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Quantifying tradeoffs between electricity generation and fish populations via population habitat duration curves

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ABSTRACT

Water resources management and the interaction between society and the environment are an integral part of the energy-water nexus. Thermal pollution from thermoelectric power plants poses a potential threat to aquatic ecosystems, particularly in regards to optimal water temperature regimes for sustaining fish populations. To quantify and address the tradeoffs in power plant electricity generation and associated thermal pollution (from cooling water discharges) on aquatic populations, population habitat duration curves (PHDCs) were generated. The Shawnee Fossil Plant on the Ohio River - and specific fish populations - were assessed with regard to water temperature dynamics. Following the concept of thermal performance curves, Electric Power Research Institute biological data were used to demonstrate the relationship between temperature and fish population. Using those biological data and temperature duration curves, PHDCs were generated, which can be used as ecological models in decision-making frameworks and economic analyses. The tradeoff in loss of electricity generation and gain of ecosystem value (via fish populations) is presented for a 1.1 °C change in thermal pollution. PHDCs demonstrate the quantification of water temperature as a resource, and the economic tradeoffs between thermoelectric power plants and aquatic ecosystem sustainability.

1. Introduction

Large quantities of water are necessary in the generation of electricity, with environmental (e.g., climate change) and resource management implications (Chini et al., 2018; Chu et al., 2019; Dale et al., 2015; Gaudard et al., 2018; Lee et al., 2018; Lubega and Stillwell, 2018; Macknick et al., 2012; Maupin et al., 2014; van Vliet et al., 2012; Wang et al., 2020; Zhou et al., 2019). Though water use patterns (withdrawal and consumption) by thermoelectric power plants are undergoing a transition period due to shifts in the power sector (Peer and Sanders, 2018), water quality and quantity are still major concerns within the energy-water nexus (Chai et al., 2018; Dilekli et al., 2018; Langford, 1990; Miara and Vörösmarty, 2013). As the energy landscape shifts, environmental energy policy, beyond climate change alone, will need to be addressed (Holland et al., 2018). To address the concerns of the energy-water nexus, particularly in light of aquatic ecosystem impacts and climate change, firmer understandings of the tradeoffs between sectors and stakeholders are warranted.

Water quality changes, via thermal pollution, can have impacts on aquatic ecosystems, as water temperature has a direct impact on body temperature for most fishes (Beitinger et al., 2000). Thermoelectric power plants that utilize open-loop cooling typically pose the largest threat to water quality via thermal pollution from cooling water. In particular, quantifying and modeling the direct impact of thermal pollution on aquatic ecosystems has, until recently, been a gap in the literature (Logan and Stillwell, 2018a). Furthermore, the water quality impacts from temperature change are expected to create shifts in the spatial distribution of some fish species (Pandit et al., 2017).

Previous work by Logan and Stillwell (2018b) demonstrated the creation of temperature duration curves (TDCs) in relation to thermoelectric power plant thermal pollution. TDCs are a visual tool that model the temperature conditions of a waterway over a given time and

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downstream distance, much like flow duration curves (FDCs) are used to show flow conditions over time (Logan and Stillwell, 2018b). Previously, quantification or modelling of thermal pollution within a biological context has been scarce. Additionally, thermal pollution's impact on aquatic ecosystems can be viewed as an externality of the electricity generation process, with tradeoffs between electricity production (and thus associated thermal pollution) and aquatic ecosystem degradation (via reduced fish populations) occurring. The quantification of these tradeoffs is another gap in the literature, which should be addressed to aid energy-water-biology nexus decision-making within ecosystem services frameworks. Han et al. (2020) note that many nexus studies lack analysis of the interactions of economic, social, and environmental impacts. In this work, a direct biologic use of TDCs in population assessments and economic analyses is proposed. The method utilizes TDCs and population versus temperature curves, modeled after thermal performance curves (TPCs), to create population habitat duration curves (PHDCs). In literature, habitat duration curves (HDCs) demonstrate the relative availability (e.g., weighted usable area, WUA) of flow, as a habitat variable/resource, within a waterway. A criticism of past work using WUAs is that such studies often lacked the inclusion of temperature as a resource (Orth, 1987); this work adds to the WUA and HDC literature by isolating temperature and bringing population-temperature relationships to the forefront. PHDCs are presented as an exceedance probability for fish community population values following the forms commonly used for water quality standards (see Vogel and Fennessey, 1995). Temperature is considered a resource within waterways (Magnuson et al., 1979), as fish will seek out optimal temperature conditions, if able. PHDCs provide the integration of water resources (e.g., temperature) and aquatic species modelling to assist in decision-making frameworks (e.g., policy and economic assessments) concerning thermoelectric power plants.

Within decision-making frameworks, the evaluation and comparison of scenarios is beneficial for policy formulation, and systems-level predictions (Dixon, 2012). As Preston and White (1978) note, observations of aquatic life are beneficial for predicting environmental conditions, with fish serving as a reflector of long-term water quality trends. Monetary tradeoffs between fish populations and power plant discharge temperature changes are identified in this study using benefits transfer methodology. The method is demonstrated using a meta-analysis of Electric Power Research Institute (EPRI) fish population and temperature data collected at the Shawnee Fossil Plant on the Ohio River. Using the meta-analysis of empirical data for plume conditions and ambient conditions within the waterway, an additional scenario in which the power plant must mitigate the temperature output by 1.1 °C is presented. This temperature change was chosen, as 1.0 °C is the point at which some species react to temperature shifts (Kennedy, 2004). The results of this study show how the values of electricity generation and fish populations change with the constraints of plume conditions, ambient conditions, and the 1.1 °C temperature mitigation scenario.

By including an economic application of PHDCs, this work demonstrates one method by which decision-makers can monetarily interpret the environmental impact of power generation on aquatic ecosystems. Such work serves to inform decision-makers and power plant operators seeking to balance electricity generation and aquatic ecosystem environmental impact. In particular, thermal limits administered by regulators could also be accompanied by economic impact assessments based on the realized and/or potential loss to local fish populations.

2. Background

2.1. Water temperature and fish

As temperature is a major regulator of life cycles (Kennedy, 2004), changes in water temperature can disrupt aquatic ecosystems (Coutant, 1987; Poole and Berman, 2001). Temperature tolerance has long been a staple in understanding fish behavior (Beitinger et al., 2000). Fish behavior is linked to habitat selection, with behavioral changes attributed to stress and/or stimuli (Beitinger, 1990). Furthermore, temperature is a resource within the water column (Magnuson et al., 1979), thus fish might seek optimal temperature conditions as part of habitat selection. Within the context of optimal temperature conditions, thermal pollution can be viewed as a stress to the system, and the risk of exceeding thermal preferences are quantifiable (Logan and Stillwell, 2018a). Temperature is tied to other resources within aquatic habitats, such that temperature changes affect dissolved oxygen content. A study by Abdi et al. (2020) demonstrated the improvements in fish habitat associated with thermal river restoration and increased dissolved oxygen content. Such studies demonstrate there is a tradeoff in resource quality and fish populations.

Such tradeoffs can be further analyzed within the context of thermoelectric power plant electricity production, water quality (e.g., temperature), and aquatic species populations. Given the beneficial uses of fish (e.g., recreational and commercial value), fish can be used as an economic measure of environmental quality in waterways (Preston and White, 1978). Ecosystem services, and how fish are valued within an ecosystem, can be applied to the current study via benefits transfer methodology. As such, the monetary quantification of electricity generation (via operating criteria) and the relationship to downstream water quality (e.g., temperature) can be assessed from the lens of impacts to fish populations. For additional information on ecosystem services and benefits transfer methodology, refer to A.1. Building off of the quantification of risk and resources, habitat time series analysis has been presented in the literature with planning and management applications.

2.2. Habitat time series analysis

Use of habitat metrics for time series analysis is commonly used in environmental design standard applications (Castellarin et al., 2013) such as determining minimum flow requirements and instream-flow water rights (Milhous et al., 1990). Time series analysis of biological data, as outlined in Milhous et al. (1990), generates a weighted usable area (WUA) as a function of physical habitat and streamflow (also referred to as a habitat duration curve (HDC) in Vogel and Fennessey (1995) and relative suitability index in Payne (2003)). WUAs are discrete values that relate the relative amount of usable habitat metric within a waterway (Bovee, 1982). Milhous (1984) previously presented the concept of habitat and streamflow functions as surrogates for the production function commonly used in economic analyses. In environmental analyses, the production function can be used as a valuation method and has been applied frequently in fisheries management studies (Armstrong et al., 2016). WUAs should be thought of as an index for comparison (e.g., percentage of habitat loss), and not a true reflection of direct habitat units (e.g., fish per m^2) (Payne, 2003).

When generating HDCs, the habitat and species metrics used can include a variety of data such as water velocity and pool depth; and population size, fecundity, and biomass, respectively. Selecting metrics as useful measures of performance for the species of interest is important for assessing biologic sustainability (Milhous et al., 1990). In the conceptualization of HDCs, the graphs of streamflow discharge versus time, and relative habitat metric versus discharge are necessary. Typically, the habitat metrics are averaged or weighted to generate a weighted usable habitat on a scale of 0 to 1 for use in the generation of an HDC and associated weighted usable area. Vogel and Fennessey (1995) present a simplified development of an HDC, which is a component of the instream flow incremental method commonly used by the U.S. Fish and Wildlife Service. The graph of an HDC can be used to demonstrate when water resources (flow) are limiting, integrated to determine relative changes in habitat over time, or as comparative analysis between flow scenarios (Milhous et al., 1990). Recent work by Ceola et al. (2018) expands the HDC literature, demonstrating a habitat suitability duration curve with application in ecologically and hydrologically homogeneous catchments.

