How might Planned Hydropower Dams Alter River Temperatures Around the World?

Shahryar Khalique Ahmad[1], Faisal Hossain[1], Gordon William Holtgrieve[1], Tamlin M Pavelsky[2], and Stefano Galelli[3]

[1]University of Washington
[2]University of North Carolina at Chapel Hill
[3]Singapore University of Technology and Design

November 28, 2022

Abstract

Selective water release from the deeper pools of reservoirs for energy generation alters the temperature of downstream rivers. Thermal destabilization of downstream rivers can be detrimental to riverine ecosystem by potentially disturbing the growth stages of various aquatic species. To predict this impact of planned hydropower dams worldwide, we developed, tested and implemented a framework called '*FUture Temperatures Using River hISTory*' (*FUTURIST*). The framework used historical records of in-situ river temperatures from 107 dams in the U.S. to train an artificial neural network (ANN) model to predict temperature change between upstream and downstream rivers. The model was then independently validated over multiple existing hydropower dams in Southeast Asia. Application of the model over 216 planned dam sites afforded the prediction of their likely thermal impacts. Results predicted a consistent shift toward lower temperatures during summers and higher temperatures during winters. During Jun-Aug, 80% of the selected planned sites are likely to cool downstream rivers out of which 15% are expected to reduce temperatures by more than 6@C. Reservoirs that experience strong thermal stratification tend to cool severely during warm seasons. Over the months of Dec-Feb, a relatively consistent pattern of moderate warming was observed with a likely temperature change varying between 1.0 to 4.5@C. Such impacts, homogenized over time, raise concerns for the ecological biodiversity and native species. The presented outlook to future thermal pollution will help design sustainable hydropower expansion plans so that the upcoming dams do not face and cause the same problems identified with the existing ones.

How might Planned Hydropower Dams Alter River Temperatures Around the World?

Shahryar K. Ahmad[1*], Faisal Hossain[1], Gordon W. Holtgrieve[2], Tamlin Pavelsky[3], Stefano Galelli[4]

[1]University of Washington, Department of Civil and Environmental Engineering

[2]University of Washington, School of Aquatic and Fishery Sciences

[3]University of North Carolina, Department of Geological Sciences

[4]Singapore University of Technology and Design, Engineering Systems and Design

Corresponding author: Shahryar K. Ahmad (skahmad@uw.edu)

https://orcid.org/0000-0002-9789-3137

Key Points:

- Past records of thermal impacts can help predict the likely impact of future dams
- Shift toward lower summer temperatures and higher winter temperatures for downstream rivers is predicted
- Reservoirs with strong thermal stratification tend to severely impact downstream thermal regime

Abstract

Selective water release from the deeper pools of reservoirs for energy generation alters the temperature of downstream rivers. Thermal destabilization of downstream rivers can be detrimental to riverine ecosystem by potentially disturbing the growth stages of various aquatic species. To predict this impact of planned hydropower dams worldwide, we developed, tested and implemented a framework called '*FUture Temperatures Using River hISTory*' (*FUTURIST*). The framework used historical records of in-situ river temperatures from 107 dams in the U.S. to train an artificial neural network (ANN) model to predict temperature change between upstream and downstream rivers. The model was then independently validated over multiple existing hydropower dams in Southeast Asia. Application of the model over 216 planned dam sites afforded the prediction of their likely thermal impacts. Results predicted a consistent shift toward lower temperatures during summers and higher temperatures during winters. During Jun-Aug, 80% of the selected planned sites are likely to cool downstream rivers out of which 15% are expected to reduce temperatures by more than 6˚C. Reservoirs that experience strong thermal stratification tend to cool severely during warm seasons. Over the months of Dec-Feb, a relatively consistent pattern of moderate warming was observed with a likely temperature change varying between 1.0 to 4.5˚C. Such impacts, homogenized over time, raise concerns for the ecological biodiversity and native species. The presented outlook to future thermal pollution will help design sustainable hydropower expansion plans so that the upcoming dams do not face and cause the same problems identified with the existing ones.

Plain Language Summary

Today, aquatic biodiversity is at very high risk in many large river systems such as the Congo, Amazon, and Mekong, where extensive hydropower dams are planned. In this study, we present a global study to map the impact of planned hydropower dams on the thermal regime of the river system. A machine learning model was used to learn how the operations of existing dams in the U.S. have altered river temperatures downstream of the dams. This model was validated over other existing dams in Southeast Asia and then used for predicting the impact of future hydropower dams. An assessment of 216 such future dams revealed that the vast majority will likely reduce the summer temperatures and increase the winter temperatures. Our framework, which is easy to implement and produces quick results, can aid in prioritizing hydropower infrastructure in the context of renewable energy generation and proactively address the serious impacts on our ecosystem and river habitat.

1 Introduction

The arguments for or against building dams, particularly hydropower dams, are many. Hydropower dams serve as a source of relatively low-carbon energy, guarding against extreme floods and meeting a steadily increasing water demand. Many countries have included the expansion of hydropower infrastructure as part of their climate mitigation strategy, following the United Nations Climate Change Conference in Paris in 2015 (Zarfl et al., 2019). To date, about 3600 medium and large hydropower dams are either under construction or planned, predominantly in South America, Africa, and South/East Asia, area with relatively untapped hydropower potential (Zarfl et al., 2015). Laos, for example, has pursued an ambitious initiative to become the 'Battery of Southeast Asia' by building an unprecedented number of dams in the Mekong River Basin (Schmitt et al., 2019; Chowdhury et al., 2020). However, hydropower dams also substantially affect surrounding ecosystems, and these long-term ecological impacts are often discounted in decision-making processes (Winemiller et al., 2016). In addition to fragmenting almost two-thirds of the world's free-flowing large rivers (Nilsson et al., 2005), dams in general have modified natural sediment transport (Zarfl and Lucía, 2018; Yang et al., 2005), disrupted natural hydrologic variability (FitzHugh and Vogel, 2011), contributed to greenhouse gas emissions (Deemer, 2016), and led to resettlement of local communities and loss of culture and heritage (Moran et al., 2018; Hecht et al., 2019). Such impacts have threatened freshwater biodiversity and harmed fisheries (Barbarossa et al., 2020).

Among the many negative impacts of hydropower dams, dramatic alteration of river's thermal regime is amongst the most adverse impacts (Bonnema et al., 2020). In the storage dams used for extensive hydropower generation, reservoirs are designed for higher hydraulic head and a large storage capacity. This relatively stagnant and deep body of water tends to thermally stratify into multiple horizontal layers or pools (Imboden and Wuest, 1995). Water for flood control tends to be released from the uppermost pool via the spillway, while water for irrigation or other downstream users is mostly released from the uppermost and middle pools (often called 'conservation' pool). However, it is the water for hydropower production that causes the most drastic difference in temperature to downstream water, as it is drawn from the bottom pool. This pool is often colder than the rest of the pool and the downstream river, especially during summer seasons. The selective release of water from the deeper pools is the main cause of river's thermal pollution, that is the modification of the natural thermal regime of downstream river segments (Niemeyer et al., 2018; Olden and Naiman, 2010). Because river temperature plays a vital role in sustaining the aquatic habitat (Angilletta, 2008), thermal pollution can damage aquatic biodiversity, potentially disturbing the growth stages of various fish and other aquatic species.

The significance of riverine thermal pollution caused by existing dams has been acknowledged but only partially addressed in the literature (Bonnema et al., 2020, Caissie, 2006; Poole and Berman, 2001). Moran et al. (2018) presents several challenges with building large dams which need to be addressed in order to achieve sustainable hydropower in developing countries. However, the authors did not include thermal pollution which can be a major factor in harming native fish species. Current approaches for estimating dam-driven thermal pollution rely on either statistical approaches such as regression (Benyahya et al., 2007; Ahmad and Hossain, 2020b) or more complex and physically distributed river temperature (Yearsley, 2012) and hydrodynamic models (Niemeyer et al., 2018, Buccola et al., 2016; Cole and Wells, 2015). While some of these models use ambient conditions and flow variables to predict downstream river temperatures (Mohseni et al., 1998; Neumann et al., 2003), others solve thermal energy budget and heat advection-dispersion equations (Cole and Wells, 2015; Yearsley, 2012). However, current models have multiple limitations when it comes to studying the impact of planned hydropower dams. On one hand, hydrodynamic and thermodynamic models are complex and require inputs on quantities difficult to measure or estimate such as for non-radiative fluxes (Mohseni et al., 1998, Toffolon and Piccolroaz, 2015; Van Vliet et al., 2011). For instance, there may be no boundary condition data for flow and temperature to initialize such models when a dam has not been built yet. On the other hand, simpler statistical models cannot be extrapolated to predict thermal response of dams with unobserved hydro-climatological and geophysical characteristics (Toffolon and Piccolroaz, 2015). Both classes of models, however, suffer from the inability to work on large number of dams, which instead require a rapidly transferrable yet skillful technique of modeling dam's thermal response.

Given the pace at which future hydropower dams are being built, it is imperative to identify development pathways where the proposed infrastructure can serve its purpose while maintaining a sustainable and productive river system (Grill et al., 2015). As predicted by Zarfl et al. (2019), the majority of future hydropower development is planned in catchments with a high share of threatened megafauna species. This requires a study of future dams in the context of their potential impacts on the ecosystem. Towards that end goal, we outline three key traits for a modeling framework to 'predict', or infer, the thermal modification impact of planned dams. As the aquatic biodiversity is more sensitive to alterations in thermal regime than the absolute change (Haxton and Findlay, 2008), we need a technique that is reliably accurate in providing the qualitative understanding of thermal regime change. Second, the technique should be transferrable for use over any planned dam site around the world. Finally, there should be minimal input data requirement, a fundamental prerequisite for working on the data-scarce conditions characterizing the Global South, where the majority of hydropower dams are planned. Thermal Infrared (TIR) remote sensing from the vantage of space offers the only feasible method over data-limited regions to monitor spatial and temporal patterns of surface water temperature due to hydropower development (Ling et al., 2017). The potential of TIR data has already been demonstrated by Bonnema et al. (2020) using the 3S (Sekong, Sesan, and Sre Pok) river basins as a microcosm of hydropower development for the rest of the Mekong basin.

