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Global river temperatures and sensitivity to atmospheric warming and changes in river flow

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[1] This study investigates the impact of both air temperature and river discharge changes on daily water temperatures for river stations globally. A nonlinear water temperature regression model was adapted to include discharge as a variable in addition to air temperature, and a time lag was incorporated to apply the model on a daily basis. The performance of the model was tested for a selection of study basin stations and 157 river temperature stations globally using historical series of daily river temperature, air temperature, and river discharge for the 1980–1999 period. For the study basin stations and for 87% of the global river stations, the performance of the model improved by including discharge as an input variable. Greatest improvements were found during heat wave and drought (low flow) conditions, when water temperatures are most sensitive to atmospheric influences and can reach critically high values. A sensitivity analysis showed increases in annual mean river temperatures of +1.3 °C, +2.6 °C, and +3.8 °C under air temperature increases of +2 °C, +4 °C, and +6 °C, respectively. Discharge decreases of 20% and 40% exacerbated water temperature increases by +0.3 °C and +0.8 °C on average. For several stations, maximum water temperatures on a daily basis were higher under an air temperature increase of +4 °C combined with a 40% discharge decrease compared to an air temperature increase of +6 °C (without discharge changes). Impacts of river discharge on water temperatures should therefore be incorporated to provide more accurate estimations of river temperatures during historical and future projected dry and warm periods.

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1. Introduction

[2] Water temperature is an important physical property of rivers, having a direct impact on water quality (e.g., concentrations of dissolved oxygen) [*Ozaki et al.*, 2003], and on the growth rate and distribution of freshwater organisms [*Mohseni et al.*, 2003]. Additionally, river temperature is of economic importance in water requirements for industry, electricity and drinking water production, and recreation [*European Environment Agency (EEA)*, 2008a; *Webb et al.*, 2008]. Several studies found a gradual increase in river temperatures during the last century in relation to an increase in air temperatures [e.g., *Lammers et al.*, 2007; *Liu et al.*, 2005; *Kaushal et al.*, 2010; *Webb*, 1996]. In addition, rising water temperatures have also been related to changes in river flow. For example, for the Danube an increase in water temperature was observed as a consequence of lower summer flow, resulting from earlier onset of the snowmelt period and decreased summer precipitation [*Pekarova et al.*, 2008a]. Water temperature trends in major rivers over the past century are thus a complex function of both climate and hydrological changes [*Moatar and Gailhard*, 2006; *Webb and Nobilis*, 2007]. In addition, anthropogenic influences, like thermal effluents from power stations [*Edinger et al.*, 1968a; *Webb and Nobilis*, 2007], flow regulation and construction of reservoirs [*Lowney*, 2000; *Webb and Walling*, 1993], and land use changes (e.g., urbanization [*Nelson and Palmer*, 2007]) also affect water temperature. These anthropogenic influences vary considerably between catchments and river basins [*Caissie*, 2006].

[3] To estimate river temperature as a function of climate variables, different model approaches varying in complexity and data input requirements have been developed [*Mohseni et al.*, 1998]. The most complex approach uses deterministic (physically based) water temperature models, including heat advection-dispersion transport equations [*Haag and Luce*, 2008; *Sinokrot and Stefan*, 1993; *Yearsley*, 2009]. Another group applies the equilibrium temperature concept that incorporates only net heat transfer processes at the water surface [*Bogan et al.*, 2003; *Caissie et al.*, 2005; *Edinger et al.*, 1968b; *Mohseni and Stefan*, 1999]. A recent development is the application of artificial neural networks (ANNs) which use unknown (nonlinear algebraic) functions to predict water temperatures [*Chenard and Caissie*, 2008; *Sahoo et al.*, 2009]. In addition, statistical approaches have been applied, like stochastic models which separate the water temperature time series into an annual component which is represented by a Fourier or sinusoidal function,

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and a short-term component using Box and Jenkins methods and/or a Markov process [*Ahmadi-Nedushan et al.*, 2007; *Caissie*, 2006]. Finally, water temperature regression models are widely used, calculating stream or river temperature from air temperature, either based on linear or nonlinear regression relations. These models are attractive because of their simplicity and limited requirement of meteorological and hydraulic data, while still being frequently characterized by high levels of explained variance in the absence of detailed information on heat fluxes [*Webb and Nobilis*, 1997].

[4] Air temperature is commonly used as a predictor variable in water temperature regression models, because it is a major component in calculating net changes of heat flux at the water surface [*Webb et al.*, 2003; *Webb et al.*, 2008]. As a result, there is a strong correlation between air and water temperatures. Linear water temperature regression models have been widely applied using weekly and monthly mean values of water temperature [e.g., *Webb and Walling*, 1993; *Webb and Nobilis*, 1997]. In addition, linear regression analysis has also been successfully applied on two-hour and daily time step by including a time lag in the regression model [*Stefan and Preudhomme*, 1993].

[5] Several studies have shown that the water–air temperature relationship deviates from linearity when air temperature is below 0 °C and above ~20 °C [e.g., *Mohseni et al.*, 1998; *Mohseni and Stefan*, 1999]. At low temperatures, this departure is because of both the dominant influence of groundwater and the existence of ice cover that prevents surface heat exchange. At high temperatures, the departure results from extensive evaporative cooling and enhanced back radiation. As a result, the water–air temperature relationship resembles an S-shaped function, rather than a linear function [*Mohseni and Stefan*, 1999].

[6] Although several studies have demonstrated that water temperature is inversely related to river discharge, reflecting a reduced thermal capacity under decreasing flow volumes [e.g., *Hockey et al.*, 1982; *Webb*, 1996; *Webb et al.*, 2003], only a few addressed the influence of river flow on the water–air temperature relationship or included river discharge as an additional variable in water temperature regression models [*Ozaki et al.*, 2003; *Rivers-Moore and Jewitt*, 2007; *Webb et al.*, 2003]. A multiple linear regression analysis by *Webb et al.* [2003] showed that an inverse relation between water temperature and discharge exists for all catchments and timescales, with greater impact at shorter timescales and in larger catchments of the Exe basin (UK). Limited knowledge exists, however, with regard to the influence of discharge on water temperatures for large river basins. In addition, relatively few water temperature studies focused on river temperatures outside Europe and North America, although some examples exist: e.g., for South African rivers [*Dallas*, 2008; *Rivers-Moore and Jewitt*, 2007] and for Russian Pan-Arctic rivers [*Lammers et al.*, 2007; *Liu et al.*, 2005].

[7] Considering future perspectives, river temperatures are expected to be affected by warming and modifications in river regime as a result of climate change and other anthropogenic influences (e.g., flow regulation, water withdrawals) [*Caissie*, 2006]. A few studies addressed the impact of climate change on stream temperatures by using air temperature scenarios as input into a water temperature regression model applied on a weekly or monthly basis [*Mantua et al.*, 2010; *Mohseni et al.*, 1999; *Mohseni et al.*, 2003; *Webb*, 1996]. The robustness of water temperature regression models and sensitivity of water temperatures have not yet been studied on a daily basis and in particular not on a global scale. However, atmospheric warming and changes in river flow are expected to affect river temperatures globally, with possibly negative consequences for freshwater ecosystems and several usage functions (e.g., industry, thermal power, drinking water, recreation).

[8] Hence, the objectives of our study are as follows: (1) to test the performance of a water temperature regression model that estimates daily river temperatures based on both air temperature and river discharge data for river temperature stations on a global scale; and (2) to quantify the sensitivity of river temperatures to both atmospheric warming (air temperature increases) and changes in river flow (river discharge). To address these objectives, a nonlinear water temperature regression model based on air temperature was modified to include river discharge as an additional variable. In addition, a time lag was incorporated to apply the model on a daily basis. This resulted in a daily water temperature regression model with air temperature and discharge as predictor variables (reflecting net heat fluxes and river flow) without requiring detailed meteorological and hydraulic input data, which are scarce for large parts of the world.

[9] The performance of the model was tested for a selection of study basin stations, in particular during a heat wave when river temperatures are highest. Subsequently, a global database with water temperature linked to discharge stations was created, and the regression model was applied to 157 river temperature and discharge stations globally. In addition, the sensitivity of river temperatures was assessed under different rates of air temperature increase and changes in river discharge realistic in the context of climate change. Hence, this study is a global assessment of river temperatures and the sensitivity to both atmospheric warming and changes in river flow.

2. Data and Methods

2.1. River Temperature and Discharge Data

[10] Worldwide data on river temperatures are available from the United Nations Environment Programme Global Environment Monitoring System (GEMS/Water; http://www.gemswater.org/). Although the availability of river temperature data in this database is very limited during the period 1979–1987, especially for the Southern Hemisphere [*Webb*, 1996], marked improvements have been made over the last 10 years in both spatial coverage and the amount of data [*Lammers et al.*, 2007]. For river discharge, daily mean and monthly mean series for stations on a global scale are available from the Global Runoff Data Centre (GRDC; http://grdc.bafg.de/).

[11] In our study, river temperature and discharge data series have been used from 157 stations globally, for which both water temperature data from GEMS/Water and discharge data from GRDC were available over the 1980–1999 period. In addition to the GEMS/Water data, we used high-resolution temporal water temperature series for 14 stations in a selection of study river basins, which were provided by different data sources listed in Table 1. The

Table 1. Overview of Data Sources and Characteristics of Water Temperature Measurements of Selected Study Basin Stations for 1980–1999

River	Station	Data Sources	Number of Measurements (%)	Time Resolution	Annual Mean River Discharge (m^3/s)	Upstream Drainage Area ($\times$1000 km^2)	Impact of Upstream Reservoirs	Impact of Thermal Effluents	Impact of Melt Water	Continent
Columbia	The Dalles	StreamNet (http://www.streamnet.org/online-data/ids.cfm)	3584 (49.1)	daily instant.	5250	614	++	+–	+	North America
Mississippi	Clinton	USGS (http://waterdata.usgs.gov/nwis/qw)	3418 (46.8)	daily instant.	1610	222	+	+	+	North America
Missouri	Omaha	USGS (http://waterdata.usgs.gov/nwis/qw)	1190 (46.8)	daily instant.	1074	846	+	+–	+	North America
Potomac	Washing-ton D.C.	USGS (http://waterdata.usgs.gov/nwis/qw)	3687 (50.5)	daily mean	365	30	+–	+	+	North America
San Joaquin	Vernalis	USGS (http://waterdata.usgs.gov/nwis/qw)	6560 (89.8)	daily mean	157	35	+–	+	–+	North America
Danube	Bratislava	Dataset [*Pekarova et al.*, 2008a]	7243 (99.2)	daily instant.	2055	131	+	+	+	Europe
	Budapest[a]	Dataset via Zsolt Kozma	3287 (45.0)	daily mean	2284	184	+–	+	+	Europe
Meuse	Eijsden	Waterbase (http://live.waterbase.nl)	6560 (89.8)	daily instant.	269	27	–+	++	–+	Europe
Rhine	Lobith	Waterbase (http://www.waterbase.nl)	7283 (99.7)	daily instant.	2361	161	–	++	+–	Europe
Orange	Oranjedraai[b]	Department of Water Affairs and Forestry (DWAF)	246 (3.4)	daily instant.	186	851	+–	–	–	Africa
Darling	Burtundy	Murray-Darling Basin Commission (MDBC) (http://www.mdbc.gov.au)	1998 (27.4)	daily instant.	40	647	–+	–+	–	Australia
Lena	Kusur	ART-Russia River temperature dataset [*Lammers et al.*, 2007]	215 (29.9)	10 day mean	17,140	2430	+–	–	++	Asia (Arctic)
Ob	Salekhard	ART-Russia River temperature dataset [*Lammers et al.*, 2007]	290 (40.3)	10 day mean	12,774	2950	+–	–+	++	Asia (Arctic)
Yenisey	Igarka	ART-Russia River temperature dataset [*Lammers et al.*, 2007]	289 (40.1)	10 day mean	18,949	2440	++	–	++	Asia (Arctic)

[a]For discharge, data of station Nagymaros have been used because discharge data (from GRDC) were not available for station Budapest;
[b]For discharge, data of station Vioolsdreef have been used because discharge data (from GRDC) were not available for station Oranjedraai.

number of measurements during the 1980–1999 period is highest for the Rhine (Lobith) with 7283 (99.7% of record) and lowest for the Orange (Oranjedraai) with 246 measurements (3.4%). For the Lena (Kusur), Ob (Salekhard) and Yenisey (Igarka), water temperature data could only be provided as mean values for every 10 days. The coverage of the records by water temperature measurements for these Arctic rivers is less than 50%, as the rivers are covered with ice during a large part of the year. For all study basin stations, daily instantaneous measurements with one observation per day at a fixed time were available except for the rivers Potomac (Washington, D.C.), San Joaquin (Vernalis) and Danube (Budapest) for which daily (24 h) mean values were provided.