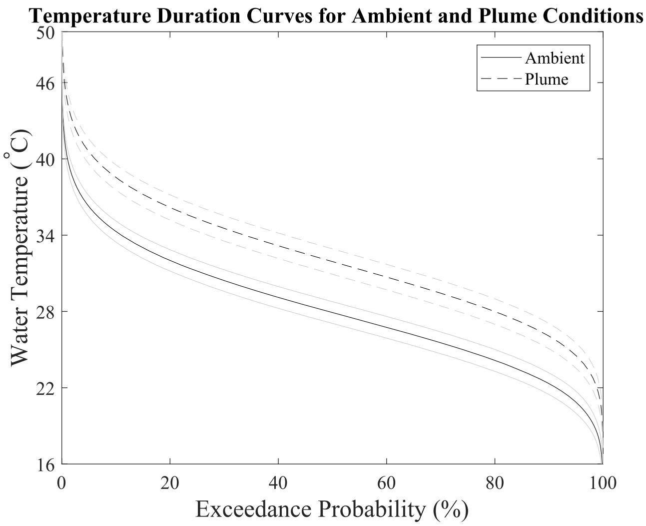

Fig. 1. Temperature duration curves (TDCs) for the Shawnee Fossil Plant on the Ohio River. Grey lines indicate uncertainty using the standard error of the mean (SEM) on temperature and plume size data. Ambient conditions assume no presence of a thermal plume, and plume conditions are for the plume only. TDCs were averaged over a 1000 m downstream distance to match the catch per effort (CPE, #/km) reported in the EPRI biological data used for population versus temperature meta-analysis.

3. Methodology

In the case of thermoelectric power generation, thermal pollution and its impact on aquatic ecosystems can be viewed as an externality of the electricity generation process. The tradeoff between electricity production (and thus associated thermal pollution) and aquatic ecosystem degradation (via reduced fish populations) can be quantified and used as a decision-making tool within ecosystem services frameworks. Using fish populations and TDCs for the Shawnee Fossil Plant, PHDCs were generated, and an economic analysis was completed as a demonstration using benefits transfer methodology.

3.1. Power plant data and temperature duration curves

The Shawnee Fossil Plant (SFP), located near Paducah, Kentucky, on the Ohio River, is a baseload, coal-fired power plant using open-loop cooling technology, and has been the focus of previous work by Logan and Stillwell (2018a,b). In this work, TDCs were generated for a 1000 m section of river and a temperature range of 16 to 50 °C, following the methods outlined in Logan and Stillwell (2018b). U.S. Energy Information Administration (EIA) and United States Geological Survey (USGS) data concerning power plant cooling water flow (discharge) and temperature, and river flow (discharge), respectively, were used to generate TDCs. Fig. 1 demonstrates the TDCs for the Shawnee Fossil Plant on the Ohio River using 26 years of summer data of the maximum temperature differential between intake and effluent (ΔT) and average discharge for each year. Plume conditions are the conditions found within the thermal plume, and ambient conditions are the expected waterway conditions in the absence of thermal pollution. For the 26 years of available (at time of study), feasible data, the average ΔT was 6.9 °C (see A.2 for more on power plant and river data). CORMIX, an EPA approved mixing software with special emphasis on power plant mixing zone dynamics (Doneker and Jirka, 1991; 2002), was used to generate plume and mixing dynamics (see A.2). Matlab was utilized for curve fit analysis and creation of TDCs. As described in Logan and Stillwell (2018b), probability distributions were analyzed based on CORMIX output of ambient and plume dimensions and temperature conditions (following Logan and Stillwell (2018a)). Using the probability distributions of temperature versus downstream distances (e.g., probable plume size and ΔT conditions), an average across the river channel for the chosen downstream distance (1000 m) is used to generate one probability of exceedance curve ($P(T)$) for 0.56 °C intervals within the full temperature range of the ambient and plume data. The trapezoidal rule was used to find the area under each exceedance curve, and a singular TDC is created following Eq. (1) (Logan and Stillwell, 2018b)

$$P(T_j) = \frac{\int_0^{1000} P(x)dx}{1000} \tag{1}$$

where $P(x)$ is the probability of exceedance curve, 1000 is the total downstream distance (m), and j is the temperature range of interest (T_{lower} to T_{upper} over the full temperature data range).

TDCs follow the form of flow duration curves (FDCs), which are commonly used in hydrologic analysis of waterways. Streamflow discharge data over a given time period are used to generate a waterway's FDC; a cumulative frequency curve which demonstrates the percentage of time a discharge is expected to occur or be exceeded over that specified time period (Searcy, 1959). In a similar fashion, TDCs represent the cumulative frequency of temperature conditions over a given time period (with a collection of yearly EIA data being analogous to the summer season). Reading Fig. 1, a temperature of 32 °C is expected to be equaled or exceeded, under ambient conditions, slightly over 20 % of the time in the Ohio River at the SFP location. For the same 32 °C temperature under plume conditions, the exceedance jumps to roughly 60 % of the time. For a complete demonstration of the data and methods used to generate the TDCs, refer to Logan and Stillwell (2018b).

3.2. Fish and temperature data

Biological data were cross-referenced across EPRI studies through the Ohio River Ecological Research Program (ORERP) to find suitable data availability at the location of the SFP. The Ohio River is a major river providing both aquatic species habitat (Stark, 2013) and cooling water for thermoelectric power plants (Butz et al., 1974). Fish are an appropriate biological indicator species for river ecosystems, as they spend their entire life cycles in the water, and fish species tend to have wide population ranges, making them easy to sample (ORSANCO, 2016).

To demonstrate PHDCs, fish populations, recorded as catch per effort (CPE, # /km) by EPRI, were used. Abundance (population level) is considered to be a larger indicator of the effect a species has on the local ecosystem than presence/absence (Ehrlén and Morris, 2015). The freely available EPRI data consist of yearly studies as part of ORERP, with specific power plants featured in different years (the SFP was included in seven years since 2005, at the time of study). In each yearly study, three upstream and three downstream sampling events occur in June, August, and October, and include physical parameters such as water temperature, water clarity, and conductivity, and fish species name and population reported as CPE. For more information on EPRI data, refer to A.3. For this work, the water temperature and CPE data were retained. For reference, Preston and White (1978) noted that the lower reaches of the Ohio River contained the highest fish biomass per unit area compared to upper river reaches.

3.3. Population versus temperature plots

To generate population versus temperature curves following the form of thermal performance curves (TPCs), 40 population values (6 values per year, 3 upstream and 3 downstream per year, less the November data points from 2009) recorded as CPE were plotted against the corresponding temperature condition. On average, the temperature differential between upstream and downstream temperature was 2.0 °C (warmer downstream), and the CPE value differed by an average of 100 fish (more fish upstream). For this study, the CPE value is interpreted to be a population value, as the downstream distance of interest (1000 m in

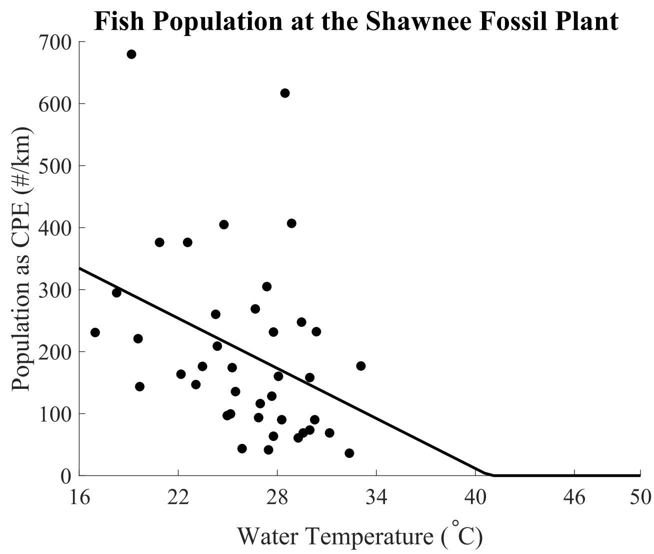

Fig. 2. Population of all fishes at the Shawnee Fossil Plant. Data include 7 years of ORERP upstream and downstream sampling at the SFP (black dots). Meta-analysis of EPRI data shows a linear trend (black line), where population decreases as temperature increases ($p = 0.02$, $R^2 = 0.13$). A Rosner outlier test showed no outliers in the dataset. Extrapolation of the linear trend past temperature values of 35°C was necessary for the creation of PHDCs.

this study) is equivalent to the CPE measurement (per 1000 m). A downward sloping line was best fit to the data following a linear regression ($p = 0.02$, $R^2 = 0.13$), as shown in Fig. 2. A Rosner outlier test was performed on the 40 CPE versus temperature data points, with results indicating that no outliers exist in the CPE dataset. Note that the two largest CPE values were recorded in the upstream portion of the river. Although temperature is not the only determinant of population, even small temperature changes can have an impact on aquatic species, as noted by Kennedy (2004). Thus a value of $R^2 = 0.13$ is interpreted as a correlation between temperature and fish, but other factors also contribute to the presence or absence of individuals within the aquatic ecosystem, which are inherently complex with multiple factors interacting to create a complete habitat.

In this analysis, temperature is isolated as the variable of interest in predicting total fish population. However, temperature is not the only indicator of fish presence. Analysis of biological and physicochemical data collected in the EPRI studies (see A.4 and A.5) suggest a non-negligible correlation between population and flow, but reinforces a greater correlation with temperature. This conclusion is confirmed by studies such as Lessard and Hayes (2002), which found temperature to be the most important predictor of species richness within a Michigan waterway affected by small dams. Thus, in this study, temperature is isolated as the variable of interest. However, exercise caution when using temperature alone as a predictor of population values.

