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Investigating controls on the thermal sensitivity of Pennsylvania streams

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Abstract:

Stream temperature, an important measure of ecosystem health, is expected to be altered by future changes in climate and land use, potentially leading to shifts in habitat distribution for aquatic organisms dependent on particular temperature regimes. To assess the sensitivity of stream temperature to change in a region where such a shift has the potential to occur, we examine the variability of and controls on the direct relationship between air and water temperature across the state of Pennsylvania. We characterized the relationship between air and stream temperature via linear and nonlinear regression for 57 sites across Pennsylvania at daily and weekly timescales. Model fit (r^2) improved for 92% (daily) and 65% (weekly) of sites for nonlinear *versus* linear relationships. Fit for weekly *versus* daily regression analysis improved by 0·08 for linear and 0·06 for nonlinear regression relationships. To investigate the mechanisms controlling stream temperature sensitivity to environmental change, we define 'thermal sensitivity' as the sensitivity of stream temperature of a given site to change in air temperature, quantified as the slope of the regression line between air and stream temperature. Air temperature accounted for 60–95% of the daily variation in stream temperature for sites at or above a Strahler stream order (SO) of 3, with thermal sensitivities ranging from low (0·02) to high (0·93). The sensitivity of stream temperature to air temperature is primarily controlled by stream size (SO) and baseflow contribution. Together, SO and baseflow index explained 43% of the variance in thermal sensitivity across the state, and 59% within the Susquehanna River Basin. In small streams, baseflow contribution was the major determinant of thermal sensitivity, with increasing baseflow contributions resulting in decreasing sensitivity values. In large streams, thermal sensitivity increased with stream size, as a function of accumulated heat throughout the stream network. Copyright © 2011 John Wiley & Sons, Ltd.

KEY WORDS hydrology; water temperature; streams; thermal sensitivity

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INTRODUCTION

Stream temperature is an important measure of water quality and ecosystem health affecting physical, chemical, and biological river processes (Caissie, 2006). It determines both biotic and abiotic ecosystem productivity (Poff *et al*., 2002) and affects the geographic distribution of fish species and other aquatic life forms within the river network (Ebersole *et al*., 2001; Poff *et al*., 2002). Water temperature sustains vital functions in fish, including reproduction, development, and growth (Christie and Regier, 1988; Jensen, 1990; Magnuson *et al*., 1990; Tonn, 1990). Many physical, chemical, and biological properties of water are a function of water temperature, including dissolved oxygen, metabolic activity, and nutrient distribution and cycling (LeBosquet and Tsivoglou, 1950; Ducharne, 2008).

The temperature of stream water is affected by a variety of complex processes related to atmospheric, hydrogeologic, geomorphic, and anthropogenic river and near-land characteristics (Caissie, 2006). Changes in stream temperature are a function of energy and water exchange across the water surface, streambed, and banks, as is illustrated in Figure 1, and have been investigated in numerous studies (Brown, 1969; Sinokrot and Stefan, 1994; Webb and Zhang, 1997; Evans *et al*., 1998; Hannah *et al*., 2004; Moore *et al*., 2005b, Hannah *et al*., 2008). Heat exchange with the atmosphere occurs through both short and long-wave radiation and turbulent transfers (sensible and latent). Advection of heat through groundwater inputs or anthropogenic discharge (e.g. wastewater or cooling water from power plants) can also affect stream temperature (Evans *et al*., 1998; Story *et al*., 2003; O'Driscoll and DeWalle, 2006; Tague *et al*., 2007; Burkholder *et al*., 2008). Other anthropogenic factors that influence stream temperature include riparian deforestation and climate change (Johnson, 2003, 2004; Malcolm *et al*., 2008; Moore *et al*., 2005a,b), which ultimately impact the energy input to the surface of the water column. Factors that influence stream temperature vary spatially and temporally. It is this variation of controls at multiple scales that makes comprehension and prediction at the regional scale a complex task. Excellent reviews on factors affecting stream temperature can be found in

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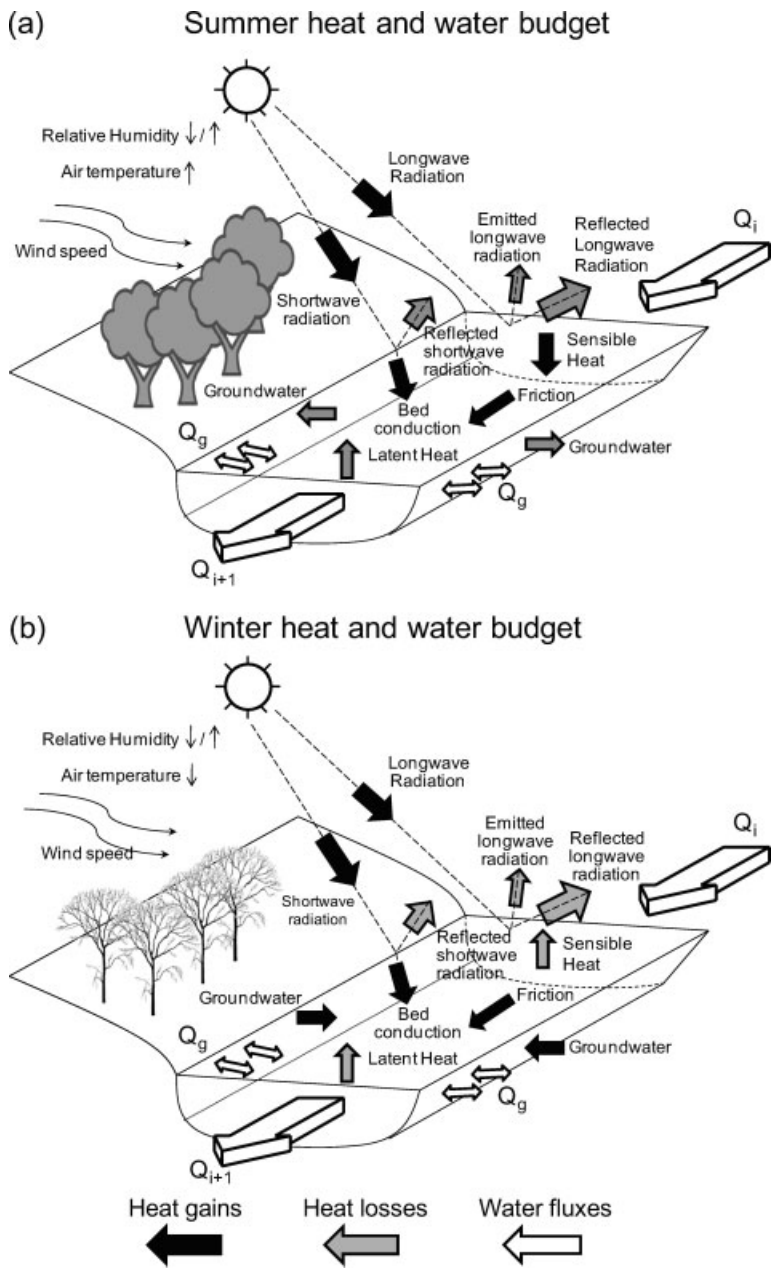

Figure 1. The figure illustrates a conceptual model of water and heat fluxes within a given river segment for a temperate climate. Water fluxes are groundwater (Q_g) and upstream (Q_i) and downstream (Q_{i+1}) discharge, where i refers to a spatial index term. Water fluxes, sources of heat (heat gains), and heat sinks (heat losses) are indicated by different arrow colouring. The figure illustrates heat fluxes during (a) summer and (b) winter for a stream in a temperate climate

the studies of Poole and Berman (2001), Caissie (2006), and Webb *et al*. (2008).

