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Indicators of thermal alteration in US waters reveal patterns of climate risk at the energy-water nexus

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ABSTRACT

Anthropogenic changes in water temperature can pose significant risk to thermoelectric and hydroelectric generation. In this study, we developed indicators of thermal risk (ITRs) to assess risk to water-dependent electricity generating assets under future climate. We projected future changes in water temperature and quantified ITRs for plants across the conterminous US for a baseline and future period. One goal of our study was to tailor ITRs to measure climate risks mediated by aquatic biota. When using local species' thermal tolerances as thresholds, we estimated that future conditions would expose an additional 53 GW or 30 % of once-through-cooled thermoelectric power (OTE) capacity and an additional 7.1 GW (10 %) of total hydropower capacity to slightly higher risk. Meanwhile, the future proportion of species exposed to risk increased by 25 % (OTE) and 15 % (hydropower). Because seasonal timing can be important when understanding competing demands for cold water, we developed two metrics of risk timing (median date of exceeding thermal thresholds and the duration of exceedances). Although changes were small (<5 d) for most plants, for some plants timing shifted by +/- five weeks and for others the duration of exceedances increased by 10 to 15 d. Geographically, elevated future risk was highest for plants in the southeastern US, reflecting future exposure to warming and the high aquatic biodiversity of rivers draining to the Gulf of Mexico and South Atlantic coast. We discuss how results from our ITR analysis can be used to plan climate-adaptation measures at both grid and plant scales.

1. Introduction

A high proportion of electricity production in the US relies on water and the ability to discharge or release water at temperatures that are protective of aquatic life. Cooling water for thermoelectric plants and irrigation are the two largest users of water in the US (Pan et al., 2018). The future risk to electricity generation and reliability caused by climate change is expected to be considerable (Van Vliet et al., 2016). Understanding when and where grid reliability is threatened by thermal risk is an important need when factoring in trade-offs between risk to aquatic biota of elevated effluents and the electricity demand (Madden et al., 2013). Already, curtailments in thermal power plants have increased, and they are projected to increase by up to 1 % of production with each °C of warming (Coffel and Mankin, 2021). Under the US Clean Water Act of 1973, utilities are required to use the 'best available technology,' which, if enforced, could lead to many conversions from once-through cooling to expensive recirculating technologies, such as cooling towers (Miara et al., 2013).

Climate risk assessments use downscaled climate from global climate models (GCMs) to drive models of freshwater flow and temperature. Results are then used to assess the risk of droughts and extreme temperatures that could constrain electricity generation (Hoang et al., 2016; van Vliet et al., 2012). Thermal risk is typically estimated as the frequency of violating upper temperature thresholds. Among

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thermoelectric plants, those with once-through cooling (OTE) plants are at greatest risk. Previous assessments have quantified the risk that electricity generation would be curtailed when an upper regulatory threshold is exceeded. For example, van Vliet et al. (2012) estimated a future decrease of 16 % of capacity for thermoelectric plants in the US using a constant 27 °C threshold. Others (Miara et al., 2017; Miara et al., 2018; Miara et al., 2013) assumed US state-level upper temperature limits specified under §303(d) of the Clean Water Act (CWA; US Code vol. 33, section 1251 *et seq*.). Results varied regionally. For example, one study focused on the Mississippi River basin estimated that thermal pollution could affect over 30 % of river reaches during summer months, with the highest impacts from thermal effluent in the Ohio-Tennessee river basin (Miara et al., 2018).

Electricity generation that relies on freshwater will also face indirect threats, i.e., threats mediated by aquatic biota under future climate conditions (Wedekind and Kung, 2010). Previous climate assessments have rarely considered indirect threats to electricity. In hydropower research, ecological indicators have mainly focused on flow. In particular, Indicators of Hydrologic Alteration (IHA) (Boavida et al., 2020; Carlisle et al., 2010; Jumani et al., 2018; Poff et al., 2010) have been used very successfully to extract causal signatures for anthropogenic influences on flow regimes. Despite this success, they neglect the fact that effects of flow are often mediated by water temperature (Jager, 2014; Maheu et al., 2016; Olden and Naiman, 2009; Rosenfeld, 2017). Temperature is arguably the most important driver of life history patterns in aquatic biota, often outperforming flow as a predictor (Graham and Orth, 1986). The importance of temperature to aquatic biota has long been recognized (Magnuson and DeStasio, 1997; Pyne and Poff, 2016; Vannote and Sweeney, 1980). Yet, the focus of river management has barely shifted away from flow. In climate-change research, temperature effects on cold-water species, such as salmonids, have been a primary focus (Chambers et al., 2017; Kusnierz et al., 2023; McCullough et al., 2009), with much less emphasis on other taxa. Yet, biological responses to temperature have important implications for all freshwater communities as they track non-stationary climate conditions (Rosenfeld, 2017).

Climate risk assessment has usually focused on increased risk of exceedances rather than changes in the timing of events (Isaak and Rieman, 2013). However, changes in the timing of risk can also be important because of conflicts between the availability and demand for cold water. For thermoelectric generation, any increase in the need for cooling water when coldwater is in short supply can be problematic. Similarly, threats to hydropower are likely to occur in late summer and fall, when the cold block of water stored in a reservoir is depleted and inflows are substantively reduced (Zhao et al., 2023), particularly if, as expected, summer water demands increase under future climate (Jager et al., 2018; Payne et al., 2004).

Indirect risks mediated by biota could also involve shifts in timing. One concern about climate warming for biota is the potential for a mismatch between the timing of reproductive maturation and the timing of other critical events, such as flow pulses that cue spawning migration (Peer and Miller, 2014) or the availability of prey resources (Wilson et al., 2023). Shifting temperature regimes can result in changes in migration timing and lead to early onset of adult mortality and declines is reproductive success (Hinch et al., 2012). For many aquatic species, thresholds in degree-day accumulation can describe life history events such as maturation, reproduction, development rates, and growth (Chezik et al., 2014). Less critically, thermal habitat can be viewed as a resource (Magnuson et al., 1979), and temporal niche partitioning among species can be disrupted by climate change (Bloomfield et al., 2022).

In this study, we present a suite of ITRs to assess thermal risks to both thermoelectric and hydroelectric generation for waters in the conterminous US. We quantify changes in direct and indirect (ecologically mediated) risk to water-based electricity generation that may lead to changes in plant operations. We introduce two novel approaches to assessing thermal risk at the energy-water nexus. First, we introduce ITRs that assess ecologically mediated risk by using species tolerances as thresholds. Second, we introduce ITRs that measure shifts in timing and duration. We present visualization of metrics across multiple sites and seasons (i.e., to address spatial and temporal questions) to help make our results meaningful for electricity planners and resource managers.

2. Methods

2.1. Simulation of daily water temperature under baseline and future climate

Our analysis focuses on reservoirs in the conterminous US (CONUS). Our research builds on a recent effort to assess the effects of climate change on federal hydropower generation in the US (Kao et al., 2022a). The effort resulted in an ensemble of downscaled climate and hydrologic projections across the CONUS based on six Coupled Model Intercomparison Projects Phase 6 (CMIP6) Global Climate Models (GCMs) under the high end SSP585 emission scenario (Rastogi et al., 2022), a socioeconomic trajectory with minimal mitigation and adaptation (Meinshausen et al., 2020). This trajectory is the most-consistent with observed recent trends in climate (Schwalm et al., 2020).

In this study, we illustrate the development of thermal risk indicators and communication of results using one GCM, paving the way for an ensemble approach by including more GCMs in future, as discussed in Section 6. We chose the Australian Community Climate and Earth System Simulator (ACCESS) model (Ackerley and Dommenget, 2016; Dix et al., 2019) because it performed well in a comparison among models in the CMIP6 suite (Ashfaq et al., 2022; Evans et al., 2013). ACCESS has previously performed especially well over the conterminous US domain with respect to both precipitation (Raju and Kumar, 2020) and temperature (Sillmann et al., 2013).

