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Statistical Models to Predict and Assess Spatial and Temporal Low-Flow Variability in New England Rivers and Streams

Naomi E. Detenbeck

Ecologist (Detenbeck), U.S. Environmental Protection Agency, Atlantic Ecology Division, 27 Tarzwell Drive, Narragansett, RI 02882

Abstract

In the northern hemisphere, summer low flows are a key attribute defining both quantity and quality of aquatic habitat. I developed one set of models for New England streams/rivers predicting July/August median flows averaged across 1985 to 2015 as a function of weather, slope, % imperviousness, watershed storage, glacial geology and soils. These models performed better than most USGS models for summer flows developed at a statewide scale. I developed a second set of models predicting interannual differences in summer flows as a function of differences in air temperature, precipitation, the North Atlantic Oscillation Index (NAO), and lagged NAO. Use of difference equations eliminated the need for transformations and accounted for serial autocorrelations at lag 1. The models were used in sequence to estimate time series for monthly low flows and for two derived flow metrics (tenth percentile (Q10) and minimum 3-in-5 year average flows). The first metric is commonly used in assessing risk to low flow conditions over time while the second has been correlated with increased probability of localized extinctions for brook trout. The flow metrics showed increasing trends across most of New England for 1985-2015. However, application of summer flow models with average and extreme climate projections to the Taunton River, MA, a sensitive watershed undergoing rapid development, projected that low flow metrics will decrease over the next 50 years.

Keywords

surface water hydrology; rivers/streams; statistics; base flow; New England

INTRODUCTION

In the northern hemisphere, summer low flows are a key determinant of the quality of aquatic habitat, directly influencing habitat volume for fish populations (Stalnaker et al.

Detenbeck: detenbeck.naomi@epa.gov.

DATA AVAILABILITY

Data associated with figures in this manuscript will be available at: <https://edg.epa.gov/metadata/catalog/main/home.page>.

SUPPORTING INFORMATION

Additional supporting information may be found online under the Supporting Information tab for this article: This includes a map of GAGESII gaging stations used in development of regression equations, the full suite of potential independent variables in regressions developed to predict monthly streamflow or base flow at GAGESII gaging stations, an example plot of residuals versus year from earlier analyses showing pattern of serial autocorrelation, a summary of USGS predictive equations for low flow statistics for New England states, and validation tests for the Variable Infiltration Capacity model applied to the Taunton River Basin.

1995), stream and river velocity, and sediment transport capacity (Engelund and Hansen 1967). Low flows also indirectly influence habitat quality by modifying water quality parameters such as temperature, dissolved oxygen, and salinity, and by altering substrate qualities such as embeddedness (Zorn et al. 2008, Armstrong et al. 2011, Novak et al. 2016). Consideration of low flow characteristics is often required for derivation of water withdrawal permits, water quality criteria, discharge permit guidelines, and dam licensing in the United States (US EPA 1988, MA EEA 2012, US EPA 1991, US EPA 2007, Novak et al. 2016). Classifications of stream and river flow regimes have been used to establish guidelines for water withdrawals (MA EEA 2012, Armstrong et al. 2011, Zorn et al. 2008), but have not yet been widely used in evaluating aquatic life use class designations, reference condition, or differential risks to aquatic populations over space or time (Eddy et al. 2017, Patterson et al. 2017, Phelan et al. 2017).

Systematic use of base-flow characteristics and low-flow statistics such as 7Q10 in development of water quality criteria, permit thresholds, and dam relicensing requires broad-scale classification of reference condition as well as an understanding of anthropogenic influences on flow regimes. Regional estimates of base flow have been developed by hydrologic landscape region in the United States (Santhi et al. 2008) and other countries (Lacey and Grayson 1998, Smakhtin 2001, Mwakilila et al. 2002, Mazvimavi et al. 2004). Predictors include relief, soils or surficial geology, climate indices, land-cover, and watershed storage. In addition, a water balance model and regional regressions based on runoff, temperature, precipitation inputs and a base-flow index have been applied in the U.S. to predict mean monthly flows for the period 1971-2000 for individual stream reaches in the National Hydrography Dataset Plus version 2 (NHDPlus). Estimates were modified to match discharge measured at United States Geological Survey (USGS) gaging stations (McKay et al. 2012, McCabe and Wollock 2011). Statewide prediction of peak flow statistics for different recurrence intervals is a standard practice for the USGS, but prediction of low flow statistics is less common (Ries et al. 2008). Prediction of July and August flows, critical drivers of fish population persistence (Zorn et al. 2008), are even less common. Determination of low-flow statistics through regional regression analysis typically has produced estimates with wide confidence intervals (Smakhtin 2001) and was often based on assumptions of stationarity (Bent et al. 2014, Dudley 2004, 2015; Flynn 2003, Lombard 2004, 2010; Lombard et al. 2003, Ries and Friesz 2000). In reality, low-flow statistics could change over time, rendering the regulations and policies that depend on these either under- or over-protective.

Anthropogenic influences can alter low flow characteristics. Urban development can contribute either positively or negatively to summer low flows, depending on the relative magnitudes of 1) diminished evapotranspiration with loss of vegetative cover, 2) reduced infiltration with gains in impervious cover, 3) leakage of drinking water and sewer infrastructure, 4) surface and ground water withdrawals and return flows, lawn watering, and interbasin transfers (Lerner 2002, Brandes et al. 2005, Roy et al. 2005, Meyer 2005).

My primary objective in this study was to develop and evaluate simple regression models to predict long-term median and interannual variability in summer flows and base flows for streams and rivers in New England based on both natural landscape features and

anthropogenic influences. I demonstrated the utility of these models in describing the spatial and temporal variability of low flows using two low flow indices pertinent to management goals: tenth percentile of flows (Q10) and 3-in-5 year low flows. I defined 3-in-5 year low flows (MA3in5) as the lowest average flow for three consecutive years in every five. The latter index has been used as an indicator of the probability of persistence of brook trout populations (Kanno et al. 2015). I also assessed the potential influence of low flows on quality of fish habitat through indirect effects of flow on water temperature. I examined variability both over the past three decades as well as projected changes in future decades (2036 – 2065) to determine if trends are likely to persist.

