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Predicting the Likely Thermal Impact of Current and Future Dams Around the World

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Key Points:

- Past records of thermal impacts can help predict the likely impact of future dams
- We predict a shift toward lower summer temperatures and higher winter temperatures for downstream rivers due to planned dam operations
- Reservoirs with strong thermal stratification tend to severely impact downstream thermal regime

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract

Selective water release from the deeper pools of reservoirs alters the temperature of downstream rivers. Thermal destabilization of downstream rivers can be detrimental to the riverine ecosystem by disturbing the growth stages of various aquatic species. To predict this impact of planned hydropower dams worldwide, we present a framework called "*FUture Temperatures Using River hISTory* (*FUTURIST*)." The framework used historical records of in-situ river temperatures for existing dams in the U.S. and remote sensing observations for those in other regions to train an artificial neural network (ANN) model that predicts temperature change between upstream and downstream rivers. Validation of FUTURIST-modeled impacts for dams worldwide showed promising results with a root mean squared error of 2.5°C (0.9°C) and categorical accuracy of 63% (88%) during the summer (winter) season. The trained ANN model afforded prediction of the likely thermal impacts of 216 planned dams. Results suggest that during the summer season, 73% of future dams will potentially cool downstream rivers by up to 6.6°C. Winter season operations were predicted to consistently warm downstream rivers by temperatures of up to 2°C. Reservoirs that experience strong stratification have the most potential to impact downstream pre-dam thermal regimes. For copious existing or planned dams worldwide that are yet to be mapped of their thermal impacts, FUTURIST provides an efficient path forward to carry out a global thermal assessment and design sustainable hydropower expansion plans so that the upcoming dams can be operated in a more eco-sensitive manner than the existing ones.

Plain Language Summary

Today, aquatic biodiversity is at a 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 design and operations of existing dams across the globe have altered river temperatures downstream of the dams. This model was validated globally over another set of dams and then used to predict the impact of future dams. An assessment of 216 such planned dams revealed that the vast majority will likely to reduce the summer temperatures and to 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, guard against extreme floods and meet 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 3,600 medium and large hydropower dams are either under construction or planned, predominantly in South America, Africa, and South/East Asia, regions 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 (MRB) (Chowdhury et al., 2020; Schmitt et al., 2019). 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 (Yang et al., 2005; Zarfl and Lucía, 2018), disrupted natural hydrologic variability (FitzHugh and Vogel, 2011), contributed to greenhouse gas emissions (Deemer et al., 2016), and led to resettlement of local communities and loss of culture and heritage (Hecht et al., 2019; Moran et al., 2018). 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 high hydraulic head and 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 spillways, 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 aquatic habitat (Angilletta et al., 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 that 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 (Ahmad & Hossain, 2020; Benyahya et al., 2007) or more complex and physically distributed river temperature (Yearsley, 2012) and hydrodynamic models (bib_Cheng_et_al_2020abib_Cheng_et_al_2020bBuccola et al., 2016; Cole and Wells, 2015; Cheng et al., 2020a, 2020b; Niemeyer et al., 2018). 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 stream temperature models have multiple limitations when it comes to studying the impact of planned hydropower dams. On one hand, these hydrodynamic and thermodynamic models are complex and require inputs on geophysical quantities difficult to measure or estimate, such as 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 & Piccolroaz, 2015). Both classes of models, moreover, suffer from the inability to be easily set up for large number of future dams. This limitation makes the development of a rapidly transferrable yet skillful technique of modeling dam's thermal response very timely. Hereafter, the term "dams" refer to mostly hydropower dams. Hereafter, "dams" refer to the hydropower dams.

Given the pace at which future 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. Toward that end goal, we outline three key traits for a modeling framework to "predict," or infer, the thermal modification impact of planned dams. The first stage to any thermal predictive model for understanding the thermal impact of a planned dam is to understand which side of the thermal axis (cooling or warming) the impact will occur. Due to global warming, most studies report that lakes will undergo gradual warming (Daly et al., 2020); however, the localized or regional impact due to more direct anthropogenic factors such as dams has not yet been clearly mapped. As the aquatic biodiversity is sensitive to absolute water temperature and alterations therein (Haxton & Findlay, 2008), we need a technique that is reliably accurate in providing a qualitative and quantitative 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, which is a fundamental prerequisite for working on the data-scarce conditions characterizing the Global South, where the majority of dams are planned. Existing tools, such as WBM-T2PM by Miara et al. (2018) or those available in earth system models (see Li et al., 2015; Yigzaw et al., 2019), are complex and based on physically based thermo-hydrodynamic modeling that require extensive data on boundary conditions for calibration. Most importantly, current physically based river temperature modeling tools cannot be applied in a globally consistent manner due to lack of extensive in-situ temperature and hydrodynamic data. Thus, we need an efficient pathfinder to prioritize which planned dams need to be studies more for dialogue and further studies.

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 recently 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 dams around the world on their likely change to downstream river temperatures. Our predictions are based on a novel data-based framework for planned 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 dams. More specifically, we use FUTURIST framework to answer the following questions: (a) can we learn patterns of thermal impact on downstream rivers caused by the existing dams based on known climate, hydrology, and dam characteristics? (b) having identified, or learned, 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 river temperature changes from in-situ gages and remote sensing observations over a set of dams across the globe capturing variability in climate and hydrology to train an artificial neural network (ANN) model. This data-based ANN approach predicted temperature change between upstream and downstream rivers. The ability of ANN model to capture nonlinearities in predicting dam's thermal impacts makes the technique transferrable to other dams with unobserved conditions. This was demonstrated by the high predictive skill over dams in varying climates across the continents 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. The ANN model was then applied at planned hydropower sites worldwide to predict the likely thermal impacts. Finally, we explored the effect of climate change on riverine thermal regime change using our framework by forcing the ANN model with different warming scenarios toward the end of the century. Our analysis elucidates the need to include thermal pollution as an integral part of dam planning and operations 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 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., 2011a, 2011b). This resulted in 87 dams, out of which 60 locations had at least a year of overlapping temperature records on upstream and downstream stations. We selected the USGS gauges closest to dam and at a maximum distance of 50 km from the dam for both upstream and downstream temperatures. The temporal record length exceeded more than 10 years for most of the selected sites. 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.

To expand the database of dams with information on thermal impacts in the past, we used remote sensing observations of surface water temperature from TIR data. Because the satellite-based temperature extraction is limited by its spatial resolution (see Section 2.2), it is challenging to obtain pure water pixels over narrower rivers, unless the river is wide enough to reflect pure water signal. Upstream of a dam, however, with the larger expanse of reservoir, the spatial resolution of TIR remote sensing is not an issue. We therefore filtered out additional sites in US with USGS stations located downstream for which the upstream reservoir temperatures were obtained from remote sensing, sampled over the reservoir.

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 sites in different parts of the world such as in South Asia, parts of Europe, and South America where a large number of hydropower dams have been built during the satellite with more dams at different planning stages. These additional dams allow for calculating thermal regime change as the difference between pre- and post-dam temperatures of the river reach. The selected set of existing dams thus consisted of a diverse range of climates, dam types (storage and run-of-river), sizes (with reservoir capacities varying from 10 to ~6,500 mcm), and topography, so that the model trained on these sites can capture the variability across other dam sites with unobserved conditions (see Supporting Information S1, Figure S1 showing the wide ranging characteristics of the selected dams).

Location and relevant information for dams in the Mekong River Basin (MRB) were obtained from CGIAR WLE Database (Mekong Dam Database, 2011), the Mekong River Commission (MRC, 2009), Räsä;nen 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 other dams in other regions was retrieved from the GRanD database. Only the dams with river channels (upstream or downstream) wider than 120 m (see Section 2.2) were used, so as to avoid the impure non-water pixels during retrieval. Further, only non-cloudy days were used with no-ice conditions to obtain reliable estimate of the surface water temperature.

Information on planned 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 (MRC, 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 the remaining countries. Individual reports from dam authorities were also consulted to fill in the missing data and to cross-validate the retrieved information. The selected planned dams also represented a wide variety in characteristics, types (storage and 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. Detailed information on the dams selected for training and validating the FUTURIST framework as well as the 216 planned dams is provided in the Supporting Information S1.

2.2. Monitoring Thermal Impacts From Space

Despite the advantage of a robust temperature monitoring network in the U.S., developing nations still lack in-situ measurements. We therefore used TIR band observations to obtain estimates of surface water temperature for upstream reservoir (for selected dams within the U.S., where upstream USGS stations were absent). For dams in other parts of the world with no in-situ observations, satellite-based thermal change observations were obtained in a couple of ways. For dams built before the Landsat era, temporally synchronous observations of surface temperature upstream and downstream of dams were used to quantify the change in thermal regime. Landsat-7 ETM+ (available 1999 onwards) provided TIR observations for such dams. Second, for dams built during the Landsat era, dam's thermal impact was quantified as change in temperature of river reach before and after the dam construction. In this scenario, both Landsat-5 TM (available 1984–2012) and Landsat-7 ETM+ (1999 onwards) observations were used to retrieve pre-dam and post-dam temperature timeseries to calculate the thermal changes.

