instruments (± 0.2 °C).

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 that were placed in waterproof housings of three different colors: white, metallic, and transparent. The data loggers were placed in a sunlit portion of a stream at approximately 0.5 m depth. Maximum water temperatures measured by loggers in clear housings were up to 5 °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 warmer water temperature measurements. Temperature differences between white and metallic housings were not evident. Black data logger housings may also bias temperature measurements because they can absorb and reradiate 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. Delayed deployment can also ensure that temperatures are taken at the same times for all data loggers, if necessary. 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 for shorter intervals during the summer when daily variability in temperature is higher.

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 Onset Computer Corporation 1995). 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 (for example, a large cooler with ice water). Be sure to use fresh water (dissolved minerals 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 °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 °C (fig. 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 °C.
6. If temperature measurements are to be synchronized among different data loggers or measured on a short time interval (for example, less than 30 minutes), calibration to determine the accuracy of time recorded by data loggers may also be necessary.

Choosing a sampling interval

Most data loggers can be programmed to measure and record temperatures at a variety of time intervals. Obviously, longer intervals will result in lower resolution and greater potential for bias. For some measures of temperature, 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 (for example, greater than 2 hour sampling intervals) in systems with variable daily temperatures may not adequately describe the true thermal regime at a site. This may be particularly true of instantaneous measures of temperature, such as the daily maximum temperature. With longer sampling intervals, it is more likely that estimates of maximum temperatures will be negatively biased (that is, measured maximum temperatures are cooler than actual maximum temperatures). For a given daily range of

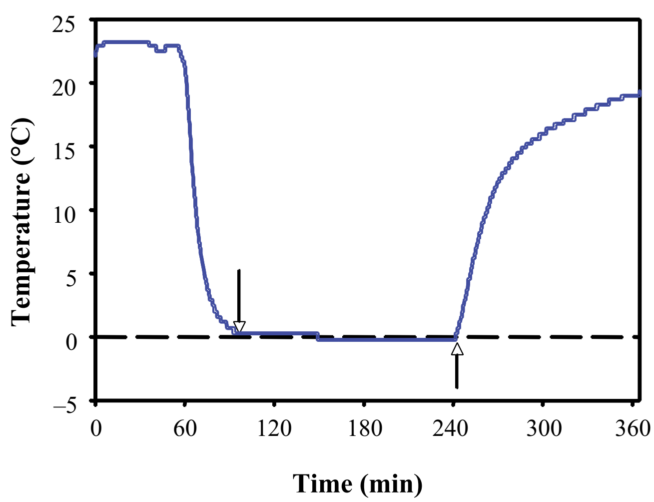


Figure 3—Illustration of data logger calibration using the "ice bucket" method. The first arrow indicates the point at which the logger reached 0 °C, and the second arrow is the point at which the logger was removed from the bath. The steep decline of the temperature represents when the logger was placed in the bath. The dashed horizontal line is the temperature of the water bath as recorded with NIST handheld thermometers. This calibration "check" was carried out over a period of 6 hours.

variation in temperatures, it should be possible to prescribe sampling intervals that ensure temperature regimes are adequately described.

To quantitatively address the bias associated with temperature sampling frequency or sampling interval, we used temperature data from data loggers deployed at 1,252 sites sampled in the Pacific Northwest and Rocky Mountain regions (Dunham 1999; Dunham and Chandler 2001; Rieman and Chandler 1999). Sampling intervals at these sites ranged from as few as five 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 with the daily range of temperature (fig. 4). The maximum range in daily temperature for the entire data set was 17.8 °C.

We focused our analyses on the influence of sampling interval on the observed maximum daily temperature. Both maximum and minimum daily temperature should be sensitive to sampling interval, because either may only be observed for a short time within a day. 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, there were 211 samples, and the shortest sampling interval for which there were sufficient data to analyze was 30 minutes.

To compare maximum daily temperatures observed in the baseline data samples to those observed with sampling at greater than 30 minute-intervals, we subsampled observations from the baseline data sets to simulate sampling at 1-, 2-, 3-, and 4-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. We selected a 1 °C unit of measure to detect measurement bias likely attributable to sampling interval and not instrument error. The obvious consequence of missing the maximum temperature during sampling is underestimating the warmest temperatures that occurred at a given site. We predicted the probabilities of missing the maximum temperature with 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 (fig. 5). A daily range of 8 °C would have an error rate of 4.5 percent and 8.5 percent for 3- and 4-hour sampling intervals, respectively.

