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Short-term stream water temperature observations permit rapid assessment of potential climate change impacts

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Abstract:

Assessment of potential climate change impacts on stream water temperature (T_s) across large scales remains challenging for resource managers because energy exchange processes between the atmosphere and the stream environment are complex and uncertain, and few long-term datasets are available to evaluate changes over time. In this study, we demonstrate how simple monthly linear regression models based on short-term historical T_s observations and readily available interpolated air temperature (T_a) estimates can be used for rapid assessment of historical and future changes in T_s. Models were developed for 61 sites in the southeastern USA using ≥18 months of observations and were validated at sites with longer periods of record. The T_s models were then used to estimate temporal changes in T_s at each site using both historical estimates and future T_a projections. Results suggested that the linear regression models adequately explained the variability in T_s across sites, and the relationships between T_s and T_a remained consistent over 37 years. We estimated that most sites had increases in historical annual mean T_s between 1961 and 2010 (mean of +0.11 °C decade^{-1}). All 61 sites were projected to experience increases in T_s from 2011 to 2060 under the three climate projections evaluated (mean of +0.41 °C decade^{-1}). Several of the sites with the largest historical and future T_s changes were located in ecoregions home to temperature-sensitive fish species. This methodology can be used by resource managers for rapid assessment of potential climate change impacts on stream water temperature. Copyright © 2014 John Wiley & Sons, Ltd.

KEY WORDS stream temperature; climate variability/change; water quality; aquatic ecology; modelling; adaptation

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INTRODUCTION

Stream water temperature (T_s) is a critical water quality parameter that affects the chemical, biological, and ecological processes and functions of watersheds (Caissie, 2006). In turn, stream water temperature influences the growth and distribution of aquatic organisms (Mohseni *et al*., 2003). Concern has focused on how climate change might affect stream temperatures and the ecosystem services streams provide (Mohseni *et al*., 1999; Webb *et al*., 2008). Warming stream water temperature is of particular concern for coldwater fish species such as Eastern Brook Trout (*Salvelinus fontinalis*) found in the southern Appalachians of the Southeastern USA. Unfortunately, it is difficult to broadly isolate and assess the impact of climate change on T_s because (1) few long-term regional T_s data exist (Arismendi *et al*., 2012), (2) human activities and other disturbances in the watershed can influence T_s and (3) relationships between T_s and climate are site specific (Caissie, 2006). For example, factors such as total stream flow, the relative groundwater contribution to flow (Matthews and Berg, 1997; Poole and Berman, 2001; Bogan *et al*., 2003; Webb *et al*., 2008), canopy cover over the stream and riparian area (Studinski *et al*., 2012), runoff from impervious surfaces (Nelson and Palmer, 2007), thermal discharges (Webb and Nobilis, 2007) and reservoir releases (Webb and Walling, 1993) can have a significant influence the relationship between climate and T_s.

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Detecting changes in T_s in response to climate change or other factors can be accomplished by performing trend analyses for those sites with a sufficiently long period of T_s observations (e.g. Kaushal *et al*., 2010; Arismendi *et al*., 2012) or developing T_s models and analysing predictions and model parameters. Modelled T_s is most often used to assess climate or anthropogenic impacts due to the lack of long-term observations.

Stream water temperature models fall into three categories: regression, stochastic and deterministic models (Caissie, 2006). Deterministic models (e.g. Theurer *et al*., 1984; Sinokrot and Stefan, 1993; Younus *et al*., 2000) are amongst the more complex approaches and include all of the meteorological processes involved in calculating the heat energy balance. Regression and stochastic models typically use air temperature (T_a) as a surrogate for changes in the energy budget to compute T_s as a function of air temperature (T_a). The use of T_a to predict T_s does not imply that there is a causal relationship between T_s and T_a, rather, that correlation between T_s and T_a is useful for inferring potential changes in T_s under climate change scenarios (Johnson, 2003). Regression models may calculate T_s by a simple linear regression with T_a (e.g. Stefan and Preud'homme 1993; Pilgrim *et al*., 1998; Webb *et al*., 2003; Morrill *et al*., 2005; O'Driscoll and Dewalle, 2006), a logistic regression with T_a (e.g. Mohseni *et al*., 1999; Morrill *et al*., 2005; O'Driscoll and Dewalle, 2006; Webb *et al*., 2003) or multiple regression with T_a and other basin characteristics such as drainage area and discharge (e.g. Webb *et al*., 2003; Mayer 2012). Logistic regression models are often preferred over linear models at the weekly scale because non-linearities in the T_s and T_a relationship have been observed at the low and high ends of the T_a range for some sites (Mohseni and Stefan, 1999). However, linear models have been found to reasonably predict monthly T_s and are often used for climate change assessments at this timestep (Caissie, 2006).

The type of model used to predict T_s depends on the research question and the availability of input data. Deterministic models are best suited for daily estimates of T_s under climate change scenarios, or to interpret causal factors, but are more complex and difficult to apply at large scales due to a lack of information for model parameterization and required meteorological inputs (Caissie, 2006). Regression models require fewer inputs and are well suited for providing weekly and monthly T_s estimates but assume that historical–correlational relationships between T_s and T_a will hold under future climate regimes. Daily T_s projections are often desired by aquatic biologists and water resource managers because high extremes in T_s are viewed as critical for organisms and because lethal limits of T_s are known (e.g. Meisner 1990; Matthews and Berg 1997). However, few T_a projections from General Circulation Models (GCMs) are readily available at the daily scale and if daily T_a projections are available or estimated on the basis of historical observations, the uncertainty associated with projection of daily T_a into the future is significant especially for extremes in daily T_a (Räisänen and Räty, 2012). On the other hand, monthly bias corrected T_a projections from the Intergovernmental Panel on Climate Change (IPCC) GCM and Special Report on Emission Scenarios (SRES) emission scenarios are readily available through the World Climate Research Programme's Coupled Model Intercomparison Project phase 3 (CMIP3) Climate Projections website (Maurer et al. 2007; Meehl *et al*. 2007).

Although monthly models may not always be useful for linking with finer-scale aquatic ecosystem responses, they are useful for rapid assessment of potential climate change impacts on T_s at larger spatial scales. For example, simple linear regression models that relate T_s to readily available interpolated T_a estimates (e.g. PRISM or DayMet) permit a rapid assessment of potential climate change impacts. We used the southeastern USA as a case study to demonstrate that monthly linear T_a and T_s relationships can easily be developed and applied for climate change assessment using short-term (e.g. 20 months) T_s records and readily available and downloadable T_a estimates. Although several regional assessments of potential climate change impacts on T_s have been conducted in the Pacific Northwest (e.g. Arismendi *et al*., 2012; Mayer, 2012; Ficklin *et al*., 2013), the Southeastern USA has been largely unstudied. Specifically, we aim to demonstrate that monthly linear T_s models (1) reasonably predict T_s observations across large gradients in climate and watershed characteristics compared with less parsimonious logistical regression approaches, (2) remain valid and have acceptable predictive performance over longer (e.g. 30 years) periods of record and (3) can be used for rapid assessment of historical and future changes in T_s.

METHODS

T_s databases

The T_s data used in this study were obtained from two sources. The first included 57 United States Geological Survey (USGS) T_s sites in the Southeastern USA selected from the Hydro-Climatic Data Network (HCDN) (Slack *et al*., 1993). The HCDN gauges are located downstream of watersheds with limited anthropogenic hydrologic alteration such as dams, diversions and significant withdrawals or effluent and thus are likely less affected by flow alterations that may influence the relationship between T_a and T_s. However, land cover in watersheds of the HCDN gauges is not necessarily representative of undisturbed conditions.

The second T_s dataset consisted of measurements from four United States Forest Service (USFS) experimental control watersheds in the United States Environmental Protection Agency (EPA) Level II ecoregions Appalachian Forest and Southeastern Plains in North Carolina (Commission for Environmental Cooperation Working Group, 1997). These sites were included in this study to fill the gap in the USGS database for smaller catchments. The two Appalachian Forest sites are control watersheds WS02 and WS18 at the US Forest Service Coweeta Hydrologic Laboratory located in Otto, NC, USA. Both watersheds were approximately 0.12 km^2 in size. The two Southeastern Plains sites are watersheds HFW1 and UF2 that were approximately 0.29 km^2 in size and located in the North Carolina piedmont near Raleigh, NC, USA (Boggs *et al.*, 2013).

