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Key Points:
- Summer stream temperatures in regulated rivers are lower than those in unregulated rivers, but they are more sensitive to climate change
- Reservoirs with long residence times will be more stratified in the future, but the effects on tailwater temperature will dissipate faster
- Simulated summer stream temperatures in regulated rivers are more sensitive to errors in hydrology than those in unregulated rivers

Supporting Information:
- Supporting Information S1

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Reservoirs Modify River Thermal Regime Sensitivity to Climate Change: A Case Study in the Southeastern United States

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Abstract Seasonal thermal stratification in reservoirs changes the thermal regime of regulated river systems as well as stream temperature responses to climate change. Cold releases from the reservoir hypolimnion can depress downstream river temperature during warm seasons. Recent large-scale climate change studies on stream temperature have largely ignored reservoir thermal stratification. In this study, we used established models to develop a framework which considers water demand and reservoir regulation with thermal stratification and applied this model framework to the southeastern United States. About half of all 271 reservoirs in our study area retain strong thermal stratification by the 2080s (2070–2099) under RCP8.5 even as median residence times decrease to 60 days from 69 days in the historic period (1979–2010). Reservoir impacts on downstream temperatures become slightly weaker in the future because of higher air temperature and stronger solar radiation. We defined a “cooling potential” to quantify the thermal energy that a water body can absorb before exceeding a water temperature threshold. In the future, higher river temperatures will reduce the cooling potential for all river segments, but more so for river segments minimally impacted by thermal stratification. Reservoir impacts on cooling potential remain strong for river segments downstream of reservoirs with strong thermal stratification. We conducted a sensitivity analysis to evaluate the robustness of our findings to errors in the hydrological simulations. Although river segments subject to reservoir regulation are more sensitive to errors in hydrology than those without regulation impacts, our overall findings do not materially change due to these errors.

Plain Language Summary River temperature is influenced by both climate change and human activities, especially dam regulation. Large dams impound deep reservoirs where only the top layer is warmed while the bottom stays cold. This phenomenon, with colder, heavier water at the bottom and warmer, lighter water on top, is known as thermal stratification. Large reservoirs usually release water from the bottom and thus cool downstream river temperature in the summer. In this study, we use computer models to simulate river flow and temperature while considering the influence of reservoir regulation and thermal stratification. Thermal stratification will strengthen for about half of the 271 reservoirs in the southeastern United States, but the cold outflow warms up faster due to global warming. Environmental agencies regulate maximum allowable river temperature, constraining a river's ability to provide cooling water for power plants. The cool release from the bottom layer provides more downstream cooling potential, that is, the energy that a river can absorb before exceeding a water temperature threshold, than would be possible in an unregulated river. In the future, the cooling potential will decrease as the climate warms, especially in unregulated rivers. Although our models are subject to errors, these errors do not change our overall findings.

1. Introduction

The objective of the paper is to advance our understanding of the effects of climate change on thermal regimes in heavily regulated rivers and of climate change as a stress multiplier on currently existing water resources infrastructure. We are particularly interested in large spatial domains, as opposed to single reach or small basin studies, to capture the river thermal constraints on regional power networks as well as aquatic ecosystems. Here, we describe a study in the southeastern United States (SEUS), where the power sector is particularly vulnerable to projected changes in stream temperature (Liu et al., 2017; van Vliet et al., 2016). The study region coincides roughly with the service area of the SERC Reliability Corporation, which is responsible for the reliability and security of the electric grid across the southeastern and central regions of the United States. The study region contains a number of highly regulated river systems with more than 300 dams. One third of the region's electricity generation portfolio depends on thermoelectric plants with once-through cooling that require large amounts of water for supporting power operations (Averyt et al., 2013). Once-through cooling systems are legally mandated to not produce effluent that exceeds certain environmental temperature thresholds. However, historical stream temperatures are already close to environmental thresholds as we will show in Section 3.2.

Previous studies have generally shown that projected increases in stream temperature under climate change will put great pressure on potential electricity generation globally (van Vliet et al., 2012, van Vliet et al., 2013, van Vliet et al., 2016) and over regions of the United States (Bartos & Chester, 2015; Boehlert et al., 2015; Liu et al., 2017; Miara et al., 2017; Zhang et al., 2020) by reducing the cooling efficiency of thermoelectric plants. Power plants face capacity derating and resulting power outages if their thermal effluent temperature exceeds specific environmental thresholds (McCall et al., 2016; Raptis et al., 2016). This generation curtailment risk is particularly relevant for power plants using once-through cooling techniques because they release thermal effluent directly into nearby river systems. Liu et al. (2017) showed that the average generating capacity in the United States is expected to decline by up to 12% by the 2060s if environmental regulations are enforced, with the power system in the eastern United States most vulnerable to increases in stream temperature (Liu et al., 2017; van Vliet et al., 2012, van Vliet et al., 2016).

Reservoir regulation can change a river's thermal response to surface meteorology and its thermal sensitivity to climate change. Manmade reservoirs can modify a river's thermal regime in two ways: (1) reservoirs store a large amount of water with a smaller surface area to volume ratio than a regular river reach and hence modify the thermal response to surface energy fluxes, and (2) deep reservoirs thermally stratify on a seasonal basis and store cold water for later release (Chapra, 2008). Multiple catchment-scale studies have investigated the impacts of simple reservoir systems on downstream river temperatures in a number of locations around the world, for example, Canada (Maheu et al., 2016), China (Cai et al., 2018), Europe (Arora et al., 2018; Kędra & Wiejaczka, 2018), and the United States (Lowney, 2000). These studies show that seasonal thermal stratification has significant impacts on downstream river temperatures. Stratification results in a density gradient that inhibits mixing between the colder bottom layer (hypolimnion) and the warmer upper layer (epilimnion). Because many reservoir releases (e.g., for hydropower) are made from the bottom layer, summer stream temperatures are often cooler downstream of reservoirs.

Although a number of large-scale stream temperature studies (Boehlert et al., 2015; Isaak et al., 2012; Li et al., 2015; Mantua et al., 2010; Strzepek et al., 2015; Sun et al., 2015; van Vliet et al., 2012; Zhang et al., 2020) accounted for the effects of reservoir regulation, most of them did not explicitly consider seasonal thermal stratification and therefore underestimated the effects of regulation on stream temperature, particularly downstream of large reservoirs. For example, Li et al. (2015) showed a warm bias of over 10°C in summer stream temperature downstream of Hoover Dam and Yearsley et al. (2019) showed a warm bias of as much as 8°C downstream of a reservoir in the Connecticut river basin. Those studies that did include the effects of stratification, including recent studies by Boehlert et al. (2015) and Strzepek et al. (2015), did not explicitly evaluate reservoir impacts on river temperature further downstream.

Detailed models exist to simulate reservoir temperatures in regulated river systems, for example, CE-QUAL-W2 (Cole & Wells, 2015), WQRRS (USACE-HEC (U.S. Army Corps of Engineers-Hydrologic Engineering Center), 1986), and HEC-5Q (Willey, 1986). These models have been used mainly in single-reservoir studies (Gelda et al., 1998; Hanna et al., 1999), in part because of their extensive data requirements. CE-QUAL-W2 (Hanna et al., 1999) and WEAP (Rheinheimer et al., 2014) have also been used to study temperature control device applications.

Water resources management requires coordinated decisions at the basin level and consequently needs tools and models that can account for the combined actions and effects of multiple reservoirs. Many regional applications, such as power system planning, require the ability to examine coordinated impacts across an even larger region, consisting of multiple river basins. Boehlert et al. (2015) and Niemeyer et al. (2018) developed simplified modules that represent reservoirs as two-layer systems that account for thermal stratification and incorporated these modules into distributed stream temperature models that can represent the aggregate effect of tens or even hundreds of reservoirs.

In this study, we include the reservoir module of Niemeyer et al. (2018) in a regional model setup to examine climate change effects on stream temperature across a large region with hundreds of reservoirs. We account explicitly for reservoir regulation, including the effects of seasonal thermal stratification, on system-wide stream temperatures, enabling us to evaluate the individual and joint contributions of climate change and reservoir impacts on river thermal regimes. We focus on thermal regimes during the summer when high air temperature, high water demand, and low streamflow coincide in our study region and when thermal stratification is strongest and has the greatest impact on downstream river temperature.

Although a large-domain model setup allows for a system-wide evaluation of the thermal response and thermal sensitivity to climate change, large-domain model applications are typically subject to larger errors than small-domain or single-site applications. These larger errors result from process simplifications, limited information about site characteristics, and model parameters that cannot always be calibrated across all sites in a consistent manner because of limited observations and computing resources. To address this general shortcoming of large-domain model implementations, we conclude this paper with a sensitivity experiment to assess the robustness of our findings to errors in the hydrological simulations.