Another suggested metric for comparison is species-specific populations. For species with narrow or cold-water temperature tolerances affected by thermal pollution, other species could serve as opportunists and thrive at higher temperatures in the river. PHDCs could be used to demonstrate the effect of temperature on such opportunists, as well as invasive species that can thrive in thermally altered waterways such as at thermoelectric power plant sites (Emde et al., 2016). For a range of temperature conditions, all species present in a system will have varied and partially or fully overlapped species-specific TPCs.

Like TPCs, the shape in Fig. 2 demonstrates the relationship between a habitat variable (temperature) and response (fish population). To capture uncertainty in the analysis, the standard error (SE) from the linear regression of population versus temperature data points was used, as were the resulting curves generated from the uncertainty bands of ± SE, to solve for additional PHDCs. Fish populations can vary widely due to species interactions and environmental factors (Shelton and Mangel, 2011), thus uncertainty analysis was applied to reflect such factors.

To analyze population data, Eq. (2) was followed,

$$N_j = \sum_{i=1}^{n} N_{ij} \tag{2}$$

where N_{ij} is the total number of individuals in population i at temperature j, and N_j is the sum of all populations at temperature condition j. In this work, only the total fish population is considered within the waterway (thus $i = 1$), but Eq. (2) is presented to allow for future analysis either at the species level where i represents individual species, or across multiple populations (mussels, fish, etc.). All population values are for the SFP location as reported in the EPRI data. Only within plume and ambient conditions are considered for a 1000 m river segment. In this analysis, three possible waterway temperature conditions (j) exist,

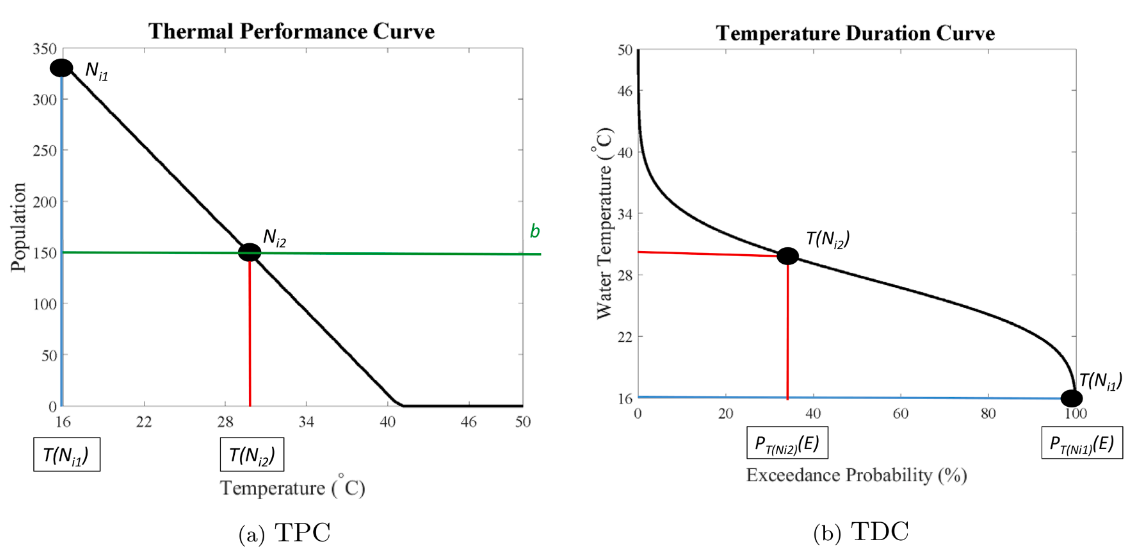

Fig. 3. Graphical representation of the creation of a population habitat duration curve (PHDC) from a a) thermal performance curve and b) temperature duration curve is shown, following Eqs. (3a) and (3b). To find the $P(E)$ value associated with a given population threshold b, the probability of being between the temperature range $T(N_{i1})$ and $T(N_{i2})$ corresponding to N_{i1} (maximum population in the case of the linear TPC as found using EPRI data) and N_{i2} (threshold population value) is found by solving Eqs. (3a) and (3b). In this example, the population value $b = 150$ is met or exceeded approximately 65% of the time ($P(N_{ij} \geq 150) = 0.65$, or 65%).

of which the thermally reduced plume conditions represent a scenario in which the power plant must mitigate the temperature output by 1.1 °C. A 1.1 °C shift in ΔT was chosen, as 1.0 °C is the point at which some species react to temperature shifts (Kennedy, 2004). Each condition is listed and described below.

- AC: ambient conditions; $j = (\Delta T = 0\ ^\circ\mathrm{C})$
- PC: empirical data plume conditions; $j = (\Delta T = 6.9\ ^\circ\mathrm{C})$
- RC: thermally reduced plume conditions; $j = (\Delta T = 5.8\ ^\circ\mathrm{C})$

Thermally reduced conditions (RC) correspond to a reduction in ΔT as outlined in Section 3.6, while empirical data plume conditions (PC) correspond to the plume conditions expected using EIA data.

3.4. Generation of population habitat duration curves

To generate a PHDC, both a TPC and TDC are necessary. The form of a TDC follows that of flow duration curves (see Logan and Stillwell (2018b)). Flow duration curves are typically presented as the complement to the cumulative distribution function (cdf) for streamflow (Vogel and Fennessey, 1994) (also referred to in some literature as "1 - cdf"). Thus, the form of a TDC (Fig. 1) is the complement of the cdf for temperature in a waterway. To solve for the probability of exceeding a given population value b, or threshold, as presented in the form of TPCs (Fig. 2), Eqs. (3a) and (3b) were used,

$$P(N_{ij} \geq b) = P(T(N_{i1}) \leq T \leq T(N_{i2})) \tag{3a}$$

$$P(N_{ij} \geq b) = P_{T_{Ni1}}(E) - P_{T_{Ni2}}(E) \tag{3b}$$

where N_{ij} is total number of individuals in population i at temperature j with a desired population threshold b, and $T(N_{i1})$ is the temperature along the TPC at which the maximum population value occurs, and $T(N_{i2})$ is the temperature along the TPC at which the threshold population value N_{ij} occurs. Solving Eq. (3a) requires finding the probability of exceedance values associated with $T(N_{i1})$ and $T(N_{i2})$ on the TDC, and subtracting the difference following Eq. (3b). The above equations represent an expected temperature range on the TDC, which correlates to a population threshold b that is exceeded over the expected temperature range. Note that since the TPC in this study is linear, the population threshold b is compared to the maximum population at the lowest temperature, which occurs at $P(E) = 100\%$ (see Fig. 3). If the TPC was parabolic as discussed in A.6, two occurrences of N_{ij} would exist along the curve, and would be used to solve for $P(N_i \geq b)$. Using a generated PHDC, the value $P(N_i \geq b)$, which is an expected population value, corresponds to an individual $P(E)$. Moving forward, the population value associated with $P(N_{ij} \geq b)$ will be referred to as Λ in future equations. A graphical representation of Eqs. (3a) and (3b) is presented in Fig. 3. These curves were used to generate the PHDCs specific for this study. Refer to A.6 for additional figures demonstrating PHDC generation using a parabolic TPC.

PHDCs graphically demonstrate the probability of exceedance for population values, such that at a given $P(E)$ value, the population is expected to be equivalent or greater than the corresponding population value. Since the temperature range of TPCs in this study is smaller than the total temperature range of the TDCs, the PHDCs reflect a probability of exceedance value above which the population is expected to be zero. Defining habitat-related thresholds is consistent with past work on HDC conceptualizations (e.g., Capra et al., 1995).

When interpreting PHDCs, the area under a PHDC corresponds to the total expected availability of temperature as a resource over the entire summer season, also known as a weighted usable area (WUA) as described in Section 2.2. Integration of PHDCs is an existing method for quantifying the impact of different conditions (Bovee, 1982). Effectively, curve integration produces a quantification of available resource or habitat metric (for this study, temperature as a resource for fish populations). Comparison of the change in area under the curve under different thermal regimes shows the relative loss or gain in temperature as a resource for the population of interest. The WUA is a comparative metric for the temperature conditions for fish population over the summer season in the given river reach, following WUA literature. Following water quality index duration curves (Vogel and Fennessey, 1995), the PHDCs also demonstrate the probability of exceedance for a given population value. The comparison of ambient conditions (expected) versus plume conditions (thermally elevated) via PHDC integration provides relative comparison metrics specific to this location, but the method applies broadly in any resource-species scenario. Refer to Section 3.3 and A.6 for more on TPCs.

3.5. Valuation of fish species and populations

Using benefits transfer methodology, the monetary valuation of fish species from other studies is applied to this work (refer to A.1 for more information). One method to assess fish economically is using the replacement cost per individual. Replacement cost can represent the cost to replace an endemic individual with one grown at a hatchery. Predicated upon the idea that power plants can have a direct effect on fish mortality, replacing fish from affected populations is a simple indicator of the possible environmental damages associated with thermal pollution. *Southwick & Lotfus 2017* (Southwick and Loftus, 2003) present a thorough catalog of fish replacement cost, by species/family and U.S. region. Replacement costs are intuitive and simple to calculate. However, the replacement cost of a resource can seriously underestimate or overestimate the value that people gain from that resource (Brown, 2017).