Environmental change, represented by the combined effect of changing land use, climate, and other local and global landscape alterations, is likely to cause fundamental transformations in natural processes and system features, with direct and indirect impacts on stream ecology (Milly *et al*., 2008; Wagener *et al*., 2010). The combined effects of climate change, altering patterns of precipitation and air temperature, resulting in changes to the quantity, quality, and timing of river flows (Moore *et al*., 1997; Hayhoe *et al*., 2007; Bates *et al*., 2008; Huntington *et al*., 2009), as well as land cover change (dams, agriculture, urbanization), causing reduced river connectivity and decreased riparian vegetation, are expected to impact water temperature, thereby threatening already stressed aquatic ecosystems around the world. Further problems will result from the coupling of these effects with an already altered hydrologic cycle, for example resulting in summer stress for riverine habitats when low flows and high temperatures prevail (Poff *et al*., 2002; Buisson *et al*., 2008). With regard to stream temperature, of particular interest is the question of how differing controls on stream temperature will inform the sensitivity of summer stream temperatures for sites at a range of scales to climate change.

This problem is especially pronounced in Pennsylvania, a temperate region in the northeastern United States,

where habitats for many native species have already experienced negative anthropogenic impacts (Trout Unlimited, 2007). Disappearing thermal habitat for many cold and cool water fish species is a particular danger for the state of Pennsylvania, where recreational fishing provides an economic benefit of $1·3 billion (US Department of the Interior, Fish and Wildlife Service, and US Department of Commerce, 2006). Pennsylvania is projected to experience a warming climate, increasing annual and winter precipitation, and slightly increased runoff and streamflow variability (Shortle *et al.*, 2009). Cold water habitat may be endangered during summers, where water temperatures exceed a species dependent maximum tolerance (Eaton and Scheller, 1996). Smaller order (Strahler order 1 or 2) streams, Pennsylvania's primary refuge for cold and cool water species, typically have little to no long-term monitoring, meaning that determination of change impacts within these locations is challenging (Poff *et al.*, 2006).

To examine how controls on water temperature can predict the sensitivity of streams to change, we define the term *thermal sensitivity* to represent the relative sensitivity of the temperature of a given stream to environmental change. This term is related to the idea of *elasticity*, which was first used within hydrology by Schaake (1990) and defined as proportional change in streamflow to change in precipitation. Performing a linear regression between daily, weekly, or monthly values of air and water temperature yields both slope and intercept values that best describe the data. The slope of this relationship, which we call thermal sensitivity, indicates how sensitive a given stream is to changes in water temperature due to changes in air temperature; the strength of this relationship (r^2) is an indicator of how well water temperature can be approximated by air temperature. Thermal sensitivity represents an estimation of the seasonal change in stream temperature relative to air temperature, and as such, requires a minimum of 1 year of stream temperature data.

The magnitude of thermal sensitivity is a function of the behaviour of stream temperature at both low and high air temperatures, which is quantified by both local and non-local controls. Local controls are represented by the heat balance at the stream site, which is a function of heat fluxes, and site characteristics that will influence the heat budget, such as vegetative and topographic shading, described by Figure 1, as well as anthropogenic heat inputs that will mediate these linkages. Non-local controls represent the summed influences of the upstream network, in terms of both heat accumulation and groundwater inputs. We will consider thermal sensitivity differences between stream sites that fall into five broad categories.

- Groundwater fed streams: These are typically smaller streams, in which groundwater is a heat source during winter and a heat sink during summer. As such, little seasonal variation in water temperature will result in a low thermal sensitivity.
- Shaded (riparian/topographic) streams: Shading will affect smaller streams especially during summer by reducing solar radiation, a major source of summer heat, thereby reducing both stream temperature at higher air temperatures and thermal sensitivity.
- Streams with inputs of heated effluent from wastewater or power plants: Thermal sensitivity will be a function of when and how much heated effluent is released. If most effluent is released during winter, stream temperatures will be higher and thermal sensitivity will be lower. If effluent is primarily released during summer, stream temperatures and thermal sensitivities will be higher.
- Streams below dams: Thermal sensitivity at sites below dams depends on the reservoir depth that water is released from and the distance from the dam to the stream temperature measurement location. Dams that release water from the bottom of the reservoir will have colder stream temperatures less sensitive to air temperature, and low thermal sensitivities. Dams that release water from the top of the reservoir will have higher stream temperatures and thermal sensitivities, sometimes artificially high for the river's size.
- Small, exposed streams: Small streams without riparian shading or significant contributions from groundwater will see stream temperature fluctuations approximating air temperature fluctuations, as a function of weather and streamflow. Very small streams will have thermal sensitivities approaching a value of one, with decreasing thermal sensitivities for increasing stream size, as controls switch from weather to streamflow.
- Large streams: Stream temperature in large streams is often closely related to air temperature, as a function of the accumulation of heat through the stream network. Stream temperatures asymptotically approach zero at low air temperatures, during winter, and are high during summer, when flows are low and heat inputs from solar radiation are at their peak. Thermal sensitivities for streams within this category will be higher, and tend to approach a value of one.

With respect to the possible range of results, a near zero thermal sensitivity is characteristic of sites where air temperature explains very little of the variation in water temperature, usually because of buffering from vegetation, anthropogenic factors, such as heated effluent release from power or wastewater treatment plants, or upstream temperature controls via groundwater or dam releases (Caissie, 2006). In this sense, thermal sensitivity is a first-order assessment of how stream temperatures at a site will respond to climate change.

The thermal sensitivity of streams to air temperatures, without referring to it as such, has been widely investigated by quantifying how the sensitivity of water temperature to air temperature changes at different spatial and temporal scales (Crisp and Howson, 1982; Mackey and Berrie, 1991; Stefan and Preud'homme, 1993; Mohseni *et al.*, 1998, 1999, 2002; Mohseni and Stefan, 1999; Erickson and Stefan, 2000; Morrill, *et al.*, 2005). Most

studies have found that the correlation and slope of the linear relationship between air and water temperature increases from daily to weekly to monthly time series (Webb and Nobilis, 1997; Caissie, 2006). Other studies examining the relationships between site characteristics and thermal habitat have directly incorporated other site characteristics directly as mediators on the linear relationship between stream and air temperature (Tague *et al.*, 2007) or have investigated the relationship between thermal classifications (cold, cool, and warm water sites) and site characteristics (Chu *et al.*, 2009).

The sensitivity of stream temperature to change has also been investigated via the equilibrium temperature concept (Bogan *et al.*, 2003; Caissie *et al.*, 2005). Equilibrium temperature represents the temperature of a water body at which net heat flux across the interface between the air and stream surface is zero (Edinger *et al.*, 1968). This value is also dependent on site characteristics (Mohseni and Stefan, 1999; Bogan *et al.*, 2003). Approximations between stream temperature and equilibrium temperature can distinguish stream sites dominated by atmospheric heat exchange from stream sites controlled by other site factors (e.g. shading and sheltering, groundwater or meltwater, inputs from reservoirs) (Bogan *et al.*, 2003). Model form, however, does not allow this approach to distinguish between the effects of groundwater and anthropogenic impacts, which are lumped into the shading and sheltering term.

While using linear regression to relate air and water temperatures is well established, and many studies agree that the slope of the linear regression line between air and water temperatures is controlled by site characteristics, no study has yet been performed that quantifies the relationship between the regression slope and physically based site characteristics across a range of stream sites on a regional scale (Erickson and Stefan, 2000; Bogan *et al.*, 2003; Caissie, 2006; O'Driscoll and DeWalle, 2006). Also, missing from previous investigations is a spatial scale that allows for an understanding of how site characteristics relate to susceptibility to change in thermal habitat. Investigations either focus on a few rivers or watersheds (Stefan and Sinokrot, 1993) or gage locations at coarse spatial scales.

The objective of the proposed work was to assess the nature of stream temperature variability and its sensitivity across the state of Pennsylvania. Stream thermal regimes were investigated for 57 United States Geological Survey (USGS) gauges with temperature record lengths of 2 years or greater. We specifically address the following questions:

1. To what extent can changes in air temperature alone explain changes in stream temperature?
2. What other site characteristics improve the prediction of stream temperature sensitivity?

The answers to these questions will inform how sensitive Pennsylvania stream sites are to environmental change by identifying site characteristics that control thermal sensitivity.