[12] Water temperatures of the selected stations in the Columbia, Mississippi, Missouri, and Yenisey rivers are considerably affected by reservoir operations, while several stations in the European rivers (Danube, Meuse, and Rhine) are mainly impacted by thermal effluents of power plants and industries (see Table 1). River temperatures at the stations of the Lena, Ob, Yenisey, and Columbia are highly influenced by melt water. Water temperatures of the Orange and Darling are not affected by melt water, and experience only minor influences of upstream dams or weirs and thermal effluents.

[13] Global river stations involved in our analysis were selected based on the following criteria. First, both water temperature data of GEMS/Water and daily discharge data from GRDC during the period 1980–1999 had to be available. In addition, we selected stations with river temperature observations at between 0 and 1 m below surface level, and a minimum of 40 measurements. Water temperatures of the selected GEMS/Water stations were measured instantaneously (on average around 11:30 a.m. local time, with a standard deviation of two hours) using a mercury thermometer, battery thermometer, or a conductivity-temperature (battery) meter with a precision of 0.1 °C. The location of the selected GEMS/Water stations and number of water temperature measurements is shown in Figure 1, along with the location of the study basin stations. About 37% of the stations have 40–100 water temperature measurements; the largest group (45%) has 100–200 water temperature measurements, and 13% and 5% of the stations have 200–500 and more than 500 measurements, respectively, during the 1980–1999 period. The amount of stations and number of measurements is highest in Europe, while the availability of water temperature stations for Africa and South America is limited (see Table 2). A high percentage of the GEMS/Water stations in Oceania (70%) have a small upstream basin area (<6000 km^2), while a relatively high number of stations in Africa, North America, South America, and Asia are characterized by large upstream basin areas (>75,000 km^2).

[14] In general, daily mean discharge series for all study basin stations and selected global GEMS/Water stations were used. However, for 31 out of 157 GEMS/Water stations, discharge data from GRDC was only available on a monthly basis and therefore monthly discharge data series were used for these stations. For the period 2000–2005 (see section 2.4), daily mean discharge series of the Rhine (Lobith) and Meuse (Eijsden) were provided by the

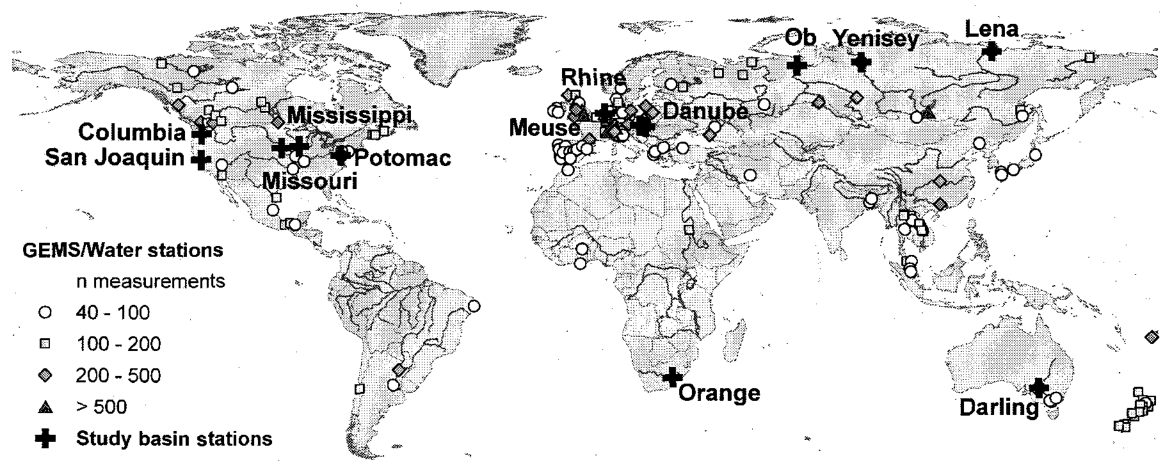

Figure 1. Number of measurements for selected GEMS/Water stations for the 1980–1999 period, and location of study basin stations.

water monitoring program of the Netherlands (http://live.waterbase.nl) and daily discharge series of the Danube (Bratislava) were supplied by the Slovak Hydrometeorological Institute [*Pekarova et al.*, 2008b], as discharge data was not available from GRDC during this period.

2.2. Air Temperature Data

[15] For surface air temperature, we used the global gridded half-degree meteorological data set developed within the EU FP6 Water and Global Change (WATCH) project [*Weedon et al.*, 2010]. This data set for 1958–2001 originates from ERA40 analysis (http://www.ecmwf.int/research/era/do/get/era-40). Air temperature (at 2 m above surface) and other forcing variables were corrected for elevation differences between ERA40 one-degree elevations and CRU (http://www.cru.uea.ac.uk/~timm/grid/CRU_TS_2_1.html) half-degree elevations and have been monthly bias-corrected using CRU-TS2.1 observations. Daily (24 h) mean air temperature for the 1980–1999 period was extracted from the half-degree grid cells where the study basin and global GEMS/Water stations are located. In addition, daily mean air temperature from the Twente and Maastricht meteorological stations provided by KNMI (http://www.knmi.nl/klimatologie/daggegevens/), and the Vienna station (http://eca.knmi.nl/) [*Klein Tank et al.*, 2002] were used for the period 2000–2005 (see section 2.4).

Table 2. Availability of Water Temperature Data of GEMS/Water Stations per Region

Region	n GEMS/ Water Stations	Percentage Stations With Upstream Basin Area: < 6000 km^2	6000–75,000 km^2	> 75,000 km^2	Mean n Measurements per Station
North America	28	21	36	43	135
South America	4	0	50	50	111
Europe	74	27	39	34	227
Africa	3	0	33	67	66
Asia	25	24	32	44	101
Oceania	23	70	22	9	138
Globally	**157**	**31**	**35**	**34**	**171**

2.3. The Nonlinear Water Temperature Regression Model

[16] The regression model in our study is based on the approach of *Mohseni et al.* [1998], who developed a nonlinear regression model representing the S-shaped function between air temperature and water temperature to calculate mean weekly stream temperature for monitoring stations in the United States. Modifications to the regression model have been made to include discharge as a variable in addition to air temperature, and to apply the model on a daily time step. Although it is recognized that water temperature and air temperature are better correlated at weekly and monthly timescales than at hourly or daily scales [*Erickson and Stefan*, 2000; *Pilgrim et al.*, 1998], we decided to apply the regression model on a daily basis by introducing a time lag between water temperature and air temperature. A practical reason for this daily time step is the need for high temporal resolution estimates of water temperature by river basin managers, in particular with regard to freshwater habitat conditions and usage functions such as cooling (industry and thermal power plants), drinking water production, and recreation [*Stefan and Preudhomme*, 1993]. In addition, river temperature measurements of GEMS/Water stations were available at an irregular time interval, and calculation of weekly (or monthly) mean water temperatures based on a highly variable number of measurements would thus result in less representative values [*Preudhomme and Stefan*, 1992; *Webb et al.*, 2008]. We therefore decided to test the performance of the regression model on a daily time step, and thus water temperature measurements were related to daily mean air temperatures and discharges for that specific date.

[17] River discharge was added as a variable to the nonlinear regression model to include the effects of changes in river flow conditions on water temperature. Although water temperatures depend on water depth and flow velocity, river discharge was selected as an additional predictor variable because it strongly relates to both river depth (thermal

capacity) and flow velocity (residence times) and is well-measured on a global scale. An inverse relation between discharge and water temperature was added to the regression model, reflecting higher warming rates under lower discharges as demonstrated in previous studies [e.g., *Rivers-Moore and Jewitt*, 2007; *van Vliet and Zwolsman*, 2008]. A separated discharge term to the regression relation allows the effect of discharge to be isolated. An inverse relation instead of a negative linear relation with discharge [e.g., *Ozaki et al.*, 2003; *Webb and Nobilis*, 1994] was included, because it reflects both a reduction in the thermal capacity and reduced dilution capacity for anthropogenic heat sources (e.g., wastewater or cooling water discharges) under low river flows. Hence, the modified nonlinear regression model used in our study is

$$Tw = \mu + \frac{\alpha - \mu}{(1 + e^{\gamma(\beta - Tair)})} + \frac{\eta}{Q} + \varepsilon, \quad (1)$$

$$\text{with } \gamma = \frac{4 \tan\theta}{\alpha - \mu}$$

where μ = lower bound of water temperature (°C); α = upper bound of water temperature (°C); γ = measure of the slope at inflection point (steepest slope) of the S-shaped relation (°C^{-1}); β = air temperature at inflection point (°C); η = fitting parameter (°C m^{3}s^{-1}); Tw = water temperature (°C); $Tair$ = air temperature (°C); Q = river discharge (m^{3}s^{-1}); ε = error term (°C); and $\tan\theta$ = slope at inflection point (-).

[18] In addition, a function was included to relate the measure of slope (γ) at the inflection point to the discharge variability compared to the variability in water temperature.

$$\gamma_Q = \gamma(\tau \frac{\sigma_Q}{\sigma_{Tw}}), \quad (2)$$

where γ_Q = measure of slope for discharge term (°C^{-1}); σ_Q = standard deviation of discharge (m^{3}s^{-1}); σ_{Tw} = standard deviation of water temperature (°C); and τ = fitting parameter (°C m^{-3}s^1).

[19] A comparable function was previously applied by *Webb et al.* [2003] to calculate the beta coefficient of the discharge term. In our study, the improvement in model performance was higher when this function was applied on the gamma component, resulting in an increase in the measure of slope for rivers with a high discharge variability compared to water temperature variability, and vice versa. The function generally increases the explained variance and sensitivity to air temperature and discharge changes, especially for monitoring stations with a relatively high discharge variability.