The TIR band from Landsat-7 band is acquired at 60 m and that from Landsat-5 at 120 m, due to which we restricted the selection to dams with rivers wider than 120 m (to avoid impure water pixels). The single channel algorithm (Jiménez-Muñoz et al., 2008; Jiménez-Muñoz & Sobrino, 2003) for temperature extraction was used with atmospheric correction for top-of-atmosphere (TOA) reflectance. The procedure is described in detail by Ahmad et al., 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. Poor quality retrievals were filtered out to minimize bias in resulting predictions.

Quantitative evaluation of Landsat-derived surface temperature was performed against in-situ observations from USGS stations over a subset of 14 dams in the U.S (see Supporting Information S1, Figure S2). Respective error metrics are tabulated in Table S1. It can be observed that RMSE ranges around 3 C–5 C while Pearson's correlation varies between 0.61 and 0.93. Validation of upstream and downstream temperatures from Landsat observations has also been presented for multiple dams in the U.S. against USGS records in our previous study (Ahmad & Hossain, 2020).

2.3. Dam Operation-Induced Thermal Regime Change

Dam operations affect downstream thermal regime in multiple aspects (see Supporting Information S1, 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 thermal regime (Olden & Naiman, 2010). Here, the variable of interest is the change in thermal regime of rivers caused by dam operations with respect to the natural thermal regime. For dams built during the Landsat era (mostly outside the U.S.), dam's thermal impact was quantified as change in temperature of river reach before and after the dam construction. To this end, we defined thermal regime change, ΔT as,

$$\Delta T = \overline{T_{post\ dam} - T_{pre\ dam}} \tag{1}$$

where ΔT is the thermal change averaged over the season in consideration, calculated as difference between the post-dam (T_{post})and pre-dam (T_{pre}) river temperatures over those months.

However, for dams that pre-date Landsat-era (such as most dams in the U.S.), pre-dam temperatures were challenging to obtain from USGS gauges or any other source. For those dams, the temperature of upstream river flowing into the reservoir was considered as a proxy to the unaffected natural riverine thermal regime. We considered the mean difference between upstream and downstream temperatures over multiple years on record to capture the change in thermal regime, homogenized over time. Thermal change, ΔT, in this scenario was obtained as,

$$\Delta T = \overline{T_{up} - T_{down}} \tag{2}$$

where seasonal averaged difference between upstream (T_{up})and downstream water temperatures (T_{down}) was used.

In light of the previous efforts to assess dam impacts on different ecosystem aspects using qualitative categories (Barbarossa et al., 2020; Grill et al., 2015; Zarfl et al., 2019), we introduced the 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 −5°C and 0°C), severe cooling (less than −5°C), moderate warming (between 0°C and 5°C), and severe warming (more than 5°C). Because, the spread of temperatures was relatively smaller in the winter season, a further subclass of mild cooling (−1.5°C to 0°C) and mild warming (0°C–1.5°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.

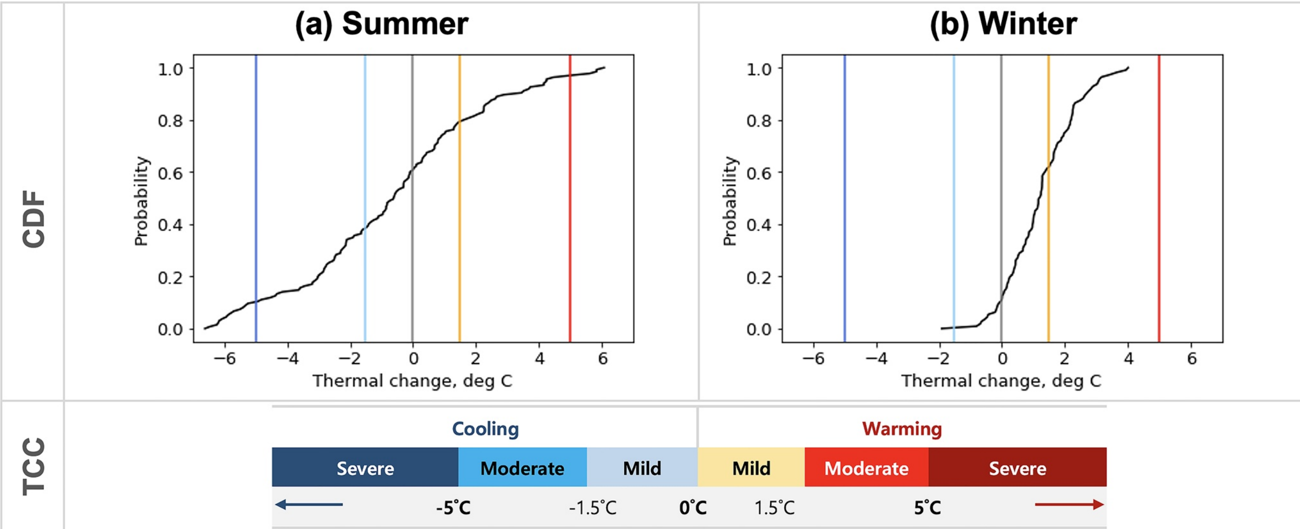

Figure 1. Upper panel: Cumulative Distribution Functions (CDF) for thermal regime changes during (a) summer and (b) winter seasons across the existing dams (used for training and validation). Lower panel: Respective thresholds (for defining Thermal Change Class (TCC) for subclassifying the cooling and warming regimes during the two seasons. The vertical bars in the upper panel mark those thresholds on the CDF.

2.4. FUTURIST Framework

Our proposed framework, FUTURIST, is designed to predict the qualitative category of thermal regime change caused by a planned dam. The procedure 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 to predict the temperature changes, which were subsequently converted to classes of thermal change (see Figure 1, lower panel). The architecture, designed based on hyperparameter tuning, consisted of 1 hidden layer with 16 nodes, where the input layer comprised of 8 nodes (see Supporting Information S1, Figure S4). A sensitivity analysis was performed on the number of hidden layers and layer nodes to arrive at the optimal configuration. Further details on the neural network model design and sensitivity analysis for different configurations are provided in the Supporting Information S1 (Figures S5 and S6).

Predictor variables were selected that (a) directly impact reservoir stratification and river temperature, and (b) can be acquired either from the dam operating agency or derived from globally available remote sensing or atmospheric products. The second criterion was used to ensure our framework is transferable in data-constrained regions. The selected input nodes thus comprised of dam height (in meters), reservoir area (in km^2), storage capacity (in million m^3), mean seasonal flow averaged with mean annual flow (dimensionless), 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 from https://developers.google.com/earth-engine/datasets/catalog/ECMWF_ERA5_DAILY), and a dimensionless bathymetry coefficient (see Supporting Information S1, Table S2 for range of covariates over existing dams).

Seasonal flow was included as a predictor in FUTURIST to capture the dynamics of river's hydrology over each season. Average seasonal discharge [climatology averaged for months of Jun–Aug (JJA) or Dec–Feb (DJF)] was obtained for all the dams used for training or validation. The Global Reach-scale A priori Discharge Estimates (GRADES) dataset (Lin et al., 2019; https://www.reachhydro.org/home/records/grades) was used to extract naturalized streamflow at the location of dams. As GRADES dataset does not consider the impact of lakes or dams in the modeled flows, which makes the flow estimates suitable for our case especially in reflecting pre-dam conditions. To use as predictor to ANN, seasonal flow was normalized with the average annual discharge for each dam. Air temperature is input as an average of the daily time series during the respective season (JJA or DJF) over the period of record. The Köppen-Geiger climate classes were reclassified into five major regimes of snow, temperate dry, temperate humid, dry, and tropical climates. These were input as a categorical variable pre-processed using ordinal encoding (values of 0.1–0.5). 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.

The FUTURIST ANN model was developed separately for the summer and winter seasons. Summer season correspond to months of JJA in Northern Hemisphere (NH) and DJF in Southern Hemisphere (SH) while the definitions reverse for winter seasons. FUTURIST models per season are necessary because the reservoirs exhibit unique thermal stratification in each season (Yigzaw et al., 2019), with turnover of the regimes during fall/winter in most cases. To capture such an ongoing thermodynamic change to the reservoir water that takes much longer to evolve than the seasonal air temperature, and hence, air temperature alone cannot be a sufficient proxy for seasonal behavior of thermal modification. Having two separate models allows for capture such an ongoing thermodynamic change in the reservoir's thermal regime, given that the FUTURIST framework only uses a minimal set of inputs without the need of complex modeling.