STUDY REGION AND DATA

Pennsylvania is located in the northeastern portion of the United States. State-wide climate is temperate, with evenly distributed mean monthly precipitation across the year summing up to an annual average of 1016 mm (Shortle *et al.*, 2009). Air temperature, and hence potential evapotranspiration, is seasonally distributed, peaking in the summer months. Pennsylvania is divided into three major river basins, (1) the Ohio [basin drainage area (DA) is 40 021 km^2], (2) the Susquehanna (54 028 km^2), and (3) the Delaware (16 531 km^2) river basins. Its hydrography is dominated by first-order streams, which account for 50·2% of the total stream length across the state. By comparison, sixth and higher order streams represent only 0·026% of the total stream length in Pennsylvania (Environmental Resources Research Institute, 1998). The majority of Pennsylvania streams are perennial, with flow mainly derived (about 66%) from groundwater (Shortle *et al.*, 2009). Deciduous forests account for 57% of land cover across the state (US Geological Survey, 2000).

Pennsylvania's aquatic ecology consists of a wide range of fish species. Coldwater fish species, including the trout family (brown, rainbow, and brook) and steelhead, require cool temperatures, abundant dissolved oxygen, and shading. They are often found in cooler streams or in dam tailwaters, with optimal temperature tolerances between 10 and 15·6 °C and upper limits of around 20–25 °C (Inskip, 1982; Krieger *et al.*, 1983; Cook and Solomon, 1987). In contrast, warm water fish species, which include largemouth bass and carp (Steiner, 2002), have an optimal temperature range between 20 and 30 °C, and an upper thermal tolerance of 35 °C (Edwards and Twomey, 1982; Stuber *et al.*, 1982). While smaller streams are cooler and will support cold water fish species, larger rivers are generally warmer and will support warm water species. Cool and cool water transition fish species inhabit intermediate to large rivers (Steiner, 2002). Figure 2 summarizes and contrasts optimal and lethal temperature limits for brook trout, a cold water species, and largemouth bass, a warm water species.

Water temperature data for 57 stream sites across Pennsylvania was available for analysis (Figure 3). All data were obtained from USGS temperature gauges with records of daily stream temperature longer than 2 years (http://waterdata.usgs.gov/pa/nwis/rt). Air temperature data were obtained from the National Climatic Data Center (NCDC) daily surface record (http://www7.ncdc.noaa.gov/). The closest air temperature station was selected for each water temperature site. A total of 37 air temperature sites were used in the analysis, with the maximum distance between air and water temperature measurements being 32·5 km. Previous studies have shown good agreement between air and water temperature data

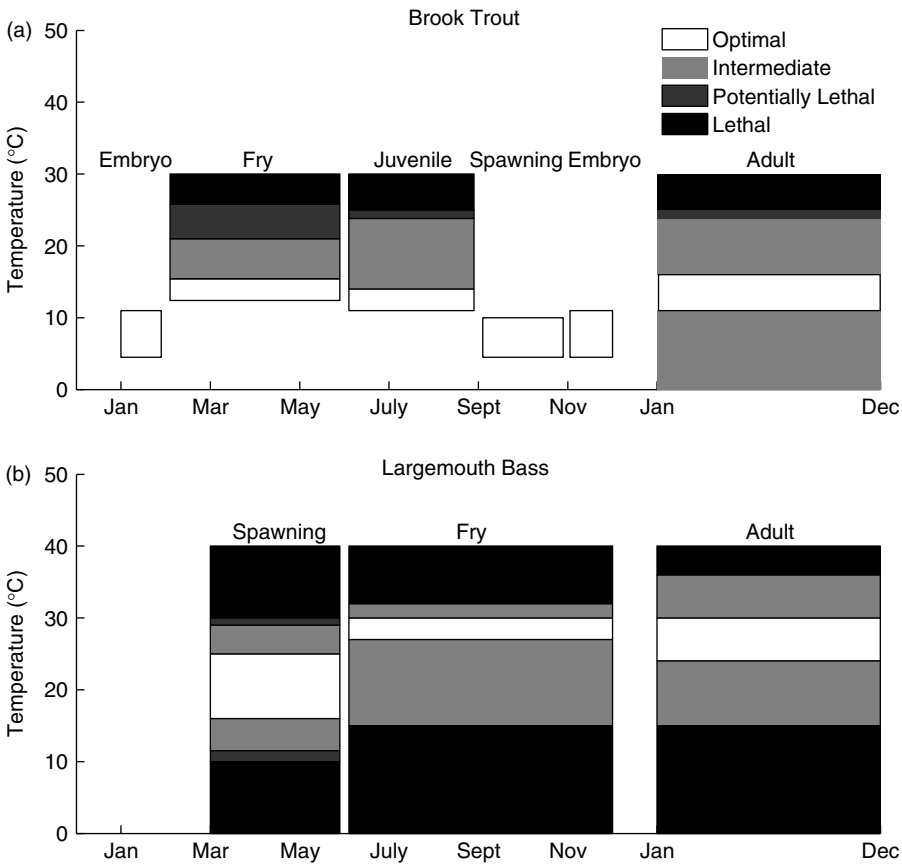

Figure 2. Thermal tolerance corresponding to time of year and life cycle stage of (a) brook trout, a cold water fish and (b) largemouth bass, a warm water fish. Thermal tolerance is represented using a scale between optimal and lethal

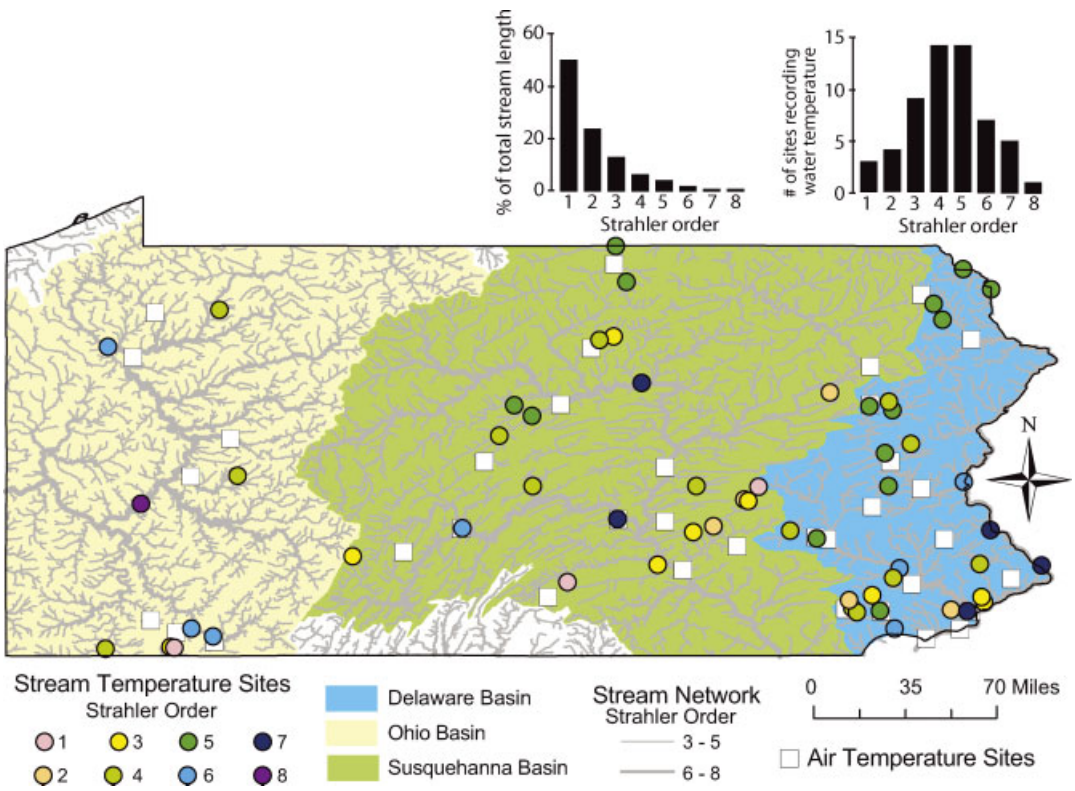

Figure 3. The state of Pennsylvania, with the river network imposed for third and higher order streams, along with the 57 water temperature and 37 air temperature sites used in the analysis. Water temperature sites are coloured according to SO at the site. Pennsylvania's three major river basins—the Ohio, Susquehanna, and Delaware—are denoted by background colour, with white areas representing smaller parts of other river basins. SOs are represented by line thicknesses. Above the figure are two histograms depicting the percentage of cumulative stream length by SO and the number of sites with water temperature measurements by SO in Pennsylvania

for distances of up to 270 km (Mohseni *et al.*, 1998), and we also found that the distance did not seem to negatively impact correlations in our data.