METHODS

Study area and site selection

New England, comprising six states in the northeastern United States in the humid continental climate zone, was chosen as the focus for analysis. New England hydrology and climate are driven by north-to-south, coastal-to-inland, and elevation gradients (Lent et al. 2015). Streamflows are generally highest in the spring when soils are saturated and snowmelt greatest. Streamflows are generally lowest in August and September following spring runoff recessions and increases in evapotranspiration. The timing of peak spring runoff varies as a function of temperature, although the ocean also can influence the location of the snow/rain boundary and thus the timing of runoff (Kingston et al. 2007, Hodgkins et al. 2003)

I based my analyses on the 78 reference stream gaging stations and a subset of 34 of the nonreference gaging stations in New England included in the GAGESII dataset (Figure S1, Falcone et al. 2010, Falcone 2011). The GAGESII dataset includes USGS gaging stations that have at least 20 years of complete flow records since 1950 (the original GAGES dataset) plus those defined as active in water year 2009. Other GAGESII criteria for inclusion are watershed area ($< 50,000$ kilometers²), watershed predominance ($>95\%$ of area) in United States, association with natural as opposed to artificial channels, compatibility with the NHDPlus 100k stream network, and confidence in ability to delineate meaningful watersheds (sufficient topographic relief and not dominated by anthropogenic drainage; Falcone et al. 2010). In the GAGESII dataset, gages are classified as “reference” or “nonreference” based on a hydrological-disturbance index related to degree of flow alteration (impoundments, manmade discharges and withdrawals, degree of development). I included nonreference gaging stations that were not influenced by impoundments immediately upstream or proximal anthropogenic withdrawals or return flows, as indicated in the GAGES database. I did not exclude gages based on degree of development, as I was interested in determining the influence of impervious cover on base flows at intermediate levels of development. The most developed watershed in the reference set has an imperviousness of only 2% while the maximum watershed imperviousness in the combined set is 28.1%.

Summer discharge and base-flow calculations

I used the USGS Groundwater Toolbox (Barlow et al. 2014, 2016; <https://water.usgs.gov/ogw/gwtoolbox/>) to download freshwater daily discharge time series corresponding to the selected USGS gaging stations in New England from the GAGESII dataset (Falcone et al. 2010, Falcone 2011) for available years of data between 1985 and 2015. I used the Groundwater Toolbox to calculate average monthly (July, August) streamflow and base flow for each year. I estimated base flow by each of the six methods available in the toolbox and then averaged across all methods: (PART, HySEPFixed, HySEPLocMin, HySEPSlide, ROFIStandard, and ROFIModified). Although the toolbox generates summaries of both discharge (cfs) and depth (in), the latter after correcting for watershed area, I used the depth estimates in subsequent analyses because of the limited precision in base flow estimates for smaller watersheds (one significant digit), and recalculated discharge where needed based on the GAGESII-reported watershed areas.

Regression models

In this analysis, I estimated yearly summer base flows and total flows through a two-step process. First, I modeled the long-term average of median July/August flows (LTAM) as a function of long-term climate averages, seasonal distribution of precipitation, topography, depression or soil storage, and surficial geology or soil characteristics. Second, I modeled interannual variability in summer base and total flows through the use of difference equations. These are referred to throughout the paper as LTAM and interannual difference (IDM) models, respectively. Finally, I combined these approaches to predict time series of summer total flows or baseflows and of low flow statistics across New England. I originally attempted to model yearly values for monthly summer flow or baseflow through stepwise regression analysis with SAS using a variety of error structures to try to account for potential serial autocorrelation. However, I could not eliminate patterns of serial autocorrelation and heterogeneity of variance in model residuals (see Supplemental Information for example).

Long-term average of median (LTAM) summer flow regressions—I first developed linear regression equations to predict long-term (1985 – 2015) averages of median monthly base and total stream flow for both July and August. The median of daily flows was calculated by month then averaged over years. Separate models were created for July versus August to mirror different sampling windows used by state agencies for monitoring stream temperature and fish communities. I analyzed two different datasets separately: a reference dataset (R, composed only of reference sites) and a full dataset (F) composed of combined reference plus nonreference sites. This allowed me to determine whether controls on base flow are changing as the result of development as well as whether the direction of impact of imperviousness on base flow changes between low and high density development. I tested a subset of watershed attributes included in the GAGESII database as predictors, supplemented by additional variables that I calculated independently (Table S1).

For the final model, I assessed two substitute values for slope: main channel slope and percent slope derived based on the 30-meter resolution National Elevation Dataset (NED). Falcone (2011) had based slope calculations on the 100-meter NED, which is no longer available. I also evaluated alternative values for freshwater withdrawal beyond those

included in the GAGES dataset. I substituted values for freshwater withdrawal that are available throughout New England at HUC12 (hydrologic units of 10,000 to 40,000 ha) or equivalent scales. Water use data are available for New England through the USGS National Water Information System (NWIS) but are reported at county scales or coarser resolutions. Falcone (2011) calculated area-weighted averages of water use for gaging station watersheds from these county-level data. I supplemented these estimates by compiling water use data at approximately HUC12 scales from a variety of USGS sources for four of the six New England states for which data at these scales were available (Table 1) and calculated total net freshwater withdrawals and separate net surface water and groundwater withdrawals. For both HUC12 and county scale measures, I calculated area-weighted average values for gaging station watersheds. To reduce the potential for cross-correlation, I substituted one equivalent variable (or combination of variables) as indicators of each of the following characteristics: drainage area (n=1 variable option), annual variation in effective precipitation (n=2 variable options), seasonal variation in effective precipitation (n=2), withdrawals (n=2), flashiness (n=1), permeability (n=4), and storage (n=2) (Table 2). Each initial model included one predictor or set of independent predictors (e.g., soil permeability plus slope) for each characteristic. Variable sets are defined in Table 2. For example, either PPT_AVG plus TMP_AVG or PPT_AVG plus PET was used in each model. Thus, a generalized form of the equation for median August streamflow would be:

$$\text{Median August Streamflow} = a + b_1 (\text{annual effective precipitation}) + b_2 (\text{drainage area}) + b_3 (\text{seasonal precipitation}) + b_4 (\text{withdrawals}) + b_5 (\text{flashiness}) + b_6 (\text{permeability}) + b_7 (\text{storage}) + \text{error}$$

(1)

I used PROC REG in SAS 9.4 (SAS Institute, Carey, NC) to carry out backwise stepwise regressions for analysis of LTAM, using Aikake's Information Criterion (AIC) to select the best model. I analyzed residuals for normality, evidence of nonlinearities in models, and assessed homogeneity of variance. I ran a stepwise regression with each potential combination of variables described in Table 2.

For each starting model, I retained the model subset with the lowest value for Aikake's Information Criteria (AIC) as well as any models with an AIC value within 2 units of the best model. The difference between AIC values can serve as an indicator of the relative probability that the lowest AIC is the "best" model (Burnham and Anderson 2002). For cases in which more than one equation was retained, I calculated weighting factors (AIC weights) to construct weighted model averages.

Interannual difference models (IDM)—To eliminate serial autocorrelation of model residuals for predictions of interannual variation in monthly base flows and total streamflow, I evaluated mixed (repeated measures) models using PROC MIXED in SAS with difference terms for both independent and dependent variables, e.g.:

$$\text{DMedJulSFlow} = a + b \text{DifPPT_AVG} + c \text{DifTMP_AVG} + \text{Station} + \varepsilon \quad (2)$$

where DMedJulSFlow = difference in median July streamflow between year t and year t-1, DifPPTAVG = difference in annual precipitation between year t and year t-1, DifTMPAVG = difference in annual average temperature between year t and year t-1, Station = random effects term for gaging station, and ε = error.