Here, we predict the thermal impact of 216 planned hydropower dams around the world on their likely change to downstream river temperatures. The dams were selected to represent a diverse range of dams with different structural characteristics, types (storage or run-of-river), hydrology, and climates. Also, most of these dams are planned at. locations far apart to avoid the thermal pollution of upstream dams from impacting the downstream ones. Our predictions are based on a novel framework for planned hydropower dams called 'FUture Temperatures Using River hISTory' (FUTURIST). The FUTURIST framework is based on the key premise that a long record of the past thermal impact is a reasonable representation of the near-future impact due to planned hydropower dams. More specifically, we use FUTURIST framework to answer the following questions: (i) can we learn patterns of thermal impact on downstream rivers caused by the existing dams based on known climate, hydrology, and dam characteristics? (ii) having identified, or learnt, such a relationship over existing dams, can we predict the thermal impact of the future (planned or under construction) dams?

To answer these questions, we employed a historical record of in-situ river temperature changes from 107 dams in the U.S. to train an artificial neural network (ANN) model. This data-based ANN approach predicted temperature change between upstream and downstream rivers.

The ANN model was able to capture nonlinearities in predicting dam's thermal impacts that makes the technique transferrable to other dams with unobserved conditions. This was demonstrated by the high predictive skill over tropical climate of Southeast Asian dams during model validation. Also, the challenges with existing data-intensive models were tackled by FUTURIST for which the required inputs were either one of the dam's structural properties or variables derived from remote sensing products. TIR remote sensing-based thermal change was used for model training and validation where in-situ monitored values were absent or scarce. Finally, the ANN model was applied at planned hydropower sites worldwide to predict the likely thermal impacts and elucidate the need to include thermal pollution within dam planning to ensure safety and sustainability of the ecosystem.

2 Materials and Methods

2.1 Dam Sites and Temperature Data Preparation

For establishing the FUTURIST framework, we first selected dam sites in the U.S. where in-situ temperature measurements are available both upstream and downstream of the hydropower dams. For in-situ temperature data, we used the network of stream temperature monitoring stations from the United States Geological Survey (USGS). A total of 4,186 sites were first filtered out from the USGS gage database based on the availability of temperature measurements. To filter out stations that are located upstream and downstream of the existing dam sites, we used the Global Reservoir and Dams (GRanD) database (Lehner et al., 2011). This resulted in 87 hydropower dams, out of which a final selection of 68 locations had atleast a year of overlapping temperature records on upstream and downstream stations. The temporal record length exceeded more than 10 years for most of the selected sites.

To expand the database of hydropower dams with information on thermal impacts in the past, we used remote sensing observations of surface water temperature from TIR data. Because the remote sensing-based temperature extraction is limited by the spatial resolution of the satellite (see next section), it is difficult to obtain pure water pixels over narrower river channels downstream of dams. Upstream of a dam, however, with the larger expanse of reservoir, the spatial resolution of TIR remote sensing is not an issue. We filtered out 39 additional sites with

USGS station located downstream for which the upstream reservoir temperatures were obtained from remote sensing to prepare a total of 107 dam locations (see supplementary information, Figure S1). The selection of sites consisted of a diverse range of climates, dam, and topography, so that the trained model on these sites can capture the variability found in various other regions with unobserved conditions.

Developing a thermal change model that can be scaled globally requires validation over sites that are devoid of in-situ measurements. Thus, for a robust validation of our approach, we selected existing dam sites in Southeast Asia, where a large number of hydropower dams may be built in the near future. Location and relevant information for dams MRB were obtained from CGIAR WLE Database (Mekong Dam Database, 2011), the Mekong River Commission (MRC, 2009), Räsänen et al. (2017), Piman et al. (2013), and other reports from dam authorizing agencies. Data for existing dams in India were retrieved from the National Register of Large Dams (NRLD, 2012).

Information on planned hydropower dams was retrieved from multiple sources, as no global scale database exists yet with information on dam design features. Some of the sources used here include Georeferenced Information System of the Electric Sector (SIGEL – https://sigel.aneel.gov.br/portal/home/) of the Brazilian National Hydroelectric Agency (ANEEL) and Anderson et al. (2018) for Brazilian dams, Finer and Jenkins (2012) and Forsberg et al. (2017) for Andean dams, Hydropower Project Database from MRC (Hydropower Project Database, 2012), Piman et al. (2016), and Wild and Loucks (2014) for dams in MRB, and AQUASTAT (FAO AQUASTAT Main Database, 2016) for the dams in remaining countries. Individual reports from dam authorities were also consulted to fill in the missing data and to cross-validate the retrieved information. Detailed information on the dams selected for training and validating the FUTURIST framework as well as the 216 planned dams is provided in the supplementary information.

2.2 Monitoring Thermal Impacts from Space

Despite the advantage of a robust temperature monitoring network in U.S., developing nations still lack in-situ measurements. We therefore used Landsat-7 ETM+ TIR band observations to obtain estimates of surface water temperature for upstream reservoir (for selected dams within U.S. where upstream USGS stations were absent) and both upstream and downstream for dams in Southeast Asia (used for validation). Landsat-7 TIR band was acquired at 60 m, due to which we restricted the observations to dams with rivers wider than 100 m (to ensure pure water pixels are used). Single channel algorithm (Jiménez-Muñoz et al., 2008; Jiménez-Muñoz and Sobrino, 2003) for temperature extraction was used, with atmospheric correction for top-of-atmosphere (TOA) reflectance. The procedure is described in detail by Ahmad and Hossain (2019). Because for some reservoirs, ice formation on the lake surface during winters resulted in sub-zero temperatures when using TIR band, only positive values were considered in the analysis.

A comparison of Landsat-derived surface temperature and insitu observations from USGS stations upstream of a few dams in the U.S. was performed (see supplementary information, Figure S2). Temporally synchronous measurements of in-situ and Landsat-derived temperatures for the upstream and downstream waters were used to quantify the change in thermal regime.

2.3 Dam-Induced Thermal Change

Dam operations affect downstream temperature regime in multiple aspects (see supplementary information, Figure S3). Marked changes occur in the timing, magnitude and duration of peaks and lows of the temperature distribution over the year relative to the natural pre-dam regime (Olden and Naiman, 2010). Here, we considered the mean difference in temperature during warm and cold seasons over multiple years on record to capture the key aspects of thermal impact, homogenized over time. The temperatures of upstream river flowing into the reservoir are considered as proxy to natural riverine thermal regime when the pre-dam data are absent. Thus, we defined thermal change, $\Delta\boldsymbol{T}$ as,

$$\Delta\boldsymbol{T}_{\boldsymbol{warm}} = \overline{\boldsymbol{T}_{\boldsymbol{up}} - \boldsymbol{T}_{\boldsymbol{down}}} \tag{1}$$

where, $\Delta\boldsymbol{T}_{\boldsymbol{warm}}$ is the thermal change over warm season in Northern Hemisphere (months of Jun-Aug, JJA) calculated as difference of the upstream ($\boldsymbol{T}_{\boldsymbol{up}}$) and downstream water temperatures ($\boldsymbol{T}_{\boldsymbol{down}}$) over those months. A similar equation is used for the cold season ($\Delta\boldsymbol{T}_{\boldsymbol{cold}}$) where averaging is performed over the months of Dec-Feb (DJF).

In light of the previous efforts to assess dam impacts on different ecosystem aspects using qualitative categories (Zarfl et al., 2019; Barbarossa et al., 2020; Grill et al., 2015), we introduced Thermal Change Class (TCC) for categorizing and assessing the thermal impact. We used the cumulative distribution function (CDF) plots of thermal change for existing dams as a guide (Figure 1) to formulate TCC. The thermal change values were first classified into two basic categories of cooling and warming, which were then broken down into four sub-categories: moderate cooling (between 0˚ C to -6˚ C), severe cooling (less than -6˚ C), moderate warming (between 0 to +5˚ C), and severe warming (more than + 5˚ C). It should be noted that the FUTURIST framework is independent of the choice of thermal thresholds, and the output classes can be adapted based on the needs of the stakeholder.

Further, to capture the impact of dams on a basin-wide scale, we mapped the average thermal regime changes on the river basins containing planned dams. We used the global dataset for watershed boundaries and sub-basin delineations called HydroBASINS (Lehner et al., 2013) to aggregate the thermal impacts. The aggregation was performed Pfafstetter Level 5 of HydroBASINS using the median of individual thermal impact classes when multiple dams were present in the considered basin.

2.4 FUTURIST Framework

Our proposed framework, FUTURIST, begins with developing a data-based model to learn historical patterns of the impact on rivers due to dam operations. Various dam characteristics, hydrology, topography and climate of the reservoir basin were used for training. A multilayer perceptron feedforward ANN model was selected, and hyperparameter tuning was performed for designing the network architecture. The model architecture consisted of three hidden layers with 256, 16 and 4 nodes, while the input layer contained seven nodes (see supplementary information, Figure S4). Further details on the neural network model design and development are provided in the supplementary information. The training was performed over dams in U.S. and then validated over selected sites in Southeast Asia (MRB and India).

