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Development and application of a hydroclimatological stream temperature model within the Soil and Water Assessment Tool

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[1] We develop a stream temperature model within the Soil and Water Assessment Tool (SWAT) that reflects the combined influence of meteorological (air temperature) and hydrological conditions (streamflow, snowmelt, groundwater, surface runoff, and lateral soil flow) on water temperature within a watershed. SWAT currently uses a linear air-stream temperature relationship to determine stream temperature, without consideration of watershed hydrology. As SWAT uses stream temperature to model various in-stream biological and water quality processes, an improvement of the stream temperature model will result in improved accuracy in modeling these processes. The new stream temperature model is tested on seven coastal and mountainous streams throughout the western United States for which high quality flow and water temperature data were available. The new routine does not require input data beyond that already supplied to the model, can be calibrated with a limited number of calibration parameters, and achieves improved representation of observed daily stream temperature. For the watersheds modeled, the Nash-Sutcliffe (NS) coefficient and mean error (ME) for the new stream temperature model averaged 0.81 and −0.69°C, respectively, for the calibration period and 0.82 and −0.63°C for the validation period. The original SWAT stream temperature model averaged a NS of −0.27 and ME of 3.21°C for the calibration period and a NS of −0.26 and ME of 3.02°C for the validation period. Sensitivity analyses suggest that the new stream temperature model calibration parameters are physically reasonable and the model is better able to capture stream temperature changes resulting from changes in hydroclimatological conditions.

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1. Introduction

[2] As a primary driver of aquatic ecosystems, stream temperature has direct (species distribution, juvenile survival) and indirect (e.g., concentrations of dissolved oxygen, chemical reaction kinetics) effects on the health and productivity of aquatic biota. Additionally, stream temperatures are often regulated for industry and power plant water discharge, as well as drinking water production. Consequently, there has been considerable research on stream temperature in natural and altered settings, with the goal of predicting stream temperatures for forecasting under varying hydroclimatological conditions [e.g., *Webb et al.*, 2008].

[3] Stream temperatures reflect the combined influence of both meteorological and hydrological factors at all time scales and watershed sizes [*Smith and Lavis*, 1975]. The heat balance, which is closely tied to meteorological conditions such as air temperature, has a large influence on stream temperatures, as shown by the strong correlations of air and water temperature [e.g., *Stefan and Preud'homme*, 1993]. Variations in streamflow are also important because lower discharges mean lower thermal capacity of streamflow [*van Vliet et al.*, 2011]. Additionally, stream temperature is greatly influenced by the source characteristics of the water, where snowmelt, surface runoff, or groundwater inflow entering the stream have different temperature signatures [*Webb and Zhang*, 1997; *Mohseni and Stefan*, 1999]. As a result, the relative influence of meteorological and hydrologic factors on stream temperature can vary greatly with watershed and/or season. For example, *Webb and Zhang* [1997] found that radiative fluxes accounted for more than 70% of the heat inputs for 17 sites in southwest England, while *Bogan et al.* [2003] determined that for 596 sites in the eastern and central United States 20% of the sites had temperatures dominated by atmospheric forcing, while the remaining were influenced by local hydrology or impacted by human activities. *Storey et al.* [2003] showed that groundwater inflow was responsible for 40% of a 3°C cooling effect in the daily maximum temperature of a small stream in British Columbia, Canada. *Kobayashi* [1984] used stream temperatures to separate a hydrograph into hydrologic components and found that in times of high snowmelt discharge, the heat from the soil column and water increased the stream temperature by 3 to 4°C.

[4] Due to the often complex and sparse data availability, several previous studies have successfully modeled

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stream temperature based solely on a relationship with air temperature [*Stefan and Preud'homme*, 1993; *Mohseni et al.*, 1998; *Mohseni and Stefan*, 1999; *Webb et al.*, 2003, 2008]. These linear and nonlinear regression models, where air temperature is the independent variable and stream temperature is the dependent variable, have been effectively used at daily, weekly, and monthly time steps [*Stefan and Preud'homme*, 1993; *Webb and Nobilis*, 1997; *Pilgrim et al.*, 1998; *Erickson and Stefan*, 2000; *Mohseni et al.*, 1998, 1999; *Webb et al.*, 2003, 2008]. The strength of the air-water temperature correlation has been shown to improve as the length of the data aggregation period increases from subdaily to monthly [*Stefan and Preud'homme*, 1993; *Caissie*, 2006]. The nonlinear regression models use an S-shaped logistic function, where the stream-air temperature relationships deviate from linearity when air temperature is below 0°C and above approximately 20°C [*Mohseni et al.*, 1998; *Mohseni and Stefan*, 1999]. These deviations occur largely due to the influence of snowmelt and groundwater at low temperatures and evaporative cooling and enhanced back radiation at high temperatures [*Mohseni and Stefan*, 1999].

[5] While the linear and nonlinear regression models successfully model stream temperature using only air temperature, they do not include the influence of the watershed hydrology (e.g., snowmelt, groundwater inflow, surface runoff, stream discharge) and thus lack the capability to project the effects of hydrologic changes on stream temperature. Thus, recent studies have incorporated river discharge as an additional variable into stream temperature regression models to improve stream temperature predictions [*Lowney*, 2000; *Webb et al.*, 2003; *van Vliet et al.*, 2011]. Using a nonlinear stream temperature model with a discharge variable, *van Vliet et al.* [2011] reported an average increase of the Nash-Sutcliffe coefficient [*Nash and Sutcliffe*, 1970] by 0.02 and a decrease in root mean square error by 0.17°C on 13 large rivers throughout the world. The influence of groundwater inflow on stream temperature is often ignored when modeling large rivers, but may be significant for smaller streams under low flow conditions [*Brown*, 1969; *Smith and Lavis*, 1975; *Constantz and Essaid*, 2004; *Sridhar et al.*, 2004]. Thus, while linear and nonlinear regression models simulate stream temperature using only air temperature with reasonable success, there is evidence that modeling predictions can be improved when watershed hydrology is incorporated into the model. Furthermore, models that include the watershed hydrology (e.g., snowmelt, groundwater inflow, surface runoff, stream discharge) possess the capability to project the effects of hydrologic changes such as those expected from climatic changes on stream temperature.

[6] Numeric physically based hydrologic and standalone stream temperature models have been effectively used to simulate stream temperature and develop management plans for aquatic ecosystems and resources. Reach- and basin-scale stream temperature models are often used to examine the effects of localized environmental changes, such as alterations in the riparian shading or cold and warm water discharges, on stream temperature. A number of mechanistic stream temperature models exist (Table 1). These models vary in their methods to estimate stream temperature, with some requiring hydrology as an input, while others dynamically model hydrology and streamflow. Other simplified stream temperature models attempt to be parsimonious with input requirements employing solely air temperature (e.g., Soil and Water Assessment Tool (SWAT) model; *Arnold et al.* [1998]) or air temperature and watershed characteristics (multiple regression stream temperature model; *Issak et al.* [2009]). The approach of modeling hydrology and stream temperature together is especially useful where varying inflow components drive differences in stream temperatures, such as small mountain basins, where snowmelt runoff is important. As can be seen from Table 1, even those models that incorporate hydrology consider surface runoff from rain and that from snowmelt as one flow contribution. However, these two components of runoff may have very different temperatures, with surface runoff close to the ambient air temperature and snowmelt just above freezing. Thus to the best of the authors' knowledge, the influence of all hydrologic sources has yet to be explicitly incorporated into stream temperature models and the effect of snowmelt and variations in the snowmelt runoff component on stream temperature is not estimated in any current hydrologic model with a stream temperature component.

[7] SWAT is a hydrologic/water quality model developed by the United States Department of Agriculture–Agricultural Research Service (USDA-ARS) to predict the impact of agricultural or land management on water, sediment and agricultural chemical yields in watersheds [*Arnold et al.*, 1998]. SWAT has been successfully employed for many different types of hydrologic, stream temperature, and stream quality applications [*Gassmann et al.*, 2007]. However, due to the linear air-water relationship used to estimate stream temperature in SWAT, climatic, and their associated hydrologic and stream temperature changes, are not well represented. The contribution of the current work then is to develop a stream temperature model that includes the effects of air temperature, discharge, snowmelt, surface runoff, and groundwater inflow on stream temperature within a watershed using simple calibration parameters. The SWAT model is used here to demonstrate the validity of the new approach; however, the new stream temperature model could be used in any hydrologic model where the needed hydrologic components are available. The new routine can be solely based on quantities that the SWAT hydrologic model already provides as well as four additional calibration parameters. We then further test the updated model at several sites with high quality stream temperature data throughout the western United States for which the different flow components, and especially snowmelt, play an important role.

2. Materials and Methods

2.1. The Current SWAT Hydrologic Model

[8] The SWAT model simulates the entire hydrologic cycle, including surface flow, lateral soil flow, evapotranspiration, infiltration, deep percolation, and groundwater return flows. A temperature index-based approach is used to estimate snow accumulation and snowmelt processes. Input data for SWAT include spatially distributed information basin topography, soil properties, land use/cover, and climate time series data. A detailed description of SWAT can be found by *Neitsch et al.* [2005].