For difference models, I also evaluated the North Atlantic Oscillation (NAO) index and lagged NAO as potential predictors. The NAO has been shown to be correlated with New England peak flows in winter and early spring, which in turn influences base flow at the end of the growing season (Ahn et al. 2017, Coleman and Budivoka 2013, Steinschneider and Brown 2011, 2012).

Model applications

I applied the LTAM and IDM full models to predict the spatial distribution of July and August base flow and streamflows across New England for dry (1999), average (1985), and wet (2006) years. I calculated watershed attributes in the final models for all NHDPlus watersheds in New England using the NHDPlus version 1 Catchment Attribute Allocation and Accumulation Tool (CA3T; http://www.horizon-systems.com/NHDPlus/NHDPlusV1_tools.php). To initiate the time series, I predicted flow values for 1985 by substituting values for 1985 temperature and precipitation into the LTAM statistical models, then added predicted interannual changes to 1985 values and subsequent years based on IDM (difference) models. I used the resulting time series to estimate the 10th percentile of July and August median flows (Q10) across the full time span (1985 – 2015) and again using a 10-year moving minimum to determine if Q10 values were stationary between 1995 and 2015. To examine potential variation in fish habitat quality for fall spawners over time (Kanno et al. 2015), I also calculated the minimum 3-year average August base flow for 5-year moving windows for each NHDPlus watershed outlet and mapped these for HUC8 outlets. To assess temporal trends, I applied a nonparametric modified Mann-Kendall test using the R *mkTrend* function in the fume package (Bedia 2013; <https://cran.r-project.org/src/contrib/Archive/fume/>) to the Q10 time series and to the MA3in5flows for watersheds associated with HUC10 outlets. The modified Mann-Kendall test includes corrections for serial autocorrelation.

To determine whether measured trends are likely to continue, I applied the flow models with future climate projections. I estimated expected changes in median July and August base flows and streamflows for the Taunton River watershed in Massachusetts in response to annual changes in precipitation and temperature projected by 24 climate change model ensembles that have been shown to perform well in retrospective analyses of past climate (Sheffield et al. 2013). I chose the Taunton River for analysis because this watershed is experiencing the second largest rate of population growth in the state with associated increases in water demand, while still retaining significant areas of biodiversity in need of protection (Wild and Scenic River designation). I projected changes in annual precipitation and temperature for two Representative Concentration Pathways (RCP 4.5 and RCP 8.5)

between a base period of 1975 – 2004 and future period of 2036 -2065 using the US EPA Locating and Selecting Scenarios Online (LASSO) tool (Presentation by Phillip Morefield, US EPA. 2016. Locating and Selecting Scenarios On-line (LASSO). http://www.chesapeake.org/stac/presentations/258_Morefield_climate_tool_STAC_scenarios%20workshop_v2.pdf) for each of 24 climate models to determine extreme predicted values (combined minimum and maximum temperature and precipitation changes) and average predicted values across all climate models.

Low flow conditions have indirect effects on other water quality variables that impact the survival of aquatic organisms. Water volume (discharge) affects the thermal inertia of streams and rivers, so that water bodies with low depth to surface area ratios are more sensitive to solar radiation (Poole and Berman 2001). To determine the potential implications of spatiotemporal variability in summer low flows for water quality criteria, I refined an existing stream and river temperature model for New England by adding measured or modeled July and August base flows and streamflows to the models predicting median or daily range of July or August stream temperatures (Detenbeck et al. 2016). Measured base flows were not available for all reaches with temperature observations so I substituted values averaged at the HUC6 scale. I used AIC values to determine whether addition of flow variables improved temperature model performance.

RESULTS

LTAM regression models

The root mean square error (RMSE) for model fits of average median flows ranged from 3.6 to 6.6 mm per month, as compared to the ranges for July base flow (0.5 – 43 mm/month), August base flow (0.3 – 37 mm/month), July streamflow (0.8 – 50 mm/month), and August streamflow (0.5 – 41 mm/month). Regression equations explained 60–65% of variation for reference watersheds and slightly less (47-54%) for the full set.

Percentage coarse surficial deposits was a significant and strong predictor of increased base flow and streamflow during July and August months in reference (R) watersheds, with an increase in 25 – 33 mm flow for every percentage increase in coarse surficial deposits (Table 3). For full models, the CRSRF variable was replaced by a combination of percent hydrologic soil group A (July) or soil permeability (August) and a negative interaction between soil group A or permeability and slope. Effective precipitation (a combination of annual precipitation and either temperature or potential evapotranspiration (PET)) contributed positively to base flow and streamflow in July, while an increased proportion of precipitation falling as snow was associated with decreased flows. The seasonal distribution of precipitation correlated with August flows, with a positive effect of average August precipitation and a negative effect of the ratio of spring to winter precipitation. Soil water storage capacity was consistently associated with increased August flows, while surficial depression storage (lakes and wetlands) was positively associated with summer base flows for reference watersheds but not the combined full set. Percent imperviousness was associated with increases in both July base flow and streamflow for the R watersheds (0-2% IC) but only with increased July streamflow for the combined set (0 – 28.1% IC). There was no detectable effect of freshwater withdrawals, either summarized from county-scale data or

summarized from HUC12-scale summaries, on summer base flows or streamflows in the reference or full datasets (Table 3).

IDM regression models for interannual change in flows

Difference models explaining interannual changes in July and August flows were highly significant ($p < 0.001$) but had higher RMSE values than corresponding predictions for median values (Table 4). Best fit difference models explaining interannual changes in July and August base flows and streamflows, which had relatively few independent variables, were simpler than predictive models for median condition (Table 4). Interannual increases in precipitation, decreases in temperature, a positive interaction between change in precipitation and temperature, and mixed effects of the NAO index were all associated with interannual increases in flows. The lagged NAO difference index (reflecting differences across two years) had a consistent negative association with summer flows, while the NAO difference index had either a negative association (with July flows) or a positive association (with August flows).

Model verification

I compared the performance of the new regression models produced in this study against results of other regional modelling approaches: first comparing performance against that of statewide regression models for median summer flows and/or Q10 values, and second, comparing performance with results from a coarse-scale Variable Infiltration Capacity (VIC) model calibrated for the U.S. (Maurer et al. 2002). The latter has been used to predict potential changes in hydrology under future climate scenarios (Hayhoe et al. 2007).

The New England-wide models for summer monthly streamflows and base flows had higher adjusted r^2 values (R models: 0.60 – 0.65; F models: 0.47 – 0.54) than the USGS statewide predictive models (except for Maine) after the latter equations were adjusted for area effects (Table S2). The USGS adjusted r^2 values for original models for median July or August flows (0.95 – 0.97) or for 7Q10 values (0.69 – 0.98) were extremely high in most cases, but about half of the explained variance was due to watershed area effects on flows. Once the area effect was removed from models to make them comparable to the New England-wide models, the adjusted r^2 values dropped to 0.12 – 0.67 (0.44 average) for median July or August flows and 0.43 – 0.96 for 7Q10 values. For the 7Q10 models, only Maine had an adjusted r^2 value > 0.9 ; the others ranged from 0.43 to 0.7.