The Double Bias Correction Constructed Analogs method, DBCCA, was used to downscale GCM projections from 1° to 1/24° horizontal resolution (Rastogi et al., 2022). Downscaled precipitation was used to drive a calibrated Variable Infiltration Capacity (VIC) model to simulate total runoff (Hamman et al., 2018; Liang et al., 1994). Runoff and climate drivers were then fed into the transport part of the Water Balance Model (WBM) (Fekete et al., 2001; Stewart et al., 2013) to simulate routing and water temperature. WBM accounts for multiple geophysical processes and routes discharge along a discretized (grid based) representation of the hydrological network (Fekete et al., 2010). Runoff water temperatures were equilibrated to wet-bulb air temperatures (Mohseni and Stefan, 1999) and adjusted to reflect mixing during routing (Miara et al., 2017). From the results, we drew two samples of simulated water temperatures at 1-min^2 grid cells (1) containing hydropower projects with capacity greater than 30 MW cells and (2) containing OTE plants. Both samples include values simulated over a 20-year baseline period (2000–2019) and future period (2040–2059). More detail is provided in the 'Data Sources' section.

We used quantile mapping to compare the distribution of ITRs for the baseline and future periods (Ashfaq et al., 2010; Jager et al., 2018). Quantile mapping relies directly on process-based model projections and is considered the most appropriate method for using simulated data when extreme values of the distributions are of interest (Smith et al., 2014). First, the ITR of interest was calculated for each grid cell containing a thermoelectric or hydropower plant as described in sections below. Next, we ranked ITR values (years) within each period (i.e., baseline and future), $q = 1, \ldots, T$, where both baseline and future simulated data include the same number of years, $T = 20$. We then calculated differences between corresponding quantiles, q, of the ITR distributions for the two periods. In the equation below, $x_q^{(f)}$ represent the q^{th} ranked annual value of a specified ITR, $q = 1 \ldots T$ simulated years. We refer to the difference between the two periods as a delta for each ITR, for example, differences in *ECO-dur* between periods is represented as $\Delta ECO\text{-}dur$.

$$\Delta x_q = x_q^{(f)} - x_q^{(b)}, where:$$
$$x_q^b = ITR\ value\ with\ rank\ q\ across\ years\ in\ the\ baseline\ period,\ b,\ and$$
$$x_q^f = ITR\ value\ with\ rank\ q\ across\ years\ in\ the\ future\ period,\ f \tag{1}$$

Values can then be summarized in ways that reveal when and where threats are most likely to emerge or increase. The details of the analysis vary depending on the ITR.

2.2. Indicators of thermal risk (ITRs) relevant to electricity generation

We developed a suite of indicators to relate temperature changes to electricity generation. These can be classified in several ways. One subset measures the duration of exceeding thermal conditions that might place electricity production at risk, whereas others measure changes in seasonal timing or phenology. Changes in timing can alter the synergies and trade-offs between temperature-sensitive water uses. An overview is depicted in Fig. 1.

Three categories of indicators are listed in Table 1. Definitions for indicators are given in Appendix A. Table A1.

2.3. ITRs that measure frequency and duration of thermal exceedance

2.3.1. Thermal risk to thermoelectric power

Once-through thermoelectric generation requires cooling water below a certain temperature to avoid discharges that exceed thresholds in absolute water temperatures or changes set by the US Environmental Protection Agency (EPA) or individual US states. Although hydroelectric power uses some cooling water, its temperature is not as important as for OTE. As a measure of thermal risk to OTE, we calculated *NM-risk*, the frequency of exceedances of state-level CWA upper thresholds specified by EPA as required under §304(a) (See 'Data sources' section). The concern is that future warming might lead to curtailment of thermoelectric generation when ambient water temperatures are high.

The risk of exceedance was calculated annually for state thermal criteria, T^*, and time series of daily temperatures simulated at thermal plants, T_t, as $\frac{\sum\{Tt>T^*\}}{365}$. State criteria ranged from 27 to 34 °C (US Environmental Protection Agency (EPA), 2023). We note that these criteria are generally higher than those at individual water bodies, where National Pollution Discharge Elimination System permits are informed by local designated uses assigned to a waterbody. We used the run-length encoding algorithm (RLE) in R (R Core Team, 2021) to obtain the longest run of exceedances for each year as a duration metric, *NM-dur*. We present a comparison of these ITRs for a climate run using the WBM model for baseline (2000–2019) and future climate conditions (2040–2059) with no influence of reservoirs or thermal pollution. Results were summarized across OTE plants and years within each period.

Table 1
Indicators of thermal risk to electricity generation. Acronyms are NM = non-mediated and ECO = ecological.

Category	Non-mediated risk(EPA / state thresholds)	Ecologically mediated risk (species thresholds)
Exceedance	*NM-risk, NM-dur, NM-nspp*	*ECO-risk, ECO-dur, ECO-nspp*
Capacity-weighted exceedance	*NM-MW*	*ECO-MW*
Phenological (temporal context)	*NM-date*	*ECO-date, ECO-Js, ECO-Je*
Geographic (spatial context)	Mapping of *NM-dur* and capacity (MW)	Mapping of *ECO-dur* or *ECO-nspp* and capacity (MW)

To examine impacts of future climate on OTE, we graphed the cumulative impact on thermoelectric capacity as a function of future change in risk. Similarly, we graphed the cumulative impact of future increases in the duration of exceedances. We report the proportion of years with an increase in *NM-dur* or *ECO-dur*. To provide an energy-relevant metric, we also report the 25, 50, 75, and 100 percentiles of the risk frequency-weighted sum of nameplate capacity.

2.3.2. Thermal risk to hydropower mediated by threats to aquatic biota

We assumed that thermal risk to hydropower is mediated by its effects on species because hydropower generation does not depend on the temperature of cooling water. Ecological risk was estimated by calculating the frequency, *ECO-risk*, or duration, *ECO-dur*, of exceedances for a set of species. We used an estimated upper thermal limit for each of 573 species to estimate exceedances (see 'Data Sources' section). To illustrate *ECO-dur* (**Appendix A.** Table A2), we compare these risk metrics for duration using species-specific thresholds for the same WBM baseline and future simulations as in **2.3.1**, sampled at OTE plants.

The change in risk-weighted number of species at a plant is a composite indicator of projected additional number of future species at risk, $\Delta ECO\text{-}nspp$. For hydropower, $\Delta ECO\text{-}nspp$ is calculated by **Eq. (2)** summed over species in the same WBM cell as plant (hydropower or OTE). Similarly, we calculated the metric, $\Delta NM\text{-}nspp$ (**Eq. (3)**, where *nspp* is the total number of species and *q* refers to the quantile (i.e., ranking) of the year, and superscripts refer to the baseline (*b*) and future (*f*) periods. Note that, from probability theory (Hogg and Craig, 1979), the sum of risks (probabilities) is the expected number [of species] at risk.

$$\Delta \text{ECO-nspp}_q = \sum_{k=1}^{nspp} \left(ECO\text{-}risk_q^{(f)} - ECO\text{-}risk_q^{(b)} \right) \tag{2}$$

$$\Delta \text{NM-nspp}_q = \sum_{k=1}^{nspp} \left(NM\text{-}risk_q^{(f)} - NM\text{-}risk_q^{(b)} \right) \tag{3}$$

For two metrics Y = duration and midpoint day of the year, we fitted a mixed model $Y = \alpha + \beta\ time\text{-}period + \sigma\ grid\text{-}cell + \varepsilon$. We report parameter estimates for the intercept, α, the fixed effect of period (baseline or future), and the random effect (variance) associated with

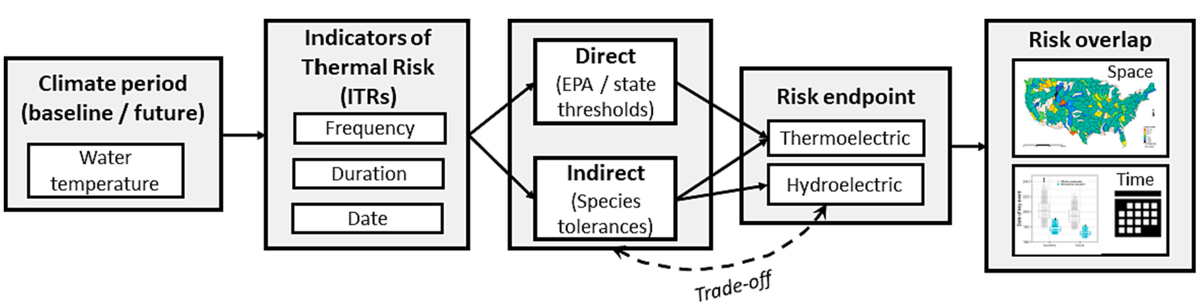

Fig. 1. Overview diagram showing how indicators of thermal risk (ITRs) linking climate change to electricity generation are defined by 1) the ITR statistic (frequency, duration, Julian date), the risk pathway (i.e., mediated by species or not), and the risk endpoint (electricity generation). Summaries of ITRs become meaningful to energy and water resource managers when they provide information about the overlap between energy and changes to the aquatic environment in time and space.

grid cells.