Other economic preference valuation methods estimate the true value people have for fish, known as their willingness to pay (WTP). Johnston et al. (2006) completed a meta-analysis of WTP values for a range of recreational fishes, and found that the average WTP per fish was \$22.57 (converted to 2017 dollars to match with electricity price data in Section 3.7), with a range of \$0.06 to \$822.36. For this study, the average WTP as found in Johnston et al. (2006) was utilized, with sensitivity analysis completed over a range of replacement cost and WTP values. A comparison of replacement cost and WTP values for select species found in the Ohio River is presented in Table 1.

The total population value follows Eq. (4a), which can be downscaled to a species level for a more species-specific assessment under a given temperature condition using Eq. (4b). In this study, a holistic

Table 1
Replacement cost values and willingness to pay (WTP) values are presented for four fishes known to exist at the Shawnee Fossil Plant. Replacement cost values per individual are reported as the range found in Southwick and Loftus (2003). WTP values are reported as the range found in Johnston et al. (2006). For catfish and carp, no species was specified in Johnston et al. (2006), thus the ranges from Southwick and Loftus (2003) include all species of catfish and carp. Additionally, only a single value was reported in Johnston et al. (2006) for catfish and carp. Values presented are adjusted to 2017 dollars.

Species/Group	Striped Bass	Smallmouth Bass	Catfish	Carp
Replacement Cost ($)	0.07 - 3.50	0.53 - 6.89	0.18 - 2.04	0.12 - 16.76
Willingness to Pay ($)	2.99 - 42.92	18.39 - 36.88	1.05	1.88

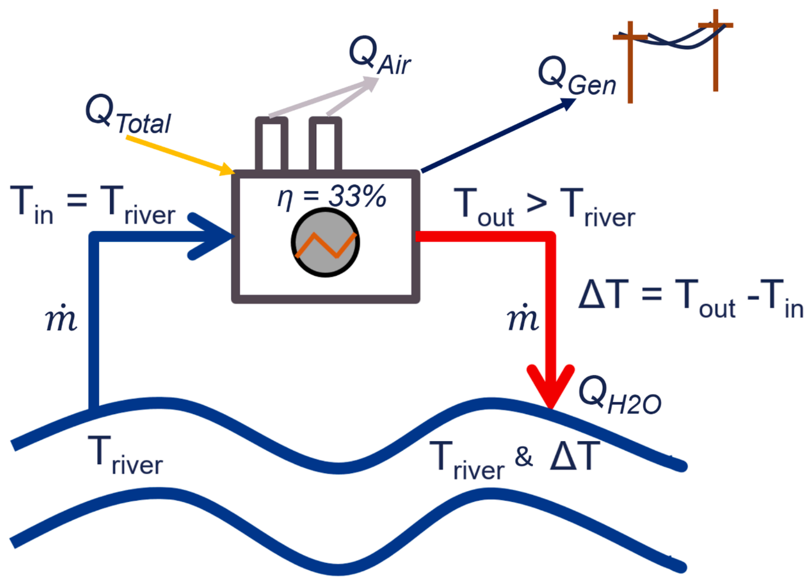

Fig. 4. The relationship between Q_{Total}, Q_{Gen}, Q_{H2O}, and Q_{Air} is shown. Variables match those described in Eqs. 5 and 6. In this work, ΔT was the variable of interest, and $\dot{m}$ was held constant such that Q_{H2O}, and thus Q_{Gen}, were found. Efficiency (η), defined as $\eta = \frac{Q_{Gen}}{Q_{Total}}$, is assumed to remain constant at 33%.

population value is assessed via a sensitivity analysis on price per individual, with the range in value per individual fish assessed at the minimum and maximum value as presented in Table 1.

$$FV_{ij} = \Lambda(R_i + K_i) \tag{4a}$$

$$FV_j = \sum_{i=1}^{n} FV_{ij} \tag{4b}$$

where FV_{ij} is the monetary value of population i under condition j in \$, Λ is the total population i under condition j, where Λ is defined in Section 3.4 as the population value associated with $P(N_{ij} \geq b)$, and j is defined in Section 3.3, R_i is the value for population i per individual as defined in Table 1, K_i is the non-use value for population i, and n is the total number of populations of interest (one in this analysis, fish). As discussed in Section 5.2, i could represent specific species that sum to a total population value if a species-specific assessment is of interest. Due to the difficulty in identifying site-specific, non-use values of individual fish species, the K_i term is neglected in the calculations presented here, but included in the equation for clarity and use in future applications (see Section 5). Following Eq. (4b), the summation of all FV_{ij} values for a given PHDC probability of exceedance value produces the community-level monetary value of all populations (mussels, fish, etc.) under condition j.

To generate a dollar value for a given population of fish, the minimum and maximum value, as found in Table 1, were used to complete a sensitivity analysis. The average WTP reported by Johnston et al. (2006) was used as the average value for the population found at the SFP in the absence of more species and community specific economic data. In a broader context, the use of a resource and the value of using that resource are important factors in valuing fisheries, particularly in light of sustainable management practices (Blicharska and Rönnbäck, 2018). Gentner and Bur (2010) note that commercial and recreational per-fish values can differ, further complicating the desire to define fish by a single use value. In this study, both replacement cost and use-value WTP were included, but it is acknowledged that other valuations exist.

3.6. Power plant generation and discharge temperature

Assuming all other operational conditions remain the same, power plant cooling water thermodynamics are governed by a mass and energy balance following Eq. (5),

$$Q_{H2O} = \dot{m} C \Delta T \tag{5}$$

where Q_{H2O} [kJ/hr] is the heat rate, $\dot{m}$ [kg/hr] is the discharge flow rate, C [kJ/kg °C] is the specific heat of water, and ΔT [°C] is the temperature differential between intake and effluent. The overall power plant thermal efficiency for a coal-fired power plant is tied to the heat loss through cooling water and heat loss to air through the exhaust (see Urieli, 2010 and Martín, 2012 for thorough power plant thermodynamics discussions). Using Eq. (5), and a constant power plant efficiency, the tradeoff between cooling water flow rate and cooling water discharge temperature (e.g., thermal pollution ΔT) was determined. The tradeoff equation is simplified here, but work by others such as Cook et al. (2015) and Koch and Vögele (2013) follow a similar thermodynamic balance.

The operational efficiency of the SFP was assumed to be 33% ($\eta = 0.33$), which is consistent with average EIA reported efficiency (via average operating heat rate) for coal-fired power plants (Energy Information Administration, 2018a). Further examination of EIA Form 923 data for the SFP shows variability monthly (post 2010) and annually (prior to 2010) in terms of efficiency, thus a static efficiency is used to represent average conditions. Note that for this analysis, efficiency and operational conditions are held constant and assumed to be the average operating conditions for a summer season. In reality, efficiency, water flow rates, and generation fluctuate (Tidwell et al., 2019). Typically, heat rates are used to solve for efficiency such that the total fuel input of coal (Q_{Total}) is divided between electricity generation (Q_{Gen}), and losses to condenser cooling water (Q_{H2O}) and flue gas (Q_{Air}) following Eq. (6) and Fig. 4.

$$Q_{Total} = Q_{Gen} + Q_{H2O} + Q_{Air} \tag{6}$$

Table 2
Assumed energy flows and relative proportion of energy flows for the Shawnee Fossil Plant based on literature values (Grubert et al., 2012; Martín, 2012). Numbers are rounded.

	Q_{Total}	Q_{Gen}	Q_{H2O}	Q_{Air}
Heat Rate ($\frac{kJ}{kWh}$)	10,900	3600	6210	1090
Percentage of Total Heat Rate (%)	100	33	57	10

where Q_{Total}, Q_{Gen}, Q_{H2O}, and Q_{Air}, are in kJ/hr.

To validate the efficiency assumptions and solve for the relative percentage of heat load parsed between Q_{Air} and Q_{H2O}, data from Martín (2012) and Grubert et al. (2012) were used. Energy (heat) losses via flue gas to the air (Q_{Air}), while non-negligible, are roughly one-sixth the heat loss via condenser cooling water (Q_{H2O}) (see Fig. 1 in Grubert et al. (2012)). Comparing heat rate values for coal-fired power plants, a 10% heat rate loss via air (and other small losses) was assumed for the SFP. Comparing heat rate losses to water, a loss of 57% is assumed for the SFP. Heat rate values in units of kJ/kWh are presented in Table 2. While the kJ/kWh heat rates remain essentially constant during operation, the electricity production in kWh can change. The fixed generation, water, and air relationship is used to determine the loss in electricity generation from shifting ΔT while holding discharge flow rate constant.

To solve for changes in ΔT while holding the flow rate $\dot{m}$ constant, Eq. (5), following Martín (2012), was used. Generation was calculated for the summer season, defined by the EIA as April through September (e.g., one half of a full year).

Using EIA reported data on discharge flow rate $\dot{m}$ (kg/hr) and ΔT as discussed in Section 3.1, the expected summer losses of electricity generation when ΔT is reduced (RC) was calculated, as indicated by a shift in the TDC for the SFP. To shift a TDC, the shift is applied to post-CORMIX data during curve fit analysis in Matlab (for more on the curve fit analysis, refer to Logan and Stillwell (2018a)). The years of available data generated similar plume shapes and temperature decay, with even spread among shapes and sizes. To reduce computational complexity, any changes to plume mixing mechanics as a result of reducing ΔT at the power plant scale are assumed to be within the bounds of uncertainty presented in Logan and Stillwell (2018a). As such, shifting the TDC by incremental temperature values while still capturing a predicted shift in TDCs, and resultant PHDCs, is possible without the need to replicate CORMIX prediction files to generate new plume mixing characteristics. Additionally, 2D averaged downstream cross-sections are utilized to produce a TDC for a 1000 m river section, thus any greater accuracy provided by completing additional CORMIX runs would potentially be negated in the distance-averaged creation of the TDCs. Average SFP data for 26 years were used to calculate Q_{Gen}, and uncertainty is reported as a range using the SEM on the 26 years of generation data, with resulting Q_{Gen} values.