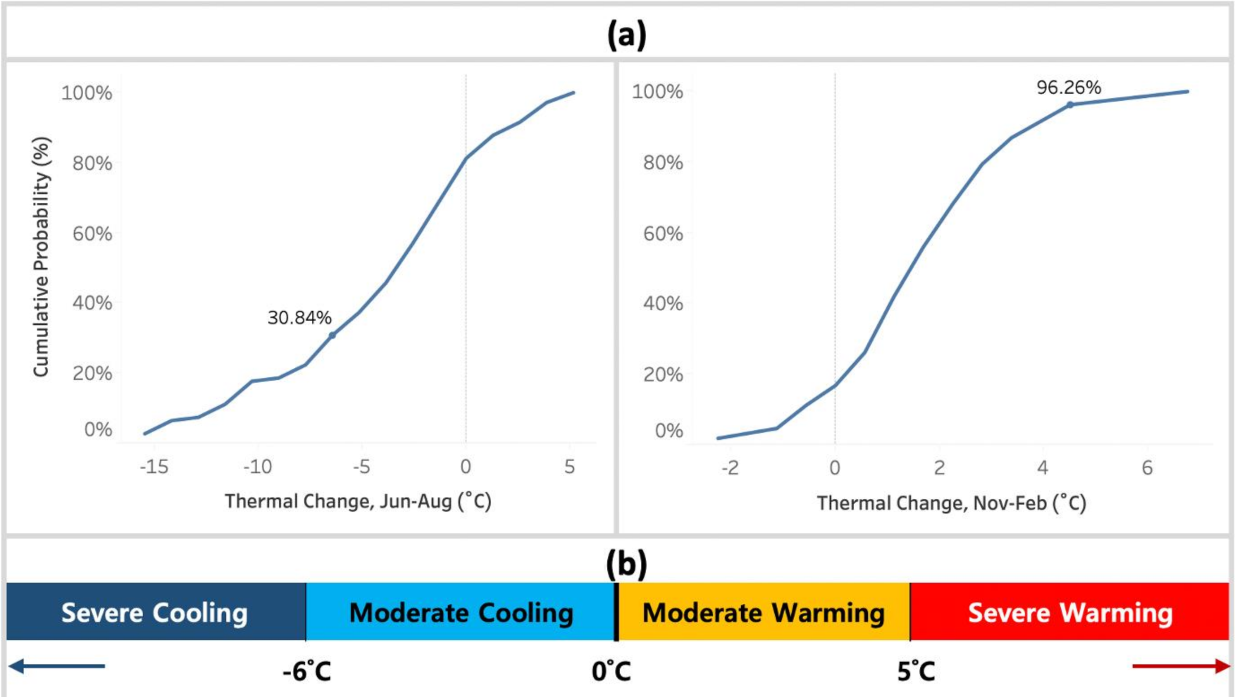

Figure 1. (a) Cumulative Distribution Functions (CDF) for thermal regime changes during cold and warm season. **(b)** Thermal Change Class (TCC) based on the selected thresholds of -6˚C and 5˚C for subclassifying the cooling and warming regimes, respectively.

The input nodes comprised of dam height (in meters), reservoir area (in km^2), storage capacity (in million m^3), Köppen-Geiger climate class (Peel et al., 2007) , terrain elevation (in meters, retrieved from the Digital Elevation Model (DEM) from Shuttle Radar Topography Mission (SRTM), ambient air temperature (in ˚C, extracted from the ECMWF's ERA5 reanalysis product from https://developers.google.com/earth-Engine/datasets/catalog/ECMWF_ERA5_DAILY), and a dimensionless bathymetry coefficient (see supplementary information, Table S1). The bathymetry coefficient is a measure of similarity between reservoir's bathymetry and a rectangular cross-section, calculated as the ratio of storage capacity with the product of reservoir's maximum area and depth. A similar dimensionless ratio called reservoir coefficient was proposed by Mohammadzadeh-Habili et al. (2009) where lower values correspond to reservoirs with gorge-like bathymetry. The modeling framework is open-source and available on the GitHub repository at: https://github.com/shahryaramd/futurist.

2.5 Climate Change Impact Assessment

By the end of the 21st century, air temperatures are projected to increase due to global warming according to all the climate models under the Coupled Model Inter-comparison Project Phase 5 (CMIP5) (Taylor et al., 2012). The ANN model developed for the prediction of thermal impact includes ambient air temperature as one of the predictors (see section 2.4). Therefore, we used different air temperature scenarios as forcings to the FUTURIST framework for studying the effect of climate change on riverine thermal regime change. Specifically, we used two Representative Concentration Pathway (RCP) scenarios, RCP4.5 and RCP8.5, and a retrospective (historical) run from globally downscaled Coupled Model Intercomparison Project Phase 5 (CMIP5) climate projections (Collins et al., 2013). The climate scenarios were acquired from GFDL-ESM2M General Circulation Model (GCM) runs conducted under CMIP5, distrubuted by NASA Earth Exchange (NEX) GDDP dataset (https://developers.google.com/earth-engine/datasets/catalog/NASA_NEX-GDDP). The GFDL-ESM2M air temperatures were averaged over the dam's location over 2000-05 for baseline scenario and over 2095-99 for the two RCP scenarios.

3 Results

3.1 Thermal Impact of Existing Dams in US

The large number of U.S. dams with long temperature records form an ideal testbed to study the thermal impact of their operations and use that knowledge to predict the impact of planned hydropower dams. We found that most U.S. dams in general tend to cool downstream rivers during the warm season (JJA) and have a warming impact during the cold season (DJF). These impacts reflect homogenized changes over the available data during the past two decades. During months of JJA, 74 (69%) hydropower dams in the U.S have cooled downstream rivers when compared to their upstream (used as the proxy to natural baseline) thermal regime (Figure 2a). Sub-categoring this impact further, 27 of the dams (25%) caused severe cooling to the downstream rivers. Interestingly, only five hydropower dams (5%) severely warmed the tailwaters (defined as an increase of 5˚C or more in the downstream river temperature). In contrast, during the cold season (DJF), most hydropower dams (85%) caused moderate warming, while only 11% led to moderate cooling and 4% led to severe downstream cooling (Figure 2b).

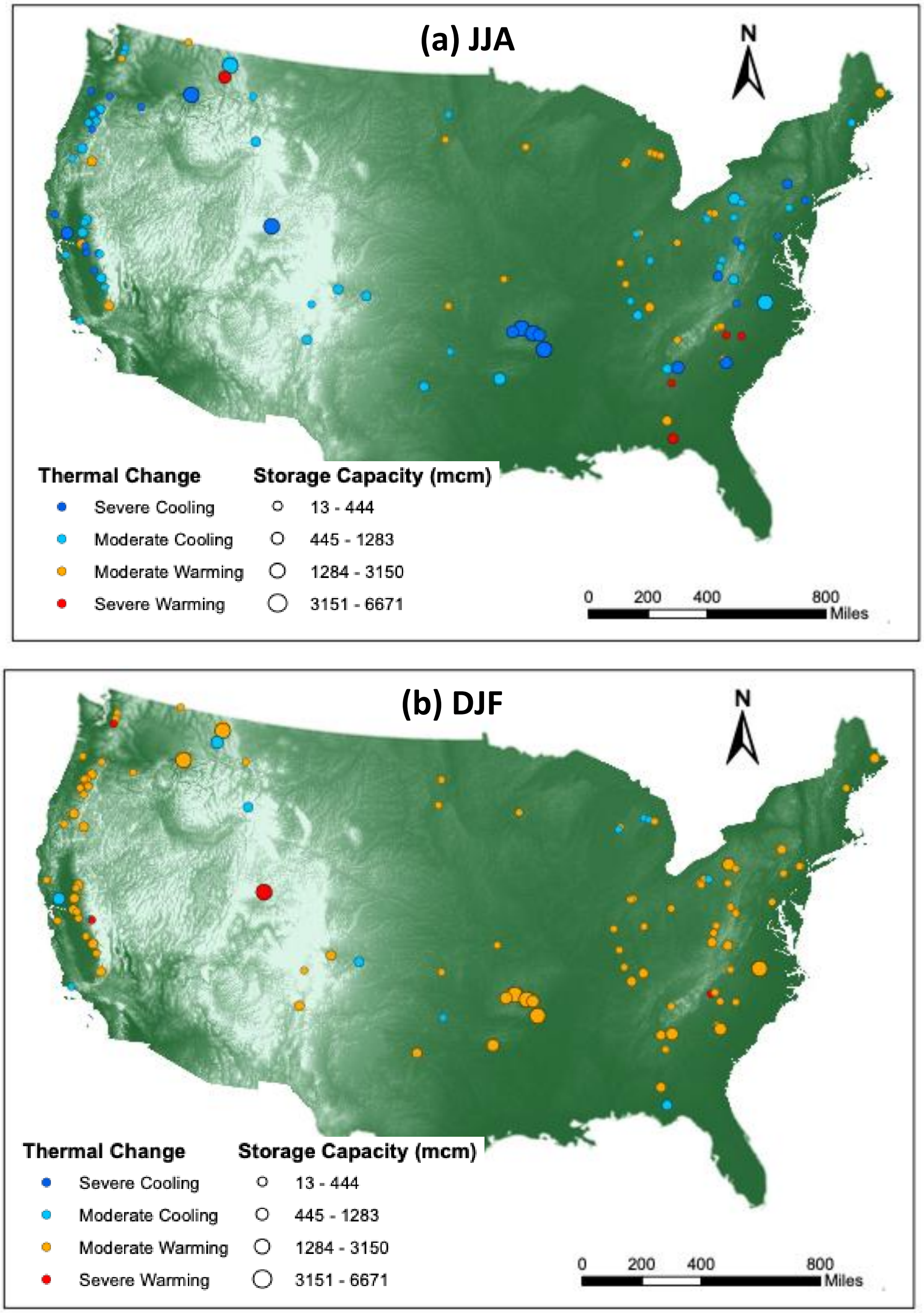

Figure 2. Dams used for training ANN model to learn thermal regime change (mean difference of upstream and downstream temperatures) over months of **(a)** JJA and **(b)** DJF. Classes of the thermal change are defined using quantiles of temperature distribution, see Methods section.