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 (for example, greater than 10 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. Smaller scale (less than 10 m) variability in the temperature of lakes and reservoirs can be caused by groundwater (for example, 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 (fig. 6).

If the objective is to characterize the well-mixed or "thalweg" temperature in a stream, then small-scale variability in

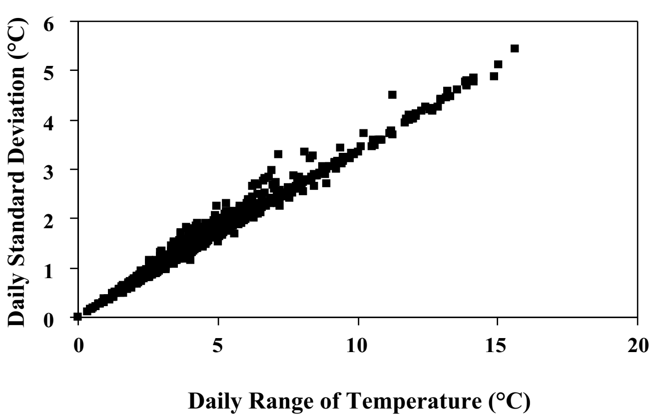


Figure 4—Linear correlation of mean daily range of temperature with mean daily standard deviation (square root of variance) for each site in the data set (*r*=0.98).

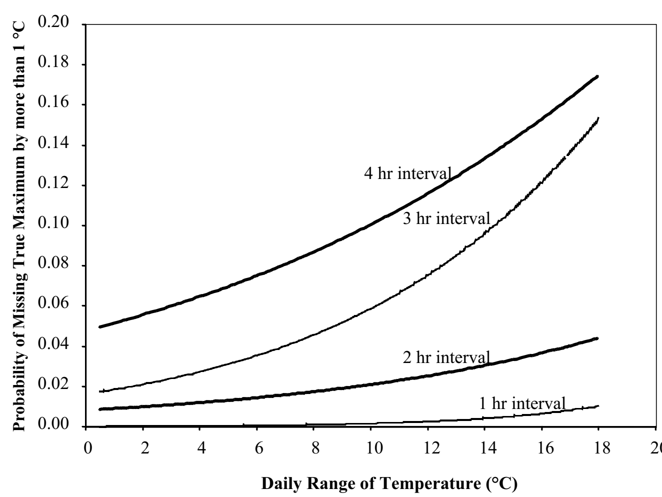


Figure 5—Probability of underestimating the maximum daily temperature by at least 1 °C in relation to daily range of temperature and sampling interval.

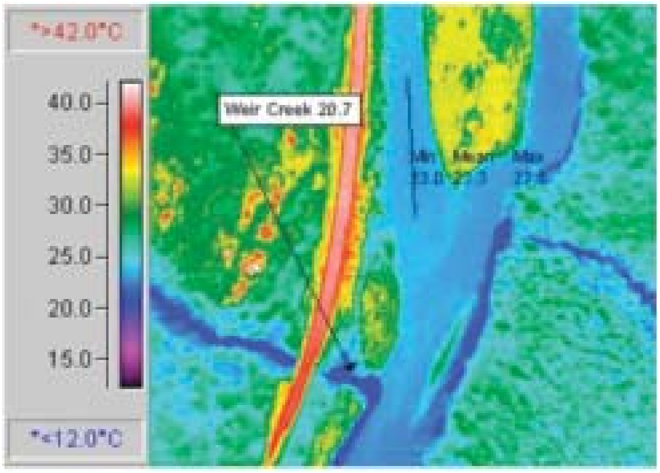


Figure 6—An illustration of spatial variation in temperature in the Lochsa River, Idaho. Note the influence of tributary inflow. The image was generated using infrared aerial videography (Torgerson and others 2001; image provided by Don Essig, Idaho Department of Environmental Quality). The colors represent different surface temperatures.