[20] To apply the model on a daily basis, a lag effect was incorporated into the regression analyses, because water temperature variations tend to lag behind air temperature fluctuations at short timescales (on an hourly or daily basis) [*Erickson and Stefan*, 2000; *Jeppesen and Iversen*, 1987; *Webb et al.*, 2003]. In addition, water temperature has lower variability than air temperature because of the high thermal inertia of water. *Stefan and Preudhomme* [1993] concluded, for streams in the central United States, that measured water temperatures follow air temperature closely with a time lag ranging from hours to days, which increases with stream depth. Because water depth information was not available for the majority of river stations, the optimal time lag was estimated by calculating correlation coefficients between water temperature, air temperature, and discharge. The optimal time lag was calculated for each station individually using a time lag between 0 and 20 days. The time lag with the highest correlation coefficient was assumed to be the optimal time lag for that river station and was thus selected.

2.4. Model Application and Validation

[21] For the study basin stations and GEMS/Water stations, we generally used daily instantaneous measurements of water temperature and daily mean measurements of air temperature and discharge during the 1980–1999 period to fit the regression relations. For air temperature, daily mean rather than daily maximum values were used because slightly higher correlations between water temperature measurements and daily mean values of air temperatures were obtained. For discharge, daily mean values were provided and therefore used to fit the regression model. However, for the 31 GEMS/Water stations with discharge only available as monthly averages, we calculated monthly mean water temperatures and related these to monthly mean air temperature and discharge (without time lag). For the study basin stations of the Yenisey, Ob, and Lena, mean water temperatures were available for every 10 days (see section 2.1). Therefore, 10 day averages of air temperature and discharge were calculated to fit the regression model. The least squares method was used to estimate the five parameters α, β, γ, μ, and η, minimizing the sum of squared errors between the observed and fitted values of water temperatures. The parameters were estimated numerically using the Gauss-Newton algorithm. To obtain physically reliable estimates of the lower bound of water temperature for rivers with freezing periods, zero was assigned as the lower limit of μ [*Mohseni et al.*, 1998]. Although some studies demonstrated better estimations of the upper bound of water temperature (α) by using the standard deviation method [*Bogan et al.*, 2006; *Mohseni et al.*, 2002], only moderate improvements were observed in our study, and therefore α was estimated according to the least squares method.

[22] Hysteresis occurs for river sites affected by seasonal snow- and ice-melt runoff or reservoir operations, which involves a lag in stream temperature response to air temperature [*Webb and Nobilis*, 1994]. This is mainly because of the inflow of cold snowmelt or deep reservoir water during spring and summer, resulting in cooler water temperatures despite warmer air temperatures. In this case, two regression relations were applied to the water temperature measurements for the rising and falling limb separately, by splitting the data set for the period January to June and for July to December. As only one α and μ physically exist at each monitoring station, we used the lower μ, upper α, and an average of the two γ, β, and η values, which ultimately resulted in one fitted model for each monitoring station [*Mantua et al.*, 2010; *Mohseni et al.*, 1998].

[23] To test the improvement of the regression model by the introduction of discharge as an additional variable, both the original regression model [*Mohseni et al.*, 1998] applied on a daily basis with time lag included (NONLIN) and the modified regression model including discharge and time lag (NONLIN_Q) were fitted. The model performance (goodness of fit) was determined for both regression models by

calculating the Nash-Sutcliffe coefficient (NSC) [*Nash and Sutcliffe*, 1970] (equation (3)), which is the coefficient of determination showing the efficiency of the fit. The quality of the fit was calculated by using the root mean square error (RMSE) [*Janssen and Heuberger*, 1995] (equation (4)).

$$\mathrm{NSC} = 1 - \frac{\sum_{i=1}^{n} (Tw_{\mathrm{simi}} - Tw_{\mathrm{obsi}})^2}{\sum_{i=1}^{n} (Tw_{\mathrm{obsi}} - \bar{T}w_{\mathrm{obs}})^2} \quad (3)$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (Tw_{simi} - Tw_{obsi})^2}{n}}, \quad (4)$$

where Tw_{simi} = predicted daily water temperature at time step i (°C); Tw_{obsi} = observed daily water temperature at time step i (°C); $\bar{T}w_{\mathrm{obs}}$ = average of daily observed water temperature (°C); and n = number of data pairs to be compared.

[24] For each station the NSC was calculated for the fitted regression model for the rising and falling limb separately and for a single fitted model. When the average NSC from the fitted regression model for the rising and falling limb was higher than calculated for a single fitted model, river stations were assumed to exhibit hysteresis [*Mantua et al.*, 2010].

[25] In order to test the performance of the regression model and the degree of validity of the parameter estimates for another time period and during a heat wave specifically, the regression model fitted for 1980–1999 for the European study basin stations Rhine (Lobith), Danube (Bratislava), and Meuse (Eijsden) was applied for the time slice 2000–2005 including the heat wave and drought of 2003. These study basin stations were selected because they were well measured during the period of 2000–2005 and the summer of 2003 specifically, and are characterized by different river regime characteristics and snowmelt influences. The fitted regression model was applied by using daily mean discharge series from one monitoring station and daily mean air temperature data for 2000–2005 from the nearest meteorological stations, as the global gridded air temperature data set for the 1958–2001 period does not include data for this validation period (see section 2.2). The performance of the regression models was tested by comparing the calculated water temperatures with daily instantaneous water temperature observations for the Rhine (Lobith), Danube (Bratislava), and Meuse (Eijsden) for 2000–2005. These water temperature series came from the same sources as for the fitting period (1980–1999) (see Table 1).

2.5. Sensitivity to Increases in Air Temperature and Changes in River Discharge

[26] To explore the sensitivity of river temperatures to atmospheric warming and changes in river flow on a global scale, we applied the adapted nonlinear regression model including discharge (NONLIN_Q) with the five parameters α, μ, γ, β, and η fitted for the period of 1980–1999 with perturbed air temperature and discharge series. The parameter values of the regression model thus were kept similar for this sensitivity analysis, implying that the physical setting of the river (groundwater input, river geometry, influence of melt water, upstream reservoirs, thermal effluents) remains the same [*Mohseni et al.*, 1999]. The original historical daily air temperature series for 1980–1999 were augmented incrementally with air temperature increases of +2 °C, +4 °C, and +6 °C. Additionally, the sensitivity of water temperatures to changes in river flow was assessed by calculating river temperatures under an air temperature increase of +4 °C in combination with a change in river discharge of +20%, −20%, and −40%. The selected increments in air temperature include the likely range of the projected global average surface air temperature increase of 1.1–6.4 °C for 2090–2099 relative to 1980–1999 [*Intergovernmental Panel on Climate Change (IPCC)* 2007]. The changes in river discharge are based on the range of projected changes in global runoff of −40% to +40% according to *Milly et al.* [2005] for 2041–2060 compared to 1900–1970 under the SRES A1B emissions scenario [*Nakicenovic et al.*, 2000]. The selected rates of warming and changes in river discharge thus are plausible in the context of climate change.

3. Performance of the Nonlinear Water Temperature Regression Model

3.1. Model Performance for Study Basin Stations

[27] For all selected study basin stations, the mean annual cycle of calculated daily water temperatures with the modified regression model including discharge (NONLIN_Q) represents the observed water temperature regime more realistically than those calculated without discharge (NONLIN) (see Figure 2). Furthermore, the underestimation of water temperatures during summer and overestimation during winter is generally less for NONLIN_Q compared to NONLIN. This is probably because of the higher values of γ (measure of slope) found for NONLIN_Q as compared to NONLIN for all study basin stations except for the Yenisey (Igarka) (see Table 3). These higher values are obtained by the incorporation of the function relating the measure of slope at the inflection point to the discharge variability compared to the variability in water temperature (equation (2)). The fitted values of μ, α, and β for NONLIN_Q were lower for the majority of study basin stations, except for the stations of the Missouri, Orange, Darling, Lena, and Ob, which were slightly higher or remained the same. This might be explained by differences in the flow regime when compared to the thermal regime for these rivers. The majority of river stations are characterized by high-flow conditions during winter when river temperatures are low, and low-flow conditions during summer when river temperatures are high, resulting in distinct inverse relations between water temperature and discharge. However, for the selected stations of the Missouri, Orange, Darling, Lena, and Ob, peak discharge is in summer and coincidences with the peak in water temperature. Therefore, no distinct inverse relation between water temperature and discharge was found for these river stations. The fitted optimal time lag ranges from 3 to 10 days. High time lags were obtained for stations characterized by high annual discharges, which generally correspond with higher depths and thermal inertia [*Stefan and Preudhomme*, 1993]. In contrast, moderate or low values of time lag were generally calculated for stations with a lower annual discharge (except for the Darling and Meuse) (see Table 3). For the three Arctic river stations fitted on a 10

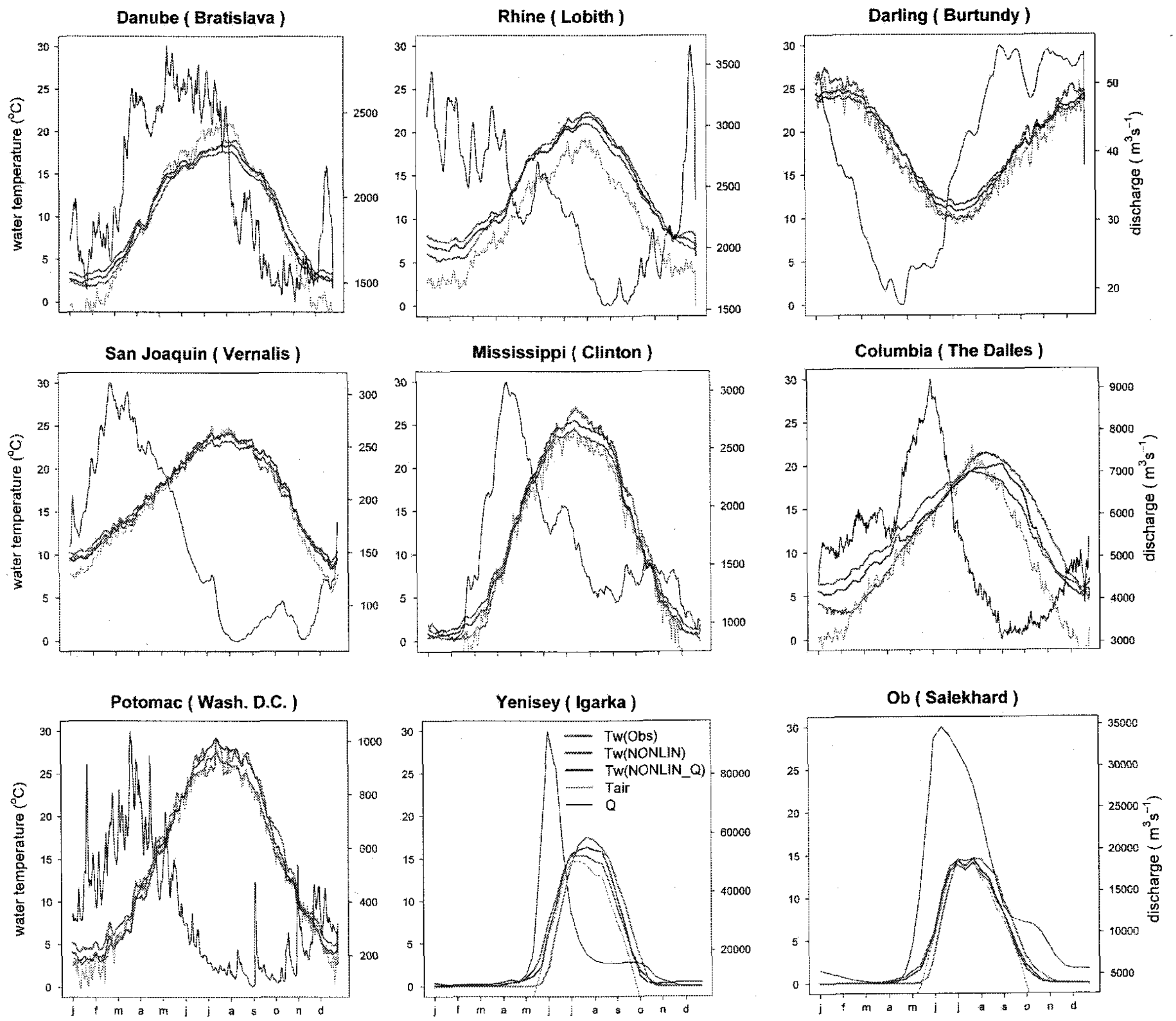

Figure 2. Mean annual cycles of observed daily water temperatures (Tw(Obs)) and simulated daily water temperatures for the original regression model with time lag included (Tw(NONLIN)) and for the adapted regression model including time lag and discharge (Tw(NONLIN_Q)), for a selection of study basin stations averaged over the fitting period 1980–1999.

day mean basis (see section 2.1) a time lag of 10 days was found for the Ob and Yenisey and a time lag of 20 days was obtained for the Lena. These long time lags correspond with the relatively high values of annual mean river discharge (see Table 1) and related water depth, resulting in high thermal inertia.