3.7. Valuation of power plant generation

To determine the estimated net value of a power plant producing 1 MWh of electricity, the wholesale price of electricity ($/MWh) less the marginal cost of that same MWh was used. The economic loss expected when a power plant reduces their MWh output was found following Eq. (7). The expected summer losses in value from decreasing the ΔT associated with thermal effluent, when all other operational conditions were held constant, was found.

$$PV_j = G_j(W - M) \tag{7}$$

where PV_j is the monetary value of generation under conditions j in $, G_j is the generation in MWh of under conditions j, W is the wholesale price of electricity in $/MWh, and M is the marginal cost of electricity in $/MWh.

Price paid to the power plant per MWh less the cost to produce electricity per MWh provides a estimated per-MWh value for electricity generation. In order to find the per MWh value, wholesale price, fuel cost, and operations and maintenance cost were assessed. The wholesale summer (April-September) 2017 price of electricity, as reported by the Intercontinental Exchange for the hub closest to the SFP within the Midwest region, averaged $38.56 per MWh, with a range of $27.00 to $81.75 per MWh (weighted-average values) (Energy Information Administration, 2018b). The SEM for weighted-average values over the summer season was $1.44, and was used to generate upper and lower uncertainty bounds on the expected wholesale price of electricity. Using National Renewable Energy Laboratory data for 2017 (National Renewable Energy Laboratory, 2017), the range in fuel costs for coal-fired power plants were $20 to $25 per MWh, and the variable operations and maintenance costs were $5 to $9 per MWh. These numbers bring the total range (e.g., uncertainty) in marginal cost (fuel cost plus operations and maintenance cost) for coal-fired electricity generation to $25 to $34 per MWh (average $29.50 per MWh). Though variation exists in regional pricing, specific generator operations, etc., using $38.56 per MWh wholesale price, and $29.50 per MWh marginal cost, the SFP's value is estimated to be $9.06 per MWh under average conditions for a summer season using 2017 price data. Using the SEM, the range in value is $3.12 to $15.00 per MWh. To calculate the expected loss in value from a decrease in ΔT, the lost generation in MWh was multiplied by the expected value price of $9.06 per MWh. Electricity prices are dependent on demand, environmental factors, and more, but overall, the expected pricing structure is likely to stay closer to the expected average as opposed to the extremes for a baseload, coal-fired power plant. Additionally, electricity dispatch is optimized to help stabilize cost and price trends while maintaining efficient electricity supply to the grid (Federal Energy Regulatory Comission, 2015).

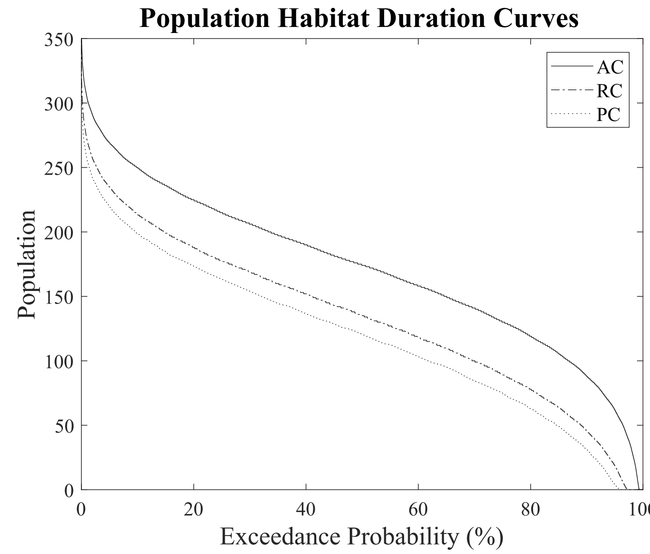

Fig. 5. Population habitat duration curves (PHDCs) demonstrating the relationship between population and probability of exceedance under AC (ambient), PC ($\Delta T = 6.9$ °C), and RC ($\Delta T = 5.8$ °C). Population corresponds to total fish expected at the location of the Shawnee Fossil Plant based on meta-analysis of population and temperature data from EPRI. The area under each curve corresponds to the weighted usable area (WUA) with temperature as the habitat resource. $P(E)$ values are presented as percentages, analogous to time during the summer season.

4. Results

Following Eqs. 3a and 3b using population versus temperature curves (modeled after TPCs, see Fig. 2) and TDCs (see Fig. 1), PHDCs were produced (see Fig. 5) for fish located near the SFP on the Ohio River. Three temperature conditions (AC, PC, RC) as defined in Section 3.3 were analyzed.

4.1. Population habitat duration curves

The area under the PHDCs represents the relative availability of temperature within the waterway under ambient (AC), plume (PC), and thermally reduced (RC) conditions. Comparison of the PHDCs under AC and PC demonstrates that the available thermal resource (temperature), or usable habitat area as defined by population, is reduced such that

Table 3
SFP expected generation and expected value under expected operating conditions (PC) and thermally constrained conditions (RC). Expected fish population (at $P(E) = 50\%$) and value under PC, RC, and ambient conditions (AC). All monetary values presented are in 2017 dollars. Numbers in parentheses indicate the total range when all uncertainty combinations are applied.

	Shawnee Fossil Plant		Fish Population	
Thermal Conditions	Generation MMWh	Value Thousand $	Expected Population at $P(E) = 50\%$	Value $
$\Delta T = 6.9$ °C **(PC)**	3.76 (3.58 – 3.93)	34,054 (11,180 – 59,014)	119 (0 – 451)	2,686 (0 – 19,357)
$\Delta T = 5.8$ °C **(RC)**	3.16 (3.00 – 3.32)	28,604 (9,357 – 49,727)	134 (0 – 462)	3,024 (0– 19,829)
$\Delta T = 0$ °C **(AC)**	n/a	n/a	175 (0 – 485)	3,950 (0 – 20,816)

approximately 31% of the thermal resource becomes unavailable under plume conditions as compared to ambient river conditions. When the thermal pollution in the plume is reduced by 1.1 °C by reducing ΔT under RC, approximately 22% of the thermal resource becomes unavailable as compared to ambient conditions in this analysis.

4.2. Comparison of Population Values Under Different Thermal Conditions

A $P(E)$ value of 50% was selected for method demonstration purposes, but any $P(E)$ of interest could be selected for regulatory frameworks (refer to Section 5). While under different sets of environmental conditions the population of fish could increase or decrease, it is assumed that the PHDCs presented in Fig. 5 are indicative of a typical summer season. Under ambient conditions, the expected population is at least 175 individuals for 50% of the season (where $P(E)$ is a proxy for the time in a season). Under plume conditions ($\Delta T = 6.9$ °C), the expected populations at the same $P(E)$ declines to 119 individuals. Decreasing the plume ΔT by 1.1 °C under thermally reduced conditions ($\Delta T = 5.8$ °C), the expected population is 134 individuals. Ranges were found when all uncertainty conditions were applied on the population data (using SE) and TDCs (using SEM), and are reported in Table 3.

4.3. Economic valuation of fish via PHDCs

Under ambient conditions, the expected fish population has a higher number of individuals, and correspondingly has a higher economic value. Using the average WTP of \$22.57, the population has a value of \$3,950 under ambient water conditions. When thermal pollution from the power plant is assessed, the population decreases, and has a value of \$2,686. If the SFP reduces thermal pollution by 1.1 °C under thermally reduced conditions, the fish population increases in value compared to expected thermal pollution conditions with a value of \$3,024. A summary of values with uncertainty ranges is presented in Table 3. The range in expected population monetary value applies all uncertainty conditions, including the range in replacement cost and WTP as found in Table 1, and uncertainty ranges associated with Fig. 5.

4.4. Economic valuation of power generation

The expected electricity generation over the summer season for the SFP, following the methods presented in Section 3.6, averaged 3.76 MMWh under plume conditions. When the ΔT is reduced by 1.1 °C under the scenario of thermally reduced conditions, holding all other operational conditions constant including cooling water withdrawal/discharge rate, the expected generation was 3.16 MMWh. This change reflects a 16% reduction in electricity generation under thermally constrained operating conditions. Solving for summer value via Eq. (7), the value of \$34,054,000 is reduced to \$28,604,000 when the ΔT is reduced by 1.1 °C. This translates to a loss of \$5,450,000 under thermally constrained conditions. A comparison of generation and value, with uncertainty bounds, is found in Table 3.

5. Discussion

Ambient river conditions (AC) and thermoelectric power plant plume conditions (PC) that cause thermal pollution are compared for a population of fish using population habitat duration curves (PHDCs). For the plume conditions, empirical data were analyzed for normal operating conditions ($\Delta T = 6.9$ °C,), and the analysis was repeated under the scenario of thermally constrained conditions (RC) where the average ΔT was reduced by 1.1 °C ($\Delta T = 5.8$ °C). PHDCs visually and mathematically demonstrate the availability of thermal resources (water temperature) in waterways using adapted thermal performance curves (TPCs) and temperature duration curves (TDCs). The Shawnee Fossil Plant (SFP) on the Ohio River was used as a demonstration site for the TDCs necessary for PHDC creation. In this analysis, roughly 31% of the temperature resource becomes unavailable under plume conditions as compared to ambient conditions. Even when the thermal pollution from the SFP was reduced by 1.1 °C under thermally reduced conditions, 22% of the temperature resource is still unavailable as compared to ambient conditions. Visual comparison of the different PHDCs highlights the shift in temperature both with respect to a decreased range in relation to the TPC, and overall decrease in resource availability. This resource reduction is due to the compression of temperature availability over the temperature range of the fish community under thermal pollution conditions as shown in the TDCs for plume and thermally reduced conditions.