Table 1. Comparison of Selected Stream Temperature Models [Adapted From *Norton and Bradford*, 2009]

Reference	Model	Model Heat Fluxes	Minimum Time Step	Additional Information
Allen et al. [2007]	BasinTEMP	Surface, groundwater	Daily	Physically-based; accounts for topographic and riparian shade, GIS output
Arnold et al. [1998]	SWAT		Daily	Empirical; accounts for air temperature only; effect of hydrology not included
Beschta and Weatherred [1984]	TEMP-84	Surface, groundwater, bed conduction	Equal to travel time	Accounts for topographic and riparian shade
Bicknell et al. [1997], *Chen et al.* [1998]	HSPF, SHADE-HSPF	Surface, groundwater, bed conduction	Hourly	Physically-based; accounts for topographic and riparian shade, interflow and overland runoff temperature
Boyd and Casper [2003]	HEAT SOURCE	Surface, groundwater, bed conduction	Hourly	Physically-based; Accounts for topographic and riparian shade
Chapra et al. [2006]	QUAL2K	Surface, groundwater, bed conduction	Less than hourly (output in daily mean, maximum, and minimum)	Physically-based; accounts for topographic and riparian shade
Cole and Wells [2003]	CE-QUAL-W2	Surface, groundwater, bed conduction	1 second	Physically-based; accounts for topographic and riparian shade, two-dimensional model (longitudinal and vertical)
Issak et al. [2009]	MRSTM	Stream network, geomorphology, climate, landscape features, fire effects		Empirical; multiple regression model where landscape features and fire effects are categorical predictors
LeBlanc et al. [1997]	CrUSTe	Surface, groundwater	Hourly	Physically-based; Accounts for riparian shade and impact of urbanization on stream width and baseflows
Morin and Couillard [1986], *St-Hilaire et al.* [2000]	CEQUEAU	Surface, groundwater	Daily	Physically-based; accounts for riparian shade, interflow, and overland runoff temperature
Rutherford et al. [1997]	Streamline	Surface, groundwater, bed conduction	15 min	Physically-based
Theurer et al. [1984]	SNTEMP	Surface, groundwater, bed conduction, friction	Daily	Physically-based; mean and maximum daily output only

[9] The SWAT model uses an air-water temperature linear relationship developed by *Stefan and Preud'homme* [1993] to calculate average daily stream temperature of a well-mixed stream. *Stefan and Preud'homme* [1993] developed an air-water regression model based on daily and weekly water temperature data from 11 streams in the central United States. The resulting regression model is:

$$T_{\mathrm{water}} = 5.0 + 0.75 T_{\mathrm{air}}, \tag{1}$$

where T_{air} is the average daily air temperature for the day (°C) and T_{water} is the temperature of the water (°C). Due to the thermal inertia of the water, the response of water temperature is dampened and delayed, which are depicted in coefficients in equation (1). As shown in equation (1), the water will be warmer than air temperature if the air temperature is below 20°C. This may be consistent with most rivers, but may not be the case when the stream temperature might be influenced by snowmelt, surface runoff, and groundwater inflow volumes that decrease stream temperature.

2.2. The New SWAT Stream Temperature Model

[10] The new stream temperature model incorporated into SWAT determines in-stream water temperature by three components: (1) temperature and amount of local water contribution within the subbasin; (2) temperature and inflow volume from upstream subbasin(s); and (3) heat transfer at the air-water interface during the streamflow travel time in the subbasin. Accordingly, the new stream temperature model estimates stream temperature by calculating each of these components in three steps. A schematic of the approach can be found in Figure 1. For the first step, stream temperature of the local water contribution ($T_{w,\mathrm{local}}$ (°C)) is estimated using a basic mixing model, by the volumes and temperatures of snowmelt, groundwater, surface, and lateral inflow volumes to the stream reach from within the local basin by

$$T_{w.\mathrm{local}} = \frac{(T_{\mathrm{snow}}\mathrm{sub\_snow}) + (T_{\mathrm{gw}}\mathrm{sub\_gw}) + (\lambda T_{\mathrm{air.lag}})(\mathrm{sub\_surq} + \mathrm{sub\_latq})}{\mathrm{sub\_wyld}}. \tag{2}$$

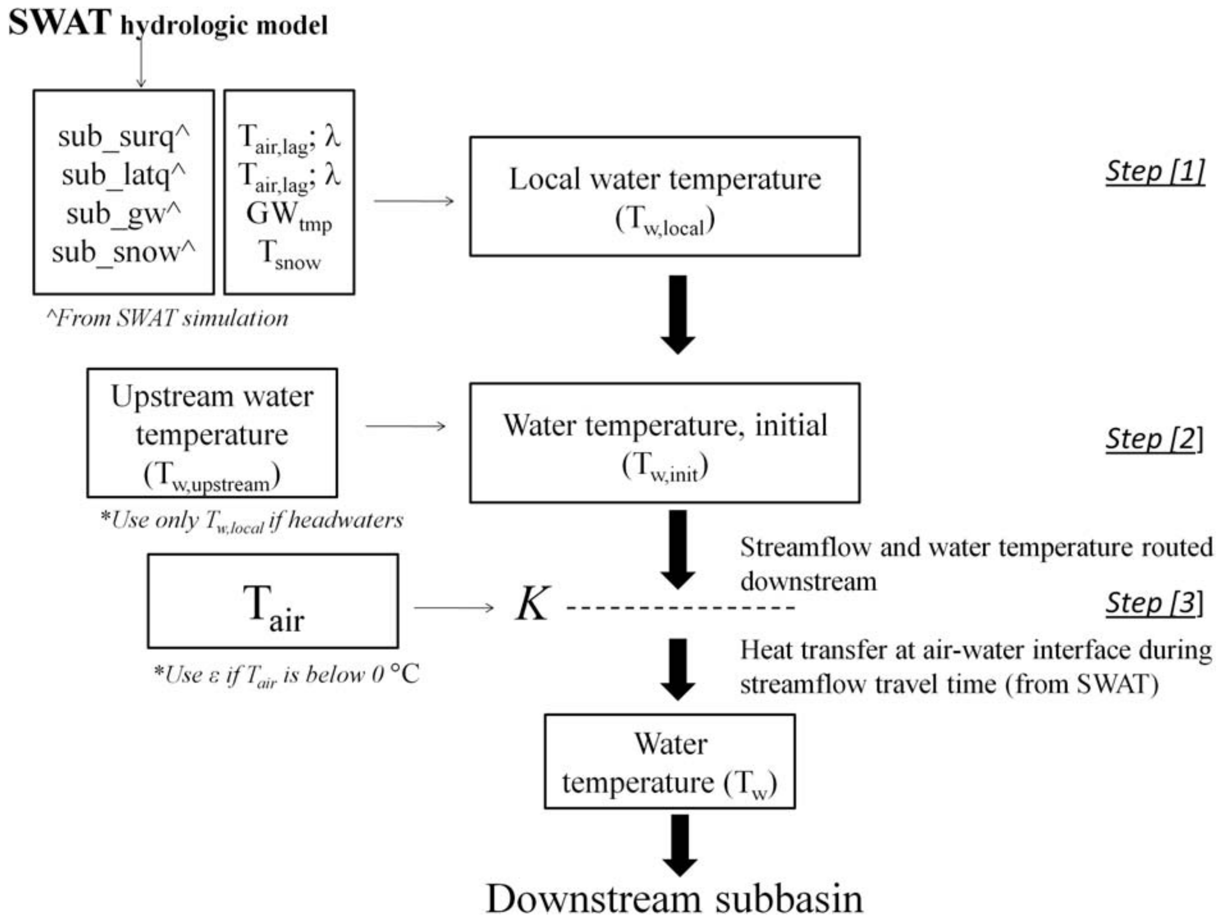

Figure 1. Schematic of new stream temperature model The following parameters are passed to the temperature module from the SWAT hydrologic model: sub_surq, sub_latq, sub_gw, and sub_snow.

Here, sub_snow is the snowmelt contribution to streamflow within the subbasin (m^3 d^{-1}), sub_gw is the groundwater contribution to streamflow within the subbasin (m^3 d^{-1}), sub_surq is the surface water runoff contribution to streamflow within the subbasin (m^3 d^{-1}), sub_latq is the soil water lateral flow contribution to streamflow within the subbasin (m^3 d^{-1}), sub_wyld is the total water yield (all hydrologic components) contribution to streamflow within in the subbasin (m^3 d^{-1}), T_{snow} is the snowmelt temperature (°C), T_{gw} is the groundwater temperature (°C), $T_{air,lag}$ is the average daily air temperature with a lag (°C), and λ (–) is a calibration coefficient relating the relationship between $T_{air,lag}$ and sub_surq and sub_latq. The volumes of sub_snow, sub_gw, sub_surq, and sub_latq are simulated from SWAT. The lag (days) is a calibration parameter incorporated to allow the effects of delayed surface runoff and soil water flow into the stream. For example, if the lag is 3 the air temperature used is the average air temperature of the previous 3 days. Lag can be estimated by examining the day-to-day variation in observed stream temperatures. If $T_{air,lag}$ is ≤ 0°C, then $T_{air,lag}$ is set to 0.1°C. T_{gw} is an annual time series that must be input by the user. Each year can have a different T_{gw}. Groundwater temperature is often 1–2°C higher than mean annual air temperature of a region [*Todd*, 1980] and can be estimated from climatic input data. Examining the influence of snowmelt on stream temperature, *Kobayashi* [1984] found that snowmelt temperature is approximately 0°C, and therefore we assume a snowmelt temperature value of $T_{snow} = 0.1$°C.

[11] For the second step, the stream temperature before the effects of air temperature is then calculated as a weighted average of the contributions within the subbasin and the contribution from the upstream subbasin(s). It is given by

$$Tw_{\text{initial}} = \frac{T_{w.\text{upstream}}(Q_{\text{outlet}} - \text{sub\_wyld}) + T_{w.\text{local}}\text{sub\_wyld}}{Q_{\text{outlet}}}, \tag{3}$$

where $T_{w,\text{upstream}}$ is the water temperature of the streamflow entering the subbasin (°C) and Q_{outlet} is the streamflow discharge at the outlet of the subbasin (m^3 d^{-1}). In the case of headwater streams, $Tw_{\text{initial}} = T_{w,\text{local}}$. As noted by *Moore et al.* [2005], a mixing model such as this assumes complete mixing of densities and may not be valid until some distance downstream of the point of mixing, which for this model is implicitly assumed to be at every stream segment throughout the watershed. This assumption is valid in cases where the streamflow is turbulent, which is applicable for all natural streams [*Jarrett*, 1990].

[12] In a third step, final stream temperature is calculated by adding a change to the initial stream temperature in the

subbasin. This change is based on the difference between stream and air temperature, a transfer parameter, and the travel time of water through the subbasin. It is given by the following equations, depending on $T_{\rm air}$:

$$T_w = Tw_{\rm initial} + (T_{\rm air} - T_{\rm initial})K(TT) \quad \text{if} \quad T_{\rm air} > 0, \quad (4)$$

$$T_w = Tw_{\rm initial} + [(T_{\rm air} + \varepsilon) - Tw_{\rm initial}]K(TT) \quad \text{if} \quad T_{\rm air} \leq 0, \quad (5)$$

where $T_{\rm air}$ is the average daily temperature, K (1/h) is a bulk coefficient of heat transfer and ranges from 0 to 1, TT is the travel time of water through the subbasin (hour) and is calculated from the SWAT simulations, and ε is an air temperature addition coefficient, which was included to account for water temperature pulses when $T_{\rm air}$ is below 0°C. When $T_{\rm air}$ is below but close to 0°C, the maximum air temperature can reach above-freezing temperatures during part of the time step, thus resulting in a surface and soil water snowmelt pulse in the observed data, which the model cannot reproduce without the use of ε. Therefore, ε allows the modeled water temperature to rise above 0°C when $T_{\rm air}$ is below 0°C. The value of K is dependent on the relationship between stream and air temperature within a subbasin. For example, if stream temperature is approximately the same as air temperature, then K is 1. If there is a short travel time or extensive tree shading, then K will be less than 1. For the case when the effects of $T_{\rm air}$ and the hydrologic contributions are such that the final is $T_w < 0$°C, the stream temperature model sets T_w to 0.1°C. T_w is also assumed to be the temperature of water discharge to downstream subbasin, and is further routed along the stream network. If the SWAT hydrologic model predicts periods of "no flow," the stream temperature model returns the value "NaN," informing the user that the stream temperature value is "not a number." Using air temperature as a proxy for the radiative forcing within a stream reach is conceptually analogous to the temperature index snowmelt model in SWAT as well as some of the basic formulations for potential evapotranspiration available to SWAT users [*Hargreaves and Samani*, 1985]. The calibration parameter K acts as a proxy for reach-specific adjustment of the radiative forcing, such as shading due to a vegetation canopy or geomorphic changes resulting in differing geometry. It should be noted that a calibration of this parameter for a river reach would not necessarily be applicable under future conditions where stream shading or river geometry change dramatically.

