Evaluation and Use of Stream Temperature Prediction Models for Instream Flow and Fish Habitat Management

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ABSTRACT

The SNTEMP (U.S. Fish and Wildlife Service), QUAL2E (U.S. Environmental Protection Agency), and RQUAL (Tennessee Valley Authority) stream temperature prediction models were evaluated. All models had high predictive ability with the majority of predictions, >80% for Back Creek (Roanoke County, VA) and >90% for the Smith River tailwater (SRT) (Patrick County, VA), within 3°C of the measured water temperature. Sensitivity of model input parameters was found to differ between model, stream system, and season. The most sensitive of assessed parameters, dependent on model and stream, were lateral inflow, starting-water, air, and wet-bulb temperature. All three models predicted well, therefore, selecting a model to assess alternative water management scenarios was based on model capabilities. The RQUAL model, used to predict SRT temperatures under alternative hydropower release regimes, illustrated potential thermal habitat improvement for brown trout (*Salmo trutta*) compared to existing conditions. A 7-day/week morning 1 hr release was determined to best concurrently increase occurrence of brown trout optimal growth temperatures (+10.2% mean), decrease 21°C (state standard) exceedances (99% prevention), and decrease hourly changes in temperature (-1.6°C mean) compared to existing thermal conditions. The SNTEMP model was used to assess thermal habitat under flow, shade, and channel width changes occurring from future urbanization within the Back Creek watershed. Predictions reveal that additional urban development could limit thermal habitat for present fish species by elevating summer mean daily temperature up to 1°C and cause 31°C (state standard) exceedances compared to existing conditions. Temperature impacts were lessened by single rather than cumulative changes suggesting mitigation measures may maintain suitable thermal habitat.

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INTRODUCTION

Anthropogenic influences have the potential to alter stream temperatures and thermal regimes. Water temperature influences fish survival, geographical distribution, growth rate, spawning period, egg incubation survival/development, and cues migration (Chavin 1973; Reynolds and Casterlin 1979; Brooker 1981; Saltveit 1990; Armour 1991; Ojanguren et al. 2001). For example, during winter the hypolimnetic water released by a dam is warmer than pre-dam conditions, which can prolong the growth season for trout and salmon fry due to warmer incubating habitat (Jensen 1987; Wilson et al. 1987). Fish can tolerate thermal fluctuations, but the magnitude and duration over which a temperature change occurs determines the severity of the impact on fishes (Coutant 1976). For instance, a fish may be able to survive over a 30°C temperature range, but only if temperature changes from 0° to 30°C over many months, not a few hours. Experiments conducted to investigate increases in upper thermal tolerance when acclimated to fluctuating temperatures found stable or fluctuating temperatures do not increase the upper lethal temperature maximum (Heath 1963; Dickerson and Vinyard 1999). Hokanson et al. (1977) found that rainbow trout experiencing diel fluctuations around their mean upper tolerance reduced their growth. The thermal range fish can tolerate also differs with life stage. Other attributes of temperature that may be of biological importance are minimum temperature, mean temperature, time of day of maximum daily temperature, and duration or persistence of that maximum (Bartholow 1999). Frequently, temperature is not the sole influence affecting fish growth and survival, but a compounding effect where temperature alters dissolved oxygen levels, contaminant toxicity, suspending or precipitation of solids, and/or the level at which chemical and biochemical reactions occur (Bartholow 1997; Theurer et al. 1984; Calow and Petts 1992).

Stream temperature is altered by logging, urbanization, water withdrawal for agriculture, hypolimnetic releases from hydropower facilities, industrial and electric generation cooling-water discharge, and global warming (Brown 1980; Jensen 1987; Bartholow 1989; Sullivan et al. 1990; Webb and Walling 1993; LeBlanc et al. 1997).

Logging and urbanization near streams removes shade-producing trees. In Georgia, logging altered stream temperature in small streams by as much as an 11.1°C increase in the summer and a 5.6°C decrease in the winter (Hewlett and Fortson 1982). Other studies conducted in the western U.S. have found similar temperature increases, ranging from 3.89°C to 15.56°C during summer months (Brown 1972; Brown 1980; Hostetler 1991). Increased temperatures occur because the loss of shade allows increased amounts of short-wave radiation to be absorbed by the water. Long-wave radiation escapement increases at night with the loss of riparian vegetation, which can reduce water temperatures during the winter as well as increase the daily temperature fluctuation (LeBlanc et al. 1997).

Shade loss can occur from urbanization, which also creates large areas of impervious surfaces that increase overland runoff during rain events. Impervious surfaces restrict infiltration of rainwater into the ground thereby decreasing cool groundwater inflow into a stream (Sullivan et al. 1990; LeBlanc et al. 1997; Rutherford et al. 1997). Stream temperature is further altered by the amount of water in a stream. Urbanization results in "flashy" flow regimes, agricultural and industry withdraw water, and dams manipulate flow. Smaller amounts of water require less energy to warm it, thus increased temperatures and temperature fluctuations occur (Calow and Petts 1992; LeBlanc et al. 1997; Rutherford et al. 1997). The surface area (i.e., air-water interface) is the primary location of energy exchange (Theurer et al. 1984; Bartholow 1989; Sullivan et al. 1990; Bartholow 1997). Changes in flow alter the cross-sectional geometry of the stream, thus changing the amount of surface area exposed for heating or cooling.

Hydroelectric dams not only alter flow but also can directly alter temperature. This occurs because the reservoir formed behind the dam stores heat and thermally stratifies (Wilson et al. 1987). If intake pipes of the dam are below the thermocline, water released from the dam can be much cooler (i.e., hypolimnetic release) than pre-dam stream temperatures. Alternatively, overflow dams can release only the warmest top layer of water downstream.

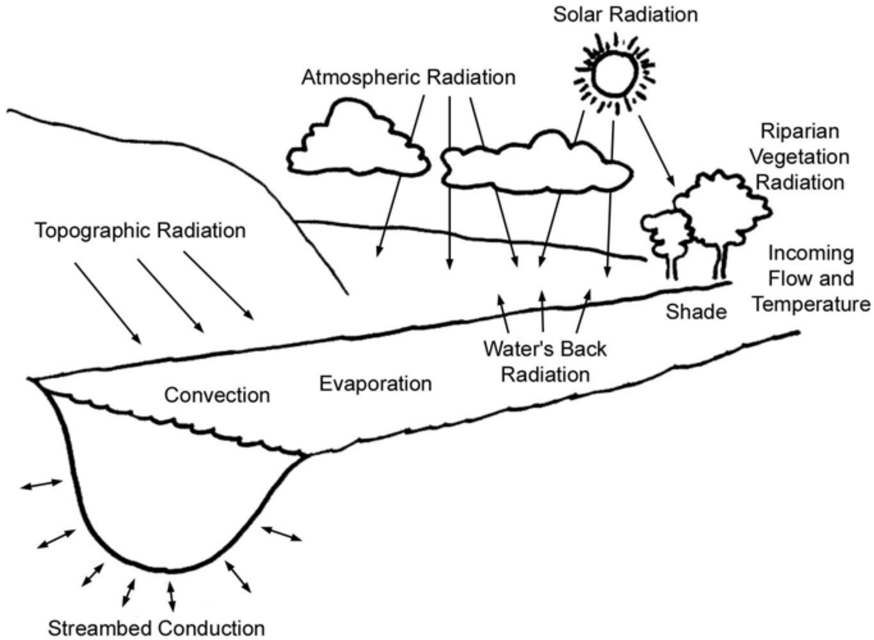
Water quality regulations aim to reduce the anthropogenic effects on aquatic habitat. The Virginia Department of Environmental Quality (DEQ) regulates water quality for different water classes that include maximum temperature, maximum rise above natural temperature, and maximum hourly temperature change (DEQ 1997). Even though the importance of water temperature is known and regulated, temperature remains a factor often left out of instream flow management. A cause for this in the past may have been the difficulty and large expense required to monitor water temperature multiple times per day. This task is no longer arduous with the advent of small, accurate, reliable, and inexpensive submersible water temperature loggers. Additionally, a computer model can predict a stream's thermal regime under various management options. The use of such models is limited because they are thought to be difficult to use and not user-friendly. In addition, the model user may not know which model to use because not every model is suitable for every stream and situation. This is due to varying assumptions and limitations between models.

Modeling stream temperatures under altered conditions become most useful when coupled with thermal tolerance data for the stream's fish species. This coupling of information can determine the quantity and/or quality of thermal habitat available throughout a stream or watershed for fish of various thermal tolerances, the presence or absence of thermal bottlenecks that may inhibit migration, and the suitability of temperature ranges and fluctuations for survival, egg incubation, growth, feeding, and spawning. Such information can assist in defining minimum flows, managing for a cold-water fishery, regulating dam releases, and assessing the temperature effect prior to the occurrence of logging, urbanization, or hydroelectric dam development. The use of models in temperature management issues is not widespread in the literature. Rather, much of the stream temperature modeling literature addresses development and testing of temperature models (Brown 1969; Hewlett and Fortson 1982; LeBlanc et al. 1997; Rutherford et al. 1997; Chen et al. 1998). Limited information is available on temperature model use in actual management issues such as cold-water fishery development/management (Bartholow 1991), dam release regulation to benefit fish and wildlife (Lifton et al. 1985; Zedonis 1997), and assessment of temperature effects of a dam prior to its construction (Wilson et al. 1987).

There are limitations to using temperature models for solving management issues. Assessment of temperature while assuming that other factors (e.g. water quality, depth, velocity, substrate, cover, DO, flow, food resources) remain unchanged is not realistic

(Jensen 1987; Bartholow 1997). However, because of the strong effect of temperature on fish, such assessments are valuable in determining if thermal habitat is limiting. If, for example, growth is of interest other key factors such as food resources, flow, and competition should be evaluated in addition to temperature (Jensen 1987). Temperature is usually assessed only during the summer months to determine if temperatures exceed maximum tolerances for a species (Bartholow 1989; Sullivan et al. 1990; Bartholow 1997). Temperature modeling during winter is often neglected, but in cases where winter conditions were modeled, thermal habitat conditions were found to influence other life stages such as eggs and fry (Wilson et al. 1987).

Models developed to predict water temperature are typically empirical or analytical models. These models have varying levels of data requirements, predictive abilities, and ability to model various scenarios. Empirical (i.e., statistical) water temperature models are based on single and/or multiple linear regression to discern common patterns of water temperature in relation to other factors (Crisp and Howson 1982; Sinokrot and Stefan 1993; Stefan and Preud'homme 1993). In most streams air temperature is the influential factor in that water temperature typically mimics air temperature at some lag time due to water's high heat capacity (Waddle 1989). Based on this observed phenomenon, studies have attempted to model water temperature with only air temperature and have found that predictions averaged over greater time periods are more accurate (Crisp and Howson 1982). Knowledge of predicted average water temperature over a week or month may be useful for broad scoping exercises, but they do not provide the detail needed for many of today's management issues and are valid only if surrounding conditions remain constant (Bartholow 1989). For instance, an empirical model fails to provide accurate estimations of diel temperature fluctuations, nor does it allow for temperature predictions under various scenarios such as altered flows, riparian vegetation, or channel structure. To answer management questions the model must include parameters that can be altered. A model that does so allows a manager to assess various scenarios to determine options that will achieve the desired water temperature. Such models are called analytical models (i.e., process-oriented model), which in terms of temperature modeling are based on an energy budget. This budget is comprised of the factors that either add or remove energy (i.e., heat) from the stream's water (Figure 1.1).



INPUTS

Incoming short-wave solar radiation
Long-wave atmospheric radiation
Long-wave forest radiation
Energy gained by condensation
Energy advected in precipitation
Heat entering from groundwater
Heat content of streamflow entering reach
Energy advected by tributary inflow

OUTPUTS

Reflected solar radiation
Reflected atmospheric radiation
Reflected forest radiation
Back radiation from water surface
Energy used in evaporation
Energy advected by evaporating water
Heat content of streamflow leaving reach

GAINS/LOSSES

Energy gained or lost by convection
Energy gained or lost by conduction to or from atmosphere
Heat conduction to or from stream bed and banks

Figure 1.1. Primary heat flux components affecting stream temperature. Adapted from Calow and Petts (1992) and Bartholow (1997).

The primary factors are solar radiation (short-wave), radiation (long-wave) with the sky, vegetation and topography, convection with the air, evaporation, conduction with the streambed, and advection from incoming water sources (Bartholow 1989; Sullivan et al. 1990; Bartholow 1997). By determining the primary factors causing heat flux an energy budget can be developed. Converting the budget into an energy balance equation allows for calculations on measurable parameters to determine the net change in stored energy, which through further calculation allows prediction of water temperature. The model assesses changes in stored energy by adding or removing energy to a parcel of water (where the parcel's upstream temperature and volume is known) as it progresses downstream experiencing different heat fluxes. A generic energy balance equations looks like:

$$\Delta S = Q_{nr} \pm Q_e \pm Q_h \pm Q_c \pm Q_a$$

where

$\Delta S =$ net change in energy stored
$Q_{nr} =$ net thermal radiation flux (net short and long-wave radiation)
$Q_e =$ evaporative flux (energy transfer due to the water changing from a liquid to a vapor)
$Q_h =$ convective flux (energy transfer between water and air interface)
$Q_c =$ conductive flux (energy transfer from molecule to molecule)
$Q_a =$ advective flux (energy transfer due to water at a different temperature being added to the stream such as a tributary inflow, overland flow, direct precipitation, or groundwater inflow)
(Brown 1969; LeBlanc et al. 1997).

Prior to widespread computing resources, analytical stream temperature models were simplistic enough for hand calculation. During the 1960's models to predict stream temperature were developed by G. W. Brown to predict how much riparian buffer should be left along small streams adjacent to logging (Brown 1969, 1972, 1980). During the 1980's computers assisted the development of models and the complexity of stream temperature prediction models increased. Models that could account for many of the parameters presented in Figure 1.1 became available in the 1980's to predict temperature over a segment (i.e., reach) of river experiencing steady flow (known as reach models) (Brown 1969, 1972; Sullivan et al. 1990; Bartholow 1997). The next step in model complexity that occurred was temperature prediction over a watershed by linking stream segments for the mainstem and tributaries together (known as basin models) (Sullivan et al. 1990; Bartholow 1997). The latest stage of temperature model development is modeling basins with unsteady flows caused by hydropeaking water releases from a hydroelectric facility (known as dynamic models) (Bartholow 1997). Though dynamic models are capable of modeling most situations, their data requirements are much greater than that of steady-state models (i.e., basin models that assume constant flow), which in turn have greater requirements than reach models. As data requirements increase, model users may have to estimate some parameters due to time and cost restrictions, which in turn offsets the model's ability to accurately predict temperatures. Reach and basin models both have similar amounts of required parameters, and even though basin models split data input per reach to account for energy budget component variation in time and space (Calow and Petts 1992), reach models are typically able to predict temperature more accurately (Sullivan et al. 1990). More accurate prediction by reach models is due to assessing smaller, more homogeneous sections of stream that naturally have less energy factor variation and compounding influences (Sullivan et al. 1990; Calow and Petts 1992). The ability of reach models to predict more accurately does not preclude the practicality of basin models as most stream/fish management questions pertain to the majority of a stream's length and not a small section. Unless necessary, dynamic models are usually not used due to their substantial data requirements to predict temperature under daily fluctuating flows. Though data collection may seem daunting it has become easier with relatively cheap data loggers to measure air temperature, relative humidity, dewpoint, rainfall, light intensity, and atmospheric pressure as well as a wealth of obtainable flow and meteorological data from U.S. Geological Survey (USGS) and the National Climatic Data Center (NCDC).

Choosing a model that is most appropriate to answer particular questions for a specific stream or watershed requires knowledge of a model's limitations. All temperature prediction models have assumptions and limitations such as not accounting for shade, diel weather fluctuation, or daily flow variation. Thus, for example, if the objective is to predict temperature change under an increased or decreased riparian buffer in a river where flow varies hourly due to a hydropeaking power generation schedule, the model must account for shade and hourly flow fluctuation. To assist a manager in choosing the best model for such a situation, documentation that evaluates multiple models for predictive accuracy and ease of use under different objectives is helpful. Such information is essentially nonexistent because academicians and researchers want to publish new research rather than test past concepts (ASCE Task Committee 1993). Therefore, companies and agencies often conduct their own evaluations of multiple models to determine the best model for their needs (Waddle 1989; Sullivan et al. 1990). The majority of model evaluation studies as well as research/development studies were conducted on streams in the western United States. Sullivan et al. (1990) evaluated Brown's model, TEMP-86, SSTEMP, TEMPEST, QUAL2E, SNTEMP, and Model Y in Washington; and Tu et al. (1992) evaluated SNTEMP and WQRRS in California. In the eastern United States a study was conducted in New York to assess three different temperature models (QUAL2E, RIV1, and SSTEMP) for use on the regulated Salmon River (Waddle 1989). To the author's knowledge there is no readily available published material documenting temperature model use in Virginia or the southeastern region of the United States. Other than model user manuals and model development research papers, which do not provide comparative information, the limited model evaluation studies are all that managers have to assist them in quickly determining an appropriate model. Therefore, the first objective of this study is to evaluate three models using Virginia streams and assess model predictive ability, model validation, parameter sensitivity, and model advantages & shortcomings. This evaluation will provide information necessary to select an appropriate model capable of answering questions pertaining to the study streams.

Two stream systems were assessed; the Smith River, a hydropeaking tailwater, and Back Creek, a 3rd order tributary. The Smith River supports a naturalized self-sustaining brown trout (*Salmo trutta*) population which produces limited numbers of trophy size (406+ mm) trout, thus causing fishing organizations and the state fish management agency to desire changing the hydropeaking release regime to benefit the brown trout population. Therefore, the second objective of this study determined if existing thermal conditions may be stress inducing or growth limiting as well as assess alternative release regimes that may improve thermal conditions for brown trout. Back Creek will likely see future increases in urban development due to the watershed's close proximity to the city of Roanoke, Virginia. Therefore, the third objective of this study determined if urbanization effects could impair the thermal regime for the existing fish community.

CHAPTER 2. Applications of Three Temperature Models in Virginia Streams: Approaches and Guidelines

ABSTRACT

Physical process (i.e., based on energy balance) temperature prediction models enable assessment and quantification of thermal habitat under existing and alternative conditions. Multiple models are available, however a lack of scientific reviews and performance evaluations can make choosing a model capable of answering study objectives challenging. The objective of this study was to evaluate the Stream Network Temperature model (SNTEMP) developed by the U.S. Fish and Wildlife Service, the Enhanced Stream Water Quality model (QUAL2E) developed by the U.S. Environmental Protection Agency, and the Tennessee Valley Authority's river modeling system (RQUAL). Model evaluation included assessing predictive ability, parameter sensitivity, and advantages/shortcomings to provide information for informed model selections. All models were developed for the Smith River (hydropeaking tailwater), and SNTEMP and QUAL2E were developed for Back Creek (unregulated tributary); both located in southwestern Virginia. All models had high predictive ability with the majority of predictions, >80% for Back Creek and >90% for the Smith River, within 3°C of the measured water temperature. Predictive ability was decreased for Back Creek because smaller channels and water volumes are more easily thermally altered. Sensitivity of model input parameters was found to differ among models, stream system, and season. The most sensitive of assessed parameters, dependent on model and stream, were lateral inflow, starting-water, air, and wet-bulb temperature. Choosing the "best" of the assessed models based on predictive ability was not possible due to similar predictive ability. Therefore, model choice can be based on model capabilities such as RQUAL's ability to predict hourly temperature or SNTEMP's ability to assess alternative shade levels.

INTRODUCTION

Temperature models are important tools that enable managers to plan mitigation measures and assess future hydrological and watershed land-use changes on thermal habitat. With increasing awareness of human impacts on rivers and movement toward maintaining ecosystem friendly instream flows, aquatic resource managers need to be able to assess and quantify thermal habitat. Though thermal regime is not the only parameter affecting habitat suitability, it is highly important for optimum survival, growth, and reproduction of aquatic biota (Chavin 1973; Reynolds and Casterlin 1979; Brooker 1981; Saltveit 1990; Armour 1991; Ojanguren et al. 2001).

Water temperature is a key parameter because its effects are wide reaching. Temperature influences dissolved oxygen (DO), contaminant toxicity, suspension or precipitation of solids, and the rate at which chemical and biochemical reactions occur (Theurer et al. 1984; Calow and Petts 1992; Bartholow 1997). Temperature also influences fish growth rate, spawning period, egg incubation survival/development, migration cues, and level of disease resistance (Brown 1974; Brungs and Jones 1977; Brown 1980). Perhaps more important than water temperature is the thermal regime, which accounts for minimum, maximum, rate of change, frequency, and duration of temperatures (Bartholow 1999).

As more instream flow studies are conducted to assess physical habitat, the need and realization to also assess thermal habitat is growing. The Instream Flow Incremental Methodology promotes the Physical Habitat Simulation System model (PHABSIM) for predicting microhabitat conditions and the Stream Network Temperature model (SNTEMP) and Stream Segment Temperature model (SSTEMP) for predicting temperature (Bovee 1996). However, there are multiple temperature models available. Choosing a model that will predict accurately, is suitable for the river system of interest, and is capable of answering one's study objectives is an important task. The lack of reviews and performance evaluations on temperature models causes uninformed model selection. Lack of such information and the daunting task of learning how to use a model that may have inadequate documentation may result in contracting work to consulting firms or not taking advantage of models at all.

Choosing a particular model is important because nearly all available temperature models are different from one another. Some models only predict on a reach scale while others are capable of predicting over a dendritic network of streams. One model may be steady-state predicting daily temperature and another dynamic predicting hourly temperatures. A model may or may not incorporate riparian shade or be capable of predicting additional water quality parameters such as DO or coliforms. Some models have self-study or training courses and others simply have a user manual. Knowledge of these types of model capabilities as well as information on model predictive ability, parameter sensitivities, data requirements, and data collection methods requires understanding to make an informed model choice. Therefore, the objective of this paper is to provide information on parameter collection, model predictive ability, parameter sensitivity, and advantages & shortcomings of three stream temperature prediction models to enable managers to make informed model selections.

METHODS

Description of Study Sites

The Smith River flows through Patrick, Franklin, and Henry Counties in Virginia and is a sixth-order regulated tributary in the Roanoke Basin. Philpott dam located in Henry County creates a tail-water fishery in the Smith River (Figure 2.1). The Smith River tailwater (SRT) extends 32 river kilometers (rkm) from Philpott dam to Martinsville dam. The drainage area above Philpott dam is 549 km^2 and above Martinsville dam is 968 km^2. Philpott dam forms a 1,166 hectare reservoir for flood control, power generation, and recreation. The dam is operated by the U.S. Army Corps of Engineers and generates electrical power on a hydropeaking schedule. This schedule results in weekday flow fluctuation from approximately 1.3 to 36.8 cms in 30 minutes. For the year 1999 the U.S. Geological Survey (USGS) gage (#02072000) near the Philpott dam recorded a minimum discharge of 0.35 cms, a maximum of 42.2 cms, and an annual mean discharge of 5.0 cms. Due to hypolimnetic releases, water temperature in the SRT is cold (8-17°C summer monthly means) enabling stocked rainbow trout (*Oncorhynchus mykiss*) and a naturalized population of reproducing brown trout (*Salmo trutta*) to persist. However, the large weekday flow fluctuations result in hourly water temperature changes up to 8°C. Lower sections of the river achieve daily maximum temperatures of 24°C. The SRT was chosen for study because the Virginia Department of Game and Inland Fisheries (VDGIF) is interested in determining alternative flow regimes that may create more suitable thermal regimes and habitat for trout.

Back Creek is located in southern Roanoke County, Virginia and is also in the Roanoke River drainage basin (Figure 2.1). Back Creek is 42 km in length, has a

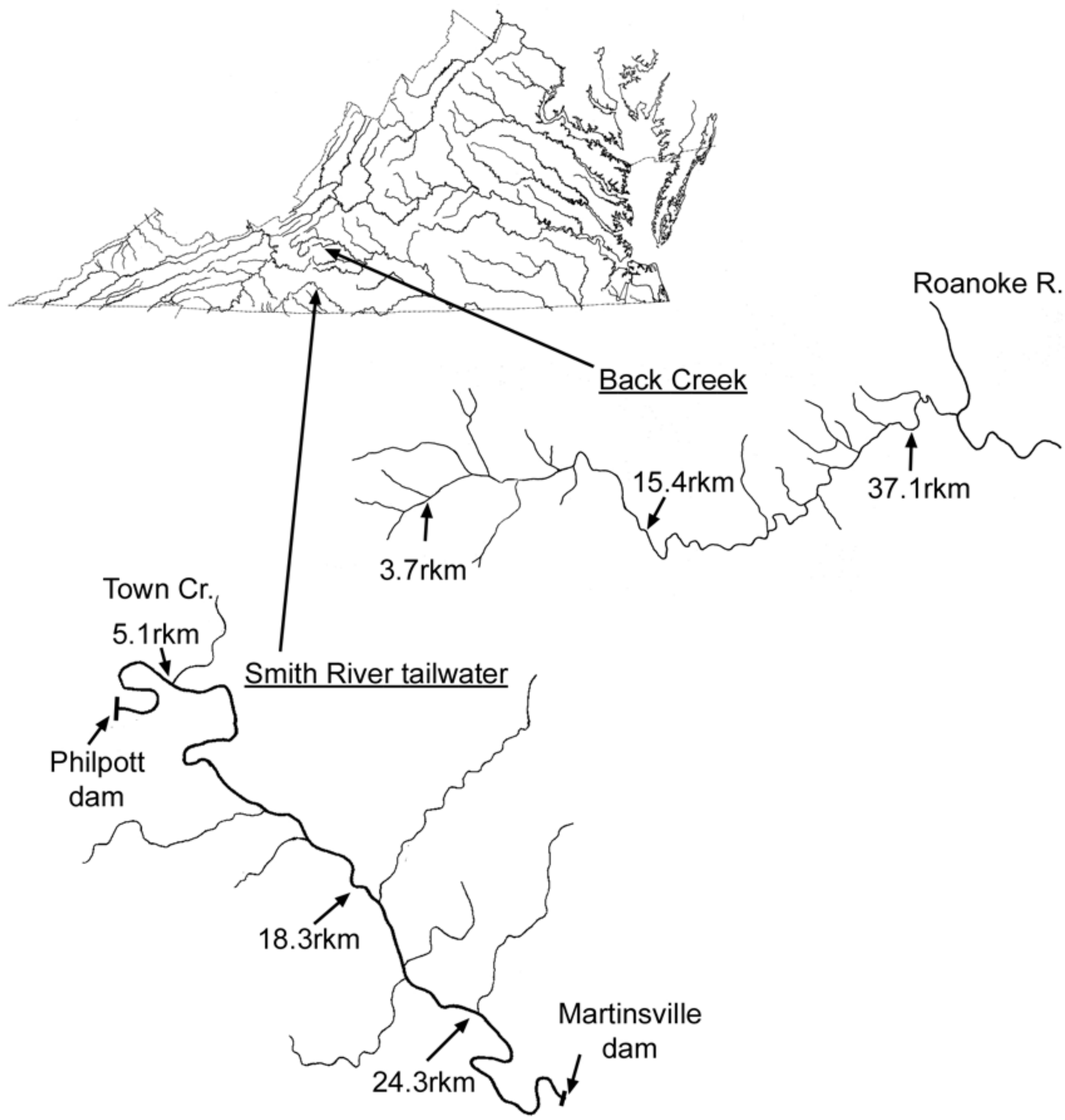


Figure 2.1. Location of Back Creek and Smith River tailwater in southwestern Virginia. River kilometer (rkm) locations of measured temperature compared to model predictions.

watershed area of 153.8 km^2, and is an unregulated tributary (Hambrick 1973). Channel width ranges from 9-15 m near the mouth and 2-6 m at the headwaters. For the year 1999 the USGS gage near Dundee, VA (#02056650) recorded a minimum discharge of 0.04 cms, a maximum of 22.98 cms, and an annual mean discharge of 0.75 cms. Back Creek contains primarily warm-water fish species (Table 2.1). Monthly average summer minimum water temperatures (1999 and 2000) were 17°C, maximums were 28°C, and means were 22°C. Monthly average winter minimum water temperatures (1999 and 2000) were 0.2°C, maximums were 10°C, and means were 4°C. Back Creek is located near Roanoke City and thus much of its watershed may be urbanized. Therefore, there is interest in assessing Back Creek's thermal regime prior to increased degradation. This would allow development of mitigation measures to prevent the creek from further thermal alteration and/or return the creek to its unaltered thermal regime.

Description of Models

Models selected for study were the Stream Network Model (SNTEMP) developed by the U.S. Fish and Wildlife Service, the Enhanced Stream Water Quality Model (QUAL2E) developed by the U.S. Environmental Protection Agency, and the Tennessee Valley Authority River Modeling System which consists of the ADYN flow model and the RQUAL water quality model developed by the Tennessee Valley Authority (TVA) (Table 2.2). Models SNTEMP and QUAL2E were selected because they can easily be obtained for free via the Internet, are well documented with available training, and their use is prevalent in the literature (Theurer et al. 1984; Lifton et al. 1985; Brown and Barnell 1987; Wilson et al. 1987; Bartholow 1989; Waddle 1989; Sullivan et al. 1990; Bartholow 1991; USEPA 1995; Bartholow 1997; Zedonis 1997). The ADYN & RQUAL model was chosen because it is one of few available dynamic models and is currently being used by the TVA in the southeastern region of the United States (TVA 1995). Other temperature models were not considered because they typically were either not publicly available (e.g. models developed by Army Corps of Engineers) or not widely represented in the literature (e.g. a model developed by and presented in a single study). These models were developed in the United States and are therefore assumed to work in temperate latitudes of the Northern Hemisphere. Evidence presented in the literature

Table 2.1. Fish species present (X) in the Smith River tailwater and Back Creek in Virginia ordered by family (Orth 2001; Stancil 2000).

Common Name	Scientific Name	Smith River	Back Creek
white sucker	Catostomus commersoni	X	X
Northern hogsucker	Hypentelium nigricans	X	X
Roanoke hogsucker	Hypentelium roanokense		X
golden redhorse	Moxostoma erythrurum	X	X
v-lip redhorse	Moxostoma pappillosum		X
black jumprock	Scartomyzon cervinus	X	X
redbreast sunfish	Lepomis auritus	X	X
green sunfish	Lepomis cyanellus	X	
bluegill sunfish	Lepomis macrochirus	X	
smallmouth bass	Micropterus dolomieu	X	X
largemouth bass	Micropterus salmoides	X	X
central stoneroller	Campostoma anomalum	X	X
rosyside dace	Clinostomus funduloides	X	X
cutlips minnow	Exoglossum maxilingua	X	
white shiner	Luxilus albeolus	X	X
crescent shiner	Luxilus cerasinus	X	X
rosefin shiner	Lythrurus ardens	X	X
bluehead chub	Nocomis leptocephalus	X	X
golden shiner	Notemigonus crysoleucas	X	
spottail shiner	Notropis hudsonius	X	
swallowtail shiner	Notropis procne		X
mtn. redbelly dace	Phoxinus oreas	X	X
blacknose dace	Rhinichthys a. atratulus		X
creek chub	Semotilus atromaculatus		X
yellow bullhead	Ameiurus natalis		X
margined madtom	Noturus insignis	X	X
fantail darter	Etheostoma flabellare	X	X
johnny darter	Etheostoma nigrum		X
riverweed darter	Etheostoma podostemone	X	X
Roanoke logperch	Percina rex	X	
Roanoke darter	Percina roanoka	X	X
rainbow trout	Oncorhynchus mykiss	X	X
brown trout	Salmo trutta	X	X

Table 2.2. Summary of capabilities of the SNTEMP, QUAL2E, and RQUAL model.

Model Capabilities	SNTEMP	QUAL2E	RQUAL
Prediction Time-Step	Daily	Daily	Hourly
Able to predict over a Reach vs. Basin network	Basin	Basin	Basin
Predict multiple water quality parameters	No	Yes	Yes
Predict under alternative shade scenarios	Yes	No	No
Predict maximum water temperature	Yes	No	Yes
User-Model Interface	MS-DOS	Windows	DOS (for input files) with Windows Interface
Documentation available in addition to the user manual	Yes	No	No
Training course available	Yes	Yes	No

suggests that stream temperature models do not behave differently in various geographical locations because their algorithms are based on physical processes (Waddle 1989; Sullivan et al. 1990; Bartholow 1997; LeBlanc et al. 1997). Physical process models are based on energy balance equations, which predict temperature as a function of stream distance and environmental heat flux. If a model designed for the northern hemisphere were used in the southern hemisphere or at very high or low latitudes, the model's algorithms should be examined to insure it will correctly model solar radiation and shade variables. The SNTEMP, QUAL2E, and RQUAL model are capable of modeling temperature in streams/rivers throughout a watershed (i.e., basin model). The QUAL2E and RQUAL model can also predict water quality constituents other than water temperature. The QUAL2E model can predict 15 water quality constituents including DO, nitrogen (organic, ammonia, nitrite, nitrate), phosphorous (organic and dissolved), algae as Chlorophyll a, an arbitrary non-conservative, carbonaceous biochemical demand (CBOD) (ULT or 5-day), up to three conservative minerals, and coliform bacteria (Brown and Barnell 1987; USEPA 1995; Bartholow 1997). The RQUAL model can predict DO, CBOD, and nitrogenous biochemical oxygen demand (NBOD) (TVA 1995).

The QUAL2E model does not incorporate the influence of shade on water temperature, whereas SNTEMP and RQUAL do. Thus, QUAL2E is not helpful in assisting shade management questions and may be better at modeling large wider rivers, which have less shade influence than small mountainous streams (USEPA 1995). The SNTEMP and QUAL2E models are steady-state models, thus assuming flow is constant over a 24 hour period due to their input and output being based on daily averages. Daily averaged input reduces data requirements and averages out daily variation, which can either help or hinder the model from providing accurate daily mean predictions depending on meteorological conditions (e.g. clear day/cloudy night looks the same to the model as cloudy day/clear night) (Bartholow 1997). If daily variations are dramatic enough to be considered important to fish survival, a model capable of predicting temperature multiple times per day should be used, but for most management situations daily averages are suitable. QUAL2E can also function in a quasi-dynamic mode, which still assumes steady flow, but accounts for the influence of diel climate fluctuation through input of meteorological parameters at three hour time steps (USEPA 1995). If the steady flow assumption is broken the model's ability to accurately predict temperature may decline. The dynamic ADYN model is capable of modeling flows fluctuating within a 24 hour period due to frequent input parameters (e.g. hourly) (TVA 1995).

Data Collection

The data required to develop model input parameters was measured in the field and collected from existing sources (e.g. weather services, USGS gage stations). Certain parameters were measured at multiple locations to represent homogeneous stream sections (i.e., reaches). One reach is distinguished from another by differences in slope, flow, width, riparian corridors, and neighboring topography. Obtaining measurements for each reach over the study stream enables the model to account for longitudinal stream variability. Parameters for each model can be divided into five main categories: stream geometry, shade, meteorological, discharge, and water temperature parameters (Table 2.3).

Data collection of continuous parameters (e.g., meteorological, water temperature, and discharge) extended from July 1999 through February 2001. The SNTEMP and QUAL2E model were developed to predict temperature in Back Creek and the SRT, whereas RQUAL was only developed for the SRT. The RQUAL model was not used for Back Creek because this system was assumed to meet the steady state flow assumption of SNTEMP and QUAL2E, thus a dynamic model was unnecessary. The models were developed from 0.7 rkm to 24.3 rkm below Philpott dam in the SRT and from 0.0 rkm to 38.0 rkm below the Back Creek headwater.

The following stream geometry and shade parameters were measured at transects perpendicular to flow within representative reaches: wetted stream width, topographic altitude, vegetation height, vegetation offset, vegetation crown, and vegetation density. To ensure parameters measured in each representative reach were adequately represented regardless of reach length and variability I conducted a pilot survey. The pilot survey entailed sampling parameters at 20-25 randomly placed transects within a 1-2 rkm representative reach that possessed the greatest amount of parameter variability as estimated from aerial photographs, topographic maps, and field visits. This approach

Table 2.3. Parameters used (X) by the QUAL2E, SNTEMP, and ADYN & RQUAL models.

Parameters	QUAL2E	SNTEMP	ADYN & RQUAL
Stream Geometry and Time Parameters			
Mean basin elevation	X		
Reach elevations	X	X	X
Mean basin latitude	X	X	X
Mean basin longitude	X		X
Standard meridian	X		
First and last day of simulation period	X	X	X
Distance of modeled reaches	X	X	X
Stream width coefficient		X	
Stream width exponent		X	
Manning's n	X	X	X
Travel time		X	
Cross-sectional area at nodes			X
"Full channel" depth (i.e., bankfull)			X
Shade Parameters			
Stream width		X	X
Channel azimuth per stream reach		X	X
Topographic altitude		X	
Vegetation height		X	X
Vegetation offset		X	X
Vegetation crown		X	
Minimum and maximum vegetation density		X	
Time of morning fog lift			X
Meteorological Parameters			
Air (dry bulb) temperature	X	X	X
Wet bulb temperature	X		
Relative humidity		X	
Solar radiation		X	X
Percent possible sun or cloudiness	X	X	X
Wind speed	X	X	X
Ground reflectivity		X	
Dust coefficient	X	X	
Evaporation coefficient	X		X
Mean annual air temperature		X	
Barometric pressure	X		X
Dewpoint temperature			X
Fraction of drybulb/dewpoint depression by which drybulb is cooler over shaded water			X

Table 2.3 (continued). Parameters used (X) by the QUAL2E, SNTEMP, and ADYN & RQUAL models.

Parameters	QUAL2E	SNTEMP	ADYN & RQUAL
Flow Parameters			
Depth exponent	X		
Depth coefficient	X		
Velocity exponent	X		
Velocity coefficient	X		
Discharge	X	X	X
Water/Streambed Temperature Parameters			
Water temperature at the modeled reach start-point	X	X	X
Streambed thermal gradient or diffusivity		X	X
Ground temperature (surrogate for lateral inflow temperature)		X	X
Effective channel bed thickness (upper layer) for bed heat conduction			X
Effective channel bed thickness (deep layer) for bed heat conduction			X
Bed heat storage capacity			X
Fraction of solar radiation absorbed in surface 0.6 m of water			X
Albedo of bed material			X
Fraction of solar radiation absorbed by shaded water			X

ensured that the determined sample size (i.e., number of transects) per length of stream would be appropriate for all reaches along the study stream. Sample size was calculated by taking five of the 20-25 sampling units (SU) at random and calculating the arithmetic mean. Next, another five randomly selected SU were added to the first five and a mean calculated for 10 SU. This continued until means were calculated for 5, 10, 15, 20, and 25 SU. The means were plotted against sample size and the sample size where the means cease to fluctuate ±5% determined the suitable sample size (Simonson et al. 1994). This method resulted in 168 transects from 2.7-37.0 rkm in Back Creek that were sampled for stream width and shade. In the SRT, 102 transects from 0.5-24.0 rkm were sampled. The location of each transect within a representative reach was chosen at random using a uniform distribution random number generator. Sampling locations were marked on a topographic map and then located in the river.

Stream Geometry Parameters

Elevation, latitude, longitude, and rkm distances were determined from a topographic map. Elevation at the top and bottom of the stream network is required for model calculations regarding slope (which results in frictional heat), atmospheric pressure, and depth of the atmosphere (which influences solar radiation strength). The intensity of the sun varies with latitude and time of year, therefore latitude and days of the year are needed for the model to correctly assess solar radiation and define the time periods for simulation. Distance from the most downstream (endpoint) and upstream (start-point) locations were determined so the model could calculate heat transport according to exposure time.