The resulting database included 61 sites distributed across the Southeast region with drainage areas ranging from 0.12 to 44,548 km^2 (Figure 1 and Table I). Segura *et al.*, 2014 demonstrated that approximately 20 months of T_s observations were sufficient to establish the relationship between T_s and T_a at monthly scale by examining the variation in the best fitted slope of the linear regression between T_s and T_a and the corresponding R^2 with varying sample sizes for several sites across the conterminous USA. In this study, sites were selected such that at least 18 monthly T_s measurements were available between years 1960 and 2012 to allow for a larger sample sites while still retaining the approximate number of observations required to develop the T_s models. Daily average T_s were used to compute monthly average T_s for development of the T_a and T_s models. A minimum of 20 days of T_s observations in each month were used to compute a monthly average T_s. Months with less than 20 daily T_s observations in that month were not included. For the USGS HCDN sites, T_s observations are reported as a daily average, daily maximum, daily minimum and/or an instantaneous observation. Where daily average T_s was not reported but daily maximum and minimum T_s were reported, the average of the daily maximum and minimum T_s was used to approximate the daily average. No instantaneous T_s observations were used.

T_a databases

The historical and future T_a data used in this study were obtained from readily available gridded climate datasets. For both historical and future T_a, the nearest climate grid point of each T_s site was used to represent T_a for each site. The 4 × 4 km resolution, historical monthly weather data available from the PRISM Climate Group (www.prismclimate.org) were used to fit the T_s model for each site over their respective period of record and as model input for historical T_s trend analysis. The PRISM T_a estimates were computed using the Precipitation Elevation Regression on Independent Slopes Model (Daly *et al.*, 1994).

For future projections of T_s, 12 × 12 km downscaled and bias corrected monthly T_a projections from 2011–2060 were downloaded from the World Climate Research Programme's CMIP3 Climate Projections website (Maurer *et al.* 2007; Meehl *et al.* 2007). IPCC AR4

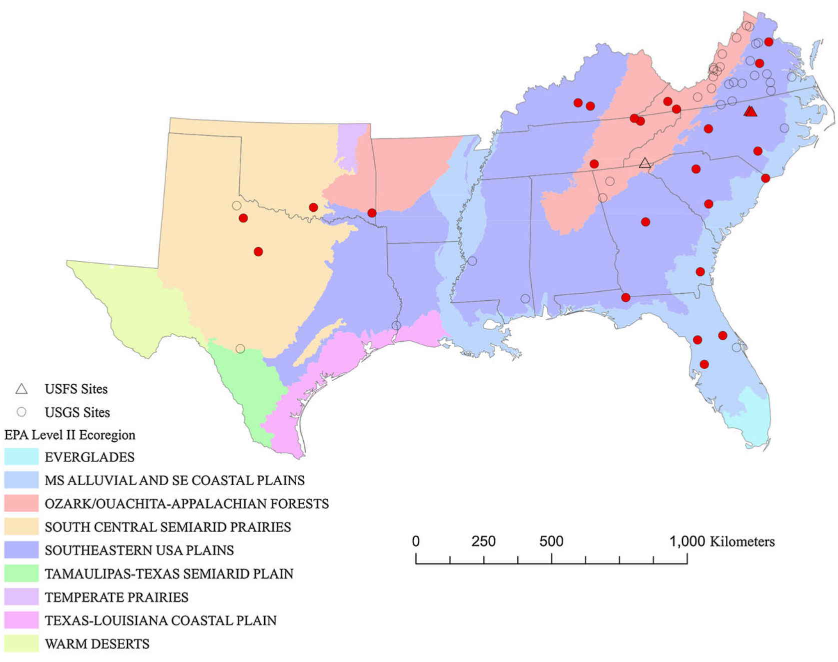

Figure 1. Stream temperature sites evaluated in this study. Sites in red were used to validate linear T_s models developed based on 20 months of observations over longer periods of record

Table I. Summary of site characteristics

Site ID	Description	EPA level II ecoregion	Drainage area (km^2)	Observed t_s period of record	Months of record/total possible
01631000	SF Shenandoah River at Front Royal, VA	Ozark/Ouachita-Appalachian Forests	4232	3/2007–9/2008	18/19
01632000	NF Shenandoah River at Cootes Store, VA	Ozark/Ouachita-Appalachian Forests	544	3/2007–3/2009	25/25
01634000	NF Shenandoah River Near Strasburg, VA	Ozark/Ouachita-Appalachian Forests	1994	2/2006–8/2008	30/31
01666500	Robinson River Near Locust Dale, VA	Southeastern Plains	464	10/2006–9/2008	24/24
01667500	Rapidan River Near Culpeper, VA	Southeastern Plains	1212	10/2006–9/2008	20/24
01668000	Rappahannock River Near Fredericksburg, VA	Southeastern Plains	4131	3/2004–7/2008	50/53
02013000	Dunlap Creek Near Covington, VA	Ozark/Ouachita-Appalachian Forests	420	2/2007–9/2008	20/20
02014000	Potts Creek Near Covington, VA	Ozark/Ouachita-Appalachian Forests	396	1/2007–3/2009	27/27
02015700	Bullpasture River at Williamsville, VA	Ozark/Ouachita-Appalachian Forests	285	3/2007–9/2008	19/19
02016000	Cowpasture River near Clifton Forge, VA	Ozark/Ouachita-Appalachian Forests	1194	3/2007–9/2008	19/19
02017500	Johns Creek at New Castle, VA	Ozark/Ouachita-Appalachian Forests	272	3/2007–9/2008	19/19
02018000	Craig Creek at Parr, VA	Ozark/Ouachita-Appalachian Forests	852	2/2007–3/2009	26/26
02030000	Hardware River near Scottsville, VA	Southeastern Plains	300	10/2006–9/2008	24/24
02035000	James River at Cartersville, VA	Southeastern Plains	16193	1/2004–12/2012	101/108
02039500	Appomattox River at Farmville, VA	Southeastern Plains	782	3/2007–9/2008	18/19
02041000	Deep Creek near Mannboro, VA	Southeastern Plains	409	4/2007–9/2008	18/18
02044500	Nottoway River near Rawlings, VA	Southeastern Plains	821	10/2006–9/2008	24/24
02047500	Blackwater River near Dendron, VA	Southeast Coastal Plains	751	3/2007–9/2008	19/19
02051500	Meherrin River near Lawrenceville, VA	Southeastern Plains	1430	1/2007–10/2009	31/34
02053800	S F Roanoke River near Shawsville, VA	Ozark/Ouachita-Appalachian Forests	282	3/2007–9/2008	19/19
02059500	Goose Creek near Huddleston, VA	Southeastern Plains	487	10/2006–9/2008	24/24
02061500	Big Otter River near Evington, VA	Southeastern Plains	816	10/2006–9/2008	24/24
02064000	Falling River near Naruna, VA	Southeastern Plains	427	3/2007–9/2008	18/19
02070000	North Mayo River near Spencer, VA	Southeastern Plains	280	4/2007–9/2008	18/18
02074500	Sandy River near Danville, VA	Southeastern Plains	287	3/2007–9/2008	19/19
02091500	Contentnea Ck. at Hookerton, NC	Southeastern Plains	1898	4/2002–8/2004	29/29
02105500	Cape Fear River Tarheel, NC	Southeastern Plains	12567	7/2000–1/2004	41/43
02110500	Waccamaw River near Longs, SC	Southeast Coastal Plains	2875	5/2007–12/2012	68/68
02118000	South Yadkin River near Mocksville, NC	Southeastern Plains	793	10/1961–3/1973	114/138
02156500	Broad River near Carlisle, SC	Southeastern Plains	7226	10/1996–12/2012	194/195
02173000	S F Edisto River near Denmark, SC	Southeastern Plains	1865	1/1960–9/1966	81/81
02212600	Falling Creek near Juliette, GA	Southeastern Plains	187	9/1965–9/1979	143/169
02228000	Satilla River at Atkinson, GA	Southeast Coastal Plains	7226	11/1974–9/1981	79/83
02232500	St. Johns River near Christmas, FL	Southeast Coastal Plains	3986	9/2000–10/2002	26/26
02236000	St. Johns River near De Land, FL	Southeast Coastal Plains	7941	12/1985–12/2012	137/325
02303000	Hillsborough River near Zephyrhills FL	Southeast Coastal Plains	570	3/2001–4/2005	50/50
02313000	Withlacoochee River near Holder, FL	Southeast Coastal Plains	4727	3/1987–9/1992	51/67
02358000	Apalachicola River at Chattahoochee FL	Southeastern Plains	44548	1/1974–12/2012	55/468
02387500	Oostanaula River at Resaca, GA	Ozark/Ouachita-Appalachian Forests	4149	3/2005–12/2006	21/22
02397500	Cedar Creek near Cedartown, GA	Ozark/Ouachita-Appalachian Forests	298	2/2005–12/2006	23/23
02479000	Pascagoula River at Merrill, MS	Southeastern Plains	17068	6/1970–9/1972	26/28
03167000	Reed Creek at Grahams Forge, VA	Ozark/Ouachita-Appalachian Forests	668	1/2007–6/2009	30/30
03307000	Russell Creek near Columbia, KY	Southeastern Plains	487	1/2000–12/2012	140/156