From the set of dams prepared in Section 2.1, 30% of the sites were selected randomly to perform the validation while the rest were used to train the model. This resulted in a total of 136 sites (95 for training and 41 for validation) in the warm season, while 112 sites (78 for training and 34 for validation) during the cold season. The distribution of training/validation sites along with their locations in major climate class is shown in Figure 2.

2.5. 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 toward the final model outcome. Using LIME model, we analyzed our trained ANN model for the contributions from selected input nodes for modeling the thermal change. Figure S7 shows these contributions for a sample of existing and future dams.

2.6. 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 21 different runs of General Circulation Models (GCM) conducted under CMIP5, available in Google Earth Engine data catalog as NASA Earth Exchange (NEX) GDDP dataset (https://developers.google.com/earth-engine/datasets/catalog/NASA_NEX-GDDP). The details on the selected CMIP5 models are provided in the Supporting Information S1. The analysis of predicted thermal changes under climate change was carried out using the ensemble mean of all the 21 models and averaged around the dam location over a period of 25 years (1980–2005 for the baseline scenario and 2075–2099 for the two RCP scenarios).

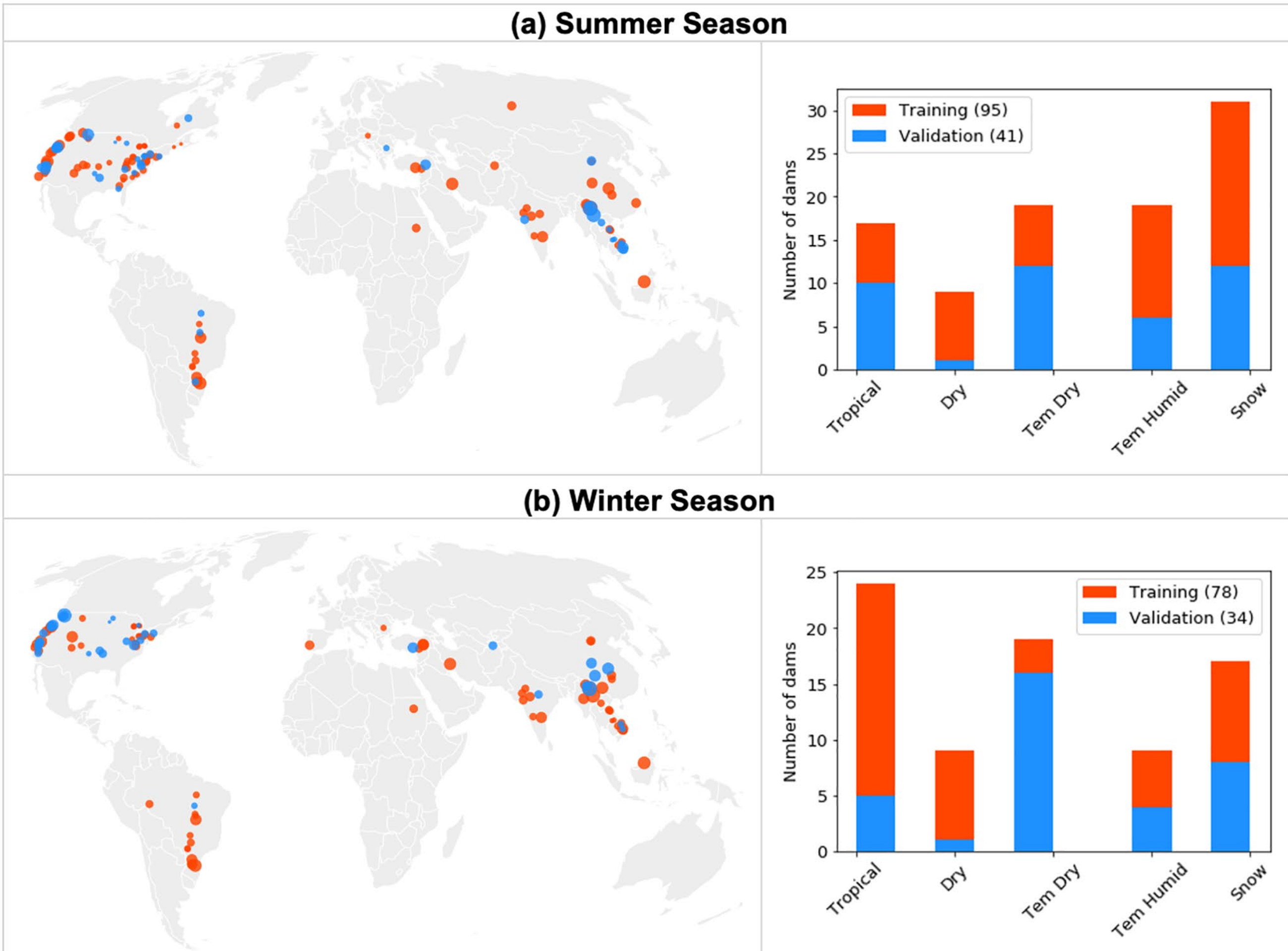

Figure 2. Distribution of training (red) and validation (blue) sites used to develop FUTURIST ANN model for (a) summer (JJA in NH; DJF in SH) and (b) winter (JJA in NH; DJF in SH) seasons (left panel), along with the distribution of dams with major climate classes (right panel). Dams are sized with their respective heights, and total number of dams used in each set is shown in parentheses.

3. Results

3.1. Thermal Impact of Existing Dams

The large number of existing dams worldwide with long temperature records (insitu or satellite-based) form an ideal testbed to study their thermal impact and use that knowledge to predict the impact of planned dams. We first assess how the existing dams have impacted natural thermal regimes around the world using the prepared dam database to be used for training and validating the FUTURIST model. We found that most U.S. dams tend to cool downstream rivers during the summer season (JJA in NH and DJF in SH) and have predominantly a warming impact during the winters (DJF in NH and JJA in SH). These impacts reflect homogenized changes in water temperatures during the past two decades. During the summer season, 82 (60.3%) dams of the selected 136 dams have cooled downstream rivers when compared to their upstream (used as the proxy to natural baseline) thermal regime (Figure 3a). Sub-categorizing this impact further, 14 of the dams (10.3%) caused severe cooling to the downstream rivers. Interestingly, only five dams (3.7%) have severely warmed the tailwaters (defined as an increase of 5°C or more in the downstream river temperature). In contrast, during the winter season, out of the 112 dams, 99 (88%) caused moderate warming, out of which 56 (50%) dams only led to a mild warming (defined as warming of <1.5°C). Only 11.6% cooled downstream moderately with no severe impacts (Figure 3b).