[28] Although hysteresis because of upstream reservoir operations and melt water was taken into account, the modeled water temperatures for the stations of Columbia, Lena, Ob, and Yenisey are still overestimated during spring and underestimated during summer and autumn (see Figure 2). However, including discharge in the regression model improved the model performance, especially for the Columbia (The Dalles). This was reflected by a higher NSC (0.83 versus 0.73) and lower RMSE (2.4 °C versus 3.1 °C) (see Table 4). For the majority of study basin stations, the NSC was slightly higher for NONLIN_Q compared to NONLIN. For the Danube (Bratislava and Budapest), Missouri (Omaha), and San Joaquin (Vernalis) rivers the values remained the same and were already high (NSC $\geq$ 0.90) without including discharge. The RMSE values also reflected an improvement of the performance and decreased for all study basin stations except for the Lena and Ob, for which values remained the same. Despite this improvement in model performance for the majority of study basin stations, the RMSE is still quite high (> 3.0 °C) and NSC relatively low (<0.75) for the Orange, Lena, and Ob stations. For the Orange, this can be explained by the limited data availability and by the use of discharge series from a different station (see Table 1). For the Lena and Ob, the limited performance of NONLIN and NONLIN_Q is mainly because of the dominant influence of the snowmelt peak during the period with the highest water temperatures, resulting in a less strong relation between water temperature and air temperature and river discharge. The snowmelt peak for the Yenisey (Igarka) is earlier (and shorter)

Table 3. Fitted Parameters of the Original Regression Model and of the Adapted Regression Model for Study Basin Stations[a,b]

River	Station	μ (°C)	μ _Q (°C)	α (°C)	α _ Q (°C)	γ (°C^{-1})	γ _ Q (°C^{-1})	β (°C)	β _ Q (°C)	Time Lag (days)
Columbia	The Dalles	4.6	0.5	20.3	15.2	0.26	0.33	9.2	9.0	10
Mississippi	Clinton	0.0	0.0	28.9	28.6	0.17	0.20	13.5	13.4	9
Missouri	Omaha	0.0	3.0	30.0	31.0	0.15	0.18	13.2	13.8	7
Potomac	Washington D.C.	0.0	0.0	35.3	33.3	0.12	0.15	17.1	16.9	6
San Joaquin	Vernalis	6.3	4.5	26.8	25.8	0.19	0.20	15.8	15.0	3
Danube	Bratislava	0.2	0.0	20.6	19.7	0.18	0.21	10.3	10.1	9
Danube	Budapest	0.0	0.0	24.0	22.8	0.16	0.19	11.2	10.9	9
Meuse	Eijsden	5.3	5.1	25.0	24.6	0.23	0.28	11.0	10.9	8
Rhine	Lobith	4.2	2.0	24.1	22.1	0.24	0.27	11.0	11.0	9
Orange	Oranjedraai	11.2	11.6	22.6	23.0	0.48	0.55	17.7	17.6	5
Darling	Burtundy	6.2	7.3	26.9	27.1	0.22	0.26	14.9	15.1	8
Lena	Kusur[c]	0.0	0.6	11.9	12.0	0.21	0.25	7.2	7.7	20
Ob	Salekhard[c]	0.0	0.1	16.4	16.4	0.29	0.35	7.4	7.4	10
Yenisey	Igarka[c]	0.0	0.0	17.6	16.5	0.29	0.28	7.1	6.0	10

[a]Original regression model; with time lag included (NONLIN).
[b]Adapted regression model; including time lag and discharge (NONLIN_Q).
[c]Stations fitted on 10 day mean basis instead of daily basis.

compared to the Lena and Ob. As a result, the performance for this study basin station and improvement by the introduction of discharge is much better. Despite the limited performance for the Orange, Lena, and Ob, the overall median NSC and RMSE for stations of the Mississippi, San Joaquin, Danube, Meuse, Rhine, and Darling are 0.92 and 1.76 °C, respectively, indicating the usefulness of this regression model on a daily basis.

3.2. Performance During the Heat Wave and Summer Drought of 2003 in Europe

[29] Time series of observed and calculated water temperatures for the Rhine (Lobith), Danube (Bratislava), and Meuse (Eijsden) for the period 2000–2005 (see Figure 3) show that both regression models slightly overestimate low and underestimate high river temperatures. This is the result of the fixed values of upper bound (α) and lower bound (μ) of water temperature calculated from the data series of 1980–1999, which tend to be slightly underestimated and overestimated, respectively. However, the water temperature regression model including the impact of river flow and thermal capacity (NONLIN_Q) shows better results during the whole period. This is also reflected by slightly higher values of NSC and lower values of RMSE for NONLIN_Q (mean of 0.90 and 1.9 °C) compared to NONLIN (mean of 0.87 and 2.1 °C). Comparing the performance coefficients of NONLIN_Q during 2000–2005 with the values during the fitting period 1980–1999, the NSC is slightly lower (mean of 0.90 versus 0.91) and RMSE is slightly higher (mean of 1.9 °C versus 1.8 °C), although the differences are small.

Table 4. Nash-Sutcliffe Coefficient (NSC) and Root Mean Squared Error (RMSE) for the Original Regression Model and for the Adapted Regression Model for Study Basin Stations[a,b,c]

River	Station	NSC	NSC_Q	RMSE (°C)	RMSE_Q (°C)
Columbia	The Dalles	0.73	**0.83**	3.1	**2.4**
Mississippi	Clinton	0.95	**0.96**	2.1	**1.9**
Missouri	Omaha	0.94	0.94	2.2	**2.1**
Potomac	Washington D.C.	0.87	**0.88**	3.4	**3.3**
San Joaquin	Vernalis	0.90	0.90	1.7	**1.6**
Danube	Bratislava	0.92	0.92	1.8	**1.7**
Danube	Budapest	0.92	0.92	2.0	**1.9**
Meuse	Eijsden	0.90	**0.91**	2.0	**1.8**
Rhine	Lobith	0.89	**0.92**	2.0	**1.7**
Orange	Oranjedraai	0.61	**0.62**	3.5	**3.4**
Darling	Burtundy	0.91	**0.93**	1.7	**1.5**
Lena	Kusur[d]	0.55	**0.56**	3.2	3.2
Ob	Salekhard[d]	0.74	**0.75**	3.1	3.1
Yenisey	Igarka[d]	0.86	**0.89**	2.3	**2.1**

[a]Original regression model; with time lag included (NONLIN).
[b]Adapted regression model; including time lag and discharge (NONLIN_Q).
[c]Study base stations; values in bold indicate a higher performance for NONLIN_Q compared to NONLIN.
[d]Stations fitted on 10 day mean basis instead of daily basis.

[30] The validity of the regression models and parameter estimates for the European rivers was also tested specifically for the heat wave and drought of July and August 2003 (see Figure 3). Both regression models showed an underestimation of river temperatures, especially during the period when water temperatures are highest (end of July and first two weeks of August). This is because of an underestimation of the defined upper bound of water temperature (α) of the nonlinear regression model of *Mohseni et al.* [1998], which has also been discussed by *Bogan et al.* [2006] and *Mohseni et al.* [1999, 2002]. However, introduction of discharge into the regression model resulted in a strong decrease in the underestimation of the modeled water temperatures during this warm, dry period. The mean underestimation by NONLIN_Q compared to NONLIN during July–August is 0.9 °C versus 3.0 °C for the Rhine, 1.3 °C versus 3.4 °C for the Danube, and 0.4 °C versus 1.4 °C for the Meuse. In addition, a distinct improvement in model performance was reflected by large decreases in RMSE of 1.9 °C, 2.0 °C, and 0.7 °C for the Rhine, Danube, and Meuse, respectively.

3.3. Model Performance for Global GEMS/Water Stations

[31] Although the number of measurements for the selected GEMS/Water stations was generally less than for the study basin stations, the nonlinear regression models NONLIN and NONLIN_Q were successfully applied to the