As shown in Fig. 5, plume conditions drastically reduce the availability of optimal temperature conditions. To make specific cross-species comparisons of expected populations, individual TPCs would need to be analyzed. To plot the PHDCs, each population threshold on the TPC is associated with a temperature range on the associated TDCs. Expected population values for economic analysis use a $P(E)$ value of 50%. The $P(E)$ value could be selected by biologists to provide a minimum viable population (MVP), particularly if timing of temperature extremes and other environmental disturbances are known. Vélez-Espino and Koops (2012) found that the mean MVP for many freshwater fish species was 272 adults. Although the total population level drops to 0 at a $P(E)$ of 100% due to the shape of the TPC is each scenario, it is assumed that avoidance by the individual fish will be employed as a coping strategy during brief temperature extremes, though temperature still has a large impact on the overall and long-term fish community (see Section 2). Additionally, the EPRI data used for the meta-analysis do not necessarily reflect total populations, but are indicative of population and temperature trends (see Sections 3.2 and 3.3 and the Appendix).

This analysis involves a baseload, coal-fired power plant on a large river, but the method applies to other situations. Under different power plant conditions, the reduction in thermal resources could become larger, particularly if a power plant operates using a larger ΔT value (difference between intake and discharge cooling water temperature). As the temperature differential is a large factor in the form of a TDC (Logan and Stillwell, 2018b), the operational conditions of a power plant are expected to largely influence the produced PHDC. Increasingly, engineers are being asked to make waterway conservation and improvement recommendations for a variety of issues including fish passage and maintaining habitat (Vogel and Fennessey, 1995). Tools like PHDCs could be used in tandem with TDCs to conduct site- and species- specific investigations of the affects of thermal pollution in waterways as a way to model, predict, and monitor such population and diversity changes.

It is important to note that WUAs, while respected by many and used by the U.S. Fish and Wildlife Service as a comparative metric for habitat availability (Gallagher, 1999), do not present a direct correlation between fish biomass and habitat suitability (Mathur et al., 1985). The discrepancy can be attributed in large part to the typical derivation of WUAs from multiple habitat metrics simultaneously (e.g., depth, velocity, temperature, and flow), where all metrics are given equal weight (Mathur et al., 1985). In some cases, all habitat metrics are given a relative 0 to 1 weighting (see *Bovee* Bovee, 1982), such that the TPCs presented in this work would present temperature as a variable against which a scale of 0 to 1 were plotted for "suitability." In this study, the relationship between number of individuals (population) and temperature was isolated to avoid arbitrary weighting of habitat variables that would, in nature, not interact in equal weight. As temperature is noted as a large factor in species' response to habitat (Coutant, 1987; Kennedy, 2004; Poole and Berman, 2001), the use of WUAs is justified in this study. Furthermore, Rüger et al. (2005) note that habitat suitability studies are useful for ecological impact assessments, and can aid in water management frameworks.

5.1. *Expanded use of population habitat duration curves*

In planning and management applications, particularly concerning species populations and diversity, PHDCs can serve as a useful ecological model to assess the relative availability of temperature as a resource. Not only can different conditions be compared among a population, but cross-species comparisons can also be assessed, particularly when critical assessment of species-specific TPCs is made. With river warming likely under climate change scenarios, fish species, particularly those species with lower temperature preferences, will likely be affected (Sinokrot and Stefan, 1992). Temperature shifts, and thus changes in habitat, can cause shifts in population distributions (Chapman, 2009). Reductions in usable habitat space can have similar effects like changes in biodiversity and food web structures (McHugh et al., 2015). Changes in population could lead to localized and regional disruptions in diversity and dominance patterns, as shown by Daufresne and Boët (2007). Because temperature has been shown to be one of the most important factors influencing fish behavior and abundance (Buisson et al., 2008), using PHDCs as a measure of thermal resources to indicate the likelihood of finding fish species is useful. Extending beyond examining communities or species-specific populations, PHDCs could be used to assess different life stages of the same species. In life-stage assessments, care should be taken in using the appropriate months and data to distinguish spawning fish, juvenile fish, and adult fish (Milhous, 1986). Such population monitoring could be compared against future conditions predicted as a result of climate change. Scenario analysis under given thermal conditions would provide insight into localized climate change planning efforts.

To take PHDCs another step further, PHDCs using temperature as a resource could be coupled with PHDCs using flow (discharge) to provide insight into projected impacts of droughts and climate change scenarios (as mentioned previously). Pools, when available under low to adequate flow conditions, serve as thermal refuge for fish species in times of severe temperature conditions (Foster et al., 2001). Considering water flow to be a resource in the same manner as temperature, PHDCs could be used to compare both resources individually, with the combined results indicative of overall habitat conditions. Bovee (1982) presents methods to combine stream metrics of interest with WUAs to provide more holistic water quality assessments.

In a study of the Northeastern United States, Stewart et al. (2013) found that almost 30% of thermoelectric power plant generated heat ends up in rivers, further demonstrating the need for adaptable tools to assess thermal pollution in riverine ecosystems. While direct quantification of the risk of exceeding species' thermal preferences is valuable (Logan and Stillwell, 2018a), PHDCs refocus decision-making on temperature as a relative resource within waterways. As described by Milhous (1986), habitat time series analyses are principally used for water management decisions. Instead of addressing fish under varying flow regimes, the temperature-based PHDCs could address varying temperature regimes, particularly in regards to changing cooling water flow rates and temperatures. Variability in a TDC will produce variability in the resultant PHDC, and scenarios of power plant effluent could be compared against the relative loss or gain in thermal resources such as is demonstrated in this work. Increasing power plant cooling water flow rates can decrease the thermal impact on rivers from power plant effluent following thermodynamics as shown in Eq. (5), which could prove to be a useful tradeoff depending on future climate conditions in regards to water temperature (Miara et al., 2017), and during times of drought (Mu et al., 2020). However, water scarcity concerns might reduce the amount of water available for cooling purposes (Ganguli et al., 2017; Stillwell and Webber, 2013), negating the potential temperature/flow rate tradeoff. Nevertheless, PHDCs could provide a useful comparison of such tradeoffs in adapting to climate change concerning thermoelectric power plants.

In regulatory settings, temperature as a resource could serve as a useful metric by which planning and management could be complemented. Regulations aimed at protecting aquatic species, such as the CWA §316(a), could use PHDCs to provide comparable metrics for population levels. For example, populations of fish are known to be mobile, and thermal avoidance of adverse temperature conditions can occur. Metrics for balancing thermoelectric power plant thermal pollution with desired populations of indigenous or endangered species could come in a form such as "an expected population of 300 individuals for no less than 35% of a season," for example. Such population levels could be used to determine MVPs, or correlate to the number of adults necessary for successful reproduction. Likewise, the WUA for PHDCs could complement similar frameworks such that the desired WUA, analogous to the availability of temperature, is reduced by no more than a certain percentage. Regulatory Mixing Zones (RMZ) are commonly described as varied and plentiful in terms of how they are defined and measured. Incorporating TDCs and PHDCs into the analysis of a "protection and propagation of balanced and indigenous populations," as is required by NPDES thermal variance permits, could be beneficial. Henley (1995) calls for strategic planning in the Ohio River, particularly in the monitoring of fish populations, and PHDCs could aid in such efforts.

5.1.1. *Limitations of the current study*

With climate change, both water temperature and flow are likely to be affected (Pyne and Poff, 2017; Wu et al., 2012; Zhang et al., 2020), and with environmental change, altered species distribution and abundance patterns are expected (Ehrlén and Morris, 2015). Simultaneous consideration of the effects of temperature and flow on fish species has been the focus of prior work, such as by Wenger et al. (2011). In this work, flow is used as an input to CORMIX to generate TDCs and, therefore, the combined effects of flow and temperature cannot be fully uncoupled. The comparative extension of PHDCs, beyond isolating temperature as the only resource over which fish compete, is proposed. In regards to temperature, as an individual factor, precise monthly or weekly calculations could be completed given appropriate data availability. In the present form, the translation of EIA yearly summer data as a comparable dataset to a summer season is not ideal, but is warranted given a lack of more precise data. This translation also follows past work by Logan and Stillwell (2018a,b).

In terms of fish population data, it is important to note that the consideration of fish populations as static or instantaneous numbers during a season is not ideal, as current population levels are dependent on both past and present habitat conditions (Orth, 1987). Future use of PHDCs could include more targeted timing analysis of temperature (intensity and duration of localized thresholds throughout a season) following the general framework outlined by Capra et al. (1995). Large seasonal abundances of fish within river reaches can be indicative of episodic events (Lohner and Dixon, 2013), thus using data collected over several years without young-of-year populations provides a more stable indicator of expected community population conditions (see A.4).