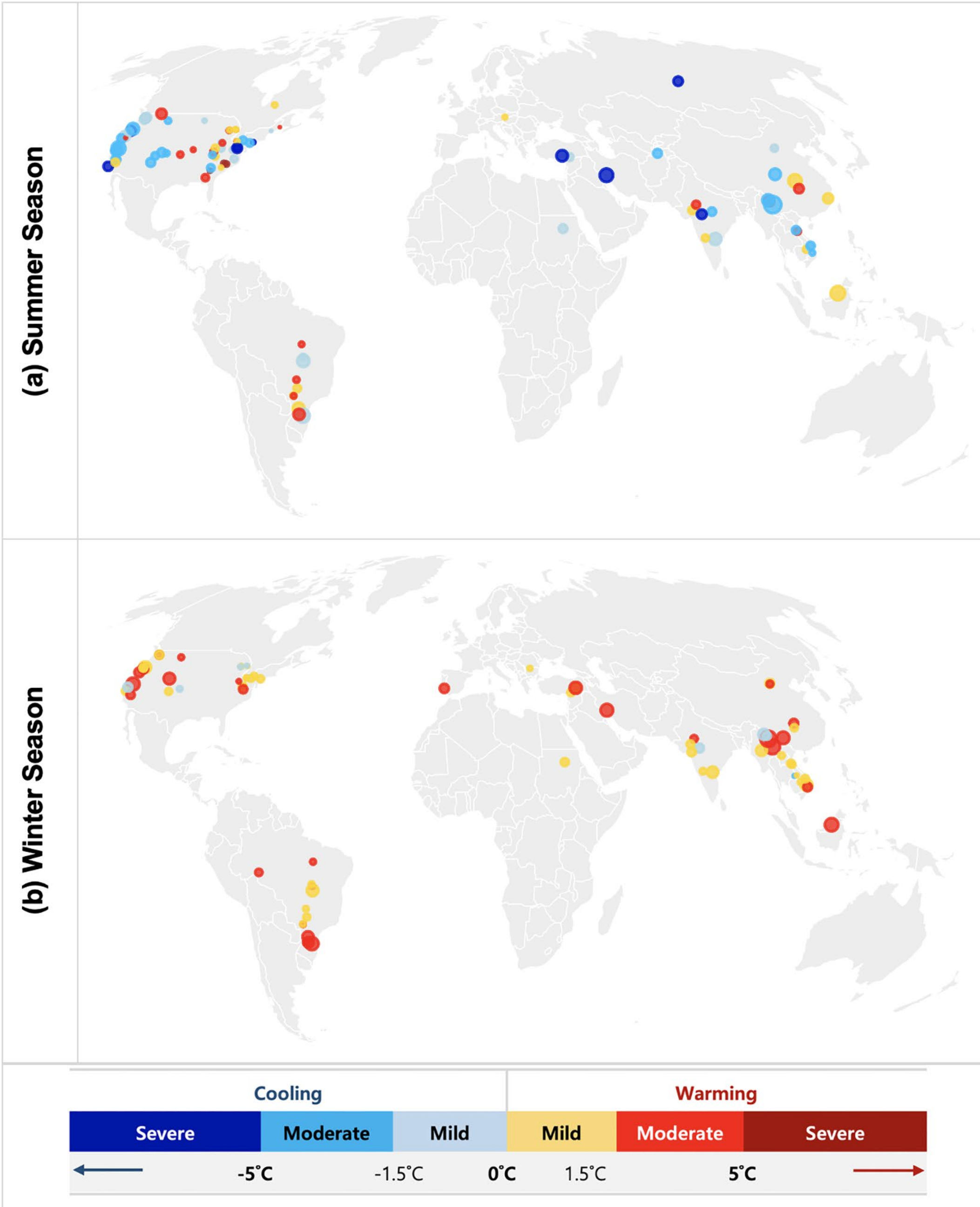

Figure 3. Dams used for training the FUTURIST ANN model to learn thermal regime change (mean difference of upstream and downstream temperatures) over (a) summer [Jun–Aug (JJA) in Northern Hemisphere (NH); Dec–Feb (DJF) in Southern Hemisphere (SH)] and (b) winter (DJF in NH; JJA in SH) seasons. Classes of the thermal change are defined using thresholds as explained in Figure 1.

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 (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 4a (first column), where dams with lower area-storage ratio exhibit large negative thermal change. Deeper reservoirs (with larger

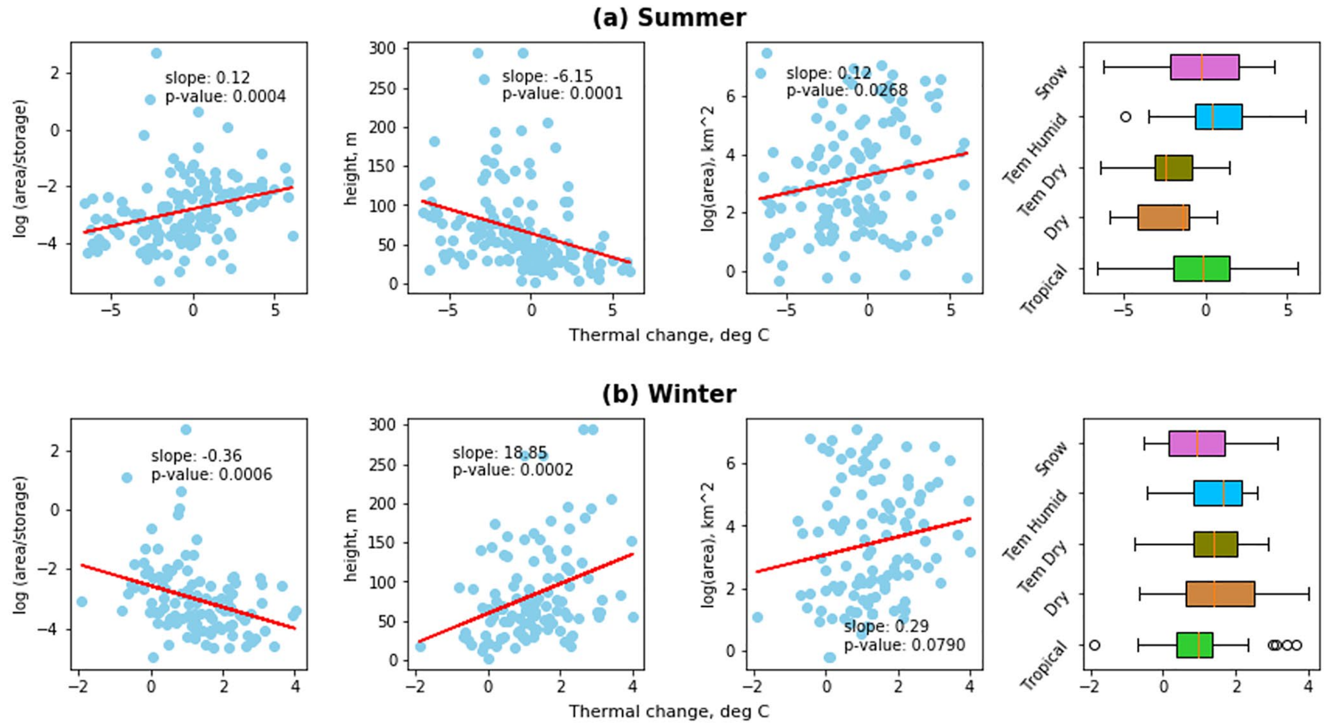

Figure 4. Bivariate plots for thermal regime change (*X*-axis) and area-storage ratio (measure of reservoir's thermal stratification), reservoir area, storage, and climate class (*Y*-axis) for existing dams during (a) summer and (b) winter seasons. A p-value of less than 0.05 shows statistically significant trends, slope signifies the direction of relationship.

heights as shown in second column of Figure 4a) further intensified the stratification and subsequently their cooling impact. In contrast, smaller storage reservoirs with large area (third column in Figure 4a) 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. All the relationships described here were statistically significant at a confidence level of 95% (p-value < 0.05).

Considering the effect of climate, dams lying in arid and warm regions with hotter summers (dry and temperate dry Köppen classes) favored to shift the downstream thermal regime toward cooling (fourth column in Figure 4a). This is likely as the surface water temperatures rise under contact with warm air and high solar radiation which intensify the stratification, in particular for deeper reservoirs, leading to cooler releases. Dams located in more humid and snowy climates experience relatively cooler air temperatures, which were not high enough to cause a significant reservoir stratification. Such dams exhibited weaker cooling impact and even led to warming under several cases.

In contrast, during the winter seasons, reservoirs that experience strong stratification (lower area-storage ratio, larger heights, or smaller areas) intensify in their warming of the downstream thermal regime (Figure 4b). This can be explained based on the fact that 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 to or lower than that of the hypolimnion, breaking the thermal stratification. Thus, dams in such conditions release water that is at similar temperatures as the upstream layer. Further, in cases when the winter temperatures drop below the temperature of maximum density of water, 4°C (for example, for the dams in snowy climates), 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 4b, fourth column). Again, all the covariate relationships were found to be statistically significant (p-value < 0.05) with the exception of reservoir area. The bivariate plots for all the other predictors to the FUTURIST model are shown in Figure S8.