03308500	Green River at Munfordville, KY	Southeastern Plains	4333	1/2000–9/2011	110/141
03473000	S F Holston River near Damascus, VA	Ozark/Ouachita-Appalachian Forests	785	10/1967–9/1973	72/72
03524000	Clinch River at Cleveland, VA	Ozark/Ouachita-Appalachian Forests	1380	4/2007–12/2012	67/69
03528000	Clinch River above Tazewell, TN	Ozark/Ouachita-Appalachian Forests	3818	4/1962–9/1975	97/162
03532000	Powell River near Arthur, TN	Ozark/Ouachita-Appalachian Forests	1774	10/1962–7/1975	89/154
03571000	Sequatchie River near Whitwell, TN	Ozark/Ouachita-Appalachian Forests	1041	5/1962–9/1971	106/113
07290000	Big Black River near Bovina, MS	Southeastern Plains	7283	7/1978–9/1981	38/39
07307800	Pease River near Childress, TX	South Central Semiarid Prairies	7133	10/1994–10/1997	34/37
07311700	N Wichita River near Truscott, TX	South Central Semiarid Prairies	2427	10/1988–9/2011	177/276
07331000	Washita River near Dickson, OK	South Central Semiarid Prairies	18653	1/1997–9/2011	116/177
07339000	Mountain Fork near Eagletown, OK	Southeastern Plains	2038	12/1992–9/2007	105/178
08030500	Sabine River near Ruliff, TX	Southeastern Plains	24162	6/1996–3/1999	33/34
08086212	Hubbard Creek bl Albany, TX	South Central Semiarid Prairies	1588	4/1982–4/2012	219/361
08195000	Frio River at Concan, TX	South Central Semiarid Prairies	1008	1/1997–8/1998	20/20
HFW1*	Hill Forest Watershed 1, NC	Southeastern Plains	0.29	11/2007–9/2011	47/47
UF2*	Umstead Forest Watershed 2, NC	Southeastern Plains	0.29	11/2007–9/2011	47/47
WS02*	Coweeta Hydrologic Lab WS 02, NC	Ozark/Ouachita-Appalachian Forests	0.12	12/2009–7/2011	19/20
WS18*	Coweeta Hydrologic Lab WS 18, NC	Ozark/Ouachita-Appalachian Forests	0.12	12/2009–7/2011	19/20

*USFS sites.

GCMs CGCM3.1, CM2.0 and HadCM3.1 under the A2 (High) SRES growth and carbon emission scenario were used. The A2 (High) SRES scenario was selected because it represents a potentially worst-case scenario and because post-2000 global carbon emissions estimates indicate that current emissions are tracking the higher of the SRES emissions projections (Raupach *et al*., 2007) making the A2 scenario potentially more likely given current trends. The three GCMs were selected because they represent a range of projections amongst the 16 GCMs evaluated in CMIP3, including 'warm' (CGCM3.1), 'mid-range' (CM2.0) and 'hot' (HadCM3.1) climate futures for the USA (Treasure *et al*., 2014).

T_s model development

We developed monthly linear regression models to predict T_s as a function of T_a at each site to demonstrate the ability of the monthly T_s models to predict T_s observations across large gradients in climate and watershed characteristics compared with logistical regression approaches. We first compared model fit statistics for logistic and linear regression models at monthly timestep to demonstrate that the more parsimonious linear regression model was sufficient to predict T_s at this timestep. Both logistic and linear models were fit using the complete record of monthly T_s and T_a for each site. The best slope and intercept of the linear model were identified using the least squares regression method that maximizes the coefficient of determination between T_a and T_s. In colder climates, there is curvature in the relationship between T_s and T_a at low T_a, particularly at sub-monthly timesteps. There are a number of methods to account for this non-linearity when using linear T_s models, including the removal of T_s/T_a pairs from the database where $T_a < 0\,°C$, constraining T_s to the intercept of the linear model when $T_a < 0\,°C$ or constraining T_s to $0\,°C$ for months when the predicted T_s using the regression models was less than $0\,°C$. We used the latter approach, constraining T_s to $0\,°C$ when the predicted T_s using the regression equations was less than $0\,°C$. T_s in flowing water with groundwater inputs is likely greater than $0\,°C$, but this assumption did not affect the results significantly because only 20 of the 61 sites had a month where $T_a < 0\,°C$, and of these sites, only about 5% of the observations had $T_a < 0\,°C$. There was only one observation at one site where T_s was predicted to be less than °C and was subsequently constrained to °C using this method.

The logistic models used the formulation of Mohseni *et al.* (1998), where T_s was computed as

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

The parameter μ (estimated minimum T_s) in the logistic model was assumed to be zero, an assumption supported by a previous work by Mohseni *et al.*, (1999). The parameters α, γ and β were estimated for each site by simultaneously varying individual combinations of these three parameters, over a uniform grid of more than one million values, and finding the parameter set that yielded the lowest overall sum of the squared differences between the observed and calculated mean monthly T_s as normalized by the number of degrees of freedom. Hysteresis in the relationship between T_s and T_a has been observed when using weekly (e.g. Mohseni *et al.*, 1998; Mayer, 2012) and monthly (e.g., Webb and Nobilis, 1994; 1997) timesteps in basins where hydrologic response is controlled by snowmelt. Linear and logistic models in these cases are often fit by season or by month to account for seasonal differences in the T_s and T_a relationship. For our sites in the Southeast with minimal snowmelt influences and at monthly timestep, hysteresis was negligible and models were developed with one parameterization for all seasons.

The second set of linear regression models were fit at 26 sites that had at least 40 months of T_s observations to demonstrate that monthly linear T_s models based on short-term observations remain valid and have acceptable predictive performance over longer periods of record. The linear model was fit to this set of sites using only the most recent 20 months of T_s and T_a observations, and the 20 to 199 additional months of T_s observations prior to the most recent 20 months were used to test the ability of the short-term models to predict T_s over a longer period. Model fit statistics (Root Mean Squared Error (RMSE) and R^2) for the validation period were compared with those of the 20-month model fit period.