5.2. Application of population habitat duration curves in economic tradeoff analysis

Using PHDCs as a method by which to complete economic analysis is a suggested application of the tool presented in this study, particularly for ecosystem services analyses. As such, a tradeoff analysis of the value of electricity generation and the value of fish populations was completed. By calculating expected loss and gain in dollars, the tradeoff analysis has been framed in equivalent terms. Oftentimes, ecosystem services are used as the accounting unit in environmental economics and policy, but ecosystem services can be difficult to adequately value (Boyd and Banzhaf, 2007). This analysis shows the replacement cost for fish using a range of species (specifically four species, which were found at the study site and for which replacement cost data were available) within a complex river ecosystem, which may undervalue the holistic ecosystem services of the Ohio River at the Shawnee Fossil Plant. Other fish species are present in the system, as well as non-fish aquatic species, which could result in a different monetary valuation. In terms of using replacement cost, a study by Strange et al. (2004) compared the restocking value, via replacement cost using hatcheries data, of fish lost due to entrainment and impingement with that of equivalent habitat restoration for the same size of fish population loss (termed the habitat-based replacement cost method). Strange et al. (2004) assert that simply restocking lost fish every year is not ecologically equivalent to maintaining natural populations (e.g., restocking versus allowing natural reproduction of the natural population). Strange et al. (2004) found that the cost to *replace* a community of fish was on the order of $200,000 dollars, but to *conserve and replace* the necessary habitat space to prevent the loss of fish cost on the order of $25,000,000. Additionally, natural fish populations include unique diversity and richness relationships at the community level that might not otherwise be available from hatcheries fish (e.g., not all wild species are grown in hatcheries) (Strange et al., 2004). News reports discuss the failings of hatchery-raised fish to provide equivalently adapted fish as replacements in natural ecosystems (Goldfarb, 2014).

As for reported monetary damages to fish populations as a result of thermal pollution or other pollution (e.g., chemical) events, news articles also vary widely. For example, one news report valued a fish kill in Iowa at $8,000 for 53,500 fish (Associated Press, 2016), while another article for Iowa valued 58,000 fish at just over $10,000,000 (Sutterman, 2012). Thus a large range in value exists for fish kills of the same size within the same state. The infamous 2009 Black River fish kill, in which an estimated 218,000 fish died as a result of manure pollution, resulted in a $75,000 fine to the farm deemed responsible for the incident (Gross, 2017). Variation in estimated damages in news reports comes from the type of fish killed, and the methods/data used for valuation (e.g., replacement cost versus habitat-based replacement cost versus WTP).

The direct dollars to dollars comparison of electricity generation and fish populations can aid in future ecosystem services studies, and particularly in fish kill assessments. For example, the Natural Resources Defense Council has placed an annual damage pricetag of $30 million on fish kills at the Bay Shore Power Plant located on Lake Erie (Lyndersen, 2011). The economic valuation, completed by Gentner Consulting Group, utilized fisheries data and benefits transfer methodology to monetarily assess the damages from impingement and entrainment at the Bay Shore facility (Gentner and Bur, 2010). As such, there is precedent for this current economic valuation study, and the economic comparison of power plants and the associated damages to fisheries. This work adds to the literature by developing a tool, specifically PHDCs via thermal performance curves and temperature duration curves, to assess expected population changes as a result of changing thermal pollution.

The PHDC method is demonstrated for a fish population at the SFP location in the Ohio River. To accurately scale the economic damages by species from thermal pollution, a full understanding of all the species present, and their respective population estimates and monetary value, would be necessary. Species-specific population information is available in the ORERP studies conducted by EPRI, but this work focuses on the total fish community to demonstrate the PHDC method. For reference, an impingement study at power plants along the Ohio River indicated that millions of individuals are impinged on intake structures annually (Electric Power Research Institute, 2009b). Such large numbers indicate that many fishes are affected by power plants every year, and population scaling might be necessary when using the EPRI data set.

For the fish population at the SFP, the loss in value from reduced electricity generation (PV_{PC} - PV_{RC}) was compared to the gain in population i value ($FV_{i,RC}$ - $FV_{i,PC}$) when the SFP thermal pollution was reduced by 1.1 °C. Using the average values from Table 3, the reduction in thermal pollution, assuming all other operational conditions remain the same, translates to a $5,450,000 loss in value for the SFP for the summer season. This same reduction in thermal pollution translates to a meager $338 gain in the value of the fish population. Strictly by the numbers, the monetary loss in electricity generation is several orders of magnitude higher than the monetary gain in fish populations. Keeping in mind that the average WTP was used in this work, a cursory extrapolation in which species of special interest exist at the SFP, with a maximum WTP value of $822.36 as reported in Johnston et al. (2006), the loss becomes $12,335. This extrapolated value does not take into account the variation in fish value across species, nor is it based on the habitat-based replacement cost value as discussed in Strange et al. (2004).

When put into context of the entire Ohio River aquatic community (e.g., more than just fishes), the change in economic value of the aquatic community might approach that of electricity generation. What is presented in this study is a way to value populations monetarily, using a meta-analysis of fish population dependent on temperature conditions as expressed in TPCs. Future calculations could include any known habitat-based replacement cost method values, following the suggestions of Strange et al. (2004).

By assessing the tradeoff at the population level (e.g., isolating temperature and population), monetary assessment of ecosystems in which keystone, endangered, and/or commercially important species are present could be completed. Tools that support management and conservation efforts are important now more than ever, as conservation needs grow while resources decline (Zohmann et al., 2013). Furthermore, understanding the costs and benefits before species are lost will allow for better management of ecosystems (Meador and Frey, 2018). Using PHDCs, both direct and indirect damage to aquatic communities could be quantified, given adequate data, to give a more complete picture for proactive species conservation efforts. Schirpke et al. (2018) studied the environmental and socio-economic effects of payments for ecosystem services, and such a tool could be combined with PHDCs as a method to fund conservation efforts. By providing tools for the proactive quantification of ecosystem goods and services (e.g., fish), conservation efforts might not need to rely as heavily on reactive assessments of damages already done, thus providing better success in maintaining and improving waterways.

In the study by Gentner and Bur (2010), the authors analyzed not only the predator fish species of interest, but also quantified the loss in prey species that would otherwise be available to support Walleye, a fish critical to Lake Erie recreational fisheries. Similar to the approach presented here, (Gentner and Bur, 2010) do not include non-use values of fish. Inclusion of such data in this study could increase the total economic value of fish, further enhancing the economic tradeoff analysis. Additionally, the methods presented in this study are for a 1000 m downstream section of river, assuming plume or ambient conditions. As discussed in Logan and Stillwell (2018a), even small-scale changes within a waterway can affect the remainder of the waterbody. If the thermal plume associated with the SFP causes fish to leave the system within the entire river channel, with the effects extending beyond the 1000 m downstream distance, then the economic loss to the system from thermal pollution would be greater than expressed in Section 4.3. In locations where fish populations are larger or more valuable (e.g., Lake Erie Yellow Perch), and/or power plant-produced thermal pollution is greater, the monetary damages might approach the same order of magnitude as power generation revenue loss.

The tradeoff between power generation, with potentially several orders of magnitude greater revenue as compared to equivalent fish population loss, highlights why regulations, such as the CWA §316(a), are necessary. If left to market devices alone, power plants would have little to no incentive to monitor or reduce thermal pollution in waterways. Regulations that protect aquatic life are typically enacted with a holistic ecosystem view in mind, as opposed to discrete monetization of individual species or communities. In fields such as ecosystem services (refer to A.1), the value of an ecosystem as a whole is greater than the sum of the parts. Furthermore, regulations have been shown to boost the economy. A study of 10 years of federal regulations showed that the net benefits of environmental regulation outweighed the implementation costs and associated fines to industry (Spross, 2013). Additionally, regulations can serve as the drivers of efficiency and innovation (Johnstone et al., 2017), such that more environmentally-friendly technologies are created to meet/avoid regulations. Proactive assessment of ecosystem goods and services will be possible, potentially reducing the retroactive costs of environmental conservation and mitigation efforts. This valuation provides a tool for analysis, and direct comparisons between operational conditions (temperature of intake versus effluent) can be weighed against holistic ecosystem valuation. Adding to TDCs as a tool for RMZ definition (Logan and Stillwell, 2018b), PHDCs provide another method by which decision-makers can assess current conditions at a power plant, and compare those conditions to predicted or scenario-based future conditions. Integration of PHDCs into regulatory decision-making is a worthy discussion point for future ecosystem valuation studies.

5.2.1. *Emission taxes as a policy tool for optimal tradeoff between electricity generation and fish populations*

Convincing power plants (or the large-scale companies that own them) to pay for damages caused to local aquatic ecosystems from thermal pollution would be challenging. Even with an associated ecosystem services component, climate change predictions, and environmental sustainability, what incentives do power plants have to reduce pollution? Likewise, people have less incentive to reduce environmental damages in the present as the social cost will be incurred by future generations (Hanley et al., 2007). To provide such incentives, a market approach, with an appropriate monetization scheme, might be necessary. Though regulatory standards were favored prior to the 1970s, a shift in thinking towards market-based approaches has since occurred (Li and Shi, 2017). In a market approach, economic variables become the incentive to reduce pollution (Callan and Thomas, 2010). As such, value is assigned to an environmental aspect (in this work, fish populations are used as a proxy for aquatic ecosystem sustainability), and thus a price is assigned to environmental pollution. Though four types of market-based instruments exist, a common one is the pollution charge, which falls under the "polluter-pays principle" in economic theory (Callan and Thomas, 2010).

A special type of pollution charge is the product charge, which is essentially a unit charge on a good (e.g., electricity) from which the production generates an externality (e.g., loss to fish populations from thermal pollution). An alternative to a product charge is an emission charge. An emission charge is a price per unit of pollution (e.g., temperature increase from thermal pollution), that leads polluters to internalize the externalities of production so they are economically incentivized to lower pollution emissions (Hanley et al., 2007). From an economic standpoint, if a power plant is charged a certain tax per increase in temperature above ambient (ΔT), then the power plant can choose to pay those taxes or invest in pollution abatement strategies (e.g., a cooling tower), and thus the power plant will choose a welfare maximizing investment in cooling technology. Transaction costs would include considerations like increased need for regulatory reporting, and additional workforce and/or equipment to monitor (ΔT) in a more complete fashion than is currently reported. Using a tax, there is the potential for power plants to pass through additional costs to consumers by increasing electricity prices. That provides consumers with appropriate incentives to reduce the electricity use that leads to environmentally damaging power production.