Elevation, DA, stream velocity, stream width, and depth measurements were acquired from the USGS gauge site records. Velocity, width, and cross-sectional area were derived from point measurements in both space and time, with average depth taken as the cross-sectional area divided by the width. These measurements were not necessarily available exactly at the location of the temperature gauge. Although this does constitute a limitation of the study, the purpose of this study is to compare the differences in site characteristics to understand relative controls. A general estimate of the site conditions allows for a first-order investigation of these controls in relation to their spatial variation across the state.

Radiation data were downloaded from the NCDC's National Solar Radiation Data Base stations. Averaged monthly solar radiation was calculated by averaging across the available period of record (1991–2005) for each site using the closest station to each water temperature measurement location. Strahler stream order (SO), a measure of river size ranging from 1 in headwaters to 12 for the Amazon River, was determined from a Geographic Information System (GIS) shape layer of all Pennsylvania streams that conforms to National Map Accuracy Standards (Environmental Resources Research Institute, 1998).

METHODS

To determine the regional relationship between site characteristics and the thermal sensitivity of Pennsylvania stream temperatures, linear and nonlinear regression models were developed at all sites using historical stream and air temperature records. Site characteristics related to stream temperature were identified and extracted for all sites. The relationship between the site characteristics and regression model factors was quantified using multiple regression analysis.

Linear and nonlinear regression analysis of thermal sensitivity

Linear regression was performed to gain first-order estimates of the relationship between stream and air temperature (Webb and Nobilis, 1997; Erickson and Stefan, 2000; Morrill *et al.*, 2005). Linear regression is applied as

$$T_w = ET_a + b \tag{1}$$

where T_w represents water temperature (°C), T_a represents air temperature (°C), E the slope (°C/°C) of the relationship and hence the thermal sensitivity, and b the y-intercept (°C) of the regression line between the two. Points with air temperatures <0 °C were excluded from the analysis, as this model is best applied at air temperatures >0 °C, which is recognized as the limit at which additional cooling of water forms ice. Linear models have previously been shown to poorly predict below this limit (Morrill *et al.*, 2005). Deviations from the linear approximation can also occur at air temperatures slightly above freezing, and for high air temperatures, when water temperatures will asymptotically approach an upper stream temperature limit (Mohseni and Stefan, 1999). Linear regression was performed for all sites at daily and weekly time scales.

Nonlinear regression was also evaluated for its ability to relate water and air temperature data for all sites, because it more accurately predicts physical behaviour observed in water temperatures at high (>20–25 °C) and low values (<0 °C) (Mohseni *et al.*, 1998; Mohseni and Stefan, 1999). This makes nonlinear regression models better suited than linear regression models to analyse change impacts and to address ecologically relevant intervals, as aquatic ecosystems are more sensitive to extremes than to mean values (Eaton and Scheller, 1996; Mohseni *et al.*, 2002). The particular nonlinear regression equation used here was introduced by Mohseni *et al.* (1998) and has the following form,

$$T_w = \mu + \frac{\alpha - \mu}{1 + e^{\gamma(\beta - T_a)}} \tag{2}$$

where μ is the minimum stream temperature (°C), α the maximum stream temperature (°C), β the air temperature at the inflection point (°C), and γ the a measure of the slope at this inflection point (°C^{-1}). Gamma (γ) is also represented by the equation

$$\gamma = \frac{4 \tan\theta}{\alpha - \mu} \tag{3}$$

where tan(θ) is the maximum slope at the inflection point (−), which occurs where $T_a = \beta$. The term tan(θ) in Equation (3) is analogous to E.

Model and multiple regression analysis performance/goodness of fit was described using the coefficient of determination, represented by the equation

$$r^2 = 1 - \frac{\sum_{i=1}^{n}(T_{\mathrm{obs},i} - T_{\mathrm{sim},i})^2}{\sum_{i=1}^{n}(T_{\mathrm{obs},i} - \overline{T_{\mathrm{obs}}})^2} \tag{4}$$

where T_{obs} (°C) and T_{sim} (°C) represent the observed and simulated stream temperature time series, and $\overline{T_{\mathrm{obs}}}$ (°C) is the mean of the observed stream temperature time series (Devore, 2000).

Site characteristics

Although the majority of site characteristics selected for the multiple regression analysis were directly extracted from other data sources, two terms, one indicative of groundwater contribution and the other of bank-side shading, were calculated specifically for this study. Baseflow index (BFI), the ratio of a stream's baseflow

to total discharge volume, was calculated from streamflow data using the web-based hydrograph analysis tool (WHAT) across the period of record used for stream temperature analysis (Lim *et al.*, 2005). Within WHAT, baseflow separation is performed using a recursive digital filter. The filtered baseflow b_t at time step t is found using the following equation

$$b_t = \frac{(1 - \mathrm{BFI}_{\max}) \times \alpha + b_{t-1} + (1 - \alpha) \times \mathrm{BFI}_{\max} \times Q_t}{1 - \alpha \times BFI_{\max}} \quad (5)$$

where b_{t-1} is the filtered baseflow at time $t - 1$ (−), $\mathrm{BFI}_{\max}$ the maximum value for the long-term ratio of baseflow to streamflow (−), α the filter parameter (−), and Q_t the total streamflow at time t (m^3/s). As suggested by Eckhardt (2005) and Lim *et al.* (2005), $\mathrm{BFI}_{\max}$ was set to 0·80 for all streams, a value determined for perennial streams in porous aquifers, and the WHAT default value of 0·98 was used for α (0·98). Equation (5) was used to filter streamflow values at a daily time step. While BFI calculated following this method does not necessarily capture the actual groundwater contributions, this approach is assumed to capture the relative differences in BFI between sites (Arnold and Allen, 1999).

Determination of the shading factor (SF) was done using land cover data extracted from the National Land Cover Database (NLCD) (Multi-Resolution Land Characteristics Consortium, 2001; Homer *et al.*, 2007). The NLCD provides 30-m cell resolution land cover for the entire United States (http://www.mrlc.gov/index.php). Land cover within the dataset is divided into 16 separate classes, 12 of which were present at the 47 water temperature sites in Pennsylvania.

The role that shading plays in stream water heat budgets is dependent on both the size of the vegetation (canopy height, density, and vegetation type) and the size of the river (Davies-Colley and Rutherford, 2005). To determine an SF, each river was characterized in terms of both the land cover nearest to the site as well as a ratio of the potential effect of vegetation relative to the river width. A shading value between 0 and 1, intended as a multiplier to scale incoming solar radiation, was assigned to each of the land cover types; a value of 1 indicates full sun (no shading) with decreasing values from 1 to 0 quantifying increasing shading. Developed, barren, or agricultural (pasture/hay or cultivated crops) land was given a shading value of 1, because land in these areas was characterized by the NLCD as having a low value (less than 15–20%) of vegetation. Deciduous and mixed forest cells were given a shading value of 0·75, because leaf cover is only present seasonally and cells were characterized as having between 20 and 100% of the area forested. Wetlands (woody and emergent herbaceous) were given shading values of 0·5, as vegetation included within their coverage had a range of sizes, and may not always provide effective stream shading.

To determine a threshold by which to group rivers into those that would or would not be affected by vegetative shading, the width of each river was divided by 10 m, representative of an average tree height. Google Earth was used to approximate the width of each river using the imagery and latitude and longitude locations for each site. A ratio of less than 3 for river width to average vegetation height was selected as a threshold for vegetation to influence shading over the river channel. For sites with a ratio of less than 3, the land use values for the cell that the site was in as well as the eight surrounding cells were all recorded. For larger rivers where a water cell was recorded by the land cover raster at the site, the four closest cells from the land cover raster along both the left and right bank were used. The SF was then determined using a weighted average of shading values for the recorded cells. For sites with a ratio of river width to average vegetation height >3, shading was assumed to have a minimal effect and the SF was set to 1.