Estimating changes in historical and future T_s

The linear regression models fit using the complete time series of observed T_s and T_a for each site in the T_s Model Development Section was used to predict changes in historical and future T_s. The 1961–2010 monthly historical PRISM and predicted 2011–2060 T_a projections from the CGCM3.1, CM2.0 and HadCM3.1 GCMs under the A2 SRES scenario were used as input to generate monthly time series of historical and future T_s at each site for each scenario. We examined changes in August T_s in addition to annual mean T_s to determine whether seasonal high T_s extremes have changed over the historical record or change in the future. The T_s was regressed against time during both the historical and future periods to test whether T_s has or is projected to change at the annual and seasonal scales. The slope of the regression of T_s over time was used to represent the change in T_s. For future projections, the mean change in T_s over the three future climate scenarios was computed to represent the most likely future condition. The variability in projected T_s changes for each site across the three GCMs was quantified by first computing the absolute value of the percent difference between the T_s change projected by each individual GCM and the mean T_s change across GCMs and then computing the mean of these percent differences across the three GCMs.

RESULTS

T_s model evaluation

As expected, T_s was highly correlated to T_a at all study sites (Figure 2). Both the logistic and linear regression models had excellent performance in predicting monthly

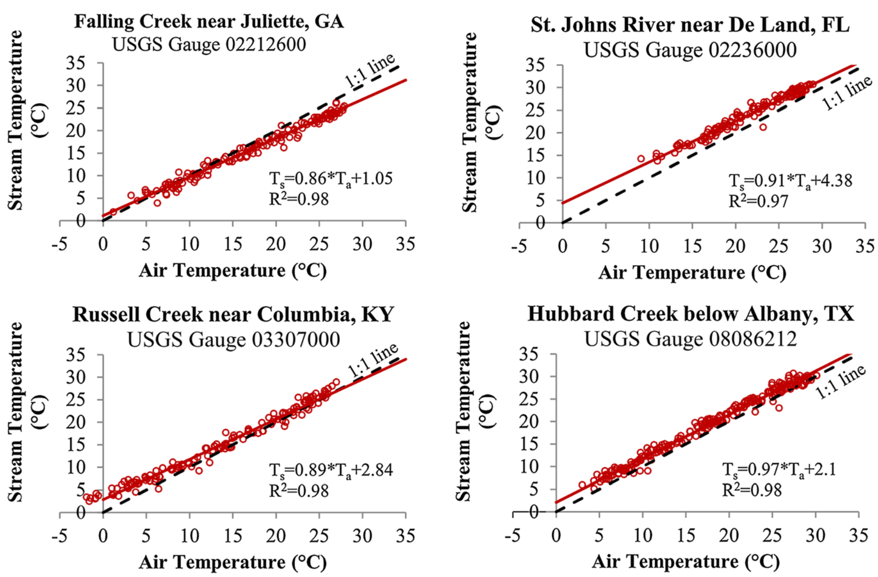

Figure 2. Examples of the relationship between T_s and T_a for four study sites over the period of record

T_s over the complete record of observations (Figure 3 and Table II). The mean RMSE over all sites was 0.8 °C and the mean adjusted R^2 was 0.98 for both the logistic and linear regression models. The distributions of RMSE and R^2 for linear and logistic models across all sites were nearly identical (Figure 3). We concluded that more parsimonious linear regression models were equally capable of predicting monthly T_s as the logistic models for these sites and thus chose to use the linear models for evaluation of trends in T_s. The R^2 between predicted and observed T_s using the linear regression models ranged from 0.89 to 0.99 across all sites (median 0.99), whereas the RMSE ranged from 0.4 °C to 1.7 °C (median 0.8 °C). Forty-six of the 61 sites (i.e. 75%) had RMSE values less than 1.0 °C, and 60 of the 61 sites (i.e. 98%) had R^2 values greater than 0.96. The T_s was greater than T_a at low T_a and T_s was less than T_a at high T_a at most sites (Figure 2). At 21 of the sites, 90% or more of the monthly T_s observations were greater than the PRISM-based observed T_a. This may indicate bias in the PRISM T_a relative to the T_a that influences T_s at these sites, or perhaps, there are unknown geothermal or otherwise heated discharges upstream. Although there may be bias in the PRISM T_a, the fit statistics for the T_s models support the use of PRISM T_a for predicting monthly T_s for these sites.

The intercept parameter of the T_s and T_a linear regression models ranged from 0.05 to 9.4 °C (median 1.9 °C), with 31 of the 61 sites (i.e. 51%) having an intercept less than 2 °C and 43 sites (i.e. 70%) having an intercept less than 3 °C (Table II). The slope of the linear models ranged from 0.49 to 1.08 (median 0.92), with 37 of the 61 sites (i.e. 61%) having a slope between 0.80 and 1.00. There were no significant differences in the slope and intercept across EPA Level II ecoregions at the 0.05 level indicating that ecoregion did not explain the spatial variability in slope and intercept across these sites, rather, that other more localized watershed characteristics are influencing the relationship between T_s and T_a.

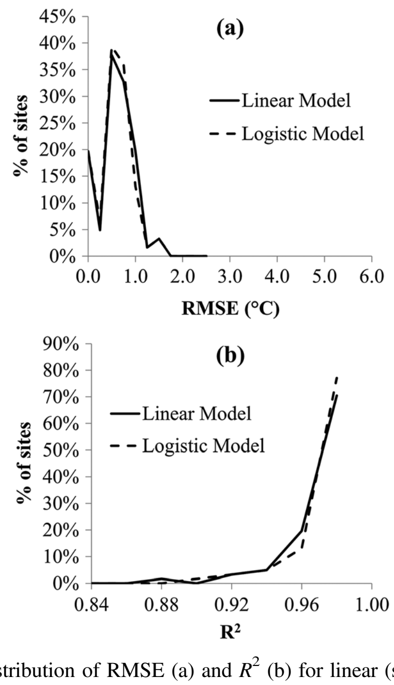

Figure 3. Distribution of RMSE (a) and R^2 (b) for linear (solid line) and logistic (dashed line) monthly T_s regression models across all 61 sites used in this study

The datasets for the 26 sites used for long-term validation of the linear T_s models spanned from 2 to 37 years beginning as early as 1960 or as late as 2007. Model fit statistics over the validation period for these sites remained quite strong and were not statistically different than fit statistics using the period of observations used to fit the model (Figures 4 and 5) suggesting that the relationship between T_s and T_a remained relatively constant over the period of record for these sites. The mean RMSE across all sites for the validation period (0.96 °C) was not significantly different ($p = 0.1827$) from the model fit period (0.85 °C), and the difference in RMSE between the validation period and the model fit period was less than 0.25 °C for 21 of the 26 sites (i.e. 81%) and less than 0.5 °C for 25 of the 26 sites (i.e. 96%), (Figure 4). Similarly, the mean R^2 across all sites for the validation period was not significantly different ($p = 0.3537$) from the model fit period (0.98), and R^2 decreased less than 0.02 from the model fit period to the validation period for 24 of the 26 sites (i.e. 92%). Visual inspection of the predicted and observed T_s time series indicated that the predicted T_s fit observed T_s over the period of record (e.g. Figure 5). For example, the linear T_s models fit using the most recent 20 T_s and T_a observations at site Hubbard Creek below Albany, TX (USGS gauge 08086212) had similar fit statistics for T_s predictions during the 26 years prior to the model fit period (RMSE = 0.88 °C, $R^2 = 0.98$) to that of the model fit period (RMSE = 0.87 °C, $R^2 = 0.98$).

Predictions of temporal changes in T_s

Using the 50-year historical and future projections of T_a as input to the T_s models at each site, we generated time series of annual mean and August T_s. The annual mean and August T_s were then regressed against time during both the historical (1961–2010) and future (2011–2060) periods, and the slope of the regression of T_s over time was used to quantify changes in T_s (Figure 6a). The mean slope of the regression of T_s over time across the three GCM scenarios was used to estimate the future change in T_s.