[13] It is important to note that the satisfactory results of SWAT hydrology based on the guidelines established by *Moriasi et al.* [2007] are a prerequisite for good water temperature simulations. Inaccurate simulation of streamflow may lead to incorrect mixing of snowmelt, surface runoff, lateral soil flow, and groundwater inflow, which would strongly affect simulated water temperatures. Conversely, inaccurate stream temperature simulations that cannot be matched to observed data may imply an incorrect representation of the relative hydrologic contributions.

2.3. Implementation of the New Stream Temperature Model

[14] The new stream temperature model is implemented at two spatial scales, using quantities that the SWAT hydrologic model provides as well as the previously mentioned calibration parameters. The spatial scales are the (1) subbasin level and (2) watershed level. Including model parameters at the subbasin spatial scale allows the user to simulate stream temperature differently based on spatial location within the watershed, which could find applications in the modeling of watersheds that span both mountainous and valley terrain. For smaller watersheds, simulating stream temperature at the watershed level may be most appropriate in terms of data availability and stream temperature model calibration. If both subbasin and watershed level stream temperature parameters are input to the model, the stream level parameters overwrite the watershed level parameters.

[15] The new stream temperature model can also be implemented at different temporal scales. Because the relationship of hydrology and air temperature to stream temperature can vary throughout the year, the user has the option of including different stream temperature model parameters for each season. An example of shifts in stream temperature can be found in Figure 2, where the seasonal boundaries are placed near the stream temperature rising and falling limb inflection points. Seasonally varying parameters allow more accurate temporal simulations, but increase the complexity of the calibration. The user includes seasonal simulations by delineating the modeling time periods by Julian calendar dates. Additionally, a time series of annual groundwater temperatures are input by the user in the file.

2.4. Study Sites

[16] We test the new stream temperature model on seven watersheds throughout the western United States (Figure 3). The sites were selected based on watershed size and type, data availability, and climate (Tables 2 and 3). All stream temperature simulations in this study are done at the watershed level, where the same stream temperature model parameters are used throughout the watershed.

3. Results and Discussion

3.1. SWAT Hydrologic Model Calibration and Validation

[17] An automated calibration technique using the program Sequential Uncertainty Fitting Version 2 [SUFI-2; *Abbaspour et al.* 2007] was used to calibrate daily streamflow for all SWAT models. Five model evaluation criteria were used to assess hydrologic model performance: (1) the Nash-Sutcliffe coefficient [NS; *Nash and Sutcliffe*, 1970], (2) ratio of root mean square error to the standard deviation of observed data (RSR), (3) percent bias (PBIAS), which is the sum of the residual errors between the observed and simulated data divided by the sum of the observed data, (4) a modified efficiency criterion (ϕ), (5) the mean error (ME), and (6) standard deviation of the errors. ϕ is a slightly modified version of the efficiency criterion defined by *Krause et al.* [2005] where the coefficient of determination R^2 is multiplied by the slope of the regression line b. This function allows accounting for the discrepancy in the magnitude of two signals (captured by b) as well as their dynamics (captured by R^2). For ϕ, a perfect simulation is represented by a value of 1. A split-sample approach was used for calibration and validation, with the time periods varying for each watershed (Table 3).

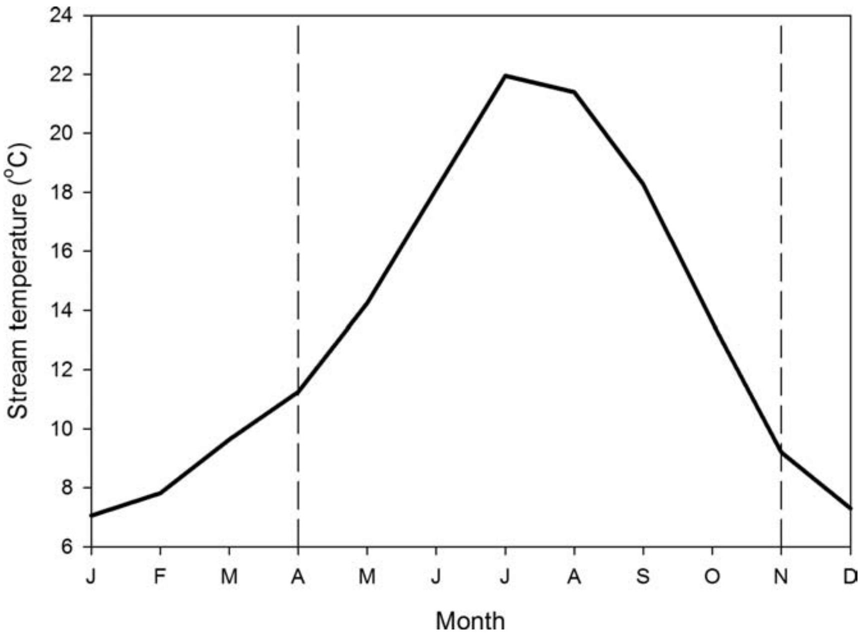

Figure 2. Example of a seasonal shift for selection of seasonal modeling boundaries. The boundaries represent the change in stream temperature model parameters.

[18] The SWAT hydrologic simulation generated good results in comparison with the observed streamflow data (Table 3 and Figure 4). The average NS coefficient of the seven watersheds for the calibration time period was 0.68, ranging from 0.59 for the North Santium River watershed to 0.78 for the Mill Creek watershed. The average NS coefficient for the validation time period was 0.61, ranging from 0.53 for Mill Creek watershed to 0.69 for the North Fork Clearwater River watershed. The calibration and validation results indicate satisfactory simulations based on the

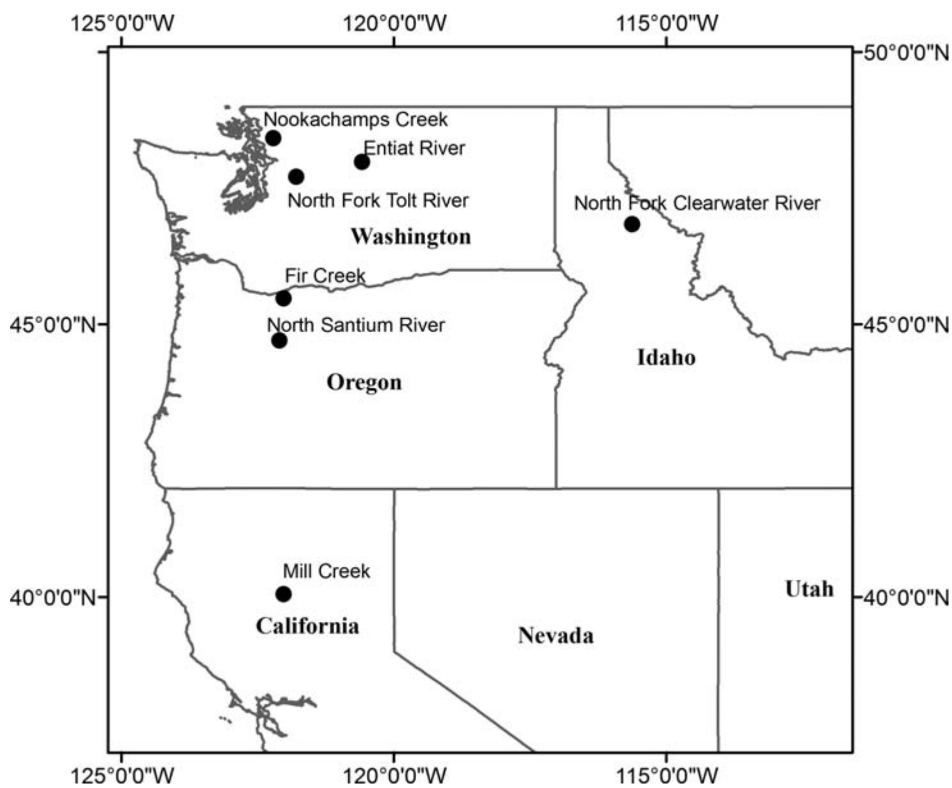

Figure 3. Location of the watershed sites across the western U.S. where the stream temperature model was tested.

Table 2. Environmental Characteristics of the Study Sites

River	Average Annual Temperature (°C)	Average Annual Precipitation (cm)	Average Daily Discharge (m^3 s^{-1})	Upstream Drainage Area (km^2)	Average Elevation (m)	Snowmelt Impact	Number of Water Temperature Measurements
Entiat River	3.4	155.6	6.5	192	1373	Yes	713
Nookachamps Creek	9.4	153.1	1.8	27	409	Yes	1,870
North Fork Tolt River	8.1	233.1	10.0	105	677	Yes	2,860
Fir Creek	9.4	231.1	1.0	14	883	Yes	11,787
North Fork Clearwater River	3.2	133.6	96.9	3354	1269	Yes	11,106
North Santium River	3.1	212.5	29.3	557	1173	Yes	16,663
Mill Creek	6.9	198.8	8.9	337	1129	Yes	2,625

guidelines established by *Moriasi et al.* [2007], where a NS >0.50, RSR <0.70, and PBIAS ±25% are considered "satisfactory." Therefore, the models were deemed suitable for testing the new stream temperature model.

3.2. New Stream Temperature Model

3.2.1. Calibration and Simulation Results

[19] The new stream temperature model was manually calibrated for each of the seven watersheds used for model testing. The final calibration parameters can be found in Table 4. K was the most sensitive parameter and was generally the only parameter that was manipulated. λ was generally left at 1; however, in a few cases, λ was decreased. ε was increased if small stream temperature increases were found during the winter in the observed stream temperature that were not captured by the model. Lag was changed from the default value of 7 days if the day-to-day variation of the simulated stream temperature values did not match the day-to-day variation of the observed stream temperature data. The Julian dates for the seasonal modeling was based on shifts in observed stream temperature data.