Multiple regression analysis of controls on thermal sensitivity

Following the determination of linear and nonlinear relationships, thermal sensitivity and site characteristics were related using multiple linear regression analysis, to both understand the controls on the nature of stream temperature sensitivity and to enable the regionalization of sensitivity values. We identified several potential variables that would be expected to control stream temperature (Table I), including those previously identified as important controls: groundwater contribution (O'Driscoll and DeWalle, 2006), river discharge (Webb *et al.*, 2003), river size (Poole and Berman, 2001), wind sheltering (Bogan *et al.*, 2003), riparian vegetation cover and shading (Johnson, 2004), and input of solar radiation (Caissie, 2006). A total of nine site characteristics were included in the multiple regression in this study.

Before performing the multiple regression analysis, we considered the relationships among site characteristics. Relations among all sites, excluding outliers, are highest between river flow (Q) and contributing DA ($r^2 = 0{\cdot}95$), SO and DA ($r^2 = 0{\cdot}35$), SO and Q ($r^2 = 0{\cdot}27$) and solar radiation and latitude ($r^2 = 0{\cdot}25$). All other relations

Table I. Site characteristics selected for multiple regression analysis, with reference dimensions and associated ranges

Variables	Dimensions	Units	Range	Description
w	L	m	3·4–192	River width
ρ	ML^{-3}	kg/m^3	1000	Water density (constant)
Rad	MT^{-3}	kg/s^3	146–162	Average annual solar radiation
v	MT^{-1}	m/s	0·04–1·01	River velocity
BFI	—	—	0–1	Baseflow index
SO	—	—	1–8	Strahler stream order
SF	—	—	0–1	Shading factor
Elev	L	m	1–604	Site elevation
Q	L^3T^{-1}	m^3/s	0·15–431	River discharge
DA	L^2	m^2	9–17560	Drainage area
Lat	D	°	39.76–42.00	Site latitude
Lon	D	°	−79.97–74.78	Site longitude

between site factors are below r^2 values of 0·2. Among sites with velocity and stream geometry measurements, flow, DA, and stream width are all related, with r^2 values between 0·89 and 0·92. Relations between SO and measures of stream size [Q, DA, width (w), depth (d), average velocity (v)] are between r^2 values of 0·26 and 0·48. Depth is also slightly related to Q, DA, and velocity (r^2 of 0·34, 0·22, and 0·22) and latitude somewhat related to radiation (r^2 of 0·31). All other r^2 values between factors were below 0·20.

We identified controls on thermal sensitivity from the site characteristics at the state scale and the basin scale using forward selection stepwise regression. Site characteristics with $p < 0{\cdot}05$ were deemed significant. We have also included the standard error of each of the multiple regression equations (Devore, 2000).

RESULTS

The r^2 values between the observed and predicted water temperature ranged from 0·09 to 0·93 when analysing the linear relationship between air and water temperatures at 57 Pennsylvania sites at a daily time step (Figure 4). Two of the 57 sites had $r^2 < 0{\cdot}6$ and 15 sites had $r^2 > 0{\cdot}9$. For the majority of rivers at or above a Strahler SO of 3, linear regressions between daily air and water temperature records show that air temperature accounts for between 60 and 95% of the variation in water temperatures.

The r^2 values for weekly air and water temperatures ranged from 0·09 to 0·98, with values greater than 0·9 at 36 of the 57 sites (Figure 4). Across all sites, r^2 improved by an average of 0·08 and thermal sensitivity (E) increased by an average of 0·05 going from the daily to the weekly time scale. Analysis of weekly and daily data indicates that thermal sensitivity generally increases with river size. Although some studies argue that introducing a lag for daily stream temperature values in the linear regression improves fit (Stefan and Preud'homme, 1993), this was not the case for the 57 streams in Pennsylvania. Lags between 1 and 7 days were applied to test improvements in r^2, but only four rivers showed an average improvement of 0·03, which was not considered significant.

The same 57 sites were analysed using nonlinear regressions between air and water temperatures. At a daily time step, r^2 values ranged from 0·13 to 0·93, with 18 of 57 sites (32%) having $r^2 > 0{\cdot}9$ (Figure 5). At a weekly time step, r^2 values ranged from 0·13 to 0·98, and 40 of 57 sites (70%) have $r^2 > 0{\cdot}9$. Increasing the time scale from daily to weekly values improved the r^2 value by 0·06 on average. For the 57 sites, the maximum and minimum values of α were 35·49 and 11·73 at a daily time scale.

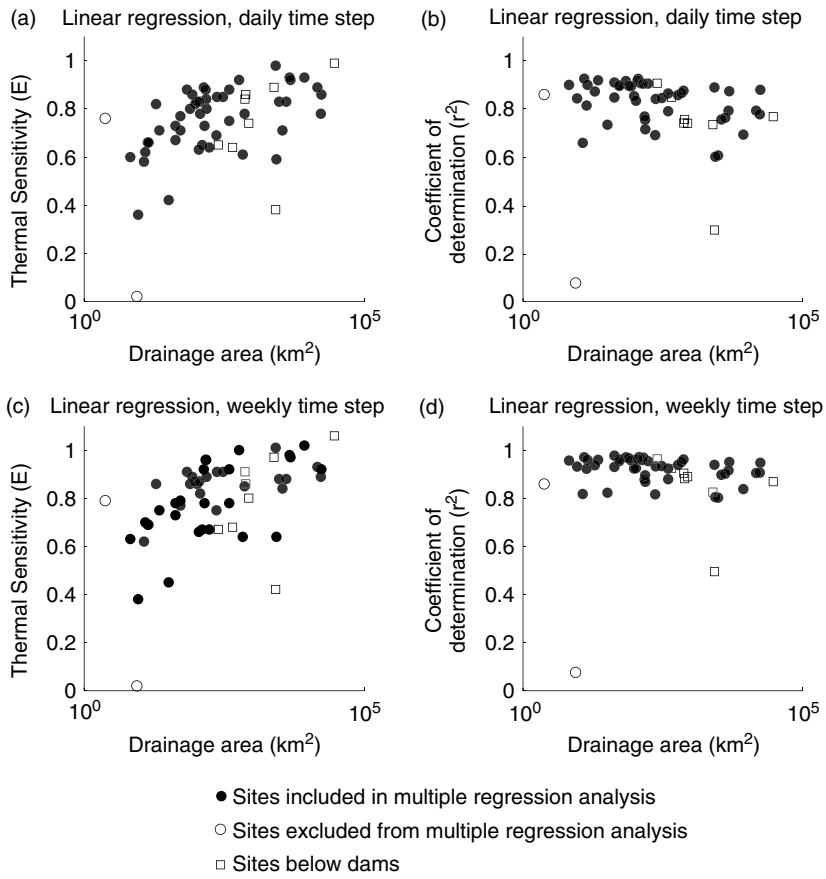

Figure 4. Results for (a) thermal sensitivity, (b) r^2 values for all daily regressions, (c) thermal sensitivity, and (d) r^2 values for all weekly regressions between air and water temperature. Both plots show the contributing DA at each site (square kilometers). Sites included and excluded from the multiple regression analysis are indicated by shape, as well as sites below dams