The mean change in 1961–2010 annual T_s across the 61 sites was 0.11 °C decade^{-1}, ranging from −0.05 to 0.33 °C decade^{-1} (Table III, Figure 6b). Predicted changes in annual mean T_s were similar across ecoregions, although the two largest and five of the 10 largest changes in annual T_s were predicted for sites located in the Ozark/Ouachita-Appalachian

Table II. Summary of linear model parameters and fit statistics using entire period of record for each site

Site ID	Mean T_a (°C)	Mean T_s (°C)	Intercept (°C)	Slope	RMSE (°C)	R^2
01631000	14.0	17.2	2.46	1.05	0.61	0.995
01632000	11.5	12.8	2.21	0.92	0.77	0.990
01634000	12.9	15.9	2.62	1.03	0.83	0.990
01666500	13.7	14.5	1.00	0.98	0.65	0.994
01667500	12.6	14.1	0.82	1.06	0.66	0.995
01668000	14.5	16.4	0.73	1.08	0.84	0.991
02013000	13.5	14.4	2.44	0.89	0.80	0.989
02014000	11.0	12.4	2.84	0.87	0.69	0.992
02015700	12.6	13.4	3.46	0.79	0.49	0.994
02016000	15.2	16.5	0.49	1.05	0.69	0.993
02017500	14.9	15.0	0.53	0.97	0.50	0.995
02018000	12.2	13.5	1.65	0.97	0.63	0.994
02030000	13.8	14.5	1.47	0.94	0.58	0.994
02035000	13.5	16.2	1.89	1.06	0.99	0.987
02039500	16.2	16.6	1.77	0.91	0.48	0.996
02041000	16.9	17.3	1.76	0.92	0.81	0.988
02044500	15.0	16.3	1.35	0.99	0.69	0.993
02047500	17.5	17.4	2.12	0.87	0.65	0.990
02051500	14.6	14.6	0.47	0.97	0.62	0.993
02053800	14.7	14.8	2.46	0.84	0.68	0.989
02059500	13.8	15.0	0.06	1.08	0.82	0.991
02061500	13.8	14.9	0.72	1.03	0.74	0.992
02064000	15.9	16.1	1.60	0.91	0.70	0.991
02070000	16.3	16.1	1.64	0.89	0.55	0.993
02074500	16.7	17.2	1.20	0.96	0.58	0.994
02091500	18.2	18.4	0.34	1.00	0.71	0.991
02105500	16.5	18.0	1.65	0.99	1.12	0.980
02110500	17.8	19.4	1.37	1.01	0.75	0.990
02118000	14.4	13.5	1.08	0.86	0.88	0.983
02156500	16.5	17.8	0.69	1.04	0.93	0.986
02173000	17.7	16.5	1.09	0.87	0.71	0.987
02212600	17.1	15.7	1.05	0.86	0.89	0.980
02228000	19.0	19.8	0.23	1.03	1.13	0.972
02232500	22.7	24.4	1.87	0.99	0.57	0.985
02236000	21.9	24.4	4.38	0.91	0.79	0.971
02303000	22.3	22.5	9.45	0.58	0.58	0.953
02313000	21.1	23.0	4.23	0.89	0.56	0.984
02358000	19.5	21.4	2.47	0.97	1.05	0.973
02387500	16.2	16.9	3.89	0.80	1.23	0.962
02397500	16.1	17.0	6.67	0.64	0.45	0.992
02479000	19.5	21.4	3.11	0.94	1.67	0.922
03167000	11.0	13.0	3.53	0.86	0.59	0.993
03307000	13.6	15.0	2.84	0.89	1.10	0.978
03308500	13.4	14.4	4.49	0.74	1.40	0.952
03473000	11.9	12.5	3.15	0.79	0.78	0.985
03524000	12.4	14.7	3.32	0.91	1.07	0.979
03528000	12.7	15.4	2.99	0.98	1.12	0.979
03532000	12.4	14.5	3.54	0.88	1.20	0.971
03571000	15.1	15.3	4.65	0.70	0.92	0.975
07290000	18.1	18.7	0.87	0.99	0.91	0.987
07307800	15.7	16.4	1.51	0.95	0.79	0.989
07311700	17.3	18.3	1.85	0.95	1.14	0.981
07331000	17.1	18.6	1.63	1.00	0.83	0.990
07339000	17.0	16.2	5.94	0.60	1.61	0.890
08030500	19.7	21.0	0.05	1.06	1.16	0.972
08086212	17.6	19.2	2.10	0.97	0.94	0.984
08195000	19.8	21.0	5.23	0.80	0.62	0.989
HFW1	14.9	14.1	3.53	0.71	0.84	0.981

(Continues)

Table II. (Continued)

Site ID	Mean T_a (°C)	Mean T_s (°C)	Intercept (°C)	Slope	RMSE (°C)	R^2
UF2	15.0	14.0	2.95	0.74	0.87	0.981
WS02	11.4	11.6	6.01	0.49	1.16	0.929
WS18	11.5	10.8	4.04	0.59	1.24	0.944

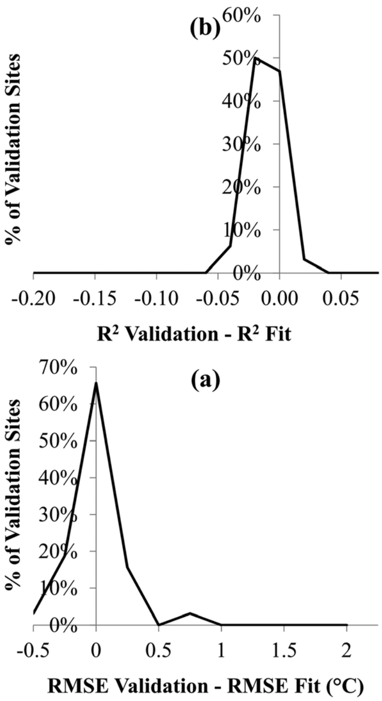

Figure 4. Distribution of the difference between the RMSE (a) and R^2 (b) for linear regression models during the model validation period and during the model fit period across 26 T_s sites (Red sites in Figure 1). Stream temperature models were fit with the most recent 20 T_s and T_a observations and validated for the prior 20 to 199 observations for each site

Forest ecoregion (Figure 7a). The mean change in August T_s across all sites was 0.20 °C decade^{-1}, ranging from 0.01 to 0.45 °C decade^{-1}. The mean change in August T_s was lower for sites in the Southeast Coastal Plain ecoregion (0.14 °C decade^{-1}, $n = 6$) compared with the Ozark/Ouachita-Appalachian Forest ecoregion (0.28 °C decade^{-1}, $n = 15$) and the Southeast Plains ecoregion (0.23 °C decade^{-1}, $n = 15$). Otherwise, predicted changes in August T_s were similar across ecoregions. Changes in August T_s were generally greater than the changes in mean annual T_s, suggesting that historic changes in climate have had more impact on the high extremes in T_s than the mean T_s. The relative changes in T_s amongst ecoregions reflect relative changes in the 1961–2010 PRISM estimates of T_a. For example, the mean change in August T_a was lower for sites in the Southeast Coastal Plain ecoregion (0.16 °C decade^{-1}) than the Appalachian Forest (0.30 °C decade^{-1}) and the Southeast Plains (0.20 °C decade^{-1}).

All 61 sites were projected to have increases in annual T_s and T_a from 2011 to 2060 under all three of the GCM projections for the A2 SRES scenario (Table III, Figures 6b and 7b). The mean change in projected T_s across all sites varied by GCM scenario, with the CGCM3.1, CM2.0 and HadCM3.1 projected to have a mean change in annual mean T_s of 0.31, 0.44 and 0.48 °C decade^{-1}, respectively. The projected change in annual T_s across all sites and GCM scenarios ranged from 0.21 to 0.51 °C decade^{-1} (mean of 0.41 °C decade^{-1}), with 56 of the 61 sites (i.e. 92%) having a projected change in annual mean T_s greater than 0.3 °C decade^{-1}. The mean change in annual T_s for sites located in the Southeast Coastal Plain ecoregion (0.34 °C decade^{-1}) was lower than that of sites in the South Central Semiarid Prairies ecoregion (0.46 °C decade^{-1}), Southeast Plains (0.43 °C decade^{-1}) and Ozark/Ouachita-Appalachian Forest (0.41 °C decade^{-1}). Otherwise, predicted changes in annual mean T_s were similar across ecoregions. The difference in mean change in T_s in the Southeast Coastal Plain ecoregion from the other ecoregions was likely because the mean change in T_a in the Coastal Plain (0.37 °C decade^{-1}) was lower than that of the Ozark/Ouachita-Appalachian Forest (0.47 °C decade^{-1}), the South Central Semiarid Prairies (0.49 °C decade^{-1}) and the Southeast Plains (0.46 °C decade^{-1}). The mean percent difference between the projected change in T_s for each GCM climate scenario and the mean projected change across climate scenarios ranged from 14% to 24% (mean of 17%) indicating general agreement amongst projected T_s change across the three GCMs.