Wetted width combined with distance allows determination of the surface-area over which heat flux can occur. Surface-area is a representation of the air-water and ground-water interfaces where heat flux takes place. The wetted width of a stream changes as flow increases or decreases, therefore, if surface area is to change accordingly with stream flow a width-flow relationship must be developed. The SNTEMP model uses either a constant width by using measured stream widths or a varying width, which was used in this study, by calculating width coefficients and exponents according to the equation, $W = a Q^{b}$, where W = width, Q = discharge, and a and b = empirically derived coefficients (Bartholow 1989). For Back Creek the width-flow relationship was developed by measuring wetted width and flow once in August 2000, January 2001, and March 2001 (to encounter a range of flow levels) at four locations (3.3, 10.5, 25.0, and 38.0 rkm). For the SRT baseflow wetted width was measured and peakflow width was estimated using the high flow mark on the banks at 102 random locations. Discharge was measured with a Price AA current meter and/or obtained from a USGS gage (USGS). Width and discharge data were manipulated according to the methods presented in Bartholow (1989) to determine the width coefficient and width exponent.

Channel cross-sectional profiles required by ADYN, were measured using standard surveying techniques with a level, stadia rod, and tape measure at 37 transects throughout the SRT. Transects were located in key hydraulic locations to resolve major pools and riffles in the model channel geometry. Bankfull elevation for each transect was obtained from a topographic map.

Manning's n is a unit-less measure of streambed and channel roughness, which is not easily measured and is typically estimated from developed tables. Manning’s n is not constant because roughness changes with discharge, but SNTEMP assumes it as constant. A value of 0.35 was used for SNTEMP and QUAL2E. The TVA model can modify Manning’s n according to discharge by entering an adjustment factor and can account for multiple Manning’s n values laterally across the channel. A value of 0.1 was used to account for near bank retardance and 0.03 for the main channel.

Shade Parameters

Shade varies daily and yearly due to the position of the sun in the sky. Factors that influence the amount and intensity of shade on a stream are streamside vegetation height, crown size, offset from the stream, and density, as well as orientation of the stream (azimuth), latitude, time of year, and topographic altitude. The vegetation height, offset, and crown parameters enable SNTEMP and RQUAL to consider shade created by riparian vegetation.

Azimuth is the orientation of the stream with respect to a north-south position. This orientation value allows the model to account for shade percentage dynamics as the sun follows an east to west solar path. Azimuth for each reach was determined from a topographic map.

Topographic altitude is the angle from the stream surface to the topographic horizon and is used by SNTEMP to determine topographic shading values. Topographic altitude was measured for both sides of the stream from the middle of the stream with a clinometer at each transect.

Vegetation height is an average maximum height of the overstory shade producing vegetation as measured from the water surface to the top of the vegetation, which includes the stream bank height (Theurer et al. 1984; Bartholow 1989). The height is calculated from

$$H = D * Tan(A)$$

where

H = height
A = angle from the water's surface to the top of the vegetation (measured with clinometer)
D = distance from vegetation to location where observer measured A (measured with tape measure) (Bartholow 1989).

The vegetation inline with the random transect on each side of the stream was measured. Care was taken to ensure the top of the tree was sighted with the clinometer and not the outer crown of the tree, which would result in overestimation of the height. To prevent this, sightings were taken at a greater distance (≥20 m) from the tree where possible.

Vegetation offset is an average distance from the trunks of the predominant shade producing vegetation to the water's edge. Vegetation crown is an average diameter of the predominant shade-producing canopy. Offset and crown was primarily visually estimated for efficiency and was periodically measured to verify estimations.

Vegetation density is an average screening factor (0-100%) of shade producing vegetation as measured near the stream surface. This parameter enables SNTEMP to account for the quantity and intensity of light reaching the stream. A spherical densiometer is one method to determine the amount of overhead cover (i.e., view-to-sky %). This method does not accurately represent vegetation density because it measures only in the vertical plane, which does not account for filtering along the path of the sun

(Bartholow 1989). It also only measures whether there is or is not shading, while ignoring light intensity. The method chosen employed a light meter and an 18% photographic gray card (Bartholow 1989). The gray card allows measurements from a standardized reflective surface and was held parallel to the water surface with the gray surface facing upward. The light meter sensor was held approximately five centimeters above and facing the gray card and the number of footcandles was recorded. This measurement was made in the shade and sun for both sides of the stream at each random transect during the summer season. The vegetation density was calculated with the following equation: ((footcandles in sun – footcandles in shade)/footcandles in sun)*100. For winter temperature predictions when leaves are off a vegetation density value of 10% was used (J. Bartholow, U.S. Geological Survey, personal communication) and verified with field measurements. Weather conditions were recorded at the time of each measurement and a discrepancy was found between measurements made during sunny versus heavy overcast skies. To correct this, an adjustment factor was calculated by dividing the average of the measurements taken during sunny skies by the average of the measurements taken during heavy overcast skies.

Meteorological Parameters

Air temperature, relative humidity, and dewpoint was measured onsite with data loggers at Back Creek and the SRT. Loggers were mounted to trees within the riparian zone approximately three to 10 vertical meters above the stream in areas representative of the overall length the study reach. To prevent vandalism, evaporative cooling, and/or an insulating effect during snow and ice storms, loggers were housed in small, well-ventilated, camouflaged PVC coverings. Air temperature was measured hourly at two locations from November 1999 to February 2001 in both Back Creek and the SRT. The logger located near the middle of the modeled stream length also measured humidity and dewpoint. The second logger, located near the upstream end of the modeled stream length provided supplementary data for comparison and if the first logger failed. The temperature loggers were downloaded monthly to minimize data loss should the logger fail. The primary logger was an Onset® HOBO H8 Pro data logger, which measured temperatures ranging from -30°C to +50°C with accuracy of ±0.2°C at +21°C and humidity ranging from 0% to 100% with accuracy of ±3%. The backup logger was an Onset® StowAway Tidbit, which measure temperatures ranging from -20°C to +50°C with accuracy of ±0.4°C at +21°C.

Hourly air temperature, wet-bulb temperature, dewpoint, barometric pressure, wind speed, and cloudiness from July 1999 to February 2001 were downloaded via the National Climatic Data Center (NCDC) from the nearest weather station that recorded and maintained hourly data (Roanoke Regional Airport) (17 km from Back Creek and 74 km from the SRT) (NCDC). Solar radiation values were obtained from Bluefield State College, Bluefield, West Virginia (124 km from Back Creek and 144 km from the SRT), which is part of the Cooperative Networks For Renewable Resource Measurements (CONFRRM). Percent possible sun used by SNTEMP, was calculated as 100 - % cloud cover. The QUAL2E and RQUAL models use cloudiness measured in tenths of cloud cover. Cloudiness data available from NCDC is formatted as descriptive sky conditions based on fractional coverage, which required conversion to decimals. Sky conditions were reported and converted to a decimal value as follows: clear sky (0/8) = 0.0, few (0/8-2/8) = 0.25, scattered (3/8-4/8) = 0.5, broken (5/8-7/8) = 0.75, overcast (8/8) = 1.0. If sky conditions varied with altitude multiple conditions were reported and the highest condition was used.

Discharge Parameters

Discharge data was obtained from established gaging stations (USGS). The models require discharge at the headwater or dam as well as contributions from large tributaries. Initial discharge for the SRT was obtained from the Philpott gage and for Back Creek the modeled reach began at its headwater with a discharge of zero. SNTEMP manuals suggest that only tributaries altering the temperature of the main-stem by five percent be included (Bartholow 1989, 1997). Comparison of data logger recorded temperatures in three tributaries of Back Creek and two tributaries of the SRT to temperatures in the main-stem determined that only the Town Creek tributary of the SRT altered temperatures by five percent. Therefore, Town Creek was modeled as a separate lateral inflow. Estimation of Town Creek discharge was calculated by taking the difference between the USGS Bassett gage (#02072500) 4.7 rkm downstream and the

USGS Philpott gage 5.4 rkm upstream and apportioning for small tributaries occurring over the 10.1 rkm. Philpott gage values used were those recorded three hours prior to power generation/flow release, which avoided ramp down discharge values and allowed at least 12 hours for peakflows from the previous day to return to baseflow. Bassett gage values used were those recorded two hours after the Philpott gage value, which accounted for the two hour travel time at baseflow from the Philpott to Basset gage. A distributed lateral inflow from the Bassett gage to the end the SRT modeled reach was estimated by taking the difference between the Martinsville gage (#02073000) and the Bassett gage. The Martinsville gage, 10.0 rkm downstream of the modeled reach endpoint, is below a dam at Martinsville, VA. Because the Martinsville gage is below a hydropower dam, weekly averages of flow were used to average out the peak and baseflows. Water withdrawal data for municipalities and industry along the SRT was obtained from the Virginia Department of Environmental Quality (DEQ). All withdrawals were <0.35 cms and were considered negligible. Back Creek lateral inflows were assumed to be the discharge at the modeled reach endpoint (38 rkm) evenly distributed from 0 rkm to 38 rkm.

The QUAL2E model uses an exponent and coefficient for velocity and depth to vary depth over a range of flow. The equation is

$$V = aQ^b \text{ and } D = cQ^d$$

where

V = velocity
D = depth
Q = discharge
a & b and c & d = empirically derived coefficients and exponents (Brown and Barnwell 1987).

The depth coefficient and exponent were determined by using stage-discharge rating tables available for each USGS gage. The velocity coefficient and exponent were determined by calculating the cross-sectional channel area at base and peakflow, which when divided by discharge results in velocity. The natural log of stage versus discharge and velocity versus discharge were graphed and a best-fit line plotted. From the equation for the best-fit line, y=mx+b, m = exponent and e^b = coefficient.

Water Temperature Parameters

The models required starting water temperature data at the upstream location where modeling began if there was an upstream discharge. To obtain accurate water temperature data, submersible temperature loggers were secured in locations of continuously moving water. Three Onset® StowAway XTI temperature loggers (measurable range -4°C to +37°C) were secured with airline cable in Back Creek at 3.7, 15.4, and 37.1 rkm to measure temperature hourly from July 1999 to February 2001. Hourly temperature data in three tributaries of Back Creek from March to June 1999 was obtained (R. Sponseller, Biology Department, Virginia Tech, personal communication). Seven Onset® Optic StowAway temperature loggers (measurable range -4°C to +37°C, accuracy ±0.2°C at +21°C) were secured with airline cable or rebar in the SRT at 0.7, 2.7, 5.1, 5.6, 10.2, 18.3, and 24.3 rkm to measure temperature half hourly from July 1999 to February 2001. An Onset® StowAway Tidbit temperature logger (measurable range -20°C to +50°C, accuracy ±0.4°C at +21°C) measured temperature every 30 minutes in Town Creek (0.5 rkm from confluence) from January 2000 to February 2001 and in Reed Creek (0.3 rkm from confluence) from February 2000 to February 2001, which are tributaries of the SRT. Temperature loggers were placed in locations of flowing water, ~0.3-0.75 meters deep, and in shaded areas where possible. Data from the temperature logger at the most upstream location was for model input and data from temperature loggers placed downstream were for model calibration and validation. Subzero temperatures recorded by loggers during the winter (typically -0.1°C to -0.2°C) were assumed legitimate (Webb and Walling 1993). All loggers were downloaded monthly to minimize potential data loss and at that time the stream's water temperature was measured with a hand-held thermometer to verify proper functioning of the logger. Additionally, all data loggers recording water temperature were tested half-way through the study to ensure proper function. Data loggers and ASTM thermometer were subjected to a cold (ice-bath) and room temperature test then temperatures were compared.

Multiple linear regression was used to fill water temperature data lost due to data logger failure or data required prior to a temperature logger deployment. Data from the month before and after the missing data was used in most cases to develop the regression.

This enabled a regression using data most similar to the seasonal characteristics of that particular year. In two cases this method was not possible due to data unavailability, therefore data from the previous year for the same time period was used. Parameters used in the regressions were water temperature (nearest data logger to site of faulty/lost logger), air temperature, dewpoint temperature, relative humidity, barometric pressure, wet-bulb temperature, wind speed, and cloudiness. Not all of these predictors were used in each regression. Six cases required regression-predicted temperature for the following number of days: 5 (0.58 adj. r^2), 60 (0.76), 38 (0.78), 37 (0.89), 209 (0.91), and 70 days (0.98).

Ground temperature influences conduction at the streambed-water interface and is a surrogate for groundwater temperature in SNTEMP. Ground temperature is typically assumed to be the same as the mean annual air temperature (Bartholow 1989, 1997). Hourly ground temperature data was obtained from the Virginia Tech College Farm Operation (Whitethorne, VA) 57 km from Back Creek and 83 km from the SRT (VAES).

Model Run-File Development

The SNTEMP and ADYN & RQUAL models are MS-DOS based requiring input data in the form of text files (i.e., *.txt). The model delineates what each number or character in the text file represents based on record number (i.e., line) and field (i.e., column) as shown in the user manuals (Theurer et al.1984; Bartholow 1989; Hauser and Walters 1995; Bartholow 1997). The QUAL2E model is Windows based and data is entered directly into rows and columns.

Building model-run text files was facilitated by using templates for data input with Excel. The templates were then saved as spaced delimited files (*.prn) and for ADYN & RQUAL the file name extension was changed to that designated by the model. Model files were developed for the prediction of stream temperature for three-month time periods, which correspond with the four seasons. Seasons were delineated based on climate local to the study streams, not solstices and equinoxes. Monthly air temperature fluctuation (i.e., difference between monthly high and low temperature) averaged over 20 years (1980-1999) allowed seasonal delineation based on monthly variation as spring (March, April, May), summer (June, July, August), fall (September, October, November), and winter (December, January, February). The SNTEMP model predicts mean daily temperature and RQUAL allows the prediction interval to be chosen. A one-hour prediction interval was chosen so that 24 hourly predictions could then be averaged for comparison with the SNTEMP and QUAL2E predictions. Limitations in the QUAL2E model require it to be run one day at a time.

Model Calibration

Each model was calibrated for individual seasons beginning in July 1999 and ending in May 2000. Model calibration consisted of adjusting input parameters until predicted water temperature closely matched the measured water temperature. Calibration adjustments that improved temperature predictions were determined by graphing the predicted and measured temperature versus time at multiple longitudinal river locations and visually assessing trends. During this ‘trial and error’ type process of adjusting parameters, the graphical analysis allowed predicted and measured temperature correspondence for all time periods to quickly be assessed. When predictive improvements could not be discerned visually, numerical analyses (e.g. average residual error) were used. The calibration process was ended when the predetermined error level was met (<10% predictions exceed the measured temperature by 4°C).

Parameters Adjusted During Calibration

To calibrate RQUAL for the SRT the following parameters were adjusted: time of fog lift, fraction of solar radiation absorbed by shaded water (SHSOL), fraction of drybulb/dewpoint depression by which drybulb is cooler over shaded water (SHDBT), lateral inflow temperature, air temperature, and dewpoint. A fog lift time of 12:00 pm was used for summer and 10:00 am for all other seasons based on personal observations. A SHSOL value of 0.05 was used for summer during leaf-out, 0.2 for fall and spring during leaf-fall and leaf-in, and 0.5 for winter during leaf-off. A SHDBT value of 1.0 was used for spring and summer, and 0.0 for fall and winter. Lateral inflow temperatures used for Town Creek for all seasons were those measured in the creek. Mean annual air temperature (13.6°C) was used for lateral inflows from the modeled reach start-point to 10 rkm downstream for all seasons. Lateral inflow temperature used from 10 rkm to the end of the modeled reach (24.3 rkm) was mean annual air temperature for Fall and Spring, and the measured temperature of Reed Creek (confluence with SRT at 19.4 rkm) for summer and winter. To reduce under-prediction during winter, negative air and dewpoint temperatures were increased to zero.

SNTEMP was calibrated for the SRT by adjusting the width A coefficient and B exponent, shade values, and mean annual air temperature. The calculated A coefficient of 31.4 and B exponent of 0.036 were adjusted to 10.0 and 0.2 from 0.5-19.0 rkm; from 19.0-24.3 rkm calculated values were used. The SNTEMP model can accept two shade values to simulate leaf-fall or leaf-in according to the dates being modeled, for example, during spring a low shade value before leaf-in occurs and a higher value for after leaf-in could be used. Therefore, measured shade values were used for the low value during summer (because there is no leaf change) and the high value during spring and fall. A shade value of 0.1 (i.e., 10%) was used for the low value during fall, spring, and winter (same shade calibrations were used for Back Creek with Back Cr. shade data). Higher predictive ability was achieved when monthly soil temperatures were used instead of mean annual air temperature for fall, winter, and spring; mean annual air temperature was used for summer.

To calibrate SNTEMP for Back Creek, shade values and mean annual air temperature were adjusted. The measured shade values for the east and west side of the upstream reach was increased from 0.24 and 0.29 to 0.70. Monthly soil temperatures were used instead of mean annual air temperature for summer, fall, and spring. A temperature of 8°C was used for winter.

QUAL2E calibration for the SRT involved adjusting the evaporation coefficient (AE) and lateral inflow temperature. An AE of 0.000005 was used for summer and winter, 0.00001 for fall, and 0.000006 for spring. Mean annual air temperature was used for the lateral inflow temperature for summer, fall, and spring. For winter the monthly soil temperatures were used.

To calibrate QUAL2E for Back Creek, AE and lateral inflow temperature were adjusted. An AE of 0.00003 was used for summer and winter, and 0.00004 for fall and spring. The lateral inflow temperature parameter from 0-4 rkm used mean annual air temperature for summer and September of fall, and used monthly soil temperatures for

October and November of fall, winter, and spring. The lateral inflow temperature parameter from 4-38 rkm used mean annual air temperature for spring and used monthly soil temperatures for summer, fall, and winter.

Model Evaluation

Model Predictive Ability

Predictive ability was assessed with multiple methods to evaluate model-predicted temperatures against measured temperatures. The primary methods used were graphical (predicted and measured temperature vs. time), average residuals (difference between predicted and measured temperature), residual plots, percentage of predictions within 1, 2, and 3ºC of measured temperature, and degree-day accumulation (summation of daily temperature predictions). These methods were employed annually, seasonally, and/or at multiple longitudinal reach locations. For SNTEMP and RQUAL, predictive ability using air temperature and relative humidity (SNTEMP) or dewpoint (RQUAL) collected onsite versus offsite was also assessed.

Model Validation

Graphical and statistical analyses were used to determine model validity. The graphical method involved graphing the calibrated predictions along with the measured temperatures over time. Time periods of calibrated predictions were summer 1999, fall 1999, and winter 1999/2000. The calibrations used to predict temperature during these time periods were then used to predict temperature with a second independent dataset from summer 2000, fall 2000, and winter 2000/2001. Predictions from summer 2000, fall 2000, and winter 2000/2001 were graphed along with measured water temperature from the same time period. Validation was assessed by visually comparing the trend of the predicted and measured temperature over time between the graph of the calibrated time period to that of the graph for the corresponding time period using the independent dataset, for example, summer 99 compared to summer 00. If the trend of the predicted and measured temperature for the independent dataset time period matched in closeness and similarity to the calibrated time period, the model was deemed valid. This graphing process also enabled identification of any irregular temporal and spatial trends.

Additionally, residual plots were used to compare the distribution of error between seasons.

Statistical analyses to assess model validation involved using a one sided chi square test to test for difference ($P \leq 0.05$) between counts of absolute residuals (i.e., difference between mean daily predicted and measured water temperature) for the calibrated and independent dataset time periods. Absolute residuals used were those from the most downstream modeled point in Back Creek (37.1 rkm) and the Smith River (24.3 rkm). Counts were tested based on 2x2 contingency tables that separated residuals within the two compared seasons based on two predictive ability categories: suitable (0-4°C) versus unsuitable (>4°C), and optimal (0-2°C) versus acceptable (2-4°C). The equation to solve for the one sided chi square test statistic is

$$T = [N^{0.5}(AD-BC)]/[(A+B)(C+D)+(A+C)(B+D)]^{0.5}$$

Where A,B, C, D, and N within the contingency table are

	Suitable	Unsuitable	Total
Calibrated Season	A	B	A + B
Test Season	C	D	C + D
Total	A + C	B + D	N

(Conover 1971; Thomas and Bovee 1993).

Significance levels for T were determined from the standard normal distribution table where a T statistic of ≤ -1.65 (i.e., $P \leq 0.05$) rejects the null hypothesis (H_o) of no statistical difference between calibrated and test season counts (Conover 1971). Acceptance of H_o indicates acceptance of model validation. To avoid the bias of zero counts, +1 was added to all categories.

Sensitivity Analysis

Sensitivity analyses assess how much influence individual input parameters have on the predicted dependent variable (water temperature). Sensitivity analysis of the models was conducted by adjusting one parameter within realistic bounds while holding all other parameters constant and observing the impact of the change on the predicted temperature. Due to the large number of input parameters, performing a complete sensitivity analysis would be very time consuming. Therefore, a limited number of the measured parameters were chosen. Four parameters were chosen for analysis based on user experience gained during model calibration, and an analysis using the automated sensitivity analysis tool of the SSTEMP model (a Windows stream-reach version of SNTEMP) for Back Creek during January and July 1999. Because this sensitivity analysis is automated it quickly enabled an analysis of every parameter used by the SSTEMP model. This provided insight as to which parameters may be the most sensitive for SNTEMP. Additionally, the chosen parameters are typically measured and not estimated, therefore the location and accuracy of measurement may be important. The parameters chosen were air temperature, relative humidity (SNTEMP), wet-bulb temperature (QUAL2E), dewpoint (RQUAL), lateral inflow temperature, and starting water temperature. Parameters were adjusted by an increase and decrease of 3°C. Because relative humidity is a percentage, an average adjustment amount was determined through calculations using one year (September 1999 – August 2000, n=366) of air and dewpoint temperature data. The following equations were used:

Es=6.11*10.0**(7.5*Tc/(237.7+Tc))
E=6.11*10.0**(7.5*Tdc/237.7+Tdc))
RH=E/Es

where

Es = saturation vapor pressure
E = actual vapor pressure
Tc = air temperature (C)
Tdc = dewpoint temperature (C)
RH = relative humidity.

First, humidity was calculated without air temperature and dewpoint adjusted. Humidity was then calculated with air temperature increased and decreased by 3°C, and with dewpoint increased and decreased by 3°C. Conditions where air temperature was less than dewpoint were excluded. The difference between the non-adjusted and adjusted humidity was averaged. Depending on the adjustment, the average difference ranged from 12-14% and the maximum difference ranged from 19-20%; an adjustment of 15% increase and decrease was used to test the sensitivity of humidity in the SNTEMP model. For QUAL2E and RQUAL, any predictions corresponding to unrealistic cases where wet-bulb or dewpoint temperature exceeded air temperature from 3˚C adjustment were excluded. In addition, predictions corresponding with lateral inflow temperatures adjusted below zero and humidity adjusted above 100% were excluded from the analysis. Because QUAL2E will not accept any negative air, wet-bulb, lateral inflow, or starting water temperatures below zero any dates that met these conditions were excluded. The time periods assessed were fall 1999, winter 1999/2000, spring and summer 2000. For each time period, SNTEMP was run daily and RQUAL was run hourly. Because QUAL2E only simulates one day per model run, it was run for six days per time period; two days randomly chosen per month. The difference between the daily mean predicted and measured temperature (at the end of the modeled reach) after input parameter adjustment (i.e., sensitivity) was assessed as seasonal and annual averages.

<u>RESULTS</u>

Model Predictive Ability

Graphical analysis of measured and predicted temperature versus time for all seasons showed all predictions followed the general trend of the measured temperature (Figures 2.2-2.5). The difference between predicted and measured temperatures rarely exceeded 4°C (4°C exceedance for Back Creek: SNTEMP=8.2%, QUAL2E=3.0%; SRT: QUAL2E=1.4%, SNTEMP=0.8%, RQUAL=0.6%) and were sometimes due to out-of-phase predictions (i.e., date/time of predictions not in sync with date/time of measured temperatures) (Figure 2.6). Daily absolute residuals averaged annually revealed a decline in predictive ability (i.e., increase in residuals) with increased distance from the start-point of the modeled reach (Figure 2.7).

Among the models, predictive ability was similar with the exception of QUAL2E at 18.3 rkm on the SRT (Figure 2.7). Seasonal assessment revealed similar predictive ability among models with the exception of SNTEMP and QUAL2E during summer 1999 and QUAL2E during spring and summer 2000 at 18.3 rkm in the SRT (Figures 2.7-2.8). Poor predictive ability of SNTEMP and QUAL2E during summer 1999 (Figure 2.9) was due to out-of-phase (i.e., date/time of prediction not in sync with date/time of measured temperature) predictions (Figure 2.4). The QUAL2E model had poor predictive ability at

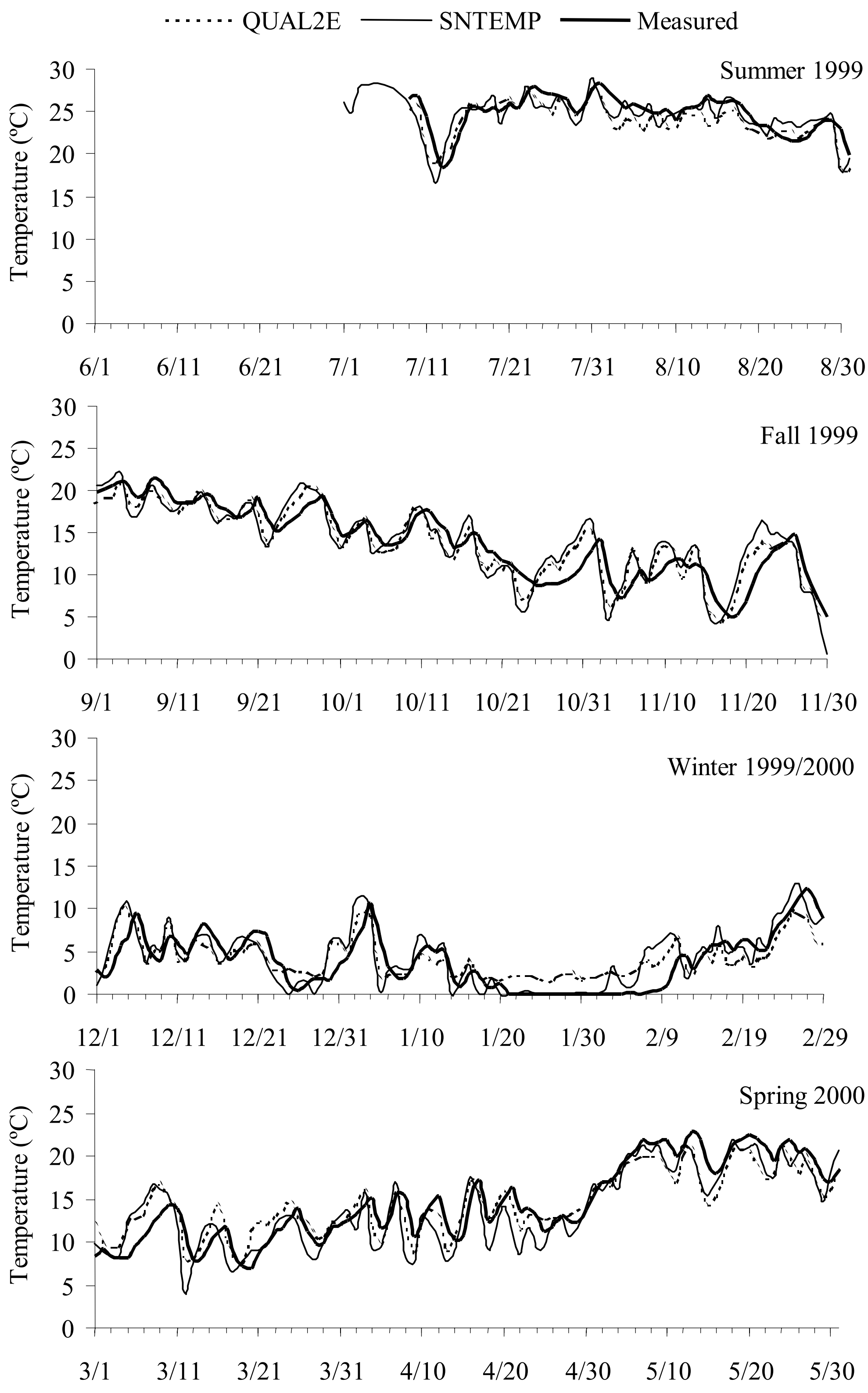


Figure 2.2. Daily QUAL2E and SNTEMP calibrated predictions and measured temperature (°C) at 37.1 rkm for summer and fall 1999, winter 1999/2000, and spring 2000, Back Creek, Virginia.

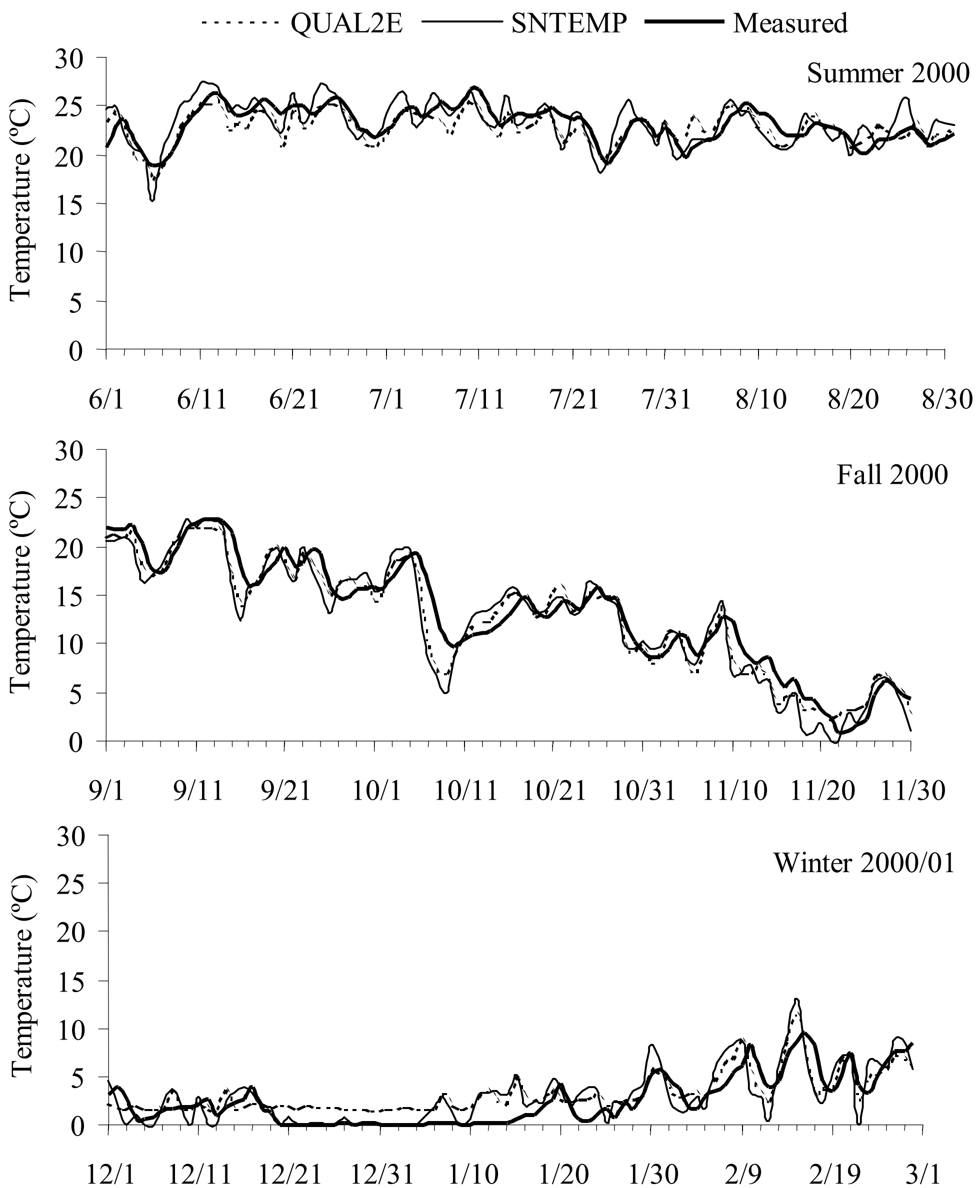


Figure 2.3. Daily QUAL2E and SNTEMP validation predictions and measured temperature (°C) at 37.1 rkm for summer and fall 2000, winter 2000/2001, Back Creek, Virginia.

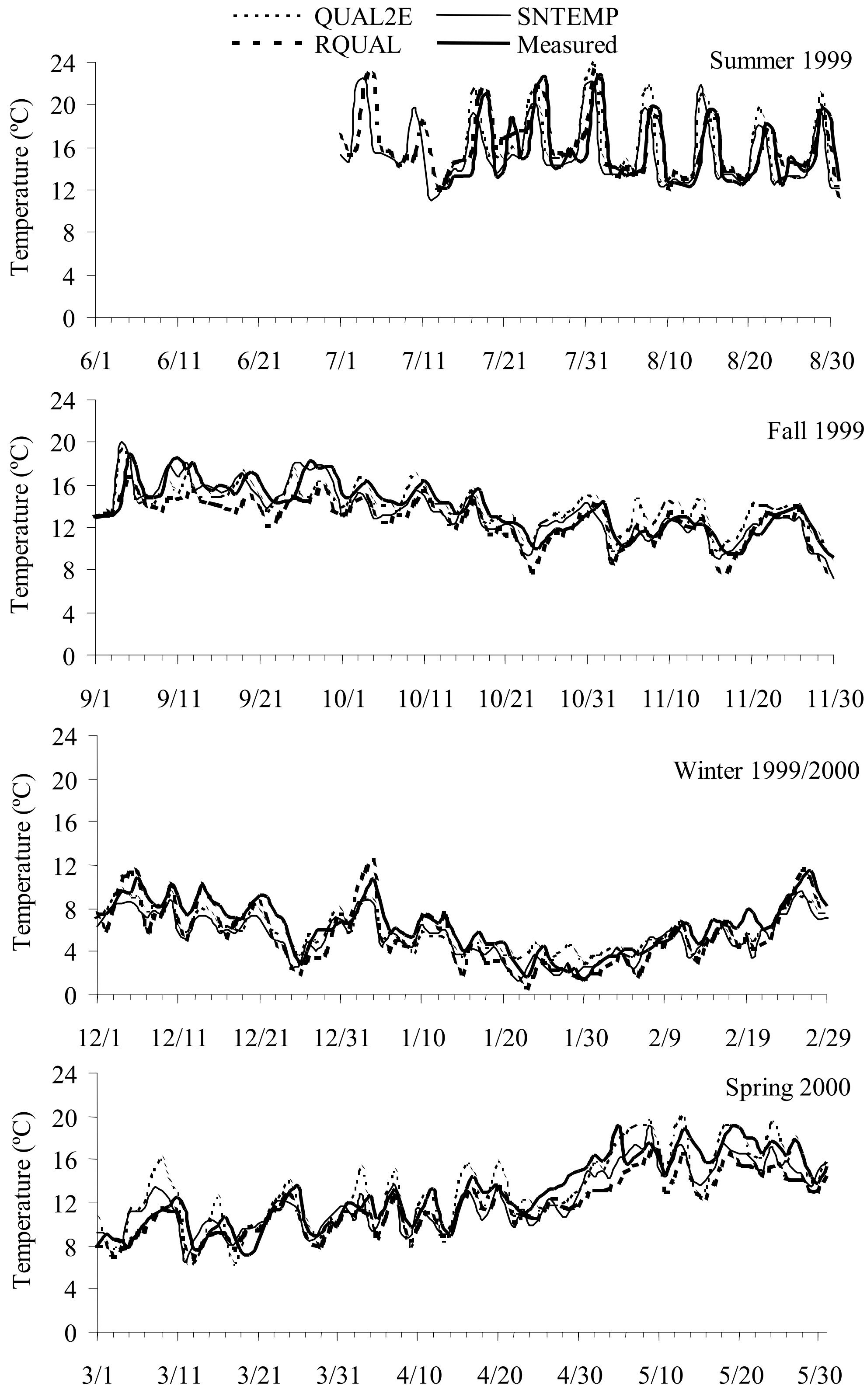


Figure 2.4. Daily QUAL2E, SNTEMP, and RQUAL calibrated predictions and measured temperature (°C) at 24.3 rkm for summer and fall 1999, winter 1999/2000, and spring 2000, Smith River, Virginia.

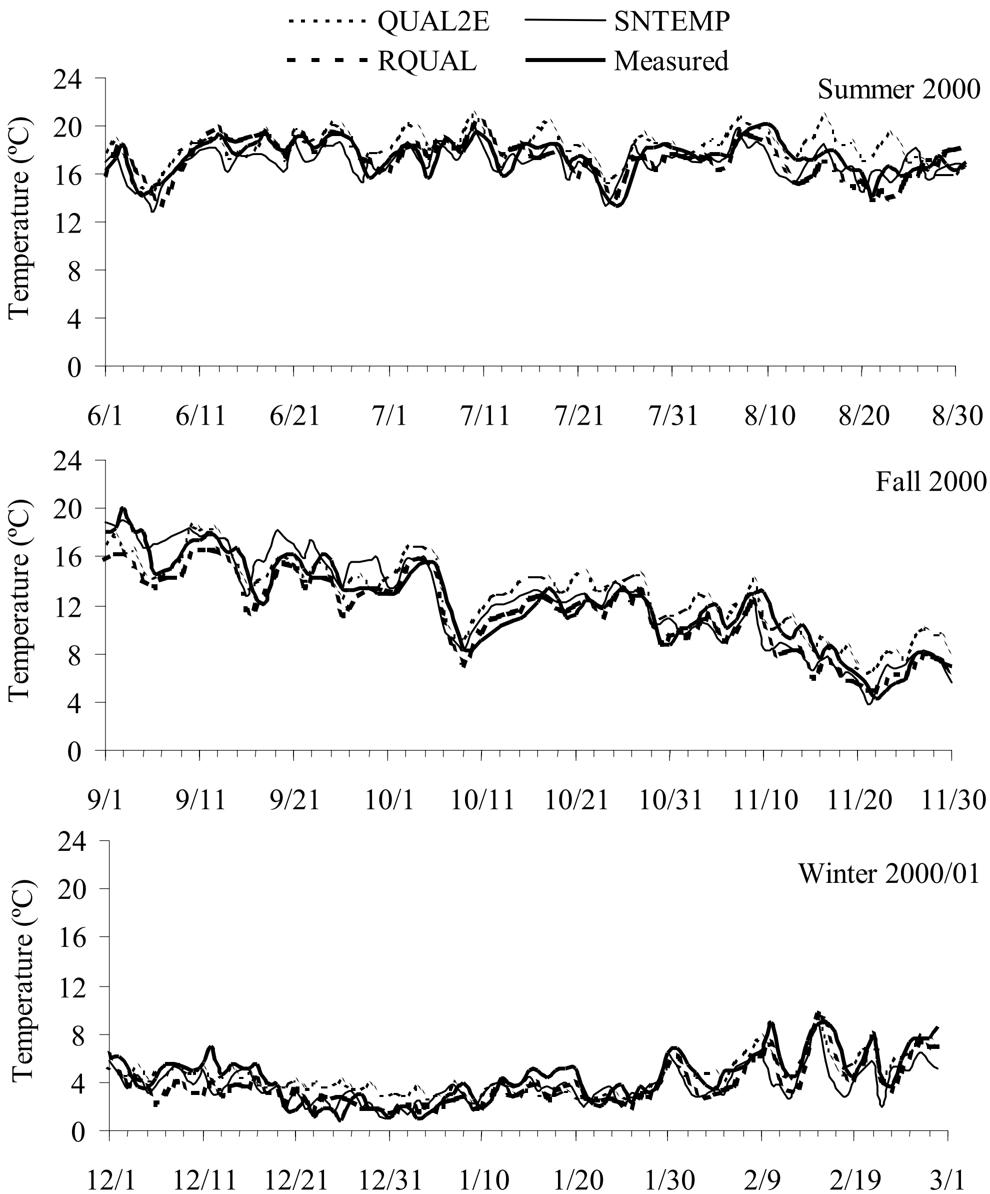


Figure 2.5. Daily QUAL2E, SNTEMP, and RQUAL validation predictions and measured temperature (°C) at 24.3 rkm for summer and fall 2000, winter 2000/2001, Smith River, Virginia.