To quantify trade-offs between species at risk and hydropower generation, we calculated curves relating the cumulative impact to hydroelectric generating capacity as a function of future change in species at risk, where species richness was calculated for cells in a 1-min^2 grid represented by WBM. We also report correlations between capacity and species at risk, calculated in two ways, i.e., those exposed in any year and weighted by daily risk.

We examined geographic patterns in risk by mapping the change in mean duration of temperature exceedances, *ECO-dur*, and the change in the risk-weighted number of species at risk, *ECO-nspp*. *ECO-risk* showed similar geographic patterns to *ECO-dur*, so in most cases only *ECO-dur* is presented.

2.4. Metrics that measure shifts in timing

Phenology metrics are designed to quantify changes in timing of events and potential mismatches in future resources available to support electricity generation. We calculated the shift in the median Julian date with exceedances posing a potential risk to thermoelectric generation, *NM-date*. We present the differences between the two periods for NM-date across plants and years. For hydroelectric power, we report two types of ITRs to compare baseline and future climate effects on critical periods for species or to compare with ITRs that measure the timing of energy demand for cold water. First, we quantified the median dates of elevated risk, *ECO-date*, summarized across species.

Second, shifts in species phenology may affect hydropower operations in the future. Therefore, we demonstrate ecological ITRs that measure shifts in the annual timing of reproduction and spring-breeding species for two species with available data (Supplemental Materials. Shifts in species phenology).

2.5. Geographic patterns in thermal risk to electricity generation

Patterns in ITRs were mapped to assess the geographic distribution of thermal risk to electricity. We evaluated spatial patterns for indicators *ECO-dur* and *ECO-nspp*. We used these maps to identify hot spots of risk. Shifts in timing, *ECO-date*, were also displayed for major river basins in CONUS.

2.6. Data sources

The data sources used in our analysis are described below. In addition, we summarize data required to apply the approach in other regions (Appendix A. Global application).

Climate projections used as drivers of WBM (Kao et al., 2022b) are available from HydroSource, https://hydrosource.ornl.gov/dataset/9505V3. Water temperature and flow data used in our analysis were simulated by the WBM model (Miara et al., 2017; Vörösmarty et al., 2000) under baseline and future climates with naturalized flow conditions (i.e., no influences of reservoirs or water withdrawals). Data are hosted by the ESRI Cloud server at https://cloud.environmentalcrossroads.net/s/ZT4TGz3NBFFodp9. Data from the Energy Information Agency were used to determine the nameplate capacity in MW for both thermoelectric and hydropower plants (www.eia.gov/electricity/data/eia860/). Only thermoelectric plants with once-through cooling technology as of 2022 were included in the analysis because plants that recirculate cooling water are not at risk to warmer river temperature. OTE plants represent a total capacity of 176.327 GW across CONUS (www.eia.gov/electricity/data/eia860/). We included some OTE plants drawing from non-freshwater (e.g., estuaries) sources, where the latter represented 76.83 GW (44 %) of generating capacity. For hydroelectric power, a total of 67.3 GW of nameplate capacity was estimated for active projects with capacities > 30 MW. These data are available from HydroSource in the HILARRI cross-linkage database (Hansen and Matson, 2021).

We calculated risks using two sets of thresholds. First, ITRs were calculated by comparing simulated water temperatures with US State thermal criteria obtained from the USEPA (US Environmental Protection Agency (EPA), 2023) (see Appendix A. Figure A1). These values were used as upper thresholds.

Two datasets were used in our assessment of risk ITRs mediated by species, upper thermal tolerances, and data required to model reproductive phenology. Thermal tolerances were assembled and organized for freshwater fishes across the conterminous US (Welch and Jager, 2022). Species names were systematized using FishBase and fish life stage classes were consolidated. These data are available at the Oak Ridge National Laboratory (ORNL) HydroSource data repository, https://hydrosource.ornl.gov/dataset/GMLC_Thermal_Metrics.

To model reproductive phenology for spring-breeding species, species-specific thresholds of temperature (range from *Tmin* to *Tmax*) and photoperiod (range from *Pmin* to *Pmax*) were required. Results are tabulated with literature references (Supplemental Materials Table 1).

3. Results

3.1. Metrics that measure frequency and duration of thermal exceedances

3.1.1. Thermal risk to thermoelectric power

Using state thresholds, we estimated changes in the duration of risk to OTE between future and baseline period. Results were similar for the frequency and duration ITRs. Under future climate conditions (2040–2059), both *NM-risk* and *NM-dur* almost always equaled or exceeded values under baseline (2000–2019) climate conditions. Among OTE plants, the average annual risk was less than 0.05 in simulated baseline years, with a maximum duration of 8 d. Typically, a higher percentage of years experienced non-zero risk in the future period. Fewer than 10 % of cases (years and plants) had a non-zero risk in the baseline period. In future years, risk exceeded zero for 25 % of cases, with an average frequency (including zeroes) of 0.0056 and average duration of just under one day. The maximum future risk was 0.16 and the maximum projected future duration was 38 d. The average projected risk difference between the two periods was 0.005 (range: -0.0027 to 0.1148) and on average the duration of exceedances increased by 0.9 d (range 0 to 31 d).

To add energy context, we estimated the expected value of additional annual OTE capacity at risk as the sum-product of the change in risk frequency times per-plant capacity. The risk-weighted average future increase was 0.927 GW (<1% of total OTE capacity) using EPA / state thresholds. The maximum change in risk-weighted capacity was 178.5 MW. In short, the estimated OTE capacity affected is much lower when the magnitude of risk is considered, and this better reflects how often generation would be affected. Across OTE plants, around 127 GW (~70 %) experienced no simulated increase in risk. The remaining 53 GW experienced additional future risk up to 0.12, with the magnitude varying across years (quantiles in Fig. 2**A**). When the duration of exceedance changed, it usually increased by five days or less (Fig. 2**B**), but a few OTE plants representing a small fraction of capacity were projected to experience prolonged future risk (Fig. 2**B**).

3.1.2. Thermal risk to electricity mediated by aquatic biota

For both OTE and hydropower, the duration of exceedances of species' thresholds was always greater in the future period than the baseline period (Fig. 3).

Thermo-electric power. When using species' thresholds, changes in the duration of risk to OTE between future and baseline period were similar for the frequency and duration ITRs. Under future climate conditions (2040–2059), both *NM-risk* and *NM-dur* almost always equaled or exceeded values under baseline (2000–2019) climate conditions. Among OTE plants, annual risk was less than 0.06 in simulated baseline years, with a maximum duration of 12 d. Ten percent of cases (years and plants) had a non-zero risk in the baseline period. In future years, risk