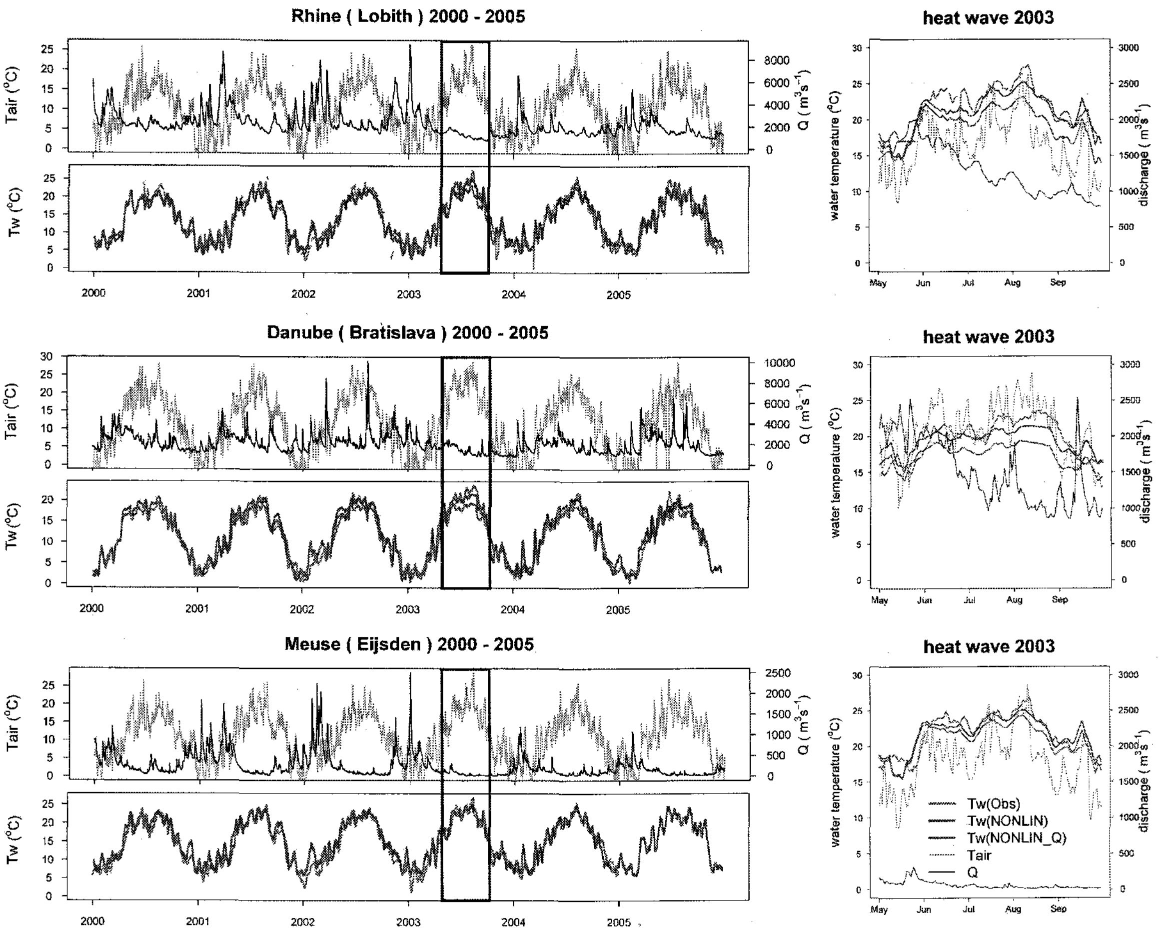

Figure 3. Observed daily water temperatures (Tw(Obs)) and simulated daily water temperatures for the original regression model with time lag included (Tw(NONLIN)) and for the adapted regression model including time lag and discharge (Tw(NONLIN_Q)) for the Rhine (Lobith), Danube (Bratislava), and Meuse (Eijsden) during the validation period 2000–2005, and during the heat wave and summer drought of 2003. The outlined boxes denote the heat wave and summer drought of 2003. The graphs on the right side present the results in more detail for this heat wave and drought.

selected GEMS/Water stations globally. For 126 stations with daily discharge data, the regression models were fitted and the performance was tested on a daily basis, according to the same procedure as for the study basin stations. For 31 GEMS/Water stations with only monthly mean discharge series available, the models were fitted and the performance was tested on a monthly basis (see section 2.4).

[32] Nonparametric Wilcoxon Rank Sum tests were performed on the calculated NSC and RMSE values to test whether the difference between the performance of NONLIN and NONLIN_Q was significant. Results showed that incorporation of discharge led to a statistically significant ($p < 0.01$) improvement in the performance of the water temperature regression model. The increase in the performance of the regression model, reflected by higher values of NSC and lower values of RMSE for NONLIN_Q compared to NONLIN, was found for 87% of the GEMS/Water stations (for 84% of the stations with daily fits and 97% with monthly fits). To show differences in estimated water temperatures between both regression models, the mean annual cycle of observed and estimated water temperatures with NONLIN and NONLIN_Q are presented for a selection of GEMS/Water stations (see Figure 4). The regression model was fitted and the performance was tested on a daily basis for the majority of river stations presented, except for the Murray, Parana, and Yangtze. However, monthly averages are shown for all stations because of the limited amount of observed water temperature data to calculate the mean thermal regime on a daily time step. Comparing the calculated water temperatures of NONLIN_Q and NONLIN, we find the strongest improvements for the Ohio, Elbe, Rio Usumacinta, and Waikato, which are rivers characterized by typical low-flow conditions during summer and high-flow conditions during winter or early spring. For rivers with a peak in discharge during the period with high water temperatures, like the Yangtze, Amur, Kolyma, and Mekong, less distinct or no improvements were found by introducing discharge as an additional variable in the

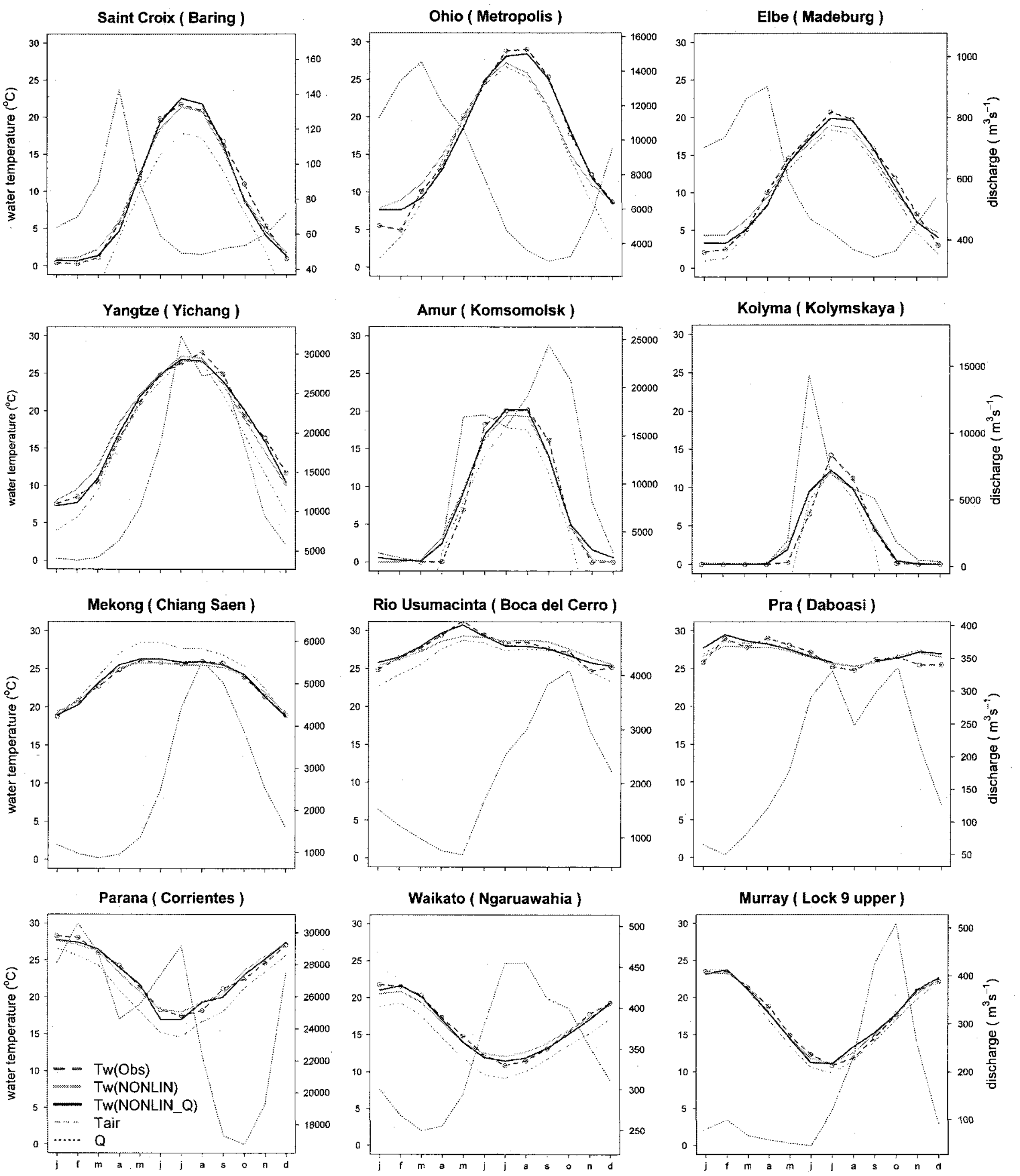

Figure 4. Mean annual cycles of observed daily water temperatures (Tw(Obs)) and simulated daily water temperatures for the original regression model with time lag included (Tw(NONLIN)) and for the adapted regression model including time lag and discharge (Tw(NONLIN_Q)) for a selection of GEMS/Water stations of the Saint Croix (Canada), Ohio (United States), Elbe (Germany), Yangtze (China), Amur (Russia), Kolyma (Russia), Mekong (Thailand), Rio Usumacinta (Mexico), Pra (Ghana), Parana (Argentina), Waikato (New Zealand), and Murray (Australia), averaged per month over the 1980–1999 period.

regression model, since no distinct inverse empirical relations between water temperature and discharge were found for these river stations.

[33] The boxplots of the distribution of NSC and RMSE values for GEMS/Water stations (see Figure 5) generally show a higher performance for NONLIN_Q compared to NONLIN both for daily and monthly fitted stations. Results of Wilcoxon Rank Sum tests indicated that NSC for NONLIN_Q is significantly higher ($p < 0.01$) than for NONLIN with an overall median NSC of 0.86 versus 0.83 on a daily basis, and 0.93 versus 0.89 on a monthly basis. The values of RMSE are significantly lower ($p < 0.01$) for NONLIN_Q, especially for the stations with monthly fits. The median value of RMSE for NONLIN_Q and NONLIN is 1.8 °C versus 2.0 °C on a daily basis and 1.4 °C versus 2.1 °C on a monthly basis. The higher performance of the regression model for monthly data compared to daily data is expected because the correlation between water temperature and air temperature increases from a daily to a monthly time step [*Erickson and Stefan*, 2000; *Pilgrim et al.*, 1998].

[34] For 38% of the stations, NSC was higher when the regression model was plotted for the rising and falling limb separately, implying that these stations exhibited seasonal hysteresis. For 21% of the stations, the number of water temperature measurements was, however, too low to fit the regression model for the rising and falling limb separately. The calculated optimal time lags are between 1 and 15 days, and the overall mean of all stations is 6 days. A positive relation was found between time lag and mean annual discharge, reflecting higher thermal inertia under higher river discharge, although the explained variance was low ($R^2 = 0.10$).

[35] Considering the spatial distribution of the relative increase in NSC between NONLIN_Q and NONLIN (see Figure 6), improvements in model performance were generally largest for river stations at middle and low latitudes. This can be explained by the flow regime of these river stations, which is generally characterized by low-flow conditions during summer and high-flow conditions during winter and spring, or by a moderate river discharge variability throughout the year. For river stations at high northern latitudes, the influence of discharge on model performance is highly variable. This is mainly dependent on the timing of the snowmelt peak in relation to the peak in water temperatures. For several stations at high latitude, the peaks in flow and thermal regimes coincide and inverse empirical relations between water temperature and discharge were therefore not found for these stations. Introduction of discharge in the regression model did not improve, or slightly decreased, the performance of the regression model for these river stations. However, the relative decrease in NSC was smaller than 2%. For several stations in North America, the introduction of discharge in the regression model also did not result in better estimates of river temperature. This may be explained by the presence of many deep reservoirs that affect river temperatures downstream. For these stations, river temperatures highly depend on reservoir thermal stratification and reservoir operation [*Sinokrot et al.*, 1995].