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 (fig. 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 (for example, 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 might be important during high spring flows, seasonal turnover periods in lakes and still pools, and 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 and others 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. The three common reasons for the loss or damage of data loggers are: (1) failure to relocate the data logger after initial field deployment; (2) human tampering or vandalism; and (3) natural disturbances, such as flooding, substrate movement, and animal influences (for example, 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 relocate 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 reflect potential changes in conditions that could affect a person's ability to relocate the data logger (for example, changes in stream flow or reservoir level, and seasonal changes in vegetation). Storing of geographic coordinates using a global positioning system (GPS) may be useful, but GPS coordinates are often insufficient by themselves.

Human disruption 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 backup 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 that are relatively impervious to physical vandalism or disruption. A third option is to use two or more data loggers in a single location as backups in the case of interference.

Human tampering can also result in 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 useful, 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 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 disturbances affecting data loggers are those associated with high stream discharges. Drag that is induced by higher water velocities and associated substrate movement and transport of debris can damage or dislodge data loggers. In our experience, housings provided by manufacturers or made by individual users generally are sufficient to protect data loggers, but stronger housings might be needed if extreme conditions are anticipated.

A common source of data loss is dislodging of the logger. Accordingly, it is important to properly anchor the data logger. A variety of anchors can be used, including large rocks, concrete blocks, and metal stakes (see also Onset Computer Corporation 1995). 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. Most data loggers can be quickly attached to sandbags using nylon zip ties. Chain, cable, or metal stakes are also useful, 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 streambed.

Burying data loggers to protect them from disturbance may not be an effective measure because influences from groundwater, subsurface flow, and the substrate can cause subsurface temperatures to deviate from temperatures in the well-mixed portion of the stream. Nonetheless, data loggers can be buried under substrate, aquatic vegetation, or accumulations of debris during deployment. The location of data loggers in such situations can be aided by use of a metal detector. The potential for biased temperature readings could be measured by comparing temperature data to records from nearby sites.

Finally, 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. We have had data loggers buried under beaver dams or impounded in associated ponds. Given the range of factors that can lead to loss of data loggers, perhaps the best approach is to use more than one data logger ("backups") in areas where problems are most likely to occur and where loss of data has the most serious consequences.

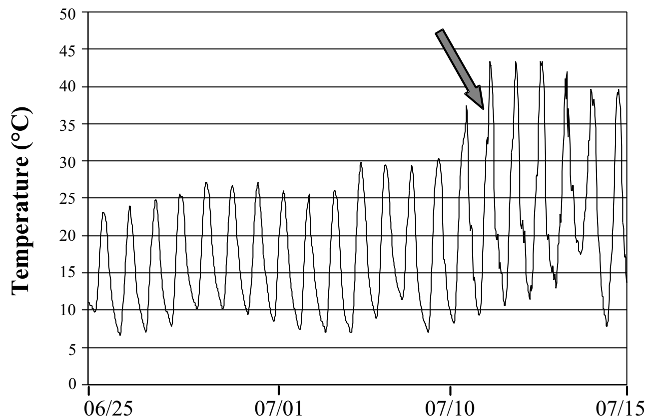


Figure 7—Example of temperature measurements from a site that was dewatered during the sampling period. Note the extreme (greater than 30 °C) daily fluctuation in temperature, and extraordinarily warm (greater than 40 °C) temperatures (at the arrow).

Step 3. Data Processing

Error screening

Once data loggers are retrieved from the field and data are 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 note any obvious data logger malfunctions or dewatering of site (fig. 7). In many cases, the data need to be trimmed. For example, if the logger was recording temperatures in the office during or after deployment, these observations should be removed before continuing with any analysis. Usually, these problems are obvious from visual inspection of the data (fig. 7).

It may be useful to automatically flag any suspect observations. For example, Rieman and Chandler (1999) flagged all temperature observations that fell below –1 °C or above 30 °C. Observations were also flagged if there was a rate of change greater than 3 °C per hour or a daily mean change of greater than 3 °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 reverified with personnel involved in data logger programming and field sampling. Flagged observations were only removed if obvious problems were found.