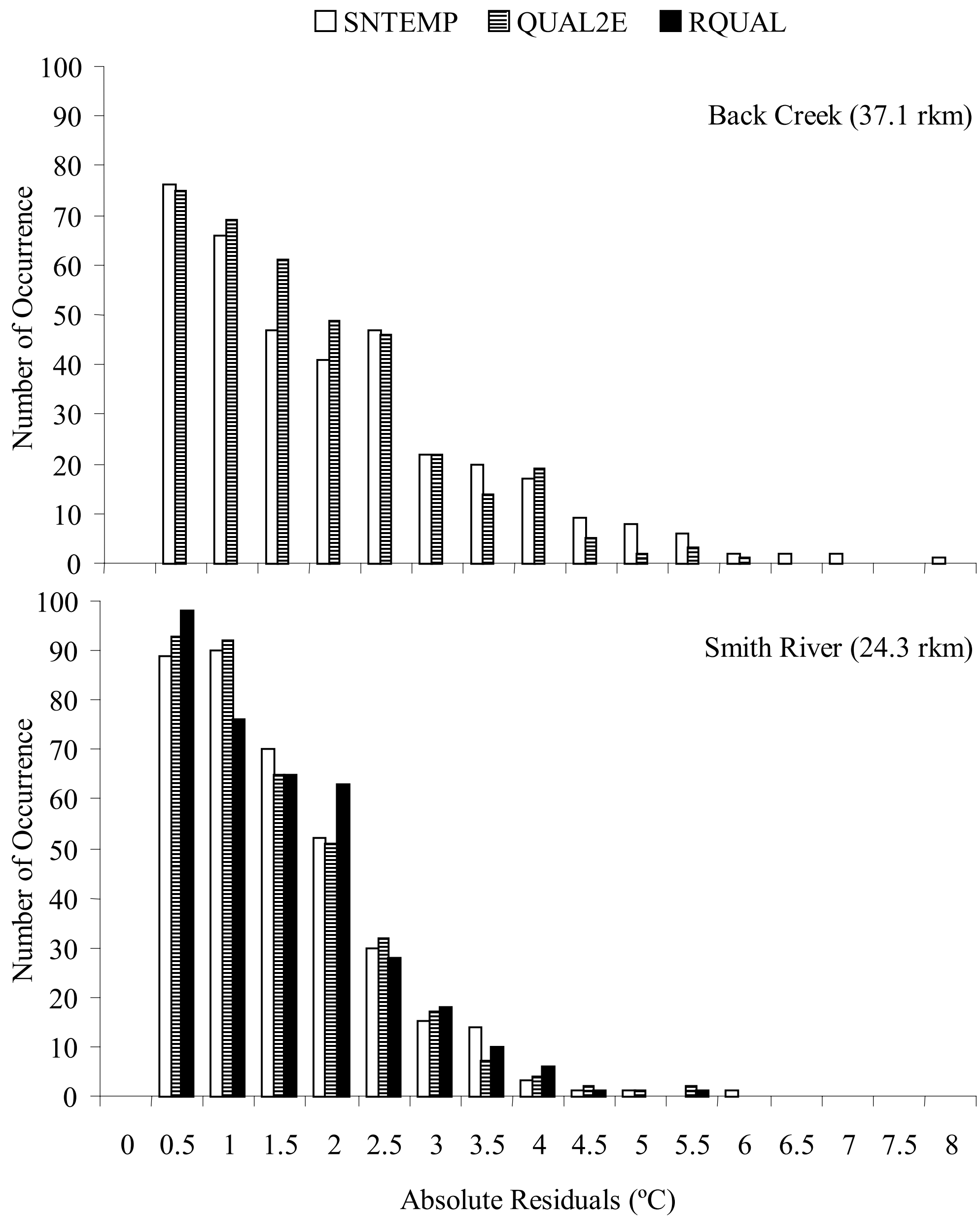


Figure 2.6. Histograms of SNTEMP, QUAL2E, and RQUAL daily absolute residuals from September 1999 to August 2000 (n=366) at the downstream end of Back Creek (37.1 rkm) and the Smith River (24.3 rkm) modeled reach.

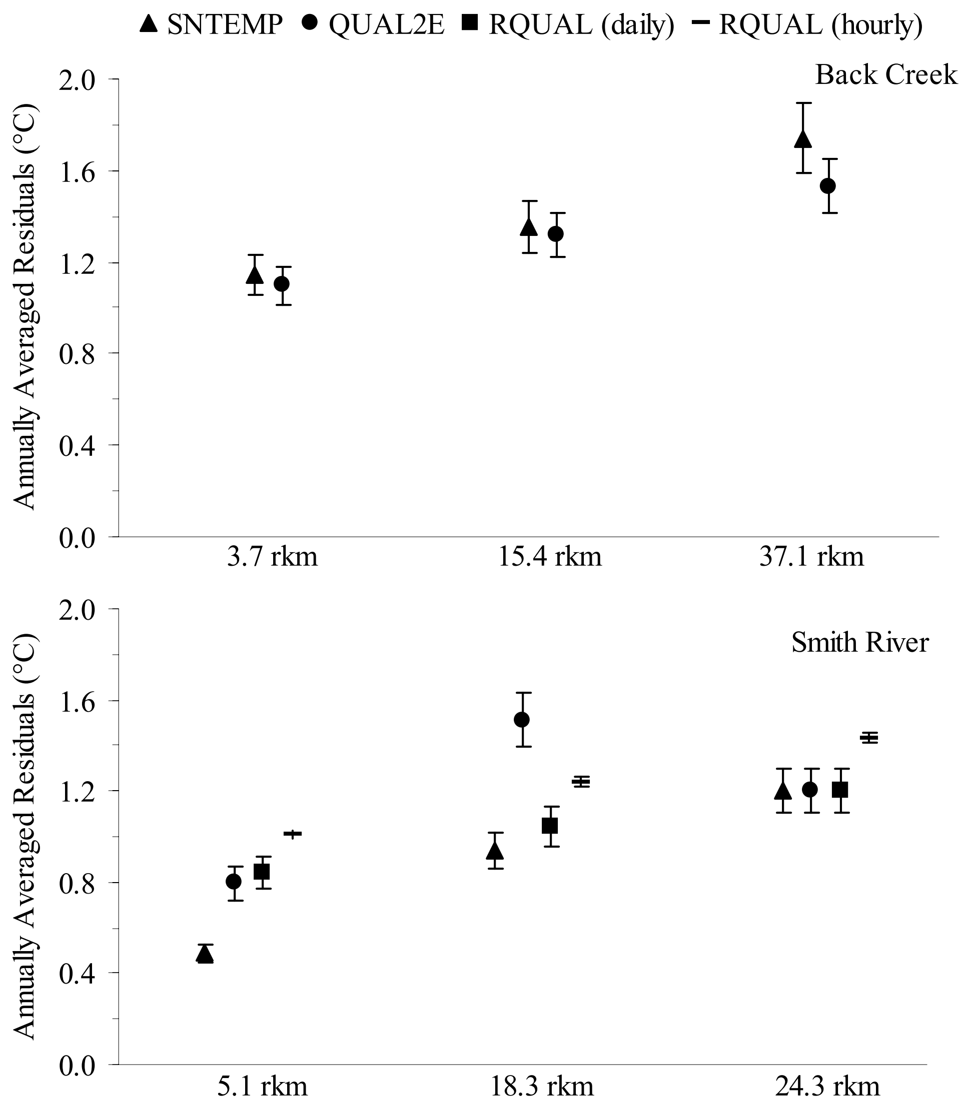


Figure 2.7. Daily absolute residuals averaged annually (September 1999 – August 2000) (2 SE) for Back Creek and the Smith River at three locations downstream of the modeled reach start-point. Residuals for RQUAL are presented as daily and hourly predictions averaged annually.

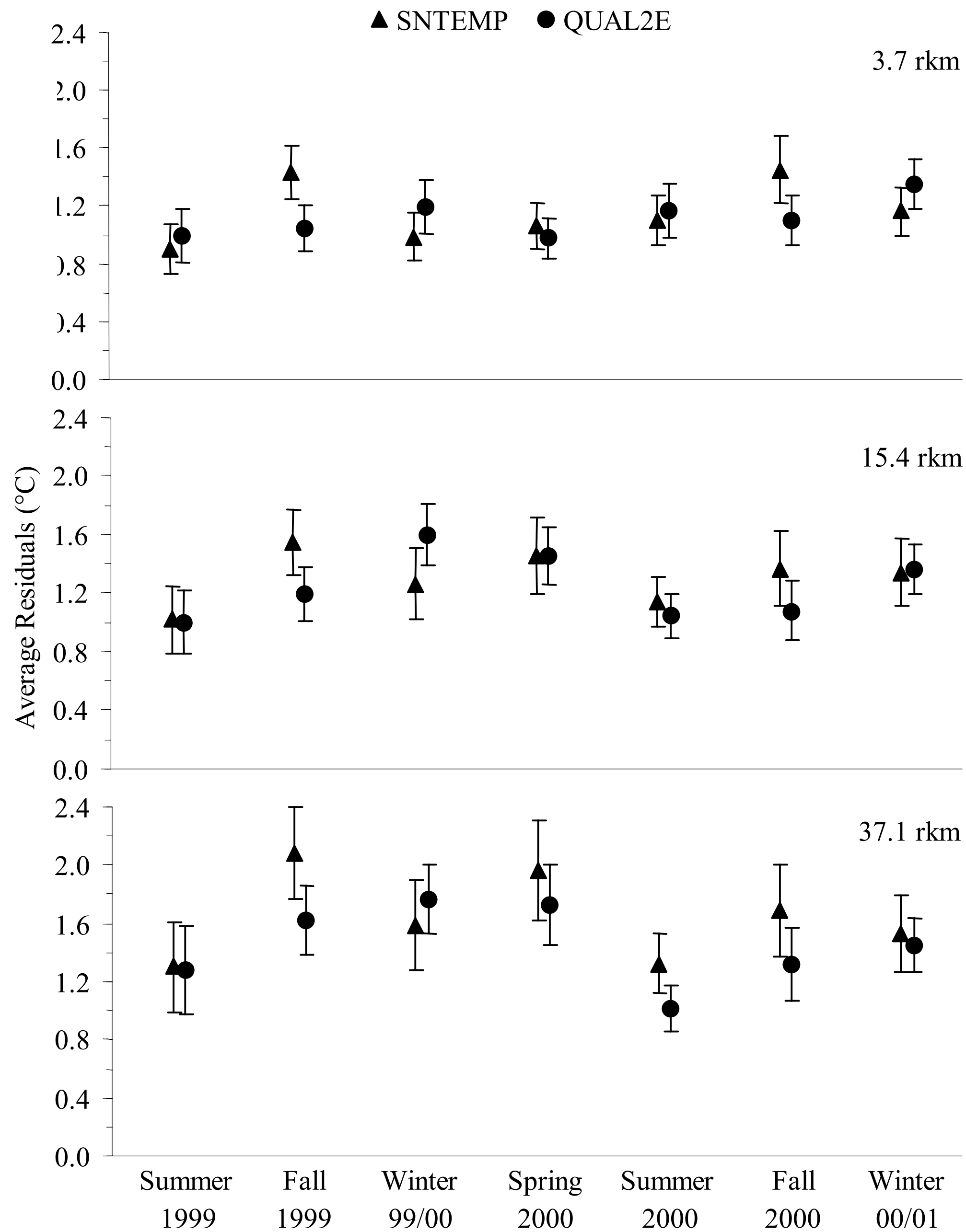


Figure 2.8. Absolute residuals averaged by season (2 SE) for Back Creek at 3.7, 15.4, and 37.1 rkm downstream of the modeled reach start-point.

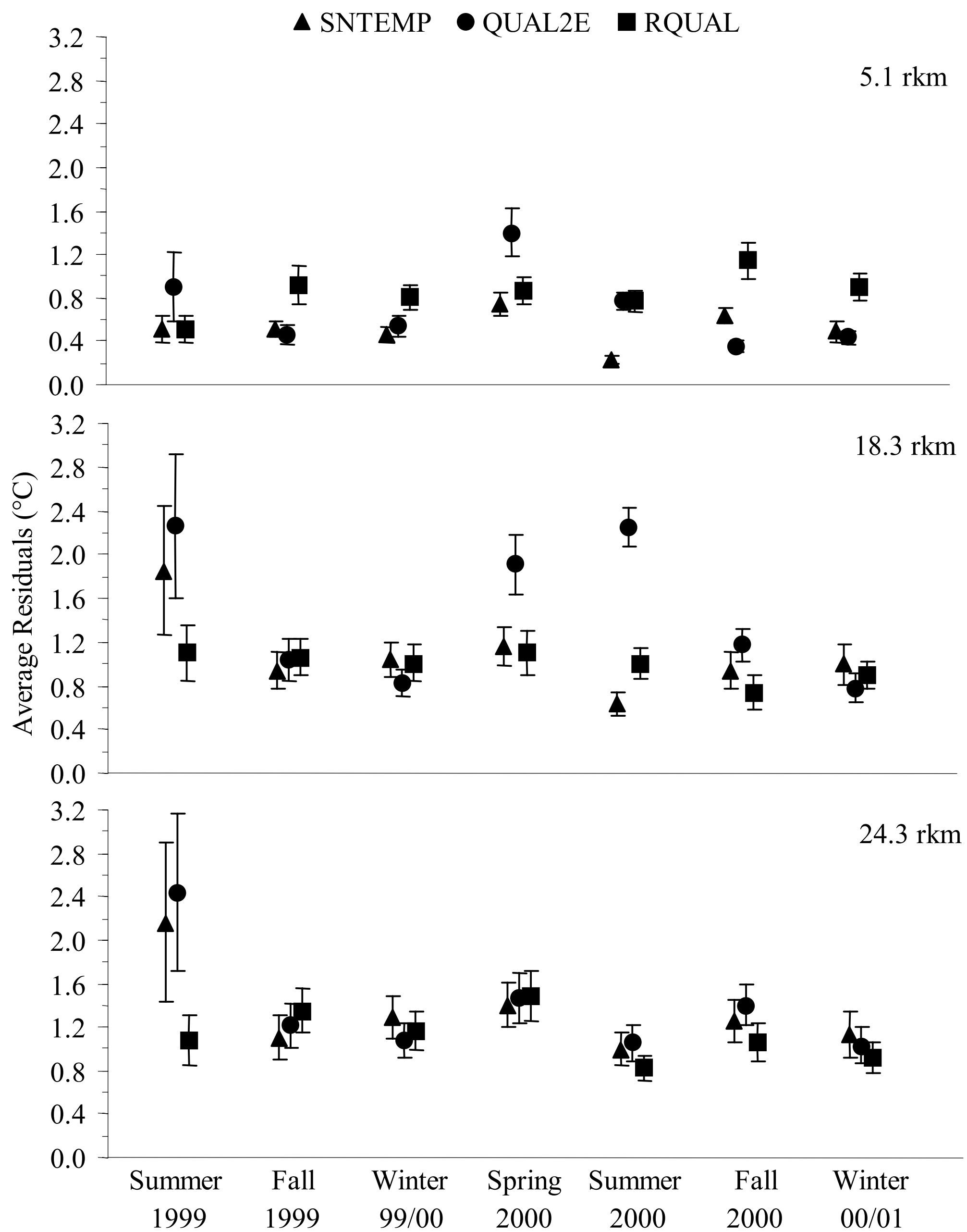


Figure 2.9. Absolute residuals averaged by season (2 SE) for the Smith River at 5.1, 18.3, and 24.3 rkm downstream of the modeled reach start-point.

18.3 rkm during spring and summer 2000 (Figure 2.9). Overall, seasonal predictive ability was best for summer, followed by winter, spring and fall (Figures 2.7-2.8).

Though the RQUAL model predicted worse for particular locations and seasons, it predicted correct temperatures more consistently than SNTEMP and QUAL2E (Figure 2.9). This is because the out-of-phase predictions and lack of predictability at a particular longitudinal location were not apparent for RQUAL. The RQUAL model predicted hourly temperatures, which were averaged daily for comparison with the other models. Predictive ability was better for the daily averages of the hourly predictions than the hourly predictions because error was averaged out (Figure 2.7).

Comparison of the two stream systems shows better predictive ability for the SRT than Back Creek at similar downstream distances (Figure 2.7). The majority of predictions, >80% for Back Creek at 37.1 rkm and >90% for the SRT at 24.3 rkm, were within 3°C of the measured water temperature (Figure 2.10). The majority of daily maximum temperature predictions were within three degrees (C) of the measured daily maximum water temperature; 70% for SNTEMP on Back Creek at 37.1 rkm, 90% for SNTEMP and 93% for RQUAL on the SRT at 24.3 rkm, (Figure 2.10).

According to degree-day accumulation, QUAL2E under-predicted five of the seven modeled seasons for Back Creek (37.1 rkm) and SNTEMP three (Table 2.4). For the SRT at 24.3 rkm, QUAL2E under-predicted one of the seven modeled seasons, SNTEMP six, and RQUAL six (Table 2.4). The extent of the over/under-predictions was most apparent for SNTEMP and RQUAL SRT (24.3 rkm) predictions because the majority of residuals for one year (9/1/99-8/31/00) were negative (Appendix A.1). QUAL2E over-predicted cold temperatures (near 0°C) for both Back Creek and the SRT (Appendix A.2).

The sufficiency of the functional part of the models is confirmed by the lack of systematic structure (i.e., normality, linearity, homoscedasticity) exhibited by the residuals (0.002-0.122 r^2) (Appendix A.1-A.2). The only systematic structure apparent was the declining number of negative residuals as the measured temperature approached zero degrees (C) (Appendix A.1-A.2). This is a logical structure because water freezes at zero degrees (C).

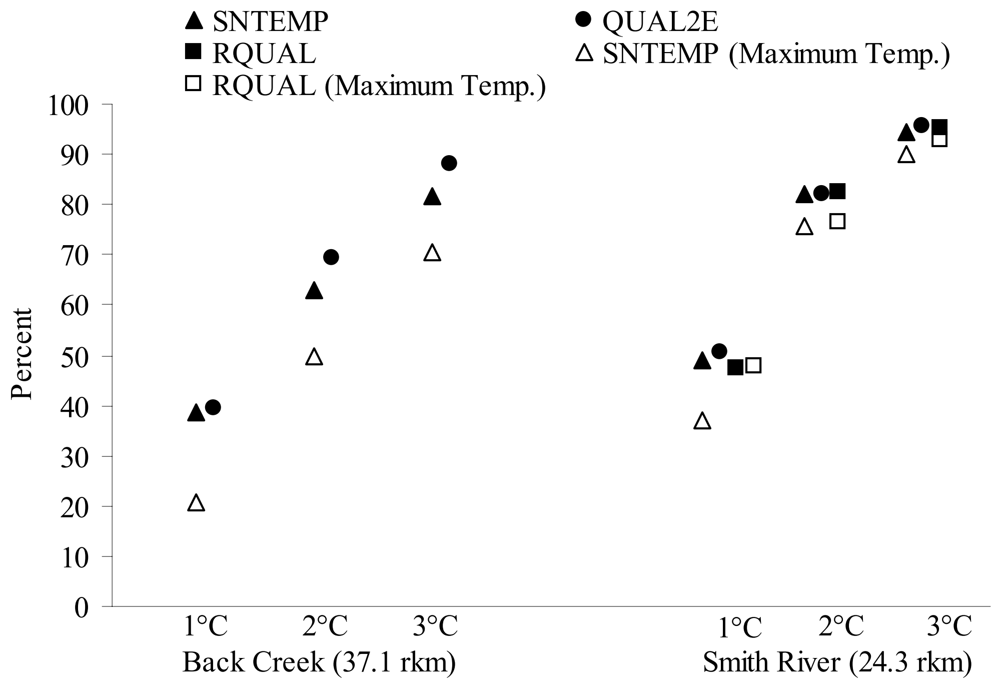


Figure 2.10. Percent of SNTEMP, QUAL2E, and RQUAL daily predicted temperatures, and percent of SNTEMP and RQUAL daily maximum predicted temperatures within 1, 2, and 3°C of the daily and daily maximum measured water temperature from September 1999 – August 2000.

Table 2.4. Mean daily temperatures summed (i.e., degree accumulation) (°C) by season for measured temperature, QUAL2E, SNTEMP, and RQUAL daily predicted temperature for Back Creek (37.1 rkm) and the Smith River (24.3 rkm). Difference (°C) between predicted and measured degree-day accumulation in ( ). The degree-day difference (in days) between measured and predicted based on: one degree day = season's measured degree-day accumulation / n is in [ ].

River/Season	n	Measured	QUAL2E	SNTEMP	RQUAL
Back Creek					
Summer ('99)	54	1338	1291 (-47) [2]	1318 (-20) [1]	
Fall ('99)	91	1263	1248 (-14) [1]	1269 (6) [0]	
Winter ('99/00)	91	359	386 (27) [7]	395 (36) [9]	
Spring ('00)	92	1343	1329 (-14) [1]	1269 (-74) [5]	
Summer ('00)	92	2127	2097 (-30) [1]	2144 (17) [1]	
Fall ('00)	91	1201	1163 (-38) [3]	1143 (-58) [4]	
Winter ('00/01)	90	231	293 (62) [24]	270 (39) [15]	
Smith River					
Summer ('99)	50	779	797 (18) [1]	759 (-20) [1]	799 (20) [1]
Fall ('99)	91	1259	1273 (13) [1]	1227 (-33) [2]	1150 (-109) [8]
Winter ('99/00)	91	583	537 (-46) [12]	485 (-98) [25]	500 (-83) [21]
Spring ('00)	92	1192	1214 (23) [2]	1135 (-57) [4]	1068 (-123) [8]
Summer ('00)	92	1604	1679 (75) [3]	1559 (-45) [2]	1588 (-17) [1]
Fall ('00)	91	1104	1175 (71) [5]	1128 (24) [2]	1032 (-72) [5]
Winter ('00/01)	90	396	403 (7) [3]	338 (-58) [23]	335 (-61) [24]

Predictive ability was also assessed between temperatures predicted using onsite versus offsite measured air temperature and humidity (SNTEMP) or dewpoint (RQUAL). The greatest difference in predictive ability at Back Creek was 0.62°C for SNTEMP during fall, and 0.49°C at the SRT for SNTEMP during winter and 0.41°C for RQUAL during fall (Table 2.5). This assessment was not made for QUAL2E because onsite wet-bulb temperature was not measured.

Model Validation

The SNTEMP, QUAL2E, and RQUAL model were accepted as valid for all seasons based on graphical analyses (Figures 2.2-2.3 and 2.4-2.5). Based on statistical analyses, models were deemed to validate (i.e., no statistical difference between residual error counts of the calibrated and independent dataset season) for the majority of the assessed seasons (Table 2.6). All models, for all assessed seasons, on both river systems, validated for the suitable (0-4°C) predictive ability category with the exception of SNTEMP and QUAL2E on the Smith River between summer 1999 and 2000 (Table 2.6). Statistical difference occurred because SNTEMP and QUAL2E predicted out-of-phase during summer 1999 on the Smith River. When these predictions are shifted by one day statistical difference no longer occurs and SNTEMP and QUAL2E validate on the Smith River during summer (suitable vs. unsuitable for SNTEMP: $T = -0.59$ $P = 0.27$; for QUAL2E: $T = 0.00$ $P = 0.50$). The optimal versus acceptable category resulted in five non-validating cases, which were SNTEMP and QUAL2E on Back Creek during fall, QUAL2E on Back Creek during winter, and RQUAL on the Smith River during summer and winter. Every non-validating case occurred because the model had higher predictive ability the second year (the independent dataset season). This means predictive ability actually improved for the year that the model was not calibrated for. The reason for improved predictive ability is theorized to have occurred due to changes in flow conditions. In the Smith River flow became more consistent (7 day instead of 5 day release) and less variable (1 hr instead of 2 hr release) during the second modeled year. In Back Creek flow was higher (1999 mean annual flow of 0.75 cms versus 2000 of 1.09 cms) and thus more stable to thermal alteration.

Table 2.5. Average absolute difference (°C) (2 SE) between predicted mean daily temperature using onsite versus offsite collected air temperature and relative humidity (SNTEMP) or dewpoint temperature (RQUAL) at Back Creek (37.1 rkm) and the Smith River (24.3 rkm).

			Back Creek	Smith River	
		n	SNTEMP	SNTEMP	RQUAL
Winter	(Dec-Jan-Feb 99/00)	91	0.46 (0.10)	0.49 (0.08)	0.26 (0.06)
Spring	(Mar-Apr-May 00)	92	0.51 (0.10)	0.48 (0.08)	0.35 (0.06)
Summer	(Jun-Jul-Aug 00)	92	0.51 (0.10)	0.48 (0.06)	0.23 (0.04)
Fall	(Sep-Oct-Nov 00)	91	0.62 (0.10)	0.47 (0.06)	0.41 (0.06)
Winter	(Dec-Jan-Feb 00/01)	90	0.36 (0.10)	0.40 (0.06)	0.20 (0.04)

Table 2.6. One sided chi square test results (T statistic), which tested for difference (P <0.05) between counts of absolute residuals from the calibrated year (summer, fall, and winter 1999) to the test year (summer, fall, and winter 2000) in Back Creek (37.1 rkm) and the Smith River (24.3 rkm), Virginia. Counts were tested within contingency tables that delineated data in to suitable (0-4°C) versus unsuitable (>4°C) predictive ability categories, and optimal (0-2°C) versus usable (2-4°C). Values in this table for each season are the number of days that residual error fell within the predictive ability category.

	Summer 1999 vs. 2000		Fall 1999 vs. 2000		Winter 99/00 vs. 00/01	
	T	P	T	P	T	P
Suitable Vs. Unsuitable						
SNTEMP						
Smith River	-3.26	0.00	-0.01	0.49	0.45	0.67
Back Creek	-1.37	0.08	-0.73	0.23	-1.05	0.14
QUAL2E						
Smith River	-3.63	0.00	-0.58	0.28	0.00	0.50
Back Creek	-1.02	0.15	0.65	0.74	-0.72	0.23
RQUAL						
Smith River	0.00	0.50	0.00	0.50	0.00	0.50
Optimal Vs. Acceptable						
SNTEMP						
Smith River	-0.10	0.46	2.13	0.99	-0.95	0.17
Back Creek	1.96	0.98	-2.61	0.00	0.83	0.79
QUAL2E						
Smith River	1.59	0.94	1.58	0.94	-0.22	0.41
Back Creek	-0.91	0.18	-2.59	0.00	-3.38	0.00
RQUAL						
Smith River	-2.00	0.02	-1.26	0.10	-2.55	0.01

Sensitivity Analysis

Parameter sensitivity differed with model, for example, air temperature was more sensitive for SNTEMP than QUAL2E (Figure 2.11). Parameter sensitivity differed with stream system, for example, the starting water temperature parameter was sensitive on the SRT but not Back Creek. Seasonal differences also influenced parameter sensitivity, for example, air temperature was more sensitive during summer than winter for SNTEMP (Appendix B.1).

The most sensitive of the assessed parameters for QUAL2E on the SRT was lateral inflow temperature (Figure 2.11). Most sensitive parameters for QUAL2E on Back Creek were wet-bulb temperature followed by lateral inflow temperature. For QUAL2E, air temperature was not sensitive on either the SRT or Back Creek and starting water temperature was not sensitive on Back Creek. The most sensitive parameters for SNTEMP on the SRT were air, lateral inflow, and starting temperature (Figure 2.11). Most sensitive parameters for SNTEMP on Back Creek were air temperature, relative humidity, and lateral inflow temperature. The most sensitive parameter for RQUAL on the SRT was lateral inflow temperature followed by starting water temperature (Figure 2.11).

DISCUSSION

Model Calibration

Before the models were calibrated, initial predictions represented the trend of the measured temperature, though there were over-predictions and under-predictions. Through the process of adjusting input parameters the predicted temperatures more closely resembled the measured temperatures. Model calibration is not a well defined step-by-step procedure; rather it can be somewhat of an art as multiple parameter adjustments are made in order to yield improved predictions. The choice of parameters to adjust is an important part of model calibration. Typically, the only parameters appropriate for adjustment are those that are estimated, poorly measured, and/or measured under conditions different than those at the stream. Parameters that adequately represent onsite conditions with high levels of confidence should not be adjusted. Parameter adjustments should stay within realistic bounds and the acceptable ranges for

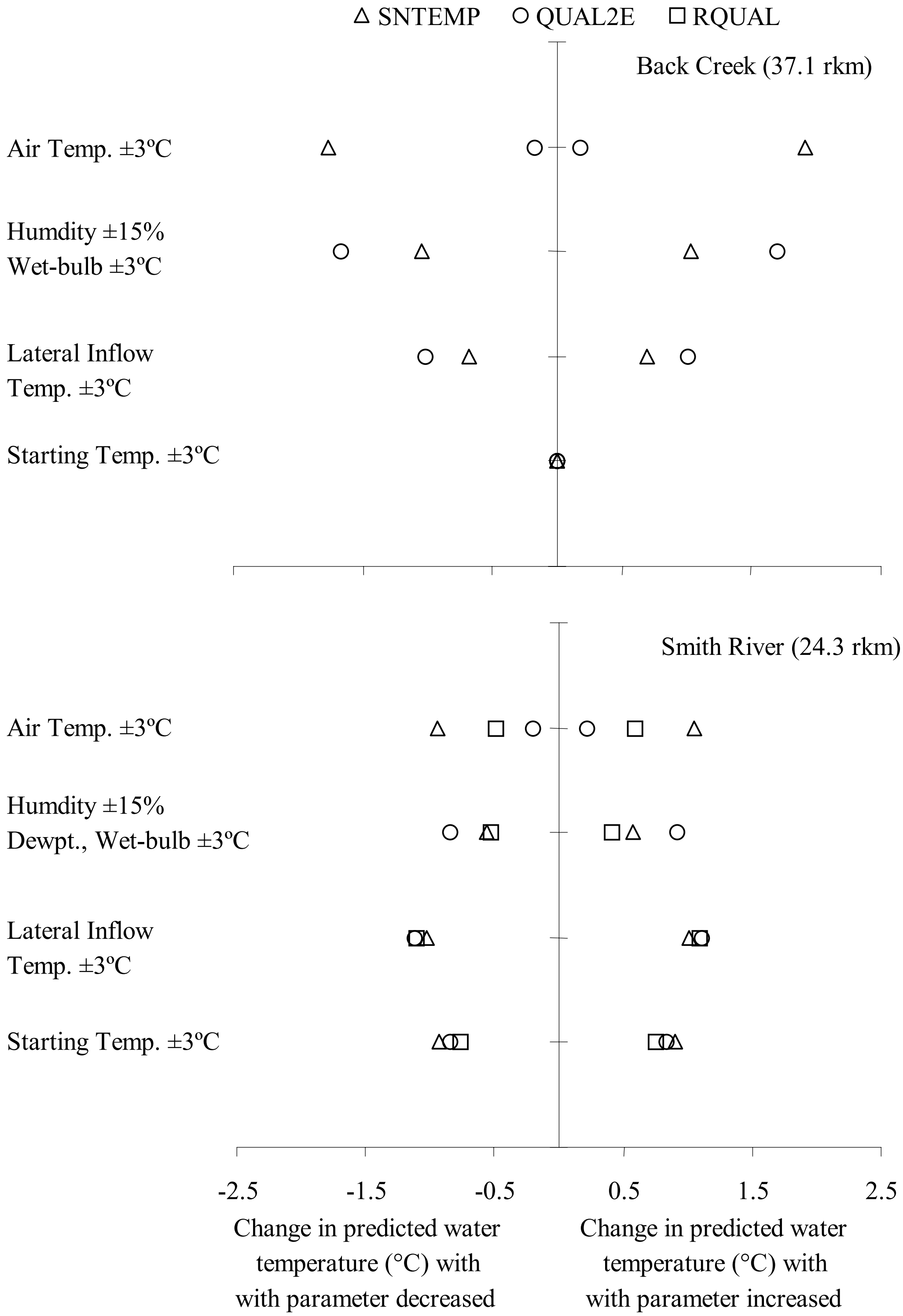


Figure 2.11. Sensitivity analysis of air, dewpoint (RQUAL), wet bulb (QUAL2E), lateral inflow, and starting water temperature parameters adjusted ±3ºC, and humidity (SNTEMP) adjusted ±15% (15% approximates a 3ºC change based on equations that calculate humidity with air and dewpoint temperature). Change in predicted temperature (i.e., sensitivity) represented as an annual average (Sept 1999 – Aug 2000, n=366).

many parameters are listed in the model's user-manual. For this study, individual parameters were initially adjusted to gain an understanding of the direction and impact of change on the predicted temperatures. Trials of various combinations of adjustments followed until predictive ability could not be improved further. Because the model calibration process is not structured like the development of model run files, the outcome of the process will improve with user experience. Therefore, some additional improvement to predictive ability of the assessed models could be possible.

The calibration process used in this study allowed model simulations year after year using the same calibrations to evaluate predictive ability, validation, and alternative management scenarios. Therefore, adjustments of daily or hourly input data were standardized. In contrast, non-standardized adjustment would allow highly accurate predictions for only one modeled time period by adjusting individual daily data. Choosing to calibrate with standardized or non-standardized parameter adjustment depends on the user’s need to predict temperature for either multiple time periods or only the time period calibrated for. The calibration process can end when predictions fall within a predetermined degree error limit chosen by the user.

The calibration process for this study used a seasonal time period. However, during the transitional seasons of fall and spring predictions were improved by adjusting mean annual air temperature for SNTEMP and lateral inflow temperature for QUAL2E for each month rather than using one value for the season. Therefore, calibrations made for shorter time periods can yield greater predictive ability.

Graphical assessment of the predicted and measured temperature plotted for the modeled time period determined whether a calibration adjustment improved or worsened predictive ability. Graphical assessment quickly provided insight into the correspondence between the predicted and measured temperature at all modeled times. Once predictions closely match measured temperatures based on graphical assessment and additional improvements cannot be visually determined, numerical assessment methods can be used.

Model Predictive Ability

Predictive ability is how well model-predicted temperature matches temperature measured in the stream. The majority of the predicted versus measured temperatures had high accuracy (Figure 2.6 and 2.10), however there were occurrences of poor predictive ability. The point at which predictive ability becomes poor is user defined and is based on the accuracy needed for the user's objectives. A residual of >4°C was considered poor predictive ability for this study. The occurrence of such residuals were uncommon and were sometimes due to out-of-phase predictions (i.e., date/time of predictions not in sync with date/time of measured temperatures).

Out-of-phase predictions cause large residuals, but may have no negative effect on management decisions derived from predictions. The QUAL2E and SNTEMP models predicted with poor accuracy during summer 1999, as there are large differences between the predicted and measured temperature on weekends (Figure 2.4). However, the models predicted the trend correctly and predictions were simply out-of-phase by one day. This causes the portrayal of poor predictive ability from numerical statistics such as average residuals, whereas degree-days, a common tool for management of fish spawning and egg development times, would not be affected. The predictions could simply have been adjusted by one day to improve predictive ability, however this was not done as the predictive ability assessment needed to be standardized.

Good predictive ability must occur throughout the modeled reach. The models demonstrated a trend of declining predictive ability with increasing distance from the reach start-point (Figure 2.7). This is likely due to cumulative error as conditions downstream become more different from the initial upstream conditions input into the model. The QUAL2E SRT predictions for spring and summer 2000 did not follow this trend (Figure 2.9), by over-predicting upstream (18.3 rkm) resulting in greater residual error than further downstream (24.3 rkm) (Figure 2.9). This example of inconsistent predictive ability with longitudinal location would result in the appearance that a greater portion of the river is warmer that it actually is.

Seasonal Predictive Ability

Predictive ability was evaluated seasonally based on residuals. Summer predictions had the best predictive ability at the modeled reach end-point with the exception of summer 1999 SRT predictions (Figure 2.8-2.9). Though there were exceptions, in general, winter predictive ability was worse than summer, and fall and spring were worse than winter. The implications of seasonal prediction differences on management of aquatic biota may be better addressed by evaluating predictive ability with degree-days. The difference between the measured and predicted degree-days for each season shows winter has the largest difference (Table 2.4). This is due to winter having small degree-days, which causes greater degree-day error. Whereas other seasons which have larger degree-days, the difference between predicted and measured degree-day accumulation results in less degree-day error. For example, degree-day accumulation difference for SNTEMP predictions for the SRT were -57 degrees for spring 2000 and -58 degrees for winter 2000/01, yet degree-day difference for spring was 4 days and for winter 23 days (Table 2.4). Though winter had similar or better predictive ability than spring or fall when evaluated with average residuals (Figure 2.8-2.9), winter requires very high predictive ability if degree-day predictions are to be accurate. Therefore, methods used to evaluate a model should address the types of questions the model will be used to answer.

Model, Environment, and Physical Effects on Predictive Ability

Temperature models are typically used to predict temperatures during the most unfavorable conditions for aquatic biota, which is during the low flows and high temperatures of summer. The models were designed with this in mind, which is a possible reason for better summer predictive ability. It can be more clearly shown that the models were not designed for winter applications. The QUAL2E model does not accept any negative air, wet, or lateral inflow temperatures, which commonly occur during winter, therefore zero was used in place of negative values. As a result, QUAL2E over-predicted near zero temperatures which occurred during winter in Back Creek (Figure 2.2-2.3). The RQUAL model predicted negative water temperatures during winter prior to calibration. Calibration adjustment of negative air and dewpoint temperatures to zero prevented negative predictions better than other adjustments such as wind speed reduction. Another reason summer predictive ability is highest may be because daily conditions (ex. air temperature, humidity, and lateral inflows) fluctuated more during fall, winter, and spring. Rapidly changing conditions from one day to the next can impair predictive ability. For example, heavy rainfall resulting in sudden large volumes of runoff into Back Creek caused inaccurate SNTEMP predictions when calibrated using mean annual air temperature, which the model uses as a surrogate for ground temperature. However, when monthly soil temperature was used in calibration, the predictions during storm runoff events were more accurate. Therefore, rapidly changing conditions that violate the model's steady-state flow assumption can reduce predictive ability and Back Creek temperature is strongly influenced by runoff temperature.

Using SNTEMP and QUAL2E to predict temperature for the SRT where flow fluctuates rapidly due to peaking hydropower releases violated the steady state flow assumption. Yet SNTEMP and QUAL2E were able to successfully predict temperature with predictive ability similar to RQUAL for most longitudinal locations and seasons (Figure 2.9). This may be because daily averaged flow removed the rapid fluctuations. To enable SNTEMP to successfully predict SRT temperatures the river-width coefficient and exponent were adjusted during calibration from calculated values. Widths calculated with the non-adjusted coefficient and exponent closely matched field measured widths. Widths calculated with the adjusted coefficient and exponent during baseflow (1.4 cms) were 21 meters less than width calculated using the original coefficient and exponent and 15 meters less during peakflow (39.6 cms). This calibration adjustment greatly reduced the air-water interface area from what is realistically present on the SRT. This may have enabled high predictive ability, but has prevented confident use of the model for assessing alternative shade, flow, or channel width scenarios.