[36] Regarding the absolute NSC values for NONLIN_Q for the selected GEMS/Water global stations (see Figure 6), a high model performance with NSC > 0.90 was found for 41% of the stations (32% for stations fitted on a daily basis; 74% on a monthly basis). In addition, NSC was between 0.80 and 0.90 for 35% of stations (40% for daily fitted stations; 18% for monthly fits). For 12% of the stations (16% on a daily basis, 3% on a monthly basis), the model performance was poorer, with NSC < 0.6. These

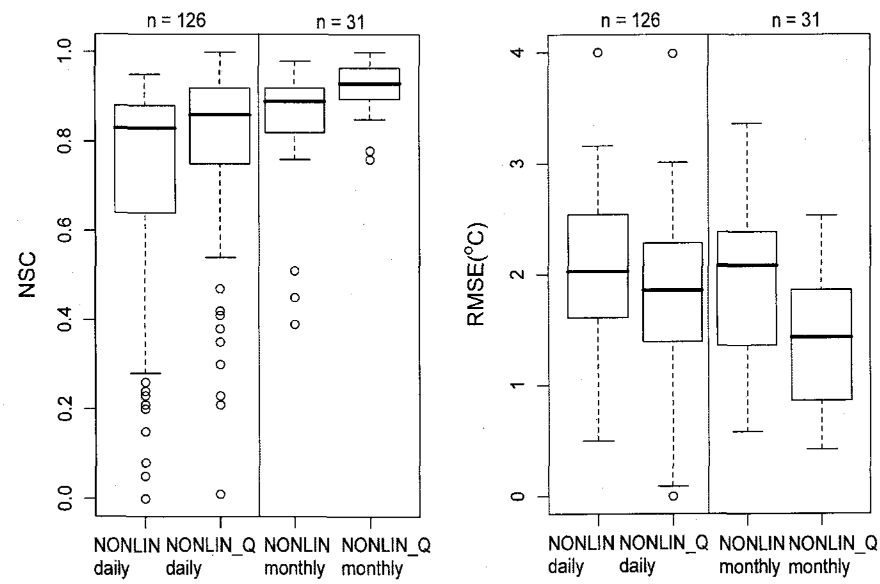

Figure 5. Boxplots of the Nash-Sutcliffe coefficients (NSC) and root mean square errors (RMSE) based on all GEMS/Water stations for the original regression model with time lag included (NONLIN) and for the adapted regression model including time lag and discharge (NONLIN_Q), presented for the daily and monthly fitted stations separately. The boxplots present the median, lower and upper quartile, minimum, maximum, and outliers (specified as more than 1.5 times the interquartile range).

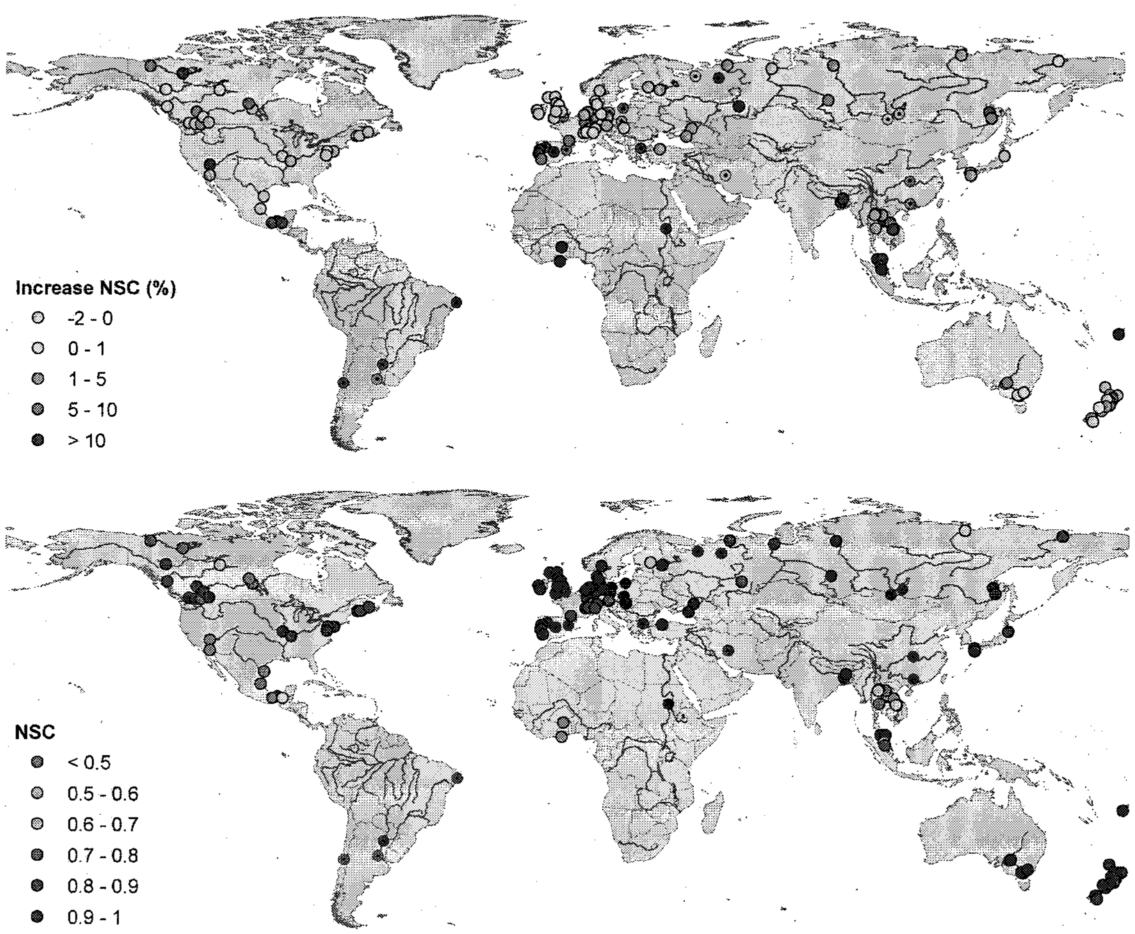

Figure 6. Global distribution of relative increase in Nash-Sutcliffe coefficients (NSC) (%) for the regression model including discharge (NONLIN_Q) compared to the regression model without discharge (NONLIN), and absolute values of NSC for NONLIN_Q for all selected GEMS/Water stations. The circles with black dots indicate river stations fitted using monthly data.

stations are situated in rivers in northern Canada (Mackenzie, Saskatchewan, and Churchill), southwestern United States and Mexico (Colorado, Rio Panuca), Southeast Asia (Mekong), and West Africa (White Volta and Pra). Although river temperatures at many stations are influenced by other factors than air temperature and discharge (e.g., reservoirs, thermal pollution), only weak relations were found between the NSC and RMSE values and river basin characteristics, such as contributing basin area (mean $R^2 = 0.02$) and latitude (mean $R^2 = 0.04$). In addition, the large-scale spatial patterns in NSC and RMSE did not show a clear correspondence with the global distribution in climate zones, melt water fluxes, thermal effluents, and location of dams and reservoirs. An explanation for the lower model performance for these river stations could be the limited availability (and quality) of river temperature data, because a low number of measurements ($n < 200$) was available for all stations with NSC < 0.6 (see Figure 1; Figure 6). In addition, a positive relation between NSC and data availability was found, and RMSE negatively related to the number of measurements (mean $R^2 = 0.12$).

4. Sensitivity of River Temperature to Changes in Air Temperature and River Discharge

4.1. Sensitivity of River Temperatures at Study Basin Stations

[37] For all study basin stations, annual mean water temperature increases linearly under air temperature increases of +2 °C, +4 °C, and +6 °C, with an annual mean (range) increase of 1.4 (0.6 to 1.8) °C, 2.7 (1.2 to 3.6) °C, and 4.0 (1.8 to 5.3) °C, respectively (see Table 5). Although the slopes at the inflection point (*tan θ*) are, on average, larger than 1 for all study basin stations (except for the Lena (Kusur)), the overall average slopes are smaller and decrease in the high temperature range resulting in a less strong increase in water temperature under specific air temperature increases.

Table 5. Mean Annual River Temperature Increase (°C) Under Different Air Temperature Increases and Changes in River Discharge for Study Basin Stations[a]

River	Station	+2 °C	+4 °C	+6 °C	+4 °C +20 % Q	+4 °C −20 % Q	+4 °C −40 % Q
Columbia	The Dalles	1.2	2.3	3.4	1.6	3.4	**5.2**
Mississippi	Clinton	1.5	3.0	**4.5**	3.0	3.1	3.2
Missouri	Omaha	1.4	2.8	**4.1**	3.1	2.4	1.7
Potomac	Washington D.C.	1.8	3.6	**5.3**	3.3	3.9	4.5
San Joaquin	Vernalis	1.6	3.0	**4.4**	2.9	3.2	3.6
Danube	Bratislava	1.3	2.6	**3.8**	2.4	2.8	3.2
Danube	Budapest	1.5	2.9	**4.4**	2.7	3.3	3.8
Meuse	Eijsden	1.7	3.3	**4.8**	3.2	3.4	3.6
Rhine	Lobith	1.7	3.4	**5.0**	3.1	4.0	4.9
Orange	Oranjedraai	1.1	2.2	**3.1**	2.3	2.1	1.9
Darling	Burtundy	1.7	3.2	**4.6**	3.3	3.1	2.9
Lena	Kusur[b]	0.6	1.2	**1.8**	1.3	1.2	1.1
Ob	Salekhard[b]	1.2	2.3	**3.4**	2.3	2.3	2.3
Yenisey	Igarka[b]	1.3	2.5	3.6	2.2	3.0	**4.0**

[a]Values in bold indicate the highest mean annual water temperature increase.
[b]Stations fitted on 10 day mean basis instead of daily basis.

[38] Considering the sensitivity of water temperature to discharge changes, an increase in discharge of +20% generally reduced water temperature increases, while decreases of 20% and 40% in discharge intensified water temperature increases for the majority of river stations. This partly reflects the higher thermal capacity of a river under increased discharges (water volumes) and lower thermal capacity when discharges are reduced. However, for stations of the Missouri, Orange, Darling, Lena, and Ob rivers, slightly higher water temperatures under an increase in discharge and lower water temperatures under a discharge decrease were observed. As previously mentioned (see section 3.1), the flow regimes at these river stations are characterized by generally high-flow conditions during summer and low-flow conditions during winter, implying that the peaks in flow regime and thermal regime coincide. The influence of changes in thermal capacity on water temperature is therefore not well reflected by the empirical relation between water temperature and discharge for these study basin stations. This regression modeling approach is therefore less suitable to studying the impact of discharge changes on water temperature for these river stations.

[39] For the majority of study basin stations, mean annual water temperatures were most sensitive to an air temperature increase of +6 °C, with of the greatest increase 5.3 °C for the Potomac (Washington, D.C.) and lowest increase 1.8 °C for the Lena (Kusur). For the river stations in the Columbia and Yenisey, however, water temperature increases were highest for a + 4 °C air temperature increase in combination with a 40% decrease in discharge, resulting in water temperature increases which are more than 1.5 °C higher than under a + 4 °C air temperature increase without discharge changes.

[40] In order to get more detailed insight into the sensitivity of river temperature on a daily basis, density plots are presented for the San Joaquin (Vernalis), Potomac (Washington, D.C.), Rhine (Lobith), and Danube (Bratislava), showing the distribution of daily water temperatures under air temperature increases of +4 °C and +6 °C, and under an air temperature increase of +4 °C combined with a 40% decrease in discharge (see Figure 7). Although the increase in mean annual water temperature is highest under an air temperature increase of +6 °C, the density plots for these stations indicate that an air temperature increase of +4 °C combined with a 40% decrease in discharge results in higher maximum water temperatures than those found for an air temperature increase of +6 °C. The impact of a 40% discharge decrease is most pronounced for the Rhine (Lobith), resulting in a considerably higher maximum (99th percentile) water temperature of 28.6 (27.0) °C, compared to 25.5 (24.6) °C under an air temperature increase of +4 °C, and 26.0 (25.0) °C under an air temperature increase of +6 °C without any discharge change.