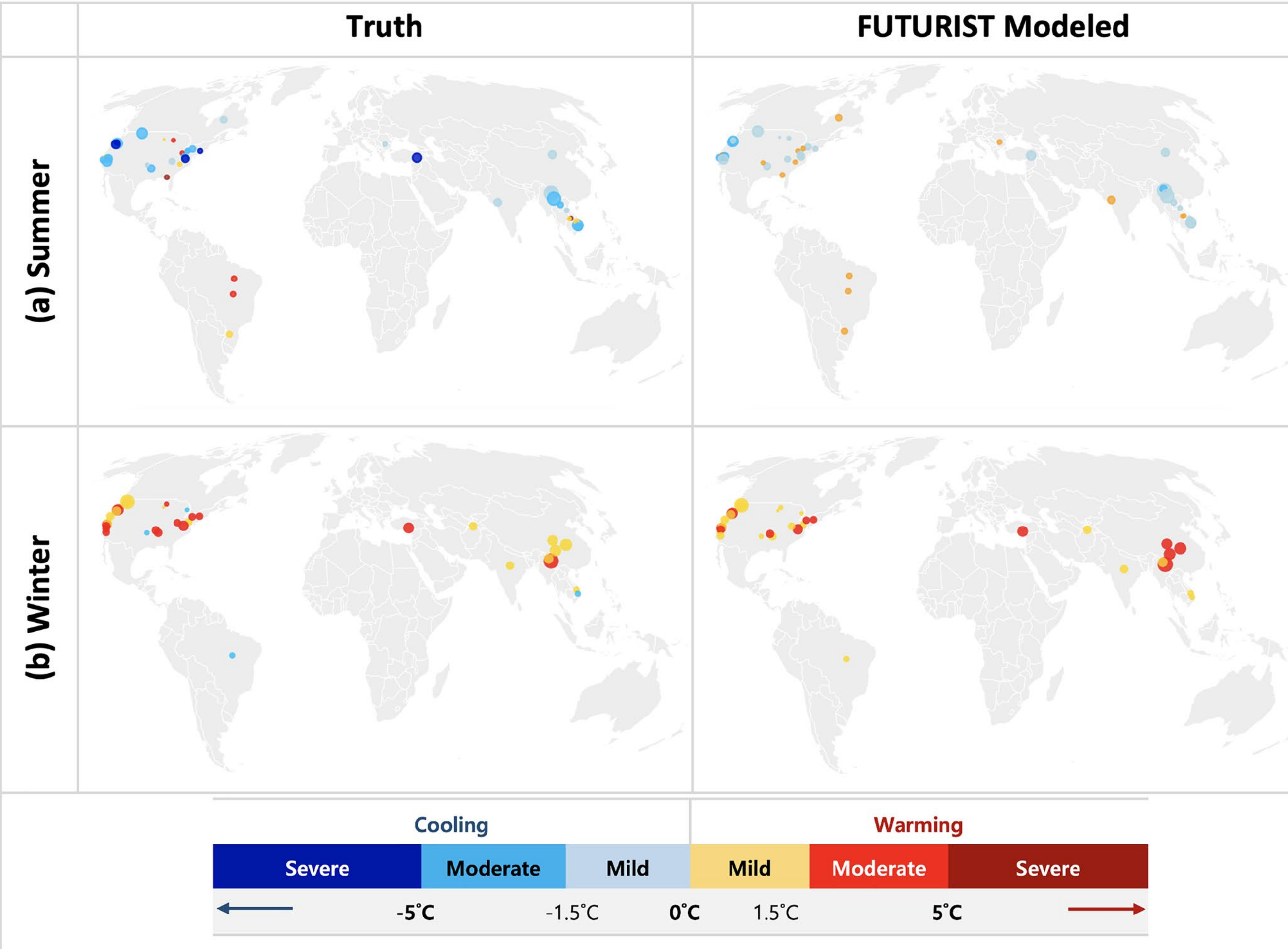

Figure 5. Validation results comparing observed thermal changes (left column) and those modeled with FUTURIST (right column) for existing dams during (a) summer and (b) winter season.

3.2. FUTURIST Thermal Change Model Development

Using the established thermal impacts of the existing dams, we then trained machine learning models over summer and winter seasons to predict those impacts using the selected set of predictors. The validation was then performed over the independent set of dams located worldwide.

During summer seasons, when observed thermal change of the 41 validation sites ranged between −6.5 and 5.9°C, 26 sites were predicted correctly (63.4% accuracy) in terms of the nature (warming/cooling) and severity (severe/moderate) of thermal regime change. Including the mild class of thermal change (with temperature change of ±1.5°C), however, reduces the accuracy to 26.8%. When considering only the nature of thermal change, the model was able to predict thermal regime changes with much higher accuracy of 80.5% where 33 dams were classified correctly (Figure 5a). The mean absolute error (MAE) and root mean squared error (RMSE) over the validation set were 1.9°C and 2.5°C, respectively. Over the winter months, where observed temperature changes range between −0.7°C and 4.0°C, 30 out of 34 validation sites (88.2% accuracy) were predicted correctly (Figure 5b). Considering the mild classes as well, a categorical accuracy of 61.8% was obtained where 21 dams were assigned to the same thermal change class. The MAE and RMSE during winters were 0.7 and 0.9°C. The results were statistically significant at 95% confidence with a p-value of less than 0.05 (Figure 6b).

In addition to the evaluation over the entire validation set, the FUTURIST model was also evaluated specifically over a few dams across the world built during the Landsat era. The thermal change was obtained

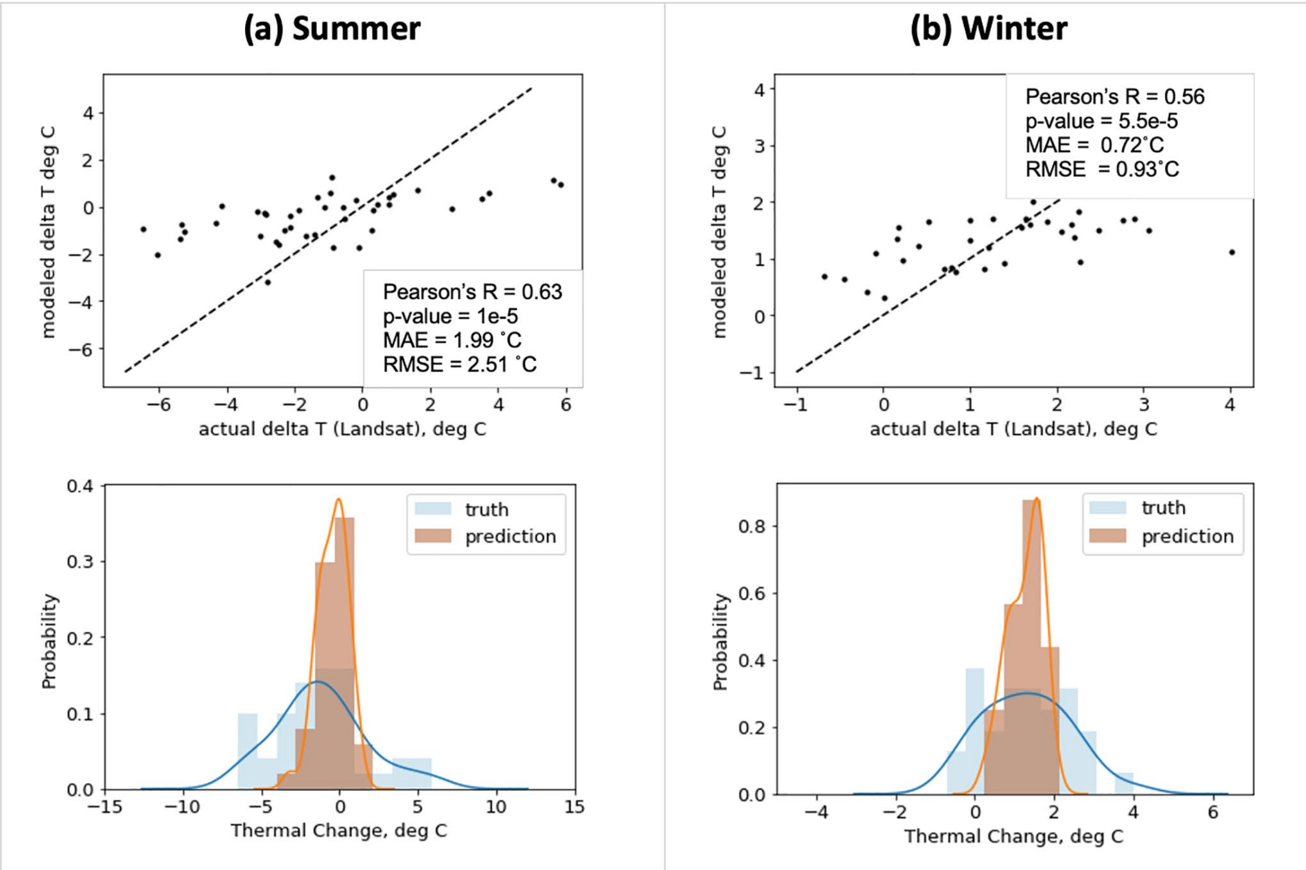

Figure 6. Scatter plots (top panel) and histograms (bottom panel) for the observed and modeled thermal changes along with the validation performance metrics.

by differencing pre-dam and post-dam temperatures over the dam location using multi-decadal remote sensing observations to avoid uncertainties in upstream temperature retrievals due to reservoir operations. For the summer season, an average bias of 1.5°C was obtained comparing the modeled and remote sensing-observed thermal changes over 11 dams, with an RMSE of 2.2°C. For the winter season, the model resulted in an average bias of 0.7°C and RMSE of 0.9°C. Detailed evaluation metrics for each dam are shown in Supporting Information S1, Tables S5 and S6. These evaluations against multi-decadal temperature observations from Landsat establish the ability of FUTURIST to predict historical trends of thermal change both in the spatial (upstream and downstream) and temporal (pre- and post-dam construction) dimensions.