The hydropower release pattern in the SRT varies depending on reservoir levels, energy demand, and flood control needs. During 1999, flow peaked five days a week (weekdays) for typically 2-5 hours a day. During 2000, flow peaked seven days a week for typically one hour. Due to the varying flow regimes, a dynamic model such as RQUAL, which demonstrated consistent predictive ability under the 1999 and 2000 regimes at all evaluated longitudinal locations is necessary for confident temperature predictions. SNTEMP and QUAL2E predictive ability was similar and even better at certain seasons and/or locations than RQUAL, but they predicted inconsistently (e.g. out-of-phase and/or didn't predicted well at all rkm). Also important is whether a model can answer objectives set by the user such as assessment of hourly temperature change. SRT temperature fluctuates greatly within one hour and of the assessed models only RQUAL is capable of predicting temperature on this time scale.

SNTEMP and QUAL2E had better predictive ability in the SRT than Back Creek for most seasons according to average residuals (Figures 2.7-2.8). It is likely that predictive ability was worse for Back Creek, which has less flow than the SRT, because smaller volumes of water are more easily and quickly altered (Calow and Petts 1992; LeBlanc et al. 1997; Rutherford et al. 1997). Predictive ability is reliant on the quality of the input data. The more closely the data represents the conditions local to the modeled system the more likely predictive ability will be high. For this study efforts were made to collect the input data using the best and most appropriate methods available as advised by the user manuals and personal communication with experienced users of the assessed models. Many field-collected parameters were measured with greater effort and detail than necessary for typical use of the models. This was done to assure the resulting predictive ability was due to the model and calibration, and not the input data. Much of the meteorological data was too costly to collect onsite such as solar radiation, cloudiness, wind speed, ground temperature, and barometric pressure. Therefore it is inherent that offsite collected data did not perfectly represent onsite conditions at all times. The use of onsite data did not always improve predictive ability, which is because calibration was conducted with offsite data. Regardless, an average improvement to predictive ability of half a degree for most model users will not warrant the additional costs and effort associated with onsite meteorological data collection.

Model Validation

Validation of a model provides the user with confidence that the model calibrated with one dataset will predict correctly with a second independent dataset. Each model was determined valid based on graphical analyses. Graphical methods are uncomplicated, efficient, and assess trend rather than point-in-time accuracy of model predictions. However, they can be can be biased according to the person assessing the graphs and do not conclusively summarize the data with definitive values. Therefore statistical analysis was used, which found the models to validate for the majority of the assessed predictive ability categories. Whether statistical difference constitutes that model predictions will be invalid for predicting biological differences is dependent on the user's objectives and acceptable level of predictive ability. Thus, if a user requires predictive ability to within 4°C of the measured temperature, all models validated (with the exception of SNTEMP and QUAL2E on the Smith River during summer, unless out-of-phase predictions were shifted by one day). Use of predictive ability categories allowed this study to determine that the assessed models validate to the 4°C predictive ability level and validate the majority of the time to the 2°C level. The non-validating cases were at the most downstream modeled point and thus the models may validate to the 2°C level at upstream locations where predictive ability was higher.

Sensitivity Analysis

Sensitivity analysis provides insight into how influential input parameters are on the predicted temperature. It is important to assess parameters individually in order to identify parameters that may need accurate collection. However this can be problematic when parameters are interrelated, which is the case with air temperature and humidity, dewpoint, and wet-bulb temperature. For example, humidity is related to the degree-spread between the air and dewpoint temperature. The closer air and dewpoint temperature are to one another the greater the humidity. However, adjusting these parameters individually for a sensitivity analysis can still be done if within realistic bounds. The average range between air and dewpoint temperature was 6.6°C and the average maximum variation was 17.3°C (based on hourly data from 9/1/99-8/31/00). The average range between air and wet-bulb temperature was 3.3°C and the average maximum variation was 6.6°C. Therefore, the adjustment of a 3°C increase and decrease was within the observed range. Additionally, air temperature is always greater than dewpoint and wet-bulb temperature, humidity does not exceed 100%, and lateral inflows below 0°C are unlikely. Any such unrealistic occurrences caused by parameter adjustment were excluded from the sensitivity analysis.

Sensitivity analysis results can be invalid depending on how a model's algorithms account for the adjusted input parameters. Simply excluding predictions from the analysis that correspond with occurrences of unrealistic adjusted input may not be sufficient. For example, RQUAL model algorithms will default to use the river main-stem temperature in place of negative lateral inflow temperatures. So any lateral inflow temperatures originally above zero that become negative during a sensitivity analysis adjustment will be replaced by the main-stem temperature. This results in an incorrect assessment of the sensitivity of the lateral inflow temperature parameter. Therefore, it can be necessary to use the original unadjusted input data in place of data that becomes unrealistic when adjusted. The predictions will then be unaffected by model algorithms which attempt to prevent the accidental use of inappropriate input data. Then when assessing sensitivity, only predictions corresponding to the date and time of the adjusted input data were used.

Seasonal differences were enough to alter the sensitivity of assessed parameters. For example, air temperature and humidity were most sensitive during summer for SNTEMP (Appendix B.1). The starting water temperature parameter of QUAL2E and SNTEMP on Back Creek did not vary seasonally because it was not sensitive, which was due to the modeled start-point being a headwater (Appendix B.1-B.2). A headwater begins with almost no flow and thus the temperature of very little water will not influence the downstream-predicted temperature. Had Back Creek been modeled beginning further downstream, starting water temperature would have been more sensitive, which was the case on the SRT where initial flows were larger. Lateral inflow temperature was sensitive for all three models on both river systems, which implies these systems are influenced more by runoff than groundwater temperature.

Advantages and Shortcomings of Assessed Models

With multiple temperature models available it is important to choose a model appropriate for site specific conditions and user objectives. Predictive ability of the models evaluated on the SRT were similar, as were those on Back Creek, which excludes predictive ability as a deciding factor in choosing a model. If shading alternatives are the purpose for using a temperature model then the model should have a shade component. The SNTEMP model allows assessment of alternative shade scenarios because the model has a vegetation density parameter, as well as vegetation height, offset, and crown width. Shade assessment may be possible with RQUAL, but because there is no vegetation density parameter the differences in water temperature under alternative shade scenarios may be indiscernible. The RQUAL model contains vegetation offset and height parameters and a parameter that accounts for the fraction of solar radiation absorbed by shaded water (SHSOL) for which a relationship with vegetation density might be developed. However, unlike SNTEMP that allows different vegetation densities at multiple longitudinal locations on each side of the river RQUAL only allows one SHSOL value for the entire modeled system and offset and height must the be same for both sides of the river. The QUAL2E model would be an unacceptable choice for shade evaluation as there is no shade component to this model.

Prediction Time-Step

The time scale at which a model can predict temperature may be of importance to users. The RQUAL model is capable of predicting temperature at the time scale of the input data. Half-hourly flow data and hourly meteorological data allowed hourly temperature predictions for the SRT. The shortest time step SNTEMP can predict is daily. For this study, QUAL2E predicted daily temperature using the steady-state model option. QUAL2E also has a quasi-dynamic mode that allows input of meteorological data at three-hour intervals and prediction of temperature at one-hour intervals. The quasi-dynamic mode enables assessment of diel variation in meteorological data, but still assumes flow is constant (USEPA 1995). Unlike RQUAL, which is a dynamic model, QUAL2E in the quasi-dynamic mode is unable to account for rapidly changing flows. The quasi-dynamic mode could not be used at the time of this study because the QUAL2E model had a bug, which prevented air and wet-bulb temperature from being varied every three hours.

Model – User Interface

Model user-friendliness was influenced by the interface between the model and user, the protocol for running each model, and available model documentation and/or training classes. First time model users will probably find the QUAL2E model easy to become familiar with because of a Windows interface. However, QUAL2E becomes very tedious to use if predictions are needed for multiple days because the model can only predict one model-run (e.g. day) at a time. Thus, data must be entered and the model run for each day predictions are desired, which makes it difficult to test different calibrations or alternative parameter scenarios. SNTEMP and RQUAL allow data entry for multiple days in one model run-file, making it easy to alter parameters and then re-run the model to compare the new predictions to the original over the desired time period. Data is input into RQUAL and SNTEMP with text files and development and modification to these files can be rather easy if templates in a spreadsheet program are developed. The RQUAL model has a Windows interface for running the model and graphing predictions. The graphing capability of this model simplifies tasks such as model calibration because measured data can be plotted along with model output. The SNTEMP model is run via MS-DOS and predictions must be imported into a spreadsheet program for graphical assessment. Both SNTEMP and RQUAL create data files containing predictions, which are suitable to import into a spreadsheet program. For QUAL2E predictions for each day must be viewed individually from an output file containing all water quality predictions.

Model Documentation

Model usability is dependent on the quality of software documentation available. The SNTEMP model had the most comprehensive documentation of the assessed models as well as a self-study course (Bartholow 1997). Bartholow (1989) provides field-data collection, calibration, and validation techniques, which are useful for more than just the SNTEMP model. The QUAL2E windows interface user’s guide provides technical model information, how to use the Windows interface, and a few example runs (USEPA 1995). This manual did not provide the level of information found in the SNTEMP documentation, however a training course and listserve are available. The training course is offered multiple times per year at different US locations and this course material is also available online (http://www.epa.gov/ost/basins/). The ADYN & RQUAL user's guide was the most simplified of the assessed models, oriented toward input file structure with no available training. To run each model for this study additional information was needed and was obtained through personal contact with experts on the SNTEMP and ADYN & RQUAL model, and through the listserve for the QUAL2E model.

Data Requirements

The amount and/or type of input-data required for a model affects user-friendliness. The ADYN & RQUAL model requires the most intensive data collection of the assessed models simply because it is a dynamic model. More data requirements inherently makes this model more complex, but this is the trade-off for hourly predictions. The SNTEMP and QUAL2E models have similar data requirements with the exception of SNTEMP shade parameters. The additional shade parameters make data collection for SNTEMP more complex than QUAL2E.

SUMMARY

All three assessed models were capable of predicting temperature well. Further improvement to predictive ability is probable because the calibration process becomes more successful with user experience and with increased amounts of baseline data. Each model was deemed to validate, ensuring user confidence in predictions when using data from a time period for which the model was not calibrated. Sensitivity analysis revealed that parameter sensitivity differed among models, river system, and season. Because some parameters were more sensitive than others, it would be sensible to invest more heavily in the collection of sensitive parameters as they play a stronger role in model predictive ability. Among the assessed models there were distinct differences in model capabilities, such as the ability to predict hourly vs. daily temperature, maximum temperature, assess shading, dynamic flows, etc. Surprisingly, SNTEMP and QUAL2E were able to predict SRT temperature while violating the steady-state flow assumption. Predictive ability by QUAL2E was not consistent among seasons and longitudinal river locations, and SNTEMP required channel width reduction to produce correct predictions.

Therefore, it is inadvisable to use these models in dynamic flow conditions. Non-regulated streams may also be capable of violating the model's steady state flow assumption, such as streams in urbanized areas with flashy flows. Choosing a temperature prediction model should be based on the model's assumptions and capabilities.

CHAPTER 3. Thermal Habitat Assessment of Alternative Flow Scenarios in a Tailwater Fishery

ABSTRACT

The Smith River tailwater (Patrick County, VA) offers a self-sustaining brown trout fishery managed for trophy trout (406+ mm), however trophy sized fish are rare. Slow growth and small size are likely caused by any one or a combination of limited food resources, physical habitat, and thermal habitat. To evaluate the potential for thermal habitat improvement, temperature changes resulting from alternative flows released from Philpott dam were assessed with a one-dimensional hydrodynamic model coupled with a water temperature model. Simulated temperatures at 13 locations under each flow scenario were assessed for occurrence of optimal growth temperatures as well as compliance with Virginia Department of Environmental Quality daily maximum temperature and hourly temperature change standards. Occurrence of optimal growth temperatures were increased by releasing water in the morning, decreasing the duration of release, and decreasing baseflow. Maximum temperatures were decreased by releasing every day of the week to prevent elevated temperatures on non-generation days, increasing baseflow, increasing duration of release, and releasing in the morning rather than evening. Hourly temperature change was decreased by ramping flow when releasing in the evening, increasing baseflow, releasing in the morning, and decreasing the duration of release. Despite conflicting adjustments to best improve all criteria concurrently, a 7-day/week, morning, one hour release regime was determined to improve all criteria compared to existing conditions.

INTRODUCTION

Water temperature is a critical parameter for the survival, growth, spawning, and embryonic development of fish. Warm water temperatures cause detrimental synergistic effects to water quality by altering dissolved oxygen levels, contaminant toxicity, suspending or precipitation of solids, and/or the level at which chemical and biochemical reactions occur (Brooker 1981; Calow and Petts 1992). Fish can behaviorally thermoregulate by avoiding harmful stream temperatures or moving to optimal habitat to maintain suitable internal homeostasis (Reynolds and Casterlin 1979). Muscle contraction and metabolic rates are dictated by temperature, which in turn regulates growth, swimming, prey capture, and food assimilation ability (Chavin 1973; Reynolds and Casterlin 1979; Wardle 1979; Saltveit 1990). When temperature quickly declines (i.e., cold-shock) the rate of body heat loss is rapid (Reynolds and Casterlin 1979) and fish can experience a loss of equilibrium or mortality (Chavin 1973; Smythe and Sawyko 2000). Downstream displacement may also result from reduced swimming ability due to cold-shock, and may be particularly acute with rapid flow releases in hydropeaking tailwaters (Ottaway and Forrest 1983; Saltveit et al. 1995).

Temperatures that are too cold or hot cause stress or mortality where 0-4°C and 19-30°C are the lower and upper critical ranges, and 24.7°C is the upper incipient lethal temperature for brown trout (Elliot 1981). Mortality is effected by the acclimation temperature, duration spent at a cold or hot temperature, and the rate at which temperature changes (Chavin 1973). Somewhere between the lower and upper critical temperature ranges lies an optimal temperature growth range, which for brown trout is approximately 12-19°C (Brown 1974; Brungs and Jones 1977; Smith 1994; Ojanguren et al. 2001). A specific optimal growth temperature often cited in the literature is approximately 13°C, however the temperature at which maximum growth occurs declines with lower rations (Elliot 1981; Jensen 1990; Lobon-Cervia and Rincon 1998). In addition to optimal temperatures, the thermal regime is also important for growth. A diel temperature cycle causes significantly greater growth rates in brown trout than constant temperature conditions (Spigarelli et al. 1982). In tailwaters, many of these restrictive temperature conditions such as cold temperatures in the dam release, warm temperatures downstream, and occurrence of large hourly temperature changes during hydropeaking may restrict growth of brown trout.

Restrictive thermal habitat conditions may be limiting the growth of brown trout in the Smith River tailwater (SRT). Located in southwestern Virginia (Patrick County), the SRT flows out of Philpott Dam and was created in 1953 by the Army Corps of Engineers (USACE) to provide flood control, hydropower, and recreational opportunities (Figure 3.1). Hypolimnetic releases support a self-sustaining brown trout population and stocked rainbow trout fishery. Cold temperatures extend from Philpott to Martinsville dam, a 32 rkm reach of which ~24 rkm are fishable by wading. The SRT, managed for

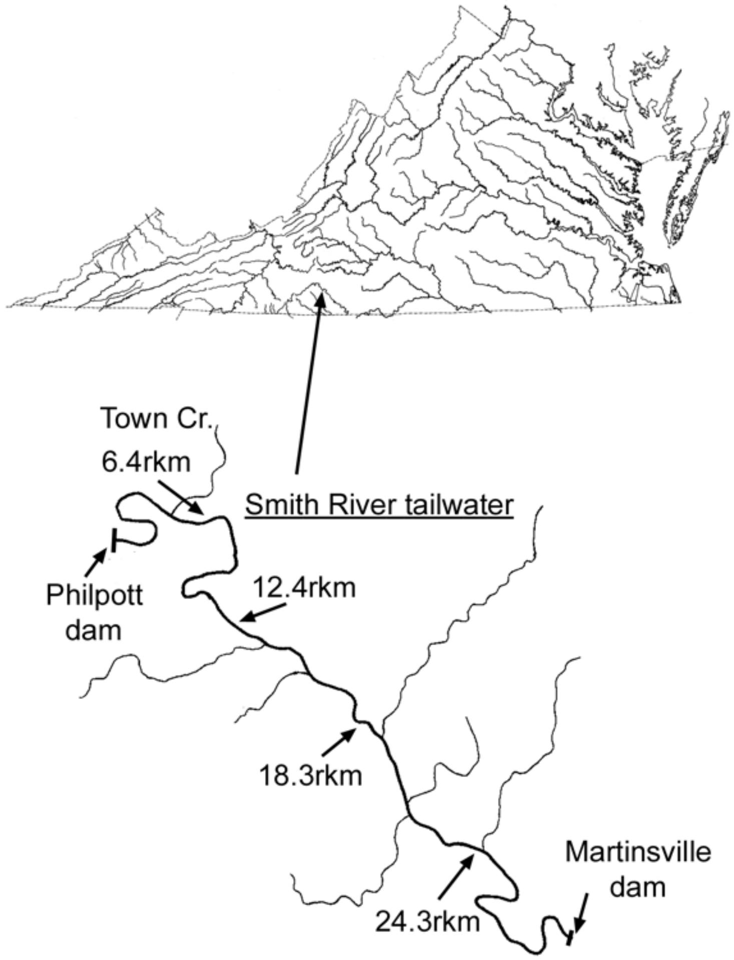


Figure 3.1. Location of Smith River tailwater in southwestern Virginia. Selected river kilometer (rkm) locations of assessed model temperature predictions.

trophy trout, produced the historic Virginia state record brown trout caught in 1979 weighing 8.48 kg (VDGIF). Presently, brown trout seldom exceed 406 mm and possible reasons are limiting thermal habitat, food resources, and/or physical habitat (Orth 2001).

Anecdotal evidence suggests thermal habitat in the SRT is limiting growth due to high temperatures at downstream locations, rapid hourly temperature fluctuations, and inadequate occurrence of optimal growth temperatures. Temperature loggers placed in the SRT for this study revealed that during non-generation periods (typically weekends) water temperatures can infringe upon the upper critical range (19-30°C) of brown trout at downstream locations (~14-24 rkm). Additionally, elevated temperatures exceed the Virginia Department of Environmental Quality's (DEQ) 21°C maximum temperature standard for stockable trout waters (DEQ 1997) (Appendix C). The hydropower operation uses a peaking regime in which flow releases vary widely and rapidly (1.4 to 36.8 cms within 30 minutes) to provide electricity during peak demand periods (USACE; USGS). Peaked hypolimnetic releases during generation cause large temperature fluctuations when mixed with downstream water warmed by ambient conditions. Temperature declines up to 7°C within an hour were recorded, which exceeds the DEQ's hourly temperature change standard of 2°C (DEQ 1997) (Appendix C). At upstream locations (~0-5 rkm) during summer, continuously cold temperatures (7-10°C) may limit growth of brown trout, which have a thermal optimal growth range of 12-19°C (Brown 1974; Brungs and Jones 1977; Saltveit 1990; Ojanguren et al. 2001).

The SRT flow regime directly influences thermal regime, therefore, adjustment to the flow regime could improve thermal habitat. Adjustments could include changes in flow duration, magnitude, time of day, days per week, and outflow temperature of the release. Additional alternatives include increases in baseflow and ramping versus peaking the release. The most time and cost efficient method to assess temperature under numerous alternative flow scenarios is with a model. The hydrodynamic model, ADYN, coupled with the water quality model, RQUAL, of the Tennessee Valley Authority's River Modeling System was designed to assess temperature and other water quality parameters under rapidly changing flows of hydropeaking tailwaters (Hauser and Walters 1995). The ADYN and RQUAL model enables assessment of alternative flow scenarios to determine which would: (1) increase occurrence of optimal growth temperatures (12-

19°C), (2) reduce occurrence and magnitude of hourly temperature fluctuations, and (3) reduce occurrence of 21°C temperature exceedance in the SRT for the improvement of brown trout growth.

METHODS

The ADYN and RQUAL model was used to predict hourly temperatures from March through September 2000 at 2 rkm intervals from 0.6-24.3 rkm below Philpott dam (Figure 3.1). To develop the model for the SRT a suite of input parameters were collected:

- Meteorological parameters were downloaded from the nearest weather station with hourly data records (Roanoke, VA 74 km away) (NCDC).
- Solar radiation values were obtained from Bluefield, WV 144 km away (CONFRRM).
- Discharge data was obtained from three gaging stations along the SRT (USGS).
- Lateral inflows were estimated by calculating flow differences between gaging stations.
- Water temperature was recorded half-hourly with Onset® data loggers near the dam outflow (0.6 rkm) for model input and at locations downstream (2.7, 5.1, 5.6, 10.2, 18.3, and 24.3 rkm) for SRT thermal habitat assessment and model calibration, validation, and predictive ability assessment.
- Cross-sectional profiles at 37 locations were measured using surveying techniques.
- Stream width, riparian vegetation offset from stream-bank, and riparian vegetation height were measured at 102 random locations per stream bank from 0.5-24.0 rkm. Riparian vegetation height was calculated by measuring the distance from observer to tree multiplied by the tangent of the angle from water surface to top of tree measured with a clinometer.
- Elevation, latitude, longitude, river kilometer locations, and azimuth were measured from a topographic map. (Chapter 2 contains detailed data collection methods).

The RQUAL model was calibrated with one year of data and validated with another year of data. Predictive ability was assessed based on the difference between measured and predicted temperature values. Predictive ability of hourly temperature predictions and daily maximum hourly temperature change (calculated from hourly predictions) was assessed as hourly residuals (i.e., difference between predicted and measured temperature) averaged by month. To calibrate the model, I adjusted input parameters (typically calibration coefficients) until the trend of the predicted and measured water temperature closely matched when viewed graphically at multiple longitudinal river locations. Model validation was tested statistically using a one sided chi square test to test for difference ($P \leq 0.05$) between counts of absolute residuals from the calibrated time period (1999/2000 predictions) to the independent dataset time period (2000/01 predictions). Counts were tested based on 2x2 contingency tables that separated residuals within the two compared seasons based on two predictive ability categories: suitable (0-4°C) versus unsuitable (>4°C), and optimal (0-2°C) versus acceptable (2-4°C) (Conover 1971; Thomas and Bovee 1993).

Fifteen alternative flow scenarios were developed in addition to the existing flow regime used by the USACE from March to September 2000 (Table 3.1). Scenarios differed from existing conditions by altering the number of days per week of generation, baseflow, time of day of generation, whether releases were peaked or ramped, generation duration, as well as no generation. A run of river flow regime was developed using daily inflow into Philpott reservoir computed by the USACE. Ramping scenarios increased flow from 1.4 cms to 36.8 cms over three hours and remained at 36.8 cms for one hour. Total quantity of water released over this four hour period (3 hr ramping + 1 hr at 36.8 cms) is equal to that of the two hour generation scenarios. Time at which flow reached 36.8 cms was 7 am or 5 pm. Hourly predictions at 2 rkm intervals from 0.6-24.3 rkm below Philpott dam for each scenario were evaluated for ability to produce optimal growth temperatures, reduce hourly temperature fluctuations, and reduce 21°C exceedances.

Hourly predicted temperatures from March-September 2000 at 13 locations (2 rkm intervals) from 0.6-24.3 rkm downstream of Philpott dam were compared between the 15 alternative flow scenarios and existing flow conditions. Percent time of each

Table 3.1. Description of flow scenarios assessed with ADYN & RQUAL model on the Smith River from March to September 2000.

Scenario Name	Days per Week of Generation	Baseflow (cms)	Release Time	Ramping Duration (hours)	Generation Duration (hours)	Peak Flow (cms)
5 day 2 hr release	5	1.4	5pm		2	36.8
5 day 5 hr release	5	1.4	5pm		5	36.8
Steady baseflow	0	1.4				
Increased steady baseflow	0	8.5				
Run of river	0	------------Daily Inflow to Philpott Reservior------------				
Evening 1 hr release	7	1.4	5pm		1	36.8
Evening 2 hr release	7	1.4	5pm		2	36.8
Morning 1 hr release	7	1.4	7am		1	36.8
Morning 2 hr release	7	1.4	7am		2	36.8
Evening 1 hr release with increased baseflow	7	2.8	5pm		1	36.8
Evening 2 hr release with increased baseflow	7	2.8	5pm		2	36.8
Morning 1 hr release with increased baseflow	7	2.8	7am		1	36.8
Morning 2 hr release with increased baseflow	7	2.8	7am		2	36.8
Evening ramped release	7	1.4	5pm	3	1	36.8
Morning ramped release	7	1.4	7am	3	1	36.8
Existing conditions	~7	~1.4	~5pm		~1	~36.8

month that 21°C was exceeded, temperature was within 12-19°C, and maximum hourlytemperature change exceeded 2°C was calculated. To assess growing conditions for fish, accrual of thermal units per month were calculated by summing all hourly predictions that fell within 12-19°C. Selection of these temperature criteria were based on the likelihood that greater than 21°C temperatures will induce stress and/or be lethal, temperatures outside 12-19°C will restrict food assimilation and metabolic activity, and rapid temperature fluctuations will induce stress.

RESULTS

Model Predictive Ability

Accuracy of RQUAL hourly temperature predictions and daily maximum hourly temperature change (MHTC) was assessed via comparison to measured water temperatures at three locations (5.1, 18.3, and 24.3 rkm) below Philpott dam. Hourly predictions closely followed the diel temperature fluctuation for most days and river locations, however there were occurrences of poor predictive ability (Figure 3.2). Mean absolute residuals (hourly predictive ability averaged from March to September 2000) did not exceed 1.50°C and mean absolute residuals for MHTC did not exceed 1.87°C (Table 3.2). Absolute residuals of hourly predictions increased with increasing distance from the dam. Absolute residuals of MHTC decreased with increasing distance from the dam. The RQUAL model tended to overpredict MHTC.

Model Validation

Model validation was assessed graphically by comparing the trend of predicted to measured temperature for calibrated seasons (summer, fall, winter 1999/2000) to the trend of predicted to measured temperature for a second independent dataset (summer, fall, winter 2000/2001). Predictions for the second dataset used the same calibrations as the calibrated seasons. The trend of the predicted and measured temperature for the independent dataset seasons matched in closeness and similarity to the calibrated seasons; deeming the model valid. Statistical (one sided chi square test) assessment found RQUAL to validate for all assessed seasons within the suitable predictive ability

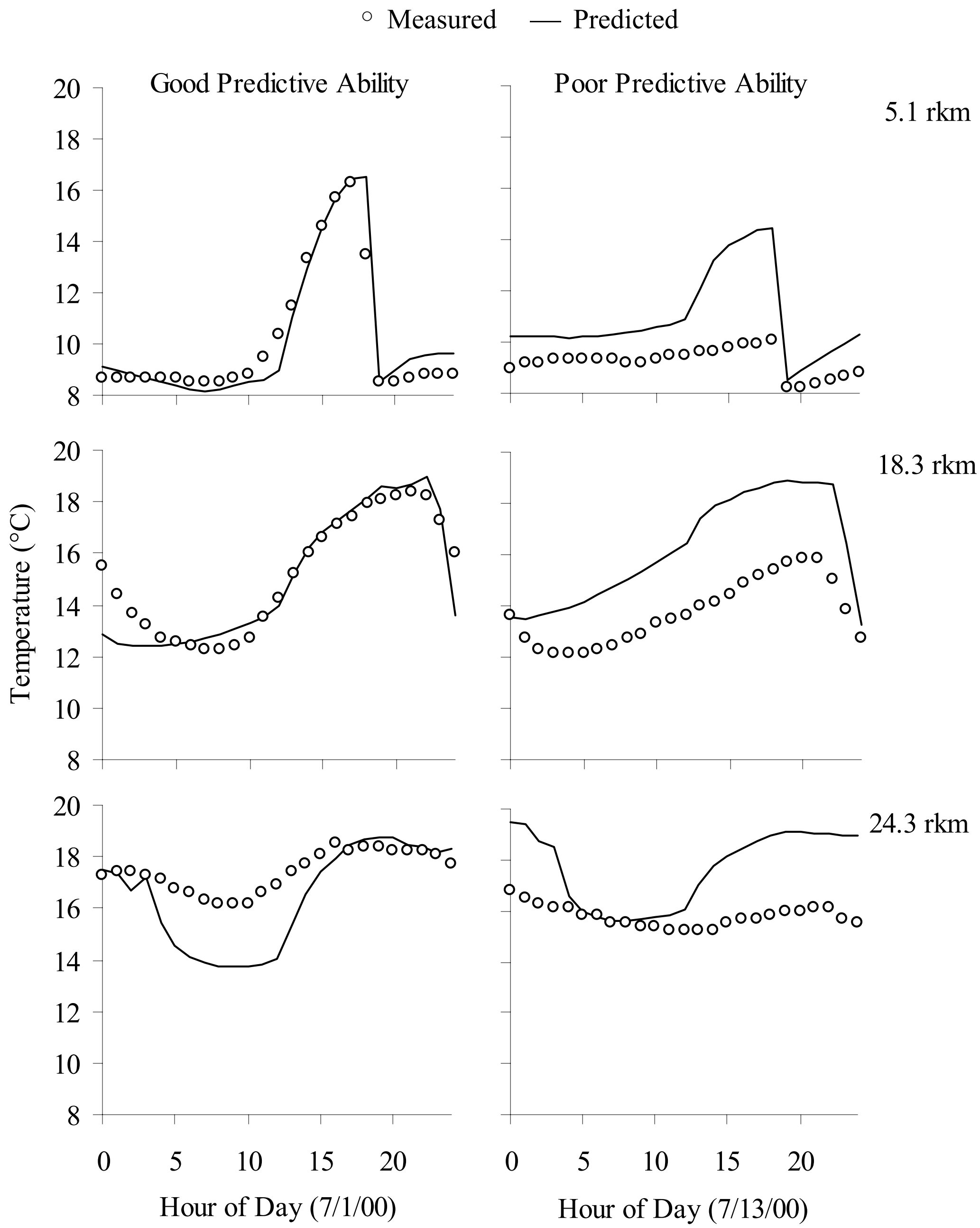


Figure 3.2. Examples of good (July 1, 2000) and poor (July 13, 2000) predictive ability over a 24-hour period. Graphs display hourly RQUAL predicted temperatures and data logger measured temperatures at 5.1, 18.3, and 24.3 rkm below Philpott dam.

Table 3.2. Hourly predictive ability and daily maximum hourly temperature change (MHTC) predictive ability of RQUAL at 5.1, 18.3, and 24.3 rkm below Philpott dam averaged from March to September 2000. Average underprediction (°C) in parenthesis, absolute average residual (°C), and average overprediction (°C) in brackets.

	5.1 rkm	18.3 rkm	24.3 rkm
Hourly Predictive Ability	(-0.75) 0.97 [0.91]	(-1.23) 1.30 [1.13]	(-1.60) 1.50 [0.96]
MHTC	(-0.72) 1.87 [1.87]	(-0.18) 1.52 [1.54]	(-0.33) 0.80 [0.81]

category (0-4°C). The RQUAL model validated for fall but not summer or winter at the optimal versus acceptable category (0-2°C)

Alternative Flow Scenarios

Exceedance of 21°C

A 5-day/week release caused temperature (6.4-24.3 rkm) to exceed 21°C during weekends when no generation occurs (Figure 3.3). Additionally, temperatures remain elevated throughout the weekend where weekend minimum temperatures are similar to weekday maximum temperatures. A 7-day/week release reduces 21°C temperature exceedances and prevents elevated temperatures occurring for prolonged durations (Figure 3.3). Elevated weekend temperatures from the 5-day/week release scenario increases the diel temperature flux when flows are peaked at the beginning of a week (Figure 3.3).

Exceedance of 21°C occurred most often with the run of river and steady baseflow scenario at lower-river sites (~12.4-24.3 rkm) (Figure 3.4). Exceedance of 21°C was prevented more than 99% of March through September (2000) by the increased steady baseflow, morning 2 hr release, evening 2 hr release with increased baseflow, morning 1 hr & 2 hr release with increased baseflow, and morning ramped release scenarios. Temperatures never exceeded 21°C during March, April, May, and September for all scenarios at all river locations (0.6-24.3 rkm) with the exception of run of river flow, which allowed up to 4% exceedance at 10.3 rkm during September.

Daily maximum temperatures were decreased, primarily at downstream locations (18.3-24.3 rkm), by releasing in the morning, for 2 hours, and/or increasing baseflow (2.8 cms) (Figures 3.5-3.7).

Maximum Hourly Temperature Change

Run of river, steady baseflow, and increased steady baseflow scenarios prevent MHTC from exceeding 2°C more than 99% of March-September (2000) at all river locations (0.6-24.3 rkm). The morning 1 hr release with increased baseflow scenario caused the largest decrease over existing conditions of percent time MHTC exceeds 2°C (up to 3% reduction, 4.2% = 1 hour per day 2°C exceeded out of 30 days) and magnitude

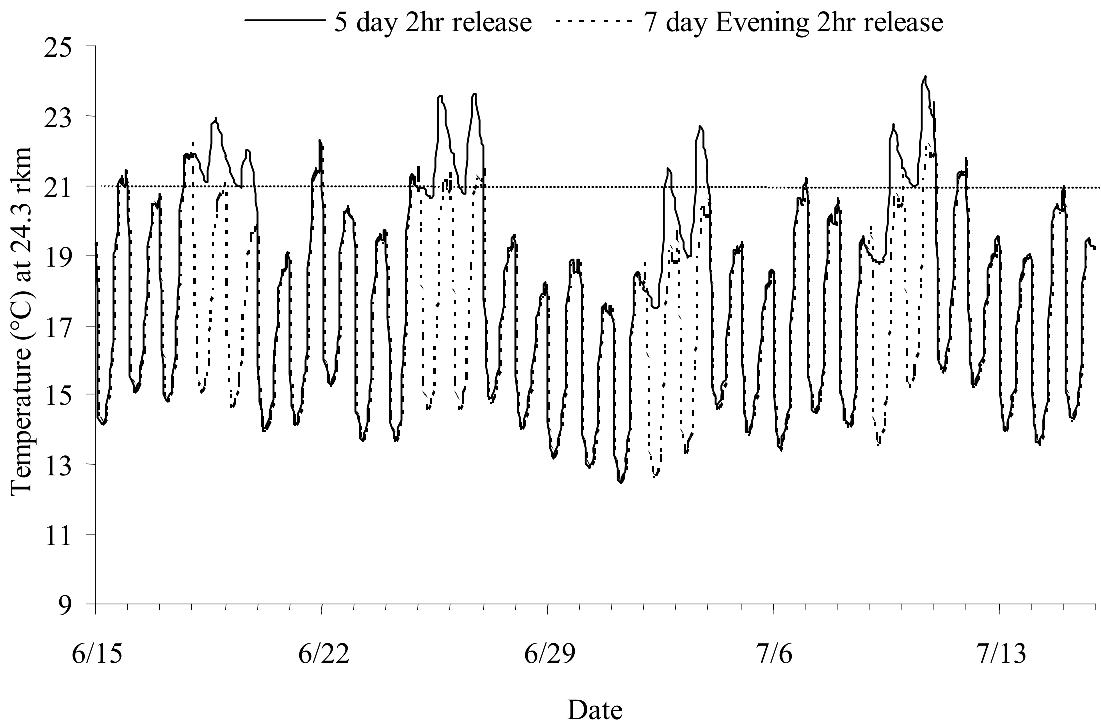


Figure 3.3. Hourly stream temperature at 24.3 rkm below Philpott dam from June 15 – July 15, 2000 under a 5 versus 7-day/week generation scenario.

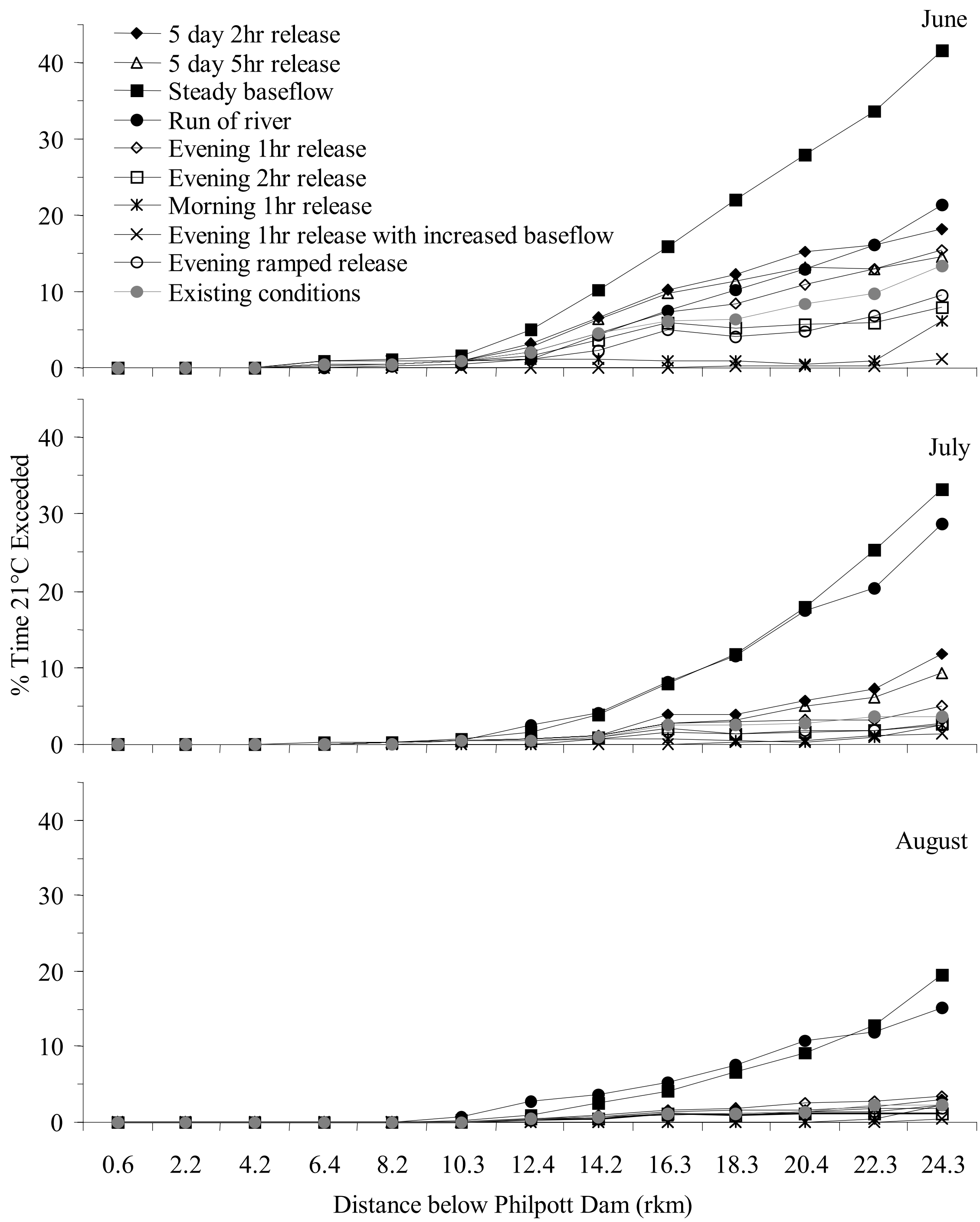


Figure 3.4. Percent time (June-August 2000) that 21ºC would be exceeded at 2 rkm intervals below Philpott Dam (0 rkm) under alternative flow scenarios.