These results can be explained based on the characteristics of reservoirs and the ambient conditions. The primary cause of cooling is the stratification of reservoirs with significant difference between the temperatures of surface water and that of deeper pools from which the water is released. Reservoirs with larger storage pool and small areal extent (and hence a small area to storage ratio) experience strong thermal stratification. During warm season, such reservoirs experience a high temperature difference between the top (termed as epilimnion) and bottom pools (hypolimnion), thus releasing water that is considerably cooler compared to the thermal regime upstream of the dam. This is also illustrated by Figure 3a where dams with lower area-storage ratio exhibit large negative thermal change. Deeper reservoirs (shown with larger sized markers in Figure 3a) further intensified the stratification and subsequently their cooling impact. In contrast, smaller storage reservoirs with large area have weakly stratified water pools which can be easily mixed, even by a light wind. Such reservoirs weaken in their cooling impact leading to comparatively warmer release downstream under warmer climates.

Considering the effect of climate, hydropower dams lying in arid and warm regions with hotter summers (Köppen climate classes 7-9) favored to shift the thermal regime towards cooling (Figure 3b). This is likely as the surface water temperatures rise under contact with warm air and high solar radiation which cannot penetrate the cooler bottom layer (hypolimnion). Dams located in more humid and snowy climates (Köppen climate classes 25 and 26) experienced relatively cooler air temperatures which were not enough to cause any significant stratification of the reservoir. Such dams exhibited weaker cooling impact and even led to warming under several cases.

During the winter months of DJF, reservoirs that experience strong stratification caused warming with positive thermal change. As the air temperature decreases with declining solar radiation input during the winter season, reservoir's surface water begins to cool. This eventually leads to the top layer cooling down to a temperature similar or lower than the hypolimnion, breaking the thermal stratification. Thus, dams in such conditions exhibited a warming effect, although with no strong relationship with the dam size (Figure 3c). In cases when the winter temperatures drop below the temperature of maximum density of water, 4˚C (for example, for dams in climate class 26), surface waters become lighter than the bottom warmer water and a so-called inverse stratification develops, again causing the release of warm water downstream (Figure 3d).

3.2 FUTURIST Thermal Change Model Development

Using in-situ data, we trained an ANN model that predicts the mean temperature difference between upstream and downstream of a dam for each season. For most reservoirs, the stations that provided upstream temperatures were located on rivers flowing into the reservoir. This minimized the impact of reservoir's surface area on water temperature. However, the dams for which upstream insitu stations were unavailable and the upstream rivers were narrow (see Methods section), remote sensing was used to observe the skin temperature of the reservoirs. Model validation was performed over 27 existing dams in Southeast Asia located in Mekong River Basin (MRB) and India.

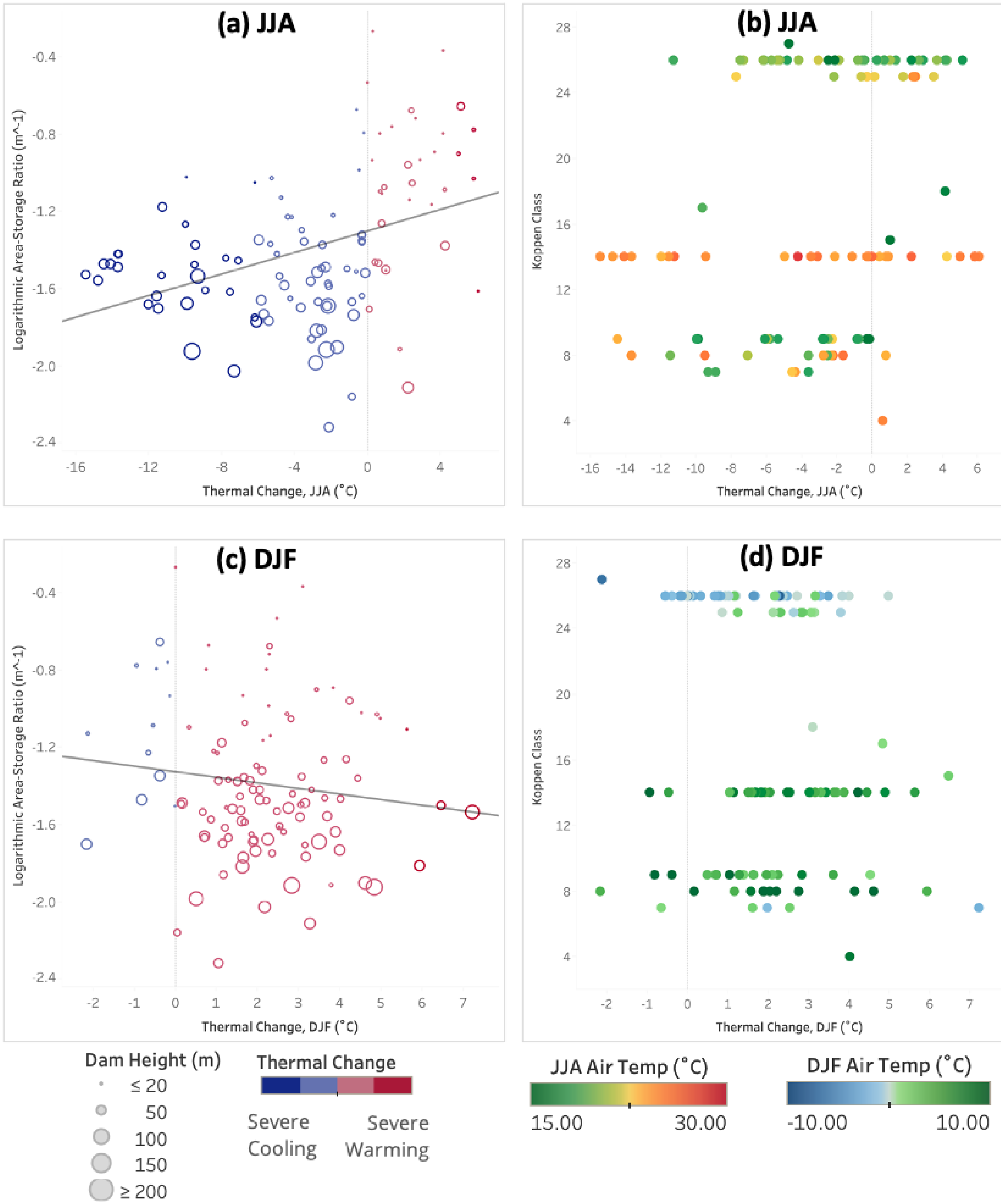

Figure 3. Trends in thermal regime change (X-axis) observed for 107 existing dams in the U.S. for **(a,b)** JJA and **(c,d)** DJF. Left panel (a & c) shows trends with the log of area-storage ratio, as a measure of reservoir's thermal stratification and right panel (b & d) denote distribution of Köppen-Geiger climate class for the respective dams.

During JJA, when observed temperature changes ranged between -6.7 to 5.6˚C, 21 out of 27 existing dams in Southeast Asia were predicted correctly (78% accuracy) in terms of the nature of thermal regime change (warming/cooling) as well as in severity (severe/moderate). When considering only the nature of thermal change, however, the model was able to predict almost all the thermal change scenarios correctly (accuracy of 93%) with just a single case of warming misclassified as cooling (Figure 4). The model was relatively less sensitive during the cold season (DJF) with observed temperature changes ranging between -1.8 to 3.8˚C (moderate cooling/warming), predicted categorically with an accuracy of 81%. We also performed assessment of the absolute temperature change values. The ANN model tended to overestimate (underestimate) thermal change by 1.3˚C (1.7˚C) during warm (cold) season. Nonetheless, it was able to accurately predict the direction and general magnitude of thermal change 78% (81%) of the time, despite the geographic differences between training and validation datasets.