All sites were projected to have increases in August T_s and T_a from 2011 to 2060 under all three GCM projections for the A2 SRES scenario. The mean change in projected August T_s across all sites for the CGCM3.1, CM2.0 and HadCM3.1 GCM scenarios was 0.26, 0.55 and 0.54 °C decade^{-1}, respectively (Table III). The projected change in August T_s across all sites and GCM scenarios ranged from 0.21 to 0.59 °C decade^{-1} (mean of 0.45 °C decade^{-1}). Also, like the change in annual mean T_s, the mean change in August T_s for sites located in the Southeast Coastal Plain ecoregion (0.34 °C decade^{-1}) was lower than that of the sites in the South Central Semiarid Prairies ecoregion (0.46 °C decade^{-1}), Southeast Plains (0.46 °C decade^{-1}) and Ozark/Ouachita-Appalachian Forest (0.49 °C decade^{-1}). Otherwise,

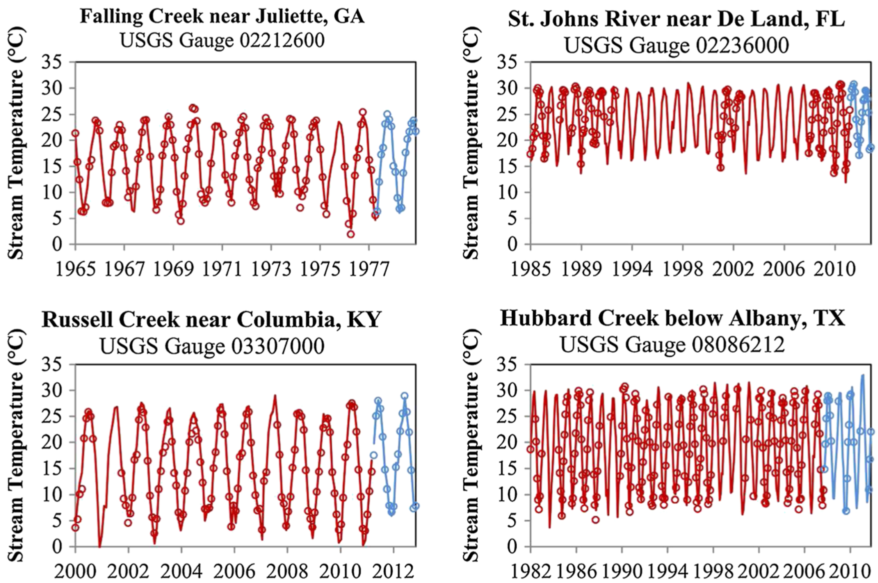

Figure 5. Example T_s model validation results for four study sites over the period of record. Hollow circles are the observed T_s, and solid lines are the predicted T_s. Stream temperatures in blue were used to fit the model for testing over the long term, and T_s in red lines were predicted using the model fit using T_s in blue

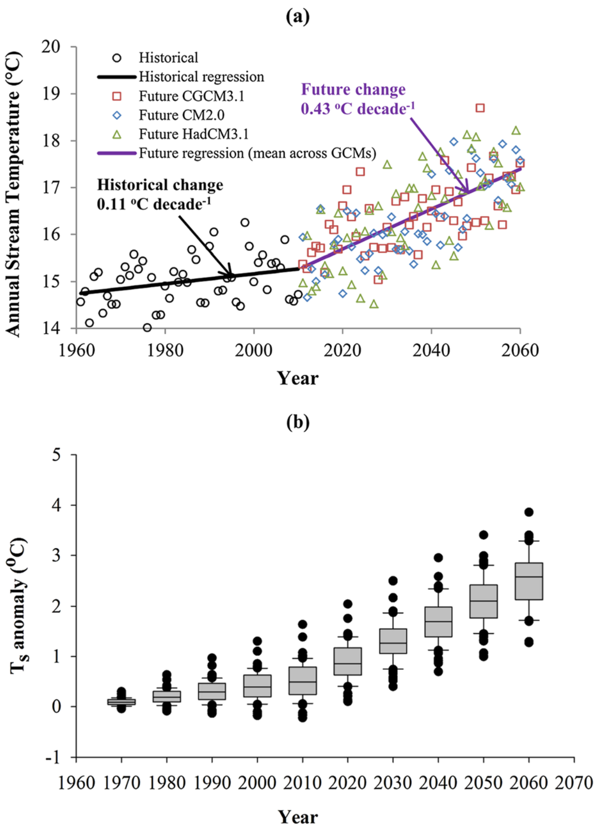

Figure 6. Example of predicted historical (1961–2010) and future (2011–2060) changes in annual T_s (slope of T_s over time) for Russell Creek near Columbia, KY (USGS gauge 03307000) (a); and the distribution of T_s anomaly from 1961 across all sites by decade (b). The future change in T_s is estimated by calculating the mean regression parameters of T_s with time across the three GCM scenarios. Box plots in (b) show the interquartile range and median, whiskers show the 10th and 90th percentiles and black circles are outliers beyond the 10th and 90th percentiles for each decade

predicted changes in August T_s were similar amongst ecoregions. The mean percent difference between the projected change in August T_s for each GCM climate scenario and the mean projected change across climate scenarios ranged from 11% to 54% (mean of 28%) indicating more variability amongst the three GCM climate scenarios for projected August T_s change than that of the changes in projected annual mean T_s.

DISCUSSION

Model evaluation

The simple linear T_s models captured the observed spatial and temporal variations in monthly T_s across the 61 sites used in this study, with 75% of the modelled sites having an RMSE of less than 1 °C. The T_a explained 89% or more (median 99%) of the variability in T_s at these sites and timestep. More complex regression methods have been used in recent years that take flow and other watershed characteristics into account (e.g. Webb *et al*., 2003), but this study suggests that the simple linear regression models with T_a were more than sufficient to achieve a robust fit to T_s observations provided flow alterations due to dams, diversions and so on are not put into place over the simulated period. We do not imply that air temperature change *causes* stream temperature change by regressing T_s with T_a. Instead, the energy exchange processes that impact variability in T_a also impact variability in T_s such that air temperature is *correlated* with stream water temperature and is a good predictor of T_s.