2. Methods

Our process-based modeling approach uses a series of established models (Figure 1). It consists of a large-scale, spatially-distributed hydrological model (Variable Infiltration Capacity or VIC; Liang et al., 1994; Hamman et al., 2018), a river routing model (Model for Scale Adaptive River Transport or MOSART; Li et al., 2013), coupled to a spatially-distributed water management model (WM; Voisin, Li, et al., 2013, Voisin et al., 2017), and a stream temperature model (River Basin Model or RBM; Yearsley, 2009, 2012) that includes a two-layer reservoir thermal stratification module (2L; Niemeyer et al., 2018). We can disable the WM and 2L modules to simulate unregulated river conditions (solid frames in Figure 1), which we also refer to as the unregulated model setup. Historic meteorological forcings and downscaled climate change projections are preprocessed using MetSim (Bennett et al., 2020) so that they can be used as input to our model chain.

2.1. Study Area

The study region (SEUS; 1.19 million km^2, Figure 2) was selected because it coincides roughly with the service area of the SERC Reliability Corporation. We adjusted the area in some places to capture river basin boundaries. The SEUS includes large river basins that cover all or parts of Florida, Georgia, Alabama, Mississippi, Louisiana, Texas, Oklahoma, Arkansas, Missouri, Iowa, Illinois, Kentucky, Tennessee, Virginia, North Carolina, and South Carolina. Over the past century, more than 300 dams and locks were constructed in the area. Some of these are run-of-river dams or navigation locks, which we excluded, because they have short residence times and do not stratify seasonally. We explicitly simulated 271 major reservoirs based on information in the Global Reservoir and Dam Database (GRanD; Lehner et al., 2011). Most of the dams in the region were built in the headwaters rather than on the mainstem of the major rivers, with the exception of the Tennessee River, which has seven mainstem reservoirs (Table S1, with "S" indicating material in the supporting information).

2.2. Meteorological Forcings

Gridded meteorological forcings were used as input to our model chain. We used gridMET (Abatzoglou, 2013) for the historical period (1979–2010). For the future climatological period (2070–2099, hereafter referred to as the 2080s), we used projections from the Coupled Model Intercomparison Project, Phase 5 (Taylor et al., 2011), downscaled using the Multivariate Constructed Analog (MACA; Abatzoglou & Brown, 2012) method. Because gridMET is the training data set for MACA, consistency between the historical data and future projections is ensured. The gridMET and MACA datasets were regridded from 1/24° to 1/8° latitude–longitude resolution for our application. We used an ensemble of 20 global climate models (GCMs; Table S2) and one representative concentration pathway (RCP; RCP8.5) for a total of 20 future scenarios. Daily gridMET and MACA data, that is, daily maximum and minimum air temperature, precipitation, and wind speed, were disaggregated to the 3-hourly VIC model time step using MetSim v2.0.0 (Bennett et al., 2020). Other subdaily meteorological forcings, including relative humidity, surface air pressure, and incoming shortwave and longwave radiation, were estimated by MetSim using algorithms from the

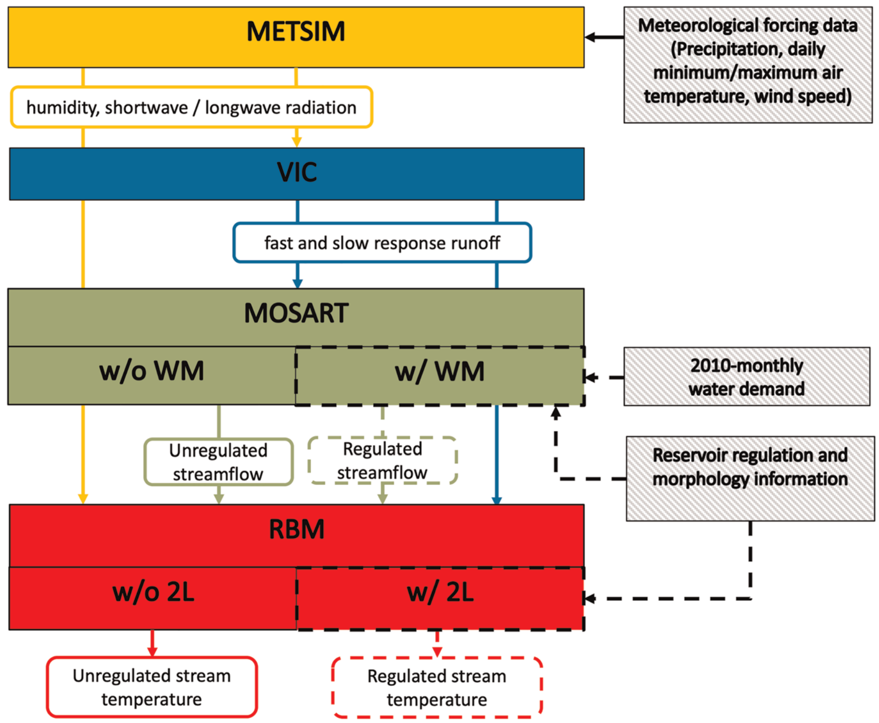

Figure 1. Model framework. Dashed boxes and arrows denote models and inputs that are only used in the regulated model setup.

Mountain Micro Climate Simulator (Bohn et al., 2013; Thornton & Running, 1999). Wind speed was assumed constant throughout the day.

2.3. Streamflow and Stream Temperature

2.3.1. Hydrology and Runoff

We used VIC version 5 (Hamman et al., 2018) at a 1/8° spatial resolution to simulate the hydrology of the SEUS. Model parameters were taken from Maurer et al. (2002) and modified over part of the domain to reduce a high streamflow bias in the South Atlantic region. VIC was run at the 3-hourly time step, and fast and slow response runoff were output at the daily time step to be consistent with the temporal resolution of the river routing and stream temperature models. We initialized the VIC simulation using a 32-year spin-up run forced by historical meteorological data to allow sufficient time for model states, for example, deep layer soil moisture, to equilibrate.

2.3.2. Streamflow and Reservoir Regulation

MOSART-WM (Voisin, Li, et al., 2013) is a fully coupled spatially distributed river routing and water management model that accounts for reservoir operations and multisectoral water demands to simulate regulated streamflow over large regions (Hejazi et al., 2015; Voisin, Li, et al., 2013, Voisin et al., 2017; Zhou et al., 2018). We implemented MOSART (Li et al., 2013) with and without the water management module (WM; Voisin, Li, et al., 2013, Voisin et al., 2017) at a daily time step with a 1/8° spatial resolution. WM estimates daily reservoir releases based on monthly storage targets and accounts for daily constraints such as environmental flow, minimum and maximum storage, and water demands. We substituted WM's original computation of dynamic storage targets at the end of each month (Voisin, Li, et al., 2013) with specified, observed monthly storage targets calculated from storage or reservoir height observations or based on a guide curve (see Text S1 for details, including Figures S1 to S4, and Tables S3 to S6). We collected guide curves or calculated them from observed storages or reservoir elevations for 92 reservoirs in the study area based on information from the Tennessee Valley Authority, United States Geological Survey (USGS), and U.S. Army Corps of Engineers (data source for each reservoir is summarized in Table S5). Storage targets for reservoirs without observations were estimated based on their primary regulation objective and the relative degree to which they were filled on average (Text S1). In addition to the storage targets, inputs for