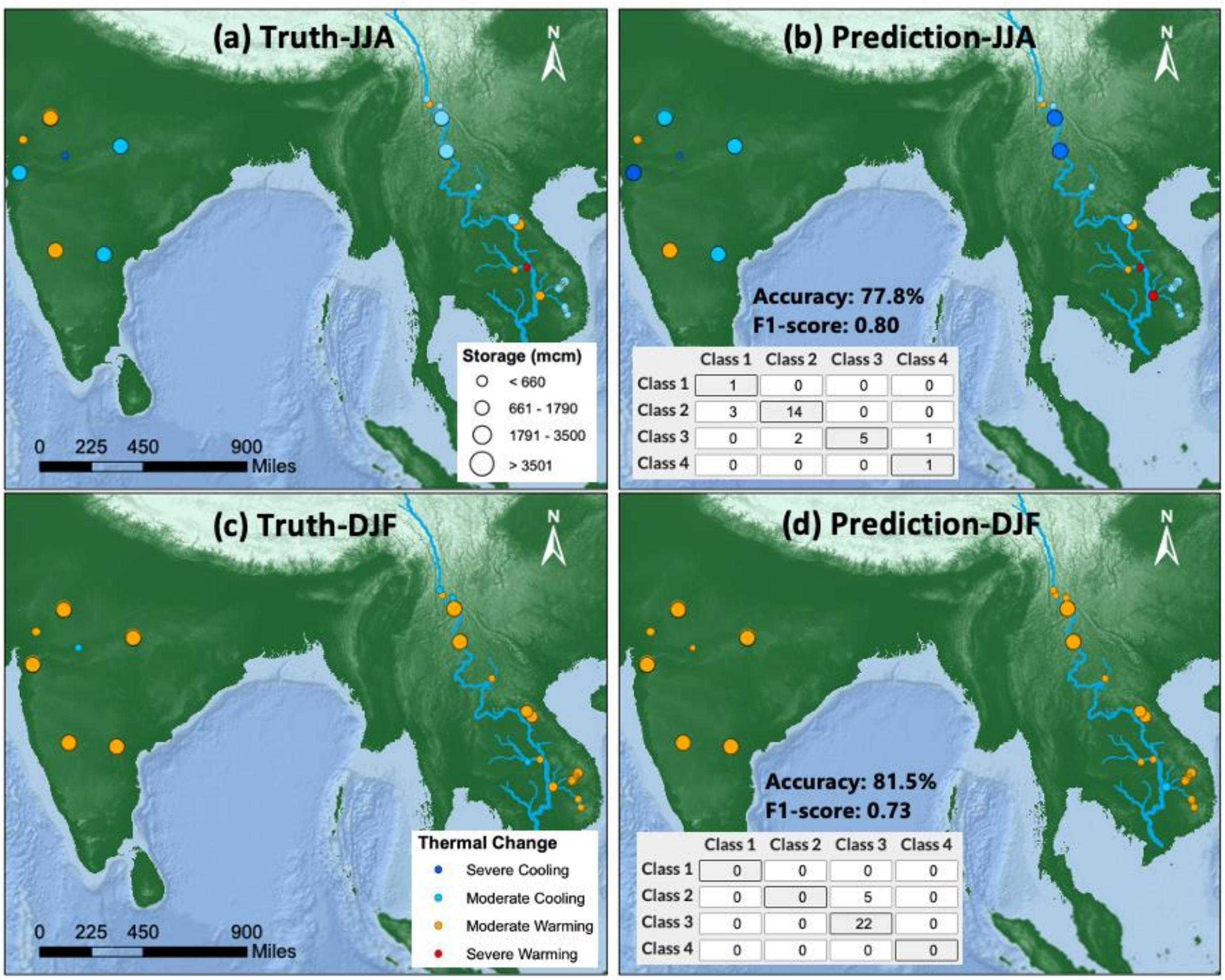

Figure 4. Validation results for existing dams in Southeast Asia during the months of JJA (top panel) and DJF (bottom panel). Reference thermal change classes are shown on the left **(a and c)** while corresponding model predictions are shown on the right panel **(b and d)**. Confusion matrices, accuracy (ratio of correct predictions and total sample dams) and F1-scores for the respective classifications are shown in the right panel.

3.2 How will Planned Hydropower Dams Alter River Temperatures Around the World?

Using the model trained and validated on a variety of existing dams in the U.S., MRB, and India, we applied the FUTURIST framework on 216 planned (including those under construction) hydropower dam sites around the world. It is worth noticing here that the predictions are an estimate of the likely changes in thermal regime due to future hydropower dam operations if the plans are executed under the current temperature data.

During the months of JJA, which are warmer in the northern hemisphere and cooler in the southern hemisphere, 172 hydropower dams (80%) are likely to cool downstream rivers, with 32 (15%) expected to exhibit severe cooling (Figure 5). In contrast, only 44 (20%) of the planned hydropower dams are likely to warm downstream rivers, out of which 11 (5%) have the potential of causing severe warming to the tailwaters. The majority of dams that cause downstream rivers to cool during summers undergo strong reservoir stratification. As such, these have either large storage pool or smaller reservoir area. This is also suggested by Figure S5 (see supplementary information) where planned dams with smaller area-storage ratio general exhibit severe to moderate cooling. A similar pattern was observed for the existing U.S. dams used for training (Figure 3), although other factors like climate and dam bathymetry resulted in apparent differences between the dams in U.S. and across the world.

During the months of DJF, the same hydropower dams show a relatively consistent pattern of moderate warming with a likely temperature change varying between 1.0˚C to 4.5˚C. These results are consistent with the thermal impact of dams used for validation where most dams also resulted moderate warming of tailwaters. It is worth mentioning that the predictions on planned dams are dependent on the diversity and variability represented by the training set of the

FUTURIST framework. As only dams in the U.S. were used for training due to limitations of data availability in other regions, uncertainty can increase in the predictions over significantly different climates such as in Southern Hemisphere. The same class of thermal change predicted across all the dams during winters could possibly be affected by this uncertainty.

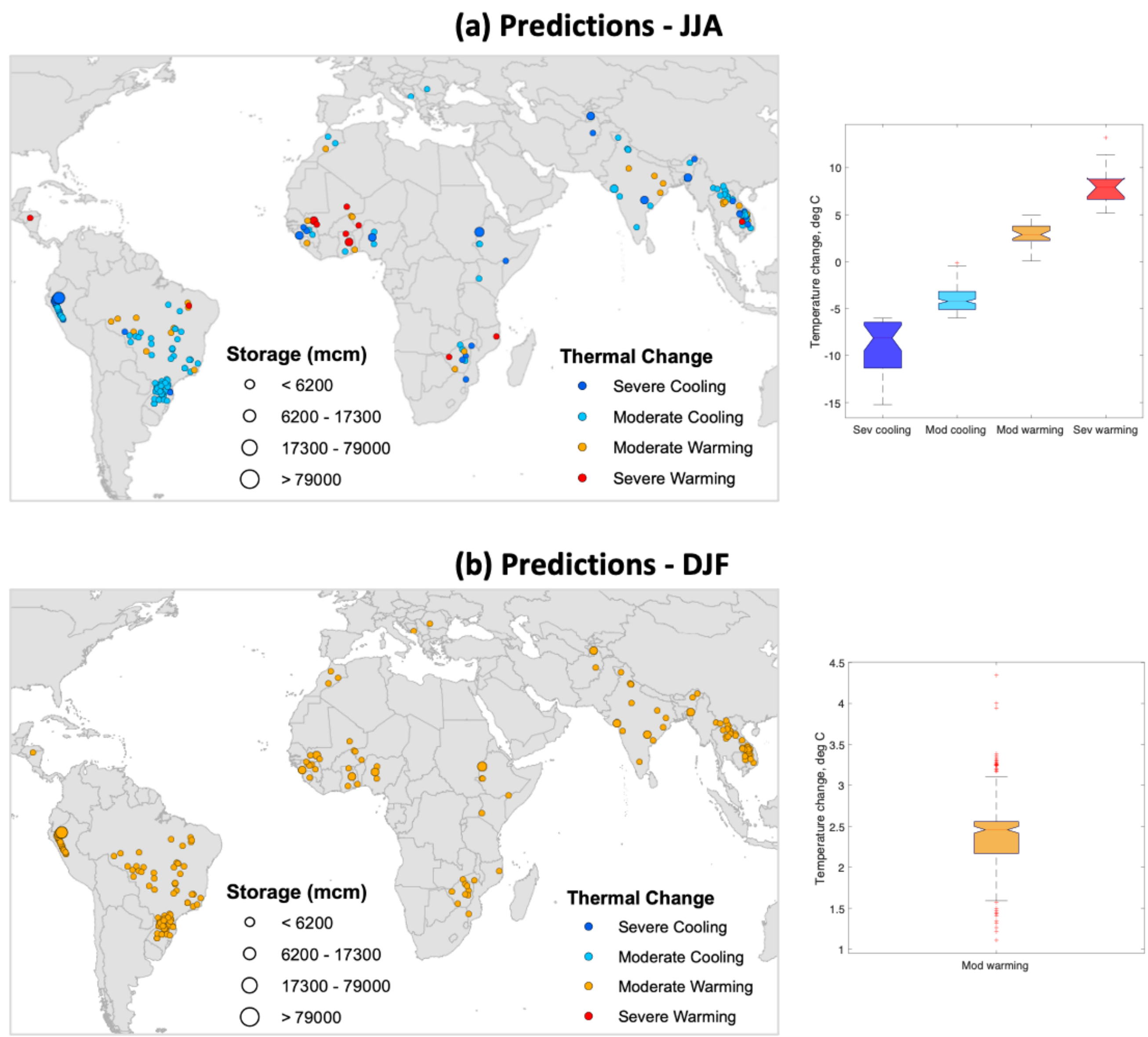

Figure 5. Thermal regime predictions for planned hydropower dams during the months of **(a)** JJA and **(b)** DJF. Variability in each class of thermal change is shown as boxplots for the respective seasons.

The effects of change in thermal regime are not only limited to the local river channel but may also translate into basin-wide impacts, in many cases over longer period of times as reported by Bonnema et al. (2020). To capture large scale impacts, we mapped the average thermal regime changes to river basins containing planned dams. The global dataset for watershed boundaries called HydroBASINS (Lehner et al., 2013) was used to aggregate the dam impacts on the respective basins containing them. More details of the procedure are provided in section 2.3. The results for the months JJA are shown in Figure 6.