[20] To assess the performance of the new stream temperature model, the new stream temperature modeling results are compared to the observed data along with the original SWAT temperature model. For all watershed sites, the new stream temperature model greatly improved stream temperature simulations as compared to the original SWAT stream temperature model. The results for the seven watersheds are given in Table 5 and Figure 5. The original SWAT temperature model had an average NS coefficient and ME of −0.27 and 3.21°C for the calibration period and −0.26 and 3.01°C for the validation period, respectively. For the new stream temperature model, the average NS coefficient and ME was 0.81 and −0.69°C for the calibration period and 0.82 and −0.63°C for the validation period. While there is no strict definition of acceptable stream temperature model performance statistics, *van Vliet et al.* [2011] report average NS and RMSE values of 0.85 and 2.26°C, while *Mohseni et al.* [1998] report average NS and RMSE values of 0.93 and 1.64°C, respectively. Therefore, our new stream temperature model that uses hydrology and air temperature to predict stream temperature produced stream temperature model performance statistics that were comparable to other published regression stream temperature models. PBIAS statistics also indicate satisfactory stream temperature model performance, with an average PBIAS of 7.1% for the calibration period and 6.4% for the validation period. The satisfactory model performance parameters with the new temperature model including hydrology also indicate a good performance of the underlying water balance simulations.

[21] Despite some discrepancies during the winter where the stream temperature model does not capture small pulses in water temperature, Figures 5 and 6 illustrate a generally good agreement between observed and simulated water temperatures with respect to magnitude and timing of the temperature variations. The incorporation of ε allows the modeling of temperature surges during negative air temperatures for some but not all cases, as shown in the Entiat River watershed (Figure 6). Not being able to capture the small winter pulses in stream temperature may also be a

Table 3. Daily Streamflow Calibration and Validation Statistics of the SWAT Hydrology Modeling for the Study Sites

Site	Years	NS	RSR	PBIAS	bR^2	Mean Error (m^3 s^{-1})	Std. Dev. of Error (m^3 s^{-1})
				Calibration			
Entiat River	2003–2004	0.71	0.56	−24.5	0.69	1.8	4.1
Nookachamps Creek	2000–2003	0.68	0.63	−12.6	0.47	−0.2	1.2
North Fork Tolt River	1990–1998	0.65	0.58	16.64	0.48	−1.8	6.0
Fir Creek	1980–1993	0.69	0.55	16.69	0.54	−0.2	0.7
North Fork Clearwater River	1970–1990	0.72	0.53	7.59	0.47	−32.1	63.0
North Santium River	1950–1980	0.59	0.65	11.27	0.42	−3.3	15.6
Mill Creek	1990–1998	0.78	0.57	−3	0.78	0.2	6.0
				Validation			
Entiat River	2005	0.6	0.61	−25	0.65	0.9	2.4
Nookachamps Creek	2004–2005	0.64	0.55	7.6	0.46	−0.1	1.4
North Fork Tolt River	1999–2005	0.57	0.65	17.4	0.37	−1.5	6.4
Fir Creek	1994–2003	0.61	0.63	8.53	0.56	−0.1	0.8
North Fork Clearwater River	1991–2005	0.71	0.53	−4.8	0.54	−24.3	53.9
North Santium River	1981–2005	0.64	0.59	4.97	0.45	−1.7	13.8
Mill Creek	1999–2005	0.53	0.53	4.9	0.53	−0.6	7.0

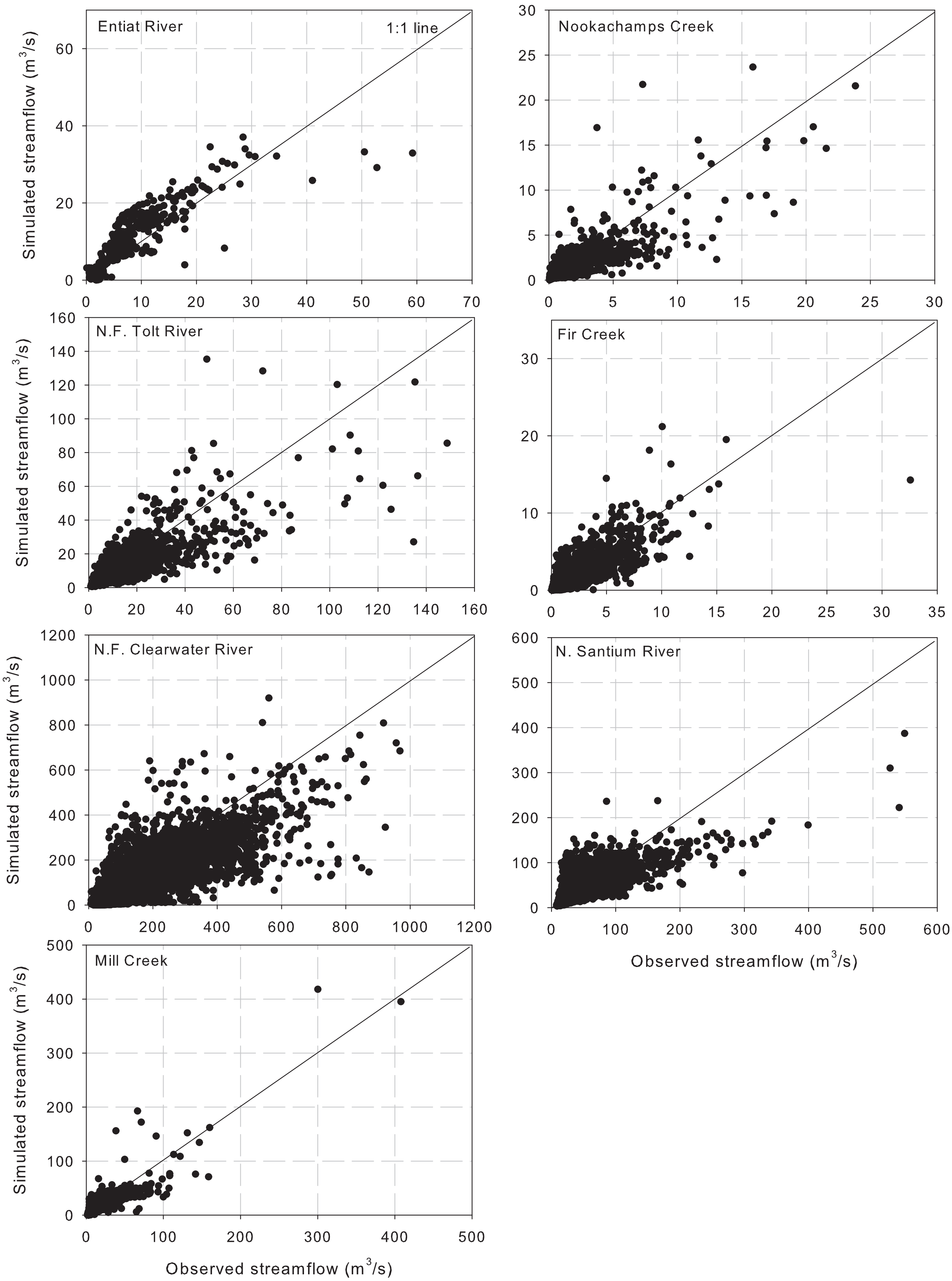

Figure 4. Daily SWAT hydrologic model streamflow simulations for the calibration and validation time periods in the seven study sites.

Table 4. Calibration Parameters of the New Stream Temperature Model for the Study Sites

River	Julian Day From	Julian Day To	λ (–)	K (1/h)	ε (°C)	Lag (Days)
Entiat River	1	65	1	0.1	4.5	7
	66	125	1	0.03	4.5	14
	126	285	0.7	0.03	0	14
	286	366	1	0.05	3	14
Nookachamps Creek	1	181	1	0.1	0	7
	182	273	1	0.5	0	7
	274	366	1	0.1	0	7
North Fork Tolt River	1	90	1	0.85	0	4
	91	306	0.55	0.065	0	7
	307	366	1	0.85	0	4
Fir Creek	1	81	0.8	0.99	0.2	4
	82	333	0.8	0.3	0	7
	334	366	0.8	0.99	0.2	4
North Fork Clearwater River	1	180	1	0.009	3	7
	181	280	0.8	0.1	0	5
	281	366	1	0.009	3	7
North Santium River	1	90	1	0.1	3.5	7
	91	325	1	0.15	0	7
	326	366	1	0.1	3.5	7
Mill Creek	1	120	1	0.05	2	7
	121	325	1	0.015	2	7
	326	366	1	0.05	2	7

result of the hydrologic simulation not capturing small peaks in groundwater, surface runoff, or lateral soil flow.

[22] Errors in hydrologic modeling led to errors in stream temperature simulations. A Pearson correlation analysis was performed between the mean errors of the observed and simulated streamflow and stream temperature for all watersheds. A significant correlation ($p < 0.05$) of 0.54 was found between the streamflow and stream temperature mean errors, indicating a relationship. Therefore, a well-calibrated model is imperative to accurately simulate stream temperature. This is further illustrated in Figure 6 and Table 5, where the larger streamflow errors are associated with larger stream temperature errors.