The VIC models produce estimates of base flow and of runoff; estimation of streamflow requires an additional routing model but this should be close to the sum of base flow and runoff for small watersheds. The LTAM predictions for average values outperform the nationwide VIC model for reference watersheds both for base flow (VIC model July $r^2 = 0.46$, August $r^2 = 0.33$) and for streamflow/runoff (VIC model July $r^2 = 0.44$, August $r^2 = 0.18$). (VIC model output was only available up to the year 2000, so averages could only be calculated over the 16-year period of 1985–2000.) In addition, the VIC models tend to overpredict 15-year averages at low base-flow or runoff values (positive intercept), but under predict at higher values (slopes less than 1; Table S3). With the exception of VIC model

predictions for July base flow, both difference and VIC models tend to under predict the magnitude of interannual changes in both base flow and runoff.

Model applications

Observed spatio-temporal variability of summer flows in New England.—I calculated median July and August base flows and streamflows for all NHDPlus reaches but mapped these and other derived metrics at coarser scales to facilitate visual assessment of regional trends. I mapped median July and August base flows and streamflows at HUC12 outlets for all HUC12s with watershed areas less than or equal to 3767 km², the upper domain of the observations used to calibrate the model (Figures 1a–d, 2a–d). For HUC12s with multiple outlets (NHDPlus HUTYPE = F, M), I assigned values based on the largest watershed within the HUC12. Similar maps were generated for Q10 values for the full 30-year period 1985–2014 (Figures 3a–d).

For a given time period, spatial patterns were similar for predicted base flow and streamflow. In July, highest predicted flows are associated with higher elevation portions of Vermont (Green Mountains), New Hampshire (White Mountains) and northern Maine (Appalachian Mountains) and with coastal New Hampshire and central Massachusetts (wet year only) (Figure 1). Lowest July flows are associated with coastal zones (Maine through Massachusetts), the Champlain Valley in western Vermont, noncoastal Rhode Island, and eastern portions of the Connecticut River basin. In the wet year of 2006, the zone of higher flows associated with mountain ranges of VT and NH expanded southward (Figure 2).

In contrast, for August flows, with the exception of the Appalachian Mountains in western Maine, most flows in Maine are lower than the 30th percentile for New England. Low flow zones are also concentrated along the Champlain Valley, in central MA, and southern RI. Zones of relatively higher base flows remain in high elevation regions and also appear in the Cape Cod region of southeastern MA.

Predicted base flows can vary significantly between wet and dry years as well. The range of Q10 values in July and August is only 63 to 71 percent of the range of values for the wettest year (2006) of this period of record. Medians of Q10 values across New England are only 45% (July) and 50% (August) of values for 2006.

Figure 4 illustrates the time series of predicted August base flow and peak flow for the HUC12 outlet which has the median August Q10 flow value across all HUC12 outlets. Peaks and increasing portions of the time series generally correspond with wet years (with NH average Palmer drought severity index (PDSI) > 2) and minima generally correspond with dry years (NH PDSI < -2). Over the 30-year period, predicted values vary by almost five-fold.

Temporal trends in Q10 and minimum 3-in-5 year average flows.—To highlight patterns of spatial variability, mapped color categories for temporal trends represent decile ranges for each individual dataset. For July base flows, both MA3in5 and Q10 values are increasing over time at most HUC10 outlets across New England with rates of increase greatest in higher elevations and lowest in southern New England (Figures 5a–d, 6a–d; $p <$

0.05). There are exceptions for August base flow Q10, showing no significant change (modified Mann-Kendall statistic $p > 0.05$) for the northern coast and central Maine, and east central New Hampshire. For August MA3in5 values, HUC10s showing no significant trend were small and scattered. Maximum rates of change for MA3in5 values were identical for July and August (0.4 mm/yr), while maximum July Q10 rates of change (0.7 mm/yr) are greater than August Q10 rates (0.2 mm/yr). In general, July rates of change for Q10 and MA3in5 are greatest in high elevation portions of northern New England, moderate in central and northern Maine, and lowest in southern New England. Spatial patterns for August Q10 and MA3in5 values are more heterogeneous, showing lowest rates of change in central (MA3in5) and north coastal Maine (MA3in5, Q10), and greatest rates of increase in eastern Massachusetts. Spatial patterns in streamflow Q10 rates of change are very similar to base-flow change patterns for both July and August, although maximum rates of change were higher (0.5 mm/yr August Q10, 1.7 mm/yr July Q10). Spatial patterns in MA3in5 change values are also similar for July and August streamflow as compared to base flow, but with greater maximum rates of change for streamflow (1.7 mm/yr July, 0.5 mm/yr August).

Potential changes in base flow with climate change.—When I applied the AIC-weighted full difference equations for July and August baseflows and streamflows to the Taunton River, MA watershed using climate change projections for 2036-2065 and either the RCP 4.5 or RCP 8.5 future scenarios, July and August base flows were projected to decrease regardless of model selected (range = -2.3 to -3.0 mm July base flow, -6.6 to -8.6 mm August base flow). Projected decreases are greater for the RCP 8.5 future scenario ensemble prediction than for the RCP 4.5 future scenario prediction. Projected decreases in July and August runoff are even greater than that for base flow (range = -5.4 to 7.0 mm July streamflow, -9 to -11 mm August streamflow; Table 5).

Influence of summer low flows on stream temperature.—I used the base flow and streamflow prediction models described here to improve an existing regional model for stream/river temperature. A previous New England stream/river temperature model developed by Detenbeck et al. (2016) had an RMSE of 1.4°C and performed well over a range of wet and dry years, except for 1999, for which temperature was underestimated. The year 1999 represented the driest year in the time series based on values for the Palmer Drought Index averaged across New England. The addition of a variable describing interannual variability in July or August base flow or streamflow improved the overall model fit significantly for predictions of July or August median temperature and July or August daily range in temperature, as evidenced by a drop in AIC value. Improvements were greatest for models including parameters describing interannual variability in measured base flow (median August temperature) or measured streamflow (median July temperature, July or August daily range) at the HUC6 scale and with the inclusion of modeled average streamflow for median July temperature (Table 6, $\text{AIC} = 6.3 - 31.8$). Although HUC6 scale measurements had greater predictive power for three temperature metrics as compared to modeled values, addition of modeled annual streamflow or base flow to the original models (Detenbeck et al. 2016) still significantly improved temperature predictions for all but July daily range. In addition, the inclusion of annual measured median August base flow at the

HUC6 scale virtually eliminated the bias in August stream temperature estimates for the drought year 1999 (mean residual = 1.3 ± 2 °C).

The model coefficients for monthly base flow or streamflow suggests that an increase or decrease in monthly flow of ten mm is associated with a respective decreased or increased median stream temperature of $0.20 - 0.24$ °C and change in daily range of $0.12 - 0.20$ °C. The modeled difference of over 50% in maximum August summer base flows between a wet year (2006, 61 mm) and average Q10 conditions (28 mm) over the past 30 years corresponds to potential decrease in 0.6 °C for median August temperature.