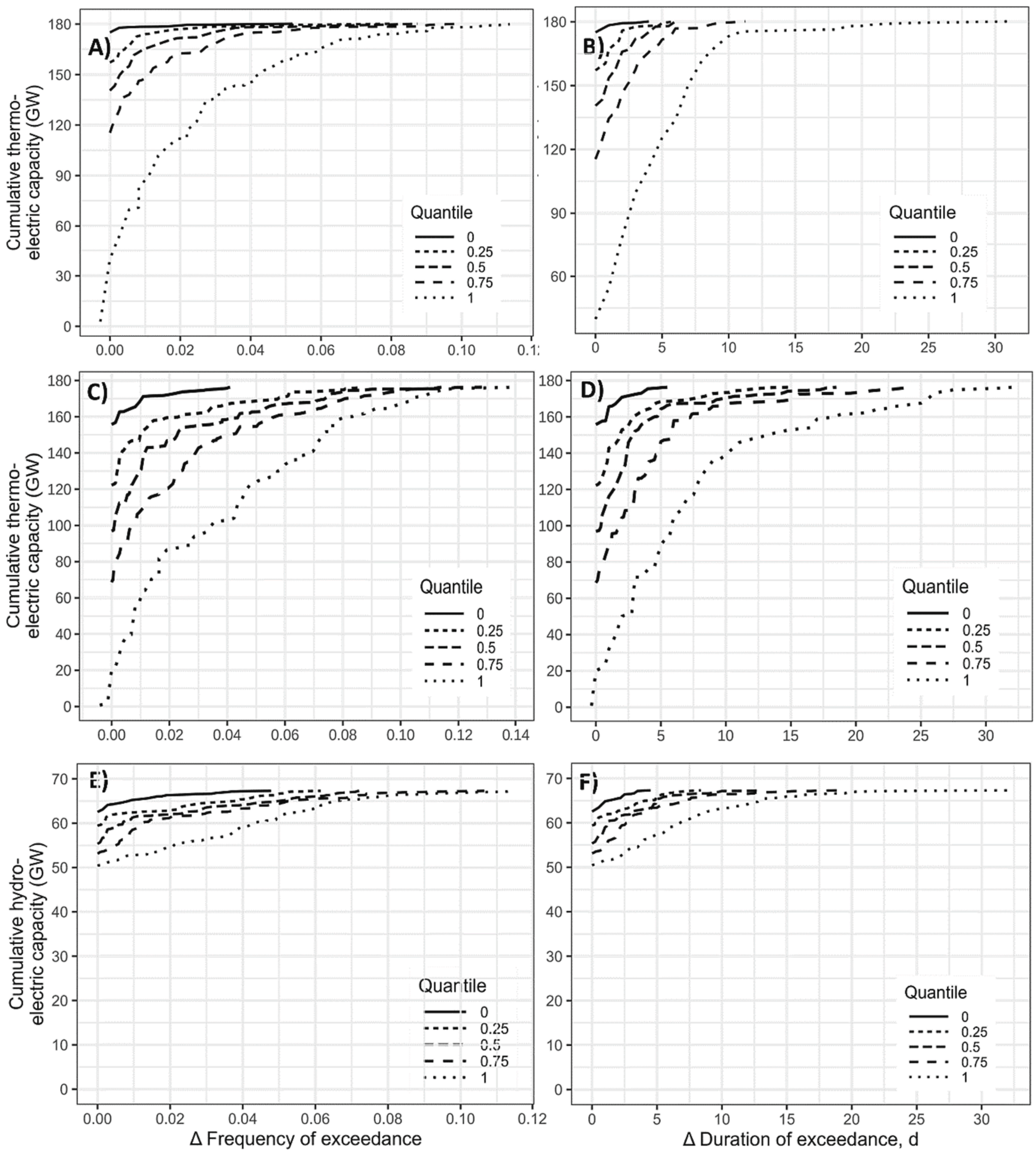

Fig. 2. Cumulative OTE capacity in the conterminous US with changes in A) frequency and B) duration of exceedances less-than-or-equal to the x-axis value based on EPA / state thresholds, C) frequency and D) duration of exceedances less-than-or-equal to the x-axis value based on species' thresholds. Cumulative hydropower capacity with changes in E) frequency and F) duration of exceedances less-than-or-equal to the x-axis value based on species' thresholds. Temporal variation is shown by curves for quantiles representing ranks for years within a period (0 = lowest-risk year, 1 = highest-risk year).

exceeded zero for 40 % of cases, with an average value (including zeroes) of 0.0145 (maximum = 0.21) and average duration of 2.45 d (maximum = 44 d). The average projected change in risk between the two periods was 0.013 (range: -0.004 to 0.139) and on average the duration of exceedances increased by 2.17 d (range -0.33 to 34.4 d). To put the results in an energy context, total OTE capacity exposed to non-zero risk increased from 21.46 GW in the baseline period to 78.12 GW in the future period, a difference of 56.66 GW. Across OTE plants, risk-weighted capacity increased by 1.668 GW (median), ranging from 0.183 to 6.327 GW in the best and worst years, respectively.

We also evaluated the number of species exposed to risk. Total species exposed to non-zero risk increased from 7,620 to 22,681 species between the baseline and future period. Weighted by risk the increase was from 75 to 776 species, a difference of 700 (1.2 %) of total species. Note that cumulative species should not be interpretted as total number of unique impacted species because the same species may occur in different cells across CONUS.

Risk to OTE was lower when using the EPA / state thresholds (Fig. 2**A and B**) than when using species' thresholds (Fig. 2**C and D**). This comparison revealed differences, especially in the extremes of the distributions. The proportion of capacity with non-zero future risk and duration (x-axes in Fig. 2) was higher for species thresholds than for EPA / state thresholds (0.70 versus 0.55). The average increase in risk was higher when using species' thresholds than when using EPA / state

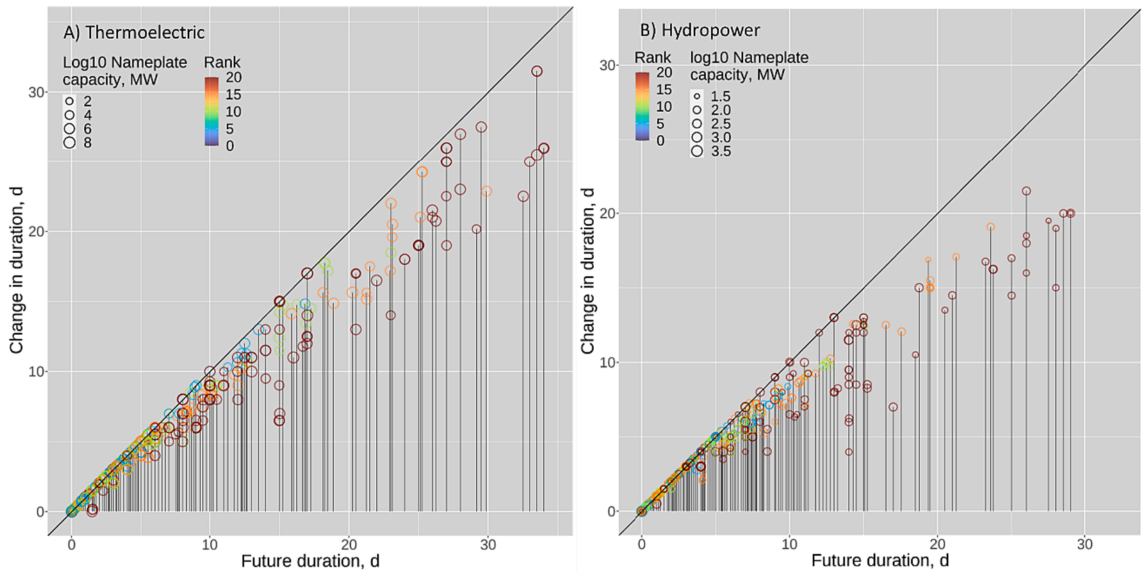

Fig. 3. Using species thresholds, risk duration in the baseline period is lower than that in the future period for both A) once-through cooled thermoelectric and B) hydropower plants. Values below the one–one line indicate a future increase in duration. Rank indicates the ranking among years within a period to allow comparison between the two periods. Nameplate capacity is indicated by symbol size.

thresholds (average 0.0052 versus 0.0123). Similarly, increases in the mean durations of exceedance were longer when using species thresholds compared to EPA / state thresholds (1.913 d versus 0.899 d) (Fig. 2**B** versus **D**).

Hydropower. We assume that risk to hydropower is often mediated by risk to aquatic biota because hydropower generation does not require cooling water. Based on species' thresholds, exposure to thermal risk occurred in only 5 % of cases (plants and years) in the baseline period, but 25 % of cases in the future period. No change in risk was predicted for over 0.152 GW of hydropower capacity (Fig. 2**E**). The increase in risk (duration) averaged 0.013 (1.43 d), reaching a maximum of 0.12 (32.2 d) (Fig. 2**E, 2F**). Between the future and baseline period, we estimated that the change in risk exposure could affect an additional 7.1 GW of the total 67.3 GW of hydropower capacity. However, the total risk-weighted change in capacity was only 0.286 GW, suggesting that exceedances occurred during a short period of time.

The indirect cumulative impact of climate to hydropower is also indicated by change in the number of species at risk. Indirect impacts mediated by species could occur through a variety of potential mechanisms. Additional species at risk can require shifts in the timing and value of reservoir releases, increase the cost of mitigation (Oladosu et al., 2021), or changes in regulation via the designated beneficial uses assigned to waterbodies. We ranked gridcells by increasing risk and calculated cumulative number of species and capacity. At the level of individual plants, the median risk-weighted change in number of species was 2.25 (interquartile range 0.80 to 5.11), with a minimum of -0.14 and a maximum of 27.1 species. Note that cumulative species should not be interpretted as total number of unique impacted species because the same species may occur in different cells across CONUS.