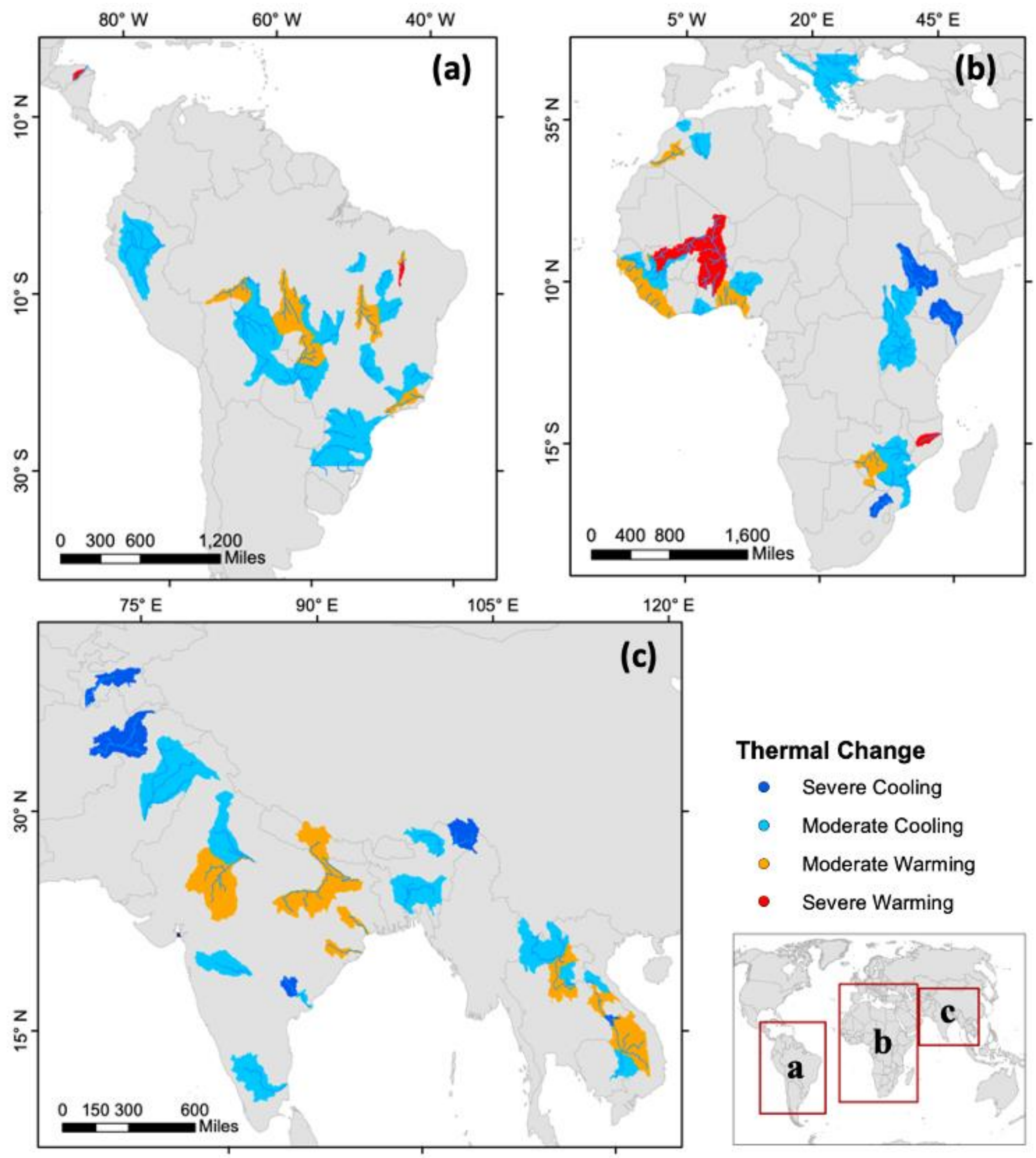

Figure 6. Basin-scale thermal regime changes for the months of JJA corresponding to the planned dam locations. Basin boundaries are obtained from HydroBASINS databases. Level 4 database is used for Africa while Level 5 is used for the rest.

3.3 Explaining Model Predictions

Neural networks have been criticized for being black-box type models with little insight into the physical processes driving the outputs. However, in order to build a trustworthy model, an explanation of the predictions made by the model is fundamental. Here, we used a technique called Local Interpretable Model-Agnostic Explanations (LIME) (Ribeiro et al., 2016). The technique provides prediction of any classifier in an interpretable manner presenting contributions (set of coefficients) of the individual predictors towards the final model outcome.

Using LIME model, we analyzed our trained NN model for the contributions from selected input nodes for modeling the thermal change. Figure S6 in supplementary information shows these contributions for a sample of existing and future dams. The magnitude of individual contributions suggest that the top contributors are, in general, the parameters that control reservoir's stratification such as reservoir area and storage capacity. Also, ambient air temperature plays significant role for the majority of dams. These findings build confidence in the model and allow the planner or manager to decide if the predictions should be trusted depending on which predictors are deriving the outcomes.

3.4 Impact of Climate Change on Predicted Thermal Pollution

To study the effect of climate change on riverine thermal regime change, we used downscaled climate scenarios of RCP4.5, RCP8.5, and a basline retrospective run derived from the GFDL-ESM2M model to force the FUTURIST ANN model. Resulting predictions of riverine thermal changes (average difference between upstream and downstream temperatures) were compared across the three scenarios. Figure 7 shows the empirical distribution of predicted temperatures and respective thermal changes over the 216 planned sites for both the winter and summer seasons.

The greenhouse gas emissions scenarios of RCP4.5 and RCP8.5 cause the temperature distribution to shift towards right with a higher amplitude of thermal change. The resulting thermal regimes also experience changes under the projections of changing climate. During JJA, the dams that are predicted to cause warming under current temperatures (dams with positive thermal change in Figure 7) will intensify in their impact with an average increase in the amplitude of thermal change by up to 1.0% and 2.6% under RCP4.5 and RCP8.5 scenarios respectively. However, the dams causing downstream cooling (negative thermal change in Figure 7), on experiencing warmer air temperatures, will have a curtailed cooling impact by up to 1.2% (2.2%) under RCP4.5 (RCP8.5) scenario. In contrast, under the projected rise in air temperatures during DJF, the dams will experience comparatively lower increases in mean downstream warming amounting to 0.2% (0.6%) under RCP4.5 (RCP8.5) with respect to the baseline scenario.

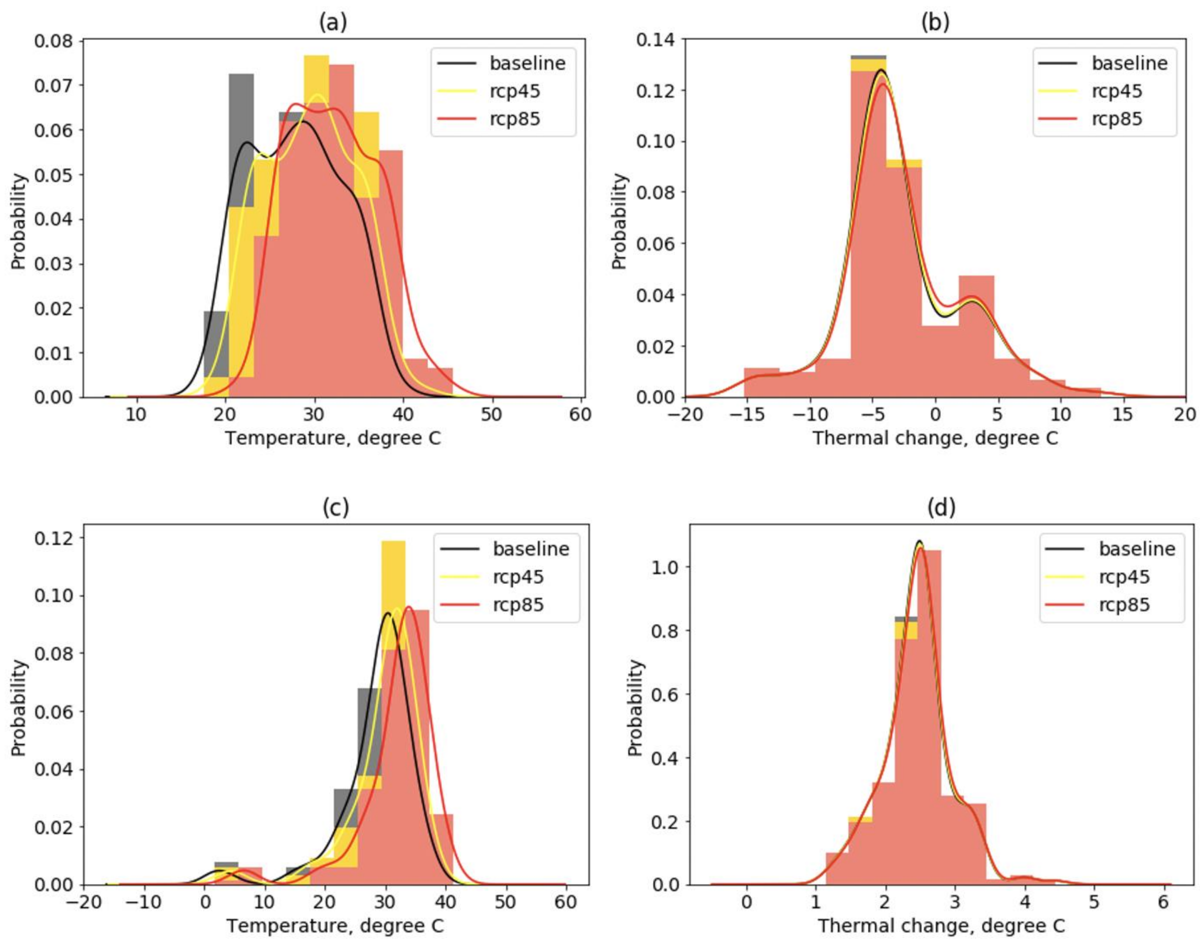

Figure 7. Probability distributions of air temperature as histogram and smoothed curves (left panel) and those for respective thermal regime changes (right panel) for three scenarios of baseline (historical temperatures during 2000-05), RCP4.5 (2095-99), and RCP8.5 (2095-99) during months of **(a, b)** JJA and **(c, d)** DJF.

4 Discussion

We have shown in this study that the past historical records of dams in the U.S. can be leveraged to predict the likely impact of future hydropower dams on river temperature in a variety of climates and basins around the world. The FUTURIST modeling framework provides an unprecedented advantage in terms of efficiently learning how future dams might affect ecosystems by altering the natural thermal regimes of rivers. It also allows for the assessment of climate drivers of water temperature in addition to dam operations. By providing a preliminary estimate of likely thermal impacts due to dam operations, our FUTURIST framework also helps prioritize the planned sites where more detailed and expensive physical studies need to be carried out.

4.1 Global Overlook of Thermal Impacts in the Future

Existing studies on dams have demonstrated the potential impacts on freshwater megafauna species (Zarfl et al., 2019), fragmentation of the fish occurrence ranges (Barbarossa et al., 2012), flow regulation and fragmentation of large rivers (Nilsson et al., 2005, Grill et al., 2015). A global overlook of thermal impacts due to future dams adds another dimension to our understanding of human-induced changes to riverine ecosystems and the services they provide.