DISCUSSION

Differences between reference and full models

Although predictive summer flow models developed with both reference and nonreference sites were very similar to those developed with reference gauges only, there were some important differences. First, the reference models included storage as positive predictors for both base flow and total streamflow, while the full models did not. With increases in development, artificial storage and regulation of outlets from impoundments is likely to increase, thus reducing the ability to detect effects of natural storage. Natural storage is likely to retain water for a longer period than detention basins designed to hold water for only short periods of time. Second, full models dropped impervious cover (IC) as a predictor for base flow, but not for total flows. Base flow could increase at low levels of imperviousness as evapotranspiration decreases and septic tank recharge increases, but this effect could be counteracted by a decrease in infiltration at higher levels of imperviousness. In contrast, runoff is likely to increase across the spectrum of imperviousness. Third, the coarse surficial deposits variable in the reference models was replaced by soil hydrologic group or soil permeability in the full models. Coarse surficial deposits are a better indicator of deep layers of permeable material as compared to surficial soil layers. In New England, municipal wells are commonly located in alluvial aquifers. As development increases, water withdrawals could reduce the contribution of these aquifers to base flow.

Comparison with other base-flow prediction models

The new predictive summer flow models presented here are the first to combine basin surficial geology or soils characteristics, climate (temperature or PET, precipitation amount and seasonal distribution), slope, and storage to predict summer base flow and streamflows across New England. It is possible that I was able to discriminate among multiple effects due to the restricted time period of my analyses (1985-2015), whereas earlier models have used all available data. Predictive models for summer/July/August median flows and/or annual 7Q10 values have been developed by USGS for five of the six states in New England (Ries and Friesz 2000, Dudley 2004, 2015; Ahearn 2010, Bent et al. 2014, Flynn 2003), but no models have been specifically developed for base flows during summer months (New Hampshire models also include observations from VT, ME, and MA). Three of the state models (MA, ME, CT) include drainage area and coarse surficial drift or sand/gravel aquifers in predictive equations, while RI models include only stream density and drainage area, and NH models include drainage area, basin temperature and precipitation. (Table S2).

Note that these models are derived independently and while there were similarities in approach, researchers did not necessarily start with identical sets of potential explanatory variables.

Previous predictive equations at the state scale have assumed stationarity in median summer flow and 7Q10 values (Ries et al. 2008), and thus have not incorporated the influence of interannual variation in temperature, precipitation, or the North Atlantic Oscillation index. The trends for increasing summer base flows are consistent with analyses conducted for the period 1950–2006 on a smaller subset of 25 New England gaging stations (Hodgkins and Dudley 2011). However, among four atmospheric teleconnection indices tested, it was the Summer Synoptic Drought Index (SSDI) index that had the highest correlations with summer 7 day low flows. Hodgkins and Dudley (2011) detected a simple correlation between 7 day low flows and NAO index for only two stations.

It is likely that USGS Maine equations perform well in comparison to other state models and our New England-wide model due to the relative lack of water withdrawals and returns in the relatively undeveloped Maine landscape, as well as the more stable distribution of median flow values across years in Maine. Performance of the USGS models for 7Q10 predictions cannot be compared directly to that of the New England-wide models because the USGS models assumed stationarity, whereas the New Englandwide models demonstrated spatially heterogeneous and positive trends in Q10 over time for much of the region.

Advantages of combined model: long-term average plus difference model

Development of predictive models of interannual variation allowed explicit examination of nonstationarity in flow statistic distributions, showing an increasing trend for median monthly July or August Q10 and MA3in5 values across most of New England. The combined use of LTAM with IDM models to produce time series enables prediction of median flows by year, allowing researchers to examine questions such as the effect of historical interannual variability on stream temperatures and fish populations, as well as to project potential shifts due to climate change. In addition, the models presented here corrected for drainage area effects prior to model development; thus models could be developed without the need for log transformations to normalize the variance, and the application of bias correction factors to final equations. An initial set of models developed to predict interannual variation in flows and base flows without differencing exhibited heterogeneity of variance and serial autocorrelation. After these were reformulated as difference models, transformations were no longer needed and serial autocorrelations disappeared.

Model limitations

Although the regional New England models have the advantage of being able to predict interannual variability in potential summer flows and base flows, they still have some limitations. In order to construct long time series, the LTAM and IDM models must be combined and the cumulative error of predictions will increase with time series length. Thus the models will be more accurate for short term projections. The models developed here

were based on a 30-year time series based on availability of suitable predictor variables across the entire time span. The input data series was not long enough to adequately evaluate (Koutsoyiannis and Montanari 2007) or attempt to correct for long-term persistence. With long-term persistence, serial autocorrelation decays much more slowly, and fractional autoregressive integrated moving average (fARIMA) models must be applied to account for the long-term memory in the system (Hosking 1984, Steinschneider et al. 2013). Lebo and Weber (2015) caution that fractional differencing can only be applied reliably to time series with a length of at least 50 years, which is longer than the time series analyzed in the current study.

Finally, the models need to be supplemented with information on water use for some applications. The models were constructed with data from a combination of reference and nonreference gaging stations, but with the exclusion of watersheds with significant impoundments, withdrawals or anthropogenic discharges near the gaging stations, and therefore represent potential summer base flows and flows in the absence of consumptive use and interbasin transfers. The failure to detect effects of water withdrawals (groundwater, surface water, or combined) on summer flows was likely due to three factors: 1) restrictions on the gaging stations chosen to develop the model to exclude those with significant water transfers, 2) the relatively coarse (county-scale) resolution of consistent region-wide water use data and 3) inconsistencies in medium-scale water use data available for individual states at the HUC12 scale. Reporting of water use for irrigation was inconsistent across state datasets and across years within state datasets, which is significant because consumptive use for irrigation can approach 100%. Consumptive use is generally in the range of 10-15% for residential uses during most of the year but can increase substantially to 25-29% in the summer due to lawn irrigation (Vickers 2001). Furthermore, residential consumptive use varies spatially and temporally due to watering bans and restrictions imposed during drought years by some towns but not others.

Differences between spatial patterns for potential base flow and for base flow adjusted for consumptive use and interbasin transfers can be illustrated for the state of MA, which has developed a database of water use at approximately the HUC12 scale (Weiskel et al. 2010). Although somewhat patchy, groundwater withdrawals as a fraction of modeled median August flows tend to be greatest in the eastern third of Massachusetts, corresponding to population centers, with some areas of net surplus discharge (from wastewater) along major tributaries (Figure 7). Potential Q10 values in July are well below average in eastern MA. In contrast, potential Q10 values in August are highest in extreme eastern MA and Cape Cod. However, water use restrictions and impacts on biological resources are high in this region due to the extensive groundwater withdrawals (Weiskel et al. 2010).

Opportunities for enhancing water quality criteria and risk management

The dual regression approach presented here allows improved prediction of Q10 conditions which have been used in numerous regulations to define acceptable risk (Novak et al. 2016). For example, the natural variation in August base flows between extreme wet and dry years (Figures 1b,2b) can be expected to add up to 0.6° C to interannual ranges in August

reference stream condition even before interannual variation in solar radiation and air temperature are taken into account.