Around 75 % of cumulative species (60,996) experienced no increase in risk and most of the remaining 25 % of species experienced less than a 0.08 change in risk (Fig. 4**A**). Similarly, a small fraction of hydroelectric plants were predicted to experience increased risk (Fig. 4**B**). To examine the potential for reducing risk to species with minimal decrease in capacity, we examined correlations. Higher future risk to species was concentrated in cells with mid-to-high species richness (Fig. 4**C**). whereas impacts on added future risk to hydropower did not have a strong relationship to either capacity or richness (Fig. 4**D**).

We conducted a mixed model analysis to assess the importance of time period and to quantify spatial variation. For both OTE and hydropower, the effect of future period was significant and positive for both *ECO-dur* and *ECO-date* (Table A2). On average, exceedances of species' thresholds persisted 1.22 d longer and occurred later in the year near hydropower plants than OTE plants. Differences in geographic location (i.e., Cell id) explained 45 % of remaining variation in duration, but only 25 % of variation in the median date of exceedances (Table A2). For OTE, the positive effect of future period on risk duration was even more significant. On average, future exceedances of species' thresholds were 2.2 d longer. For both OTE and hydropower, differences in geographic location (i.e., Cell id) explained 40–45 % of variation in duration and ~ 25 % of variation in the median dates of exceedance (Table A2).

To understand the correspondence between capacity at risk and species at risk, we calculated correlations between the two for unweighted metrics (plants or species exposed at any time and frequency). Weak relationships between capacity and local species richness were revealed by correlations for the unweighted metrics, suggesting that smaller plants with high species diversity could be targetted for mitigation with minimal impact on electricity. We observed small correlations, negative for OTE plants (-0.1227) and positive for hydropower plants (+0.1021).

3.2. Metrics that measure shifts in timing

The timing of risk at OTE plants was measured as the median date of the longest run of exceedances of species tolerances, *ECO-date*. For OTE, the median change (future minus baseline) in *ECO-mid* was 1.69 d (interquartile range -0.875 to 4.088 d; min = -63.5; max = 34.5 d). For hydroelectric plants, *ECO-mid*, was delayed by 1.74 d (median) between future and baseline simulations. Changes in date had a small interquartile range, -0.95 to 4.1 d and extremes ranged from a 49-d advance to a 57.6-d delay. The range of dates was less variable in future than baseline years (interquartile range: day of the year 200.5 to 212.4 in future, 199.3 to 210.5 in the baseline period.

3.3. Geographic patterns in thermal risk to electricity generation

Understanding where species will be vulnerable to higher future risk is important to the power industry. Spatially, results using EPA and species' thresholds were similar, so we present only those for species'

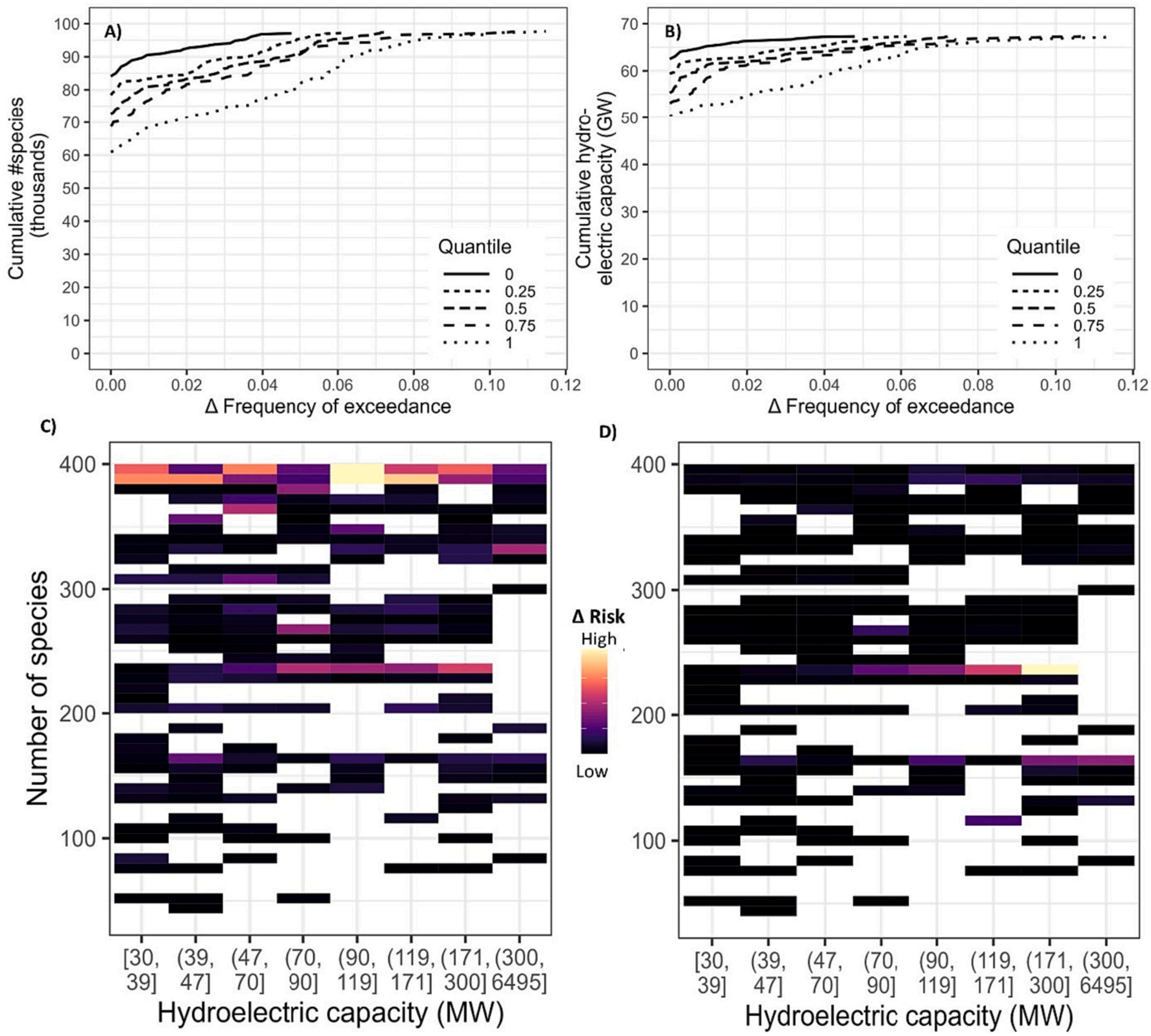

Fig. 4. Cumulative risk plots show that a large proportion of cases experienced zero increase in risk when using species' thresholds both for A) number of species and B) hydropower capacity. Quantiles indicate variation among years. 2D frequency charts show Δrisk to C) species and D) hydropower relate to the number of species and hydroelectric capacity.

thresholds. When using species' thresholds, the average proportion of years with an increased duration under future climate was 0.83 and cases of no increase were concentrated in northern states for OTE (Fig. 6**A**). The largest increases in duration of risk included OTE and hydroelectric plants in southern states in the Mississippi River basin (Texas, Arkansas, Tennessee, Louisiana, Florida), and some watersheds along the South Atlantic coast (Fig. 6**B, 6D**).

For hydropower, changes in duration occurred in all years for large parts of the Eastern US (Fig. 6**C**). We observed the largest increases in the southeast in rivers draining Texas and the Mississippi river basin, most of the Ohio-Tennessee River basin, and along the South Atlantic coast from the Chesapeake Bay south to Georgia (Fig. 6**D**).

The largest increases in species at risk were estimated in the Colorado and Trinity basins of Texas, the Arkansas-White-Red, Lower Atchafalaya and Lower Mississippi River basins for both OTE and hydropower (Fig. 7**A**). By contrast, changes in species at risk across the western and northern US were small for both OTE and hydropower (Fig. 7**A & B**).

4. Discussion

In this study, we designed ITRs to quantify thermal risk to electricity generation mediated by climate change effects on water temperature. We estimated a small magnitude increase in risk exposure for a significant proportion of electricity capacity, with high year-to-year variability in exceedances and durations.