3.3. How Might Planned Dams Alter River Temperatures?

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

Figure 7 shows the results of FUTURIST predictions as categorical thermal change classes (left panel) and quantitative thermal changes (right panel) across the summer and winter seasons. During the winter season (months of DJF in NH and JJA in SH), 160 of the 216 planned dams (73%) are likely to cool downstream rivers where a couple of those exhibit severe cooling of upto −6.6°C compared to the upstream regime. The majority of dams that are predicted to cool downstream rivers during summers exhibit characteristics that can lead to strong reservoir stratification. As such, these have either deeper pool of water or smaller reservoir area. This is also suggested by the bivariate plots in Figure 7 where planned dams with smaller

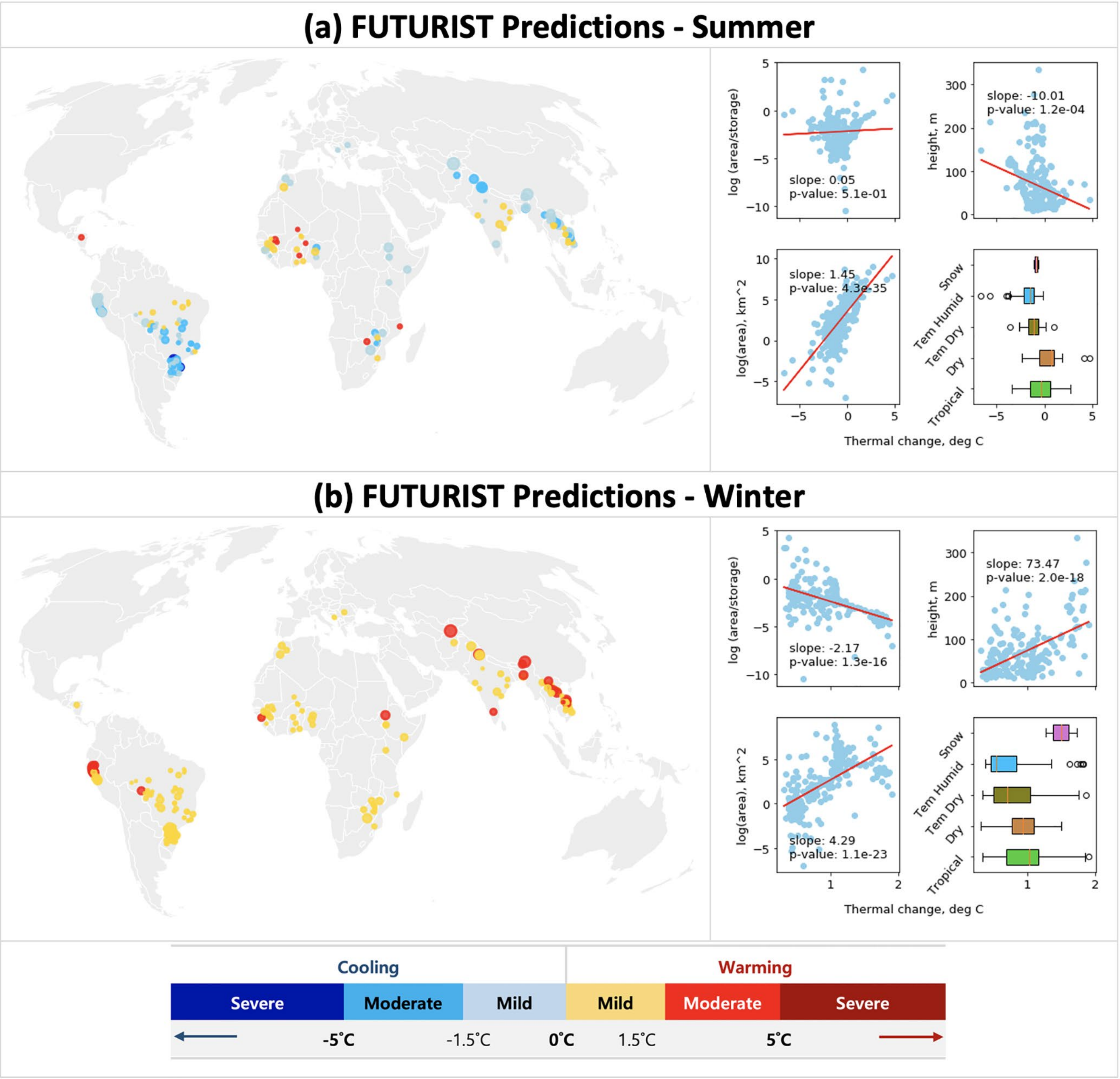

Figure 7. Thermal regime predictions for planned dams during (a) summer [Jun–Aug (JJA) in Northern Hemisphere (NH); Dec–Feb (DJF) in Southern Hemisphere (SH)], and (b) winter season (DJF in NH; JJA in SH). Variability and relationship of predicted thermal changes with different predictors is shown as bivariate plots in the right panel for the respective seasons.

areas and deeper heights in general are predicted to exhibit large negative thermal changes. There are also 56 dams (26%) predicted to warm downstream rivers by upto 4.7°C. Such dams tend to exhibit weaker stratification lying on the right-most end of the bivariate plots with larger areas and shallower heights.

During the winter months, a reverse trend was suggested by the FUTURIST predictions. Consistent downstream warming is predicted with a likely thermal change of 0.2°C–2°C. Reservoirs with smaller heights tend to exhibit milder warming as compared to deeper reservoirs, while those with weaker stratification (wide and shallow) were the ones predicted to warm the downstream rivers more.

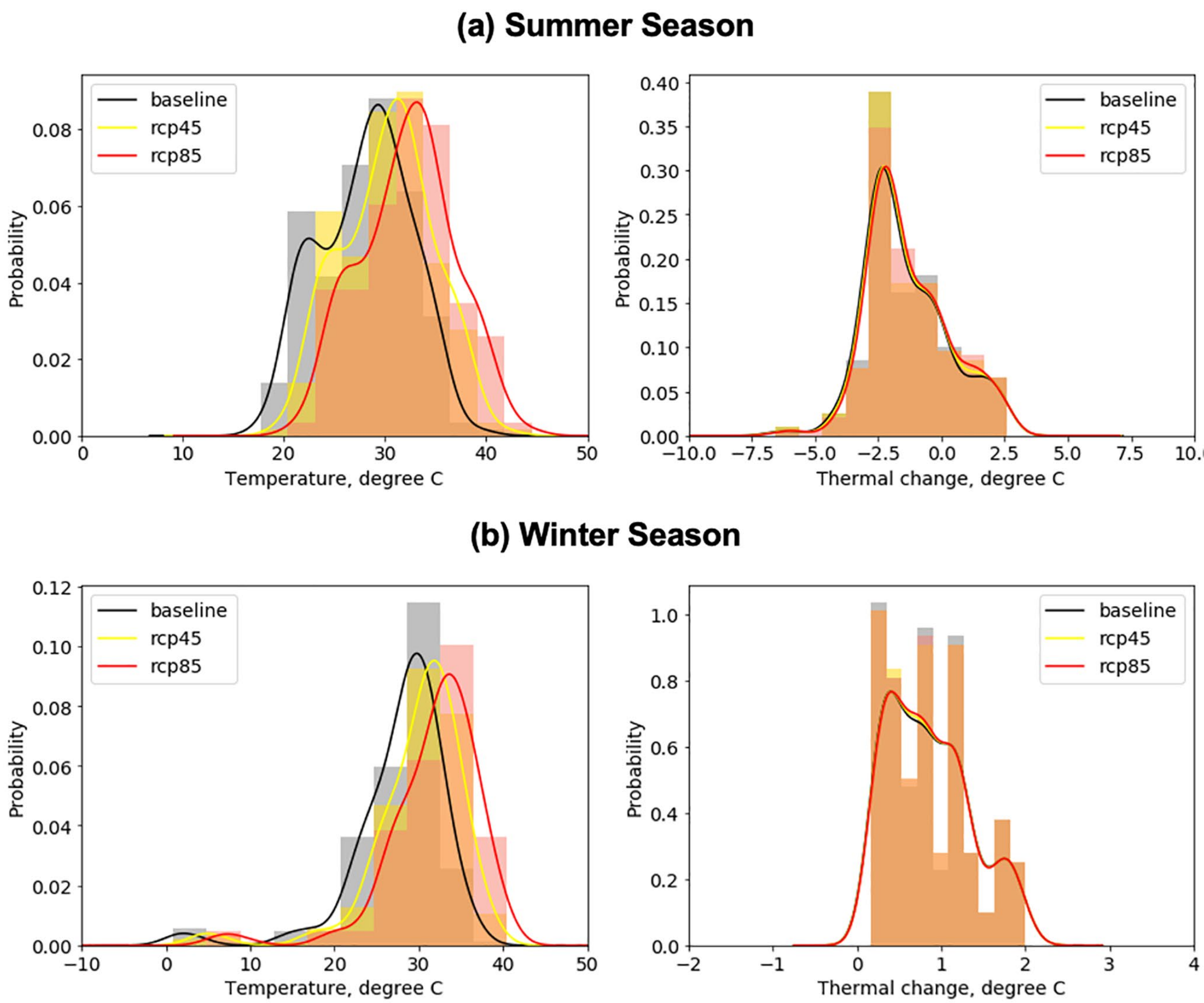

Figure 8. Probability distributions of air temperature as histogram and smoothed curves (left panel) and of respective thermal regime changes (right panel) over 216 planned dams for three scenarios of baseline (historical temperatures during 1980–2005), RCP4.5 (2075–2099), and RCP8.5 (2075–2099) during (a) summer and (b) winter seasons across the hemispheres.