3.2.2. New Stream Temperature Model Parameter Sensitivity Analysis

[23] Mathematically, the dependence of an output variable y on an input parameter x can be expressed as the partial derivative $\partial y/\partial x$. This can be numerically approximated by finite difference, where y_0 is the model output with the initial parameter value of x_0. This initial value is varied by $\pm\Delta x$ yielding $x_1 = x_0 - \Delta x$ and $x_2 = x_0 + \Delta x$ with corresponding values of y_1 and y_2. The finite approximation of $\partial y/\partial x$ is then

$$I' = \frac{y_2 - y_1}{2\Delta x}. \quad (6)$$

To get a dimensionless sensitivity index, I' must be normalized:

$$I = \frac{(y_2 - y_1)/y_0}{2\Delta x/x_0}. \quad (7)$$

I is used to represent the change in the output variable (mean and variance of stream temperature output) resulting from a change in new stream temperature model input parameters. This is the simplest way to carry out a sensitivity analysis that is frequently found in the literature [*Hamby*, 2004] and a value of $\Delta x/x_0 = 10\%$ is often used [*Lenhart et al.*, 2002; *Luo et al.*, 2008]. The sensitivity index gives a measure of the range in error in the stream temperature output to a range in error in the new stream temperature model input parameters. The larger the absolute value of I, the more sensitive the parameter is for model prediction. A negative sensitivity indicates that the parameter has an inverse effect on the prediction as compared to the original model value. In equation (7) y_0, y_1, and y_2 must be calculated from a single statistical value that describes the stream temperature time series (mean, max, min, variance, etc.). For this study, we used mean and variance from $\pm$10% changes of input parameters as the indicator values to compare the shift in mean response as well as changes in

Table 5. Calibration and Validation Statistics for the Original and New SWAT Stream Temperature Model for the Study Sites

River	Calibration Years	NS	PBIAS (%)	Mean Error (°C)	Std. Dev. of Error (°C)	Validation Years	NS	PBIAS (%)	Mean Error (°C)	Std. Dev. of Error (°C)
Original SWAT Stream Temperature Model										
Entiat River	2003–2004	−0.08	−62.2	3.43	2.13	2005	−0.16	−73.6	2.91	2.44
Nookachamps Creek	2000–2003	0.24	−44.4	3.68	1.74	2004–2005	0.31	−37.6	3.37	1.74
North Fork Tolt River	1995–2000	−1.6	−43.4	3.41	2.34	2001–2003	−1.54	−43.4	3.22	2.34
Fir Creek	1980–1992	−2.27	−73.6	4.99	2.34	1993–2003	−2.23	−70.4	4.98	2.21
North Fork Clearwater River	1970–1990	0.8	−16.1	1.23	2.43	1991–2005	0.83	−14.9	1.16	2.26
North Santium River	1951–1980	0.49	−27.7	2.19	2.06	1981–2005	0.59	−22.1	1.88	1.8
Mill Creek	1998–2002	0.54	−27.6	3.52	1.67	2003–2005	0.4	−26.1	3.61	1.68
New SWAT Stream Temperature Model										
Entiat River	2003–2004	0.89	9.4	−0.52	1.17	2005	0.89	3.3	−0.14	1.04
Nookachamps Creek	2000–2003	0.86	−6.5	−0.53	1.63	2004–2005	0.91	−4.8	−0.43	1.29
North Fork Tolt River	1995–2000	0.7	7.6	−0.59	1.29	2001–2003	0.77	6.1	−0.47	1.13
Fir Creek	1980–1992	0.75	4.2	−0.29	1.43	1993–2003	0.76	6.1	−0.43	1.46
North Fork Clearwater River	1970–1990	0.87	14.1	−1.07	1.91	1991–2005	0.84	14.8	−1.16	1.71
North Santium River	1951–1980	0.73	14.9	−1.17	1.75	1981–2005	0.7	16.6	−1.42	1.75
Mill Creek	1998–2002	0.85	5.7	−0.72	2.1	2003–2005	0.87	2.5	−0.35	1.92

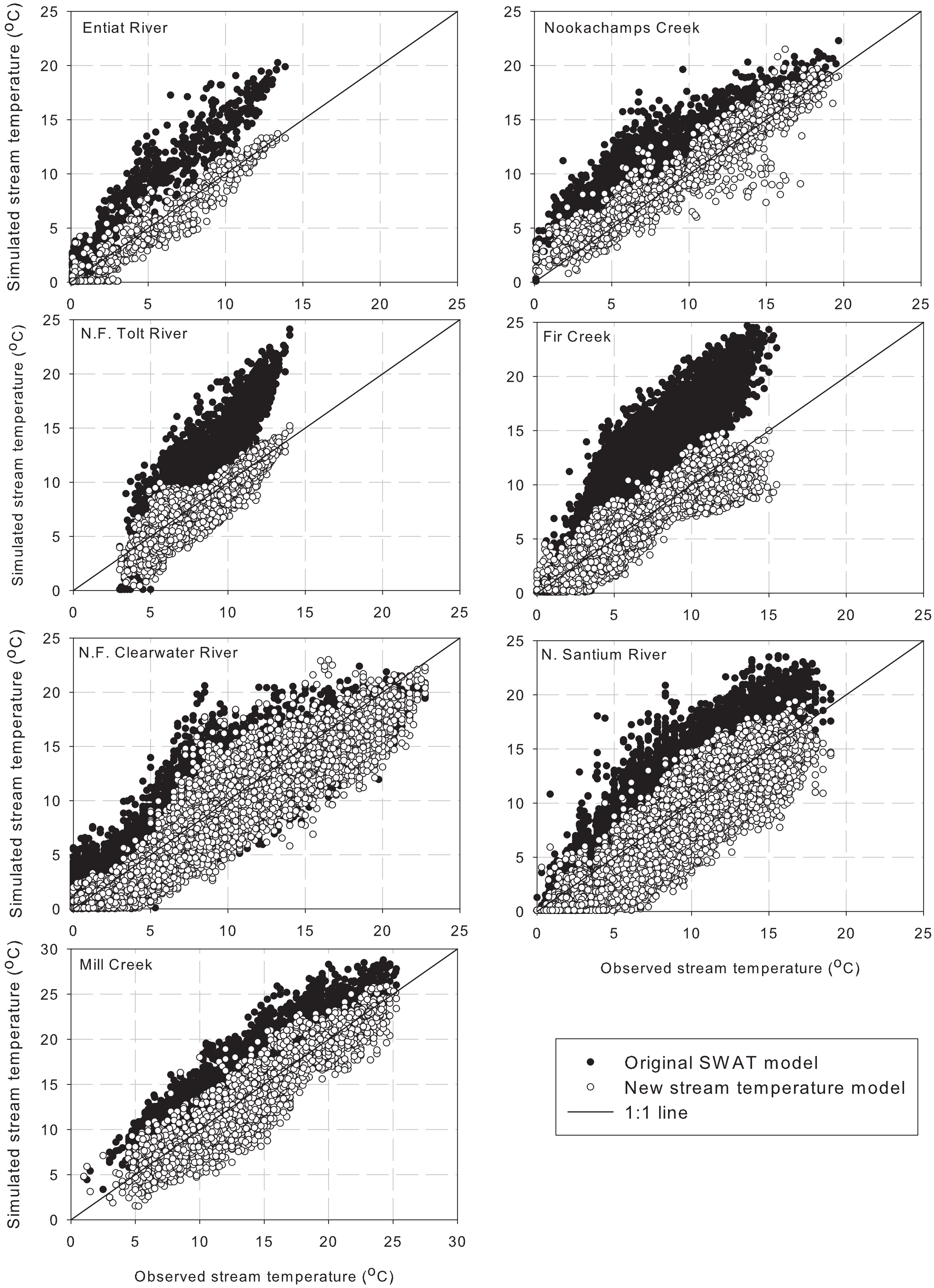

Figure 5. Scatterplots of daily stream temperature for the original and new SWAT stream temperature model for the seven study sites.

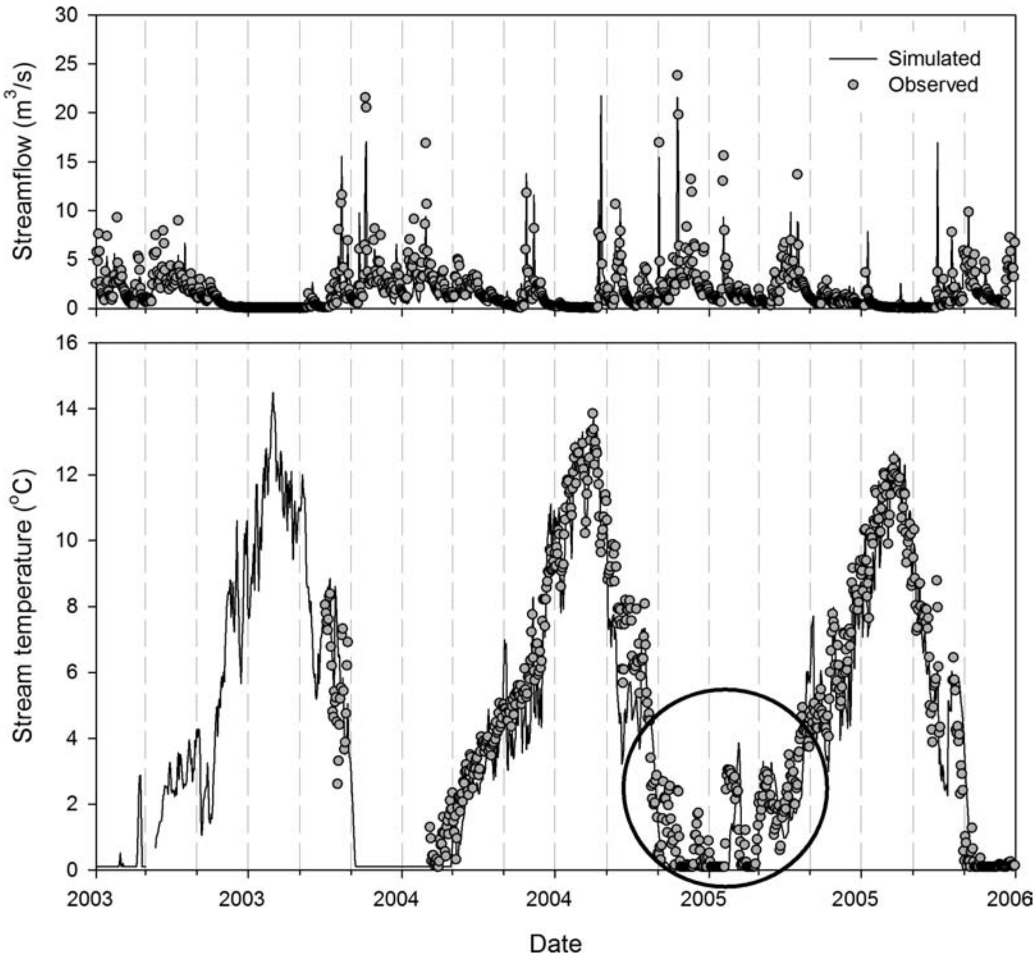

Figure 6. Observed and predicted daily streamflow and stream temperature results for the Entiat River watershed using the new stream temperature model. The circle highlights a situation where modeling problems can be encountered when average daily air temperature is near 0°C. The figure shows the improved modeling results using the episIon parameter.

the entire range of simulated stream temperatures. For assessment and comparison purposes, sensitivity indices can be ranked into the four classes found in Table 6 as defined by *Lenhart et al.* [2002]. The means and variances were compared between the calibrated new stream temperature model and the same model with one-at-a-time parameter change, as listed in Table 7. The sensitivity analyses were performed on the seven watersheds in this study for the parameters K, Lag, λ, and ε.