Statistical summaries of temperature data

A variety of statistical summaries or "metrics" 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, a number of components of thermal regimes are biologically important (for example, minimum temperatures, seasonal patterns, timing and duration of different temperatures), but we will focus our discussion on temperature metrics that describe maximum temperatures.

Maximum temperatures are often summarized within an annual timeframe. Within a year, there are a variety of timeframes 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 effects (for example, lethal or sublethal) are known to occur above a certain temperature, then the duration of exposure above that threshold may be important. Many different temperature metrics should be highly correlated, but the relationships may also vary with local conditions. We were interested in determining the degree of correlation between different metrics under different thermal regimes (daily range of temperature). This information is useful for understanding potential statistical redundancies among metrics, and for converting one metric to another when data for only one metric (for example, maximum temperatures from a max-min thermometer) are available.

To examine correlations between selected temperature metrics, we summarized 1,252 temperature records collected from throughout the Pacific Northwest and northern Great Basin 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 through 15 September to represent the summer, because this is the window in which maximum temperatures are generally realized within the area we considered. Different temporal windows may be necessary to capture maximum temperatures in other areas or unique conditions. The metrics we summarized were:

1. Daily average on the hottest day (MDAT) – The highest average temperature summarized one calendar day during the summer.
2. Overall summer maximum (MDMT) – The highest instantaneous maximum temperature recorded during the summer.
3. Maximum weekly average maximum temperature (MWMT) – The highest average temperature summarized over a continuous 7 days during the summer.
4. Maximum value of average weekly temperature (MWAT) – The highest average maximum temperature summarized over each day of a continuous 7 days during the summer.
5. Overall average summer temperature (AWAT) – The average temperature recorded across all observations from 15 July through 15 September.
6. Cumulative days maximum greater than 14 °C during hottest week (WEEK_14)
7. Cumulative days maximum greater than 18 °C during hottest week (WEEK_18)
8. Cumulative days maximum greater than 22 °C during hottest week (WEEK_22)
9. Cumulative days maximum greater than 14 °C during entire summer (SUM_14)
11. Cumulative days maximum greater than 18 °C during entire summer (SUM_18)
12. Cumulative days maximum greater than 22 °C during entire summer (SUM_22)

We categorized each site by average daily range and grouped the sites on 2 °C daily range intervals to account for the influence of local conditions on correlations among temperature metrics. The correlations and conversion factors among temperature metrics for each grouping are summarized in tables 4 through 10. As was expected, the greater the daily range of temperatures the lower the correlation of metrics. Metrics describing an instantaneous measure (for example, maximum or mean summer temperature) were more correlated among each other than correlated with cumulative exposure

Table 4a—Correlation matrix among temperature metrics (n=101) where the average daily range over the summer was 0 to 2 °C. Numbers underlined and in italics were not significant correlations (note in comparisons between tables that statistical significance is related to sample size).

	MDAT	MDMT	MWMT	AWAT	MWAT	WEEK_14	WEEK_18	WEEK_22	SUM_14	SUM_18	SUM_22
MDAT	1.00	0.98	0.98	0.96	0.99	0.72	0.46	***0.21***	0.72	0.46	***0.21***
MDMT	0.98	1.00	0.98	0.96	0.98	0.73	0.47	0.24	0.73	0.47	0.24
MWMT	0.98	0.98	1.00	0.97	0.99	0.73	0.46	***0.24***	0.73	0.46	***0.24***
AWAT	0.96	0.96	0.97	1.00	0.97	0.71	0.46	***0.22***	0.72	0.46	***0.22***
MWAT	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 to 2 °C. The conversion is row minus column (in other words, if maximum summer [MDMT] was 12 °C then the overall mean summer temperature [AWAT] would be: 12.00-2.55 = 9.45 with 95% confidence bounds of 9.22 to 9.67).

	AWAT			MWAT			MDAT			MWMT		
	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER
MDMT	2.55	2.33	2.78	1.49	1.34	1.64	1.17	0.97	1.38	0.55	0.44	0.67
MWMT	2.00	1.84	2.15	0.93	0.87	0.99	0.62	0.49	0.75			
MDAT	1.38	1.22	1.54	0.31	0.21	0.41						
MWAT	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 to 4 °C. Numbers underlined and in italics were not significant correlations (note in comparisons between tables that statistical significance is related to sample size).