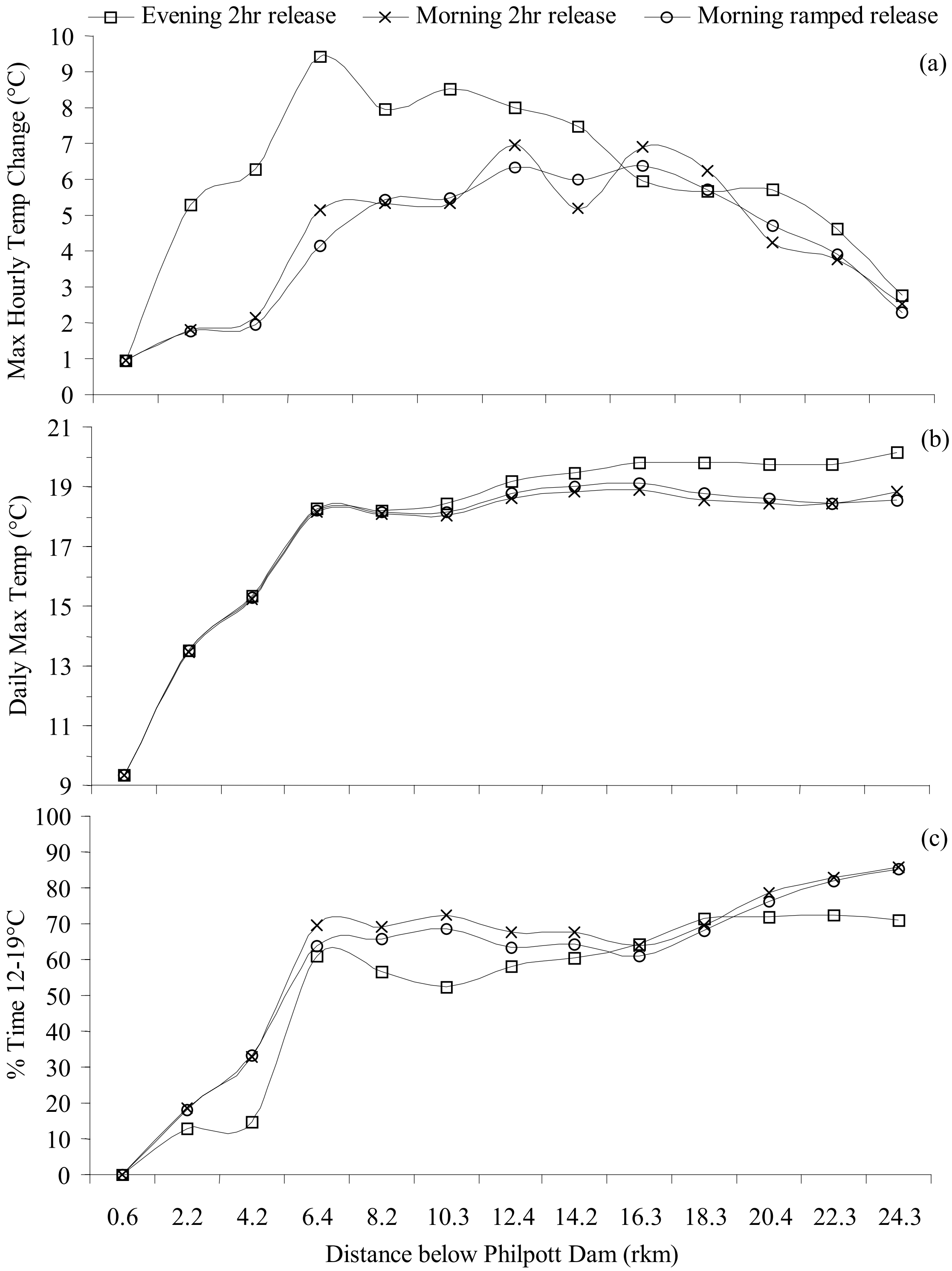


Figure 3.5. Daily maximum hourly temperature change averaged by month (a), daily maximum temperature averaged by month (b), and percent time of month that temperature is within 12-19ºC (c) for an evening vs. morning and morning ramped vs. morning peaked scenario (June 2000 shown).

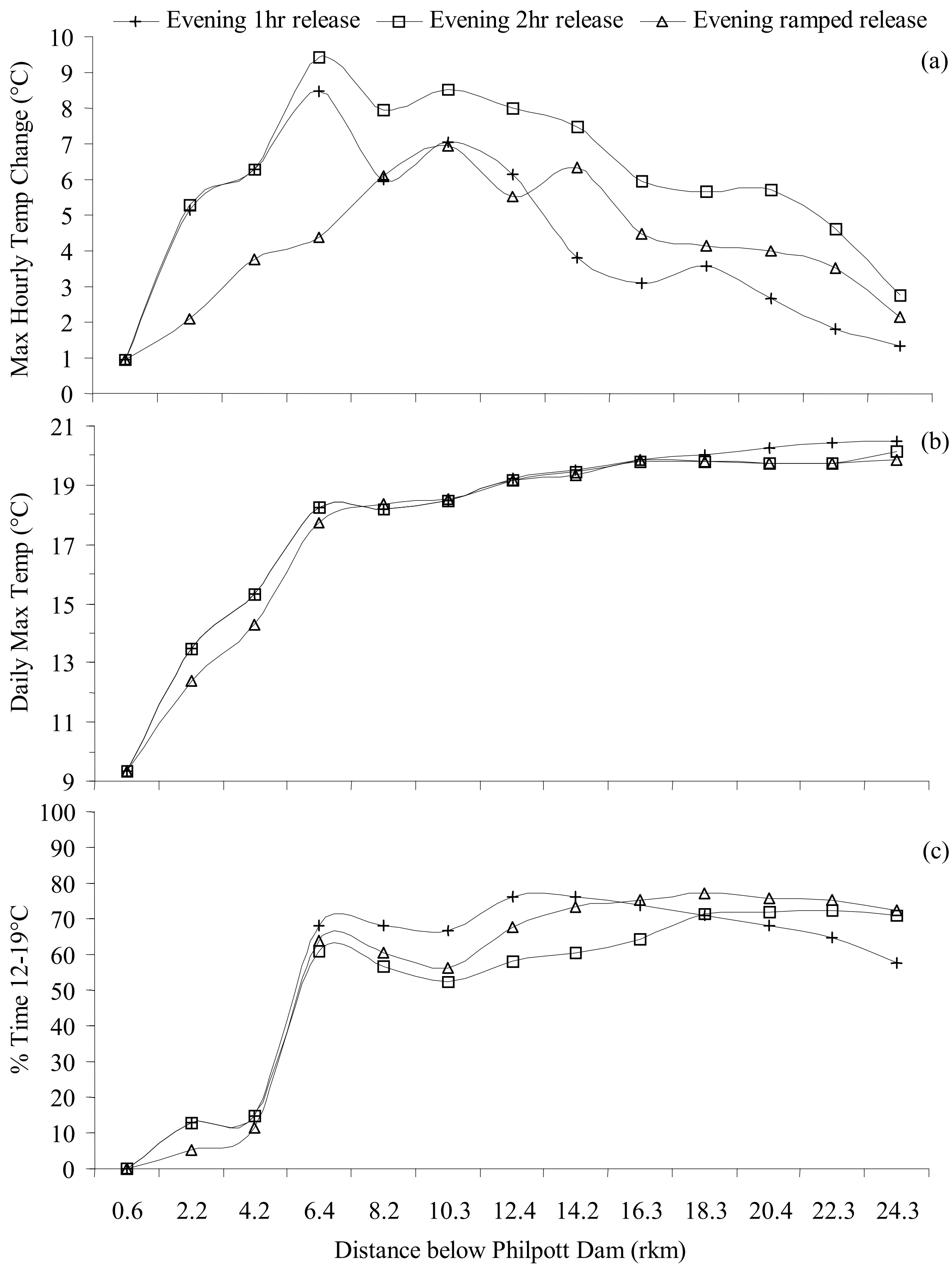


Figure 3.6. Daily maximum hourly temperature change averaged by month (a), daily maximum temperature averaged by month (b), and percent time of month that temperature is within 12-19ºC (c) for a 1 hr vs. 2 hr release and evening ramped vs. evening peaked scenario (June 2000 shown).

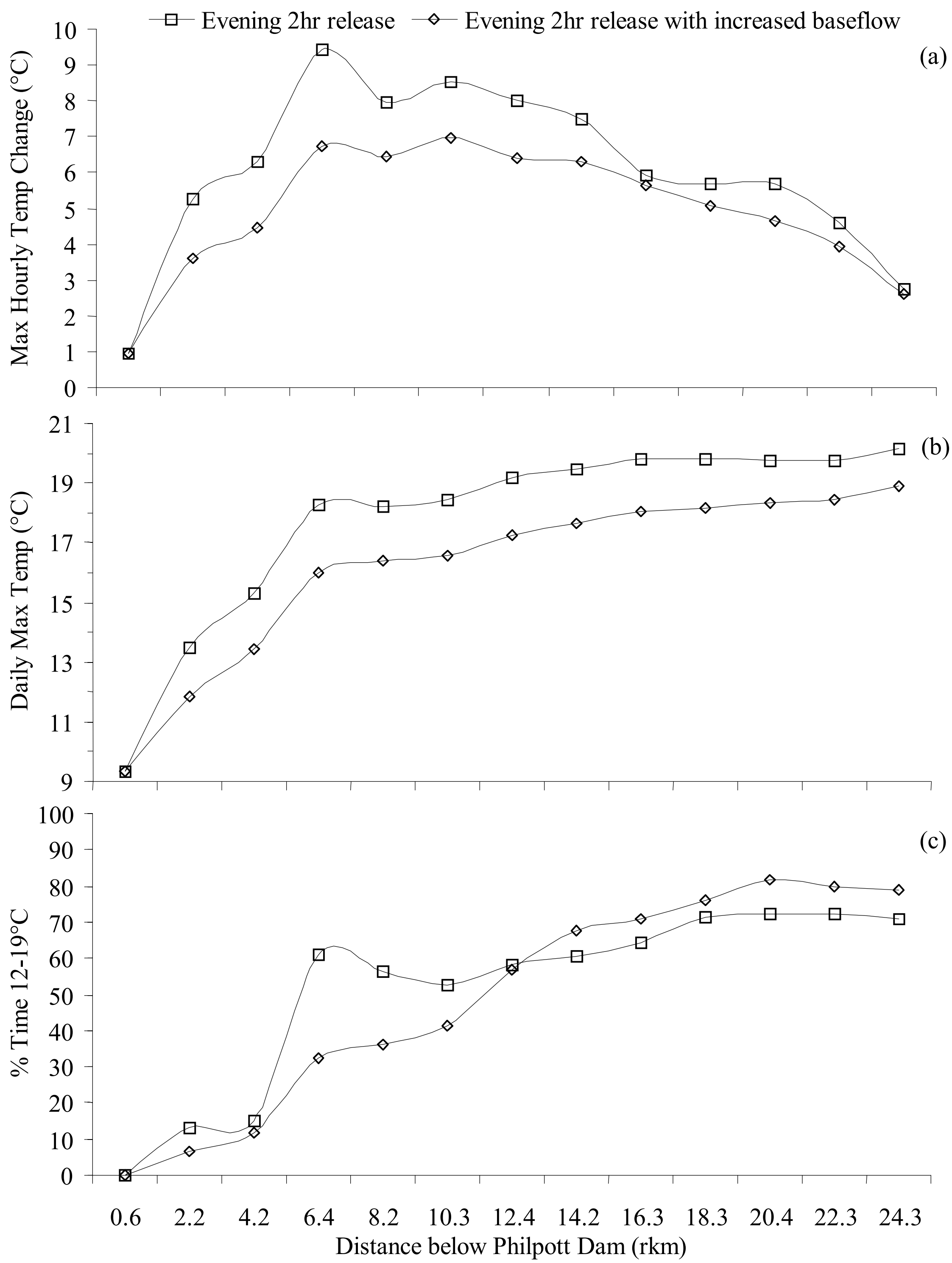


Figure 3.7. Daily maximum hourly temperature change averaged by month (a), daily maximum temperature averaged by month (b), and percent time of month that temperature is within 12-19ºC (c) for a 1.4 cms vs. 2.8 cms baseflow scenario (June 2000 shown).

of MHTC (up to 3.4°C reduction) (Table 3.3-3.4, Appendix D.1). Evening release causes the greatest MHTC to occur at mid-river locations (~6.4-14.2 rkm), whereas morning release causes the greatest MHTC to occur at lower-river locations (~12.4-18.3 rkm) (Figure 3.5, Appendix D.2). Evening ramped release decreases the magnitude of MHTC, but increases the percent time 2°C MHTC is exceeded (Figure 3.8).

Occurrence of Optimal Growth Temperatures

Release for 1 hour increases occurrence of optimal growth temperatures at mid-river locations (6.4-14.2 rkm) compared to 2 hr release (Figure 3.6). Increased baseflow (2.8 cms) reduces occurrence of optimal growth temperatures at upstream locations (2.2-12.4 rkm) compared to 1.4 cms baseflow (Figure 3.7). Evening 1 hr release was the only 7-day evening release scenario able to increase the percent time 12-19°C occurred for all months (March-September) (Table 3.5, Appendix E). However, the evening 1 hr release scenario caused greater 21°C exceedance than existing conditions and all other 7-day evening release scenarios (Figure 3.4).

Accrual of Thermal Units

The increased steady baseflow scenario caused the largest reduction from existing conditions of accrual of thermal units and percent time that temperatures were within 12-19°C (Table 3.5-3.6). With one exception (June), the morning 1 hr release scenario resulted in the largest increase of accrual of thermal units and percent time per month that temperatures are within 12-19°C (Table 3.5-3.6, Appendix E).

Best Alternative Flow Scenarios

The best morning release scenario to increase occurrence of optimal growth temperatures is morning 1 hr release and best evening release is evening 1 hr release (Table 3.7). It is clear that the morning 1 hr release scenario causes more improvement as it increases accrual of thermal units over existing conditions by 2320°C for May, 967°C for June, and 1589°C for July, whereas evening 1 hr release scenario increases by 943°C, 200°C, and 237°C (Table 3.4). The best scenarios to decrease MHTC, other than non-generation scenarios, are morning 1 hr release with increased baseflow for morning

Table 3.3. Difference between alternative scenarios and existing conditions averaged from 2.2-24.3 rkm by month (March-September 2000) for percent time maximum hourly temperature change exceeds 2ºC. Negative values indicate a reduction from existing conditions.

Scenario	Mar	Apr	May	Jun	Jul	Aug	Sep	Mean
5 day 2hr release	1.4	-0.2	-0.7	-1.0	-1.2	-0.6	-0.6	-0.4
5 day 5hr release	1.8	0.1	-0.7	-1.3	-1.4	-0.7	-0.5	-0.4
Steady baseflow	-0.7	-2.3	-4.0	-4.5	-4.3	-3.9	-3.2	-3.3
Increased steady baseflow	-0.7	-2.3	-3.9	-4.5	-4.3	-3.9	-3.2	-3.3
Run of river	-0.6	-2.3	-3.9	-4.5	-4.3	-3.8	-3.2	-3.2
Evening 1hr release	1.0	-0.2	-0.2	-0.4	-0.4	-0.6	-0.4	-0.2
Evening 2hr release	1.8	0.8	0.5	0.2	0.3	0.6	0.5	0.7
Morning 1hr release	-0.3	-1.5	-2.1	-1.8	-1.6	-1.6	-1.8	-1.5
Morning 2hr release	0.4	-0.6	-1.0	-0.6	-0.5	-0.4	-0.8	-0.5
Evening 1 hr release w/ increased baseflow	0.7	-0.6	-0.8	-1.3	-1.3	-1.1	-0.8	-0.7
Evening 2 hr release w/ increased baseflow	1.6	0.4	0.3	-0.5	-0.4	0.0	0.3	0.2
Morning 1 hr release w/ increased baseflow	-0.7	-2.1	-3.0	-2.5	-2.8	-3.0	-2.6	-2.4
Morning 2 hr release w/ increased baseflow	-0.4	-1.8	-2.2	-1.1	-1.5	-1.7	-1.9	-1.5
Evening ramped release	1.0	0.1	1.0	0.8	0.8	0.1	0.1	0.5
Morning ramped release	0.4	-0.5	-0.9	-1.1	-0.9	-0.7	-0.9	-0.6

Table 3.4. Difference between alternative scenarios and existing conditions averaged from 2.2-24.3 rkm by month (March-September 2000) for daily maximum hourly temperature change (°C). Negative values indicate a reduction from existing conditions.

Scenario	Mar	Apr	May	Jun	Jul	Aug	Sep	Mean
5 day 2hr release	0.8	-0.3	0.0	-0.3	-0.4	0.1	-0.3	-0.1
5 day 5hr release	1.2	0.0	0.6	0.5	0.3	0.7	0.0	0.5
Steady baseflow	-0.7	-1.9	-3.5	-4.2	-3.8	-2.9	-2.8	-2.8
Increased steady baseflow	-0.8	-2.0	-3.6	-4.4	-4.0	-3.1	-2.9	-3.0
Run of river	-0.7	-2.0	-3.5	-4.2	-3.7	-2.8	-2.8	-2.8
Evening 1hr release	0.6	-0.2	0.0	-0.7	-0.7	-0.5	-0.3	-0.3
Evening 2hr release	1.2	0.5	1.3	1.1	1.0	1.0	0.6	1.0
Morning 1hr release	-0.2	-1.2	-2.1	-2.3	-2.1	-1.5	-1.6	-1.6
Morning 2hr release	0.2	-0.7	-1.1	-0.7	-0.6	-0.3	-0.8	-0.6
Evening 1 hr release w/ increased baseflow	0.4	-0.7	-0.9	-1.9	-1.7	-1.4	-1.1	-1.0
Evening 2 hr release w/ increased baseflow	1.0	0.1	0.5	-0.1	-0.2	-0.1	-0.2	0.1
Morning 1 hr release w/ increased baseflow	-0.5	-1.6	-3.0	-3.4	-3.1	-2.4	-2.3	-2.3
Morning 2 hr release w/ increased baseflow	-0.2	-1.3	-2.4	-2.4	-2.3	-1.7	-1.8	-1.7
Evening ramped release	0.5	-0.3	-0.5	-0.9	-0.7	-0.4	-0.4	-0.4
Morning ramped release	0.2	-0.7	-1.2	-0.8	-0.7	-0.4	-1.1	-0.7

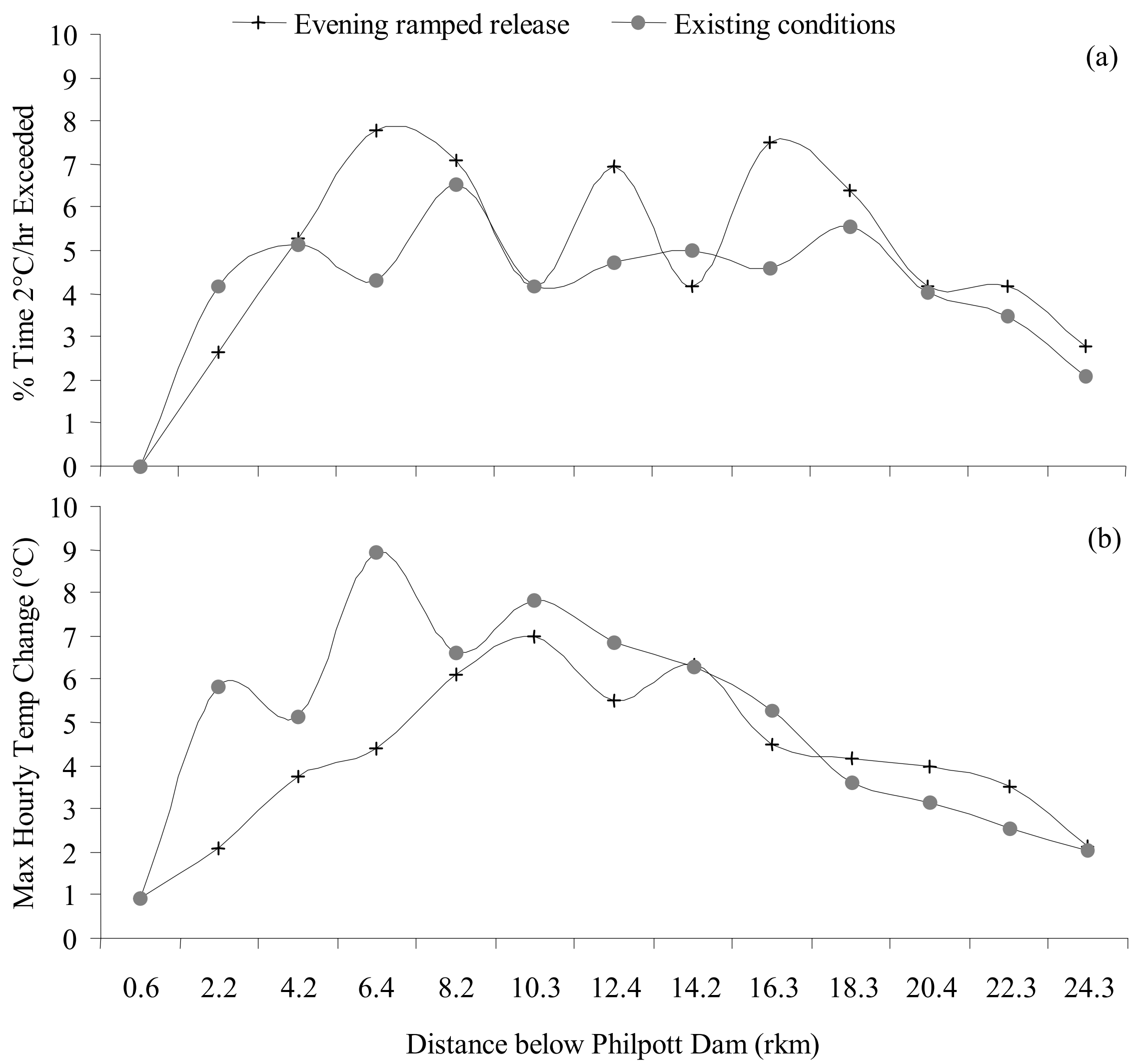


Figure 3.8. Percent time of month that maximum hourly temperature change exceeds 2ºC (a) and daily maximum hourly temperature change (b) for evening ramped release and existing conditions (June 2000 shown).

Table 3.5. Difference between alternative scenarios and existing conditions averaged by month (March-September 2000) for percent time 12-19ºC optimal growth temperatures for brown trout occur in the Smith River (2.2-24.3 rkm). Negative values indicate a reduction from existing conditions.

Scenario	Mar	Apr	May	Jun	Jul	Aug	Sep	Mean
5 day 2hr release	3.7	2.8	2.6	-6.6	-2.6	-0.7	-4.7	-0.8
5 day 5hr release	3.0	0.3	-6.3	-17.7	-14.4	-12.0	-13.8	-8.7
Steady baseflow	10.4	15.0	22.8	-9.4	-7.7	3.0	12.0	6.6
Increased steady baseflow	-3.6	-13.3	-19.3	-14.1	-21.8	-21.3	-24.4	-16.8
Run of river	1.7	-9.9	7.1	-2.8	-7.0	4.2	-0.4	-1.0
Evening 1hr release	4.0	2.1	8.8	1.1	1.6	2.5	2.7	3.3
Evening 2hr release	2.6	-2.2	-5.4	-3.1	-4.2	-6.4	-8.4	-3.9
Morning 1hr release	5.8	6.4	21.0	4.5	9.6	15.0	9.0	10.2
Morning 2hr release	3.6	2.8	16.6	6.1	9.6	13.8	4.4	8.1
Evening 1 hr release w/ increased baseflow	1.6	-4.4	-0.8	0.6	-2.5	-2.3	-5.8	-1.9
Evening 2 hr release w/ increased baseflow	0.7	-7.0	-13.4	-5.4	-11.6	-12.4	-15.6	-9.2
Morning 1 hr release w/ increased baseflow	2.1	-1.1	11.1	7.4	5.7	7.3	0.3	4.7
Morning 2 hr release w/ increased baseflow	0.8	-3.3	7.0	5.8	2.9	3.8	-3.5	1.9
Evening ramped release	1.8	-3.3	-1.9	0.7	-1.1	-2.5	-6.1	-1.8
Morning ramped release	4.2	3.6	15.6	3.7	7.8	12.3	4.3	7.3

Table 3.6. Difference between alternative scenarios and existing conditions averaged from 2.2-24.3 rkm by month (March-September 2000) for accrual of thermal units (°C) in the Smith River. Negative values indicate a reduction from existing conditions.

Scenario	Mar	Apr	May	Jun	Jul	Aug	Sep	Mean
5 day 2hr release	391.7	293.0	375.8	-686.9	-151.2	3.6	-361.7	-19.4
5 day 5hr release	312.5	58.0	-567.5	-1847.1	-1392.2	-1221.5	-1252.9	-844.4
Steady baseflow	1045.2	1479.3	2865.4	-663.2	-392.9	830.0	1604.4	966.9
Increased steady baseflow	-340.4	-1308.2	-2536.5	-1840.1	-2857.1	-2777.8	-2865.0	-2075.0
Run of river	188.0	-966.9	652.8	-60.2	-386.6	1046.2	-130.9	48.9
Evening 1hr release	426.8	224.5	943.1	200.2	237.3	352.9	315.9	385.8
Evening 2hr release	279.3	-192.0	-614.1	-442.1	-580.9	-758.1	-877.5	-455.1
Morning 1hr release	563.7	604.4	2320.8	967.2	1589.0	1983.6	1013.9	1291.8
Morning 2hr release	348.6	250.8	1677.3	1048.0	1376.6	1642.1	422.2	966.5
Evening 1 hr release with increased baseflow	164.8	-431.0	-242.7	47.7	-352.3	-358.7	-715.8	-269.7
Evening 2 hr release with increased baseflow	81.3	-678.5	-1569.3	-736.7	-1471.5	-1535.3	-1705.0	-1087.9
Morning 1 hr release with increased baseflow	200.0	-130.5	1003.4	1052.1	743.9	767.0	-97.1	505.5
Morning 2 hr release with increased baseflow	74.8	-344.1	463.6	783.2	289.8	250.7	-562.6	136.5
Evening ramped release	198.3	-303.2	-330.8	-17.0	-281.9	-391.8	-691.7	-259.7
Morning ramped release	400.7	338.1	1610.2	786.8	1201.4	1513.1	439.7	898.5

Table 3.7. Alternative scenarios ranked (e.g. 1 being best) based on ability to increase occurrence of 12-19°C optimal growth temperatures for brown trout and reduce magnitude of daily maximum hourly temperature change (by at least 1°C/hr) from existing conditions (2.2-24.3 rkm). Scenarios able to prevent 21°C exceedances more 99% of the time are designated with an X (2.2-24.3 rkm).

Scenario	Increased Optimal Growth Temp Occurrence	Reduced MHTC (°C)	Reduced Exceedance of 21°C
5 day 2hr release			
5 day 5hr release			
Steady baseflow	4	2	
Increased steady baseflow		1	X
Run of river		3	
Evening 1hr release	6		
Evening 2hr release			
Morning 1hr release	1	6	X
Morning 2hr release	2		X
Evening 1 hr release with increased baseflow		7	X
Evening 2 hr release with increased baseflow			X
Morning 1 hr release with increased baseflow	5	4	X
Morning 2 hr release with increased baseflow	7	5	X
Evening ramped release			
Morning ramped release	3		X

release and evening 1 hr release with increased baseflow for evening release. The morning 1 hr release with increased baseflow causes more improvement as it decreases MHTC over existing conditions by 3.0°C for May, 3.4°C for June, and 3.1°C for July (Table 3.6). The best scenarios to decrease exceedance of 21°C are morning 2 hr release, morning 1 hr & 2 hr release with increased baseflow, and morning ramped release for morning release and evening 2 hr release with increased baseflow for 5 pm release. These scenarios allow exceedance of 21°C <1% of the time.

DISCUSSION

The best flow scenario to improve one criteria (e.g. 21°C exceedance) was not the best to improve others. Therefore, it is important to choose a scenario that improves all criteria at the least compromise. The morning 1 hr release scenario was determined to offer minimal compromise by increasing the occurrence of 12-19°C temperatures by 10.2%, increasing accrual of thermal units by 1291.8°C, decreasing occurrence of MHTC by 1.5%, and decreasing magnitude of MHTC by 1.6°C over existing conditions averaged from March-September (Table 3.3-3.6).

Non-generation flow scenarios provided good comparative information. The run of river flow scenario, which releases the flow incoming into the reservoir, provided a natural flow regime in terms of water quantity, but not water temperature since the release is still hypolimnetic. The run of river and steady baseflow scenarios could be detrimental to the downstream trout fishery because they allow high percentages of June, July, and August to exceed 21°C from 12.4 rkm to downstream locations (Figure 3.4). The increased steady baseflow scenario prevented 21°C exceedances, but kept temperatures too cold thus causing a 16.8% decrease in occurrence of optimal temperatures from existing conditions (Table 3.3). The only clear improvement caused by non-generation scenarios was the elimination of MHTC >2°C.

The alterations in flow schedule (e.g. time of day, duration of release, etc) resulted in distinct thermal responses. Exceedance of 21°C was reduced by 7-day/week, morning, 2 hr, and/or increased baseflow release. Seven day/week release prevented the occurrence of elevated temperatures during non-generation weekends. Morning release cooled temperatures at the beginning of the day, thus reducing the ability of ambient conditions to raise temperatures above 21°C by the end of the day. The larger quantity of water released over 2 versus 1 hr, as well as with an increased baseflow, cooled downstream (~18.3-24.3 rkm) temperatures thus reducing maximum temperatures. Daily MHTC was decreased with release in the morning, for 1 hr, increased baseflow, and/or ramped flow (if evening release). Downstream temperatures are cooler in the morning and temperature of released water is closer to the channel water temperature, which reduced MHTC when mixed. The lesser quantity of water released over 1 versus 2 hrs had reduced ability to change temperature in the channel and because of attenuation, impacted less distance downstream. An increased baseflow decreased MHTC by dampening the impact of released water and by maintaining cooler temperatures within the channel. Ramping before a 5 pm release decreased the magnitude of MHTC by slowly increasing the flow of released water so that released and downstream water mixed more slowly. However, ramped release increased the percent time 2°C MHTC was exceeded due to an extended mixing period. Occurrence of optimal growth temperatures (12-19°C) was greatest with release in the morning, for 1 hr, and/or no increase to baseflow.

Measured temperature data revealed the SRT thermal regime may be causing stressful and/or growth restricting conditions for brown trout. Daily MHTC caused by peaked release of cold water mixing with water warmed by ambient conditions exceeded the DEQ 2°C per hour temperature change standard (monthly means up to 6.9°C) (Appendix C) (DEQ 1997). The longitudinal area where >2°C MHTC's occurred differed with release regime due to the quantity of water released (2 hr release during 1999 caused >2°C MHTC from ~5-24 rkm, and 1 hr release during 2000 caused >2°C MHTC from ~5-10 rkm). Temperatures exceeding the DEQ maximum temperature standard (21°C) for stockable trout waters were warmer and occurred more commonly during 1999 (up to 25.0°C) due to 5-day/week release than 2000 (up to 20.2°C) with a 7-day/week release (Appendix C). Daily maximum temperatures were reduced during 2000 because generation occurred on weekends unlike in 1999.

In addition to rapidly changing and warm temperatures, cold temperatures below the brown trout thermal growth optima (12-19°C) prevail in upstream areas near the dam. Water released from the dam averaged 8°C year round, which caused daily temperatures from 0-5 rkm to never exceed 12°C during year 2000. These cold temperatures would extend further downstream during summer if not for a major tributary (Town Creek at 5.3 rkm), which increased water temperature by an average of 2.4°C from May to September 2000. Occurrence of 12-19°C temperatures during 2000 was greatest from May to September and occurrence generally increased with downstream distance. At 24.3 rkm, 73.2% of June and 82.7% of July 2000 was within 12-19°C. However, near the special regulations area (5.3-10.0 rkm) at 10.2 rkm only 53.3% of June and 50.8% of July 2000 was within 12-19°C. From these measured temperature data it is apparent that although conditions improved (i.e., decreased daily maximum and increased occurrence of optimal temperatures) in year 2000 with a 7-day/week 1 hr release, thermal conditions are still likely to limit brown trout growth, especially within the trophy trout managed special regulations area. Though the 2000 release regime may have been an improvement, this regime was due to low reservoir storage levels and therefore was not continued during 2001.

Alternative flow scenarios considered for implementation that improve thermal conditions must also be evaluated from other physical and biological aspects. A small scale Instream Flow Incremental Methodology (IFIM) study assessed availability of physical habitat under different flow regimes in the SRT (USFWS 1986). Findings indicated habitat for all brown trout life stages are limited by the existing flow regime where baseflow (~1.4 cms) is too low and generation flow (~36.8 cms) is too high for optimal amounts of habitat. Maximum available habitat from ~0-12 rkm occurs at flows <17 cms and further downstream optimal flows are unknown. Associating IFIM information with temperature modeling information reveals that morning release with increased baseflow would improve physical habitat and thermal habitat. However, the increased steady baseflow scenario, which approximates mean annual flow, may improve physical habitat but would reduce the occurrence of optimal growth temperatures. Another aspect for consideration is the time of day of release and the associated effect on feeding as trout feed primarily during daylight hours (Forrester et al. 1994). Also, availability of food resources (e.g. drift) may improve when flow is increased. Whether growth is restricted by experiencing a smaller hourly temperature change over an extended period by ramping flow, versus a larger change over short time period by peaking flow is unknown. Also unknown is whether the magnitude of thermal improvement caused by a flow alternative will elicit a positive growth response in brown trout. Any flow regime that improves thermal habitat must enable anglers to fish the river. Alternatives causing baseflows too swift to wade safely would prevent anglers from accessing the very resource the flow was aimed to benefit. Answers to questions involving interactions between temperature, flow, habitat, and fish biology in the SRT will need to be answered to recommend an ideal flow regime.

The alternative flow regimes assessed by this study were consistent from one day to the next, however, another option is to alter the flow regime depending on daily conditions. Changing the flow regime from one day to the next could be based on a control rule, that if met by conditions one day, would determine the flow regime used the next day. Control rules are typically seasonally specific and must address selected criteria. For example, if a very warm summer day occurs surpassing a set of meteorological conditions (i.e., control rule) known to cause downstream SRT temperatures to exceeded 21°C, the flow regime would be changed (e.g. increased baseflow or release duration) to cool downstream temperatures. The implementation of day to day temperature management via flow alteration requires real-time monitoring of water temperatures, meteorological conditions, and flow. Implementing a control rule does have a downside. Because the flow regime becomes more unpredictable, anglers can no longer plan fishing trips in advance and the river becomes more dangerous with short term changes to flow.

The alternative flow regimes were assessed from a thermal habitat perspective, yet it is unknown how they differ economically. It is recommended that the USACE consider integrating the results of this habitat assessment with hydropower operations via cost-benefit analysis. This may determine if the realized cost of the fishery (post improvement) could become more valuable to the local community than the power created by Philpott dam.

Temperature predictions for the assessed scenarios demonstrates thermal conditions can improve compared to existing conditions. Implications of flow scenarios on factors (e.g. food and habitat resources) other than temperature will need evaluation. This study offers a basis toward achieving improved growth via thermal habitat enhancement by providing an understanding of flow effects on temperature. In summary, those effects are: decreased 21°C exceedance by releasing 7-days/week, in the morning, for 2 hours, and/or increasing baseflow. Decreased MHTC by releasing in the morning, for 1 hour, increasing baseflow, and/or ramping flow (if evening release). Increased occurrence of optimal growth temperatures (12-19°C) by releasing in the morning, for 1 hour, and/or not increasing baseflow.

CHAPTER 4. Influence of Urban Development on Thermal Habitat in a Warm-Water Stream

ABSTRACT

The Stream Network Temperature model (SNTEMP) was used to assess thermal habitat under flow, shade, and channel width changes occurring from future urbanization within the Back Creek watershed (Roanoke County, VA). Flow changes from the high density development scenario caused minimal heating of summer baseflow (0.14°C). However, when flow changes were combined with reduced shade and channel widening, baseflow temperature rose 1°C and daily maximum temperatures exceeded 31°C. Daily maximum temperature under existing channel conditions never exceeded 31°C; Virginia's maximum temperature standard and lethal limit for some fish species in Back Creek. Model predictions revealed additional urban development will alter stream temperature and possibly limit thermal habitat for fish species in Back Creek. Single, rather than cumulative changes, caused less impact suggesting that mitigation measures could reduce thermal impacts. If thermal impacts alone cause borderline fish habitat impairment, additional impacts such as sedimentation and pollution could exacerbate thermal changes resulting in loss of fish diversity and abundance in Back Creek as well as water quality in this tributary to the Roanoke River.

INTRODUCTION

Urbanization causes detrimental effects to stream habitat, aquatic biota and riparian vegetation, primarily due to impervious surfaces. Impervious surfaces such as rooftops and driveways, as well as compacted or low permeable surfaces, reduce infiltration and increase runoff during storm events (Ferguson and Suckling 1990; Horner et al. 1994; Leith and Whitfield 2000). Reduced infiltration, and thus reduced groundwater discharge subsequently causes declines in baseflow, which reduces stream habitat availability for fish and increases stream warming during summer months (Horner et al. 1994; Finkenbine et al. 2000). Baseflow reduction can become so severe that fish migration routes are blocked or sections of stream are desiccated (Finkenbine et al. 2000). Increased runoff causes greater peakflows, more frequent flooding, erosion, and channel widening or incision (Booth 1990; Ferguson and Suckling 1990; Horner et al.

1994; Trimble 1997). Surface runoff can warm as it passes over hot impervious surfaces thereby increasing stream temperatures (Galli 1990; James and Verspagen 1997; Van Buren et al. 2000). Increased flooding, bank erosion, and construction of buildings, roads, bridges, and culverts removes riparian vegetation, which shades and regulates stream temperature (LeBlanc et al. 1997). Stream temperatures can also become elevated when solar input is elevated due to widened and/or shallow stream channels.

Elevated temperatures can cause indirect harm to fish by, for example, lowering dissolved oxygen levels or increasing contaminant toxicity (Brooker 1981; Calow and Petts 1992). High temperatures have the potential to cause stress and mortality in fish populations (Chavin 1973; Reynolds and Casterlin 1979). Therefore, changes in thermal regime can extirpate aquatic species and/or favor new species (Wang et al. 2000).

In addition to thermal effects, runoff can impact water and habitat quality through multiple mechanisms. Surface water runoff impairs water quality via non-point source pollution of nutrients, bacteria, pathogens, pesticides, and toxins (Horner et al. 1994). Habitat quality is impaired by sedimentation, removal of habitat structure such as large woody debris, low baseflow, high velocity storm flows, and channelization (Horner et al. 1994; Finkenbine et al. 2000). Though pollution, flow, and thermal impacts are unlikely to return to a pre-disturbed state over time without mitigation, sedimentation will decline and bed coarsening will occur as the stream channel reaches equilibrium with the new flow regime (Finkenbine et al. 2000). However, this process takes decades (Finkenbine et al. 2000). In the short-term, sedimentation can cause loss of species year-class strength or even extirpation due to filling of interstitial spaces in spawning substrate, which reduces interstitial flow and thus dissolved oxygen (Horner et al. 1994). Loss of suitable spawning substrate therefore impairs spawning and egg survival. Additionally, increased flood frequency and high flow velocities may destroy spawning nests and dislodge eggs.

Loss of aquatic-system function is related to the amount of impervious surfaces within a watershed. Degradation to streams and aquatic biota (e.g. loss of diversity, low Index of Biotic Integrity scores) caused by urbanization are shown to occur at a threshold 10% imperviousness level (Horner et al. 1994; Booth and Jackson 1997; Wang et al. 2000). Once this level within the watershed is reached the stream system is no longer resilient to impacts, thus numbers of fish species decline (Wang et al. 2000). Water quality problems cause species shifts from intolerant (i.e., sensitive to poor water quality) to tolerant species and hydrologic changes (e.g. frequent and larger floods, and lower baseflows) can cause fish community shifts (Wang et al. 2000). The most significant impacts on fish will be caused by multiple changes, such as flow, water quality, sedimentation, temperature, etc., occurring concurrently. The effects on stream habitat of such urban development induced effects are well documented, with the notable exception of temperature (Galli 1990; Horner et al. 1994; James and Verspagen 1997; Finkenbine et al. 2000; Van Buren et al. 2000). Therefore, this study will focus on temperature to assess the level of thermal change resulting from urbanization. The goal of this study is to assess thermal changes and effects on fish habitat in Back Creek resulting from the predicted hydrologic regimes, as well as shade reduction and channel widening.