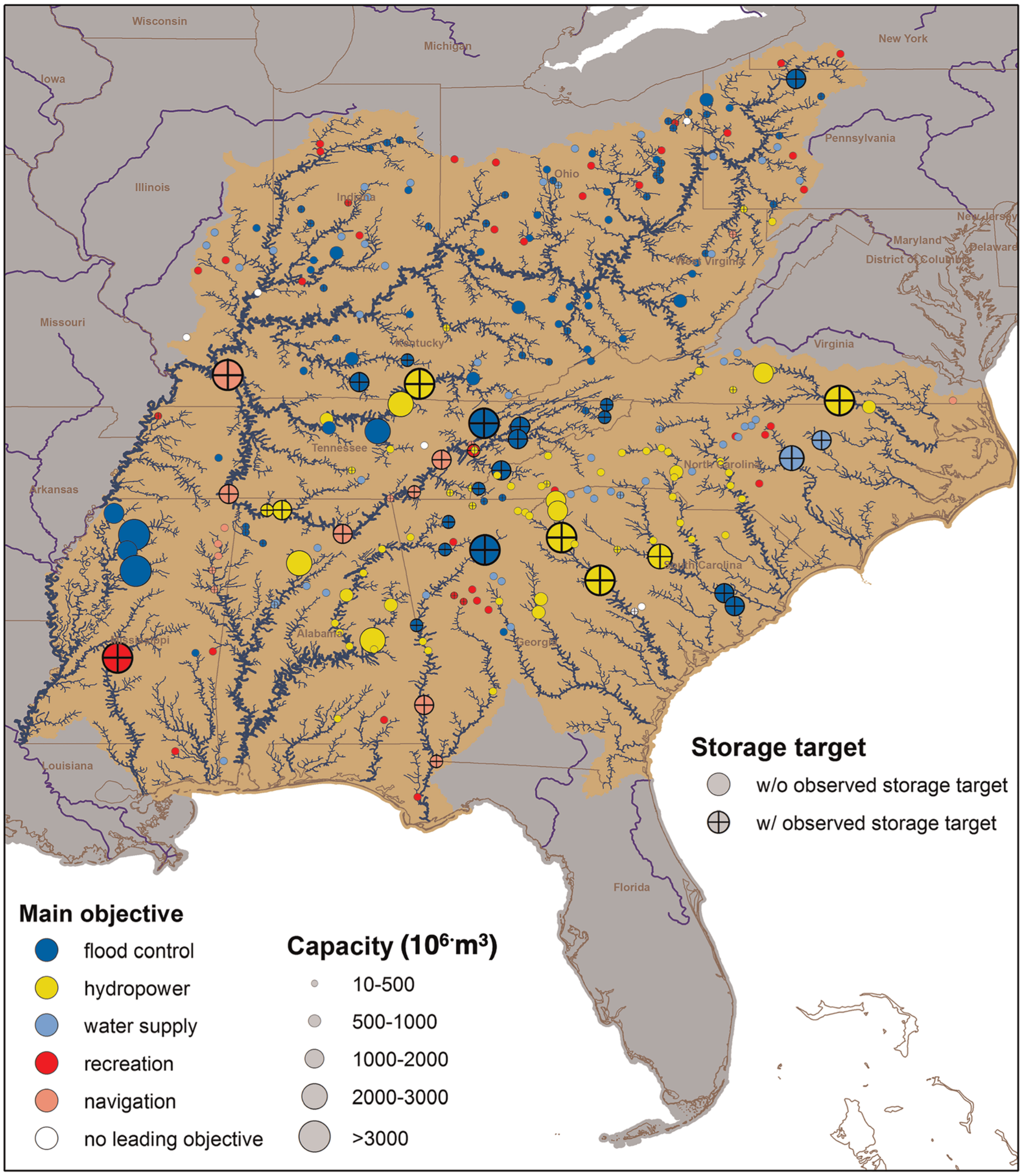

Figure 2. Study region. All reservoirs included in this study are represented by the circles.

MOSART-WM included runoff from VIC, reservoir information from the GRanD Database, and 2010 level water demand as used in Voisin et al. (2017) and Zhou et al. (2018). We used fixed water demand from year 2010 for all years to isolate the effects of climate change from other anthropogenic influences which can significantly impact the hydrologic response (Voisin, Liu, et al., 2013, Voisin et al., 2016).

2.3.3. Stream Temperature

RBM is a one-dimensional stream temperature model which solves the energy balance equation for surface energy fluxes in the river channel (Yearsley, 2009, 2012). To account for seasonal thermal stratification, we used a module (2L) developed by Niemeyer et al. (2018) that simulates the temperature in two thermally distinct layers: an epilimnion (top layer) and a hypolimnion (bottom layer). This module uses inflow, outflow, and storage data for each reservoir as simulated by MOSART-WM. To calculate surface energy exchange between the water and the overlying atmosphere, RBM and RBM-2L (i.e. without and with reservoir representation) use output from VIC and MetSim. Headwater temperatures, that is, the most upstream river

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temperature, which form a boundary condition when solving the energy balance equation for river systems, were estimated using a nonlinear relationship with air temperature (Mohseni et al., 1998). Fitted parameters for the Mohseni equations were taken from Niemeyer et al. (2018). We assumed that all reservoir releases were made from the hypolimnion so our results represent a lower bound of possible river temperatures under reservoir regulations. RBM and RBM-2L were initialized separately by setting all model elements to the same water temperature and running the model for a one-year spin-up period.

2.4. Evaluation Metrics

We examined the impacts of climate change on water availability, residence time, regulated stream temperature, and "cooling potential," a metric used to evaluate the compound impacts of water availability and stream temperature. Reservoir residence time was calculated as the mean annual storage divided by the mean annual outflow from that reservoir. In summer, reduced streamflow and increased stream temperature can both constrain the operations of thermoelectric power plants. The cooling potential (E^{cp} [W]) combines the effects of stream temperature and streamflow and represents the additional amount of energy that a body of water can absorb, for example, from thermoelectric power plants, before exceeding a water temperature threshold. It is similar to the concept of cooling power in Macdonald et al. (2007). We define the cooling potential as

$$E^{cp} = \begin{cases} \rho C_p (T_{threshold} - T_{summer}) Q_{summer} & if\ T_{summer} < T_{threshold} \\ 0 & if\ T_{summer} \geq T_{threshold} \end{cases}, \tag{1}$$

where ρ is water density [kg/m^3], C_p is the heat capacity for water [4,186 J/kg·°C], $T_{threshold}$ is a stream temperature threshold [°C], T_{summer} is the mean summer stream temperature [°C], and Q_{summer} is the mean summer streamflow [m^3/s]. For $T_{threshold}$, we used one single value for the entire region for a spatially consistent analysis. We set $T_{threshold}$ to 31°C, which is the median of the maximum stream temperature standards of all states in our study region as imposed by the United States Environmental Protection Agency. In other words, the cooling potential represents a river system's ability to absorb waste thermal energy from thermoelectric power plants if environmental regulations are enforced. We examine climate change impacts on the cooling potential not only at the sites of existing thermoelectric power plants, but for the entire regulated river system.

One of our goals is to quantify the effect of reservoir regulation on the thermal sensitivity of the system to climate change. To this end, we define a rate of change (ΔR) as

$$\Delta R = \left(\frac{\left| \Delta E^{\mathrm{cp}}{}_{\mathrm{reg,\ 2080}s - unreg, 2080s} \right|}{\left| \Delta E^{\mathrm{cp}}{}_{\mathrm{reg,\ hist}-unreg,\mathrm{hist}} \right|} - 1 \right) \times 100\%, \tag{2}$$

where $\Delta E^{cp}{}_{(reg,\,t\ -\ unreg,\,t)}$ is the change in cooling potential due to regulation during period t. The metric ΔR ranges from -100% to positive infinity. Positive values indicate that future climate will enhance the ability of regulation to maintain the cooling potential, whereas negative values for ΔR indicate that future climate will reduce the ability of regulation to maintain the cooling potential. In other words, negative ΔR means that rivers are less able to absorb waste heat before exceeding the threshold temperature, potentially affecting cooling for thermal power plants and hence power generation under climate change.

2.5. Sensitivity Analysis

Large-domain model simulations are typically subject to larger errors than small-domain or single-site applications, and these errors are often not easy to reduce. In our model chain, errors in regulated streamflow mainly result from biased runoff from the hydrological model and fixed monthly storage targets. To determine the robustness of our findings to errors in the hydrological simulations, we performed a sensitivity analysis.

As part of our climate change experiment, we already created 20 individual hydrological simulations, each corresponding to the downscaled meteorological forcings of a single GCM, and each resulting in a different, but internally consistent streamflow. In the sensitivity analysis, we used these 20 different hydrological simulations as alternative streamflow scenarios, which we then combined with the meteorological forcings from a single GCM as input to the stream temperature model. The subsequent spread in river temperatures resulted directly from the spread in hydrologic conditions. We repeated this process for three different climate change scenarios selected from our 20 GCM simulations (high, HadGEM2-CC365; medium, CSIRO-Mk3-6-0; low, inmcm4; based on mean projected air temperatures) resulting in 60 (3 × 20) stream temperature simulations. The three temperature scenarios account for potential differences in sensitivity to hydrological error for different changes in air temperature. We ran this experiment using both regulated and unregulated model setups, resulting in a total of 120 (2 × 60) stream temperature simulations.