Our results reveal interesting and varying patterns of thermal impacts across the selected planned dams. A general trend of lower highs (reduced temperatures during summers) and higher lows (warmer temperatures during winters) is predicted. The predictions reflect homogenized changes in the thermal regime of downstream rivers over a long period of time. Dams with strong thermal stratification tend to cool downstream rivers during warm seasons. A number of potential hotspots appear that may lead to severe changes of warming or cooling for the native biodiversity. Noteworthy conclusions can be inferred using the index of dam impact matrix (DIM) presented by Grill et al. (2015) for dam development. Basins like Amazon which have been labeled as relatively pristine in terms of fragmentation and flow regulation will be experiencing dam development that can lead to moderate cooling and, in some cases, moderate warming (Figure 6). There are also basins such as the Parana in South America and the Niger in Africa that have undergone significant fragmentation in the past due to hydropower dams. These two basins are projected to experience further hydropower dam developments in the near future. While the hydropower dams in the Niger basin will likely be causing a severe warming impact on the tailwaters, those in Parana basin are predicted to cause moderate cooling (Figure 6). This suggests that basins already fragmented due to hydropower dam operations are also susceptible to serious thermal impacts. Such basins demand reconsideration of hydropower generation plans or design of adaptive operation procedures to protect the ecosystem from long-term ecological impacts due to thermal regime change.

Climate change is a major challenge, especially for developing countries in their efforts to install more hydropower capacity (Ali et al., 2018). While the impacts of climate change on the hydropwer potential have been studied globally (Liu et al., 2016; Turner et al., 2017; Ali et al., 2018). Our FUTURIST framework also allows assessing the thermal response of downstream rivers due to dam operations under long-term changes in climate. This is pertinent for peforming more holistic environmental impact assessment studies with insights into thermal modifications due to hydropower generation and its variability. The impact of increased warming by the end of the century on thermal regime changes revealed that not all dams will respond the same to changing climate. Figure 7 shows, under increased global warming, dams that have a cooling impact on the tailwaters (negative thermal change) will get weaker in their impact, with decreasing amplitude of thermal cooling during summers. However, the dams that led to downstream warming will likely intensify in their warming impact with higher amplitude of thermal change.

Our FUTURIST modeling framework can be easily transferred to any other hydropower dam site of interest with minimal data requirements. Because the framework is trained on temperature change values and not on qualitative classes, the technique provides flexibility in the choice of output classes of moderate/severe change. Depending on the focus of stakeholders (fisheries, resource management, water management), the thermal class definitions can be tweaked and trained accordingly. Each community can assign its own priorities of the acceptable as moderate and unacceptable as severe to understand the impacts of a planned hydropower dam.

4.2 Ecological Consequences of Thermal Pollution

The established thermal impacts of the existing dams have already raised concerns for ecological processes and biodiversity (Olden and Naiman, 2010). With the understanding of the potential thermal alterations due to planned dams from FUTURIST framework, it is imperative to study how the ecology will respond to these predictions. We present here a few case examples that highlight the trade-offs and provide insight into the potential ecological response if the dam development plans are to be executed.

The operations of Xinanjiang and Danjiangkou hydroelectric dams in China, that began in 1960s, have been causing serious environmental impacts on the downstream reaches of Qiantang and Han rivers, respectively. Zhong and Power (1996) showed that these dams caused peak summer temperatures to decrease by 4-6°C and winter temperatures to increase by 4-6°C. As a result of cooler summer discharge, the fish spawning was retarded by three to eight weeks, causing extirpation of a majority of warmwater fishes. In the alpine climate of Colorado River basin, operations of Flaming Gorge dam contributed to local extinction of multiple endangered fish species in the downstream Green River. Again, this was a consequence of the significant cooling of downstream channels where peak temperatures depressed to 6 °C from a previous range of 7–21 °C (57). Also, in Australia, Preece and Jones (2002) concluded that the cooler and delayed peak temperatures hamper the spawning success of several native fish species.

Fluctuations in winter temperature have also caused damage to the biodiversity. For example, consistent warming during winters was observed downstream of a dam on the Saskatchewan River in Canada. This caused complete loss of insect fauna due to the elimination of stimuli essential for the completion of their life cycles (Lehmkuhl, 1974). Another such impact was observed by Stevens et al. (1997) where macroinvertebrate fauna of the Colorado River downstream of Glen Canyon Dam was highly depauperate compared with other unregulated rivers of the basin (Olden and Naiman, 2010).

Temperature variation of rivers is a natural phenomenon and the ecosystem is, in general, resilient to adapt to natural fluctuations. However, the intensive damming of those natural river systems has not only also caused net shifting of temperature profiles but also led to the homogenization of those temperatures over longer periods. Such homogenized changes as predicted by the FUTURIST framework (warmer cool water periods and colder warm water periods) are the drivers of negative biological responses. Our study clearly elucidates the need of frameworks like FUTURIST using which thermal pollution can be included within the dam planning to ensure sustainable river systems.

Acknowledgments

The work was supported with the generous contributions from University of Washington Global Affairs and The Ivanhoe Foundation. Authors SKA and FH were supported by the National Science Foundation project NSF EAR 1740042 titled *INFEWS/T1: Linking Current and Future Hydrologic Change to Hydropower, Human Nutrition, and Livelihoods in the Lower Mekong Basin*, and NASA Applied Science Program grant in Water Resources NNX15AC63G and NNX16AQ54G

Data Availability Statement

Dataset on the selected dams for training and validating the FUTURIST framework and on the planned dams used for predicting their thermal impacts is available in the supplementary information. Provided spreadsheet contains all the necessary inputs for simulating the FUTURIST framework along with the ancillary information on their location and logistics.

References

Ahmad, S.K., & Hossain, F. (2020). Realizing ecosystem-safe hydropower from dams. *Renewables: Wind, Water, and Solar, 7*(1), pp.1-23. https://doi.org/10.1186/s40807-020-00060-9

Ahmad, S.K., Hossain, F., Eldardiry, H., & Pavelsky, T.M. (2019). A Fusion Approach for Water Area Classification Using Visible, Near Infrared and Synthetic Aperture Radar for South Asian Conditions. *IEEE Transactions on Geoscience and Remote Sensing*, *58*(4), 2471-2480.

Ali, S.A., Aadhar, S., Shah, H.L., & Mishra, V. (2018). Projected increase in hydropower production in India under climate change. *Scientific reports*, *8*(1), 1-12.

Anderson, E.P., Jenkins, C.N., Heilpern, S., Maldonado-Ocampo, J.A., Carvajal-Vallejos, F.M., Encalada, A.C., et al. (2018). Fragmentation of Andes-to-Amazon connectivity by hydropower dams. *Science Advances, 4*(1), eaao1642.

Angilletta Jr, M.J., Ashley Steel, E., Bartz, K.K., Kingsolver, J.G., Scheuerell, M.D., Beckman, B.R., & Crozier, L.G. (2008). Big dams and salmon evolution: changes in thermal regimes and their potential evolutionary consequences. *Evolutionary Applications*, *1*(2), 286-299.

Barbarossa, V., Schmitt, R.J., Huijbregts, M.A., Zarfl, C., King, H., & Schipper, A.M. (2020). Impacts of current and future large dams on the geographic range connectivity of freshwater fish worldwide. *Proceedings of the National Academy of Sciences*, *117*(7), 3648-3655.

Benyahya, L., Caissie, D., St-Hilaire, A., Ouarda, T.B., & Bobée, B. (2007). A review of statistical water temperature models. *Canadian Water Resources Journal*, *32*(3), 179-192.

Bonnema, M., Hossain, F., Nijssen, B., & Holtgrieve, G. (2020). Hydropower's hidden transformation of rivers in the Mekong. *Environmental Research Letters*, *15*(4), 044017.

Buccola, N.L., Risley, J.C., & Rounds, S.A. (2016). Simulating future water temperatures in the North Santiam River. Oregon, *Journal of Hydrology*, *535*, 318-330.

Caissie, D. (2006). The thermal regime of rivers: a review. *Freshwater Biology*, *51*, 1389–1406.

CGIAR WLE, Mekong Dam Database (2011). WLE Greater Mekong, CGIAR Research Program on Water, Land and Ecosystems (WLE), Vientiane, Lao PDR. https://wle-mekong.cgiar.org/changes/our-research/greater-mekong-dams-observatory/. Accessed 13 July 2020.

Chowdhury, A.K., Dang, T.D., Bagchi, A., & Galelli, S. (2020). Expected Benefits of Laos' Hydropower Development Curbed by Hydroclimatic Variability and Limited Transmission Capacity: Opportunities to Reform. *Journal of Water Resources Planning and Management*, *146*(10), 05020019.

Clarkson, R.W., & Childs, M.R. (2000). Temperature effects of hypolimnial-release dams on early life stages of Colorado River Basin big-river fishes. *Copeia*, *2000*(2), 402-412.

Cole, T.M., & Wells, A. (2015). CE-QUAL-W2: A two-dimensional, laterally averaged, hydrodynamic and water quality model, Version 4.0. Portland State University, Portland, OR, USA.

Collins, M., Knutti, R., Arblaster, J., Dufresne, J.L., Fichefet, T., Friedlingstein, P., et al. (2013). Long-term climate change: projections, commitments and irreversibility. In *Climate Change 2013-The Physical Science Basis: Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (1029-1136). Cambridge University Press.

Deemer, B.R., Harrison, J.A., Li, S., Beaulieu, J.J., DelSontro, T., Barros, N., Bezerra-Neto, J.F., Powers, S.M., Dos Santos, M.A., & Vonk, J.A. (2016). Greenhouse gas emissions from reservoir water surfaces: a new global synthesis. *BioScience*, *66*(11), 949-964.

FAO, AQUASTAT Main Database (2016). Food and Agriculture Organization of the United Nations (FAO). http://www.fao.org/aquastat/en/databases/dams. Accessed 2 Aug 2020.

Finer, M., & Jenkins, C. N. (2012). Proliferation of hydroelectric dams in the Andean Amazon and implications for Andes-Amazon connectivity. *PloS One, 7*(4), e35126.

FitzHugh, T.W., & Vogel, R.M. (2011). The impact of dams on flood flows in the United States. Ri*ver Research and Applications*, *27*(10), 1192-1215.

Forsberg, B.R., et al., 2017. The potential impact of new Andean dams on Amazon fluvial ecosystems. PLoS One 12(8), e0182254.