	MDAT	MDMT	MWMT	AWAT	MWAT	WEEK_14	WEEK_18	WEEK_22	SUM_14	SUM_18	SUM_22
MDAT	1.00	0.95	0.96	0.95	0.99	0.88	0.50	0.19	0.90	0.51	0.20
MDMT	0.95	1.00	0.98	0.93	0.95	0.91	0.52	0.22	0.93	0.53	0.24
MWMT	0.96	0.98	1.00	0.95	0.97	0.91	0.51	0.19	0.93	0.51	0.20
AWAT	0.95	0.93	0.95	1.00	0.97	0.86	0.50	0.18	0.90	0.51	0.19
MWAT	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 to 4 °C. The conversion is row minus column (in other words, if maximum summer [MDMT] was 12 °C then the overall mean summer temperature [AWAT] would be: 12.00-4.08 = 7.92 with 95% confidence bounds of 7.79 to 8.04).

	AWAT			MWAT			MDAT			MWMT		
	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER
MDMT	4.08	3.96	4.21	2.76	2.67	2.86	2.28	2.18	2.37	0.80	0.71	0.88
MWMT	3.29	3.22	3.36	1.96	1.92	2.01	1.48	1.43	1.53			
MDAT	1.81	1.74	1.88	0.49	0.45	0.52						
MWAT	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 to 6 °C. Numbers underlined and in italics were not significant correlations (note in comparisons between tables that statistical significance is related to sample size).

MDAT	MDMT	MWMT	AWAT	MWAT	WEEK_14	WEEK_18	WEEK_22	SUM_14	SUM_18	SUM_22	
MDAT	1.00	0.94	0.96	0.95	0.98	0.82	0.79	0.39	0.90	0.79	0.39
MDMT	0.94	1.00	0.98	0.93	0.94	0.83	0.81	0.40	0.92	0.83	0.41
MWMT	0.96	0.98	1.00	0.94	0.97	0.86	0.82	0.39	0.94	0.83	0.39
AWAT	0.95	0.93	0.95	1.00	0.97	0.83	0.77	0.37	0.93	0.78	0.38
MWAT	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 to 6 °C. The conversion is row minus column (in other words, if maximum summer [MDMT] was 14 °C then the overall mean summer temperature [AWAT] would be: 14.00-5.60 = 8.40 with 95% confidence bounds of 8.22 to 8.57).

	AWAT			MWAT			MDAT			MWMT		
	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER
MDMT	5.60	5.43	5.78	4.13	3.99	4.28	3.55	3.42	3.68	0.95	0.85	1.05
MWMT	4.64	4.53	4.77	3.18	3.10	3.27	2.60	2.51	2.69			
MDAT	2.05	1.94	2.15	0.58	0.53	0.63						
MWAT	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 to 8 °C. Numbers underlined and in italics were not significant correlations (note in comparisons between tables that statistical significance is related to sample size).

MDAT	MDMT	MWMT	AWAT	MWAT	WEEK_14	WEEK_18	WEEK_22	SUM_14	SUM_18	SUM_22	
MDAT	1.00	0.93	0.94	0.93	0.98	0.43	0.86	0.75	0.74	0.91	0.76
MDMT	0.93	1.00	0.98	0.90	0.92	0.44	0.89	0.82	0.71	0.92	0.83
MWMT	0.94	0.98	1.00	0.93	0.95	0.45	0.92	0.82	0.75	0.95	0.83
AWAT	0.93	0.90	0.93	1.00	0.95	0.45	0.83	0.75	0.74	0.92	0.77
MWAT	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 to 8 °C. The conversion is row minus column (in other words, if maximum summer [MDMT] was 14 °C then the overall mean summer temperature [AWAT] would be: 14.00-7.27 = 6.73 with 95% confidence bounds of 6.48 to 6.98).