[24] Table 7 lists the normalized sensitivity indices of the new stream temperature model parameters. ε was determined to be 0°C for many watersheds and therefore ε was set to 2.5°C for all watersheds before assessing the sensitivity. Using mean as a statistical indicator, λ and K were found to be of "high" and "medium" sensitivity, with λ

Table 6. Sensitivity Index Categories [From *Lenhart et al.*, 2002]

Index	Sensitivity
$0.00 \leq \lvert I \rvert < 0.05$	Small to negligible
$0.05 \leq \lvert I \rvert < 0.20$	Medium
$0.20 \leq \lvert I \rvert < 1.00$	High
$\lvert I \rvert \geq 1.00$	Very high

Table 7. Normalized Sensitivity Indices for Stream Temperature Model Inputs for the Seven Watershed Outlets

Mean	K	λ	Lag	ε
North Fork Clearwater River	0.02	0.18	0.01	0.21
Fir Creek	0.17	0.23	0.00	0.04
Mill Creek	0.21	0.20	0.00	0.00
Nookachamps Creek	0.04	0.18	0.00	0.02
North Santium River	0.09	0.07	0.00	0.20
Entiat River	0.14	0.58	0.00	0.34
Tolt River	0.14	0.25	0.00	0.03
Average	0.12	0.24	0.00	0.12
SD	0.08	0.16	0.00	0.13

Variance	K	λ	Lag	ε
North Fork Clearwater River	0.06	0.17	−0.03	−0.05
Fir Creek	1.25	0.23	−0.03	−0.04
Mill Creek	0.30	0.09	−0.04	0.00
Nookachamps Creek	0.24	0.12	−0.04	−0.02
North Santium River	0.36	0.04	−0.05	−0.10
Entiat River	0.19	1.36	−0.02	−0.04
Tolt River	0.43	0.62	−0.09	−0.03
Average	0.40	0.38	−0.04	−0.04
SD	0.41	0.48	0.02	0.03

generally the most sensitive parameter. Lag was found to be insensitive, while ε was found to be of medium sensitivity using mean as a statistical indicator. Using variance as a statistical indicator, stream temperature showed a high sensitivity to perturbations in K and λ. Lag and ε were within the "small to negligible" sensitivity range. Thus, using the mean and variance as statistical indicators resulted in different I values depending on the input parameter. In physical terms, increasing or decreasing λ shifts the effect of air temperature onto stream temperature toward surface runoff and lateral soil flow. Thus the temperature of the local hydrological inputs is being increased or decreased by 10% before being affected by travel time, T_{air}, and K, which are held constant for a sensitivity analysis. Adjusting K had a larger effect on the variance than λ. These results are reasonable as K is defined as the bulk heat transfer coefficient, defining the relationship between the stream temperature and air temperature, while also determining the effect of travel time on the final stream temperature value. Therefore, K has a large affect on the relationship between initial stream temperature, air temperature, and travel time, which can have large variation from day-to-day. Furthermore, K is in the final step of the new stream temperature model and thus has a large effect on the final printed stream temperature.

[25] Lag was found to be more sensitive using variance as a statistical indicator. This is physically reasonable, as a modified Lag will result in changes in day-to-day stream temperature variation, where an increase in Lag will "smooth" stream temperature variation. Increasing ε led to an increase in I using mean as a statistical indicator, while I decreased using variance as a statistical indicator. Increasing ε will lead to an increase in the minimum stream temperatures when $T_{\mathrm{air}} < 0°\mathrm{C}$, thus increasing the mean while also decreasing the stream temperature range. As shown in Figure 6 ε can increase model performance, even when remaining inactive for most of the model simulation. The results from the sensitivity analysis indicate that the model parameters drive model output in ways that can be physically explained.

3.2.3. New Stream Temperature Model Response to Changes in Climate and Hydrology

[26] Variations in climate and hydrology were conducted to examine the hydroclimatological sensitivities of the stream temperature model (Figure 7). All sensitivity analyses were performed on the calibrated Mill Creek watershed SWAT model in northern California with a calibrated stream temperature model and presented on a monthly time scale unless noted otherwise. The Mill Creek watershed was chosen because its climate and environmental characteristics are the approximate median of all watersheds, thus representing a typical watershed for this study. It is important to note that the sensitivities may vary with each watershed and may be potentially dependent on the calibration. T

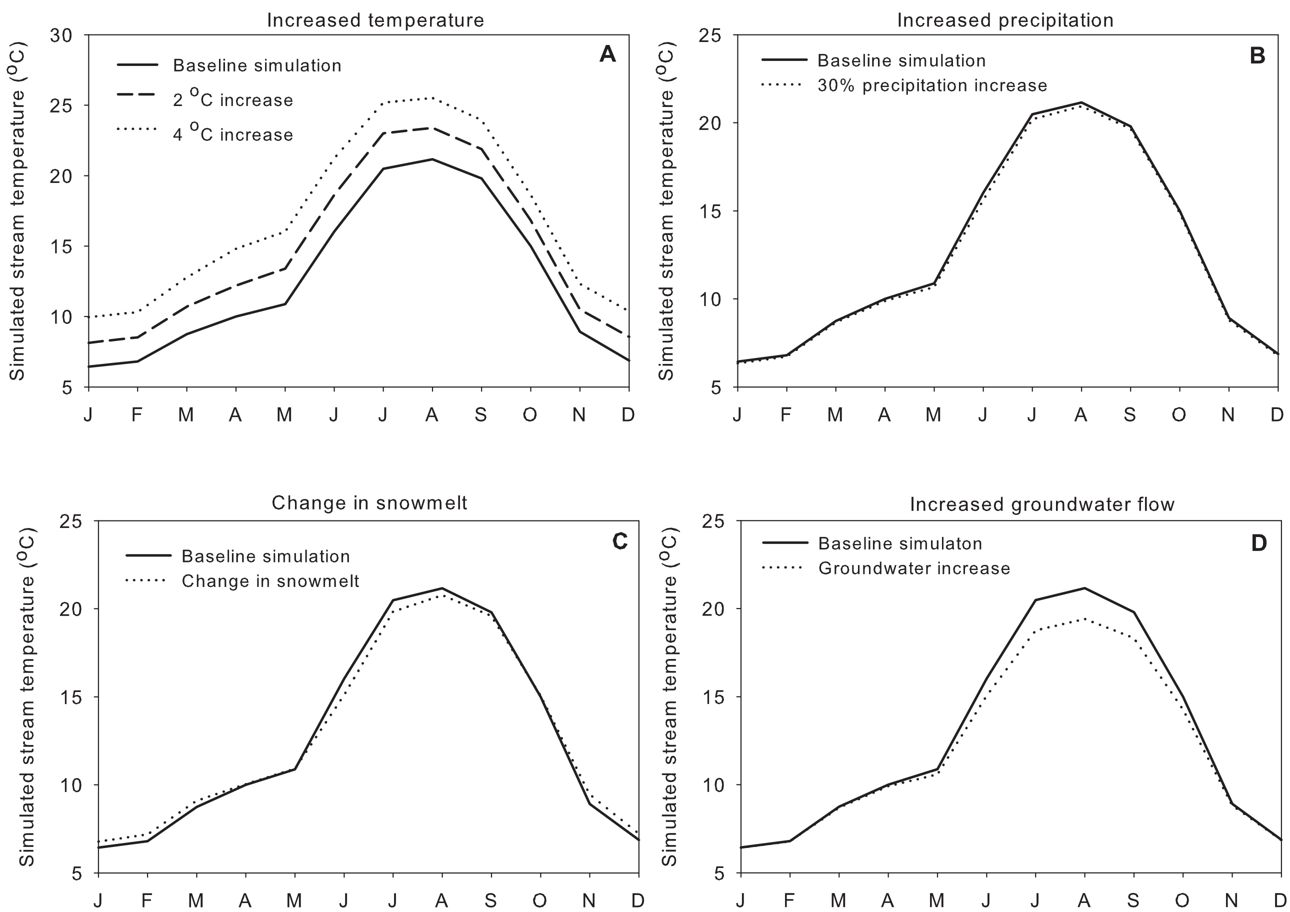

Figure 7. Stream temperature sensitivity plots for (a) an increase in air temperature, (b) increase in precipitation, (c) change in snowmelt parameters, and (d) an increase in groundwater flow.

tests for dependent samples were performed to compare all sensitivity and baseline scenarios. The target level of significance was $\alpha = 0.05$.

3.2.3.1. Effects of Increased Air Temperature on Stream Temperature Output

[27] To examine the behavior of the new model under warmer climates, daily maximum and minimum air temperatures were increased by 2 and 4°C for all months. The air temperature increases led to statistically significant ($p < 0.05$) increases in simulated stream temperatures for all months (Figure 7a). With an increase in temperature, the largest stream temperature increase was found during the summer months, where simulated stream temperature increased higher than the air temperature increase. The average summer stream temperature increase for the time period was 2.4°C for a 2°C air temperature increase and 4.6°C for a 4°C air temperature increase. During the winter months, the 2 and 4°C air temperature increase resulted in a 1.76 and 3.6°C increase in stream temperature. This potentially shows the effects of a shift in snowmelt to earlier in the year, where a lack of snowmelt would increase stream temperature. Furthermore, an increase in air temperature would result in less snowfall and more rain. Several prior studies have examined the effects of increased air temperatures on stream temperatures [*Mohseni et al.*, 1998, 2003; *Mantua et al.*, 2010; *van Vliet et al.*, 2011] and have found similar responses.