METHODS

Description of Study Site

The Back Creek watershed (148 km^2), located in southwestern Virginia (Roanoke County), is 15 km from the city of Roanoke (population 94,911) and is therefore an area considered for future urban development (Bosch et al., in review; US Census) (Figure 4.1). This watershed is the site of previous research that developed a modeling framework for evaluating land use impacts on surface hydrology, sub-surface flow regime, and channel processes controlling aquatic habitat under increases in urban development (Bosch et al., in review). However, a study of thermal impacts has not been addressed in the watershed's dominant stream, Back Creek. Back Creek is a 42 km, third order, warm-water tributary to the Roanoke River. Summer 2000 (June, July, August) measured water temperatures ranged from 16.4-29.2°C with a mean of 23.1°C at 37.1 rkm below the headwater (Appendix F). Discharge during summer 2000 at rkm 38 ranged from 0.08-160.29 cms due to natural variability from storm-events, had a mean of 0.99 cms, and a median of 0.38 cms (USGS) (Figure 4.2). Twenty-seven fish species were collected by Stancil (2000) in Back Creek during 1998-1999 and some of the more prevalent species are classified as "tolerant" and "intermediate" in their tolerance to environmental perturbation (Table 4.1) (Halliwell et al. 1999; Smogor and Angermeier 1999). Land use within the watershed is primarily comprised of forest (65.8%), urban

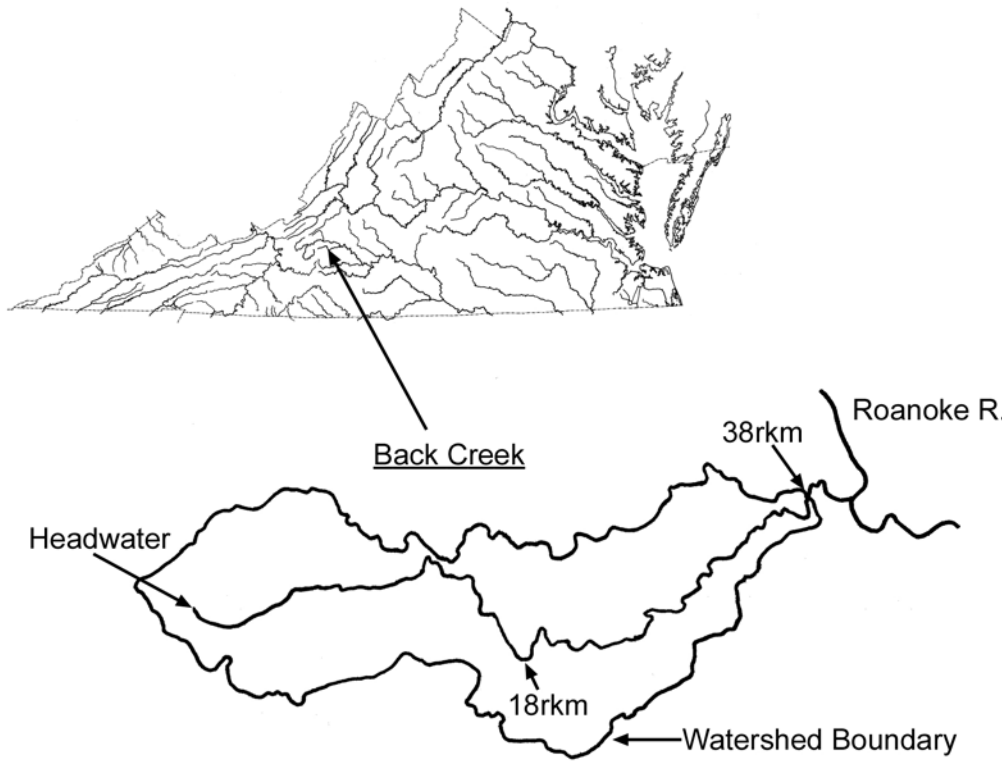


Figure 4.1. Location of Back Creek and watershed boundary in southwestern Virginia. Stream temperature predicted at 18 rkm and 38 rkm below the headwater.

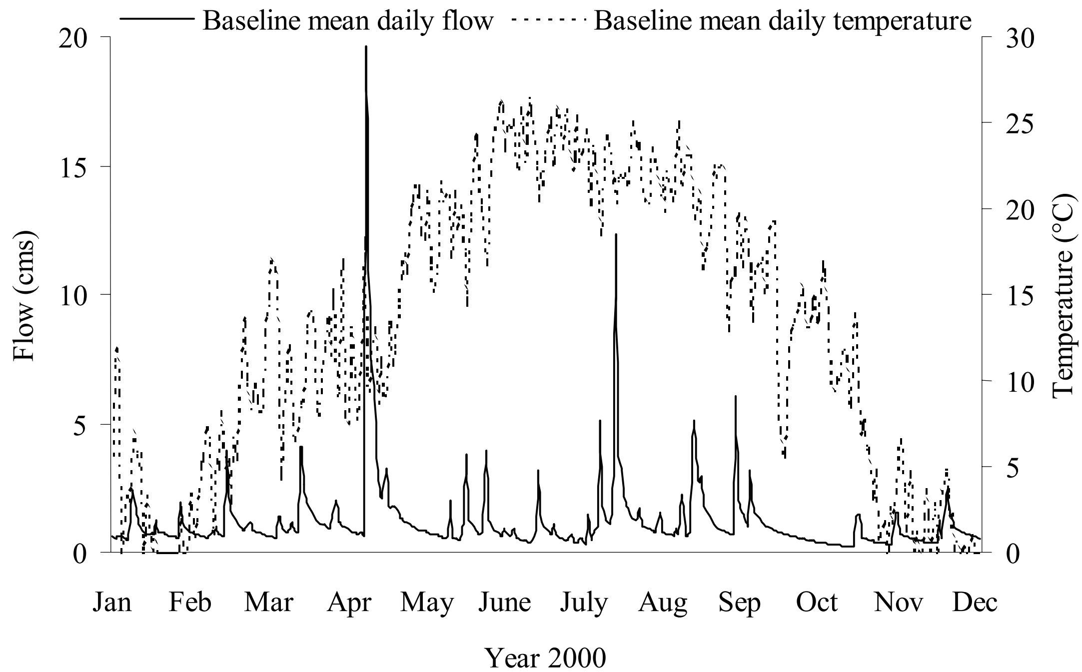


Figure 4.2. Year 2000 baseline mean daily flow (cms) and temperature (°C) at 38 rkm below the headwater.

Table 4.1. Occurrence, tolerance, and temperature criteria of fish species in Back Creek, Virginia order by family.

Common Name	Scientific Name	Occurrence[1]	Tolerance[2]	Lethal	Optimum Growth	Preferred Temp.
white sucker	Catostomus commersoni	220	T	31.6		19-21
nothern hogsucker	Hypentelium nigricans	7				
Roanoke hogsucker	Hypentelium roanokense	88				
golden redhorse	Moxostoma erythrurum	12	I			
v-lip redhorse	Moxostoma pappillosum	5				
black jumprock	Scartomyzon cervinus	97				
redbreast sunfish	Lepomis auritus	67	M	36	25-30	
smallmouth bass	Micropterus dolomieu	9	M	35	26-29	21-27
largemouth bass	Micropterus salmoides	1	M	33-36	24-30	27-28
central stoneroller	Campostoma anomalum	299	T			
rosyside dace	Clinostomus funduloides	4				
white shiner	Luxilus albeolus	1				
crescent shiner	Luxilus cerasinus	1043				
rosefin shiner	Lythrurus ardens	47				
bluehead chub	Nocomis leptocephalus	1074				
swallowtail shiner	Notropis procne	71	M	31-32		
mtn. redbelly dace	Phoxinus oreas	1636				
blacknose dace	Rhinichthys a. atratulus	192	T	29.3		
creek chub	Semotilus atromaculatus	1	T	32	12-24	
yellow bullhead	Ameiurus natalis	2	T			
margined madtom	Noturus insignis	134	M			
fantail darter	Etheostoma flabellare	1297	M			
johnny darter	Etheostoma nigrum	26	M			
riverweed darter	Etheostoma podostemone	50				
Roanoke darter	Percina roanoka	2				
rainbow trout	Oncorhynchus mykiss	1	I	25		12-18
brown trout	Salmo trutta	5	I	22-26	7-19	12-18

[1]Total number of fish per species sampled by Stancil (2000) at four sites during 1998 and 1999.
[2]Tolerance to environmental perturbations: T = Tolerant; M = Intermediate, I = Intolerant (Halliwell et al. 1999, Smogor and Angermeier 1999).
Sources of temperature criteria are Aho et al. (1986), Brown (1974), Brungs and Jones (1977), Jenkins and Burkhead (1993), McMahon (1982), Raleigh et al. (1984), Stuber (1982), Trial et al. (1983), and Twomey et al. (1984).

(17.1%), and agriculture (16.5%) (Bosch et al., in review). Total impervious area is 1%, which is low compared to the well documented 10% threshold at which aquatic habitat degradation occurs (Horner et al. 1994; Booth and Jackson 1997; Wang et al. 2000; Bosch et al., in review). However, imperviousness could reach 6-19% as another 50% (18,400 acres) of the watershed is available for future urbanization based on non-developable land comprising steep slopes, already disturbed land, preserved lands, and floodplains (Bosch et al., in review).

The SNTEMP Model

The Stream Network Temperature Model (SNTEMP) is a physical process model based on an energy balance equation and predicts temperature as a function of stream distance and environmental heat flux (Theurer et al. 1984; Bartholow 1997). The SNTEMP model was used to predict daily mean and maximum temperatures, which required a suite of input parameters.

Meteorological, Discharge, and Water Temperature Parameters

Meteorological parameters were downloaded from the nearest weather station (Roanoke, VA 17 km away) (NCDC). Solar radiation values were obtained from Bluefield, WV 124 km away (CONFRRM) and soil temperature data from the Virginia Tech College Farm Operation (Whitethorne, VA) 57 km from Back Creek (VAES). Discharge data was obtained from a gaging station located 38 rkm below the headwater (USGS). Hourly water temperatures were recorded from 8 July 1999 to 29 February 2001 at 3.7, 15.4, and 37.1 rkm below the headwater with Onset® StowAway XTI temperature loggers for model calibration and validation.

Stream Geometry and Shade Parameters

Stream width, topographic altitude, riparian vegetation height, shade density, crown width, and offset from stream-bank were measured at 168 random locations per stream bank from 2.7 to 37.0 rkm. Topographic altitude, the angle from the stream surface to topographic horizon, was measured with a clinometer (Bartholow 1989). Riparian vegetation height was calculated by measuring the distance from observer to tree multiplied by the tangent of the angle from water surface to top of tree measured with a clinometer (Bartholow 1989). Shade density was determined by comparing light (footcandles) measured with a light meter in the sun versus shade reflected off a standardized surface (18% photographic gray card) (Bartholow 1989). Vegetation crown width and offset were visually estimated and periodically measured to verify estimations. Elevation, latitude, longitude, river kilometer locations, and azimuth were determined from a topographic map. Channel width coefficient and exponent were developed from flow and width measured at four locations (3.3, 10.5, 25.0, and 38.0 rkm) once in August 2000, January 2001, and March 2001 (Bartholow 1989). (Chapter 2 contains detailed data collection methods)

Model Calibration and Validation

The SNTEMP model was calibrated and validated using standardized approaches. Calibration was achieved by adjusting input parameters (typically calibration coefficients) until the trend of the predicted and measured water temperature closely matched when viewed graphically for multiple longitudinal stream locations. Graphical (predicted and measured temperature versus time) and statistical (one sided chi square test) comparisons were made to verify model validation (Conover 1971, Thomas and Bovee 1993). The one sided chi square test tested for difference between counts of absolute residuals from the calibrated summer season (1999) to test season (summer 2000). Counts were tested based on 2x2 contingency tables that separated residuals within the two compared seasons based on two predictive ability categories: suitable (0-4°C) versus unsuitable (>4°C), and optimal (0-2°C) versus acceptable (2-4°C).

Alternative Scenarios

The SNTEMP model was used to predict mean daily and daily maximum temperatures from January 1 to December 31, 2000 at 2 rkm intervals from the headwater (0 rkm) to 38 rkm downstream. Evaluation of the thermal regime was limited to summer months (June, July, and August 2000) for evaluation of critical summer habitat at a mid (18 rkm) and lower (38 rkm) reach location. Stream temperature was also assessed separately for baseflow and storm-event flows. Base vs. storm-event flow was separated based on whether alternative urban development scenarios caused a lower or higher flow than baseline conditions (Appendix G).

Stream temperature was predicted for baseline conditions and alternative scenarios (Table 4.2). Baseline conditions represent the existing summer 2000 flow, meteorology, riparian vegetation and impervious surfaces (1%). Alternative scenarios for predicting stream temperature include changes to riparian shade, channel width, flow regime, and runoff temperature while all other parameters remained at the baseline values. Shade scenarios increased and decreased shade by 25% (not extending past 0% or 100%). Channel widening scenarios increased width by two meters concurrently with a 25% shade reduction.

Changes in flow due to increased urbanization were simulated using a low, medium, and high density urban development scenario (Bosch et al., in review). The scenarios altered flow regime based on density of people occupying the watershed if all developable land (50% or 18,400 acres of watershed) was utilized. The density of people currently living within the watershed is estimated at 0.03 people per acre. The low, medium, and high density alternatives assume 0.83, 5.94, and 10.39 people per acre respectively. With an increasing population, impervious surfaces increase (6% low, 15% medium, and 19% for the high density scenario) from rooftops, parking lots, and driveways as housing progresses from subdivisions to apartment complexes. Flow regimes resulting from precipitation falling on increased impervious surfaces and less forest, herbaceous, and agricultural land (corresponding to the urban density scenario's land use changes), were developed with the Hydrological Simulation Program--Fortran (HSPF) (Bosch et al., in review; B. Lockard, Department of Civil & Environmental Engineering, Virginia Tech, personal communication).

The urban development scenarios were also run with a 1°C and 2°C increase in runoff temperature to account for possible thermal heating from hot impervious surfaces during storm-events (James and Verspagen 1997; Van Buren et al. 2000). Though there is no runoff temperature parameter in the model, the groundwater temperature parameter, which is assumed by the model as lateral inflow temperature was adjusted to reflect warmed runoff. Adjustment of this parameter was believed a reasonable representation of increased runoff temperature because Back Creek required the use of soil temperature

Table 4.2. Description of alternative scenarios assessed with the SNTEMP model in Back Creek for summer 2000 (June, July, and August).

Scenario Name	Changes During Baseflow Conditions: Shade	Changes During Baseflow Conditions: Channel Width	Runoff Temp Change During Storm-Events	% Flow Reduction to Represent A "Dry Year"[1]
Baseline				18.5%
Shade +25%	+25%			18.5%
Shade -25%	-25%			18.5%
Channel +2m and Shade -25%	-25%	+2m		18.5%
Low Development			0°C, +1°C, & +2°C	18.5%
Medium Development			0°C, +1°C, & +2°C	18.5%
High Development			0°C, +1°C, & +2°C	18.5%
Worst Case	-25%	+2m	+2°C	18.5%

[1]All alternative scenarios were additionally assessed with a reduction in flow to represent a "dry year" flow regime.

in place of groundwater temperature to enable correct predictions. The high density urban development scenario was also assessed as a “worst case” scenario which incorporated concurrent impacts of 25% shade reduction, two meter channel widening, and during storm-events a 2°C runoff temperature increase.

Temperature for the baseline condition and all alternative scenarios was additionally predicted with a reduction in flow to represent a “dry year” flow regime. Baseline, low, medium, and high density development daily flow was reduced by 18.5%. The 18.5% reduction lowered year 2000 (a moderately wet year) mean annual flow to the lowest mean observed over 43 years of Back Creek flow records (B. Lockard, Department of Civil & Environmental Engineering, Virginia Tech, personal communication).

RESULTS

Model Validation

The SNTEMP model validated based on visual graphical assessment and the one sided chi square test. The trend of the predicted and measured temperature over time for the calibrated summer season (1999) compared to the second year (2000), which used the same calibrations, resulted in predictions following the trend of the measured temperatures. Statistical assessment resulted in no significant difference (i.e., model validates) between summer 1999 and 2000 residual counts for the suitable ($P = 0.08$) and optimal ($P = 0.98$) predictive ability categories.

Flow Changes

Increased development density caused reduced baseflow and increased storm-event flow. The high development scenario caused the largest reduction in baseflow (-0.14 cms) and increase in storm-event flow (+1.38 cms) from baseline conditions averaged over summer months (Table 4.3). Reduced flow simulating a “dry year", lowered summer averaged baseline baseflow from 0.93 cms to 0.76 cms and storm-event flow 1.68 cms to 1.37 cms (Table 4.3).

Table 4.3. Mean summer flow (cms) (Range) and difference between flow and low, medium, and high density development scenarios separated by baseflow and storm-event conditions at 38 rkm below the headwater.

	Baseline[1] Baseflow Conditions	Baseline[1] Storm-Event Conditions	Flow Reduced[2] Baseflow Conditions	Flow Reduced[2] Storm-Event Conditions
Baseline Flow (cms)	0.93 (0.46, 2.50)	1.68 (0.60, 6.16)	0.76 (0.37, 2.04)	1.37 (0.49, 5.03)
Low Dev. Diff	-0.01 (-0.04, 0.00)	-0.03 (-0.09, -0.01)	-0.01 (-0.03, 0.00)	-0.02 (-0.07, 0.01)
Med. Dev. Diff.	-0.10 (-0.27, -0.02)	0.93 (0.09, 3.19)	-0.08 (-0.22, -0.02)	0.76 (0.07, 2.60)
High Dev. Diff.	-0.14 (-0.37, -0.04)	1.38 (0.14, 4.66)	-0.11 (-0.30, -0.03)	1.12 (0.11, 3.80)
n	60	32	60	32

[1]Baseline conditions represent existing summer 2000 conditions.
[2]Flow reduced conditions represent summer 2000 flow conditions if it were a "dry year".

Alternative Scenarios

Shade and Channel Width

Evaluation of SNTEMP predictions focused on summer months, June, July, and August, which incurred the highest temperatures and some of the lowest flows during 2000 (Figure 4.2). During summer months shade scenarios had a greater effect on stream temperature than during spring and fall, and as expected nearly no effect during winter due to the amount of leaves on the trees. A 25% increase or decrease in shade resulted in a -0.67°C or +0.66°C change in mean daily temperature, respectively, during summer baseflow conditions at 18 rkm (Table 4.4). The effect of shade on temperature declined downstream (e.g. 38 rkm) and during storm-events (Table 4.4 and 4.5). This trend was consistent with the majority of the assessed alternative scenarios and is likely due to less water volume in upstream reaches. When channel width was increased by two meters the effect of shade reduction was increased (+0.94°C during baseflow conditions at 18 rkm) (Table 4.4).

Flow Regime under Alternative Urban Development Densities

Flow regime of the urban development scenarios altered temperature in the existing channel, but not as much as alternations in shade and/or channel width. The high development scenario increased daily mean temperatures by 0.14°C during summer baseflow conditions at 18 rkm (Table 4.4). During storm-events, the medium and high density urban development scenarios reduced temperature and little change occurred with low density development. However, if runoff during storm-events was warmed by hot impervious surfaces, stream temperature increased. For example, runoff increased 2°C under the low density scenario caused a 0.81°C increase in daily mean temperature during summer storm-events at 18 rkm (Table 4.5). An unexpected result was larger temperature changes occurring with low rather than high density development when runoff temperature was increased; likely due to less water in the channel during storm-events under the low density scenario.

Table 4.4. Mean summer baseline temperature (°C) (Range) and temperature difference between baseline and alternative scenarios for baseflow conditions at 18 rkm and 38 rkm below the Back Creek headwater.

Baseline[1] Baseflow Conditions	18 rkm	38 rkm
Baseline (C)	22.13 (19.21, 24.47)	23.24 (19.75, 25.81)
Shade +25%	-0.67 (-1.00, -0.26)	-0.58 (-0.86, -0.22)
Shade -25%	0.66 (0.26, 0.98)	0.57 (0.23, 0.84)
Low Development	0.01 (0.00, 0.02)	0.01 (0.00, 0.03)
Med Development	0.10 (0.02, 0.19)	0.09 (0.02, 0.19)
High Development	0.14 (0.03, 0.27)	0.12 (0.03, 0.26)
Baseline (set width) (C) [2]	22.50 (19.29, 25.05)	23.23 (19.75, 25.81)
Channel +2m & Shade -25% [2]	0.94 (0.39, 1.32)	0.70 (0.28, 0.99)
Worst Case (channel +2m, shade -25%, high dev.) [2]	1.09 (0.43, 1.53)	0.83 (0.31, 1.18)

[1]Baseline conditions represent existing summer 2000 conditions.
[2]Assessment of alternative scenarios involving channel widening required the width parameter to be set (measured channel widths used) to enable comparison. Other scenarios used a width coefficient and exponent, which varies width with flow.

Table 4.5. Mean summer baseline temperature (°C) (Range) and temperature difference between baseline and alternative scenarios for storm-event conditions at 18 rkm and 38 rkm below the Back Creek headwater.

Baseline[1] Storm-Event Conditions	18 rkm	38 rkm
Baseline (C)	21.29 (18.46, 23.17)	22.21 (18.55, 24.30)
Shade +25%	-0.46 (-0.77, -0.10)	-0.43 (-0.70, -0.11)
Shade -25%	0.46 (0.11, 0.76)	0.42 (0.11, 0.69)
Low Development	0.02 (-0.01, 0.04)	0.02 (-0.01, 0.04)
Med Development	-0.28 (-0.63, 0.13)	-0.32 (-0.77, 0.18)
High Development	-0.38 (-0.86, 0.16)	-0.46 (-1.05, 0.22)
Low Dev., Runoff +1C [2]	0.41 (0.24, 0.67)	0.28 (0.12, 0.58)
Med Dev., Runoff +1C [2]	0.20 (-0.15, 0.79)	0.02 (-0.39, 0.73)
High Dev., Runoff +1C [2]	0.12 (-0.33, 0.84)	-0.08 (-0.62, 0.79)
Low Dev., Runoff +2C [2]	0.81 (0.47, 1.33)	0.54 (0.23, 1.14)
Med Dev., Runoff +2C [2]	0.67 (0.31, 1.49)	0.37 (-0.05, 1.34)
High Dev., Runoff +2C [2]	0.62 (0.17, 1.56)	0.30 (-0.24, 1.44)
Baseline (set width) (C) [3]	21.57 (18.58, 23.59)	22.19 (18.61, 24.28)
Channel +2m & Shade -25% [3]	0.72 (0.04, 1.10)	0.56 (0.06, 0.85)
Worst Case (channel +2m, shade -25%, runoff +2C, high dev.) [3]	1.01 (0.46, 1.68)	0.76 (0.22, 1.58)

[1]Baseline conditions represent existing summer 2000 conditions.
[2]Runoff temperature increased by 1ºC or 2ºC to account for possible warming from impervious surfaces.
[3]Assessment of alternative scenarios involving channel widening required the width parameter to be set (measured channel widths used) to enable comparison. Other scenarios used a width coefficient and exponent, which varies width with flow.

A Worst Case Scenario

The largest changes to stream temperature occurred under a “worst case” scenario combining reduced shade (-25%), increased channel width (+2m), increased runoff temperature (+2°C) during storm-events, and high density development flow regime. For the "worst case" scenario summer mean daily temperature at 18 rkm increased 1.09°C during baseflow conditions and 1.01°C during storm-event conditions, and exceedance of 31°C maximum temperatures occurred (Table 4.4 and 4.5; Figure 4.3).

“Dry Year” Simulation

Flow reduction during “dry year" simulation caused additional temperature elevation. "Dry year" simulation caused a 0.18°C increase in baseline temperature during baseflow conditions and 0.16°C during storm-event conditions on average for summer months at 18 rkm (0.15°C increase for baseflow and storm-event conditions at 38 rkm) (Table 4.4-4.7).

Results Summary

The SNTEMP model predictions suggest that increases in mean daily temperature are unlikely to exceed 2°C under the assessed scenarios. A 2°C increase to the highest mean daily temperature during summer 2000 results in 28.44°C (28.56°C under "dry year" simulation), which does not exceed the Virginia Department of Environmental Quality (DEQ) 31°C maximum temperature standard for Virginia streams in mountainous zones (DEQ 1997). However, a larger temperature change occurs with daily maximum temperature. For example, the “worst case” scenario caused daily maximum temperatures to exceed 31°C 6.7% (8.3% under "dry year" simulation) of June, July, and August 2000 at 18 rkm during baseflow conditions (Figure 4.3). Whereas under baseline or baseline “dry year" conditions daily maximum temperature never exceeded 31°C (Figure 4.3).

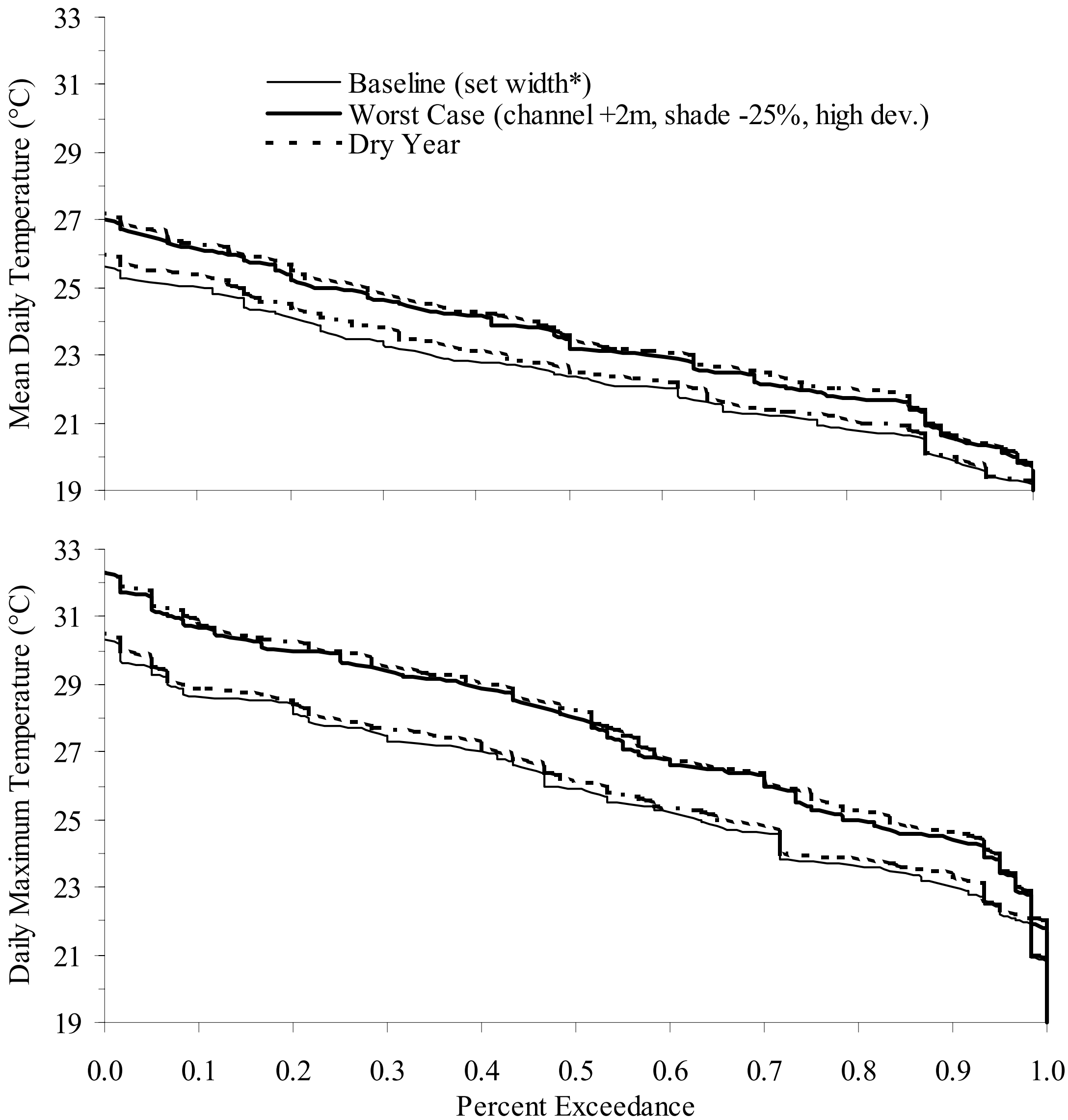


Figure 4.3. Percent exceedance of June, July, and August 2000 mean daily temperatures and maximum daily temperatures at 18 rkm during baseflow conditions.

* Assessment of alternative scenarios involving channel widening required the width parameter to be set (measured channel widths used) to enable comparison. Other scenarios used a width coefficient and exponent, which varies width with flow.

Table 4.6. Mean summer baseline temperature (°C) (Range) and temperature difference between baseline and alternative scenarios for flow reduced baseflow conditions at 18 rkm and 38 rkm below the Back Creek headwater.

Flow Reduced[1] Baseflow Conditions	18 rkm	38 rkm
Baseline (C)	22.31 (19.25, 24.68)	23.39 (19.81, 25.98)
Shade +25%	-0.50 (-0.82, -0.16)	-0.60 (-0.88, -0.23)
Shade -25%	0.69 (0.27, 1.02)	0.59 (0.23, 0.86)
Low Development	0.01 (0.00, 0.03)	0.01 (0.00, 0.03)
Med Development	0.09 (0.02, 0.18)	0.07 (0.02, 0.17)
High Development	0.13 (0.03, 0.25)	0.10 (0.02, 0.24)
Baseline (set width) (C) [2]	22.78 (19.36, 25.35)	23.39 (19.82, 25.97)
Channel +2m & Shade -25% [2]	0.85 (0.33, 1.23)	0.70 (0.28, 0.99)
Worst Case (channel +2m, shade -25%, high dev.) [2]	0.98 (0.36, 1.42)	0.80 (0.30, 1.13)

1Flow reduced conditions represent summer 2000 flow conditions if it were a "dry year".
2Assessment of alternative scenarios involving channel widening required the width parameter to be set (measured channel widths used) to enable comparison. Other scenarios used a width coefficient and exponent, which varies width with flow.

Table 4.7. Mean summer baseline temperature (°C) (Range) and temperature difference between baseline and alternative scenarios for flow reduced storm-event conditions at 18 rkm and 38 rkm below the Back Creek headwater.

Flow Reduced[1] Storm-Event Conditions	18 rkm	38 rkm
Baseline (C)	21.45 (18.42, 23.35)	22.36 (18.50, 24.46)
Shade +25%	-0.36 (-0.63, -0.10)	-0.44 (-0.72, -0.12)
Shade -25%	0.48 (0.12, 0.80)	0.44 (0.12, 0.70)
Low Development	0.01 (0.00, 0.03)	0.01 (-0.01, 0.03)
Med Development	-0.27 (-0.63, 0.15)	-0.32 (-0.89, 0.20)
High Development	-0.38 (-0.86, 0.18)	-0.42 (-1.01, 0.24)
Low Dev., Runoff +1C [2]	0.38 (0.22, 0.63)	0.24 (0.11, 0.53)
Med Dev., Runoff +1C [2]	0.16 (-0.18, 0.77)	0.00 (-0.38, 0.71)
High Dev., Runoff +1C [2]	0.09 (-0.37, 0.83)	-0.09 (-0.61, 0.78)
Low Dev., Runoff +2C [2]	0.74 (0.42, 1.26)	0.47 (0.20, 1.05)
Med Dev., Runoff +2C [2]	0.60 (0.25, 1.44)	0.31 (-0.08, 1.27)
High Dev., Runoff +2C [2]	0.55 (0.10, 1.51)	0.25 (-0.25, 1.38)
Baseline (set width) (C) [3]	21.81 (18.51, 23.89)	22.35 (18.55, 24.46)
Channel +2m & Shade -25% [3]	0.65 (0.04, 1.04)	0.55 (0.06, 0.84)
Worst Case (channel +2m, shade -25%, runoff +2C, high dev.) [3]	0.90 (0.36, 1.65)	0.72 (0.19, 1.52)

[1]Flow reduced conditions represent summer 2000 flow conditions if it were a "dry year".
[2]Runoff temperature increased by 1ºC or 2ºC to account for possible warming from impervious surfaces.
[3]Assessment of alternative scenarios involving channel widening required the width parameter to be set (measured channel widths used) to enable comparison. Other scenarios used a width coefficient and exponent, which varies width with flow.

DISCUSSION

Effects of Urban Development on Flow

Flow regimes predicted for the urban development scenarios caused baseflow to decrease and storm-event flows to increase with increased impervious surfaces. Rainfall that would have provided recharge over a longer time period now reaches the stream quickly as overland runoff. Larger amounts of overland runoff during storm-events results in a flasher flow regime; distinguished by a quick steep rise in flow with rainfall. Though the Back Creek watershed has only 1% impervious surfaces, Back Creek is runoff driven as characterized by sharp storm peaks in the hydrograph (Figure 4.2), a close association between the precipitation regime and hydrograph, and because SNTEMP predicted temperature for storm-events more correctly when soil temperature rather than groundwater temperature was input. A likely reason Back Creek displays properties of a runoff driven system is the steep topography throughout a large portion of the watershed. Though Back Creek is runoff driven, increased impervious surfaces will amplify stormflow and diminish baseflow from current levels.

As total impervious surfaces increase with development the flow regime becomes flashier and because flows change rapidly, thermal impacts may have greater magnitude on a smaller time scale than SNTEMP is capable of predicting. Hourly flow regimes were predicted for the alternative development density scenarios (B. Lockard, Department of Civil & Environmental Engineering, Virginia Tech, personal communication), however SNTEMP is only able to predict mean daily and daily maximum temperature, thus hourly flow data required daily averaging. Even with this loss of information and the possibility that temperature could change rapidly or reach extremes unsuitable for aquatic biota on a smaller time scale, noticeable mean daily thermal changes were predicted under some alternative scenarios, primarily the "worst case" scenario.

Effect of Thermally Enriched Runoff

During storm-events the increased volume of water in the stream due to more runoff, caused stream temperatures to decline. The reason temperature declined is because a greater volume of water requires more energy to heat it. When an increase in thermal energy was applied by accounting for heat transferred from hot impervious surfaces to runoff, stream temperatures increased (Table 4.5). However, SNTEMP does not contain a parameter specifically for specifying runoff temperature, rather groundwater temperature is assumed the lateral inflow temperature. Because Back Creek is mostly runoff driven, soil temperature was used and therefore an increase in this parameter was assumed to account for an increase in runoff temperature. A 1°C and 2°C increase in runoff temperature was modeled based on Van Buren et al. (2000) who recorded the average runoff temperature from a parking lot (24.9°C) at an outfall sewer before entering a stream at 23.0°C and runoff from the upstream catchment at 21.3°C.

Thermal Changes in Relation to Fish Species in Back Creek

Stancil (2000) observed 27 fish species in Back Creek during 1998 and 1999. Some species with the highest occurrence were mountain redbelly dace, fantail darter, bluehead chub, crescent shiner, central stoneroller, white sucker, and blacknose dace (Table 4.1) (Stancil 2000). Of these species central stoneroller, white sucker, and blacknose dace are classified as "tolerant" and fantail darter as "intermediate" in their tolerance to environmental perturbations (Halliwell et al. 1999; Smogor and Angermeier 1999). Tolerance is a possible reason for their high occurrence in Back Creek, but most of these species are also noted to prefer clear over turbid streams (Jenkins and Burkhead 1993). The upper lethal temperature limit for blacknose dace and white sucker are close to the 31°C DEQ maximum temperature standard for Virginia streams in mountainous zones (Table 4.1) (DEQ 1997). Under baseline and baseline “dry year" conditions daily maximum temperature never exceeded 31°C at 18 rkm or 38 rkm during June, July, or August 2000. Thus, thermal conditions never exceeded the DEQ maximum temperature limit, which is set close to the lower limit of thermal lethality for fish species in Back Creek.

Thermal regime is important not only to fish, but macroinvertebrates, upon which many fish feed. As with fish, certain macroinvertebrate taxa (e.g. stoneflies) are more thermally sensitive to maximum temperatures, thus if impaired thermal conditions persist macroinvertebrate diversity and population size can decrease. Macroinvertebrate assemblages in three tributaries of Back Creek were less diverse and even than in some streams in neighboring watersheds (Sponseller et al. 2001). Reduced diversity is likely from elevated thermal conditions, which resulted from non-forested riparian areas within the Back Creek watershed that occurred from land use activities. Mean and maximum temperatures in the Back Creek tributaries were ~3-6°C warmer than in streams in neighboring watersheds with more forested riparian land (Sponseller et al. 2001). Thus, it is likely that the effects of urbanization on thermal conditions in Back Creek could reduce the macroinvertebrate forage base for fish.

The use of SNTEMP to predict temperatures under alternative scenarios revealed that additional urban development could limit thermal conditions for fish species in Back Creek. The most likely scenario to cause thermal limitations would be an increase in urban development in conjunction with other associated changes such as reduced riparian shading and channel widening. The lessened impact on temperature by single rather than cumulative changes suggests that thermal impacts could be reduced if mitigation measures such as preservation of riparian buffers are implemented prior to urban development. However, even if thermal changes caused by urban development do not restrict survival of fish species in Back Creek, other impacts associated with urbanization (e.g. sedimentation, habitat loss, nutrient loading, toxins) may cause impairment to fish habitat.

Conclusions

This study found that water temperatures in Back Creek will be altered if shade is reduced, the channel widened, and/or if total impervious surfaces surpass 10%. Stream temperatures will likely exceed the DEQ 31°C maximum temperature standard causing stress and possible death for fish species in Back Creek. Additionally, the effects on biota of temperature approaching lethal limits more frequently are unknown. An approximate 1°C increase in summer mean daily temperature due to shade reduction, channel widening, and/or high density development could reduce fish community diversity. The thermal impacts predicted by SNTEMP are considered conservative because predictions were modeled during a wet year and because the model is only capable of predicting mean daily temperatures. Thus, during storm-events the peakflows are greatly reduced and the hourly change in flow is lost due to daily averaging. To account for flashy flows and possibly reveal additional temperature effects, future work modeling urbanizing flows with a dynamic model is recommended. Predictions under the “dry year" simulated flow were also conservative because the scenarios did not account for any change in meteorological conditions (e.g. increased air temperature, less cloudiness, etc.). The low density development scenario is the greatest development expected for the area in the near future, however, the increased population of the medium and high density scenarios could be plausible in other watersheds neighboring larger cities. If urban development proceeds to high density levels without appropriate mitigation, thermal habitat changes may be great enough to alter fish diversity and abundance in Back Creek.

CHAPTER 5. Summary and Management Implications of This Work

Predictive Ability

The stream temperature predictions models, RQUAL, SNTEMP, and QUAL2E, were capable of predicting at a level deemed useful for management decisions (82-96% of predictions were within 3ºC of the measured temperature; typical residual error ~1.0-1.5ºC). To achieve high predictive ability and ensure user confidence in predictions under alternative parameter scenarios, model assumptions should not be violated. Though high predictive ability was achieved the majority of the time with SNTEMP and QUAL2E on the Smith River tailwater (SRT), their steady state flow assumption was violated. This is a possible reason for inconsistent QUAL2E and SNTEMP predictive ability as well as unrealistic channel width adjustment required to improve SNTEMP predictive ability. For Back Creek, where the steady state flow assumption was not violated, these models did not demonstrate the problems seen when used on the SRT.