3.4. Impact of Climate Change on Predicted Thermal Pollution

The ensemble mean of climate scenarios from 21 models under GCM runs were used to force the FUTURIST ANN model and study the effect of climate change on riverine thermal regime (average difference between upstream and downstream temperatures). Resulting predictions of thermal changes were compared across the three scenarios of baseline, RCP4.5, and RCP8.5. Figure 8 shows the empirical distribution of predicted temperatures and respective thermal changes over the 216 planned sites for JJA and DJF.

The greenhouse gas emissions scenarios of RCP4.5 and RCP8.5 cause the temperature distribution to shift toward right with a higher amplitude of thermal change. The resulting thermal regimes also experience changes under the projections of changing climate. During summer season across the hemispheres, dams that are predicted to cause warming under current temperatures (dams with positive thermal change in Figure 8, right panels) will slightly intensify their impact, with an increased downstream warming over the baseline scenario by 2.8% (4.1%) under RCP4.5 (RCP8.5) scenario, with an uncertainty of 0.02C (0.04°C). However, the dams causing downstream cooling (negative thermal change), on experiencing warmer air temperatures, will have a curtailed cooling impact by 3.6% (6.8%) under RCP4.5 (RCP8.5) scenario with uncertainty bounds of 0.03°C (0.04°C). During the winter season, all the dams are predicted to intensify in their warming of downstream rivers by 0.1% (0.3%) under RCP4.5 (RCP8.5) scenario with an uncertainty of 0.001°C (0.002°C).

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 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., 2020), 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. 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). 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 7). 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 dams. These two basins are projected to experience further dam developments in the near future. While the 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 during summers. This suggests that basins already fragmented due to 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.

Further analysis of the FUTURIST ANN model was performed to reveal the predictive ability of various inputs in modeling the thermal regime change from an otherwise blackbox model. The magnitude of individual contributions suggests 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, which controls the heat available to the reservoir epilimnion, contributed significantly for a 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.

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 hydropower potential have been studied globally (Ali et al., 2018; Liu et al., 2016; Turner et al., 2017), our FUTURIST framework also allows quantifying and assessing the thermal response of downstream rivers due to dam operations under long-term changes in climate. This is pertinent for performing 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 8 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. It is also noteworthy that the projected increase in air temperature by the end of this century does not translate into thermal regime changes of the same magnitude. A possible reason could be the aggregation of all the dams for analyzing the changes. Also, from the predictive abilities of different inputs (see Supporting Information S1, Figure S7), there are other factors with higher contribution in deriving thermal regime change such as reservoir capacity or area, which can suppress the effect of air temperature.

Our FUTURIST modeling framework can be easily transferred to any other site of interest with minimal data requirements. This was one of the key reasons for selecting neural network over a simplistic linear regression model. The assessment of FUTURIST model in the temporal dimension (comparing pre-vs post-dam temperatures) using multi decadal remote sensing observations in addition to the spatial dimension (upstream vs. downstream changes) also establish its validity over simpler models in capturing the historical trends of thermal changes. The ANN framework is also applicable for dams operated for other purposes, such as water supply or irrigation, which use water released from the penstocks and alter the thermal regime. 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 dam.

4.2. Sources of Uncertainty in Thermal Impact Predictions

The predictions of thermal regime change from the FUTURIST framework are influenced by uncertainty from multiple sources. First, for around 35% of the training sites that used a combination of remote sensing (upstream) and in-situ measurements (downstream), satellite-derived upstream temperatures were sampled over the reservoir extent. This was done in order to avoid narrower upstream river channels that potentially suffer from mixed pixels. However, as the USGS stations are located on the upstream river channels, comparing the two for thermal changes can lead to biases due to mixing and stratification within the reservoir.

While the USGS gauges upstream and downstream of the dams were selected to be as close as possible to the dam, their distance from the dam location also contributes to the overall uncertainty in predictions. The possible discrepancies between water surface temperature sensed by satellite and that averaged over the water column from in-situ sensors also introduce potential uncertainty—although such biases were avoided for Southeast Asian sites (used for validation), where both the upstream and downstream temperatures were derived using remote sensing. Further, the availability of pre-dam era temperatures in the MRB due to recent dam construction in the past two decades provided a reliable estimate of natural thermal regime.

The satellite-derived temperature estimates were encouraging especially for use in data-constrained regions. However, even after filtering out for narrow rivers to avoid mixed pixels, the estimates might have retrieval errors, caused by clouds, ice sheet or subzero water temperatures, shadow caused by terrain or dense vegetation, etc. The in-situ temperature stations from USGS can also affect the estimates of thermal regime changes owing to the distance of gauges from dams, although the 50 km proximity threshold was used to minimize the bias. Also, the temperature retrievals during winter season are prone to higher occurrences of dense cloud cover as well as icing conditions over the lake. This subsequently causes higher uncertainties in thermal impact predictions during the winter season.

Finally, due to complications in defining winter and summer seasons for the equatorial regions, our database of dams for training FUTURIST ANN model entailed only a small percentage of dams located in equatorial latitudes. This helped avoid uncertainties in thermal change predictions from our dual-season setup that could be caused by dams where seasons are not clearly defined. However, including more dams in the equatorial latitudes for training with additional predictors to account for seasonal and non-seasonal streams can further improve the model performance and robustness across different sites.

4.3. Ecological Consequences of Thermal Pollution

The established thermal impacts of the existing dams have already raised concerns for ecological processes and biodiversity (Olden & 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, which 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°C–6°C and winter temperatures to increase by 4°C–6°C. As a result of cooler summer discharge, fish spawning was retarded by three to eight weeks, causing extirpation of a majority of warmwater fishes. In the alpine climate of the 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°C–21°C (Clarkson & Childs, 2000). 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 & Naiman, 2010).

5. Conclusions

Temperature variation of rivers is a natural phenomenon, and the ecosystem is, in general, resilient 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. The framework is designed to predict the changes in thermal regime defined on a wide temperature range rather than precision temperatures changes. The advantages of such a framework are (a) its wide adaptability, where the definition of thermal regime can be modified based on user's perception without affecting the model performance, and (b) reproducibility, where the framework can be reproduced with users' self-perceived thermal regime and further accompanied with a more detailed model and localized understanding of thermal regimes.

We have presented here a data-based predictive and diagnostic tool as an efficient "pathfinder" to identifying the cooling/warming impact of dams in light of many dams that are now being planned or built. To the best of our knowledge, there is currently is no such tool developed based on data and observations that can rapidly prognosticate the likely thermal modification a dam will trigger to the downstream river. FUTURIST was therefore developed as a cost-effective and rapid prognostic tool to address this critical gap and help water managers justify a more prioritized but expensive study based on physical models and surveys at a later time for the most important dam cases. When there are thousands of dams around the world that are yet to be mapped of their thermal modification record with many being planned or constructed, it is fundamentally impossible to do detailed physically based modeling of river temperature change caused by dams using current state of the art tools. FUTURIST provides a feasible path forward to carry out a global thermal assessment of planned or existing dams. It acts as a baseline filter for promoting further dialogue between stakeholders for re-assessment of dam building plans or for deciding on the merit of expensive and definitive thermo-hydrodynamic surveys for a more limited set of dams that are likely to be flagged as 'high impact' according to FUTURIST. Our study clearly elucidates the need of frameworks like FUTURIST using which future thermal pollution can be included within the dam planning and operations to ensure sustainable river systems.

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 in the study is available at the online Figshare repository via the link: https://doi.org/10.6084/M9.FIGSHARE.14766870 (CC BY 4.0 license). The spreadsheet contains all the necessary inputs for simulating the FUTURIST framework along with the ancillary information on their location, periods of analysis, and other logistics. This Figshare repository also contains the trained and validated FUTURIST ANN models for summer and winter seasons that use the inputs from the spreadsheet. All the data on Figshare repository will eventually be deposited at the online portal http://depts.washington.edu/saswe/FUTURIST by the time this article is accepted. Remote sensing data used for developing the model is available from the data catalog of Google Earth Engine at https://developers.google.com/earth-engine/datasets/catalog. These include Landsat 7 TOA Reflectance ("LANDSAT/LE07/C01/T1_TOA"), Landsat 5 TM TOA Reflectance ("LANDSAT/LT05/C01/T1_TOA"), NASA Earth Exchange Global Daily Downscaled Climate Projections ("NASA/NEX-GDDP"), and SRTM Digital Elevation ("USGS/SRTMGL1_003").