	AWAT			MWAT			MDAT			MWMT		
	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER
MDMT	7.27	7.02	7.52	5.57	5.33	5.80	4.93	4.71	5.14	1.01	0.88	1.14
MWMT	6.26	6.07	6.45	4.55	4.41	4.71	3.92	3.74	4.09			
MDAT	2.34	2.15	2.53	0.64	0.53	0.74						
MWAT	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 to 10 °C. Numbers underlined and in italics were not significant correlations (note in comparisons between tables that statistical significance is related to sample size). Dashes indicate no days exceeding 14 °C during the hottest week of the year.

	MDAT	MDMT	MWMT	AWAT	MWAT	WEEK_14	WEEK_18	WEEK_22	SUM_14	SUM_18	SUM_22
MDAT	1.00	0.82	0.84	0.92	0.97	—	0.70	0.80	0.39	0.82	0.84
MDMT	0.82	1.00	0.98	0.79	0.81	—	0.68	0.90	***0.12***	0.64	0.90
MWMT	0.84	0.98	1.00	0.83	0.86	—	0.70	0.93	***0.17***	0.68	0.92
AWAT	0.92	0.79	0.83	1.00	0.94	—	0.70	0.78	***0.30***	0.80	0.85
MWAT	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 to 10 °C. The conversion is row minus column (in other words, if maximum summer [MDMT] was 16 °C then the overall mean summer temperature [AWAT] would be: 16.00-8.79 = 7.21 with 95% confidence bounds of 6.77 to 7.66).

	AWAT			MWAT			MDAT			MWMT		
	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER
MDMT	8.79	8.34	9.23	7.07	6.63	7.51	6.42	6.00	6.84	1.06	0.91	1.22
MWMT	7.72	7.36	8.08	6.01	5.68	6.34	5.36	5.02	5.70			
MDAT	2.36	2.11	2.61	0.65	0.49	0.80						
MWAT	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 to 12 °C. Numbers underlined and in italics were not significant correlations (note in comparisons between tables that statistical significance is related to sample size). Dashes indicate no days exceeding 14 °C during the hottest week of the year.

	MDAT	MDMT	MWMT	AWAT	MWAT	WEEK_14	WEEK_18	WEEK_22	SUM_14	SUM_18	SUM_22
MDAT	1.00	0.83	0.92	0.89	0.95	—	***0.33***	0.61	***–0.05***	***0.19***	0.80
MDMT	0.83	1.00	0.93	0.83	0.92	—	***0.33***	0.61	***–0.10***	***0.08***	0.68
MWMT	0.92	0.93	1.00	0.86	0.97	—	***0.33***	0.68	***–0.03***	***0.21***	0.78
AWAT	0.89	0.83	0.86	1.00	0.90	—	***0.33***	0.59	***–0.32***	***–0.02***	0.65
MWAT	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 to 12 °C. The conversion is row minus column (in other words, if maximum summer [MDMT] was 16 °C then the overall mean summer temperature [AWAT] would be: 16.00-10.37 = 5.67 with 95% confidence bounds of 5.13 to 6.13).

	AWAT			MWAT			MDAT			MWMT		
	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER
MDMT	10.37	9.87	10.87	8.17	7.82	8.52	7.60	7.13	8.06	1.31	0.97	1.64
MWMT	9.06	8.55	9.58	6.86	6.60	7.13	6.29	5.94	6.64			
MDAT	2.77	2.28	3.26	0.57	0.30	0.84						
MWAT	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 (note in comparisons between tables that statistical significance is related to sample size). Dashes indicate no days exceeding 14 °C during the hottest week of the year.

	MDAT	MDMT	MWMT	AWAT	MWAT	WEEK_14	WEEK_18	WEEK_22	SUM_14	SUM_18	SUM_22
MDAT	1.00	0.55	0.62	0.81	0.77	—	—	***0.43***	***–0.10***	***0.14***	0.53
MDMT	0.55	1.00	0.95	0.74	0.65	—	—	***0.47***	***–0.05***	***0.27***	0.59
MWMT	0.62	0.95	1.00	0.81	0.72	—	—	***0.47***	***–0.08***	***0.28***	0.61
AWAT	0.81	0.74	0.81	1.00	0.93	—	—	***0.47***	***–0.11***	***0.25***	0.68
MWAT	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 (in other words, if maximum summer [MDMT] was 16 °C then the overall mean summer temperature [AWAT] would be: 16.00-11.82 = 4.18 with 95% confidence bounds of 3.55 to 4.81).