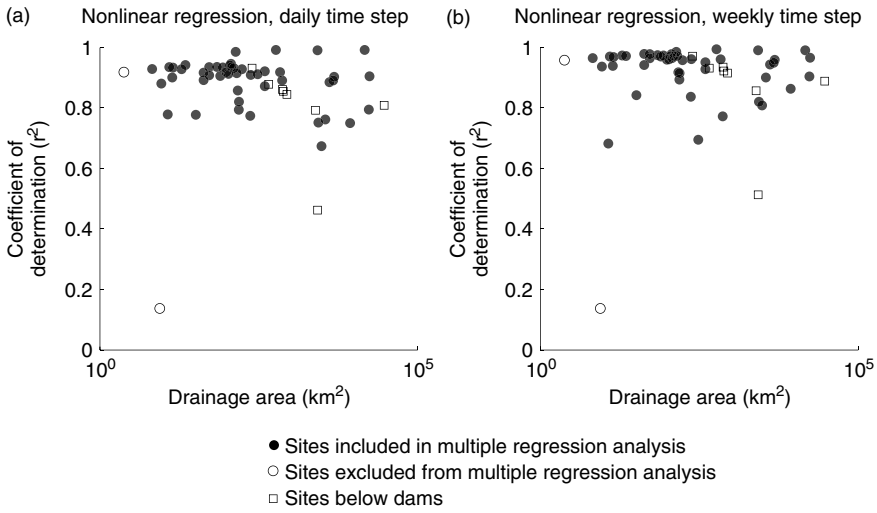

Figure 5. Goodness of fit (r^2) for (a) daily and (b) weekly nonlinear regressions plotted *versus* the DA at each site. Shape indicates sites included and excluded from the multiple regression analysis, as well as sites below dams

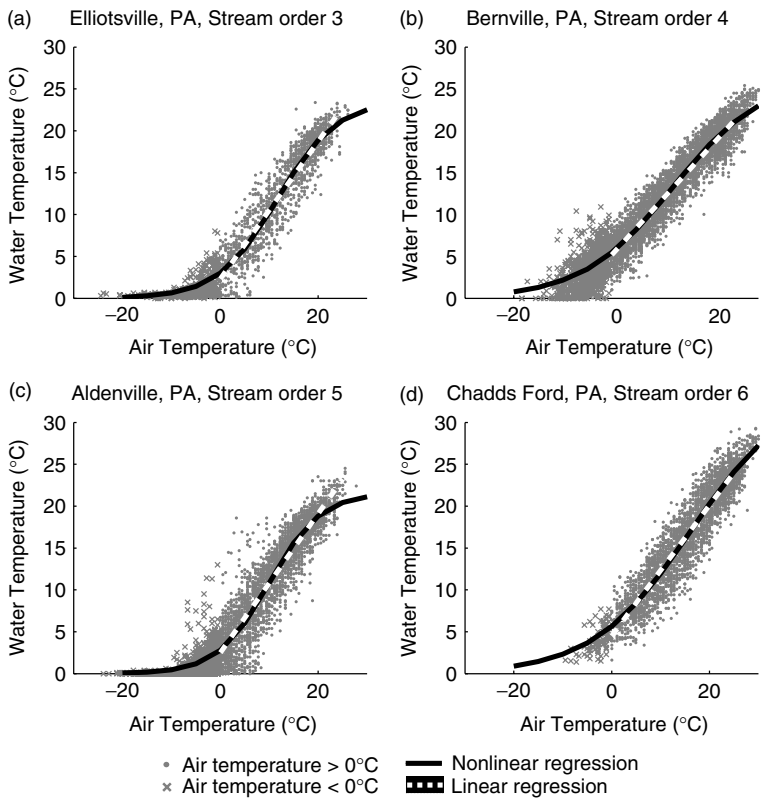

Figure 6. Performance of linear and nonlinear models compared to observed air temperatures and water temperatures for (a) Elliottsville, PA, (b) Bernville, PA, (c) Aldenville, PA, and (d) Chadds Ford, PA

Comparing linear to nonlinear regressions, 92 and 65% of sites had improved r^2 values for nonlinear regression at daily and weekly time scales, respectively. The distance to air temperature measurement sites did not appear to affect the prediction of water temperatures from air temperatures as the r^2 value for all regressions, even at large distances between air temperature and water temperature sites, remained close to 1. As can be seen in Figure 6, the nonlinear and linear models match between approximate air temperatures of 5 and 20 °C.

Within the 57 Pennsylvania sites, there were three sites where air temperature explained very little of the variation in water temperature. Two cases occur along the Youghiogheny River, a sixth-order stream. At Confluence, PA, USA, located 2·25 miles downstream of the Youghiogheny Dam, daily and weekly thermal sensitivity values were 0·38 and 0·42. Values of r^2 ranged from 0·31 to 0·50 for daily and weekly linear and nonlinear fits. At Ohiopyle, PA, USA, 11 miles downstream of the same dam, r^2 values ranged from 0·62 to 0·81 for daily and

weekly linear and nonlinear regressions. The daily and weekly thermal sensitivities for this site were 0·59 and 0·64. These sites were excluded from the multiple regression analysis because, in both cases, the sensitivity value was small relative to the size of the river, indicating that the reservoir was acting as an upstream control on thermal sensitivity. Although these sites were excluded from the multiple regression analysis, other dam-impacted sites were included because the presence of the dam did not significantly affect sensitivity or r^2 values.

Big Spring Creek at Big Spring, PA, USA, a site where groundwater was the primary control on thermal sensitivity (BFI = 0·79), was also excluded from the analysis. Thermal sensitivity was 0·02 for both daily and weekly time steps and r^2 values ranged from 0·08 to 0·14 for linear and nonlinear regressions. Stony Fork Tributary at Gibbon Glade, PA, USA, a very small stream, was also excluded from the analysis because it is not a perennial stream. Linear fits had r^2 values of 0·86 and 0·93 for daily and weekly values, and nonlinear fits showed r^2 values of 0·92 and 0·96 for daily and weekly values.

Thermal sensitivity E varied between 0·02, analogous to a low sensitivity, and 0·93, analogous to a high sensitivity, for daily values across the 57 stream temperature sites. The nonlinear regression factor $\tan(\theta)$, a measure of maximum slope, is directly analogous to E, with r^2 between E and $\tan(\theta)$ equal to 0·83 and between E and θ equal to 0·92. Figure 7 characterizes the thermal sensitivities across all sites as a function of stream size (represented by SO), and groups the streams into four broad categories of controls. The figure highlights the differences in thermal sensitivity between small and large streams, and the influences of baseflow contribution and dam water releases. The ephemeral stream, noted on the figure, has a very high thermal sensitivity relative to its size as a result of its very low streamflow, which will be easily heated during summer. In contrast, the sites below dams have very low sensitivities relative to their sizes, as a function of low summer stream temperatures. Variation in thermal sensitivities in small streams is attributed to differences in riparian shading and exposure, streamflow, urbanization (heated runoff), and weather. Small streams (SO $\leq$ 3) with high groundwater contributions have low thermal sensitivities, as streams are kept cool during summer by groundwater influx. As is shown in Figure 8(a), baseflow contribution is inversely related to thermal sensitivity in smaller streams, whereas Figure 8(b) shows that baseflow contribution does not appear to influence thermal sensitivity in large streams. Large streams (SO $\geq$ 4) have higher ($E > 0{\cdot}6$) thermal sensitivities, resulting from heat accumulation through the stream network.

Thermal sensitivities in the Delaware Basin ranged from 0·58 to 0·93. Smaller streams (SO $\leq$3, $n = 6$) had an average thermal sensitivity of 0·70, and larger streams (SO $\geq$4, $n = 23$) had an average thermal sensitivity of 0·79. The Delaware Basin unfortunately included many more sites in larger streams than in smaller streams. Sites in the Susquehanna Basin had thermal sensitivity values ranging from 0·02 to 0·94. Averaged thermal sensitivity

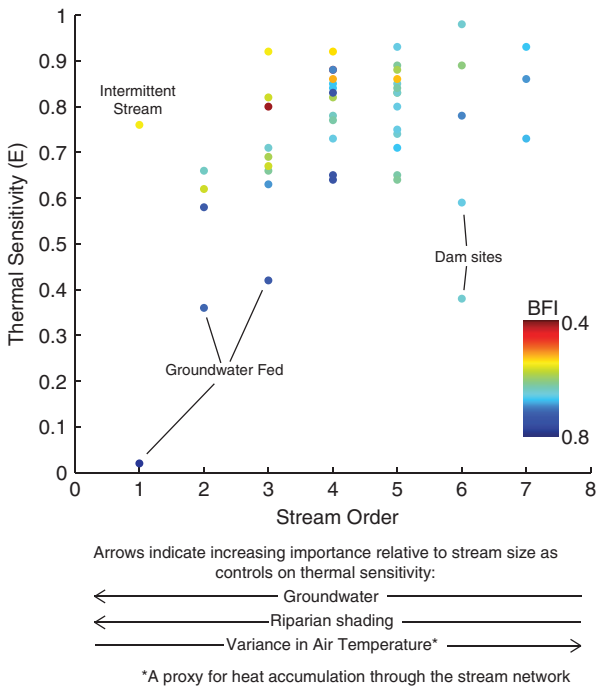

Figure 7. SO *versus* thermal sensitivity, across 57 Pennsylvania streams. Colour highlights baseflow contribution, in terms of BFI. Sites where thermal sensitivity is influenced by a unique site condition are noted on the figure. General controls on thermal sensitivity and their influence relative to stream size are conceptualized at the bottom of the figure

in small streams ($n = 9$) was 0·52 and in large streams ($n = 11$) was 0·83.