4.2. Sensitivity of River Temperatures at Global GEMS/Water Stations

[41] Considering the mean annual water temperature increases for the GEMS/Water stations, the overall average values (1 to 99 percentile range) under a + 2 °C, +4 °C, and +6 °C air temperature increase are 1.3 (0.1 to 2.3) °C, 2.6 (0.1 to 4.7) °C, and 3.8 (0.2 to 7.0) °C, respectively. Considering the calculated water temperature increases of the individual stations under these warming rates (see Figure 8), river stations at high northern latitudes (northern Canada and Siberia) show a relatively moderate water temperature increase compared to the middle and low latitude zones. This can be explained by the general low range in water temperature ($\alpha - \mu$) for these stations, as water temperature increase is positively related to $\alpha - \mu$ (mean slope of 0.07; $R^2 = 0.56$). Furthermore, generally low slopes at the inflection point (*tan* θ) were fitted for these high northern latitude stations, resulting in less strong water temperature increases.

[42] To address the sensitivity of water temperature to changes in discharge, we focused on 102 GEMS/Water stations showing distinct inverse relations between water temperature and discharge, and thus excluded stations for which our regression model is less suitable to address the sensitivity to river discharge changes (see previous section). Comparing the annual mean water temperature increases under an air temperature increase of +4 °C with the results under this air temperature increase combined with discharge changes, we found that an increase in

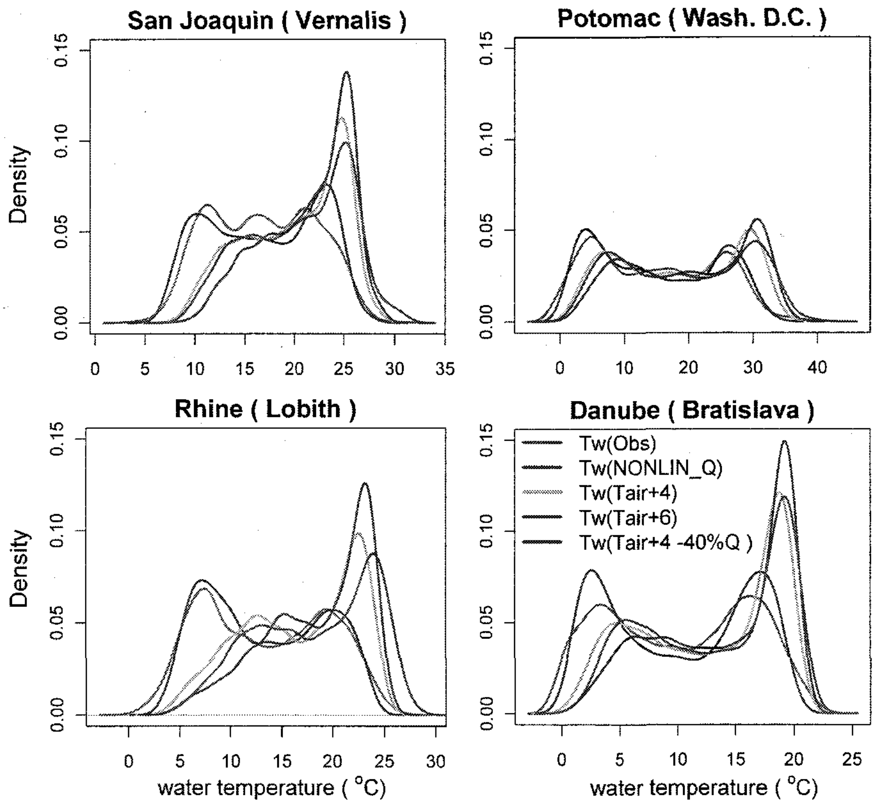

Figure 7. Density functions of observed daily water temperature (Tw(obs)) and simulated daily water temperature for the adapted regression model including time lag and discharge (Tw(NONLIN_Q)) for the reference period 1980–1999 and under an air temperature increase of +4 °C (Tw(Tair +4)) and +6 °C (Tw(Tair +6)), and under an air temperature increase of +4 °C combined with a 40% decrease in discharge (Tw(Tair +4 −40%Q)).

discharge of 20% reduced the annual water temperature increase by a mean (1 to 99 percentile range) of 0.2 (0.0 to 0.7) °C. In contrast, a decrease in discharge of 20% and 40% exacerbated the increase in water temperatures by 0.3 (0.0 to 1.0) °C and 0.8 (0.0 to 2.6) °C, respectively. In general, water temperatures showed higher sensitivity to a 20% decrease in discharge than to a 20% increase in discharge. Considering the increase in mean annual river temperatures for the selected GEMS/Water stations individually (see Figure 9), a high sensitivity to discharge decreases of 20% and 40% was found for stations in the Ganges, Ob, Yenisey, Ohio/Mississippi, and several rivers in Europe (e.g., Rhine, Danube, Elbe, Rhone, Guadiana). Estimated river temperature increases under an air temperature increase of +4 °C in combination with a change in discharge of −40% (see Figure 10), indicate highest mean annual water temperature increases (more than 4 °C) for river stations in western Europe and the eastern part of the United States (see Figure 10). The overall average in maximum river temperature increase (on a daily basis) under this air temperature and discharge change is 4.4 °C, with strongest maximum water temperature increases for rivers in western Europe, the eastern part of the United States, and Russia.

5. Discussion and Conclusions

[43] The performance of the nonlinear regression model of *Mohseni et al.* [1998] for weekly water temperatures was generally improved by the introduction of river discharge as an additional variable, and the model was successfully applied on a daily basis by incorporating a time lag. For 76% of the GEMS/Water stations, NSC values were higher than 0.8 (see Figure 6), indicating the usefulness of the modified water temperature regression model to estimate water temperatures on a daily basis for river stations on a global scale. Positive relations were found between model performance and the availability of water temperature data to fit the regression model, while only weak relations were observed between the NSC and RMSE values and river basin characteristics (latitude and basin area). A distinct improvement in the model performance by the introduction of river discharge was found for 87% of the GEMS/Water stations globally. This improvement was most pronounced for stations with typically high winter discharges and low summer discharges. Less distinct increases in model performance were obtained, however, for river stations affected by reservoir operations or characterized by distinct snowmelt peaks during summer. The improvement in model

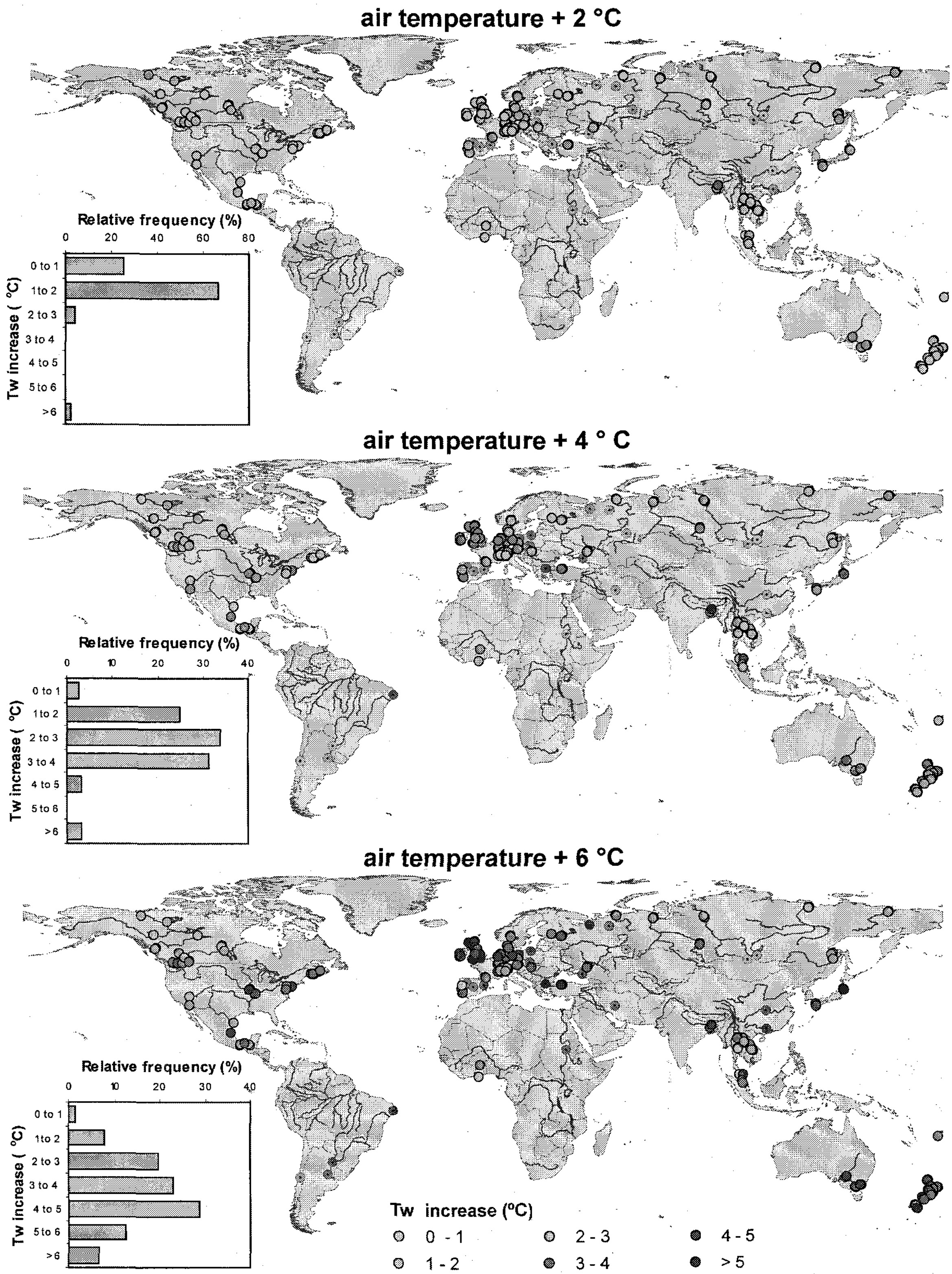

Figure 8. Mean annual river temperature increase (°C) under air temperature increases of +2 °C, +4 °C, and +6 °C for the selected GEMS/Water stations. The circles with black dots indicate river stations fitted using monthly data.