We designed a metric (ϕ) which relates the spread in stream temperature or cooling potential to the spread in hydrologic conditions. Large ϕ values indicate that changes in hydrological conditions result in a large spread in simulated stream temperature or cooling potential. For stream temperature, we calculated this metric as the ratio of the standard deviation (σ) of the projected increase in mean summer river temperature (ΔT) [°C] to the coefficient of variation of mean annual streamflow (Q). The resulting ϕ-values for stream temperature are in units of degrees Celsius. We categorized river segments based on river size and whether they are subjected to reservoir regulation. River size is based on the historical mean annual regulated streamflow (Q) with each segment receiving a classification (l) of small ($Q\in[0,50]$ m^3/s; $l = 1$), medium ($Q\in[50,100]$ m^3/s; $l = 2$), or large ($Q\geq 100$ m/s; $l = 3$). All river segments located downstream of reservoirs are subjected to reservoir regulations (m = true) while the rest are not (m = false). We calculated the metric for each group as follows:

$$\phi_{i,l,m,r} = \frac{\sigma_{\widetilde{\Delta T}_{i,[\![j]\!],[\![k]\!]_{l,m},r}}}{CV_{\widetilde{Q}_{i,[\![j]\!],[\![k]\!]_{l,m},r}}}, \tag{3}$$

$$\widetilde{\Delta T}_{i,j,k,r} = \Delta T_{i,j,k,r} - \overline{\left[\Delta T_{i,k,r}\right]_j}, \tag{4}$$

$$\widetilde{Q}_{i,j,k,r} = \frac{Q_{i,j,k,r}}{\overline{\left[Q_{i,k,r}\right]_j}}, \tag{5}$$

where i denotes the climate change scenarios (i = high, medium, low), j denotes the streamflow scenario based on each GCM (j = 1, 2, ..., 20), the double brackets $[\![j]\!]$ indicate that we calculate the statistic across all values of j, k denotes the grid cells in our model domain, $[\![k]\!]_{l,m}$ denotes all grid cells within river size l and subjected to regulation scenario m, and r denotes the regulated and unregulated model setups, that is, WM and 2L are enabled (r = reg) and disabled (r = unreg), respectively. In Equation 4, we removed $\overline{\left[\Delta T_{i,k,r}\right]_j}$, that is, the mean value across 20 GCMs, from the temperature change, $\Delta T_{i,j,k,r}$ so that the hydrology-induced spread ($\widetilde{\Delta T}$) can be aggregated across all grid cells within each group. Similarly, we divided the $Q_{i,j,k,r}$ values by $\overline{\left[Q_{i,k,r}\right]_j}$, that is, the mean across 20 GCMs (Equation 5). $\phi_{i,l,m,r}$ quantifies the temperature spread caused by hydrologic errors, with larger $\phi_{i,l,m,r}$ values indicating that temperatures are more sensitive to errors in hydrology.

We related the calculated sensitivities to the errors in our hydrological simulations during the historic period. That is, we used $\phi_{i,l,m,r}$ and the hydrologic errors from model evaluation to estimate the resulting error in the stream temperature simulations as follows:

$$\widehat{\sigma}_{\widetilde{\Delta T}_{i,l,m,r}} = \phi_{i,l,m,r} \times \widehat{\mathrm{CV}}_{\widetilde{Q}_{[\![\widehat{k}]\!]_{l,m}}}, \tag{6}$$

$$\widetilde{Q}_{\widehat{k}} = \frac{Q_{sim,\widehat{k}}}{Q_{obs,\widehat{k}}}, \tag{7}$$

where $\widehat{\sigma}_{\widetilde{\Delta T}}$ denotes errors in the stream temperature change resulting from errors in our hydrological simulations, $\widehat{k}$ denotes corresponding grid cells with USGS observations ($\widehat{k}$ =1,2, ...,111; $\widehat{[\![k]\!]}$ =[1,2, ...,111]), $Q_{sim,\widehat{k}}$ and $Q_{obs,\widehat{k}}$ denote simulated and observed mean annual streamflow for site $\widehat{k}$, and the accent hat indicates estimates based on comparison with observations. Unlike the sensitivity analysis above with

20 hydrologic scenarios, we only have one historical scenario, so we calculated a representative value of hydrological errors for each group using all corresponding USGS sites. We divided the $Q_{sim,\widehat{k}}$ values by $Q_{obs,\widehat{k}}$ (Equation 7) to aggregate multiple USGS sites within the same group.

We repeated the same analysis for cooling potentials (E^{cp}). Instead of $\widetilde{\Delta T}_{i,j,k,r}$ (Equation 4), we used the projected relative changes of cooling potentials as follows:

$$\Delta r E^{cp}{}_{i,j,k,r} = \frac{\left[E^{cp}{}_{i,j,k,r}\right]_{2080s} - \left[E^{cp}{}_{k}\right]_{hist}}{\left[E^{cp}{}_{k}\right]_{hist}}, \tag{8}$$

$$\widetilde{\Delta r E^{cp}}{}_{i,j,k,r} = \Delta r E^{cp}{}_{i,j,k,r} - \overline{\left[\Delta r E^{cp}{}_{i,k,r}\right]}_{j}, \tag{9}$$

where subscript "*hist*" denotes historical periods with other subscripts as above and $\Delta r E^{cp}$ represents the projected relative changes in cooling potential. Furthermore, we removed the mean of $\Delta r E^{cp}$ across 20 GCMs, similar to what we did for the mean summer temperature.

3. Results

3.1. Model Evaluation

3.1.1. Streamflow

To evaluate the simulated streamflow and stream temperature in a regulated river system, we used USGS observations at 111 sites with both streamflow and stream temperature data (United States Geological Survey (USGS), 2019; summarized in Table S7. Site selection was subject to two criteria: (1) each site had to have at least 1 year of observations that overlapped with our historical simulation period and (2) the contributing area of the site had to be larger than the size of a single model grid cell (approx. 150 km^2). Sixty-three of the 111 sites were located downstream of reservoirs and therefore subject to reservoir regulation. The remaining 48 sites were only minimally affected by regulation and were used to evaluate whether poor performance at regulated sites was the result of poor performance of the hydrology model or the water management model. We used the relative bias at the annual time step and the Nash-Sutcliffe (NS) coefficient at the monthly time step to evaluate overall water availability and streamflow seasonality, respectively (Figure S5).

Across the 111 sites with observations, the median relative bias in mean annual simulated streamflow was 0.05, which includes the effects of regulation for sites downstream of reservoirs. Sixty-three sites, representing a mixture of regulated and unregulated sites, had a relative bias with an absolute value less than 0.2. Seven had a relative bias with an absolute value greater than 0.5. The NS coefficient for the monthly flows showed lower values for sites with a larger relative bias. In addition, the simulated flows generally showed higher NS coefficients for sites that are not subject to regulation. The median NS coefficient for the 48 unregulated sites was 0.70 compared to 0.55 for the 63 regulated sites. Three unregulated sites and 17 regulated sites had an NS coefficient less than 0. The South Atlantic region generally had the worst performance as measured by the NS coefficient, in part because multiple sites ($n = 6$) downstream of Buford reservoir on the Chattahoochee river showed relatively poor performance. The impacts of hydrologic errors on stream temperature simulations are further investigated through the sensitivity analysis in Section 4.3.

3.1.2. Reservoir Storage

For the 92 reservoirs with guide curves (Section 2.3.2), we compared simulated storage to the specified guide curves. Because we specify the guide curves in MOSART-WM, the model storage is expected to closely follow these curves, unless streamflow is too low to fill the reservoir or daily release-constraints force a deviation from the specified guide curve. We calculated the normalized root mean square error (nRMSE) of multiyear mean monthly storage (12 mean monthly values based on the 32-year daily time series) and the relative bias of mean annual storage to evaluate seasonality and bias, respectively, in the thermal mass of the reservoirs. Simulated storage showed only a small relative bias and a small nRMSE for the 92 sites with guide curves, with median values of −0.01 and 0.06, respectively, indicating that the water management model captured the volume and seasonality of the storage in the study region.

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3.1.3. Stream Temperature

In the SEUS, low flow occurs during the summer when it coincides with high air temperatures, resulting in high stream temperatures. Summer is also the time when reservoir stratification is most pronounced. We therefore focus our evaluation on the mean summer river temperature (Figure S5), with summer defined as the 3-month period from June through August.

Simulated mean summer stream temperatures generally show a cold bias with a median value of −0.7°C across the 111 sites with stream temperature observations. The mean bias was less than ±2°C at 87 of these sites. The bias was generally smaller at the unregulated sites (median bias −0.3°C, $n = 48$) than at the regulated sites (median bias −0.9°C, $n = 63$). For the 63 regulated sites, 45 had a bias less than 2°C. Nine regulated sites had a cold bias larger than 4°C.

The supporting information contains site-specific information of model performance, including time series plots of observed and simulated streamflow (Figure S6) and stream temperature (Figure S7) for sites downstream of the five largest reservoirs with downstream temperature observations and a discussion of the source of hydrological errors (Text S2).

3.2. Historical Analysis: Reservoir Impacts Typically Maintain or Reduce Mean Summer Stream Temperature

Figure 3a,b shows, respectively, the simulated mean summer temperature for the historic period for the regulated river system and the impact of regulation on stream temperature. Seasonal thermal stratification results in lower stream temperatures immediately downstream of large reservoirs and gradually attenuates further downstream. Smaller reservoirs, which do not stratify, have little to no impact on downstream river temperature.

Larger reservoirs with longer residence times tend to have stronger thermal stratification and impact downstream temperature more strongly. For example, summer outflow from Buford Reservoir (residence time of 402 days) on the Chattahoochee River is 15.2°C cooler in the regulated than in the unregulated model setup. Youghiogheny Reservoir on the Youghiogheny River has a shorter residence time (208 days) and a smaller cooling effect of 7.4°C. Reservoirs with even shorter residence times often have little to no impact on mean summer stream temperature as shown by a number of reservoirs on the Catawba River.