Our analysis differed from previous assessments in several ways. First, we considered indirect risks mediated by climate effects on aquatic species and our assessment highlighted the importance of considering species tolerances. We compiled and used the species tolerances for hundreds of aquatic species across the US to estimate risk to electricity mediated by effects on biota. Compared to results based on regulatory thresholds (Fig. 2**A & B**), the magnitudes of frequency and duration of exceedances were greater for indirect risks evaluated using species-specific thresholds (Fig. 2**C & D)** because species tolerances were often lower than the EPA criterion. Previously, concerns have been raised that existing criteria will be sufficiently protective under future conditions (McCullough, 2010, 2011). However, state-level standards may be higher than criteria developed locally for individual waterbodies based on designated beneficial uses, which typically reflect specific thermal concerns for the local ecological community (Jager et al., 2018).

Second, we evaluated temporal ITRs (duration of exceedances and median time of exceedance) as well as the frequency of exceedance. Understanding the effects of shifts in phenology is critical to

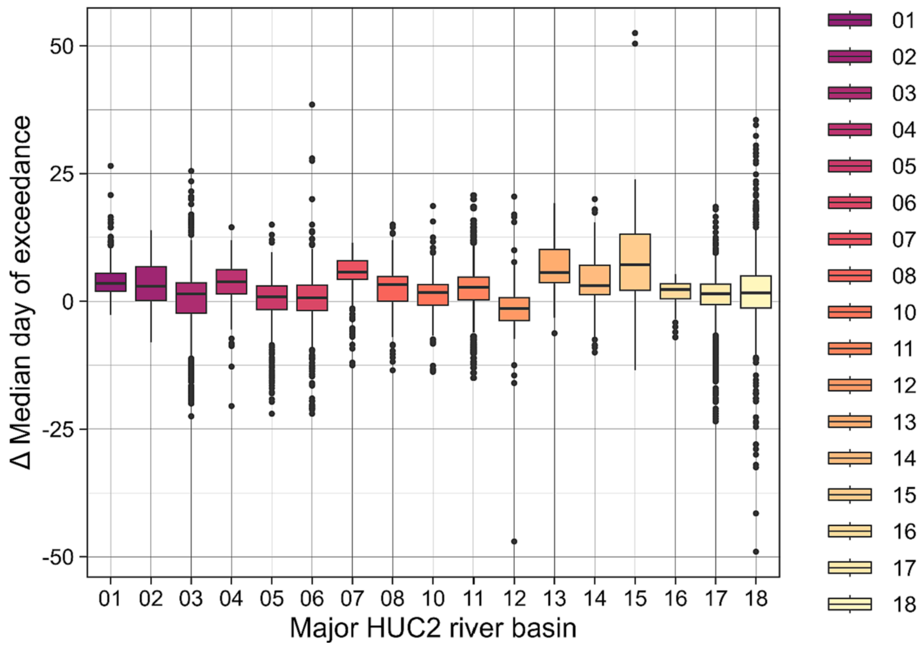

Fig. 5. Shift in median dates of exceedance (*Eco-date*) from the baseline and future period. Bars include 20 years and hydropower plants within each major river basin (01 = New England, 02 = Mid-Atlantic, 03 = South Atlantic-Gulf, 04 = Great Lakes, 05 = Ohio, 06 = Tennessee, 07 = Upper Mississippi, 08 = Lower Mississippi, 10 = Missouri, 11 = Arkansas-White-Red, 12 = Texas-Gulf, 13 = Rio Grande, 14 = Upper Colorado, 15 = Lower Colorado, 16 = Great Basin, 17 = Pacific Northwest, 18 = California). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

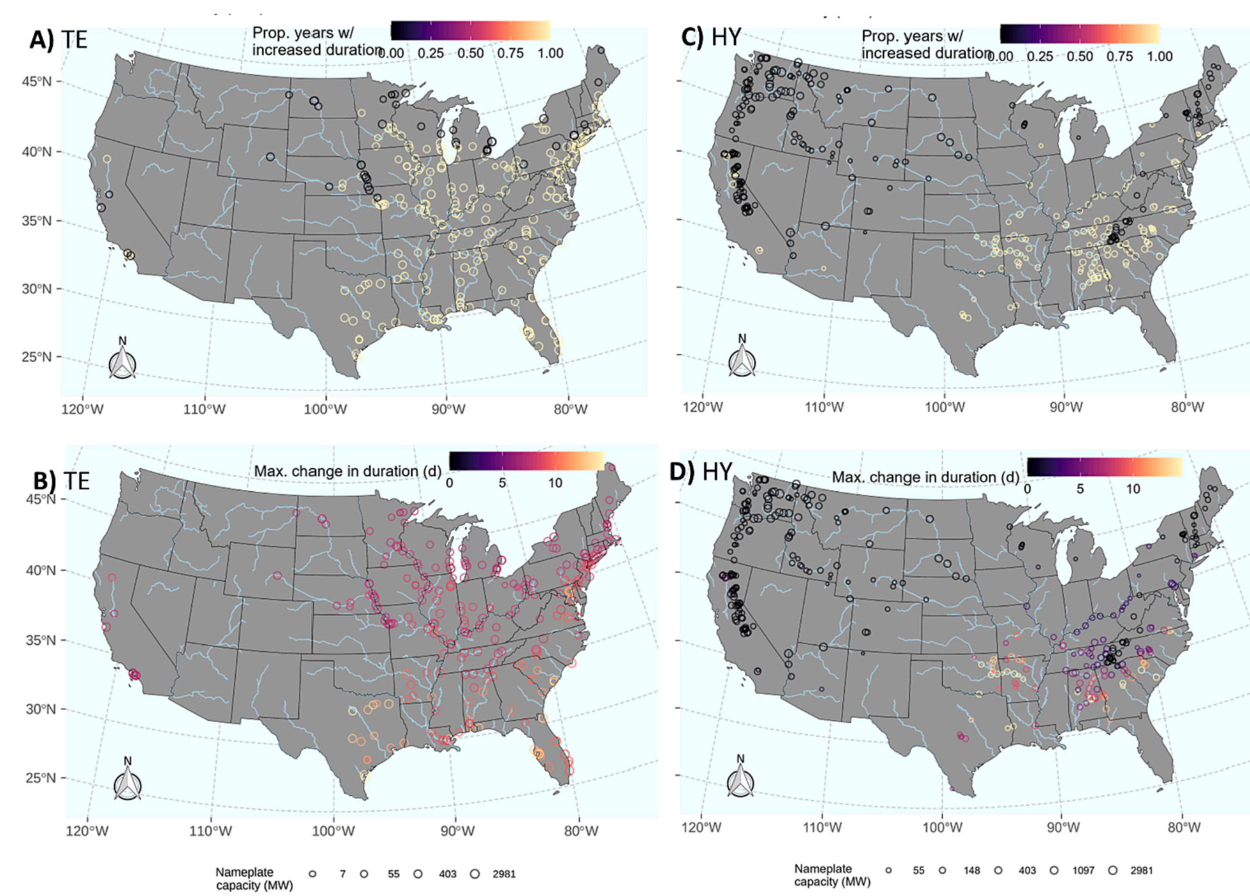

Fig. 6. Maps of changes in the proportion of years within a period that experienced a change (usually increase) in duration (top row) and median duration of exceedances of species' thresholds between a future and baseline period, Δ*ECO-dur*, (bottom row). Plant capacity is indicated by symbol size. Results are shown for one-through cooled thermoelectric (TE) and hydroelectric plants (HY).