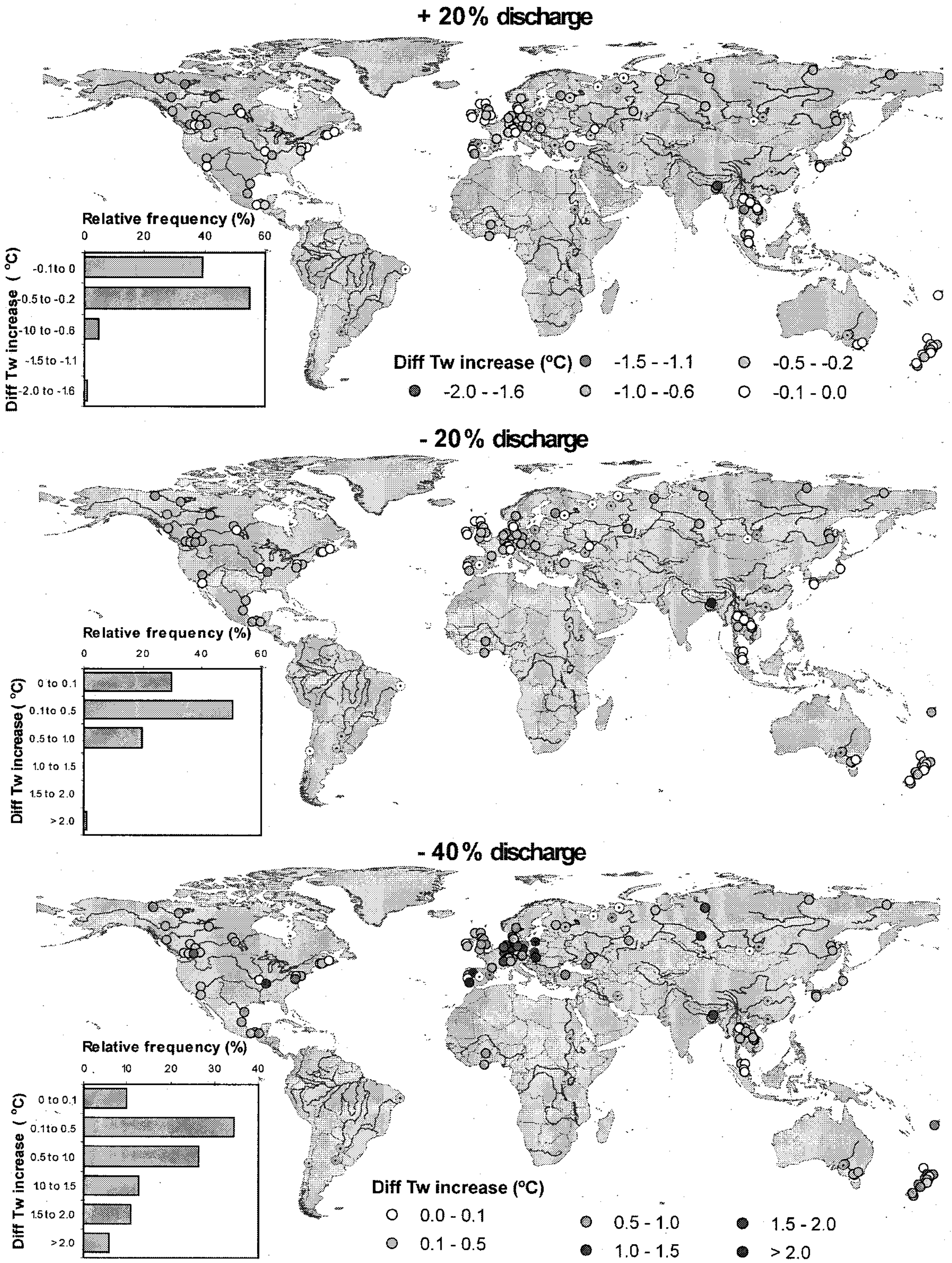

Figure 9. Difference in mean annual river temperature increase under an air temperature increase of +4 °C in combination with a change in discharge of +20%, −20% and −40% relative to an air temperature increase of +4 °C without discharge changes for the selected GEMS/Water stations. The circles with black dots indicate river stations fitted using monthly data.

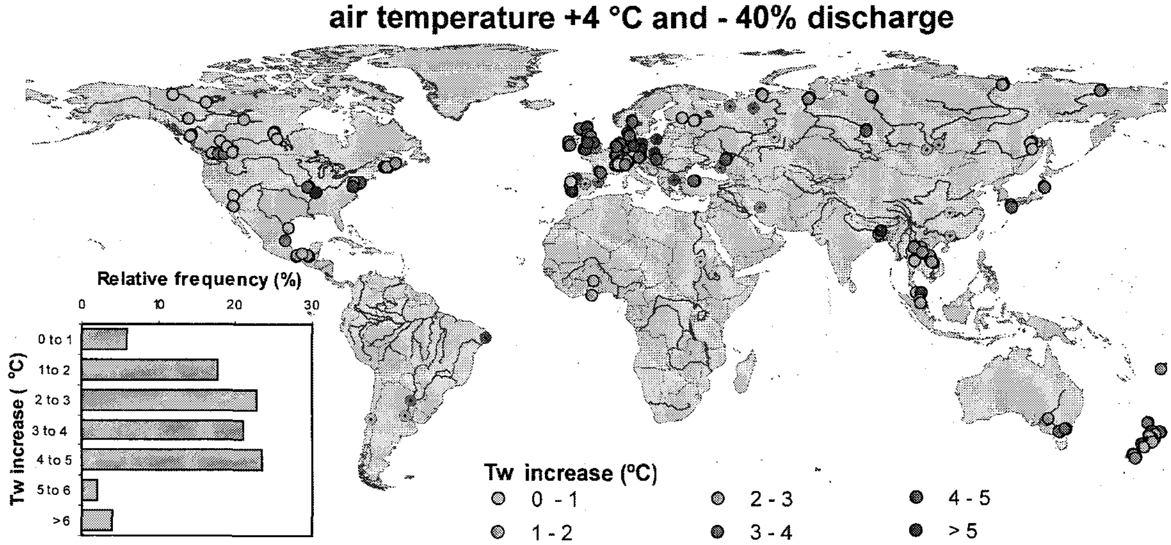

Figure 10. Mean annual river temperature increase (°C) under an air temperature increase of +4 °C combined with a change in discharge of −40% for the selected GEMS/Water stations. The circles with black dots indicate river stations fitted using monthly data.

performance by the introduction of discharge was highest during extreme dry and warm spells (droughts and heat waves), when water temperatures are most sensitive to atmospheric influences and can reach high values.

[44] Comparing our results with previous studies addressing the influence of river discharge on stream and river temperatures [e.g., *Crisp and Howson*, 1982; *Mohseni et al.*, 1999], a generally higher impact of river discharge on water temperatures was found in our study. The multiple regression analysis of *Webb et al.* [2003], however, also indicated that inverse relations between water temperature and discharge were found, with greater impact of discharge on water temperatures at shorter time scales and in larger catchments. This may explain the results of our study, in which a water temperature regression model applied to stations of generally large river basins on a daily basis showed a greater improvement by introduction of discharge than was found in previous studies that focused on stream stations in small river basins with weekly or monthly mean water temperatures.

[45] Studies that previously applied the water temperature regression model of *Mohseni et al.* [1998] found an underestimation of the upper-bound water temperature (α) with least squares regression, resulting in an underestimation of the calculated maximum water temperature [*Bogan et al.*, 2006; *Mantua et al.*, 2010; *Mohseni et al.*, 1998; *Mohseni et al.*, 1999]. Although we generally obtained lower values of α for our modified water temperature regression model compared to the original model, the underestimation in river temperatures during summer periods was less for the modified model including river discharge. Furthermore, results of the calculated water temperatures for the European study basin stations during the heat wave and drought of 2003 (see Figure 3) showed that the underestimation was greatly reduced by the introduction of discharge, indicating that the regression model is less biased by an underestimation of the upper-bound water temperature.

[46] Results of our sensitivity analyses with water temperature changes under air temperature increases and changes in river discharge indicated that the impact of discharge changes were generally moderate compared to air temperature increases on a mean annual basis. The calculated changes in mean annual water temperature averaged for all selected GEMS/Water stations are +1.3 °C, +2.6 °C, and +3.8 °C under air temperature increases of +2 °C, +4 °C, and +6 °C respectively. An increase in discharge of 20% resulted in a slight decrease in mean annual water temperature increase of −0.2 °C, while decreases in discharge of 20% and 40% slightly exacerbated the water temperature increase by +0.3 °C and +0.8 °C on average. Although the contribution of discharge is moderate on an annual mean basis, relevant impacts of discharge changes were found, especially for maximum water temperatures on a daily basis. For the study basin stations of San Joaquin, Potomac, Rhine, and Danube (see Figure 7), higher maximum water temperatures were found under an air temperature increase of +4 °C in combination with a decrease in discharge of 40% than under an air temperature increase of +6 °C (without discharge changes). This indicates that a strong decrease in river discharge under warm atmospheric conditions can have a greater impact on rising water temperatures than an extra air temperature increase of 2 °C under these conditions. The relatively high sensitivity of daily water temperatures to discharge changes during dry and warm spells is relevant, as water temperatures can reach critically high values during these periods, with possibly negative environmental effects (e.g., exceeded water temperature tolerance values of freshwater species) and economical consequences (e.g., reduced cooling water potential for industries and

thermal power plants). Considering the estimated water temperature increases of the Rhine (Lobith) (see section 4.1), the mean number of days per year that the critical limit of 23 °C for the intake of cooling water by thermal power plants is exceeded [*European Environment Agency (EEA)*, 2008b], is 16 days for the reference situation, 47 days and 83 days under a air temperature increases of +4 °C and +6 °C respectively, and 104 days per year under an air temperature increase of +4 °C in combination with a decrease in discharge of 40%. Although this is a rough estimation, it emphasizes the relevant contribution of decreasing discharges (reduced thermal capacity) to water temperature increases on a daily time step, and the associated impacts for cooling water purposes.

[47] Results of our study are preliminary rough estimates of the sensitivity of river temperatures to air temperature increases and changes in river flow on a global scale. Although the selected air temperature increases and changes in river flow are realistic in the context of climate change, further research is needed to address the impact of climate change and changes in anthropogenic influences in detail. A limitation of the model approach for future projections is the fixed value of parameter estimates, although it is likely that the upper bound in water temperature (α) and possibly also other parameters of the regression may change as a result of climate change and anthropogenic changes (e.g., cooling water discharges, reservoir operations). The use of daily climate change and river discharge scenarios as inputs into a large-scale deterministic water temperature model can be a next step to produce more detailed and realistic estimates of river temperature under climate change conditions for a specific future period.

[48] Despite these preliminary estimates, the outcomes of our study clearly demonstrate the relevant contribution of low river discharge in accounting for high water temperatures during dry, warm periods. As previous studies demonstrated an increase in flow seasonality as a result of climate change, with lower flows during the low-flow season in many rain-dominated catchments [*Arnell*, 2003a; 2003b; *Burlando and Rosso*, 2002; *Menzel and Burger*, 2002], we expect that the relative impact of river discharge on water temperatures will increase in the future. Moreover, climate variability is expected to increase, resulting in increased risks of droughts and heat waves [*Easterling et al.*, 2000; *Schar et al.*, 2004; *Stott et al.*, 2004; *Wetherald and Manabe*, 1999]. The combined effects of both atmospheric warming and changes in river flow should therefore be considered in order to produce more realistic projections of future changes in river temperature because of climate change.

[49] To conclude, the outcomes of our study demonstrated that a nonlinear regression model with air temperature, river discharge, and time lag included, is a simple and robust method to estimate river temperatures on a daily basis for monitoring stations in different river basins globally. The performance of the regression model improved for 87% of the global GEMS/Water river stations where discharge was introduced as an additional variable. Results showed that the impact of discharge changes generally increases during dry, warm periods, when rivers have a lower thermal capacity and are thus more sensitive to warm atmospheric conditions. This high sensitivity of daily water temperatures to discharge changes during dry (low flow) and warm spells is important, as water temperatures can reach critically high values for freshwater ecosystems and several usage functions (e.g., cooling for thermal power plants and industries, drinking water production, recreation) during these periods. Impacts of river discharge on water temperatures should thus be incorporated to provide more accurate estimates of high river temperatures during historical and future projected dry, warm spells.

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