Reservoirs with larger outflows depress stream temperature for a longer distance downstream of the dam because their greater thermal mass makes them (1) less sensitive to surface energy fluxes and (2) less affected by mixing of tributary flows. For example, Deep Creek Reservoir on the Youghiogheny River (upstream of Youghiogheny Reservoir) has a small mean summer outflow of 3 m^3/s and a tailwater temperature that is 12°C colder in the regulated case. This temperature difference reduces to only 3°C over a distance of less than 18 km. In contrast, J. Strom Thurmond Reservoir on the Savannah River has a much larger mean summer outflow of 111 m^3/s and the temperature difference due to regulation decreases from 11°C to 4°C over about 100 km. So, although residence time affects seasonal thermal stratification and therefore the tailwater temperature, the outflow volume affects how far downstream this temperature depression persists.

3.3. Climate Change Impacts on Regulated River Temperature

In general, stream temperature in the southeast is projected to increase, mainly resulting from stronger solar radiation and increased air temperature (Figure 4a). Stream temperature increases are larger in the northern part of the study domain and smaller in the southern coastal region. The spatial pattern of stream temperature increase is strongly correlated with the spatial pattern of air temperature increase (Figure S9). Even though reservoir residence time decreases by the 2080s, reservoir regulation still results in colder stream temperatures downstream of reservoirs with seasonal thermal stratification than would occur in the absence of these reservoirs (Figure 4b). However, the cooling effect of reservoirs on downstream river segments slightly decreases by the 2080s. Figure 4c shows the change in the median temperature effect of reservoirs between the 2080s and the historic period. Red colors indicate less cooling due to regulation in the future than in the past. Blue indicates greater cooling. By the 2080s, reservoir impacts on downstream river temperatures attenuate faster in the downstream direction, that is, tailwater temperatures return to unregulated temperatures over a shorter distance. Even if a reservoir releases cool water from the hypolimnion, this cooling effect on tailwater temperature will dissipate faster under climate change as a result of greater surface

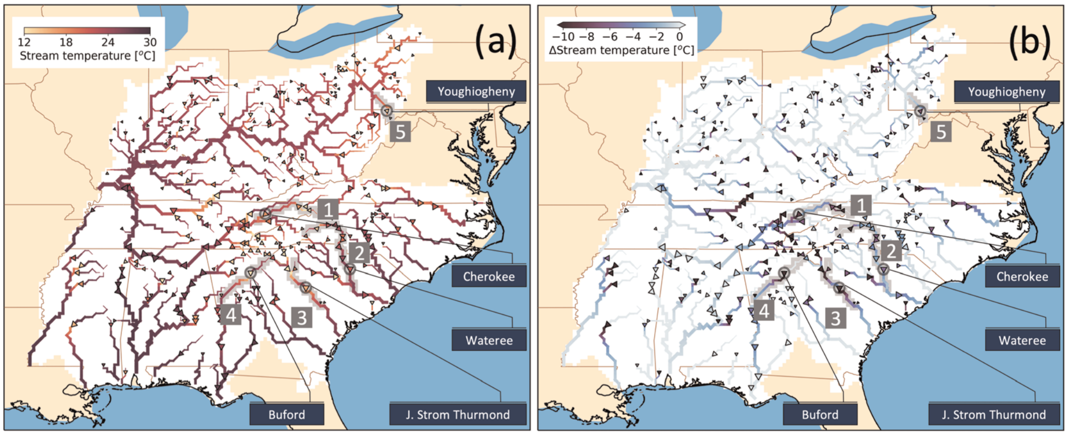

Figure 3. (a) Historical mean summer river temperature for the regulated model setup; (b) difference in historical mean summer temperature between the regulated and unregulated model setups. Triangles denote reservoir locations and point downstream; gray-shaded river channels were selected to show the temperature profile along the river, that is, (1) Tennessee River, (2) Catawba River, (3) Savannah River, (4) Chattahoochee River, and (5) Youghiogheny River (see Figure 7). Selected reservoirs discussed in the manuscript are circled with the dam names as shown.

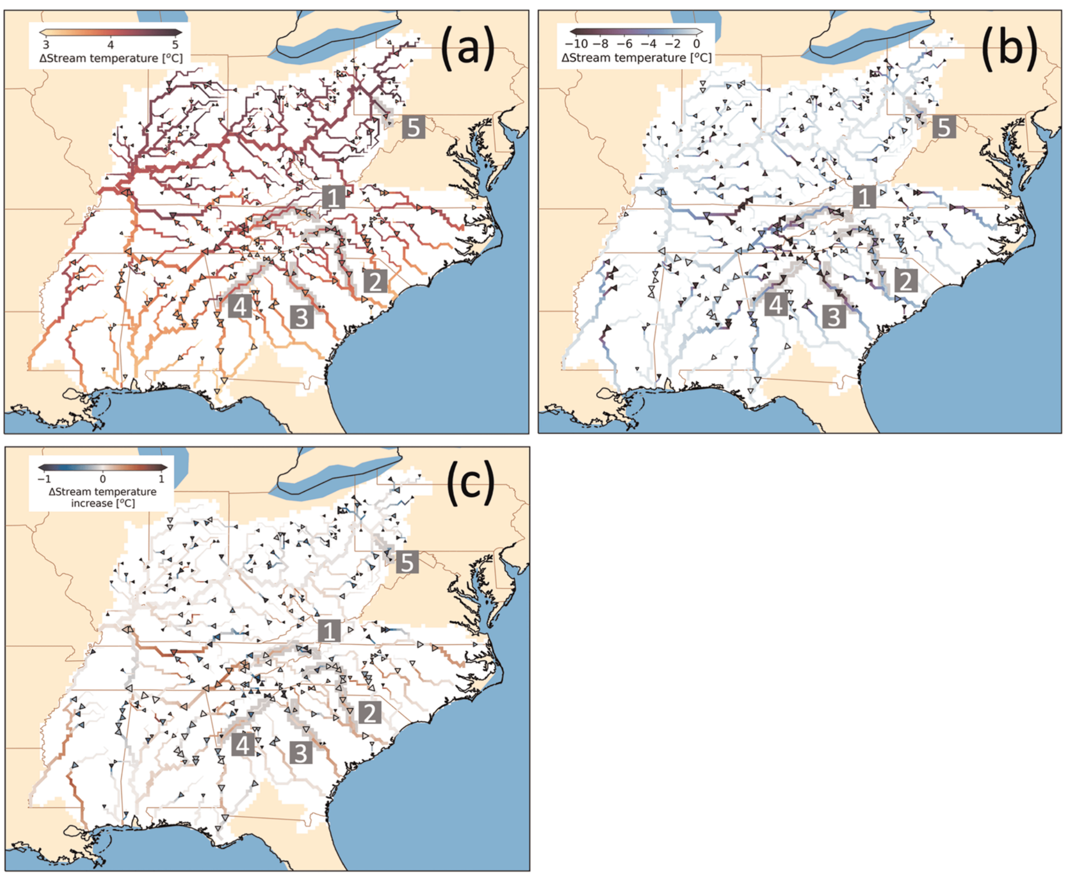

Figure 4. Projected mean summer river temperature (a) increases in regulated river system ($\Delta T_{reg,2080s\ -\ reg,hist}$), (b) differences between regulated and unregulated model setups in 2080s ($\Delta T_{reg,2080s\ -\ unreg,2080s}$), and (c) projected changes in the median reservoir impacts on temperatures between the 2080s under RCP8.5 and historical period, that is, $\Delta(\Delta T_{reg,2080s\ -\ unreg,2080s} - \Delta T_{reg,hist\ -\ unreg,hist})$. We highlight the same five rivers as in Figure 3: (1) Tennessee River, (2) Catawba River, (3) Savannah River, (4) Chattahoochee River, and (5) Youghiogheny River.

energy fluxes. In other words, under climate change, summer stream temperatures in regulated rivers increase faster than in unregulated rivers and are more sensitive to climate change.

3.4. Climate Change Modulates Reservoir Impacts Through Water Availability and Residence Time

We evaluated the projected changes in reservoir outflow and residence time by the 2080s to separate the contributions of changes in water availability from changes in thermal dynamics on the overall changes in stream temperature. Because we maintained the same storage targets in the future as during the historical period, the median projected changes for reservoir storage are within 5% for all reservoirs.

Residence times are projected to decrease for almost all reservoirs. Because we imposed the same storage targets in the future, projected increases in reservoir outflow lead to shorter residence times (Figure S10). Projected increases in reservoir outflows are generally greater in the north and coastal regions than in the central and southwestern parts of the study domain. The 20 GCM projections show strong agreement in the sign of the change signal. For most reservoirs, more than 16 out of 20 models agree that outflows will increase, and residence times will decrease (Figure S11). This increase in outflow mostly results from increased precipitation in the region. Although evapotranspiration also increases, it does not compensate for the increase in precipitation.