Extent of Data Requirements

The greater the detail of desired predictions (e.g. daily vs. hourly), the greater the time and effort needed for data collection, model calibration, model runs, and assessment of model predictions. To achieve accurate hourly predictions, ADYN & RQUAL require at least 24 data input points per day for continuous parameters like flow and air temperature. Whereas SNTEMP and QUAL2E require daily mean parameter data to predict mean daily water temperature. Additionally, RQUAL is coupled with the dynamic flow model, ADYN, which requires extensive channel geometry data collection. Effort to achieve model predicted water temperatures also differed based simply on model to user interface. The QUAL2E model, potentially very easy to use because of its Windows interface, became the most tedious to use because it was not able to predict for multiple days within one run of the model. Instead QUAL2E was run for each day individually because it only accepts one flow value, and the flow parameter was desired to change daily as in SNTEMP.

Selecting A Model

A model user can be mislead into believing a model is right for their needs based on statements in the literature. For example, QUAL2E has been stated as a widely used and accepted model for stream water quality modeling, which could be used exclusively for temperature modeling (Bartholow 1989). Though this is true, QUAL2E is unable to do many things SNTEMP is capable of, such as, predict temperature under alternative shade levels, predict maximum temperatures, and account for daily flow changes while predicting multiple days per model run. Thus, the most important decision prior to performing temperature modeling is to make an informed model selection.

The second and third objective of this study required a model capable of answering specific questions. The SRT's thermal regime, which varies hourly due to dynamic flows, required assessment of alternative hydropower releases that might benefit brown trout growth. In Back Creek, the thermal regime under alternative levels of shade, channel width, and flow, which could change with increased urbanization, required assessment in relation to thermal requirements of present fish species. To accomplish the SRT objectives the ADYN & RQUAL model capable of modeling dynamic flow alternatives and predicting hourly temperature was required. To answer the Back Creek objectives the SNTEMP model able to predict temperature under alternative levels of shade was needed.

Alternative Flow Regimes to Enhance Thermal Habitat

During March through September 2000 in the SRT, data loggers revealed monthly mean water temperature was below those suitable for optimal growth from 0-5.1 rkm, monthly means of daily maximum hourly temperature change (MHTC) (averaged by month) exceeded 2ºC (DEQ standard) from 2.7-10.2 rkm, and maximum temperatures exceed 21ºC (DEQ standard) from 10.2-24.3 rkm (Appendix C). These thermal conditions are expected to be limiting growth of brown trout in this system. Alternative flow scenarios determined that releasing 7-days/week greatly reduced or eliminated the occurrence of >21ºC temperatures. In comparison, a 5-day/week release allowed 21ºC exceedance during non-generation. For example, in 1999 the USACE conducted 5-

day/week releases causing temperatures to reach 23.8ºC at 18.3 rkm and 25.0ºC at 24.3 rkm during July.

The ideal alternative flow scenario to improve optimal growth temperatures, reduce MHTC, and reduce maximum temperatures was different for each of these three criteria and also differed with month. However, some scenarios were able to improve all three criteria with minimal compromise, with the morning one-hour (7-day/week) release providing the greatest concurrent benefit to all three criteria. This scenario increased over existing conditions the occurrence of optimal growth temperatures by 10.2%, reduced MHTC by 1.5% or 1.5ºC, and prevented >21ºC temperatures over 99% of the time (values are means of conditions from 2.2-24.3 rkm from March-September 2000).

It is clear that temperatures can be altered in favor of brown trout thermal preference via flow regime, however it is unknown whether thermal improvements and/or the magnitude of change will actually benefit growth. Further study is needed to determine which thermal criteria is most important to improve and whether other factors (e.g. habitat and/or food resources) in the SRT could still restrict growth despite thermal enhancement. Regardless, 7-day/week flow release is recommended over 5-day/week and morning release during summer is recommended over evening release.

Effects of Urbanization on Thermal Conditions

Existing thermal conditions in Back Creek do not appear limiting to the warm-water fish community. Mean monthly data logger recorded temperatures during spawning months (April-June) were within the 10-25ºC range required by present species (Table 4.1, Appendix F). Upper lethal thresholds of the warm-water species in Back Creek range from 29.3-36ºC and maximum water temperatures never exceeded the 29.2ºC during 2000. During summer of 1999, a dryer year than 2000, temperatures reached but barely exceeded the DEQ 31ºC upper temperature standard at 31.9ºC.

Though existing thermal conditions appear within suitable ranges, it was discovered that impacts of urbanization could elevate mean daily temperatures by 1ºC. Additionally, daily maximum temperature, which never exceeded 31ºC during year 2000, could exceed 31ºC up to 7% of June, July, and August with urban development.

Reduced baseflow and increased storm-event flow, resulting from impervious surfaces, had less impact than shade reduction or channel widening with shade reduction. The flow regime resulting from the low density development scenario, which is a probable future development density, raised temperatures typically no more than ~0.01ºC. Even under flow resulting from high density development, temperature was typically only raised ~0.1ºC. Whereas a shade reduction of 25% elevated temperatures over existing conditions around ~0.5ºC, and when combined with channel widening neared a 1ºC increase. During storm events, temperature was reduced due to higher flows unless runoff was thermally enriched from heated impervious surfaces in which case temperatures were elevated.

The effects of urbanization will elevate temperatures and may cause temperature to approach lethal limits more frequently. The majority of the temperature change was due to shade loss and channel widening. Therefore, preservation of riparian buffers for shade and bank stabilization may enable maintenance of the existing thermal regime. However, predictions are believed conservative due to mean daily predictive capability of SNTEMP, scenario assessment during a wet year, and predictions made with altered flow to represent a "dry year" did not account for "dry year" meteorological conditions. In reality temperatures may become more elevated than predicted and other impacts such as sedimentation and pollution should not be neglected as they may have greater impact on aquatic biota. To lessen the conservativeness of predictions a dynamic model is recommended for future research to enable thermal assessment of flashy flow regimes.

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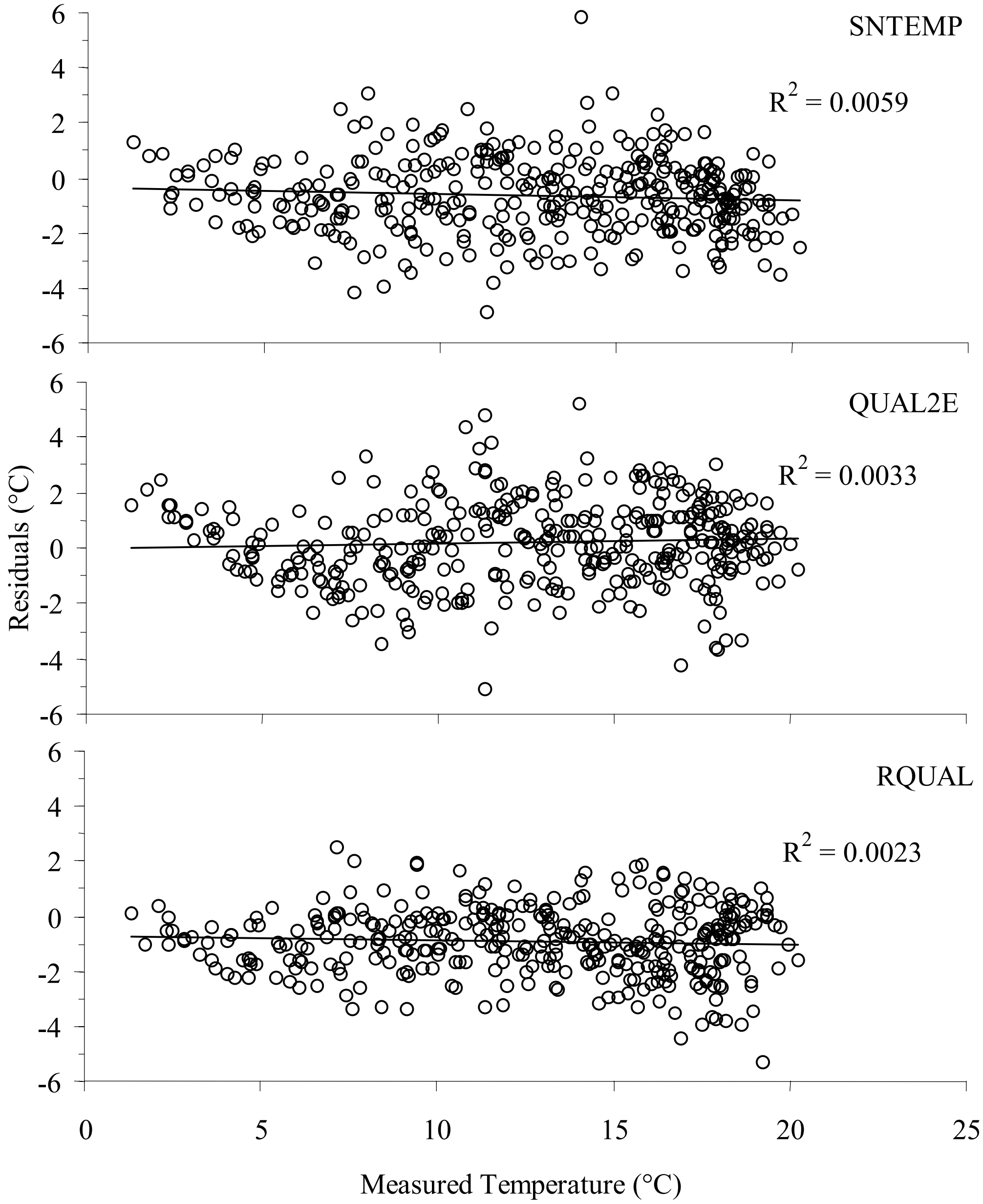
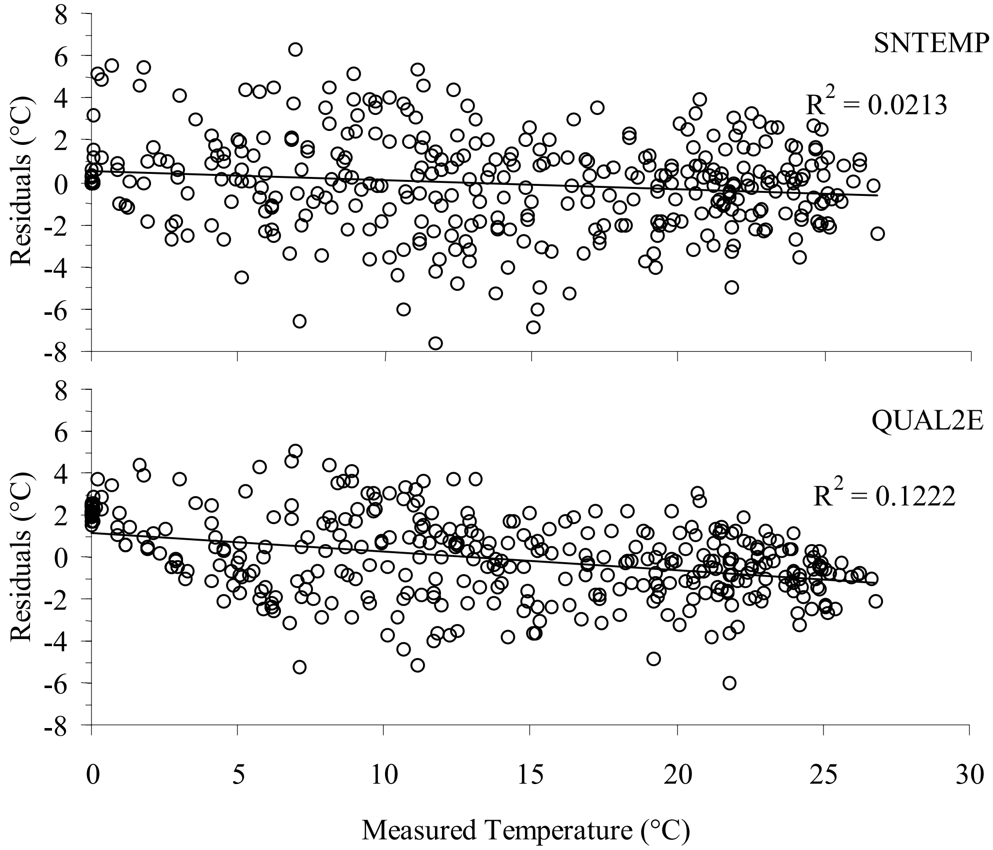
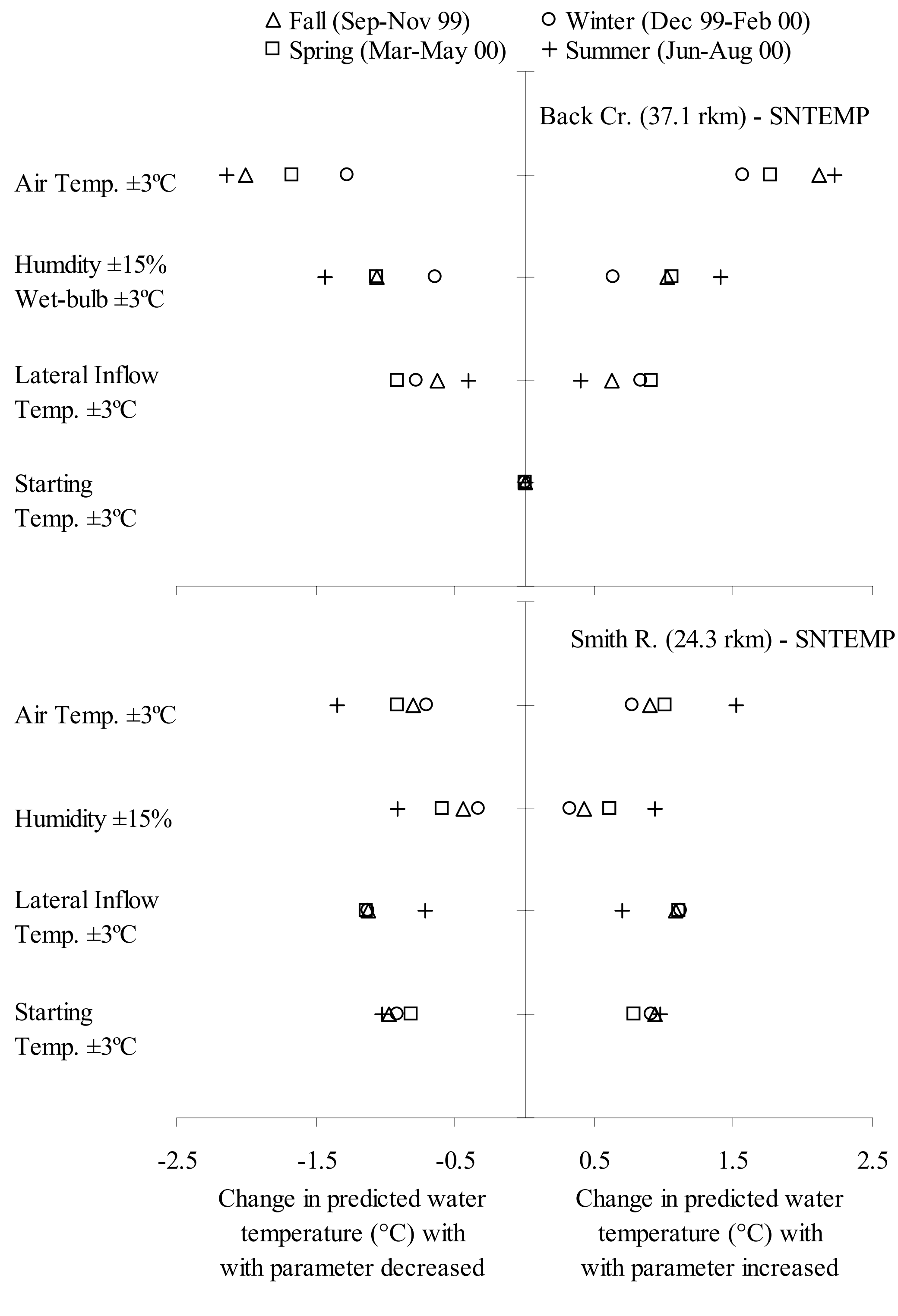
APPENDICES



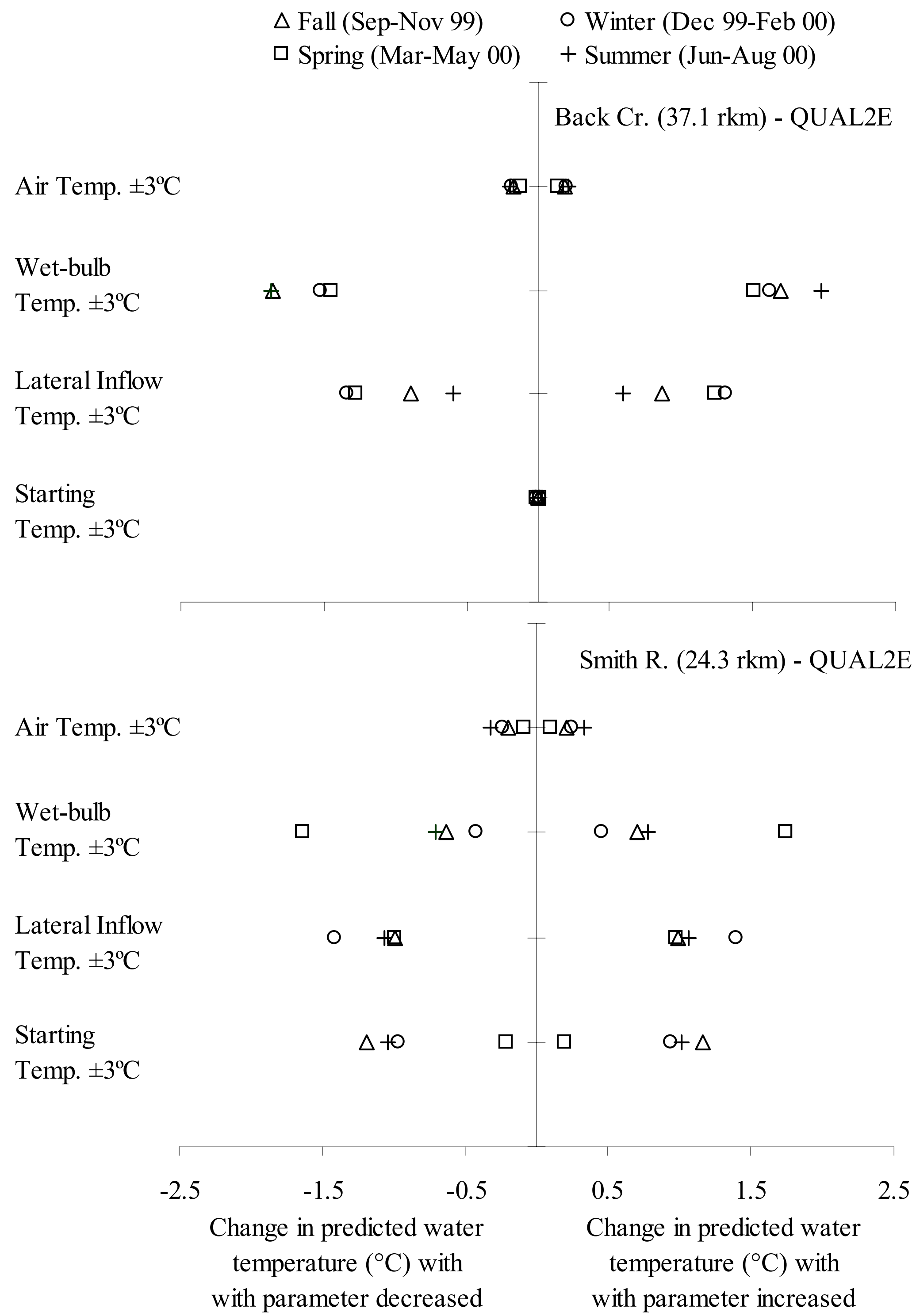
Appendix A.1. SNTEMP, QUAL2E, and RQUAL daily (9/1/99-8/31/00, n=366) residuals versus measured temperature at the downstream end of the Smith River modeled reach (24.3 rkm).



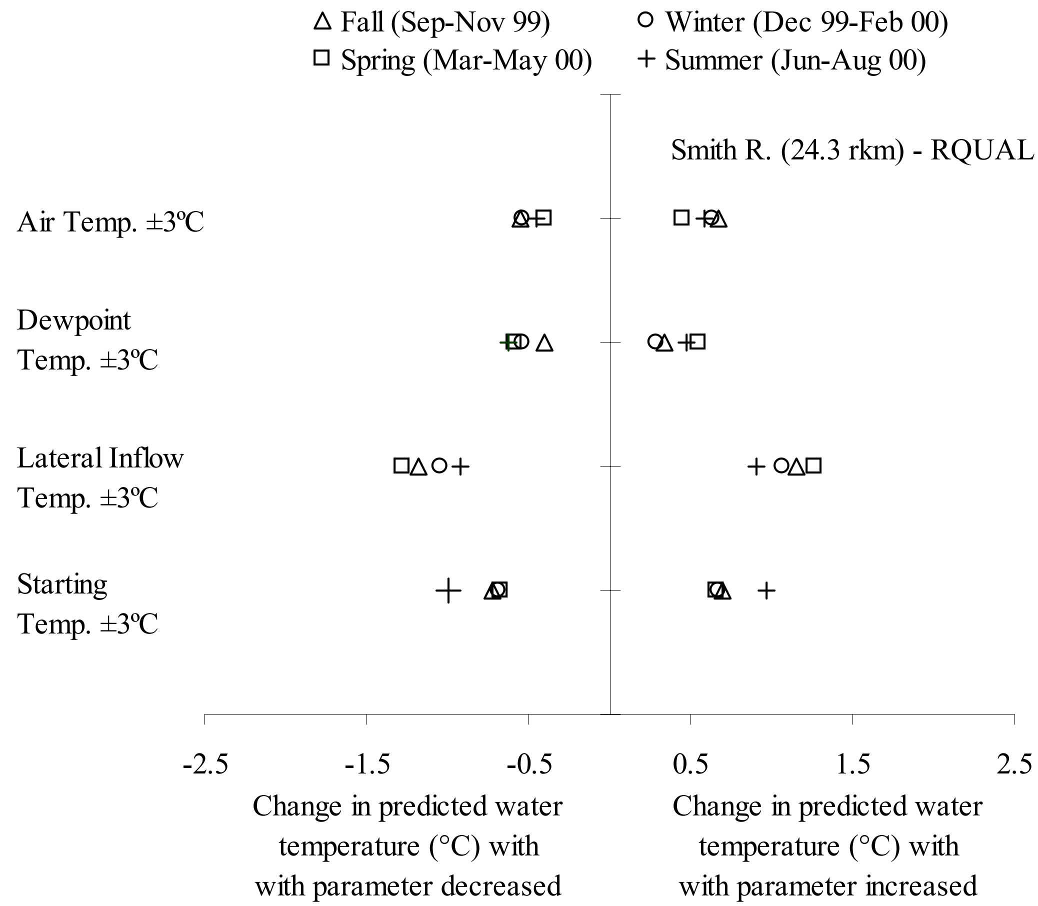
Appendix A.2. SNTEMP and QUAL2E daily (9/1/99-8/31/00, n=366) residuals versus measured temperature at the downstream end of the Back Creek modeled reach (37.1 rkm).



Appendix B.1. Sensitivity analysis of air, lateral inflow, and starting water temperature parameters adjusted ±3ºC, and humidity adjusted ±15% (15% approximates a 3ºC change based on equations that calculate humidity with air and dewpoint temperature) for SNTEMP on Back Creek and the Smith River by season.



Appendix B.2. Sensitivity analysis of air, wet-bulb, lateral inflow, and starting water temperature parameters adjusted ±3ºC for QUAL2E on Back Creek and the Smith River by season.



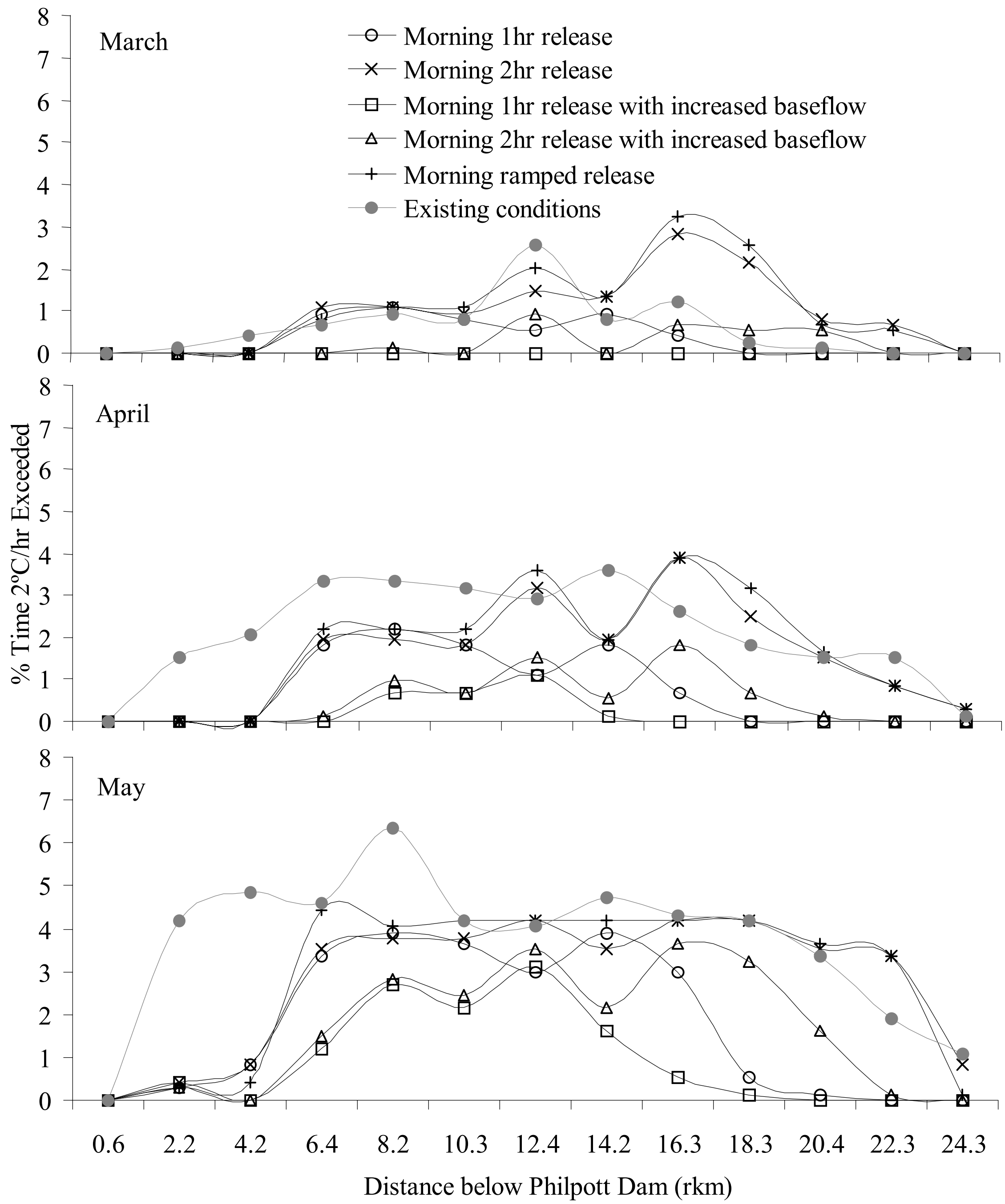
Appendix B.3. Sensitivity analysis of air temperature, dewpoint temperature, lateral inflow temperature, and starting water temperature parameters adjusted ±3ºC for RQUAL on the Smith River by season.

Appendix C. Data-logger recorded temperature (half-hourly) at 0.7, 2.7, 5.1, 5.6, 10.2, 18.3, and 24.3 rkm below Philpott dam, Smith River averaged by month (ºC). Monthly minimum and maximum temperature (ºC) in parenthesis. Daily maximum one-hour temperature change (ºC) averaged by month in brackets.

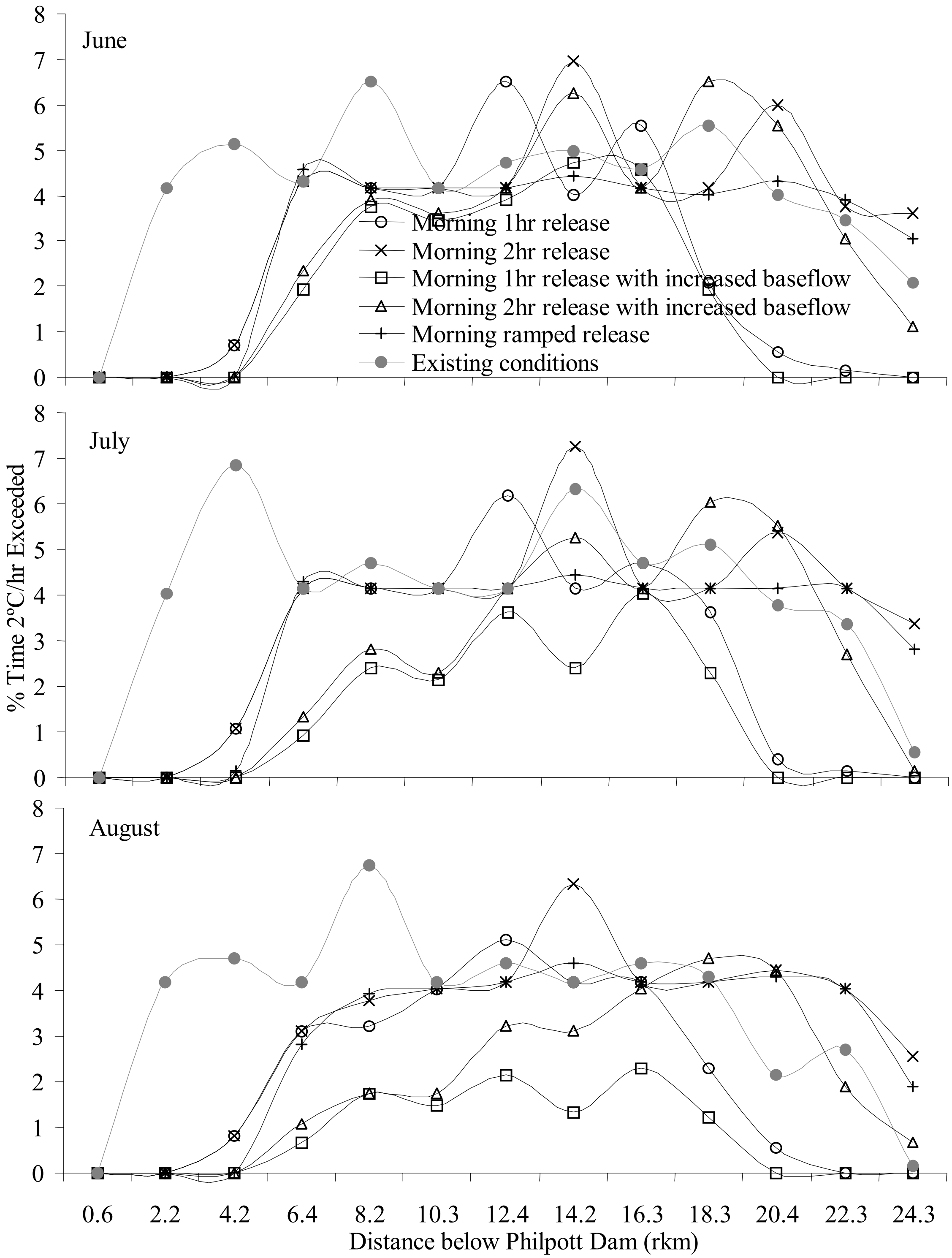
Month/Yr.	0.7 rkm	2.7 rkm	5.1 rkm	5.6 rkm
Jul-99	8.4 (7.7, 10.7) [1.4]	9.4 (7.9, 16.6) [4.0]	10.2 (7.9, 17.0) [4.2]	
Aug-99	9.1 (8.2, 10.8) [0.7]	9.9 (8.3, 16.1) [1.8]	10.7 (8.5, 16.2) [1.6]	
Sep-99	10.7 (8.7, 12.5) [0.5]	11.7 (8.6, 15.3) [1.5]	12.3 (9.3, 15.9) [1.3]	
Oct-99	11.7 (10.5, 13.2) [0.8]	12.3 (9.5, 15.1) [1.2]	12.5 (8.8, 15.1) [1.3]	
Nov-99	12.4 (11.0, 14.1) [0.6]	12.3 (9.4, 14.7) [1.4]	12.2 (8.7, 14.7) [1.4]	11.6 (8.2, 14.0) [1.5]
Dec-99	10.4 (8.0, 12.4) [0.4]	9.9 (6.9, 12.8) [1.1]	9.4 (5.0, 12.7) [1.6]	8.3 (3.4, 12.0) [2.6]
Jan-00	7.4 (4.9, 9.3) [0.5]	7.0 (3.2, 10.5) [1.2]	6.5 (1.7, 10.7) [1.6]	5.2 (1.7, 10.9) [1.8]
Feb-00	5.6 (4.9, 7.0) [0.4]	5.8 (3.6, 8.8) [1.0]	6.0 (2.6, 10.2) [1.4]	5.7 (2.3, 10.4) [1.3]
Mar-00	6.2 (5.3, 8.2) [0.6]	6.8 (4.4, 11.1)]1.1]	7.6 (3.9, 13.2) [1.4]	8.3 (4.2, 13.4) [1.4]
Apr-00	6.8 (5.7, 9.4) [0.7]	7.5 (4.6, 12.8) [2.1]	8.4 (4.3, 15.5) [3.5]	9.7 (5.6, 15.7) [3.3]
May-00	7.4 (6.2, 10.5) [1.8]	8.3 (6.0, 15.1) [4.6]	9.6 (6.5, 16.6) [4.8]	12.1 (8.0, 19.4) [5.4]
Jun-00	7.8 (6.5, 10.7) [1.6]	8.8 (6.9, 13.4) [2.4]	9.8 (7.5, 16.6) [5.7]	13.1 (8.3, 19.4) [6.9]
Jul-00	8.3 (7.3, 10.8) [1.2]	8.9 (7.5, 14.4) [3.5]	10.1 (8.2, 16.5) [5.1]	12.4 (8.4, 17.8) [5.8]
Aug-00	8.7 (8.1, 10.7) [1.4]	9.5 (8.0, 14.6) [4.0]	10.6 (8.8, 17.1) [4.5]	12.3 (9.2, 18.9) [5.3]
Sep-00	8.8 (7.9, 10.2) [0.9]	9.6 (6.6, 13.4) [2.4]	10.6 (7.5, 15.7) [3.0]	12.7 (8.3, 20.7) [4.5]
Oct-00	9.2 (7.2, 10.1) [0.4]	9.9 (6.9, 12.6) [1.6]	10.5 (7.3, 14.3) [2.0]	10.6 (7.2, 14.8) [2.1]
Nov-00	9.7 (8.9, 11.3) [0.7]	9.5 (7.8, 11.4) [0.9]	9.5 (6.5, 12.1) [1.1]	8.7 (4.5, 11.8) [1.3]
Dec-00	8.0 (5.8, 10.0) [0.6]	7.2 (3.9, 9.5) [1.5]	7.0 (3.1, 10.2) [2.0]	5.3 (2.5, 9.2) [2.8]
Jan-01	5.4 (4.4, 6.3) [0.3]	5.1 (3.0, 7.2) [1.1]	5.3 (2.1, 7.5) [1.4]	4.0 (1.7, 7.5) [1.7]
Feb-01	5.4 (4.7, 6.8) [0.4]	5.7 (3.6, 8.8) [0.9]	5.9 (2.7, 9.8) [1.2]	5.8 (2.3, 9.7) [1.0]

Appendix C (continued). Data logger recorded temperature (half-hourly) at 0.7, 2.7, 5.1, 5.6, 10.2, 18.3, and 24.3 rkm below Philpott dam, Smith River averaged by month (ºC). Monthly minimum and maximum temperature (ºC) in parenthesis. Daily maximum one-hour temperature change (ºC) averaged by month in brackets.