Indirect impacts of interannual variation in base flows could be even more significant for dissolved oxygen and for substrate quality (Kanno et al. 2015). Simulations by Kanno et al. (2015) suggest a series of three years out of five with suboptimal climate variables can be associated with local population extinctions for brook trout. Kanno et al. (2015) predicted the expected survival or pseudo-extinction of local fish populations of brook trout in the Appalachians based on seasonal climate indices and a two-stage population model with differential survival of young-of-year (YOY) and adult fish. Peak winter flows reducing the survival of overwintering YOY were the most critical indicator of local brook trout population survival. Fall low flows were the next most influential indicator of population survival, as relatively low flows increase the degree of embeddedness of spawning areas and depress dissolved oxygen levels (Hakala and Hartman 2004).

The difference equations presented here should allow managers to adopt adaptive management practices as potential summer base flows and runoff in New England increase slowly in the short-term and then decrease over the next several decades in response to changes in climate. Although the net effect of significant flow alterations from consumptive use and interbasin transfers was not included in these predictions, model projections can be adjusted for water withdrawals and returns in areas where sufficiently detailed data are available on local water balances to inform mitigation plans (e.g., Weiskel et al. 2010, MA EEA 2012). Finally, the joint application of flow and temperature predictive models for New England allows a change in natural base-flow conditions due to water withdrawals to be translated to a potential change in summer stream temperatures.

CONCLUSIONS

In northern humid continental climates such as the northeastern United States, summer base flows and total flows can be estimated through a two-step process. First, the longterm average of median July/August flows can be modeled as a function of long-term climate averages, seasonal distribution of precipitation, topography, depressional or soil storage, and surficial geology or soil characteristics. Second, interannual variability in summer base and total flows can be predicted as a function of interannual change in temperature, precipitation, and the NAO index. The use of difference equations has dual advantages of eliminating serial autocorrelation at lag 1 as well as the need for variable transformations.

This simple approach allows managers to examine both recent trends and future projections for low flow characteristics rather than assuming stationarity. New England data show evidence of recent increases in summer base flows and total flows throughout most of the region, while projection of future trends suggests a shift to declines in summer flows over the next 50 years under a wide range of climate futures.

Development has the potential to dramatically alter the natural spatial and temporal patterns in flow regimes. At low levels of development, both base and total summer flows can increase, but at intermediate levels of development (2-28% imperviousness), only total flows

continue to increase. Water use practices can shift areas with a natural abundance of groundwater supporting base flows to a condition of water deficits. Improvements in tracking water use and transfers in a consistent fashion at fine resolution over large regions are needed.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Research Impact Statement:

Summer baseflows and total flows exhibit recent increasing trends across New England. However, summer flows are projected to decline over the next 50 years under a wide range of climate futures.

Figure 1.
Mapped a) July median base flows, b) August median base flows, c) July total flows, and d) August total flows across New England states for the dry year 1999.

Figure 2.

Mapped a) median July base flows, b) median August base flows, c) median July total flows, and d) median August total flows across New England states for the wet year 2006.

Figure 3.
Mapped predicted Q10 for a) July base flow, b) August base flow, c) July total flows, and d) August total flows across the New England states.

Figure 4. Time series of predicted median August baseflow (dashed line) and total flow (solid line) based on model for reference systems. Predictions are for Lane River, NH which has the median predicted August Q10 value across all HUC12 outlets in New England.

Figure 5.

Mapped deciles of rate of change in predicted Q10 for a) July base flows, b) August base flows, c) July total flows, and d) August total flows illustrated using magnitude of Sen's slope from trends test. Hatched watersheds indicate no significant rate of change based on the modified Mann-Kendall test. Color codes vary across maps.

a) July base-flow min 3-in-5 yr trend

b) Aug base-flow min 3-in-5 yr trend

c) July flow min 3-in-5 yr trend

d) Aug flow min 3-in-5 yr trend

Figure 6.

Mapped deciles of rate of change in predicted minimum average three in five year (MA3in5) for base flows in a) July and b) August and for flows in c) July and d) August illustrated using magnitude of Sen's slope from trends test. Hatched watersheds indicate no significant rate of change based on the modified Mann-Kendall test. Color codes vary across maps.

Figure 7. Map of Massachusetts sub-basins showing potential August flow alteration (%) relative to natural condition due to water withdrawals (Weiskel et al. 2010). Impacts are patchily distributed with areas of significant net withdrawals in eastern MA and scattered areas of significant surcharges along major tributaries.

Table 1.

Alternative sources of water use data at approximately HUC12 scale for New England states.

State	Source of data	Resolution
VT, NH	USGS New England Science Center (no longer available online)	HUC12
MA	Archfield et al. 2010	Massachusetts sub basins
RI	Barlow 2003	Varies
	Wild and Nimiroski 2004	
	Wild and Nimiroski 2005	
	Nimiroski and Wild 2005	
	Wild and Nimiroski 2007	
	Nimiroski and Wild 2006	
	Wild 2007	

Table 2.

Independent variable combinations evaluated in regressions to predict mean monthly median streamflow or base flow. Shading is used to separate alternative options for input variables under each classification.

Indicator (or alternative variable combinations)	Definition	Units
<i>Watershed area (1 option)</i>		
DRAIN_SQKM	Watershed drainage area	km ²
<i>Yearly variation in inputs (2 options)</i>		
PPT_AVG	Annual average precipitation (1981-2010 calendar years) based on PRISM 800m grids	cm·yr ⁻¹
TMP_AVG	Annual average temperature (1981-2010) based on PRISM 800m grids	°C
PPT_AVG	Annual average precipitation (1981-2010) based on PRISM 800m grids	cm·yr ⁻¹
PET	Mean-annual potential evapotranspiration (PET), estimated using the Hamon (1961) equation.	mm·yr ⁻¹
<i>Seasonal variation in inputs (2 options)</i>		
AUG_PPT8100_CM or JUL_PPT8100_CM	Average August or July precipitation (1981-2010) based on PRISM 800m grids	cm·mo ⁻¹
SPRWNTRPPT	Ratio of spring (March - May) to winter (December - February) precipitation	unitless
AUG_PPT8100_CM or JUL_PPT8100_CM	Average August precipitation (1981-2010) based on PRISM 800m grids	cm·mo ⁻¹
SNOW_PCT_PRECIP	Snow percent of total precipitation (1981-2010) estimated based on methods of McCabe and Wolock (2010)	%
<i>Withdrawals (2 options)</i>		
FRESHW_WITHDRAWAL	Total freshwater withdrawal (1995 – 2000) from USGS	ML·yr ⁻¹ ·km ⁻²
FRESHW_WITHDRAWAL2	Total freshwater withdrawal based on best available state sources (Table 1) summarized at HUC12 scale (1990 – 1995)	cm·mo ⁻¹
<i>Flashiness (1 option)</i>		
IMPNLCD06	Watershed percent impervious surfaces from 30-m resolution NLCD06 data	%
<i>Permeability (4 options)</i>		
HGA	Percentage of soils in hydrologic group A	%
SLOPE_PCT	Mean watershed slope derived from 100m resolution National Elevation Dataset (NED)	% ²
HGA × SLOPE_PCT	Interaction term	
HGA	Percentage of soils in hydrologic group A	%
HGB	Percentage of soils in hydrologic group B	%
SLOPE_PCT	Mean watershed slope derived from 100m resolution NED	% ²
HGA × SLOPE_PCT	Interaction term	% ²
HGB × SLOPE_PCT	Interaction term	% ²
PERMAVE	Average soil permeability	cm·hr ⁻¹