3.5. Cooling Potential Will Decrease Under Climate Change

Cooling potential (Equation 1) is influenced by both streamflow and stream temperature. During the historical period, cooling potential is greater in the regulated model setup for river segments downstream of reservoirs with strong thermal stratification, for example, the Savannah River and the upper reaches of the Tennessee River (green in Figure 5d). Downstream of reservoirs with little to no thermal stratification, the cooling potential tends to be lower in the regulated model setup because reservoir operations and water withdrawals lead to lower summer streamflow than in the unregulated model setup, for example, mainstem Ohio River (blue in Figure 5d).

Stream temperature is projected to increase in all GCM projections, contributing to a reduction in cooling potential. At the same time, streamflow is projected to increase in most GCMs, increasing cooling potential by increasing the thermal mass. The combined effects result in a net decrease in projected cooling potential during the summer by the 2080s for most GCM projections under RCP 8.5 (blue in Figure 5c). Therefore, the change in cooling potential is dominated by projected increases in stream temperature.

Larger rivers tend to show a greater loss in cooling potential than smaller rivers because of their greater thermal mass, for example, the Ohio River, the largest river in our study region. Over most of its length, the Ohio River will lose over 10 GW (10^4 MW) of cooling potential by the 2080s under RCP8.5. Regulation impacts on cooling potential for the historical period and the 2080s under RCP8.5 are shown in Figure 5d,e, respectively. Rivers with reservoirs that experience strong thermal stratification (Figures 3b and 4b) have more cooling potential under the regulated model setup in both the historical and future periods. Rivers with reservoirs that do not stratify, have less cooling potential in the regulated model setup (Figure 5d,e). For these rivers, regulation reduces cooling potential because of water withdrawals and lower summer streamflow.

Figure 5f summarizes whether the impact of regulation on cooling potential will increase or decrease in the future. If the ΔR value is close to 0%, regulation impacts on cooling potential will persist under climate change. If ΔR approaches −100%, regulation impacts will mostly disappear. For river segments downstream of reservoirs with strong seasonal thermal stratification, the regulation impact on cooling potential remains strong in the future, with ΔR mostly larger than −25% (Figure 5f). For river segments minimally impacted by upstream thermal stratification, regulation impacts on cooling potential decrease dramatically by the 2080s under RCP8.5 ($\Delta R < -75\%$; Figure 5f). For these river segments, the effect of regulation on cooling potential largely disappears by the 2080s.

4. Discussion

4.1. Reservoir Residence Time and Thermal Stratification

We used the mean summer temperature difference between the epilimnion and the hypolimnion (ΔT_{e-h}) as a measure of thermal stratification, with larger values indicating stronger stratification. To quantify the

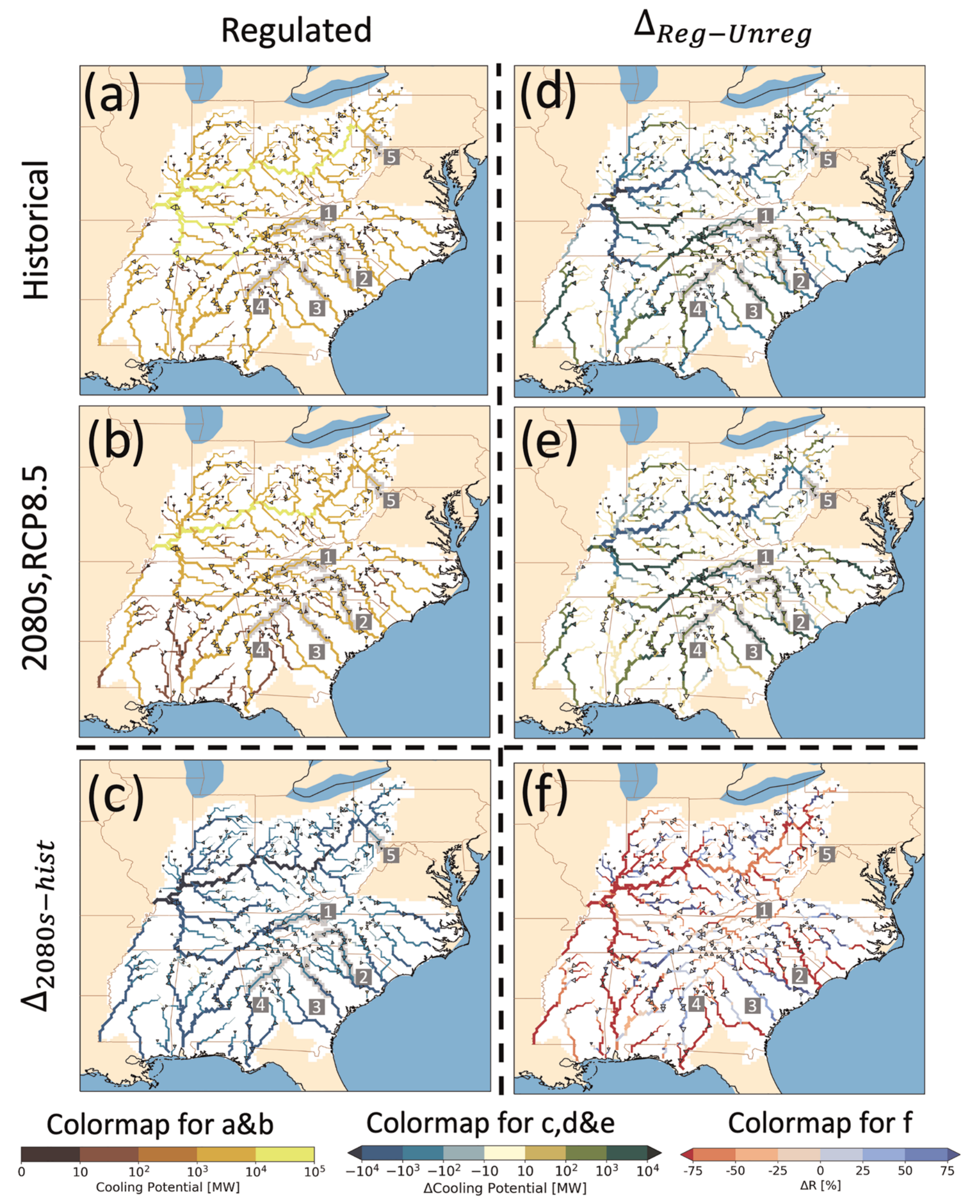

Figure 5. Spatial maps of regulated cooling potential for (a) historical period and (b) 2080s under RCP8.5; climate change impacts on regulated cooling potential under RCP8.5 (c, $\Delta E^{cp}{}_{(reg,\,2080s\ -\ reg,\,hist)}$); difference of cooling potential between regulated and unregulated model setups for (d) historical period and (e) 2080s under RCP8.5 and (f) the change in the effect of regulation on cooling between the future and historical periods (Equation 2).

impacts of reservoir residence time on thermal stratification, we compared simulated residence times and corresponding $\Delta T_{e\ -\ h}$ values for all 271 reservoirs (Figure 6a). Thermal stratification is weak when the reservoir residence time is shorter than 20 days. For reservoirs with a simulated residence time greater than 20 days, we fitted a log-linear regression model for $\Delta T_{e\ -\ h}$ as a function of residence time. Confidence intervals (95%) for the predicted $\Delta T_{e\ -\ h}$ values were calculated based on Devore (2011) and are shown as dashed lines in Figure 6. For the three reservoirs for which we had observations of reservoir storage, outflow, and reservoir temperatures with depth, we calculated the mean residence time and $\Delta T_{e\ -\ h}$values (stars in Figure 6a). Of these three, only Cherokee Reservoir had a residence time longer than 20 days. Fort Loundon and Guntersville reservoirs have short residence times of 8 and 12 days, respectively, and their thermal stratification is weak.

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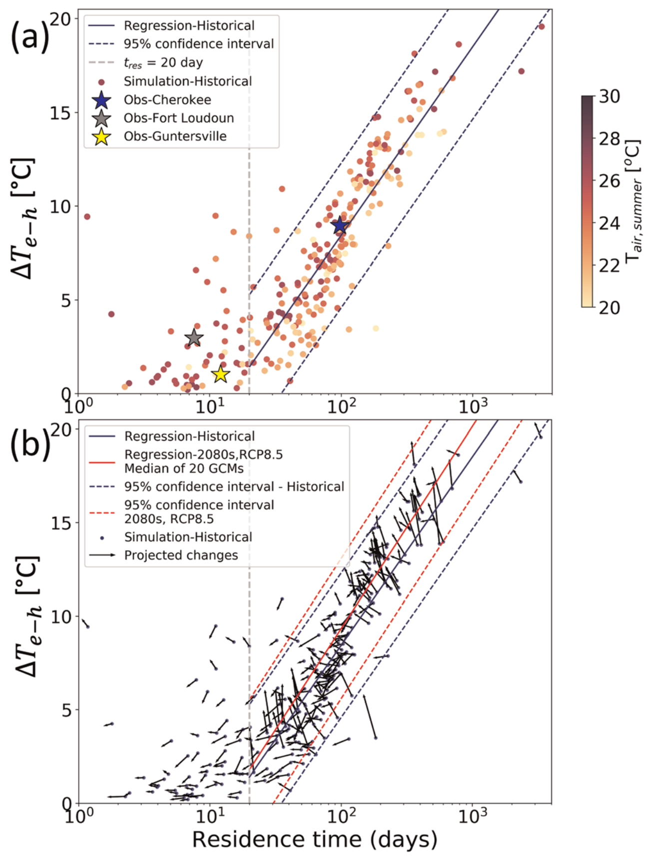

Figure 6. (a) Simulated reservoir thermal stratification ($\Delta T_{e\text{-}h}$) versus residence time during the historical period. Each dot represents the simulated result for one reservoir during the historical period. The dot color represents the mean air temperature at each reservoir location. Stars represent the observations, with blue, gray, and yellow stars representing Cherokee, Fort Loudoun, and Guntersville reservoirs, respectively. (b) Climate change impacts on the relationship between thermal stratification and residence time. Each dot is the same as in (a) with an arrow pointing to the median simulated result across 20 GCMs by the 2080s under RCP8.5 for the same reservoir.