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References

Ahmad, S. K., & Hossain, F. (2020). Realizing ecosystem-safe hydropower from dams. *Renewables: Wind, water, and solar*, *7*(1), 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. https://doi.org/10.1109/TGRS.2019.2950705

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. https://doi.org/10.1038/s41598-018-30489-4

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. https://doi.org/10.1126/sciadv.aao1642

Angilletta, M. J., Jr, 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. https://doi.org/10.1111/j.1752-4571.2008.00032.x

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. https://doi.org/10.1073/pnas.1912776117

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. https://doi.org/10.4296/cwrj3203179

Bonnema, M., Hossain, F., Nijssen, B., & Holtgrieve, G. (2020). Hydropower's hidden transformation of rivers in the Mekong. *Environmental Research Letters*, *15*(4), 044017. https://doi.org/10.1088/1748-9326/ab763d

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. https://doi.org/10.1016/j.jhydrol.2016.01.062

Caissie, D. (2006). The thermal regime of rivers: A review. *Freshwater Biology*, *51*, 1389–1406. https://doi.org/10.1111/j.1365-2427.2006.01597.x

Cheng, Y., Voisin, N., Yearsley, J. R., & Nijssen, B. (2020a). Reservoirs modify river thermal regime sensitivity to climate change: A case study in the southeastern United States. *Water Resources Research*, *56*(6), e2019WR025784. https://doi.org/10.1029/2019wr025784

Cheng, Y., Voisin, N., Yearsley, J. R., & Nijssen, B. (2020b). Thermal extremes in regulated river systems under climate change: An application to the southeastern US rivers. *Environmental Research Letters*, *15*(9), 094012. https://doi.org/10.1088/1748-9326/ab8f5f

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. https://doi.org/10.1061/(asce)wr.1943-5452.0001279

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. https://doi.org/10.1643/0045-8511(2000)000[0402:teohrd]2.0.co;2.*2000*

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

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

Daly, K., Ahmad, S. K., Bonnema, M., Beveridge, C., Hossain, F., Nijssen, B., & Holtgrieve, G. (2020). Recent warming of Tonle Sap Lake, Cambodia: Implications for one of the world's most productive inland fisheries. *Lakes and Reservoirs: Research and Management*, *25*(2), 133–142. https://doi.org/10.1111/lre.12317

Deemer, B. R., Harrison, J. A., Li, S., Beaulieu, J. J., DelSontro, T., Barros, N., et al. (2016). Greenhouse gas emissions from reservoir water surfaces: A new global synthesis. *BioScience*, *66*(11), 949–964. https://doi.org/10.1093/biosci/biw117

FAO, AQUASTAT Main Database. (2016). *Food and Agriculture Organization of the United nations (FAO)*, Retrieved from http://www.fao.org/aquastat/en/databases/dams

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. https://doi.org/10.1371/journal.pone.0035126

FitzHugh, T. W., & Vogel, R. M. (2011). The impact of dams on flood flows in the United States. *River Research and Applications*, *27*(10), 1192–1215. https://doi.org/10.1002/rra.1417

Forsberg, B. R., Melack, J. M., Dunne, T., Barthem, R. B., Goulding, M., Paiva, R. C. D., et al. (2017). The potential impact of new Andean dams on Amazon fluvial ecosystems. *PLoS One*, *12*(8), e0182254. https://doi.org/10.1371/journal.pone.0182254

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. https://doi.org/10.1088/1748-9326/10/1/015001

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. https://doi.org/10.1139/f07-175

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. https://doi.org/10.1016/j.jhydrol.2018.10.045

Imboden, D. M., & Wüest, A. (1995). Mixing mechanisms in lakes. In *Physics and chemistry of lakes* (pp. 83–138). Berlin, Heidelberg: Springer. https://doi.org/10.1007/978-3-642-85132-2_4

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.

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.

Lehmkuhl, D. M. (1974). Thermal regime alteration and vital environmental physiological signals in aquatic organisms. *AEC Symposium Series (CONF*, *730505*), 261–222.

Lehner, B., Liermann, C. R., Revenga, C., Vörösmarty, C., Fekete, B., Crouzet, P., et al. (2011b). 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. https://doi.org/10.1890/100125

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

Li, H. Y., Ruby Leung, L., Tesfa, T., Voisin, N., Hejazi, M., Liu, L., et al. (2015). Modeling stream temperature in the A nthropocene: An earth system modeling approach. *Journal of Advances in Modeling Earth Systems*, *7*(4), 1661–1679. https://doi.org/10.1002/2015ms000471

Lin, P., Pan, M., Beck, H. E., Yang, Y., Yamazaki, D., Frasson, R., et al. (2019). Global reconstruction of naturalized river flows at 2.94 million reaches. *Water Resources Research*, *55*(8), 6499–6516. https://doi.org/10.1029/2019wr025287

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. https://doi.org/10.3390/rs9111175

Liu, X., Tang, Q., Voisin, N., & Cui, H. (2016). Projected impacts of climate change on hydropower potential in China. *Hydrology and Earth System Sciences*, *20*, 3343–3359. https://doi.org/10.5194/hess-20-3343-2016

Mekong Dam Database. (2011). *WLE Greater Mekong, CGIAR Research Program on water, land and ecosystems (WLE), Vientiane, Lao PDR*. Retrieved from https://wle-mekong.cgiar.org/changes/our-research/greater-mekong-dams-observatory/

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*.

Miara, A., Vörösmarty, C. J., Macknick, J. E., Tidwell, V. C., Fekete, B., Corsi, F., & Newmark, R. (2018). Thermal pollution impacts on rivers and power supply in the Mississippi River watershed. *Environmental Research Letters*, *13*(3), 034033. https://doi.org/10.1088/1748-9326/aaac85

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. https://doi.org/10.1061/(asce)he.1943-5584.0000074

Mohseni, O., Stefan, H. G., & Erickson, T. R. (1998). A nonlinear regression model for weekly stream temperatures. *Water Resources Research*, *34*(10), 2685–2692. https://doi.org/10.1029/98wr01877

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. https://doi.org/10.1073/pnas.1809426115

Neumann, D. W., Rajagopalan, B., & Zagona, E. A. (2003). Regression model for daily maximum stream temperature. *Journal of Environmental Engineering*, *129*(7), 667–674. https://doi.org/10.1061/(asce)0733-9372(2003)129:7(667)

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. https://doi.org/10.1126/science.1107887

NRLD, National Register of Large Dam. (2012). *Under of Central Water Commission*. Retrieved from http://www.indiaenvironmentportal.org

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. https://doi.org/10.1111/j.1365-2427.2009.02179.x

Peel, M. C., Finlayson, B. L., & McMahon, T. A. (2007). Updated world map of the Köppen-Geiger climate classification. *Hydrology and Earth System Sciences*, *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. https://doi.org/10.1002/rra.3045

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. https://doi.org/10.1061/(asce)wr.1943-5452.0000286

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. https://doi.org/10.1007/s002670010188

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. https://doi.org/10.1002/rra.686

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. https://doi.org/10.1016/j.jhydrol.2016.12.023

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

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. https://doi.org/10.1126/sciadv.aaw2175

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. https://doi.org/10.1002/(sici)1099-1646(199703)13:2<129::aid-rrr431>3.0.co;2-s

Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2012). An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society*, *93*, 485–498. https://doi.org/10.1175/bams-d-11-00094.1

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. https://doi.org/10.1088/1748-9326/10/11/114011

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. *The Science of the Total Environment*, *590–591*, 663–675. https://doi.org/10.1016/j.scitotenv.2017.03.022

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). https://doi.org/10.1029/2010wr009198

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. https://doi.org/10.1002/2014wr015457

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. https://doi.org/10.1126/science.aac7082

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). https://doi.org/10.1029/2004jf000271

Yearsley, J. (2012). A grid-based approach for simulating stream temperature. *Water Resources Research*, *48*(3). https://doi.org/10.1029/2011wr011515

Yigzaw, W., Li, H. Y., Fang, X., Leung, L. R., Voisin, N., Hejazi, M. I., & Demissie, Y. (2019). A multilayer reservoir thermal stratification module for earth system models. *Journal of Advances in Modeling Earth Systems*, *11*(10), 3265–3283. https://doi.org/10.1029/2019ms001632

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), 1–10. https://doi.org/10.1038/s41598-019-54980-8

Zarfl, C., & Lucía, A. (2018). The connectivity between soil erosion and sediment entrapment in reservoirs. *Current Opinion in Environmental Science & Health*, *5*, 53–59. https://doi.org/10.1016/j.coesh.2018.05.001

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. https://doi.org/10.1007/s00027-014-0377-0

Zhong, Y., & Power, G. (1996). Environmental impacts of hydroelectric projects on fish resources in China. *Regulated Rivers: Research & Management*, *12*, 81–98. https://doi.org/10.1002/(sici)1099-1646(199601)12:1<81::aid-rrr378>3.0.co;2-9