Linear and nonlinear regressions provide a first-order estimate of the extent to which atmospheric exchange (e.g. air temperature) controls stream temperature, but do not explain how strongly individual site characteristics modulate this relationship. To predict at sites without water temperature sensors, multiple regression analysis was performed for several site characteristics. Excluding sites without a nearby flow gage, 47 locations were retained for analysis. The best relationship identified across all sites is

$$E = 1{\cdot}044 + 0{\cdot}0549 \times \mathrm{SO} - 0{\cdot}812 \times \mathrm{BFI} \qquad (6)$$

with SO and BFI accounting for 43% of the variance in thermal sensitivity ($R^2 = 0{\cdot}43$). The best-fit relationship (Figure 9) suggests that prediction at the river basin scale may reveal different relationships between site characteristics and thermal sensitivity. Table II shows best-fit relationships for the multiple regression analysis.

To better understand the differences between river basins, sites were separated for analysis. This resulted in a very strong relationship between site characteristics and thermal sensitivity in the Susquehanna Basin, with an R^2 value of 0·65. The best relationship across these sites is

$$E = 0{\cdot}834 + 0{\cdot}0826 \times \mathrm{SO} - 0{\cdot}666 \times \mathrm{BFI} \qquad (7)$$

(Figure 10(a)). SO controlled 59% of the variance for Susquehanna sites, suggesting that there is a difference

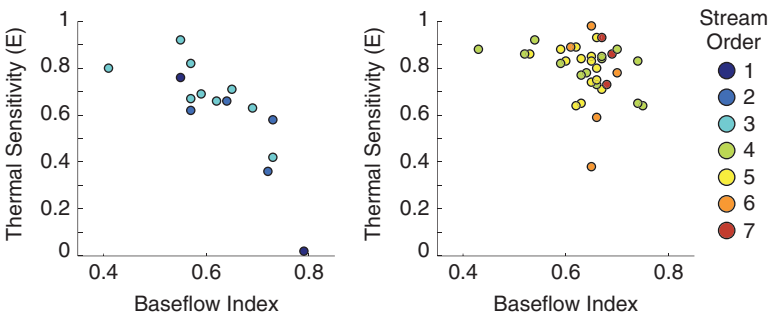

Figure 8. Relative influence of BFI on thermal sensitivity in small streams (first through third Strahler order) and in large streams (fourth through seventh order). Colour represents SO

Table II. Best fits, regression slopes, and constants for the relationships for all sites predicted by multiple regression analysis ($p < 0{\cdot}01$)

Prediction area	R^2	k_1	Term	k_2	Term	c	n	SE
All sites	0·43	0·0549	SO	−0·812	BFI	1·044	47	0·0995
Susquehanna	0·65	0·0826	SO	−0·666	BFI	0·834	17	0·0976
Delaware	0·44	0·1970	Lon	−0·008	Rad	16·96	25	0·0780

Values k_1 and k_2 are regression slopes for each term, and c is the intercept of the least squares fit between site characteristics and thermal sensitivity. Sample size (n) and estimated standard error (SE) are noted for each relationship.

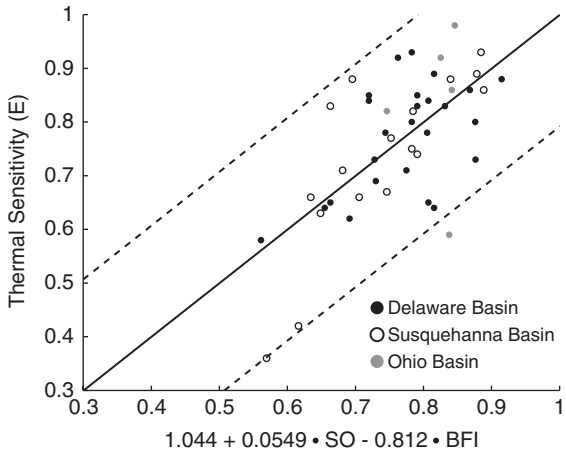

Figure 9. Scatter plot between multiple regression predictions and thermal sensitivity (E). Each point represents one of the 47 sites included in the analysis. The solid line indicates the best-fit relationship, and the dashed lines represent the 95% prediction intervals. Marker shading differentiates the three major river basins in Pennsylvania

in how these controls work across the three river basins and in what controls need consideration. The Ohio River Basin only included four sites, and was not approximated using multiple regression analysis.

Identifying a relationship within the Delaware Basin was met with mixed success. Longitude and average annual solar radiation (Rad) were found to be statistically significant predictors for sensitivity, producing the following relationship

$$E = 16{\cdot}960 + 0{\cdot}197 \times \text{Lon} - 0{\cdot}0082 \times \text{Rad} \qquad (8)$$

with an R^2 value of 0·44 (Figure 10(b)). This result indicates some sort of spatial bias to sites across the Delaware Basin, which is highly urbanized and seems not well represented by the site characteristics included within the analysis.

Application of the three equations across Pennsylvania is limited to stream sites with SOs between 2 and 7, and BFI values between 0·40 and 0·80. No stream sites above an SO of 5 had BFI values below 0·5. In addition, Susquehanna Basin sites had lower BFI variability (between 0·5 and 0·75) than sites in the Delaware and Ohio Basins.

DISCUSSION

How well air temperature predicts water temperature is dependent on the time over which the measurements are averaged, the type of regression model used, and the physical characteristics of the site itself. For a comparison of the two types of regression models, weekly regression exceeds fits for daily values. This is reflected by the relative scatter associated with daily water and air temperatures; averaging daily values to a weekly time step typically filters out noise in the data, leading to decreased scatter. This improvement is similarly corroborated by other studies that have compared both linear and nonlinear regression at multiple time scales (Crisp and Howson, 1982; Stefan and Preud'homme, 1993; Pilgrim *et al.*, 1998, Morrill *et al.*, 2005).

Regression slopes were slightly lower than those found by previous studies in other regions. Typically, slopes averaged across all sites were found to be near 1 for weekly values (Crisp and Howson, 1982; Stefan and Preud'homme, 1993). Exceptions with lower slope values in other studies were due to the upstream influence of reservoirs or impoundments (Erickson and Stefan, 2000; Morrill *et al.*, 2005) or at locations with high groundwater

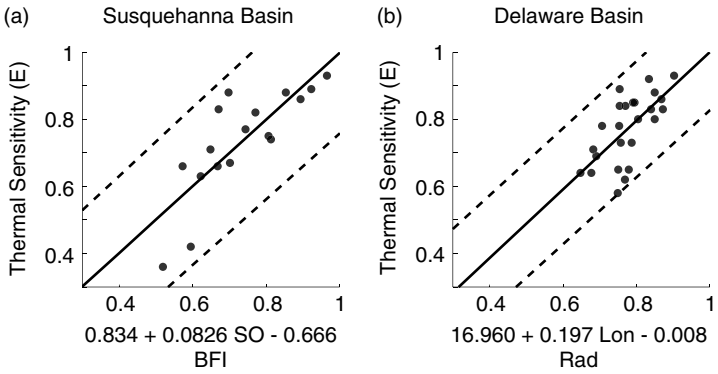

Figure 10. Scatter plots between multiple regression predictions and thermal sensitivity (E) for sites within the (a) Susquehanna Basin and (b) Delaware Basin. The solid line indicates the best-fit relationship and the dashed lines represent the 95% prediction intervals

input (O'Driscoll and DeWalle, 2006). Water released downstream of reservoirs may be colder, if it is drawn from the reservoir bottom, or warmer, if taken from the top. Morrill *et al.* (2005) also found lower slope values at high elevation sites (>1000 m), an effect that was not explained by the authors nor seen for the sites included in this study.