By the 2080s under RCP8.5, thermal stratification will be stronger in about half the reservoirs. This finding is somewhat counterintuitive. Because we assume that the future guide curves will remain the same as for the historic period, increased streamflow results in reduced reservoir residence time by the 2080s (arrows generally point left in Figure 6b) and should therefore lead to weaker stratification (Figure 6a). Median residence time of all 271 reservoirs is projected to decrease from 69 days (historic) to 60 days (2080s). This decrease in residence time should be accompanied by a median decrease in thermal stratification of 0.7°C (Figure 6a). Although some smaller reservoirs with shorter residence times show the expected decrease in thermal stratification, median thermal stratification for all reservoirs is almost identical in the historic and future scenarios and about half of the reservoirs (135 out of 271) are more stratified by the 2080s, especially larger reservoirs with longer residence times (black arrows to the right in Figure 6b).

This counterintuitive result occurs because thermal stratification is also influenced by surface energy exchange during the summer season. In general, thermal stratification increases with increasing air temperature for reservoirs with similar residence times (Figure 6a). As air temperature increases, along with solar radiation, the epilimnion temperature increases faster than the hypolimnion temperature because the latter is warmed only by advective and diffusive energy exchange with the epilimnion. As a result, seasonal thermal stratification in our study region is stronger as air temperature increases, resulting in a change in slope in the relationship between residence time and thermal stratification under climate change (contrasting red and blue lines in Figure 6b).

4.2. Stream Temperature and Cooling Potentials Downstream of Reservoirs

Cold hypolimnetic releases equilibrate with the environment as a result of surface heat fluxes. Reservoir impacts on river thermal regimes dissipate completely when stream temperatures reach the unregulated river temperature. The distance it takes from the reservoir outlet to reach the unregulated river temperature is influenced by both streamflow and surface energy fluxes.

We used the model simulations performed in support of the sensitivity analysis (Section 2.5) to evaluate the relative contribution of streamflow and surface meteorology to the tailwater thermal regimes. In reality, it is not feasible to directly calculate the distance to reach the unregulated river temperature because reservoir outflow might not reach this temperature before it flows into a downstream reservoir or merges with another stream. Instead, we evaluated the impacts of surface meteorology by comparing downstream temperatures at a fixed distance downstream of a reservoir for the cold, medium, and hot scenarios (Section 2.5).

Surface meteorology has a strong impact on tailwater thermal regimes. For example, median outflow temperature increases 6.8°C, 7.4°C, and 9.0°C under cold, medium, and hot scenarios, respectively, 50 km downstream of Youghiogheny Reservoir (Figure 7). Even though the thermal stratification is stronger in the hot scenario, the temperature of the released water also increases more rapidly downstream of the reservoir. Regulated stream temperature is relatively insensitive to changes in streamflow, in part because we use the same guide curves for all scenarios. In spite of the large spread in simulated streamflow, the spread in outflow temperature from Youghiogheny Reservoir across the 20 different hydrological inputs reduces from 3°C to about 0.2°C within 50 km (Figure 7).

Immediately downstream of reservoirs, cooling potential is impacted by changes in stream temperature as well as changes in streamflow. Compared to unregulated rivers, cold outflow from stratified reservoirs

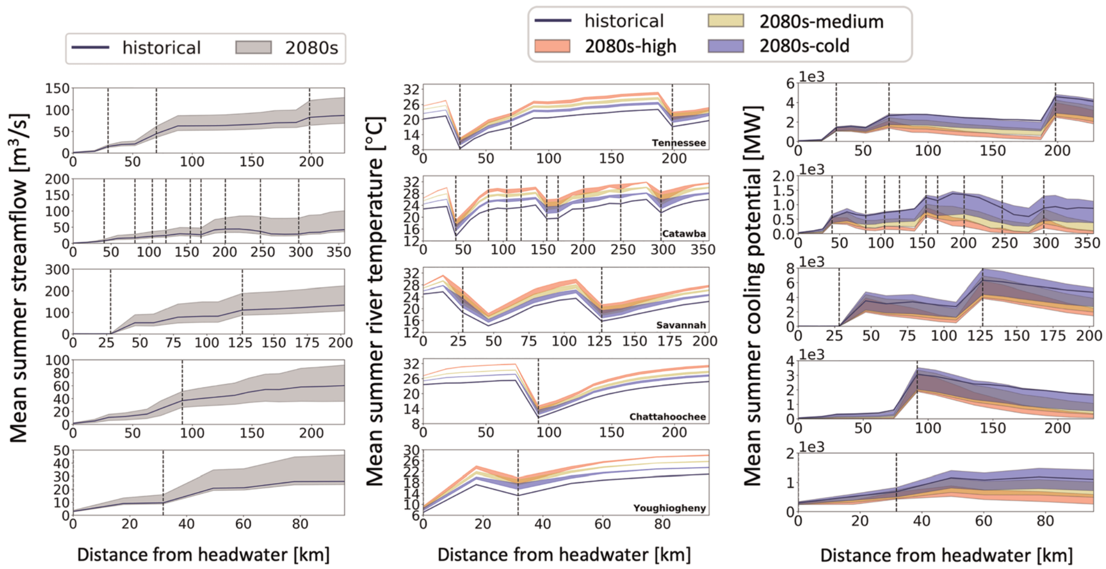

Figure 7. Sensitivity experiment: mean summer streamflow (left), stream temperature (middle), and cooling potential (right) profiles for the historical period and the 2080s under RCP8.5 along five selected river channels, that is, Tennessee River, Catawba River, Savannah River, Chattahoochee River, and Youghiogheny River (from top to bottom). In the left panel, the gray shaded area denotes ranges of projected mean summer streamflow. In the middle and right panels, the shaded areas denote the ranges in projected mean summer river temperature and cooling potential, respectively. The vertical dashed lines denote dam locations.

increases the cooling potential (Equation 1_), and the amount of flow (Q) is also different than in unregulated rivers. Once the stream temperature approaches the unregulated river temperature, regulation impacts cooling potential only by altering streamflow.

4.3. Sensitivity to Errors in Hydrology

In this section, we limit our analysis to river segments subject to regulation (m = true) and compare their behavior in the regulated and unregulated model setups (r = reg, unreg). Analysis (not shown) revealed that the sensitivity of river segments not subject to regulation (m = false) is similar to the sensitivity of river segments subject to regulation in the unregulated model setup (m = true, r = unreg).

Figure 8a shows the projected increases in mean summer stream temperature (ΔT) as well as our estimate of the error ($\hat{\sigma}_{\widetilde{\Delta T}}$). This error only reflects the effects of errors in the hydrological simulations. Each panel shows $\Delta T \pm \hat{\sigma}_{\widetilde{\Delta T}}$ (solid line) and $\Delta T \pm 2\hat{\sigma}_{\widetilde{\Delta T}}$ (dashed line) for the regulated and unregulated model setups. Projected increases in mean summer temperature range from +2°C to +6°C while the hydrology-induced errors range from 0.09°C to 1.33°C. The hydrology-induced error in stream temperature is greatest immediately downstream of reservoirs (Figure 7) and gradually decreases as the river flows downstream.

River segments in the regulated model setup (m = true, r = reg) are more sensitive to errors in hydrology ($\hat{\sigma}_{\widetilde{\Delta T}}$ ranges from 0.27°C to 1.33°C) than the same segments in the unregulated model setup (m = true, r = unreg; $\hat{\sigma}_{\widetilde{\Delta T}}$ ranges from 0.09°C to 0.11°C). This is especially true for small river segments which have greater ϕ values than larger rivers (m = true, r = reg). Although ϕ values differ across river sizes and whether we represent the effects of regulation (r = reg, unreg), they are similar across all three climate change scenarios.