Table III. Predicted historical and future trends in T_a and T_s for all sites

	Trend (°C decade^{-1})							
	Historical (1961–2010)				Future (2011–2060)			
	T_a		T_s		T_a		T_s	
Site ID	Annual	August	Annual	August	Annual	August	Annual	August
01631000	0.19	0.28	0.19	0.29	0.48	0.55	0.50	0.58
01632000	0.17	0.26	0.14	0.24	0.49	0.57	0.44	0.52
01634000	0.16	0.28	0.16	0.28	0.48	0.56	0.50	0.58
01666500	0.17	0.23	0.16	0.22	0.47	0.53	0.46	0.52
01667500	0.18	0.22	0.17	0.23	0.47	0.53	0.50	0.56
01668000	0.18	0.23	0.18	0.25	0.47	0.52	0.51	0.57
02013000	0.18	0.33	0.16	0.29	0.48	0.57	0.42	0.50
02014000	0.11	0.26	0.09	0.23	0.48	0.56	0.41	0.49
02015700	0.02	0.06	0.01	0.04	0.48	0.57	0.38	0.45
02016000	0.20	0.35	0.20	0.37	0.48	0.56	0.49	0.59
02017500	0.02	0.15	0.02	0.15	0.48	0.56	0.45	0.54
02018000	0.19	0.34	0.18	0.33	0.48	0.56	0.46	0.54
02030000	0.10	0.18	0.09	0.17	0.47	0.52	0.44	0.49
02035000	0.17	0.25	0.18	0.27	0.47	0.51	0.49	0.54
02039500	0.14	0.28	0.13	0.26	0.47	0.51	0.43	0.47
02041000	0.14	0.20	0.13	0.19	0.46	0.49	0.42	0.45
02044500	0.13	0.21	0.13	0.21	0.45	0.47	0.45	0.47
02047500	0.20	0.22	0.17	0.19	0.44	0.44	0.38	0.39
02051500	0.09	0.18	0.08	0.17	0.45	0.46	0.43	0.45
02053800	0.19	0.28	0.16	0.23	0.47	0.56	0.39	0.47
02059500	0.06	0.19	0.06	0.21	0.47	0.53	0.51	0.57
02061500	0.08	0.16	0.07	0.16	0.47	0.53	0.48	0.54
02064000	-0.03	0.02	-0.03	0.01	0.47	0.52	0.43	0.48
02070000	0.11	0.23	0.10	0.21	0.47	0.53	0.41	0.47
02074500	0.05	0.17	0.05	0.17	0.47	0.52	0.45	0.50
02091500	0.22	0.25	0.22	0.25	0.42	0.43	0.42	0.43
02105500	0.08	0.19	0.08	0.19	0.45	0.45	0.44	0.44
02110500	0.13	0.20	0.13	0.20	0.40	0.40	0.41	0.40
02118000	-0.05	0.09	-0.05	0.07	0.45	0.50	0.39	0.43
02156500	0.20	0.30	0.21	0.32	0.44	0.47	0.46	0.49
02173000	0.11	0.18	0.09	0.16	0.42	0.41	0.36	0.36
02212600	-0.03	0.09	-0.03	0.08	0.43	0.45	0.37	0.39
02228000	0.03	0.13	0.03	0.14	0.40	0.42	0.42	0.44
02232500	0.14	0.22	0.14	0.22	0.35	0.35	0.35	0.35
02236000	0.03	0.15	0.03	0.13	0.36	0.36	0.32	0.33
02303000	0.10	0.08	0.06	0.05	0.35	0.35	0.20	0.21
02313000	0.10	0.13	0.09	0.11	0.37	0.37	0.33	0.33
02358000	0.06	0.09	0.06	0.09	0.43	0.41	0.42	0.40
02387500	0.15	0.35	0.12	0.28	0.45	0.50	0.36	0.40
02397500	0.11	0.31	0.07	0.20	0.44	0.48	0.28	0.31
02479000	0.07	0.16	0.06	0.15	0.43	0.38	0.41	0.36
03167000	0.01	0.15	0.01	0.13	0.47	0.56	0.40	0.48
03307000	0.12	0.23	0.11	0.20	0.48	0.64	0.43	0.57
03308500	0.22	0.38	0.17	0.29	0.49	0.67	0.36	0.50
03473000	0.05	0.17	0.04	0.13	0.47	0.56	0.37	0.44
03524000	0.06	0.21	0.05	0.19	0.47	0.59	0.43	0.54
03528000	0.34	0.46	0.33	0.45	0.46	0.59	0.45	0.58
03532000	0.32	0.43	0.28	0.38	0.47	0.59	0.41	0.52
03571000	0.15	0.32	0.11	0.23	0.45	0.52	0.32	0.37
07290000	0.21	0.32	0.20	0.31	0.45	0.38	0.45	0.38
07307800	0.04	0.11	0.04	0.11	0.51	0.51	0.49	0.48
07311700	0.07	0.15	0.07	0.14	0.51	0.49	0.48	0.47
07331000	0.02	0.18	0.02	0.18	0.51	0.53	0.50	0.53

(Continues)

Table III. (Continued)

	Trend (°C decade^{-1})							
	Historical (1961–2010)				Future (2011–2060)			
	T_a		T_s		T_a		T_s	
Site ID	Annual	August	Annual	August	Annual	August	Annual	August
07339000	-0.06	0.21	-0.03	0.13	0.50	0.47	0.30	0.28
08030500	0.12	0.19	0.13	0.20	0.44	0.39	0.47	0.42
08086212	0.04	0.23	0.04	0.23	0.49	0.47	0.48	0.46
08195000	0.04	0.11	0.03	0.09	0.44	0.47	0.35	0.38
HFW1	0.12	0.19	0.09	0.13	0.46	0.50	0.33	0.35
UF2	0.24	0.25	0.18	0.19	0.46	0.48	0.34	0.36
WS02	0.28	0.46	0.14	0.22	0.44	0.49	0.21	0.24
WS18	0.32	0.51	0.19	0.30	0.44	0.49	0.26	0.29

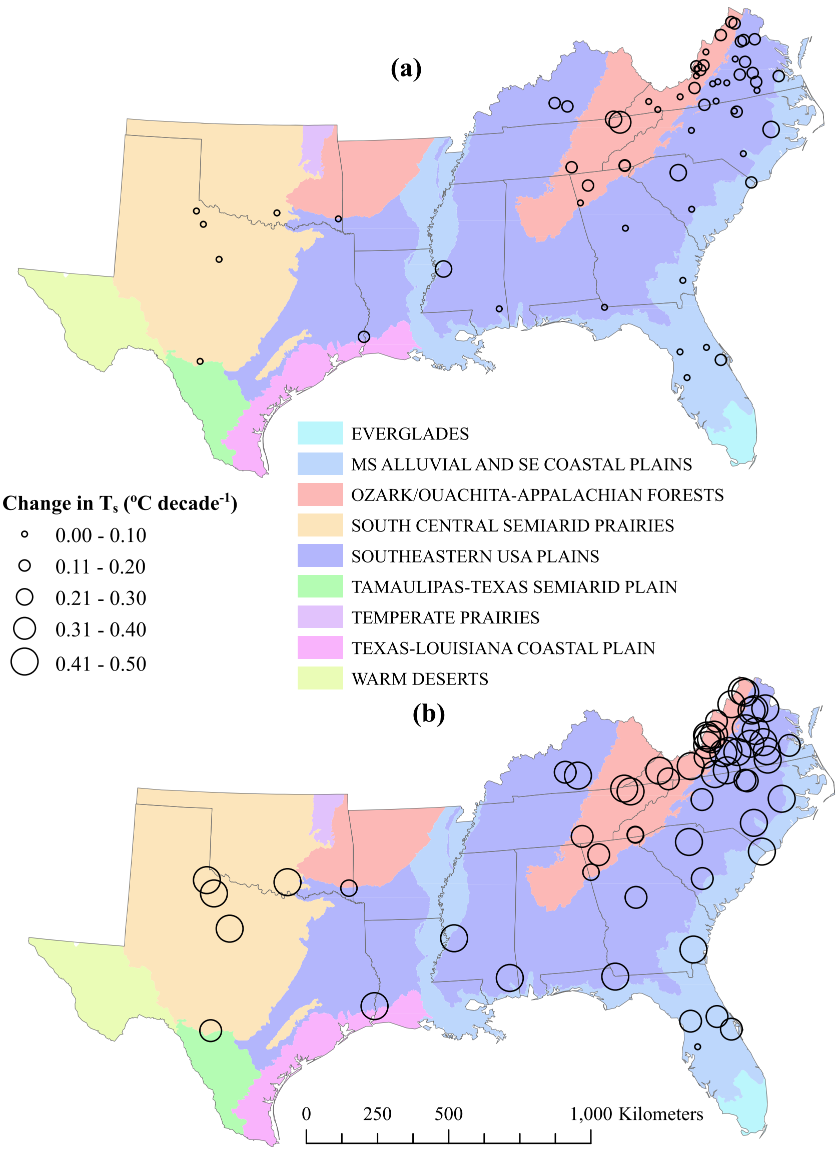

Figure 7. 1961–2010 estimated change in annual mean T_s across ecoregions of the Southeastern USA (a) and 2011–2060 projected change in annual mean T_s presented as the mean trend for each site across the three GCM climate scenarios (b)

The linear regression models in this study were fit using as few as 18 months of T_s observations, but model testing at sites with longer periods of record (as long as 37 years) suggested that approximately 20 months were generally sufficient for establishing the relationship between T_s and T_a (Segura *et al.*, 2014). By having sample sizes that are not multiples of 12, some months will receive more weight in a regression than others. However, the sites in our study were not consistently biased towards one season or another, with mean percentages of the total number of samples by season ranging from 23.4% (winter) to 27.2% (spring), within approximately 2% of equal samples for each season (i.e. 25%). We tested the impact of unequal sample distribution across months by using the most recent 18 months of data for the example sites with longer periods of record (i.e. sites in Figures 2 and 5) under four scenarios: (1) two samples for April–September and one sample for October–March (total of 18 samples), (2) one sample for April–September and two samples for October–March (total of 18 samples), (3) two samples for all months (total of 24 samples) and (4) all data points over the period of record. We found that model fit statistics were similar across sampling scenarios, with differences in RMSE over all scenarios ranging from 0.03 °C for site 02236000 to 0.09 °C for sites 02212600 and 03307000. Although our results suggest that short-term records of T_s measurements are useful for estimating the relationship between T_s and T_a, longer periods of record are preferable and will reduce the uncertainty in establishing this relationship provided they are available.