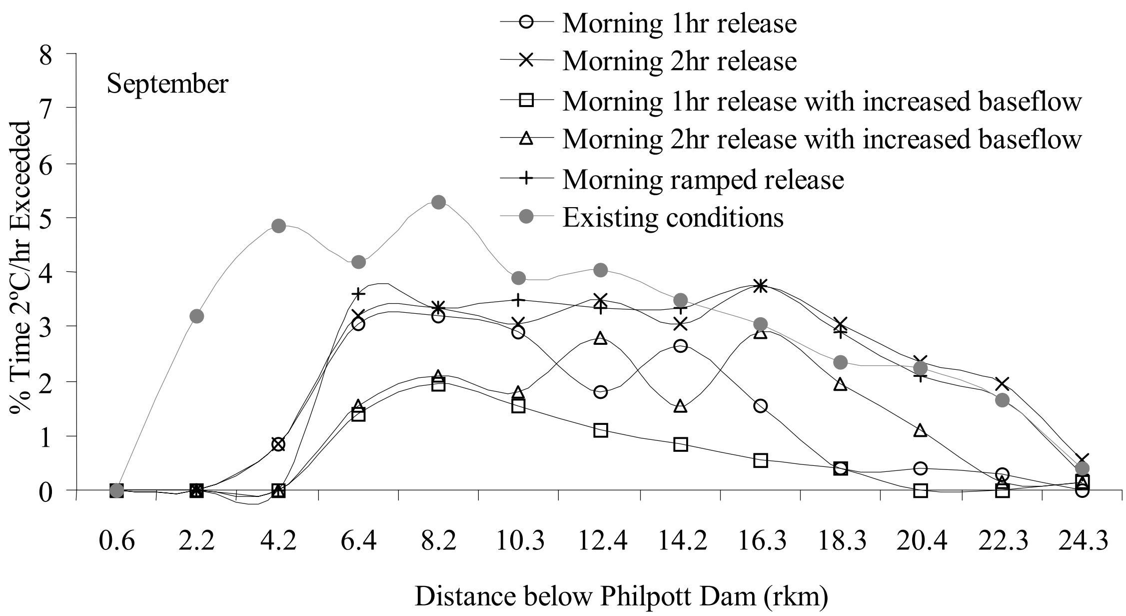
Month/Yr.	10.2 rkm	18.3 rkm	24.3 rkm
Jul-99		14.5 (8.8, 23.8) [4.6]	15.7 (9.2, 25.0) [4.0]
Aug-99		14.5 (9.6, 24.2) [2.4]	15.5 (10.1, 24.6) [2.2]
Sep-99		15.2 (10.8, 20.0) [1.5]	16.0 (11.2, 19.9) [1.0]
Oct-99		13.4 (8.2, 17.1) [1.1]	13.7 (8.6, 16.9) [0.5]
Nov-99		11.8 (7.6, 15.3) [1.1]	11.8 (8.1, 15.3) [0.4]
Dec-99		8.0 (1.5, 11.8) [1.4]	7.7 (2.2, 11.4) [0.4]
Jan-00		5.3 (0.2, 11.1) [1.3]	5.1 (0.6, 11.2) [0.5]
Feb-00		6.3 (1.3, 12.9) [0.9]	6.4 (1.7, 12.5) [0.5]
Mar-00		9.2 (5.4, 15.0) [0.8]	9.8 (6.6, 15.0) [0.6]
Apr-00		11.4 (6.2, 17.4) [1.3]	12.2 (6.9, 17.7) [1.2]
May-00	12.4 (8.1, 19.1) [5.0]	14.7 (9.6, 21.1) [1.7]	16.8 (11.8, 22.0) [1.1]
Jun-00	13.5 (8.3, 21.0) [6.8]	15.3 (10.7, 21.0) [1.7]	17.6 (12.7, 21.3) [0.8]
Jul-00	12.9 (8.9, 19.9) [5.7]	14.9 (10.7, 20.2) [1.3]	17.3 (12.7, 20.8) [0.6]
Aug-00	13.1 (9.4, 21.2) [5.1]	15.0 (11.0, 20.5) [1.3]	17.4 (12.9, 21.8) [0.8]
Sep-00	13.2 (9.4, 20.3) [4.2]	14.4 (9.8, 20.7) [1.3]	15.7 (11.3, 20.8) [0.6]
Oct-00	11.1 (7.4, 17.0) [1.9]	11.7 (7.6, 16.2) [0.7]	11.9 (6.7, 16.5) [0.6]
Nov-00	8.8 (4.7, 13.1) [1.4]	8.7 (4.4, 12.9) [0.5]	8.8 (3.3, 14.3) [0.5]
Dec-00	5.3 (0.8, 9.2) [2.6]	4.7 (0.7, 7.8) [0.7]	3.8 (-0.2, 7.7) [0.4]
Jan-01	4.3 (0.5, 7.9) [1.8]	4.0 (0.4, 7.5) [0.6]	3.5 (0.1, 7.5) [0.4]
Feb-01	6.0 (1.8, 9.9) [1.1]	6.1 (1.9, 10.4) [0.6]	6.1 (1.9, 10.1) [0.5]



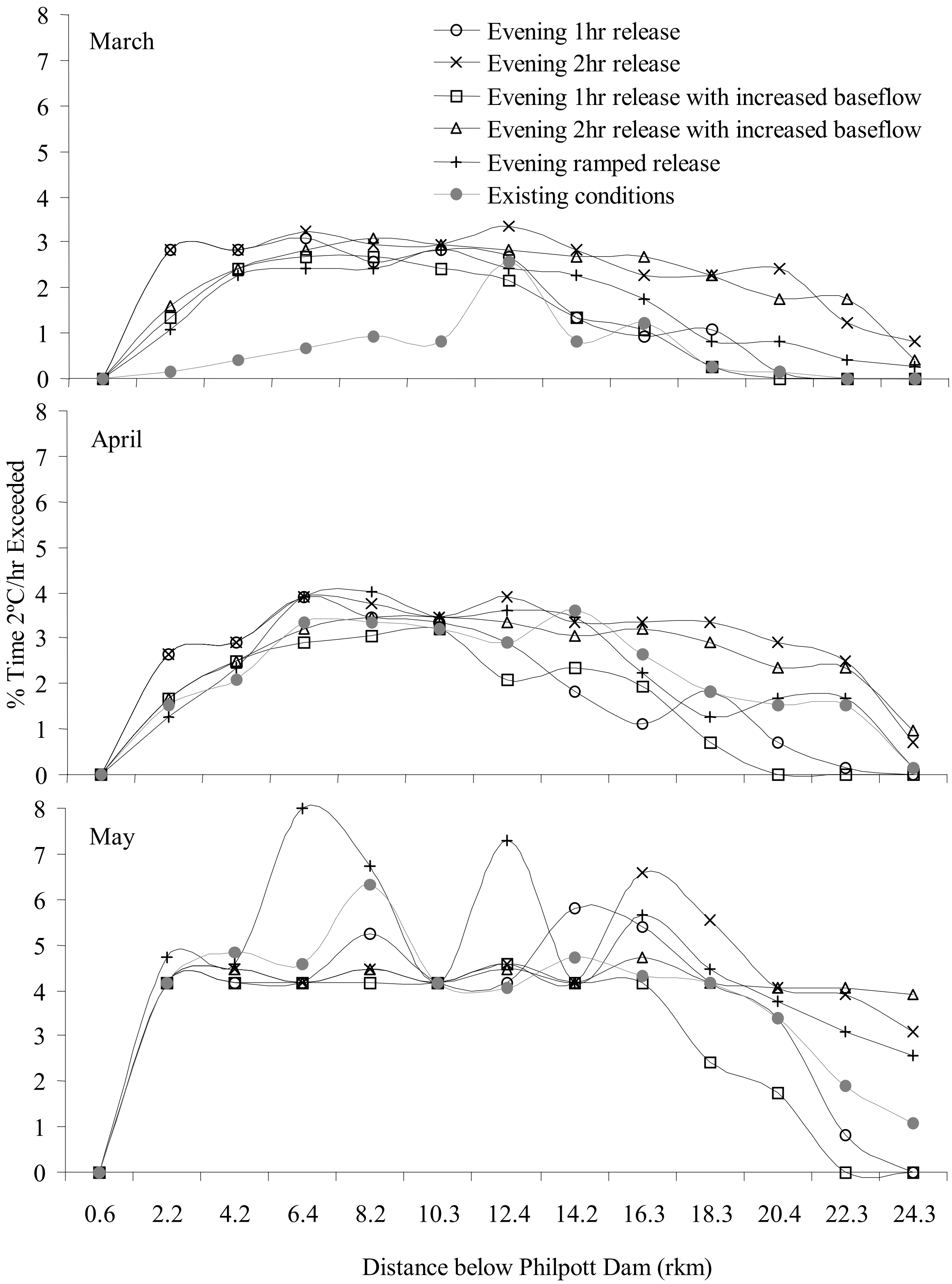
Appendix D.1. Percent time of month that maximum hourly temperature change exceeds 2ºC for flow scenarios with morning release.



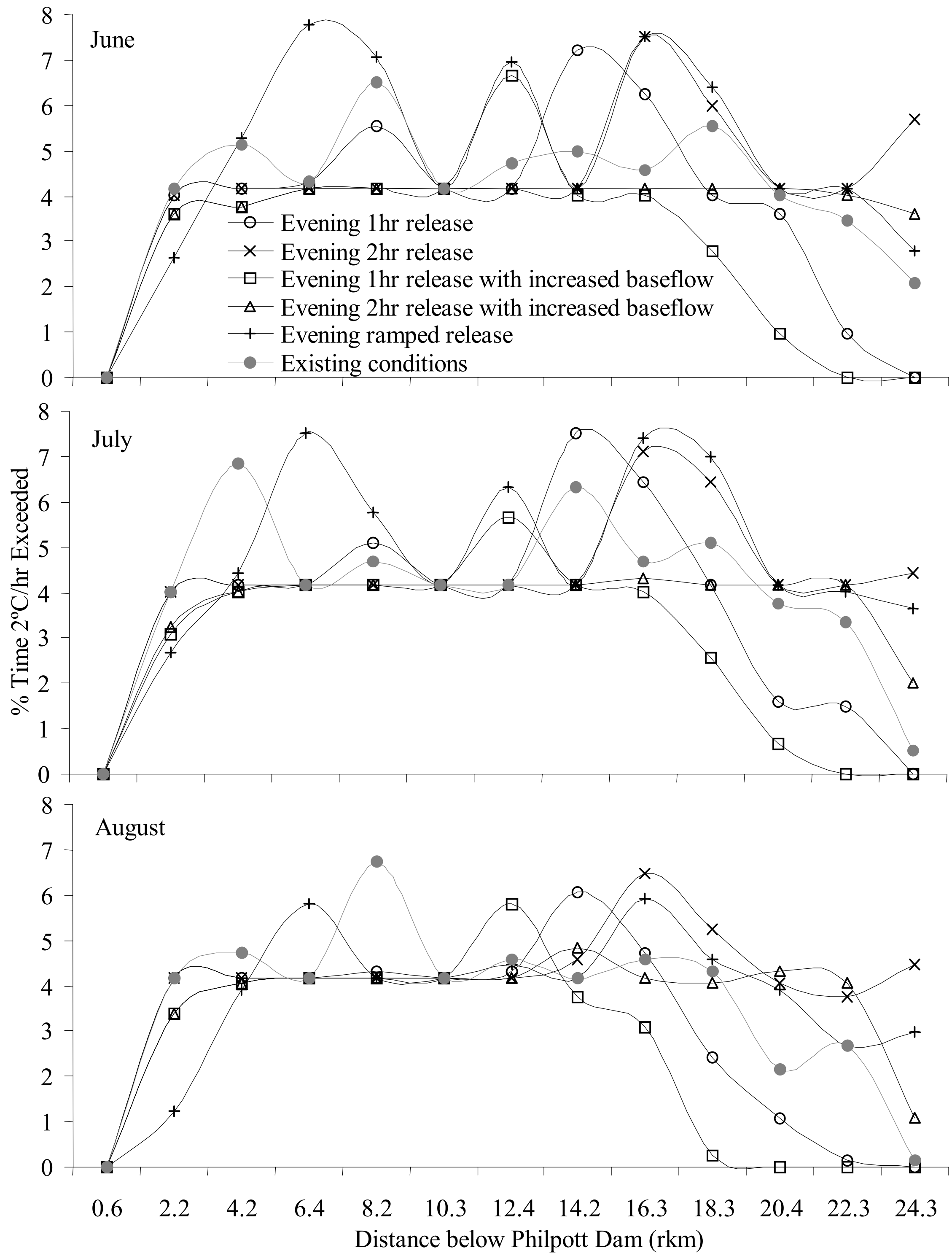
Appendix D.1 (continued). Percent time of month that maximum hourly temperature change exceeds 2ºC for flow scenarios with morning release.



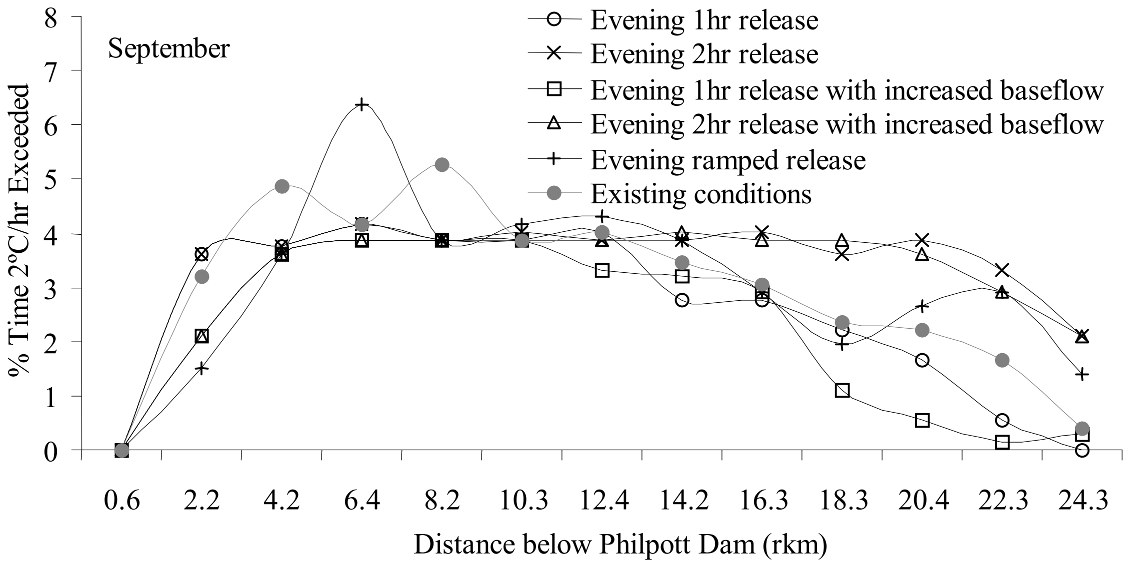
Appendix D.1 (continued). Percent time of month that maximum hourly temperature change exceeds 2ºC for flow scenarios with morning release.



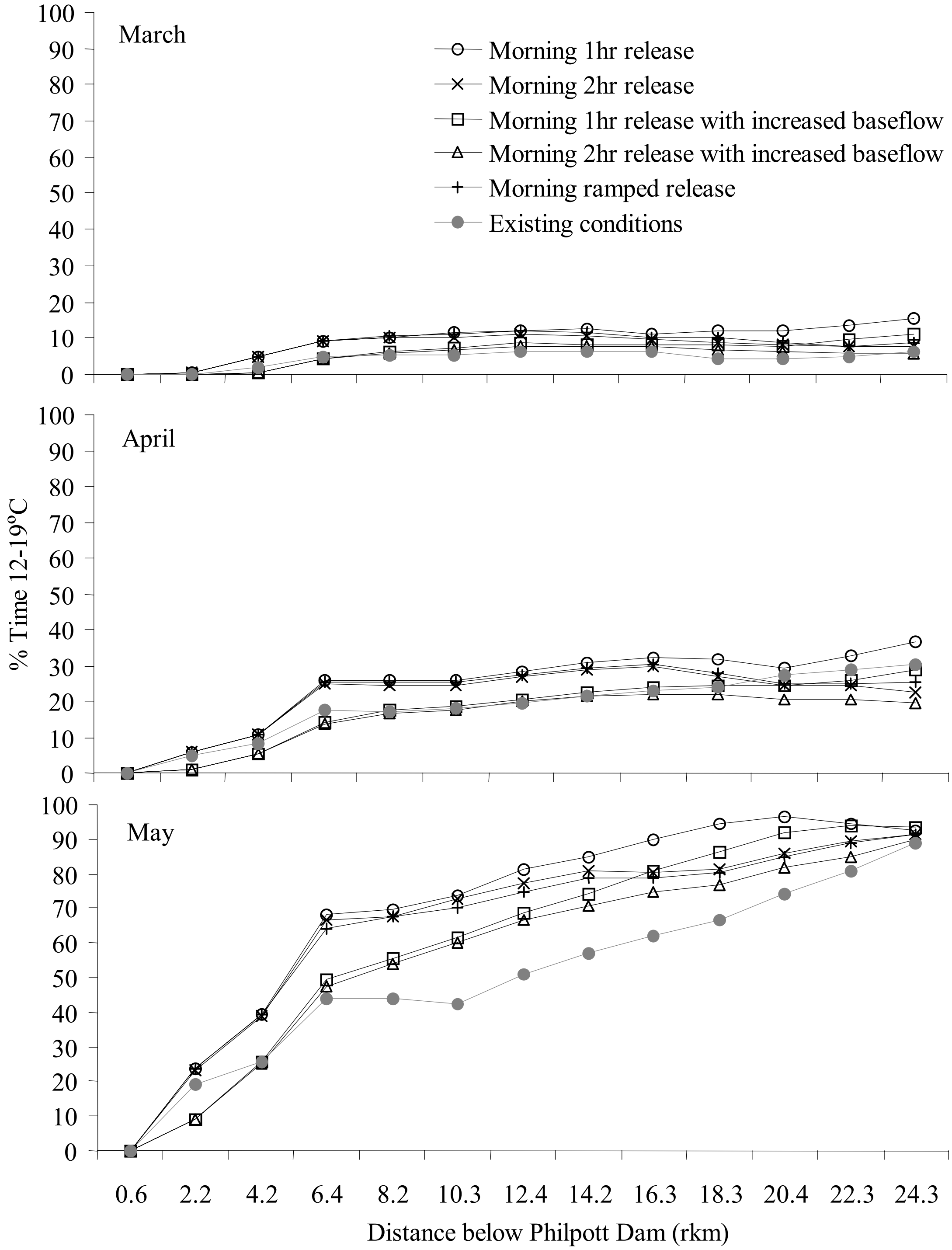
Appendix D.2. Percent time of month that maximum hourly temperature change exceeds 2ºC for flow scenarios with evening release.



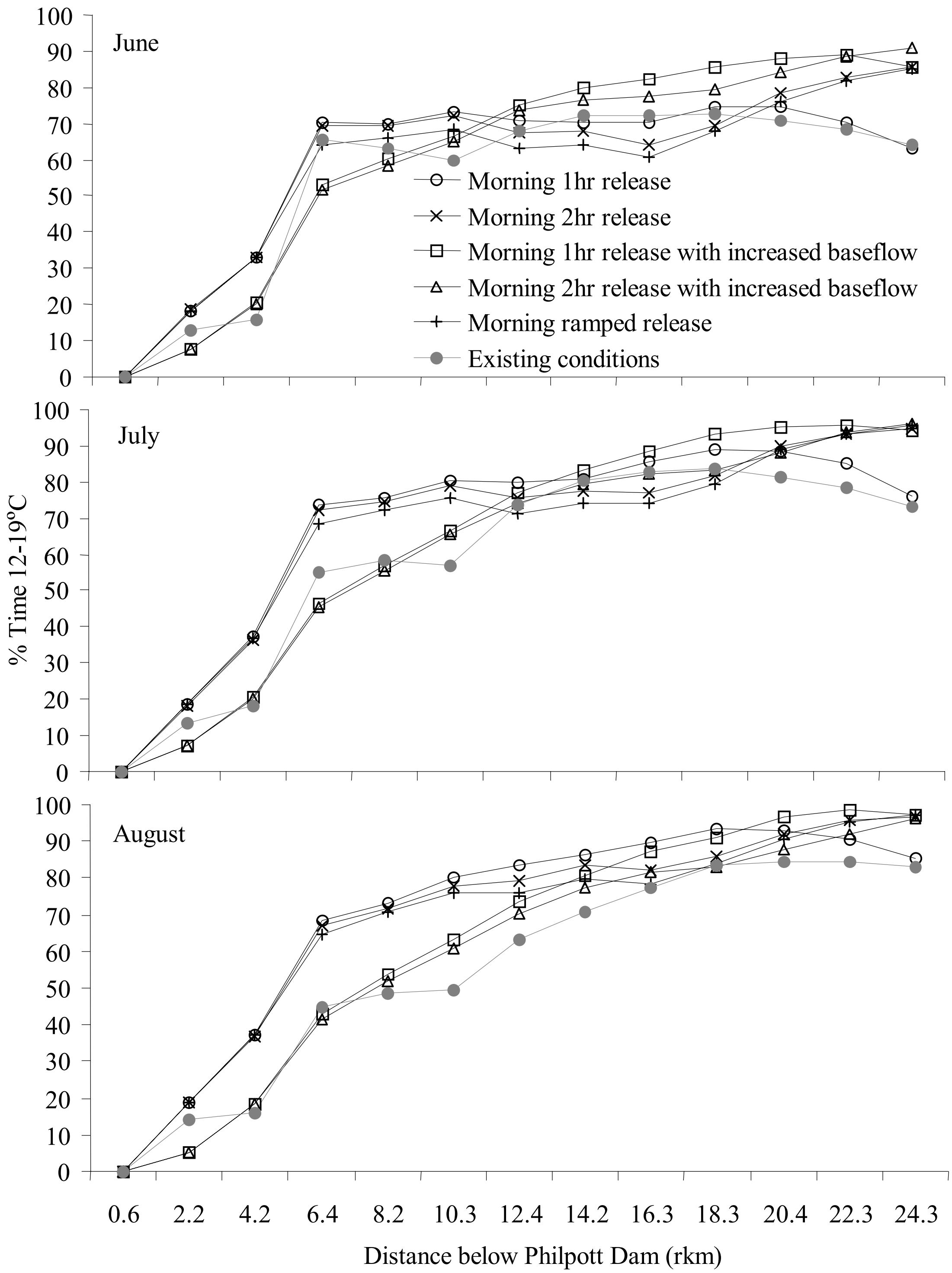
Appendix D.2 (continued). Percent time of month that maximum hourly temperature change exceeds 2ºC for flow scenarios with evening release.



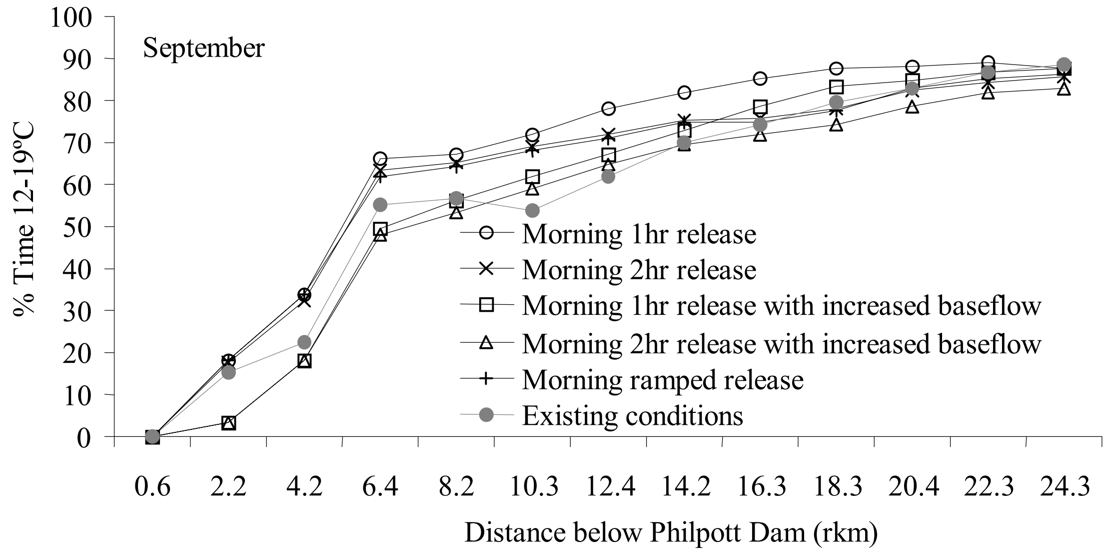
Appendix D.2 (continued). Percent time of month that maximum hourly temperature change exceeds 2ºC for flow scenarios with evening release.



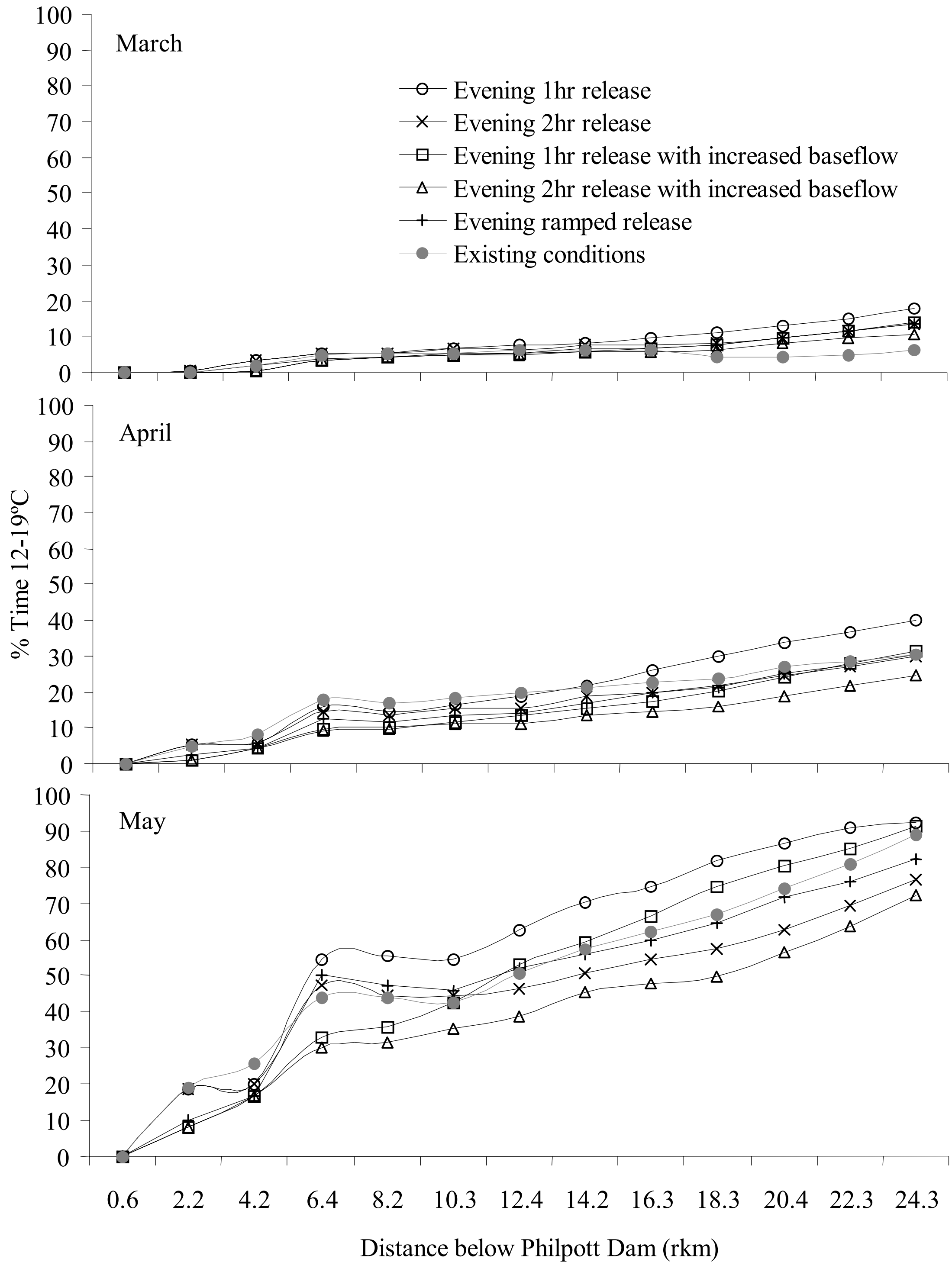
Appendix E.1. Percent time of month that temperature is within 12-19ºC for flow scenarios with morning release.



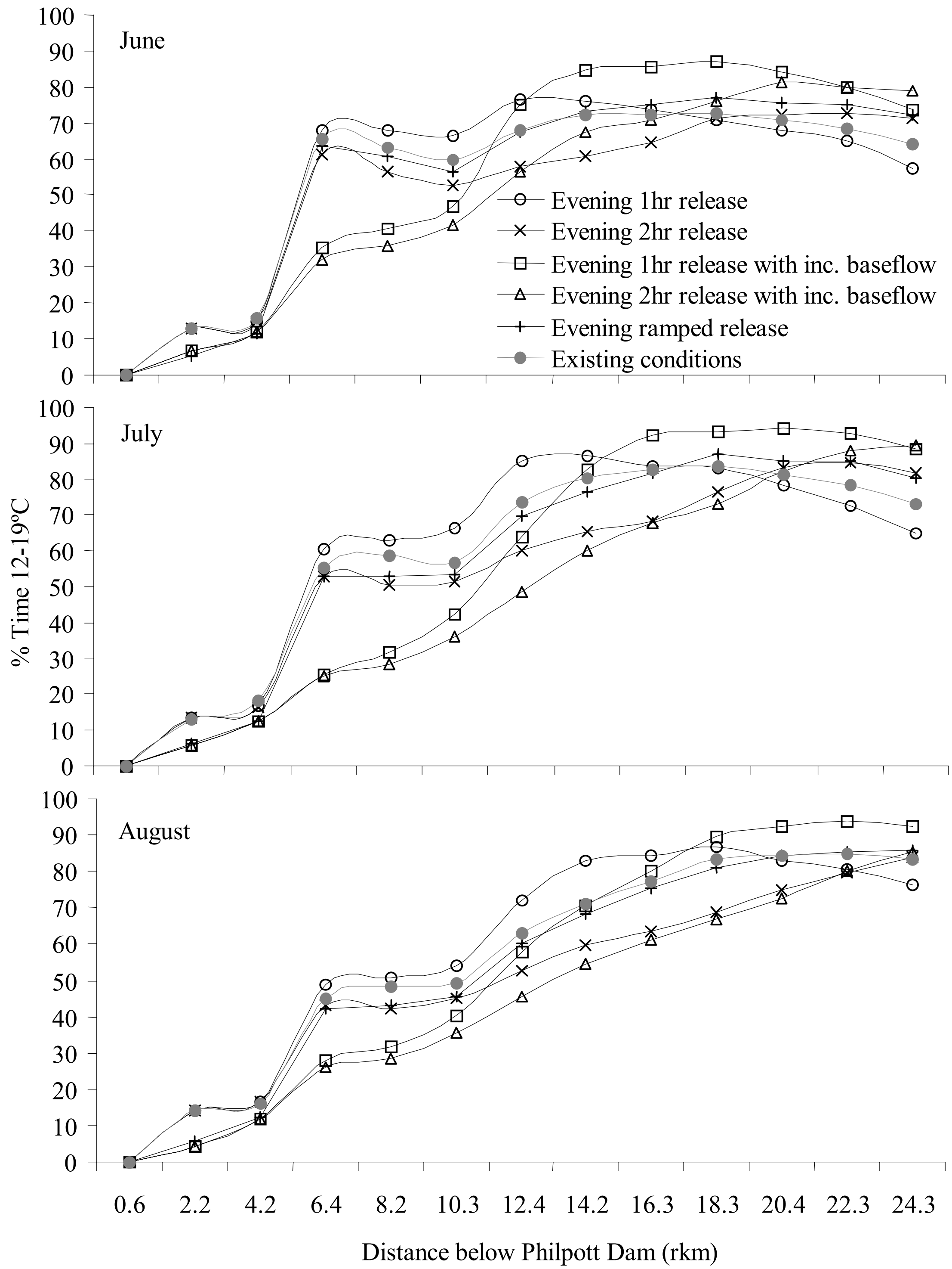
Appendix E.1 (continued). Percent time of month that temperature is within 12-19ºC for flow scenarios with morning release.



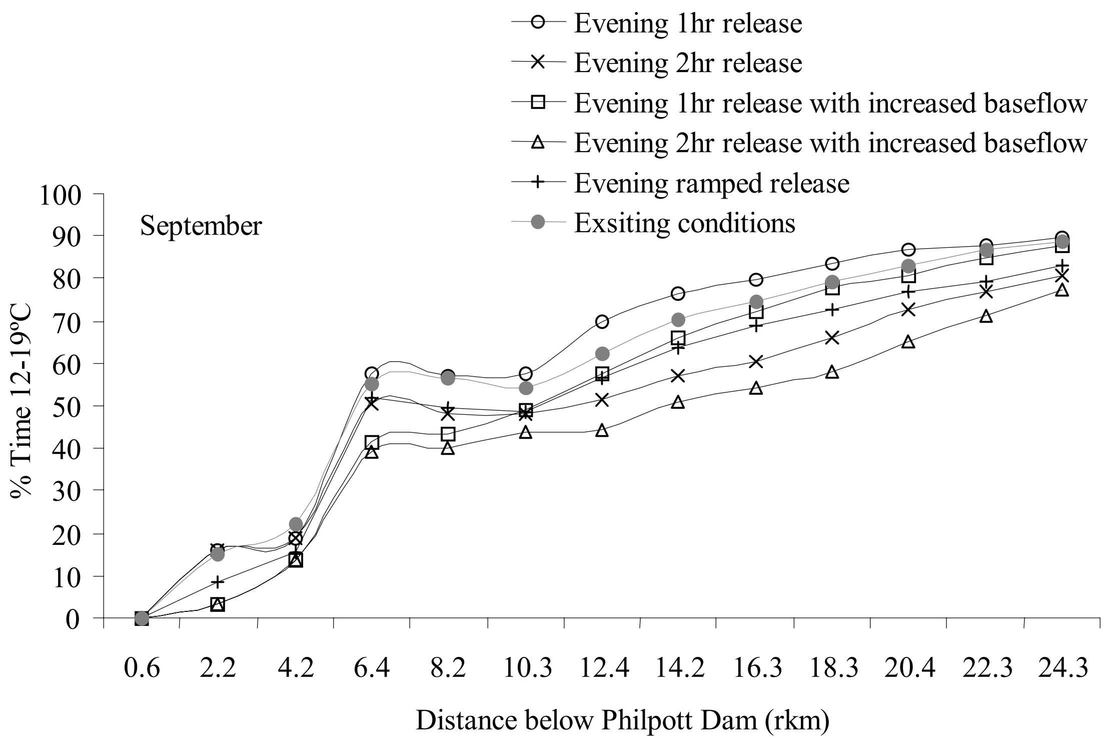
Appendix E.1 (continued). Percent time of month that temperature is within 12-19ºC for flow scenarios with morning release.



Appendix E.2. Percent time of month that temperature is within 12-19ºC for flow scenarios with evening release.



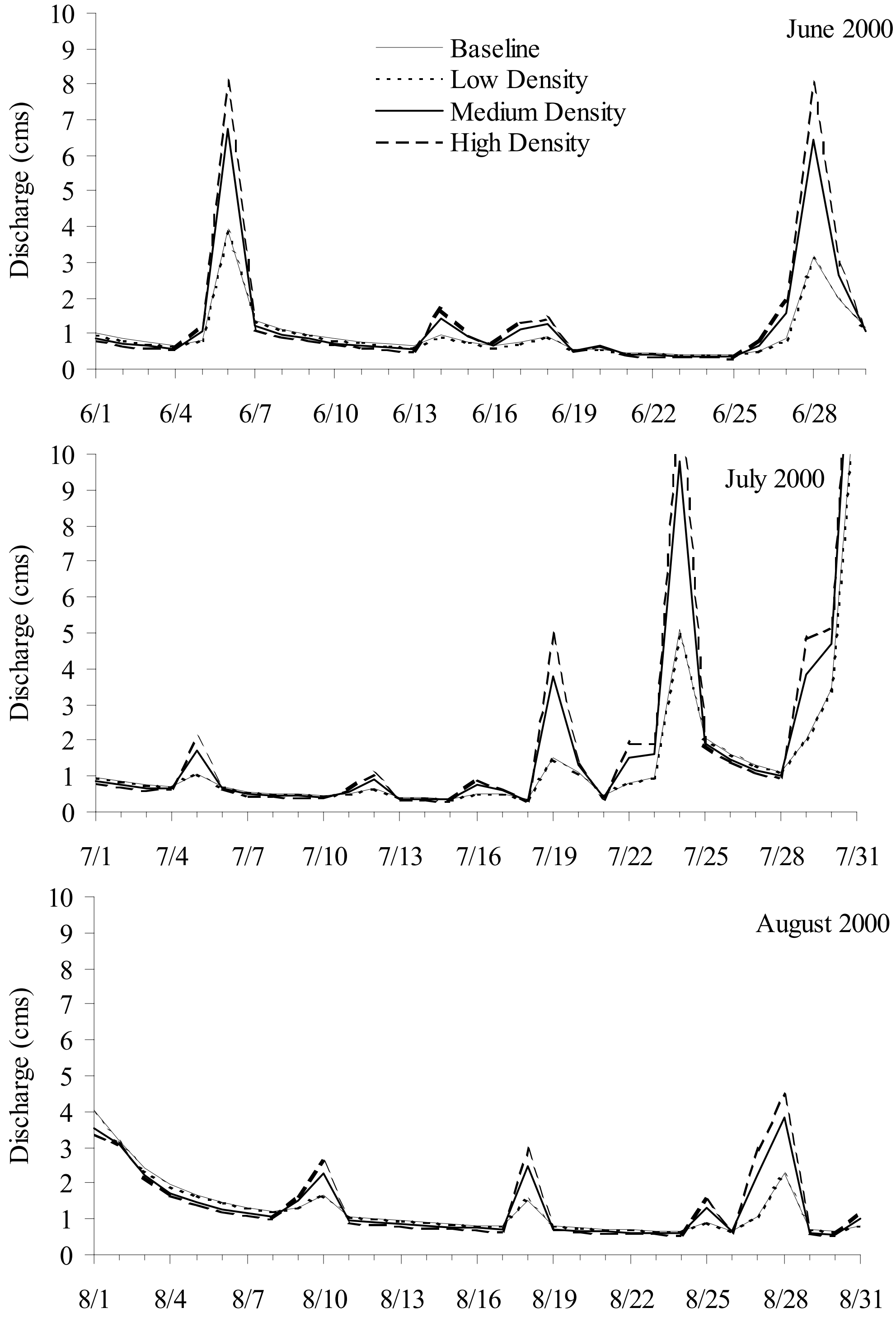
Appendix E.2 (continued). Percent time of month that temperature is within 12-19ºC for flow scenarios with evening release.



Appendix E.2 (continued). Percent time of month that temperature is within 12-19ºC for flow scenarios with evening release.

Appendix F. Data logger recorded temperature (hourly) at 3.7, 15.4, and 37.1 rkm below the headwater of Back Creek averaged by month (ºC). Monthly minimum and maximum temperature (ºC) in parenthesis.

Month/Yr.	3.7 rkm	15.4 rkm	37.1 rkm
Jul-99		23.6 (16.9, 30.0)	25.2 (17.8, 31.9)
Aug-99		22.9 (15.3, 29.9)	24.5 (17.6, 31.1)
Sep-99		17.7 (12.3, 22.8)	18.6 (13.4, 24.8)
Oct-99	12.5 (6.5, 18.5)	12.9 (6.5, 19.1)	13.1 (7.2, 18.8)
Nov-99	10.0 (3.8, 15.5)	10.1 (3.4, 15.9)	9.9 (3.8, 15.6)
Dec-99	6.0 (1.4, 11.7)	5.6 (0.8, 12.1)	4.7 (0.0, 10.6)
Jan-00	3.5 (-0.1, 11.6)	3.0 (0.0, 10.6)	2.6 (0.0, 11.7)
Feb-00	5.0 (0.1, 18.5)	5.0 (0.0, 13.8)	4.6 (0.0, 13.5)
Mar-00	8.8 (3.8, 15.8)	10.0 (3.9, 17.3)	10.4 (5.5, 16.2)
Apr-00	10.7 (5.4, 17.6)	12.3 (6.2, 19.7)	13.3 (7.8, 19.1)
May-00	15.8 (9.3, 21.5)	18.2 (10.2, 24.0)	20.0 (12.4, 25.4)
Jun-00	19.4 (13.0, 25.2)	21.7 (14.7, 26.7)	23.5 (16.4, 28.5)
Jul-00	20.3 (16.3, 26.8)	22.0 (17.6, 28.2)	23.7 (18.3, 29.2)
Aug-00	20.3 (15.8, 26.8)	21.5 (17.1, 27.2)	22.2 (18.8, 26.7)
Sep-00	17.0 (8.3, 27.5)	18.1 (12.3, 23.0)	19.1 (13.4, 23.9)
Oct-00	13.0 (7.5, 20.3)	13.4 (7.1, 20.0)	13.7 (8.2, 20.0)
Nov-00	7.2 (0.1, 13.9)	6.9 (0.0, 15.2)	6.8 (0.1, 13.7)
Dec-00	2.0 (0.1, 6.1)	1.5 (0.0, 5.3)	1.3 (0.1, 4.7)
Jan-01	2.2 (0.1, 8.1)	1.8 (0.0, 8.7)	1.2 (0.1, 6.9)
Feb-01	5.1 (0.1, 12.6)	5.7 (0.0, 10.9)	5.5 (0.3, 9.7)
Mar-01	5.3 (0.0, 12.1)	6.7 (1.2, 13.7)	7.2 (2.1, 11.9)
Apr-01	11.7 (4.7, 20.9)	13.5 (5.1, 21.8)	14.6 (6.0, 22.1)
May-01	14.5 (9.8, 23.2)	16.4 (12.6, 22.0)	18.1 (13.6, 23.1)



Appendix G. Back Creek mean daily discharge (cms) at 38 rkm below the headwater under baseline, low density, medium density, and high density urban development scenarios.

VITA

Colin Krause developed a love for the outdoors and environment from his parents who believe a vacation requires staying in a tent. Time spent camping, climbing, fishing, biking, and skiing led him onto a natural resources career path. A desire to work outdoors with the resources so valued for his recreational uses began with a bachelor of science degree in Aquatic Resources from the University of Vermont. The change in interest from a broad natural resource management education to one focused on fisheries occurred during the spring of 1997 when Colin studied abroad. The fisheries research skills and courses taught at the School for Field Studies, Center for Marine Resource Management, convinced Colin to search for fisheries jobs. After graduation in spring 1997, experience progressed from collecting fisheries data in Alaska, returning to intern at the School for Field Studies center, and to employment with the Virginia Department of Game and Inland Fisheries. With this experience and determination to pursue higher education in the fishery field, graduate school at Virginia Tech began in fall 1999.