Figure 8b shows the same information as Figure 8a, but for the change in cooling potential rather than change in mean summer temperatures. Errors in the hydrological simulations have the largest effect on the relative change in cooling potential for small rivers ($\overline{Q}$<50m^3/s) under the cold scenario. In that case, mean projected relative changes in cooling potential ($\overline{\Delta rE^{cp}}$) are −21.0% and −31.0% while the hydrology-induced errors ($\hat{\sigma}_{\widetilde{\Delta rE^{cp}}}$) are 46.0% and 57.6% for regulated and unregulated model setups, respectively (Figure 8b). In all other cases, the $\overline{\Delta rE^{cp}}$ values are larger than the $\hat{\sigma}_{\widetilde{\Delta rE^{cp}}}$ (upper bound of solid line is below zero in Figure 8b), implying that the sign of the change is not sensitive to the errors in hydrology in

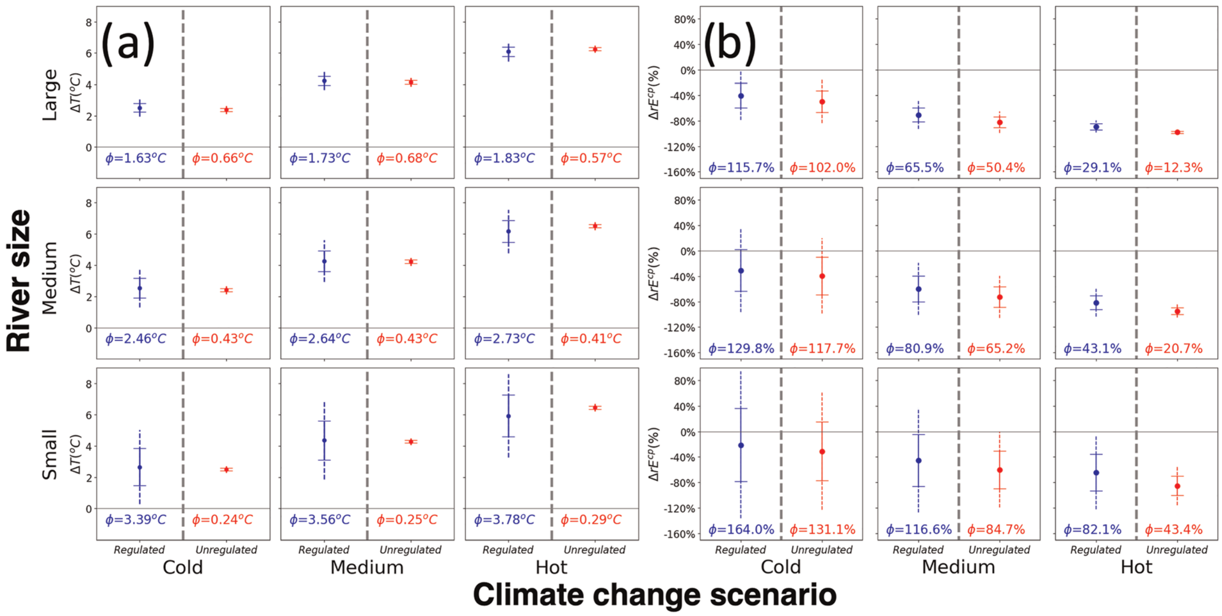

Figure 8. Projected changes in (a) mean summer river temperature and (b) mean summer cooling potential by river size and climate changes scenarios. Estimates are provided for river segments subject to regulation (m = true) for both the regulated (r = reg; blue) and unregulated (r = unreg; red) model setups. The solid and dashed bands around the mean denote one and two times the error in the estimates ($\widehat{\sigma}$ in Equation 6) as a result of hydrological errors.

our simulations. Uncertainties in the relative change in cooling potentials decrease with increasing river size and increases with projected air temperature. Reservoir regulation does not have a strong impact on the sensitivity of the relative change in cooling potentials to hydrologic errors, with similar $\phi_{\widetilde{\Delta rE^{cp}}}$ values for regulated and unregulated model setups (Figure 8b).

Overall, we conclude that the errors in our hydrological simulations affect our quantitative estimates of changes in stream temperature and cooling potential in the following way. Errors in our change estimates are greater in the regulated model setup (r = reg) than the unregulated setup (r = unreg) and are largest for the smaller river segments. However, in general, the errors do not affect the sign of the change signals nor the relative ranking of the change signals across river sizes, regulation status, or climate scenarios. The effect of hydrological simulations on changes in mean summer stream temperature for river segments not affected by regulation (m = false) is small.

5. Conclusions

River temperatures play an important role in aquatic ecosystems and affect the efficiency of once-through thermoelectric power plants. In this study, we applied a physically-based model chain to simulate hydrology and stream temperature for a large part of the SEUS. Seasonal thermal stratification was explicitly represented. We used an ensemble of future climate forcings to quantify the impacts of climate change on the summer stream temperatures and cooling potential of southeastern rivers for the 2080s. The model chain was applied with and without water management to quantify changes in the effect of regulation on cooling potential as a result of climate change. We evaluated reservoir flow, storage, and stream temperature, along with their interactions and the overall response to climate change, which has not been done before. The novel cooling potential approach provides a new opportunity to support multisectoral long-term planning. It is a direct measure of a system's capacity to absorb external waste heat without exceeding a temperature threshold. We conducted a sensitivity analysis to quantify the robustness of our findings to errors in the hydrological simulations. Our approach has the advantage that it provides a consistent evaluation over a region that spans multiple watersheds, where water management decisions may affect stream temperatures. This region may be defined by institutional governance for natural conservation, electricity operations, and other activities. The approach is applicable to other, individual watersheds, although we would recommend using operational ws for the basin of interest to simulate the hydrology.

We would like to highlight a few areas for further research and improvement. Reservoir operations are more complex than the generic operating rules or rule curves used in this study. More complex rules that use foresight and optimization across the system could be considered, especially if these rules are allowed to change with time. An explicit link with power system models could further our understanding of the response to local stresses as well as feedbacks onto electricity operations and downstream river systems. For example, Miara et al. (2018) demonstrated the dynamic link with power system operations but lacked the representation of reservoir operations and their impact on stream temperature. Finally, to isolate the effects of changes in meteorological forcings in a changing climate, we kept land use and urbanization constant in our model simulations, even though they may impact both hydrology and stream temperature. Explicit representation of these changes may enhance our understanding of the coevolution of complex interconnected systems.

Major findings are as follows:

- Reservoir regulations, and the resulting seasonal thermal stratification, influence downstream river temperatures. Reservoirs with longer residence times are more stratified and store cold water from earlier seasons in their hypolimnion. They therefore have stronger impacts on downstream river temperatures. Among reservoirs with similar residence times, thermal stratification tends to be stronger in warmer locations where reservoirs are subject to stronger surface energy fluxes.
- Reservoir regulation changes how river temperature responds to climate change, especially through changing thermal stratification. Summer stream temperatures in regulated rivers are lower than those in unregulated rivers, but they are more sensitive to climate change. By the 2080s under RCP8.5, compounded impacts of higher air temperature and shorter residence times result in stronger thermal stratification for over half of all reservoirs in the SEUS, especially for reservoirs with longer residence times. Thermal stratification impacts on downstream river temperatures mostly persist but are slightly weakened because of higher air temperature and stronger surface energy inputs.
- Cooling potential is the energy required to warm rivers to a threshold temperature and represents a river system's ability to absorb waste thermal energy from thermoelectric power plants if environmental regulations are enforced, indicating the compound impacts of both streamflow and stream temperature. For rivers experiencing strong thermal stratification impacts, regulation increases cooling potential immediately downstream of reservoirs because the cooling impact on downstream river temperature dominates the signal. For rivers minimally impacted by thermal stratification, regulation decreases cooling potential because of lower summer streamflow under reservoir regulation.
- Cooling potential is projected to decrease for all river segments under climate change. The Ohio River will lose over 10 GW cooling potential for most of its length by the 2080s under RCP8.5. Regulation changes how cooling potential responds to climate change. Regulation impacts on cooling potential remain strong when rivers are strongly influenced by thermal stratification ($\Delta R > -25\%$, Figure 6f) because cooling impacts on downstream river temperatures mostly persist under climate change. For rivers minimally impacted by thermal stratification, the magnitude of regulation impacts on cooling potential decreases dramatically ($\Delta R < -75\%$, Figure 6f) because river temperatures are higher by the 2080s under RCP8.5.
- Sensitivity analyses show that our findings about climate change effects on mean summer river temperature and cooling potentials are relatively insensitive to errors in the hydrological simulation. Mean summer temperatures in smaller rivers tend to be more sensitive to errors in hydrology than those in larger rivers. Mean summer temperatures in regulated river segments are much more sensitive to hydrological errors than those in unregulated river segments. However, regulation has little impact on the sensitivity of changes in cooling potential to hydrological errors.

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