For our study sites in the Southeast USA and at monthly timestep, the linear regression models performed as well as the logistic regression models, supporting the notion that perhaps evaporative cooling effects at high T_a are not discernible at monthly timestep (Caissie, 2006). The intercept and slope in the T_s and T_a relationship models were site specific and could not be explained by ecoregion alone. Future research should investigate the watershed characteristics that influence the T_s and T_a relationship to determine whether the slope or intercept parameters could be predicted based on these characteristics, and linear models may then be generalized for other basins (e.g. Mayer, 2012). The timestep of analysis has a significant impact on the magnitude of the slope and intercept parameters of the linear regression models and should be considered when interpreting the meaning of the regression model parameters. The slope of the linear regression between T_s and T_a has been shown to increase as the timestep is increased from daily to weekly to monthly (Caissie, 2006). Although the slopes we report here are higher than those reported in the literature at weekly timestep (e.g. Mayer 2012), they are similar to the others in the literature at monthly scale, including Webb (1987; 1992) for 36 sites in the UK, slope ranging from 0.51 to 1.16 (mean of 0.89); Erickson and Stefan (1996) for 37 sites in Oklahoma US, slope ranging from 0.79 to 1.23 (mean of 0.93) and Pilgrim *et al.* (1998) for 39 sites in Minnesota, USA, slope ranging from 0.71 to 1.23 (mean of 1.06). Although T_s may be controlled by local site conditions (e.g. shading, aspect), our study suggests that site-measured T_a was not necessary to achieve acceptable fits to T_s observations. If the objective is to simply reasonably reproduce T_s, readily available interpolated T_a estimates such as PRISM are adequate. It is unlikely that a stronger fit would be achieved using site observations of T_a. For example, we tested differences in model fits using PRISM *versus* site observations of T_a by parameterizing models for three of the four US Forest Service sites where site observations of T_a were available: WS02 and WS18 in the Southern Appalachians and HFW1 in the southeastern plains ecoregion. We found that differences in the slope and intercept of the linear models were not significant ($p > 0.26$) and differences in RMSE were less than 0.2 °C, whereas differences in R^2 were less than 0.02. Other web-accessible gridded climate data products such as Daymet (Thornton *et al.*, 2012) likely would work equally well at monthly timestep. Potential bias introduced by the difference in resolution between the PRISM T_a estimates (4 × 4 km) used to develop linear T_s regression models *versus* the CMIP3 GCM projections (12 × 12 km) used for future climate change impacts on T_s is likely small compared with the overall uncertainty associated with predicting future climates.

Use of regression models for future predictions

Prediction of climate change impacts on T_s is extremely uncertain and limited tools exist to make these predictions at large scales. Science has not identified with certainty the extent to which climate change may impact the energy balance for a given stream because projections of the required meteorological drivers for deterministic T_s models are largely unavailable and are uncertain. As a result, the use of statistical regression models based on historical relationships serves as useful tools for evaluating potential climate change impacts on T_s and in many other scientific applications. For example, Van Vliet *et al.* (2011) developed logistic regression models of T_s using historical observations to examine the sensitivity of T_s to hypothetical changes in climate. The widely used CMIP3 climate projections of Meehl *et al.* (2007) and Wood *et al.* (2004) used historical observations of precipitation and T_a to bias correct and statistically downscale future precipitation and air temperature projections for the IPCC fourth assessment report. These climate projections were subsequently used in deterministic T_s models for several climate change impact assessments (Ficklin *et al.* 2013,van Vliet *et al.* 2013,Wu *et al.* 2012).

Model validation suggested that the relationships between T_s and T_a remained consistent over time, providing some confidence that these models may be used to make T_s projections over the 50-year simulations performed in this study. However, we emphasize that although empirical models are useful for rapid assessment of climate change impacts at large scales, we suggest that users convey the underlying assumptions associated with their use when presenting results in climate change impact studies. These results also suggest that the most important factors that impact monthly T_s and T_a relationships may be those that do not change over time (e.g. drainage area, geology/groundwater contribution, aspect), the other factors that also likely impact the relationship (e.g. land cover and discharge) did not change significantly over the period of record, or in the case of land cover, the basins were too large and diverse to realize the impact of the other factors.

Historical and projected changes in T_s

In this study, we demonstrated how short-term simple linear regression models can be used for rapid assessment of historical and future changes in T_s for regional climate change impact studies. Our study suggests that T_s over the historical period has already increased at many sites in the Southeastern USA and will not only continue to do so but also the magnitude of change will increase over the region by 2060. Variability amongst projections of change in T_s around the mean projection ranged from 14% to 24% (mean of 17%) for annual mean and 11–54% for August T_s (mean of 28%). For example, if the mean predicted change in annual T_s was 0.3 °C decade^{-1} for a given site and the variability across GCMs was 17%, the change in annual T_s for the site could range from 0.25 to 0.35 °C decade^{-1}.

Sites in the Appalachian Forest ecoregion were predicted to be amongst the most impacted by climate change across the Southeast. Sites in this sensitive ecoregion were predicted to have had the highest increases in historical annual mean and historical August monthly T_s of all study sites, including the two largest and five of the 10 largest annual mean T_s changes of all sites. Four of the 10 largest changes in the future 2011–2060 annual mean T_s, and the largest four and five of the largest 10 projected changes in August T_s were located in this ecoregion. This could have significant consequences for coldwater fish species that are endemic to this region if this trend continues in the future. However, predictions of habitat loss for coldwater fish species such as the eastern brook trout using simple relationships between T_s and T_a are thought to be overly pessimistic because some brook trout habitats may persist under climate change in some localized landscape conditions (e.g. Meisner 1990; Clark *et al.*, 2001; Flebbe *et al.*, 2006).

CONCLUSIONS

In this study, we developed linear regression models relating stream water temperature and air temperature across 61 relatively unaltered stream sites of varying drainage areas across the Southeastern USA. We demonstrated that fitting the models using as few as 18 months of stream and air temperature observations resulted in models that sufficiently quantified and explained the variability in stream temperature over 37 years. We then used the models to predict historical changes in annual mean and August monthly stream temperature between 1961 and 2010 and to predict future changes under climate projections from three General Circulation Models between 2011 and 2060. We predicted that there have been substantial increases in historical stream temperatures since 1961 at many sites. The largest predicted increases in historical stream temperatures were at sites located in the Appalachian Forest ecoregion that is home to temperature-sensitive fish species such as Eastern Brook Trout. We projected that the stream temperature increases will persist and increase in magnitude overall through 2060, with sites in the Appalachian Forest ecoregion most impacted and sites in the Southeastern Coastal Plain least impacted by climate change. Our work demonstrated that stream temperature models can be developed with minimal stream temperature observations and readily available air temperature estimates to assess potential impacts of climate change at multiple scales. Future research should focus on exploring relationships between the slope and intercept parameters of the linear models and watershed characteristics so that linear models may be generalized and applied more broadly at the regional scale.

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