For the 57 Pennsylvania sites considered within this analysis, lower slope values for the linear regression were attributed to controls similar to those suggested by other studies. Low slopes, expected below dams, were especially pronounced for two sites along the Youghiogheny River, although not all sites below dams had low slope values. The influence of groundwater was also apparent for a site along Big Spring Creek, where low flows and high groundwater inputs maintained relatively little annual variation (about 3 °C). The site is within a watershed characterized by O'Driscoll and DeWalle (2006) as being underlain by carbonate geology, and therefore having a high level of connectivity with groundwater. O'Driscoll and DeWalle (2006) found the same lack of variability for sites in this region, with thermal sensitivity values of only 0·19 at some sites.

Nonlinear models performed better than linear regression models in terms of r^2 for the majority of the 57 Pennsylvania sites at daily and weekly time scales. This finding is consistent with other studies that have compared linear and nonlinear performance (Morrill *et al.*, 2005). While the nonlinear relationship improves the approximation of the relationship between water and air temperatures, it under-predicts maximum water temperatures for a number of sites by a significant amount. For 62% of the sites, the maximum water temperature on record was greater than α, the nonlinear regression term that represents an estimated maximum water temperature, by an average of 0·1 °C. In addition, 40 of 47 sites had maximum recorded water temperature values within ±1 °C of α.

Tying thermal sensitivity E directly to site characteristics via multiple regression analysis allows its prediction at sites without instrumentation and the identification of site characteristics that influence stream temperature across spatial scales. Initial investigation of controlling site characteristics identified SO and BFI as controls. For smaller rivers, the presence of other buffers at a site reduces correlations with air temperature, resulting in lower thermal sensitivity values. BFI, a measure of groundwater contribution, was expected to buffer atmospheric effects in small streams, thus reducing correlation with air temperature and decreasing for increasing thermal sensitivity. BFI can also be predicted for unmonitored streamflow locations, such that streamflow measurements are not required for regionalization by this approach (Santhi *et al.*, 2008). Thermal sensitivity was expected to increase with increasing SO, as a function of accumulated heat via exchange at the air–water interface throughout the stream network. This results in a higher degree of correlation with air temperature, and thus a higher sensitivity.

State-wide goodness of fit was low between controls and thermal sensitivity, but basin-wide predictions had slightly improved fits for relationships between sensitivity values and site characteristics. The sites within the Susquehanna River basin were well predicted ($r^2 = 0{\cdot}65$) from the same two terms, SO and BFI, identified as statistically significant predictors across all sites. Variability in intercepts and weights for multiple regression models predicted across all sites and for Susquehanna sites are probably a result of decreased land cover variability moving from state-wide to basin-wide sites, as the Susquehanna is highly forested.

The Delaware River Basin sensitivity values were best predicted by average annual solar radiation (Rad) and longitude (Lon). Although Rad is still a significant control, variance in thermal sensitivity is primarily influenced by Lon. This control approximates an increase in thermal sensitivity from the western to the eastern part of the basin, which could be caused by the drainage pattern in the basin towards the Delaware River, which is large and exposed and subsequently characterized by high thermal sensitivity values, bounding the basin to the East. It may also be reflecting increasing urbanization, which occurs towards Philadelphia in the southeastern portion of the basin, or changing geologies not captured by our streamflow-based BFI. Unexplained variance within the Delaware Basin is attributed to weaker controls

on this region due to urbanization and land cover variability. Within urbanized areas, heat exchange processes and buffers are altered, thereby leading to controls not considered within this study. Thermal sensitivity in this region may be influenced by heated water inputs from thermoelectric plants, which constitute the majority of water use in the basin, or from wastewater treatment plants (Delaware River Basin Commission, 2008). Depending on the time of year that the majority of heat inputs are released to the stream, releases have the potential to either increase or decrease thermal sensitivity, for summer or winter releases, respectively. Stream temperatures may also be influenced by heated runoff from impervious surfaces during summer, which would increase thermal sensitivity. Further work should consider what controls might be included to explain thermal sensitivity for sites in these locations and should investigate the relative locations of stream sites and thermoelectric or wastewater treatment plants.

Equations (6)–(8) are limited in applicability to the ranges of values available within the analysis. The equations should not be used for larger river sites (SO > 5) or those with low BFI values ($<0{\cdot}5$), which all three equations predict to have very high (>1) thermal sensitivity values. The analysis is limited by the lack of availability of water temperature measurements, and the lack of flow measurements at water temperature measurement locations.

Several differences between the Susquehanna Basin and Delaware Basin may also lead to varying controls across the sites. Within the forested Susquehanna Basin, primary controls on thermal sensitivity were much stronger than in the Delaware Basin. The Delaware Basin is much more variable in land cover and geology than the Susquehanna Basin, which may account for the larger amount of unexplained variance in the Delaware. The Delaware Basin also included many more large streams than small streams, whereas the Susquehanna Basin featured a more even distribution of stream sites across river size. Finally, the second- and third-order streams in the Delaware Basin were all in highly urbanized locations, which resulted in high thermal sensitivities across these sites. Thermal sensitivities in smaller streams in the Susquehanna Basin were much lower, which indicates that smaller streams in the Delaware Basin may be more sensitive to change than smaller streams in the Susquehanna Basin. Other sources of unexplained variance in the models may be due to differences in stream orientation and upstream shading, both of which would impact stream thermal signatures.

Overall, the relationships that have emerged indicate that stream temperature sensitivity in the short term can be predicted by a combination of simply calculated or measured site factors. Although terms involving river geometry and discharge measurements were introduced, the controls across a majority of sites were found to be primarily functions of SO and BFI. Thus, controls on stream temperature sensitivity in Pennsylvania are related more generally to river size and groundwater contribution. The controls were shown to corroborate results of previous studies, with groundwater contribution, shading, and stream size representing large influences on thermal sensitivity. For all river basins, changes to BFI are also important considerations for mediating thermal sensitivity. Reducing impervious watershed area, which helps improve recharge, may help to maintain baseflow and hence reduce stream temperatures.

CONCLUSIONS

Stream temperature sensitivity provides a first-order estimate of the relationship between air and stream temperature, which can be used to understand and quantify the sensitivity of a stream site to future climate change. Thermal sensitivity in smaller streams was found to be reduced at sites with high groundwater contributions, and to be near one for ephemeral or exposed stream sites. For larger streams, thermal sensitivity was related to stream size, as a function of upstream heating through the rest of the stream network. These controls were corroborated via multiple regression analysis at the state level and in the Susquehanna Basin. Although the empirical analysis performed here indicates that shading is not a control on thermal sensitivity, the presence of riparian vegetation can still significantly reduce the amount of solar radiation reaching the stream surface, and thereby buffer stream temperature.

Poor predictive capability of thermal sensitivity was observed for highly urbanized basins, where the characteristics considered in the multiple regression analysis did not seem to fully encompass controls at the sites. Results did indicate although that smaller streams in urban settings exhibit higher values of thermal sensitivity, than smaller streams in rural or forested settings. As a result, urban streams may not be able to support sensitive aquatic species during warmer parts of the year.

Methods to predict water temperature and to identify controls on stream warming are needed to understand the potential impacts that climate change will have on habitat availability for aquatic species in river networks. The definition of thermal sensitivity E used in this study and the methodology used to tie it to generally available site characteristics enables regionalization of E at sites with stream gauges that lack water temperature measurements. It also provides insights into the controls on the nature of stream temperature across large river basins, which encompass a range of land uses, geologic, and topographic settings. Quantifying the controls of the relationship between stream and air temperature is a step towards understanding how thermal habitat can be improved to ensure the survival of sensitive aquatic species.

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