Indicator (or alternative variable combinations)	Definition	Units
SLOPE_PCT	Mean watershed slope derived from 100m resolution NED	%
PERMAVE $\times$ SLOPE_PCT	Interaction term	% cm hr^{-1}
CRSRFMN	Coarse surficial deposits (Detenbeck et al. 2016)	Fraction
SLOPE_PCT	Mean watershed slope, percent. Derived from 100m resolution NED	%
CRSRFMN $\times$ SLOPE_PCT	Interaction term	Fraction %
<i>Storage (2 options)</i>		
AWCAVE * ROCKDEPAVE	Average water capacity in soil layers	cm
STORAGE	Watershed percent wetlands + open water based on NLCD 2006	%
STOR_NOR_2009	Watershed dam storage ("NORMAL_STORAGE")	1000m ³ km ⁻²
AWCAVE * ROCKDEPAVE	Average water capacity in soil layers	cm
STORAGEHR	Percent of watershed surface area covered by "Lakes/Ponds" + "Reservoirs" in NHD Hi-Resolution (1:24k) data	%
STOR_NOR_2009	Watershed dam storage ("NORMAL_STORAGE")	1000m ³ km ⁻²

Table 3.

Predictive equations for July and August median base flow and streamflow for reference (R) or combined full set (F) of watersheds in New England. Bflow = base flow, Sflow = streamflow. See Table 2 for variable definitions. Df = degrees of freedom, RMSE = root mean squared error, AIC = Akaike's Information Criteria. In some cases, multiple equations are listed for a single dependent variable when AIC values varied by less than two units.

R/F	Dependent variable	Units	Independent variable	Units	Coefficient	Adj R ²	df	RMSE	AIC	AIC weight
R	MedJulBflow	cm'mo ⁻¹	Intercept	cm'mo ⁻¹	1.31	0.6541	68	0.40	-275.16	
			CRSRFMN	percent	2.61					
			SNOW_PERCENT_PPT	percent	-0.049					
			STORAGE	percent	0.040					
			SLP130MN	percent	0.049					
			IMP06	percent	0.19					
			TMP_AVG	degrees C	-0.33					
			PPT_AVG	cm'yr ⁻¹	0.0085					
R	MedJulSflow	cm'mo ⁻¹	Intercept	cm'mo ⁻¹	2.35	0.6293	71	0.51	-240.319	0.449
			PPT_AVG	cm'yr ⁻¹	0.014					
			TMP_AVG	degrees C	-0.46					
			SNOW_PERCENT_PPT	percent	-0.070					
			CRSRFMN	percent	2.88					
R	MedJulSflow	cm'mo ⁻¹	Intercept	cm'mo ⁻¹	10.49	0.6302		0.51	-239.581	0.316
			PPT_AVG	cm'yr ⁻¹	0.012					
			PET	cm'yr ⁻¹	-0.70					
			SNOW_PERCENT_PPT	percent	-0.088					
			CRSRFMN	percent	2.9					
			DRAIN_SQKM	km ²	0.00031					
R	MedJulSflow	cm'mo ⁻¹	Intercept	cm'mo ⁻¹	0.51	0.6227	71	0.51	-238.972	0.234
			PPT_AVG	cm'yr ⁻¹	0.013					
			TMP_AVG	degrees C	-0.31					
			CRSRFMN	percent	2.62					
			PTIMP	percent	0.21					
R	MedAugBflow	cm'mo ⁻¹	Intercept	cm'mo ⁻¹	0.63	0.6153	70	0.35	-294.091	0.516
			CRSRFMN,	percent	2.77					

R/F	Dependent variable	Units	Independent variable	Units	Coefficient	Adj r ²	RMSE	AIC	AIC weight
R	MedAugBflow	cm mo ⁻¹	awcavexrockdepave,	cm	0.040				
			slp100mrs,	percent	0.046				
			sprwntprpt,	percent	-1.91				
			pp08MN8110	cm mo ⁻¹	0.0044				
			Intercept	cm mo ⁻¹	-1.86	0.616	70	0.35	-293.963
			CRSRFMIN,	percent	2.54				
			awcavexrockdepave,	cm	0.034				0.484
R	MedAugSflow	cm mo ⁻¹	sl130mn,	percent	0.063				
			storage,	percent	0.030				
			pp08MN	cm mo ⁻¹	0.0045				
			Intercept	cm mo ⁻¹	0.95	0.6027	70	0.42	-268.43
			CRSRFMIN,	percent	2.78				
			awcavexrockdepave,	cm	0.0434				
			sl130mn,	percent	0.060				
F	MedJulBflow	cm mo ⁻¹	sprwntprpt,	percent	-2.03				
			pp08mn	cm mo ⁻¹	0.0046				
			Intercept	cm mo ⁻¹	-1.40	0.543	104	0.52	-345.914
			ppt_avg	cm yr ⁻¹	0.0054				
			pp07MN8110	cm mo ⁻¹	0.0077				
			hga	percent	0.04				
			hgaxslopers	% %	-0.0017				
F	MedJulSflow	cm mo ⁻¹	awcavexrockdepave	cm	0.033				
			pet	cm yr ⁻¹	-0.12				
			Intercept	cm mo ⁻¹	3.07	0.519	105	0.65	-295.91
			ppt_avg	cm yr ⁻¹	0.011				0.418
			imnplcd06	percent	0.034				
			hga	percent	0.031				
			hgaxslopers	% %	-0.0014				
F	MedJulSflow	cm mo ⁻¹	pet	cm yr ⁻¹	-0.32				
			Intercept	cm mo ⁻¹	-0.65	0.521	105	0.65	-296.57
									0.582

R/F	Dependent variable	Units	Independent variable	Units	Coefficient	Adj r ²	df	RMSE	AIC	AIC weight
F	MedAugBflow	cm mo ⁻¹	ppt_avg	cm yr ⁻¹	0.012					
			inpnlcd06	percent	0.033					
			hga	percent	0.031					
			hgaxslopers	% %	-0.0012					
			ttmp_avg	degrees C	-0.22					
			Intercept	cm mo ⁻¹	-2.49	0.488	105	0.44	-385.285	
			ppt08MNMN8110	cm mo ⁻¹	0.0039					
			slp100mrs	percent	0.083					
			awcavexrockdepave	cm	0.052					
			permave	cm hr ⁻¹	0.089					
F	MedAugSflow	cm mo ⁻¹	permavexslopers	% cm hr ⁻¹	-0.0044					
			Intercept	cm mo ⁻¹	-2.80	0.471	105	0.52	-347.64	
			ppt08MNMN8110	cm mo ⁻¹	0.0052					
			slp100mrs	percent	0.093					
			awcavexrockdepave	cm	0.058					
			permave	cm hr ⁻¹	0.097					
			permavexslopers	% cm hr ⁻¹	-0.0049					

Table 4.