[28] We further illustrate the sensitivity of increased temperature on the new stream temperature model in the snowmelt-dominated Entiat River watershed for February 2005 through July 2005. With a 4°C increase in average daily air temperature (Figure 8a), the hydrology in the basin is altered such that snowmelt is shifted earlier in the year, and in some cases, converted to soil water lateral flow or surface runoff (Figure 8b). It can be seen in Figure 8c

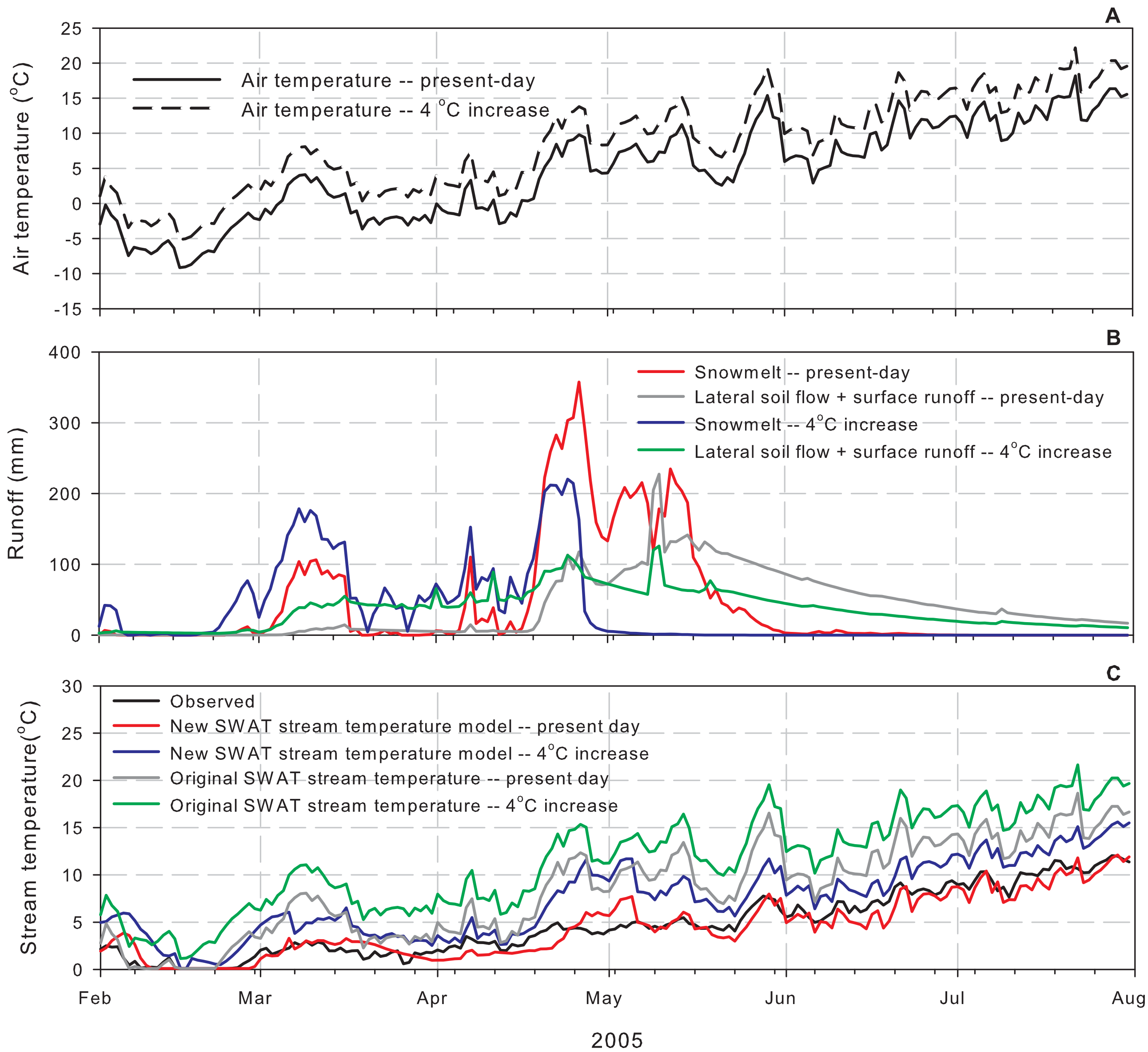

Figure 8. Panel plots showing the effects of (a) increased air temperature of 4°C, (b) on the Entiat River watershed hydrology, and (c) stream temperature simulations for the entire watershed.

that the original SWAT stream temperature already greatly over predicts stream temperature for the present-day scenario. When raising the temperature, the original SWAT stream temperature model cannot take the hydrologic shifts into account and simply raises stream temperature by an additional 4°C. By contrast the new stream temperature model produces more physically plausible results under warming scenarios than the original SWAT stream temperature model. For example, in March 2005 a period of warmer temperatures resulted in some early snowmelt and soil water lateral flow/surface runoff (Figure 8b). The original SWAT stream temperature model predicts that stream temperature will rise to approximately 10°C during this time, even though air temperature does not rise this high and the snowmelt pulse is contributing a volume of cold water (Figure 8c). The new stream temperature model gives colder estimates of stream temperature during this time, based on the inflow volumes of snowmelt and soil water flow/surface runoff, as well as warmer air temperatures. Similar observations can be made for the end of April 2005 and beginning of May 2005.

3.2.3.2. Effects of Increased Precipitation on Stream Temperature Output

[29] With air temperature held constant, an increase in precipitation should result in a decrease in stream temperature due to the increase in streamflow discharge (or decrease in streamflow travel time) [*Webb et al.*, 2003; *van Vliet et al.*, 2011]. However, one must consider the multiple sources of the hydrology (snowmelt, lateral soil flow, and groundwater) that are causing an increase in streamflow. For example, an increase in streamflow may be due to an increase in snowmelt, resulting in a lowering of stream temperature. On the other hand, an increase in streamflow may be due to an increase in groundwater flow, which may result in an increase or decrease in stream temperature depending on the time of year. Several studies have tried to quantify the effect of precipitation on stream temperature with no overall conclusion, as the overall effect differs for each watershed [*Brown and Hannah*, 2007].

[30] For the Mill Creek watershed, increasing precipitation by 30% had a statistically insignificant ($p > 0.05$) effect on simulated stream temperature (Figure 7b). This may be potentially due to the Mill Creek watershed's Mediterranean climate, where most of the annual rainfall occurs during the winter time period. Analysis of the individual hydrologic outputs indicates that increasing precipitation had an overall cancelling out effect on stream temperature because of source water mixing. The only discernable change in stream temperature was during the summer when streamflow is fed by small amounts of lateral soil water flow, thus slightly decreasing the stream temperature.

[31] This cancelling out effect was also seen during the winter time period, when increasing precipitation caused a higher snowmelt and lateral soil flow volumes. As previously stated, snowmelt in the new model enters the stream at a temperature of 0.1°C, while lateral soil flow is set to the average daily temperature. During the winter time period, the amount of snowmelt and lateral soil flow entering the stream is approximately equal, with the snowmelt having larger daily variability. Therefore, while there are day-to-day stream temperature simulation differences when precipitation is increased, the overall effect at the monthly time scale is negligible (Figure 7b).

3.2.3.3. Effects of Varying Snowmelt Parameters on Stream Temperature Output

[32] To determine the effect of an increase in the snowmelt component, the SWAT snowmelt parameters SFTEMP (temperature threshold for snowfall/precipitation to occur) and SMTMP (temperature at which snowmelt will occur) were increased by 2°C (from 3.9 to 5.9°C for SFTEMP and 1.9 to 3.9°C for SMTEMP). The temperature increase in these parameters will result in (1) an increase in the total amount of snowfall in the watershed and (2) an increase in the base temperature for snowmelt to occur, which will result in more snowmelt later in the year because the snowpack must reach a higher temperature before snowmelt occurs. It is important to note that streamflow shifted in both peak and magnitude with an increase in SFTEMP and SMTMP. The peak streamflow shifted from March to April and the peak magnitude increased from 9.3 to 11.1 $m^3\ s^{-1}$. This produced the changes in stream temperature, resulting in an overall increase in stream temperature in March and a decrease in June and July with SFTEMP and SMTMP increased by 2°C. The new stream temperature model correctly represents the changes in the snowmelt parameters (Figure 7c). Figure 7c displays an increase in simulated stream temperature by approximately 0.5°C during the winter (December through March) when there is less snowmelt occurring. Additionally, Figure 7c also shows a decrease in simulated stream temperature by approximately 0.75°C during the spring and summer (May through September) when more snowmelt is occurring. These differences, however, were statistically insignificant ($p > 0.05$). Snowmelt, and its influence on stream temperature, is an important component of the hydrologic cycle for the western United States not only for water resources, but also aquatic species survival.

3.2.3.4. Effects of Increased Groundwater Inflow on Stream Temperature Output

[33] To test the effects of an increased groundwater contribution on stream temperature, the SWAT parameter GWQMN (threshold depth of water in the shallow aquifer for groundwater flow into the stream to occur) was decreased from the calibrated value by 1/2 (GWQMN decreased from 1500 to 750 mm). Decreasing GWQMN will allow for more groundwater inflow to occur. Increasing groundwater inflow led to a statistically significant ($p < 0.05$) decrease in stream temperature by approximately 3°C during the summer months (Figure 7d). While it was not explicitly tested in this study, decreasing groundwater inflow would likely result in an increase in simulated stream temperature. The decrease in simulated stream temperature found in this study has been found for many studies [e.g., *Constantz et al.*, 1995; *Storey et al.*, 2003; *Constantz and Essaid*, 2004].

4. Conclusions

[34] A new hydroclimatological stream temperature routine was developed for SWAT to account for the effects of variation in air temperature and hydrologic inflows on stream temperature within a stream reach. The original SWAT stream temperature model uses a linear relationship between air and stream temperature, which is not appropriate

for all climatic and geographic settings, and does not represent associated hydrologic and stream temperature changes. In the new model, stream temperature is determined as a function of the hydrologic inflows, namely inflow from the upper basins, snowmelt, surface runoff, lateral soil flow, and groundwater flow, which are subsequently modified by air temperature. The model allows season specific modeling on the subbasin to watershed scale. An additional advantage of the new SWAT temperature routine is the possibility of calibration using few parameters. The model assumes that radiative forcings are represented through air temperature and a transfer parameter and that perfect mixing occurs in the stream reach [*Moore et al.*, 2005]. While other established hydrologic models account for radiative transfers and at least some of the flows, our contribution is unique in that it is for SWAT, it does not require more information beyond what is already provided by the user or calculated by the model, and it works with a very limited set of calibration parameters.

[35] The new stream temperature model is tested on seven coastal and mountainous streams and rivers throughout the western United States for which high quality stream temperature data were available. The results of the new stream temperature model suggest a great improvement over the original SWAT stream temperature model as measured by several model performance parameters. Parameter sensitivity analyses indicate that the calibration parameters are physically reasonable. Additionally, our analyses suggest that the new stream temperature model can respond to changes in hydroclimatological conditions in ways that are consistent with the changes in flow contributions to streamflow. Improved simulations of stream temperature result in improved estimates of water quality parameters, such as dissolved oxygen and can help water resource planners as well as aquatic ecosystem biologists to construct management plans to preserve sustainable aquatic habitats, especially under warmer climates.

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References

Abbaspour, K. C., J. Yang, I. Maximov, R. Siber, K. Bogner, J. Mieleitner, J. Zobrist, and R. Srinivasan (2007), Modelling hydrology and water quality in the pre-alpine/alpine Thur watershed using SWAT, *J. Hydrol. 333*(2–4), 413–430.