	AWAT			MWAT			MDAT			MWMT		
	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER	MEAN	LOWER	UPPER
MDMT	11.82	11.19	12.45	10.20	9.46	10.94	9.70	8.78	10.61	1.17	0.91	1.43
MWMT	10.65	10.21	11.09	9.03	8.45	9.60	8.52	7.76	9.29			
MDAT	2.12	1.55	2.69	0.51	-0.04	1.05						
MWAT	1.62	1.31	1.92									

metrics (for example, number of days maximum was over 16 °C). The correlations and conversions reported herein are useful for comparing the equivalence of information from different summary water temperature metrics, but local verification of these relationships is advised.

Step 4. Data Archiving

Data archiving is one of the most important steps in a temperature monitoring effort. A plan for data archiving is especially important for large studies. The volume of information data loggers can collect warrants storage within a relational database system (such as Oracle, Sybase, Access). The details of using different database programs or setting up databases are beyond the scope of this document; our intent here is to outline some of the pieces of information to be archived within a database. Spreadsheets can be useful for small datasets, but they are limited by the number of observations each sheet can hold as well as the ease of summarization of data. Relational databases, designed correctly, will have a minimal (if any) amount of redundant information. Therefore, the time needed to summarize and edit data is greatly reduced. Relational database applications also require less storage space.

There are three basic types of information to include in a temperature database: (1) pre-deployment information, (2) field deployment information, and (3) post-deployment information (table 11). Pre-deployment information includes data and notes on field site characteristics, locations, and calibration of the data loggers. Site data should include stream name, drainage and topographical map name. Data logger information should include logger type (model), logger serial number, and precalibration factor (if calibration was performed).

Field deployment information includes site definition and time of deployment. Efficient data collection at this point will

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

save hours of work at the post-deployment stage. Data needed at this stage include stream name and site number (if appropriate), UTM coordinates or other location information to georeference the site, description of site, habitat type that the 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 precalibration 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 include date and time of removal, wetted width at time of removal, and any other relevant site information (for example, "Did the site dry up during sampling?" or "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 postcalibration factors. We have found that loggers can drift (in other words, the pre- and postcalibration factors are not the same).

Stream Information

Stream Name: ________________ Site No.: ______

24K Quad Name: __________________ Basin: ❑ Panther ❑ Boise ❑ SF Salmon

Waypoint gathered: ❑ Yes ❑ No

Site noted on map: ❑ Yes ❑ No

Site Description: ____
____
____
____

Logger Information

Logger Type: ***Tidbit*** Serial No.: ________ Sampling Int.: ***30 min.***

Date placed in stream: ___________ Time placed in stream: ___________

Site Information

Habitat type of placement: (in a well mixed zone) ❑ Riffle ❑ Pool ❑ Run ❑ Pocket

Tethering Method: ❑ Sandbag ❑ Other: ________ ________

Wetted Width at logger (m): ________ Depth of logger (m): _______

Comments: ____
____
____
____

Detailed map of site:

Photo ID reference: _______________

Figure 8—An example of a field datasheet used for deployment of data loggers.

References

Allison, P.D. 1999. Logistic regression using the SAS system. SAS Institute, Cary, North Carolina.

Bartholow, J.M. 2000. The Stream Segment and Stream Network Temperature Models: A SelfStudy Course, Version 2.0 U.S. Geological Survey Open File Report 99112. 276 p. (http://www.mesc.usgs.gov/training/if312.html)

Dunham, J.B. 1999. Stream temperature criteria for Oregon's Lahontan cutthroat trout *Oncorhynchus clarki henshawi*. Final report to Oregon Department of Environmental Quality, Portland, OR. (http://www.fs.fed.us/rm/boise/publications/masterlist.htm)

Dunham, J.B. and G.L. Chandler. 2001. Models to predict suitable habitat for juvenile bull trout in Washington State. Final Report. Research Cooperative Agreement Number 134100H001. U.S. Fish and Wildlife Service, Lacey, WA.