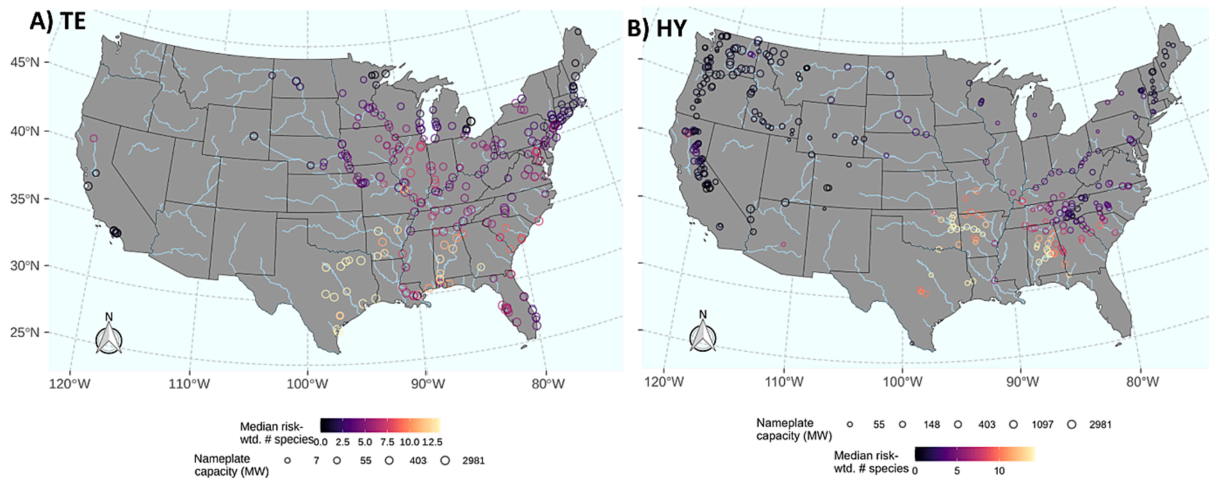

Fig. 7. Geographic distribution of change in risk-weighted number of species (Δ*ECO-nspp*) for A) thermoelectric and B) hydropower.

understanding ecological responses (Staudinger et al., 2019). Species life histories in temperate freshwater systems evolved to take advantage of predictable seasonal patterns to undertake migrations (Dalton et al., 2022), reproduce (Jager et al., 1999), and ensure that enough energy is stored to persist through winter (Shuter et al., 2012) or other seasons of adversity. For both OTE and hydropower, we observed a small average delay in the median date of thermal exceedances, but across plants, we observed both delays and advances of 5–8 weeks. Whereas durations of exceedance generally increased by a day or two, in a few cases the duration increased by 10–15 d. The few plants that experienced large shifts in timing or duration could experience significant ecological consequences. Our simulations also showed decreased inter-annual variability in the median date of thermal exceedances. Because this implies increased predictability, industry (and possibly species) could benefit from knowing with higher confidence when exceedances will occur. However, another implication for species, is that the breeding season would be compressed into a shorter period, thereby increasing density-dependent mortality [e.g., from superimposition of salmonid redds (nests)] and synchronized emergence of many offspring. Risk to mussels would also be higher for short-term brooders, which breed within a short window and have fewer hosts (Archambault et al., 2018).

Third, we explored trade-offs between ecological and energy outcomes by estimating changes in the number of species at risk. The number of species exposed to risk in the OTE sample almost tripled between the baseline and future period, although the magnitudes of added risk were low. We also found that higher future risk was concentrated in cells with lower-capacity hydropower plants and mid- to high-species numbers. These results have policy implications. They suggest that plants producing more electricity may not experience a large increase in risk to species in future. They also suggest that localized adjustments to the generating portfolio could protect biodiverse reaches at higher future risk.

Risk varied spatially, mirroring the geographic pattern of higher species richness in the wetter eastern US and in larger rivers (Muneepeerakul et al., 2008; Schweizer and Jager, 2011). The east–west precipitation gradient also reflects higher availability of cooling water in the east. Hotspots of vulnerability occurred in the southeast US, which is known to support higher aquatic biodiversity [including imperiled species (Elkins et al., 2019)], including rivers draining to the South Atlantic coast and Gulf of Mexico. Spatial patterns of risk found here are consistent with the results of a previous study (van Vliet et al., 2012). We expected to see more elevated risks in the west, which would put more hydropower at risk, but our results instead follow previously observed patterns of higher increases in temperature in the eastern US (Van Vliet et al., 2016). Understanding where species will be less vulnerable to higher future risk can help to inform future energy development and recognizing areas where species are more vulnerable can help the hydropower and TE industries to anticipate adaptive measures needed to avoid adverse ecological outcomes.

Our results have implications for electricity providers, consumers, and resource managers. For the OTE industry, curtailments during summer may impact electricity availability to consumers. Although variances to thermal limits are common in the US (Liu et al., 2017), as warm conditions become more extreme, continued operation with insufficient cooling water will be risky. Extreme heat will also increase demand for both water (e.g., irrigation) and electricity, elevating the risk of power outages. At the scale of an individual plant, converting OTE plants to a cooling technology with lower freshwater requirements can be accomplished through recirculating cooling systems (wet, dry and hybrid) (Miara et al., 2013) or using brackish- or waste-water sources (US EPA, 2023). These technologies have their own environmental costs; for example, salts and other constituents are concentrated in their (Pan et al., 2018).

At the scale of a plant, risk can be reduced by shifting away from OTE plants to energy technologies with lower demand for cold water. At the grid scale, impacts to consumers may be buffered by generators (e.g., solar, hydropower, non-OTE plants) with lower water constraints and impacts to consumers may be reduced by relying on less-vulnerable grid assets. However, simultaneous outages across a regional grid can impact consumers (Ke et al., 2016). Based on our results, future impacts would affect the Eastern and Texas Interconnections most. Electricity in this region is currently managed through a patchwork of independent system operators (ISOs) and regional transmission organizations (RTOs) (the Electric Reliability Council in Texas, the Pennsylvania-New Jersey-Maryland Interconnection, and the Mid-continent ISO), whereas transmission in the Southeast has been vertically integrated under large utilities. Improved national grid integration could improve resilience under a climate future with distinct regional profiles in the availability of variable renewables (Bloom et al., 2022) and increased risk to individual assets. Our results can be used to assess the reliability implications of projected future risks for alternative grid scenarios.

For hydropower, managing cold-block storage will likely become more challenging in future (Jager et al., 2018), and it may be necessary to assign higher priority to releasing colder water when it is most needed by fish. This can lead to conflicts during summer and require changes in seasonal operation, as well as selective withdrawal from different levels of the reservoir using temperature control devices. For example, without access to upstream tributaries, the endangered winter-run Chinook salmon is now restricted to one tailwater reach below Shasta and Keswick Dams in California. These are operated to release cold water during summer spawning and rearing (Nickel et al., 2004). Our results suggest that similar cases may be expected in southern basins draining to the

Gulf of Mexico and South Atlantic coast under future climate. Our timing metrics can be used in planning future operations.

Resource managers can also use the information here to protect aquatic species. More freshwater species will be threatened under future climate conditions (Barbarossa et al., 2021), possibly as many as 17 % (International Union for Conservation of Nature, 2023). Under the National Permit Discharge Elimination System (NPDES), thresholds are tied to species tolerances through Representative Important Species (RIS). RIS represent the biological needs of a balanced, indigenous community of shellfish, fish, and wildlife in the body of water into which the discharge of heat is made (US EPA, 2023). RIS may reflect thermal guilds (Casselman, 2002; Magnuson and DeStasio, 1997; McManamay and DeRolph, 2019; Wehrly et al., 2003), the presence of coldwater fisheries (Kusnierz et al., 2023), or the tolerances of species listed under the state or federal Endangered Species Act. The analysis presented here assembled data showing what species may be most at risk near OTE and hydropower plants under future climate. Our results can help resource managers to identify species to serve as sentinels of risk and to assess thermal risk under future climate for species of high conservation concern. In addition, our timing metrics can be used to assess potential effects on key life history events (e.g., spawning), while duration ITRs can be used to estimate physiological risk (Troia, 2023).

4.1. Study limitations

4.1.1. Model uncertainties

Uncertainty analysis can help to interpret the results of our ITR assessment. Previous assessments have evaluated uncertainties for most of the models employed here (Fig. 1). Uncertainties due to climate drivers are far higher than those due to watershed models (Joseph et al., 2018). However, air temperature projections from CMIP6 models are more reliable than precipitation projections (Pathak et al., 2023). The choice of downscaling approach, meteorologic reference dataset, and hydrologic model can also affect future hydro-climate projections (Kao et al., 2022a; Rastogi et al., 2022). We accounted for year-to-year variation in climate by including 20 years in each period.

Our analysis was restricted to one GCM (ACCESS) and one emission scenario (SSP585), so our results may not reflect the full range of variability in risk that might emerge by including a wider range of future hydroclimate projections. However, more is not necessarily better. Communicating risks to non-scientific audiences becomes more challenging when presenting results from multiple models (Carr et al., 2018). Furthermore, the 'effective' number of independent GCMs is reduced by similarities among models (Pathak et al., 2023; Pennell and Reichler, 2011). Ideally, a set of models can be selected to minimize correlation and then assigning higher weight to better-performing models (Bhowmik et al., 2017; Dethier, 2022; Steinschneider et al., 2015).