Predictive equations for interannual change in July and August median base flow and streamflow based on either reference (R) or full (F) data sets. In some cases, multiple equations are listed for a single dependent variable when AIC values varied by less than two units.

Observation set	Dependent variable	Difference Units	Independent variable	Difference Units	Coefficient	Chi-square	p > ChiSq	RMSE	AIC
R	dMedJulBflow	cm mo ⁻¹	Intercept		0.096	352.87	<0.0001	1.3	1225.5
			DifPPT_AVG	cm yr ⁻¹	0.0065				
			DifTMP_AVG	° C	-0.18				
			diff1wintmao	unitless	-0.66				
			diff2wintmao	unitless	-0.14				
R	dMedJulSflow	cm mo ⁻¹	Intercept		0.13	346.51	<0.0001	1.9	2078.7
			DifPPT_AVG	cm yr ⁻¹	0.010				
			DifTMP_AVG	° C	-0.41				
			DifPPT_AV*DifTMP_AVG	° C cm yr ⁻¹	0.0036				
			diff1wintmao	unitless	-1.04				
R	dMedAugBflow	cm mo ⁻¹	diff2wintmao	unitless	-0.30				
			Intercept		0.054	463.57	<0.0001	1.2	941
			DifPPT_AVG	cm yr ⁻¹	0.0066				
			DifTMP_AVG	° C	-0.34				
			diff1wintmao	unitless	0.38				
R	dMedAugSflow	cm mo ⁻¹	diff2wintmao	unitless	-0.24				
			Intercept		0.086	428.72	<0.0001	1.8	1866.3
			DifPPT_AVG	cm yr ⁻¹	0.0092				
			DifTMP_AVG	° C	-0.45				
			diff1wintmao	unitless	0.54				
F	dMedJulBflow	cm mo ⁻¹	diff2wintmao	unitless	-0.33				
			Intercept		0.075	481.45	<0.0001	1.4	1851.4
			DifPPT_AVG	cm yr ⁻¹	0.0059				
			DifTMP_AVG	° C	-0.14				
			DifPPT_AV*DifTMP_AVG	° C ° C yr ⁻¹	0.0011				
			diff1wintmao	unitless	-0.15				

Observation set	Dependent variable	Difference Units	Intercept	Independent variable	Difference Units	Coefficient	Chi-square	p > ChiSq	RMSE	AIC
F	dMedJulBflow	cm mo ⁻¹	diff2winternao			-0.31				
			Intercept			0.078	481.93	<0.0001	1.4	1852.4
			DifPPT_AVG			0.0060				
			DifTMP_AVG			-0.13				
			diff1winternao			-0.13				
			diff2winternao			-0.31				
F	dMedJulSflow	cm mo ⁻¹	Intercept			0.12	448.76	<0.0001	2.2	3168.8
			DifPPT_AVG			0.0091				
			DifTMP_AVG			-0.29				
			DifPPT_AV*DiffTMP_AVG			0.005				
			diff1winternao			-0.15				
			diff2winternao			-0.55				
F	dMedAugBflow	cm mo ⁻¹	Intercept			0.030	582.34	<0.0001	1.1	1283.3
			DifPPT_AVG			0.0067				
			DifTMP_AVG			-0.33				
			diff1winternao			0.38				
			diff2winternao			-0.22				
			Intercept			0.049	530.98	<0.0001	1.6	2639.6
F	dMedAugSflow	cm mo ⁻¹	DifPPT_AVG			0.009				
			DifTMP_AVG			-0.43				
			diff1winternao			0.50				
			diff2winternao			-0.27				
			Intercept			0.049	530.98	<0.0001	1.6	2639.6
			DifPPT_AVG			0.009				

Predicted change in July and August median base flow and runoff between 1975–2004 and 2036–2065 period based on 24 bias-corrected statistically downscaled climate change models applied to the Taunton watershed. Results are presented for the approximate bounding box representing range of predicted change in temperature (T) corresponding to high precipitation (P) model predictions and corresponding to low precipitation model predictions. RCP = representative concentration pathway. P_{75_04} = Taunton watershed precipitation 1975-2004.

Table 5.

RCP	BCSD	T °C	P %	P _{75_04} cm	P*P _{75_04} cm	Predicted Change (mm)			
						July Base flow	July Runoff	August Base flow	August Runoff
4.5	MIROC-ESM-CHEM	2.7	16.1	115.7	18.5	19.75	-2.2	-5.5	-7.6
4.5	CanESM2	3.3	0.8	115.7	1.0	1.15	-4.6	-9.8	-10.7
4.5	CSIRO-Mk3-6-0	1.8	19.5	115.7	22.6	16.28	-0.8	-2.7	-4.5
4.5	MPI-ESM-LR	2.1	-2.2	115.7	-2.5	-2.06	-3.1	-6.6	-7.0
8.5	MIROC-ESM-CHEM	2.3	16.2	115.7	18.8	16.61	-1.6	-4.3	-6.2
8.5	CSIRO-Mk3-6-0	2.1	0.3	115.7	0.5	0.34	-3.0	-6.5	-7.1
8.5	FGOALS-s2	3.4	19.4	115.7	22.4	30.44	-2.7	-6.9	-9.9
8.5	IPSL-CM5A-LR	2.8	-1.7	115.7	-2.0	-2.15	-4.1	-8.8	-9.3
8.5	average	2.9	9.9	115.7	11.4	12.88	-3.0	-7.0	-8.6
4.5	average	2.2	8.5	115.7	9.9	8.46	-2.3	-5.4	-6.6
both	average	2.5	9.2	115.7	10.7	10.56	-2.7	-6.2	-7.6

Table 6.

Changes in Aikake's information criteria (dAIC) following addition of median modeled or measured (HUC6 average) July (7) or August (8) base flow or flow to published spatial statistical network model equations for July or August median or daily range (DRange) stream/river temperature (Detenbeck et al. 2016). Best added variable is selected based on the magnitude of change in AIC from the null model. MedBsFIH6 = HUC6-scale average measured baseflow, MedStFlAv = average modeled streamflow, MedStFIH6 = HUC5-scale average measured streamflow.

Dependent variable		AIC	dAIC	Coefficient	Best added variable
Median8	published	2728.0			
Median8	revised	2713.1	14.9	-0.17	MedBsFIH6
Median7	published	2777.2			
Median7	revised	2771.2	6.0	-0.25	MedStFlAv
DRange8	published	2119.1			
DRange8	revised	2087.3	31.8	0.19	MedStFIH6
DRange7	published	2022.5			
DRange7	revised	2012.3	10.2	0.11	MedStFIH6