Allen, D., W. E. Dietrich, P. F. Baker, F. Ligon, and B. Orr (2007), Development of a mechanistically-based, basin-scale stream temperature model: applications to cumulative effects modeling, in *Proceedings of the Redwood Region Forest Science Symposium: What Does the Future Hold?*, edited by R. B. Standiford, et al. pp. 11–24, Forest Service, US Department of Agriculture, Albany, California.

Arnold, J. G., R. Srinivasan, R. S. Muttiah, and J. R. Williams (1998), Large area hydrologic modeling and assessment Part I: Model development, *J. Am. Water Resour. Assoc.*, *34*(1), 73–89.

Beschta, R. L. and J. Weatherred (1984), TEMP-84: A Computer Model for Predicting Stream Temperatures Resulting from the Management of Streamside Vegetation, WSDG-AD-00009.

Bicknell, B. R., J. C. Imhoff, A. S. Donigian, and R. C. Johanson (1997), *Hydrological simulation program—FORTRAN (HSPF). User's Manual for release* 11, EPA—600/R-97/080. United States Environmental Protection Agency, Athens, GA.

Bogan, T., O. Mohseni, and H. G. Stefan (2003), Stream temperature-equilibrium temperature relationship, *Water Resour. Res. 39*(9), 1245, doi:10.1029/2003WR002034.

Boyd, M., and B. Casper (2003), *Analytical Methods of Dynamic Open Channel Heat and Mass Transfer; Methodology for the Heat Source Model Version 7.0*, Oregon Department of Environmental Quality, Portland, Oregon.

Brown, G. W. (1969), Predicting temperatures of small streams, *Water Resour. Res.*, *5*(1), 68–75.

Brown, L. E., and D. M. Hannah (2007), Alpine stream temperature response to storm events, *J. Hydrometeorol.*, *8*(4), 952–967.

Caissie, D. (2006), The thermal regime of rivers: A review, *Freshwater Biol.*, *51*(8), 1389–1406.

Chapra, S. C., G. J., Pelletier, and H. Tao (2006), *QUAL2K: A Modeling Framework for Simulating River and Stream Water Quality, Version 2.04: Documentation and Users Manual*, Civil and Environmental Engineering Department, Tufts University, Medford, MA.

Chen, Y. D., R. F. Carsel, S. C. McCutcheon, and W. L. Nutter (1998), Stream temperature simulation of forested riparian areas: I. Watershed-scale model development, *J. Environ. Eng.*, *124*(4), 304–315.

Cole, T. M. and S. A. Wells (2003), *CE-QUAL-W2: a Two-Dimensional, Laterally Averaged, Hydrodynamic and Water Quality Model, Version 3.1*, US Army Corps of Engineers, Instruction Report EL-03-1.

Constantz, J. E., and H. I. Essaid (2004), The influence of ground water on stream restoration following dam removal in *Proceedings of the American Water Resources Association Conference on Riparian Ecosystems and Buffers*, Olympic Valley, California, June 2004, CD-ROM, Sec. P, pp. 1–5.

Constantz, J., C. L. Thomas, and G. Zellweger (1995), Influence of diurnal variations in stream temperature on streamflow loss and groundwater recharge. *Water Resour. Res. 30*(12), 3253–3264.

Erickson, T. R., and H. G. Stefan (2000), Linear air/water temperature correlations for streams during open water periods, *J. Hydrol. Eng.*, *5*(3), 317–321.

Gassman, P. W., M. R. Reyes, C. H. Green, and J. G. Arnold (2007), The soil and water assessment tool: Historical development, applications, and future research directions, *Trans. ASABE*, *50*(4), 1211–1250.

Hamby, D. M. (2004), A review of techniques for parameter sensitivity analysis of environmental models, *Environ. Monit. Assess.*, *32*, 135–154.

Hargreaves, G. H., and Z. A. Samani (1985), Reference crop evapotranspiration, *Appl. Eng. Agr. 1*(2), 96–99.

Issak, D., B. Rieman, and D. Horan (2009), A watershed-scale monitoring protocol for bull trout. *Gen. Tech. Rep. RMRS-GTR-223*, U.S. Department of Agriculture, Forest Service, Fort Collins, CO.

Jarrett, R. D. (1990), Hydrologic and hydraulic research in mountain rivers, *J. Am. Water Resour. Assoc.*, *26*(3), 419–429.

Kobayashi, D. (1984), Separation of the snowmelt hydrograph by stream temperatures, *J. Hydrol.*, *76*, 155–162.

Krause, P., D. P. Boyle, and F. Bäse (2005), Comparison of different efficiency criteria for hydrological model assessment, *Adv. Geosci.*, *5*, 89–97.

LeBlanc, R. T., R. D. Brown, and J. E. FitzGibbon (1997), Modeling the effects of land use change on the water temperature in unregulated urban streams, *J. Environ. Manage.*, *49*, 445–469.

Lenhart, T., K. Eckhardt, N. Fohrer, and H.-G. Frede (2002), Comparison of two different approaches of sensitivity analysis, *Phys. Chem. Earth*, *27*, 645–654.

Luo, Y., X. Zhang, X. Liu, D. Ficklin, and M. Zhang (2008), Dynamic modeling of organophosphate pesticide load in surface water in the northern San Joaquin Valley watershed of California, *Environ. Pollut. 196*, 1171–1181.

Lowney, C. L. (2000), Stream temperature variation in regulated rivers: Evidence for a spatial pattern in daily minimum and maximum magnitudes, *Water Resour. Res. 36*(10), 2947–2955.

Mantua, N., I. Tohver, and A. Hamlet (2010), Climate change impacts on streamflow extremes and summertime stream temperature and their possible consequences for freshwater salmon habitat in Washington State, *Clim. Change*, *102*(1), 187–223.

Mohseni, O., and H. G. Stefan (1999), Stream temperature/air temperature relationship: A physical interpretation, *J. Hydrol. 218*(3–4), 128–141.

Mohseni, O., H. G. Stefan, and T. R. Erickson (1998), A nonlinear regression model for weekly stream temperatures, *Water Resour. Res. 34*(10), 2685–2692.

Mohseni, O., T. R. Erickson, and H. G. Stefan (1999), Sensitivity of stream temperatures in the United States to air temperatures projected under a global warming scenario, *Water Resour. Res. 35*(12), 3723–3733.

Mohseni, O., H. G. Stefan, and J. G. Eaton (2003), Global warming and potential changes in fish habitat in U.S. streams, *Clim. Change*, *59*(3), 389–409.

Moore, D., D. L. Spittlehouse, and A. Story (2005), Riparian microclimate and stream temperature response to forest harvesting: A review, *J. Am. Water Resour. Assoc.*, *41*(4), 813–834.

Moriasi, D. N., J. G. Arnold, M. W. V. Liew, R. L. Bingner, R. D. Harmel, and T. L. Veith (2007), Model evaluation guidelines for systematic quantification of accuracy in watershed simulations, *Trans. ASABE*, *50*(3), 885–900.

Morin, G., and D. Couillard (1986), Predicting river temperatures with a hydrological model, in *Encyclopedia of Fluid Mechanics* edited by N. P. Cheremisinoff, pp. 171–209, Gulf, Houston, Texas.

Nash, J. E., and J. V. Sutcliffe (1970), River flow forecasting through conceptual models part I—A discussion of principles, *J. Hydrol. 10*(3), 282–290.

Neitsch, S. L., J. G. Arnold, J. R. Kiniry, J. R. Williams, and K. W. King (2005), *Soil and Water Assessment Tool Theoretical Documentation: Version* 2005, Texas Water Resources Institute, College Station, TX.

Norton, G. E., and A. Bradford (2009), Comparison of two stream temperature models and evaluation of potential management alternatives for the Speed River, Southern Ontario, *J. Environ. Manage.*, *90*(2), 866–878.

Pilgrim, J. M., X. Fang, and H. G. Stefan (1998), Stream temperature correlations with air temperatures in Minnesota: Impliciations for climate warming, *J. Am. Water Resour. Associ.*, *34*(5), 1109–1121.

Rutherford, J. C., S. Blackett, C. Blackett, L. Saito, and R. J. Davies-Colley (1997), Predicting the effects of shade on water temperature in small streams, *New Zealand J. Marine Freshwater Res.*, *31*, 707–721.

Smith, K., and M. E. Lavis (1975), Environmental influences on the temperature of a small upland stream, *Oikos*, *26*(2), 228–236.

Sridhar, V., A. L. Sansone, J. LaMarche, T. Dubin, and D. P. Lettenmaier (2004), Prediction of stream temperature in forested watersheds, *J. Am. Water Resour. Assoc.*, *40*(1), 197–213.

Stefan, H. G., and E. B. Preud'homme (1993), Stream temperature estimation from air temperature, *J. Am. Water Resour. Assoc.*, *29*(1), 27–45.

St-Hilaire, A., G. Morin, N. El-Jabi, and D. Caissie (2000), Water temperature modelling in a small forested stream: Implication of forest canopy and soil temperature, *Can. J. Civil Eng.*, *27*, 1095–1108.

Storey, R. G., K. W. F. Howard, and D. D. Williams (2003), Factors controlling riffle-scale hyporheic exchange flows and their seasonal changes in a gaining stream: A three-dimensional groundwater flow model. *Water Resour. Res. 39*(2), 1034, doi:10.1029/2002WR001367.

Theurer, F. D., K. A. Voos, and W. J. Miller (1984), Instream water temperature model, Instream Flow Information Paper *16*, FWS/OBS-85/15.

Todd, D. K. (1980), *Ground-Water Hydrology*, 2nd ed., John Wiley, New York, 535 p.

van Vliet, M. T. H., F. Ludwig, J. J. G. Zwolsman, G. P. Weedon, and P. Kabat (2011), Global river temperatures and sensitivity to atmospheric warming and changes in river flow, *Water Resour. Res. 47*(2), W02544, doi:10.1029/2010WR009198.

Webb, B. W., and F. Nobilis (1997), Long-term perspective on the nature of the air-water temperature relationship: A case study, *Hydrol. Processes*, *11*(2), 137–147.

Webb, B. W., and Y. Zhang (1997), Spatial and seasonal variability of the components of the river heat budget, *Hydrol. Processes*, *11*, 137–147.

Webb, B. W., P. D. Clack, and D. E. Walling (2003), Water–air temperature relationships in a Devon river system and the role of flow, *Hydrol. Processes*, *17*(15), 3069–3084.

Webb, B. W., D. M. Hannah, R. D. Moore, L. E. Brown, and F. Nobilis (2008), Recent advances in stream and river temperature research, *Hydrol. Processes*, *22*(7), 902–918.

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