Choice of ITR parameters is another source of uncertainty. Sensitivity to the choice of upper thresholds was evident based on our comparison of EPA/state thresholds and species' thresholds. In general, as values (e.g., temperatures) get closer to a threshold, sensitivity will increase. Therefore, we expect that variability in risk estimates will be higher when (and where) water temperatures are near a threshold.

4.1.2. Future directions

Future improvements to the indicators presented here are possible. For example, our business-as-usual projection of risk in the future period considers existing electricity generation assets (no retirements or new deployments) and no changes in land use/vegetation, or species distributions. Future analysis could consider capacity expansion results that include retirements and new power plant deployments along river reaches (Miara et al., 2019; Short et al., 2011) to determine whether the remaining OTE plants will be at risk. Our hydrologic modeling could also be refined by considering future changes in land cover consistent with the SSP5 socioeconomic trajectory (Estoque et al., 2020; Riahi et al., 2017).

Similar improvements are possible for the ecological risk ITRs. Like land cover, spatial shifts in biodiversity may be associated with the socioeconomic trajectories assumed here (McManamay et al., 2021). We would ideally consider future, not current, distributions of aquatic biota for those species able to migrate (Nunez et al., 2013). In addition, plasticity in life histories might allow species adaptation. For example, under warmer climate conditions, aquatic species capable of repeat spawning will likely be able to produce more broods than in the past, in both fall and spring. Our phenological ITRs can be improved by accounting for the possibility of multiple spawning events per year in favorable locations or climates.

Another refinement might be to improve representation of downstream effects of reservoirs on water temperature below reservoirs across CONUS, which is a significant challenge at regional scales. Hypolimnetic releases moderate risks (Rheinheimer et al., 2015). For example, one study found that hypolimnetic water releases from dams could alleviate climate impacts on more than 76 % of once-through power plants with a 3 % reduction in curtailment under future 2040 RCP 4.5 and 8.5 scenarios (Zhang et al., 2020).

5. Conclusions

We developed ITRs that showed significant increases in the exposure of OTE and hydropower) to risk under future climate (24 % and 10 % of capacity, respectively). However, the increased magnitudes of risk were low. The low correlation between species richness and capacity suggests that focusing mitigation on biodiverse regions could reduce future risk without significantly impacting electricity supply. Our ITRs also measured changes in timing. Although most plants experienced small changes in the timing and duration of risk, some plants experienced large changes. Shifts of 5–9 weeks were observed in both directions along with 1–2 week increases in duration. Geographically, increases were concentrated in southern basins draining to the Gulf of Mexico and South Atlantic coast. In regions where risk is projected to increase most, grid reliability can be improved through connection to climate-resilient generating assets.

CRediT authorship contribution statement

Henriette I. Jager: Funding acquisition, Conceptualization, Formal analysis, Writing - original draft, Writing – review & editing. **Karessa Manning:** Data curation, Visualization, Writing – review & editing, Formal analysis. **Jessica Nicole Welch:** Data curation; Writing – review & editing. **Fabio Corsi:** Writing – review & editing, Resources, Software. **Ariel Miara:** Funding acquisition, Project administration, Writing – original draft. **Hyun Seok Yoon:** . **Ryan A. McManamay:** Conceptualization, Writing – original draft, Writing – review & editing. **Shih-Chieh Kao:** Resources, Writing – original draft, Writing – review & editing. **Paul C. Kusnierz:** Conceptualization, Writing – original draft, Writing – review & editing. **Sudershan Gangrade:** Resources, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

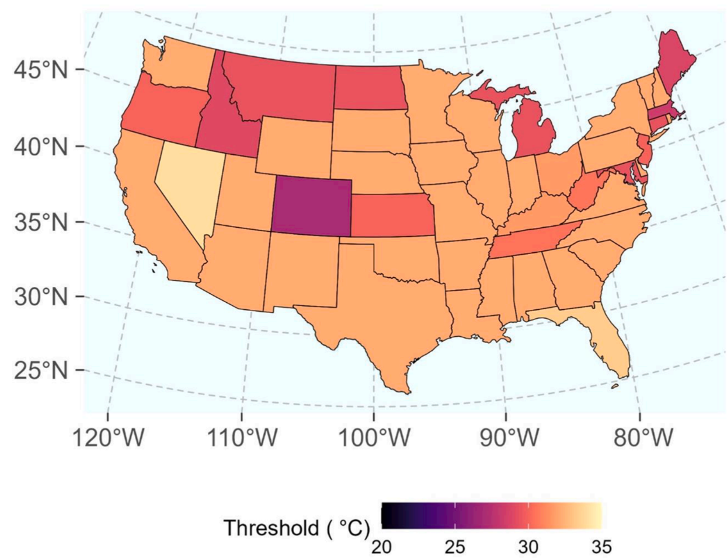

Fig. A1. State / EPA upper thermal thresholds used in our risk assessment. Note that these do not reflect the beneficial uses of individual waterbodies or the NPDES permits of electricity facilities.

Table A1
Indicators of thermal risk to electricity, definitions, and data requirements.

Category	Direct / indirect	Electricity endpoint	Indicator name	Illustrated (Figure #)	Definition	Data required
Exceedance	Direct (energy)	Thermo-electric	TE-risk	Fig. 1A	Proportion of days with surface temperature exceeding EPA threshold	Facility upper thermal limits (state regulation); WBM-ACCESS simulated water temperature sampled at thermal plants
Exceedance	Direct (energy)	Thermo-electric	TE-dur	Fig. 1B	Duration of risk to TE (d)	Same as TE-risk
Exceedance	Direct (energy)	Thermo-electric	TE-MW+ (TE-MW-)	NA	Maximum positive (negative) change in risk to generation, as measured by TE-risk.	Same as TE-risk
Phenology	Direct (energy)	Thermo-electric	TE-date	Fig. 1C	Median day of year with temperature exceeding threshold of risk to TE power (based on TE-risk)	Same as TE-risk
Exceedance	Indirect (ecological)	Thermo-electric	ECO-risk	Fig. 2A	Proportion of days with dam release temperatures exceeding species thresholds	Ecological species thresholds; HUC6 screening data; WBM-ACCESS simulated water temperature sampled at thermal plants
Exceedance	Indirect (ecological)	Thermo-electric	ECO-dur	Fig. 2B	Duration of longest annual exceedance (d)	Same as ECO-risk
Phenology	Indirect (ecological)	Thermo-electric	ECO-mid	Fig. 2C	Midpoint of exceedance date in longest run	Same as ECO-risk
Phenology	Indirect (ecological)	Thermo-electric	ECO-Js	Fig. 3A	Spawning day of year in spring	Parameters of ecological phenology model by species; WBM-ACCESS simulated water temperature sampled at thermal plants
Phenology	Indirect (ecological)	Thermo-electric	ECO-Je	Fig. 3B	Development as juvenile fish ('emergence') or end of brooding period for mussel	Same as ECO-Js
Geographic	Indirect (ecological)	Thermo-electric	ΔECO-nspp	Fig. 4A	Change in number of species at risk at HUC6 scale	Same as ECO-risk; Thermoelectric plant locations

Table A2
Mixed model results for the duration of exceedances and median date of exceedances at hydropower (HY) and once-through cooled thermoelectric plants (OTE). The model is $Y = \alpha + \beta\,\textit{time-period} + \sigma\,\textit{grid-cell} + \varepsilon$. Statistics relevant to assessing model fit included REML = Residual maximum likelihood at convergence and AICc = bias-corrected Akaike's Information Criterion. The hydropower analysis involved 14,154 observations with 335 cells and the OTE analysis involved 11,466 observations and 240 cells. The standard error (SE) is given in parentheses.

			Coefficient (fixed effects)		Variance (random effects)	
	Electricitysource	Model AICc (REML)				
Duration, d (Eco-dur)	OTE	57,240.4(57,232.4)	0.2835 (SE = 0.15)	2.165(SE = 0.05)	5.50	8.01
Median day of year (Eco-date)	OTE	88,775.2 (88,783.2)	207.06 (0.50)	1.60(0.22)	53.0	138.3
Duration, d (Eco-dur)	HY	60,734.14 (60,726.1)	0.223 (SE = 0.10)	1.220 (SE = 0.03)	3.218	3.926
Median day of year (Eco-date)	HY	106,388.8 (60,726.1)	204.6 (SE = 0.35)	1.287 (SE = 0.172)	36.2	104.2

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2024.111755.

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