Eaton, J.G., J.H. McCormick, B.E. Goodno, D.G. O'Brien, H.G. Stefany, M,Hondzo, and R.M. Scheller. 1995. A field informationbased system for estimating fish temperature tolerances. Fisheries 20(4):1018.

Lewis, T.E., D.W. Lamphear, D.R. McCanne, A.S. Webb, J.P. Krieter, and W.D. Conroy. 2000. Regional Assessment of Stream Temperatures Across Northern California and Their Relationship to Various Landscape-Level and Site-Specific Attributes. Forest Science Project. Humbolt State University Foundation, Arcata, CA. 420 p.

Natural Resources Conservation Service. 1996. National Handbook of Water Quality Monitoring. 450-vi-NHWQM. National Water and Climate Center, Portland, OR (http://www.wcc.nrcs.usda.gov/water/quality/frame/wqam/Guidance_Documents/guidance_documents.html)

Onset Computer Corporation. 1995. The honest observer newsletter 2.1. Available online: http://www.onsetcomp.com/Newsletters/Honest_Observer/HO.2.1.html

Poole, G. C., and C. H. Berman. 2001. An ecological perspective on in-stream temperature: natural heat dynamics and mechanisms of human-caused thermal degradation. Environmental Management 27:787-802.

Poole, G., J. Dunham, M. Hicks, D. Keenan, J. Lockwood, E. Materna, D. McCullough, C. Mebane, J. Risley, S. Sauter, S. Spalding, and D. Sturdevant. 2001a. Scientific Issues Relating to Temperature Criteria for Salmon, Trout, and Charr Native to the Pacific Northwest. Prepared as part of the EPA Region 10 water quality criteria guidance development project. (http://www.fs.fed.us/rm/boise/publications/masterlist.htm)

Poole, G.C., J. Risley, and M. Hicks. 2001b. Spatial and temporal patterns of stream temperature. EPA Region 10 water quality criteria guidance development project: EPA 910-D-01-002. (http://yosemite.epa.gov/R10/WATER.NSF/6cb1a1df2c49e4968825688200712cb7/5eb9e547ee9e111f88256a03005bd665?OpenDocument)

Rieman, B.E. and G.L. Chandler. 1999. Empirical evaluation of temperature effects on bull trout distribution in the Northwest. Final Report. Contract 12957242-01-0. U.S. Environmental Protection Agency, Boise, ID.

Torgersen, C.E., R.N. Faux, B.A. McIntosh, N.J. Poage, and D.J. Norton. 2001. Airborne thermal remote sensing for water temperature assessment in rivers and streams. Remote Sensing of Environment 76: 386-398.

Ward, R.C., J.C. Loftis, and G.B. McBride. 1986. The "data-rich but information-poor" syndrome in water quality monitoring. Environmental Management 10:291-297.

Webb, B.W. and Zhang, Y. 1997. Spatial and seasonal variability in the components of the river heat budget. Hydrological Processes 11: 79-101.

Zaroban, D.W. 1999. Protocol for placement and retrieval of temperature data loggers in Idaho streams. Water quality monitoring protocols report #10. Idaho Department of Environmental Quality, Boise, ID.

RMRS

ROCKY MOUNTAIN RESEARCH STATION

The Rocky Mountain Research Station develops scientific information and technology to improve management, protection, and use of the forests and rangelands. Research is designed to meet the needs of National Forest managers, Federal and State agencies, public and private organizations, academic institutions, industry, and individuals.

Studies accelerate solutions to problems involving ecosystems, range, forests, water, recreation, fire, resource inventory, land reclamation, community sustainability, forest engineering technology, multiple use economics, wildlife and fish habitat, and forest insects and diseases. Studies are conducted cooperatively, and applications may be found worldwide.

Research Locations

Flagstaff, Arizona
Fort Collins, Colorado*
Boise, Idaho
Moscow, Idaho
Bozeman, Montana
Missoula, Montana
Lincoln, Nebraska
Reno, Nevada
Albuquerque, New Mexico
Rapid City, South Dakota
Logan, Utah
Ogden, Utah
Provo, Utah
Laramie, Wyoming

*Station Headquarters, Natural Resources Research Center,
2150 Centre Avenue, Building A, Fort Collins, CO 80526