Grill, G., Lehner, B., Lumsdon, A.E., MacDonald, G.K., Zarfl, C., Liermann, C.R. (2015). An index-based framework for assessing patterns and trends in river fragmentation and flow regulation by global dams at multiple scales. *Environmental Research Letters*, *10*(1), 015001.

Haxton, T.J., & Findlay, C.S. (2008). Meta-analysis of the impacts of water management on aquatic communities. *Canadian Journal of Fisheries and Aquatic Sciences*, *65*(3), 437-447.

Hecht, J.S., Lacombe, G., Arias, M.E., Dang, T.D., Piman, T. (2019). Hydropower dams of the Mekong River basin: A review of their hydrological impacts. *Journal of Hydrology*, *568*, 285-300.

Imboden, D.M., & Wüest, A. (1995). Mixing mechanisms in lakes. In *Physics and chemistry of lakes* (83-138). Springer, Berlin, Heidelberg.

Jiménez-Muñoz, J.C., & Sobrino, J.A. (2003). A generalized single-channel method for retrieving land surface temperature from remote sensing data. *Journal of Geophysical Research, 108*, 4688.

Jiménez-Muñoz, J.C., Cristóbal, J., Sobrino, J.A., Sòria, G., Ninyerola, M., & Pons, X. (2008). Revision of the single-channel algorithm for land surface temperature retrieval from Landsat thermal-infrared data. *IEEE Transactions on geoscience and remote sensing*, *47*(1), 339-349.

Kareiva, P. (2012). Dam choices: analyses for multiple needs. *Proceedings of the National Academy of Sciences, 109*(15), 5553-5554.

Lehmkuhl, D.M. (1974). Thermal regime alteration and vital environmental physiological signals in aquatic organisms. In *AEC symposium series (CONF 730505)* (261-222).

Lehner, B., Liermann, C.R., Revenga, C., Vörösmarty, C., Fekete, B., Crouzet, P., et al. (2011). Global reservoir and dam (grand) database. *Technical Documentation, Version*, *1*, 1-14.

Lehner, B., Liermann, C.R., Revenga, C., Vörösmarty, C., Fekete, B., Crouzet, et al. (2011). High-resolution mapping of the world's reservoirs and dams for sustainable river-flow management. *Frontiers in Ecology and the Environment*, *9*(9), 494-502.

Ling, F., Foody, G.M., Du, H., Ban, X., Li, X., Zhang, Y., Du, Y. (2017). Monitoring thermal pollution in rivers downstream of dams with Landsat ETM+ thermal infrared images. *Remote Sensing*, *9*(11), 1175.

Liu, X., Tang, Q., Voisin, N., & Cui, H. (2016). Projected impacts of climate change on hydropower potential in China. *Hydrol. Earth Syst. Sci.*, *20*, 3343–3359.

Mohseni, O., Stefan, H.G., & Erickson, T.R. (1998). A nonlinear regression model for weekly stream temperatures. *Water Resources Research*, *34*(10), 2685-2692.

Moran, E.F., Lopez, M.C., Moore, N., Müller, N., Hyndman, D.W. (2018). Sustainable hydropower in the 21st century. *Proceedings of the National Academy of Sciences*, *115*(47), 11891-11898.

Mekong River Commission (MRC), 2009. Economic, Environmental and Social Impact Assessment of Basin-Wide Water Resources Development Scenarios, Assessment Methodology. Mekong River Commission, Vientiane Lao PDR.

Mekong River Commission (MRC), 2012. Hydropower Project Database.

Mohammadzadeh-Habili, J., Heidarpour, M., Mousavi, S.F., & Haghiabi, A.H. (2009). Derivation of reservoir's area-capacity equations. *Journal of Hydrologic Engineering*, *14*(9), 1017-1023.

Neumann, D.W., Rajagopalan, B., & Zagona, E.A. (2003). Regression model for daily maximum stream temperature. *Journal of Environmental Engineering, 129*(7), 667-674.

Niemeyer, R.J., Cheng, Y., Mao, Y., Yearsley, J.R., & Nijssen, B. (2018). A thermally stratified reservoir module for large-scale distributed stream temperature models with application in the

Tennessee River Basin. *Water Resources Research, 54*, 8103–8119. https://doi.org/10.1029/2018WR022615

Nilsson, C., Reidy, C.A., Dynesius, M., & Revenga, C. (2005). Fragmentation and flow regulation of the world's large river systems. *Science*, *308*(5720), 405-408.

NRLD, National Register of Large Dam, Under of Central Water Commission (2012). http://www.indiaenvironmentportal.org.in. Accessed 22 July 2020.

Olden, J.D., & Naiman, R.J. (2010). Incorporating thermal regimes into environmental flows assessments: modifying dam operations to restore freshwater ecosystem integrity. *Freshwater Biology, 55*(1), 86-107.

Peel, M.C., Finlayson, B.L., & McMahon, T.A. (2007). Updated world map of the Köppen-Geiger climate classification. *Hydrol. Earth Syst. Sci.*, *11*, 1633-1644, https://doi.org/10.5194/hess-11-1633-2007

Piman, T., Cochrane, T.A., & Arias, M.E. (2016). Effect of proposed large dams on water flows and hydropower production in the Sekong, Sesan and Srepok rivers of the Mekong basin. *River Research and Applications, 32*(10), 2095-2108.

Piman, T., Cochrane, T.A., Arias, M.E., Green, A., & Dat, N.D. (2013). Assessment of flow changes from hydropower development and operations in Sekong, Sesan, and Srepok rivers of the Mekong basin. *Journal of Water Resources Planning and Management*, *139*(6), 723-732.

Poole, G.C., & Berman, H. (2001). An ecological perspective on in-stream temperature: natural heat dynamics and mechanisms of human-caused thermal degradation. *Environmental Management, 27*, 787–802.

Preece, R.M., & Jones, H.A. (2002). The effect of Keepit Dam on the temperature regime of the Namoi River, Australia. *River Research and Applications*, *18*, 397–414.

Räsänen, T.A., Someth, P., Lauri, H., Koponen, J., Sarkkula, J., & Kummu, M. (2017). Observed river discharge changes due to hydropower operations in the Upper Mekong Basin. *Journal of hydrology*, *545*, 28-41.

Ribeiro, M.T., Singh, S., & Guestrin, C., (2016). " Why should I trust you?" Explaining the predictions of any classifier. In *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining* (1135-1144).

Richter, B.D., Baumgartner, J.V., Braun, D.P., Powell, J. (1998). A spatial assessment of hydrologic alteration within a river network. *Regulated Rivers: Research & Management: An International Journal Devoted to River Research and Management*, *14*(4), 329-340.

Schmitt, R.J., Bizzi, S., Castelletti, A., Opperman, J.J., Kondolf, G.M. (2019). Planning dam portfolios for low sediment trapping shows limits for sustainable hydropower in the Mekong. *Science advances*, *5*(10), eaaw2175.

Stevens, L.E., Shannon, J.P., & Blinn, D. W. (1997). Colorado River benthic ecology in Grand Canyon, Arizona, USA: dam, tributary and geomorphological influences. *Regulated Rivers: Research & Management*, *13*(2), 129-149.

Taylor, K.E., Stouffer, R.J., & Meehl, G.A. (2012). An overview of CMIP5 and the experiment design. *Bull. Am. Meteorol. Soc.*, *93*, 485–498.

Toffolon, M., & Piccolroaz, S. (2015). A hybrid model for river water temperature as a function of air temperature and discharge. *Environmental Research Letters*, *10*(11), 114011.

Turner, S. W. D., Ng, J. Y., & Galelli, S. (2017). Examining global electricity supply vulnerability to climate change using a high-fidelity hydropower dam model. *Sci. Total Environ.*, 590–591, 663–675.

Van Vliet, M.T.H., Ludwig, F., Zwolsman, J.J.G., Weedon, G.P., Kabat, P. (2011). Global river temperatures and sensitivity to atmospheric warming and changes in river flow. *Water Resources Research*, *47*(2).

Wild, T.B., & Loucks, D.P. (2014). Managing flow, sediment, and hydropower regimes in the Sre Pok, Se San, and Se Kong Rivers of the Mekong basin. *Water Resources Research, 50,* 5141– 5157.

Winemiller, K.O., McIntyre, P.B., Castello, L., Fluet-Chouinard, E., Giarrizzo, T., Nam, S., et al. (2016). Balancing hydropower and biodiversity in the Amazon, Congo, and Mekong. *Science*, *351*(6269),128-129.

Yang, S.L., Zhang, J., Zhu, J., Smith, J.P., Dai, S.B., Gao, A., Li, P. (2005). Impact of dams on Yangtze River sediment supply to the sea and delta intertidal wetland response. *Journal of Geophysical Research: Earth Surface*, *110*(F3).

Yearsley, J. (2012). A grid-based approach for simulating stream temperature. *Water Resources Research*, *48*(3).

Zarfl, C., Berlekamp, J., He, F., Jähnig, S.C., Darwall, W., & Tockner, K. (2019). Future large hydropower dams impact global freshwater megafauna. *Scientific Reports*, *9*(1), pp.1-10.

Zarfl, C., & Lucía, A. (2018). The connectivity between soil erosion and sediment entrapment in reservoirs. *Current Opinion in Environmental Science & Health 5*, 53-59.

Zarfl, C., Lumsdon, A.E., Berlekamp, J., Tydecks, L., & Tockner, K. (2015). A global boom in hydropower dam construction. *Aquatic Sciences*, *77*(1), 161-170.

Zhong, Y, & Power, G. (1996). Environmental impacts of hydroelectric projects on fish resources in China. *Regulated Rivers: Research and Management, 12,* 81–98.

Ziv, G., Baran, E., Nam, S., Rodríguez-Iturbe, I., & Levin, S.A. (2012). Trading-off fish biodiversity, food security, and hydropower in the Mekong River Basin. *Proceedings of the National Academy of Sciences*, *109*(15), 5609-5614.