An emission tax could be applied at the power plant level using tools such as temperature duration curves (Logan and Stillwell, 2018b) or population habitat duration curves for economic tradeoff analysis. A power plant could be assessed for current ambient TDC and above ambient TDC conditions, and a certain desired percentage change above ambient TDC conditions could be taxed as an incentive to reduce thermal pollution. Alternatively, the value of local aquatic populations could be assessed via the methods outlined in this work, and a direct tax that matches the loss in value of local fish populations could be assessed. This tax approach assumes a system with perfect information. Additionally, productivity (e.g., electricity generation), even within the United States, is widely dispersed between a range of power plants with unique operating and localized conditions. When dealing with productivity dispersion, the response to environmental taxes might differ greatly (Li and Shi, 2017). A tax, while effective at internalizing the environmental damages of pollution to the company-level instead of the damages being externalities, does increase the marginal cost of production in an effort to induce abatement (Li and Shi, 2017). Thus market forces will interact such that the marginal cost of electricity will become a driver of how much electricity is produced, and by which producers (e.g., thermal polluters vs. non-thermal polluters). The shift in production caused by a thermal pollution tax might be similar to how other forces, such as fuel costs and air pollution externalities, affect the levelized cost of electricity, especially from a policy perspective (Rhodes et al., 2017).

6. Conclusion

Using a meta-analysis of fish population and temperature data, the creation and application of population habitat duration curves (PHDCs) using the Shawnee Fossil Plant on the Ohio River as a study site was demonstrated. In particular, comparison between ambient river conditions and two thermal effluent plume conditions, empirical conditions from data where $\Delta T = 6.9$ °C, and a scenario of thermally reduced conditions where $\Delta T = 5.8$ °C, highlighted the availability of temperature as a resource. The results show that for the fish population, 31% of the temperature resource becomes unavailable under plume conditions. For thermally reduced conditions representing a lower ΔT, 22% of the temperature resource becomes unavailable. PHDCs demonstrate the effect thermal pollution can have on aquatic populations.

In planning and management settings, PHDCs can be incorporated into habitat and population monitoring where temperature is a resource of concern (e.g., as a quality metric, or resource quantity metric). Comparison of populations in climate change scenario analysis could serve to inform decisions made now, which will impact waterways in the future. PHDCs can aid in regulatory mixing zone analysis by serving as a quantifiable metric to set site-specific expected population and/or temperature guidelines.

As a specific application of PHDCs, a dollar value was applied to the increase in expected fish populations over the summer season when shifting from plume conditions to thermally reduced conditions as compared to the value of power plant electricity generation. Decreasing thermal pollution by 1.1 °C increased the summer value of the fish population by $338. With the same shift in thermal pollution (all other power plant operational conditions remaining constant), economically the expected loss in electricity generation was valued at $5,450,000. Scaling the method to a full aquatic community and incorporating non-use value and habitat-based replacement cost values for fish could prove to place the economic value of electricity generation and aquatic ecosystem populations closer in comparison. Additionally, PHDCs could serve useful in scenario analyses of the tradeoffs in power plant discharge flow rates and thermal pollution (ΔT), particularly under climate change scenarios. Furthermore, PHDCs provide a proactive method to value fish as opposed to reactive valuations (e.g., after fish kill events), after which conservation efforts might be less effective.

CRediT authorship contribution statement

Lauren H. Logan: Conceptualization, Methodology, Software, Data curation, Formal analysis, Writing - original draft, Writing - review & editing. **Rohini S. Gupta:** Conceptualization, Software, Data curation, Writing - original draft, Writing - review & editing. **Amy Ando:** Conceptualization, Writing - review & editing. **Cory Suski:** Conceptualization, Writing - review & editing. **Ashlynn S. Stillwell:** Conceptualization, Writing - original draft, Writing - review & editing.

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. Supporting Information

Additional details on natural resource economics, population and temperature data, and thermal performance curves (TPCs), are included in this appendix.

A1. Ecosystem services and benefits transfer methodology

Krugman and Wells (2005) state that the most serious external costs to modern lifestyle are those associated with environmental damages (e.g., loss of ecosystem functions and/or resources). Many studies focus on ecosystem services as a metric by which society can monetarily value an ecosystem and its resource flows (Boyd and Banzhaf, 2007). Recent work by Hanes et al. (2018) incorporates ecosystem services into the food-energy-water nexus, demonstrating the need for such tradeoff analyses in the nexus space. Inherently, ecosystem valuation involves tradeoffs between society and nature, often with sustainability as a component of human welfare (Farber et al., 2002). Furthermore, the tradeoffs between ecosystem services and economic services cause much of the debate surrounding valuation of the ecosystem (Bolgrien et al., 2005). Decision-making concerning water resources in particular has often relied upon the inclusion of cost-benefit analysis, but with increasingly visible and pressing externalities, such analyses are becoming inherently more complex (Freeman III et al., 2014).

Natural resources and environmental attributes provide flows of services to people, such as a commercial fishery in a resource-rich water body (Freeman III et al., 2014). Here it is noted that in the context of fish in a river, an ecosystem service is the “fishability” of the river, and fish would be considered an ecosystem good (Bergstrom and Loomis, 2017). Furthermore, fish population trends, especially as evidenced by long-term monitoring programs, can improve fishery management plans (Lohner and Dixon, 2013), tying fish species directly back to biodiversity and ecosystem services via valuation methods. Bergstrom and Loomis (2017) found that 25% of river restoration valuations are focused on fish, further emphasizing the economic importance of fish in ecosystem valuation discussions.

Benefits transfer methodology, common for U.S. riverine ecosystems (Bergstrom and Loomis, 2017), is a useful method by which to quantify the value of fish in a river system. It is important to note that the total value of fish in a river includes use value and non-use value. The use value includes the on-site recreational benefit of fishing, consumption, and direct economic gains (e.g., commercial fishing), whereas the non-use value includes aspects like the benefit of knowing the fish exist in the river (Bergstrom and Loomis, 2017). Benefits transfer methodology has been commonly used within environmental regulation and policy since the 1980s, but current practices emphasize the need for value adjustments between studies (Freeman III et al., 2014).

Several methods exist for assigning monetary values to fishes and fish populations. Replacement cost is found as the cost of providing an ecosystem service using an artificial substitute for an element of nature that provides a naturally occurring ecosystem service (Sundberg, 2004). For fish, replacement cost is equal to the fishery/hatchery costs of adding an individual fish to a stream, such as in *Southwick & Lotfus 2017*. Applying nonmarket values obtained from one study to another study (e.g., willingness to pay for recreational fishing at one lake to a study on another lake) is also common (Freeman III et al., 2014). Recreational use studies (e.g., creel surveys) can provide insight into management strategies for fisheries (Schell et al., 1996), while providing fish population and popularity information. Fish kill assessments, such as the procedures outlined in Southwick and Loftus (2003), can be used to economically quantify existing fish populations. Other methods for valuing recreational fishing include the travel cost method and contingent valuation (Cameron, 1992).

The overall concept of benefits transfer is highlighted here to provide additional background for the use of fish kill assessments and replacement cost in this study. The true social value of an incremental amount of a natural resource is defined as marginal WTP; in the case of fish, that is the maximum amount of money people would be willing to pay to increase the population of the fish by one unit. Marginal WTP can be estimated with stated preference valuation methods that use hypothetical survey questions, or revealed preference valuation methods that use data on actual human decisions such as where and how much to go fishing. The estimate in Johnston et al. (2006) use revealed preference methods to estimate use-value marginal WTP for having one more fish.

A2. Power plant and river data

Data for the Shawnee Fossil Plant (SFP) were collected from the Energy Information Administration (EIA) forms 767 and 923. Such data included the intake temperature and effluent temperature, reported (1985-2009) or interpreted (2010-2014) as a seasonal (summer) maximum. Cooling water discharge flow rates were also utilized, reported as yearly averages in forms 767 and 923. In total, 26 years of data were available and feasible as reported by the EIA (1985-2014), with the year 2014 being the most recent year available in entirety at the time of this study.

River data were collected from the United States Geological Survey stream gage (gage no. 03611500) located at Metropolis, IL, within two miles upstream of the SFP. Average seasonal (summer) discharge, paired to match the years of feasible data for the SFP, was used in this study. Simplifying assumptions to complete CORMIX runs were made for the river including a Manning's n of 0.025, average wind speed of 2 m/s, and a rectangular river cross section with variable depth and fixed width (1220 m), as is consistent with Logan and Stillwell (2018a). River channel geometry followed continuity using the fixed width, discharge and rating curve (USGS stream gage data), and velocity data from the Ohio River Valley Water Sanitation Commission (ORSANCO).

To determine the plume geometry and mixing dynamics for each year of data, CORMIX software was utilized. CORMIX is considered to be an empirical model, as data input is grouped and used to identify relationships among variables (Davis, 1999). Using empirical data input, CORMIX completes length scale analysis to classify flow and determine the correct hydrodynamic equations for plume trajectory. In general, length scale models assess the comparative importance of variables of force, in length terms, and based on those comparative relationships, classify flow (Davis, 1999). CORMIX assumes steady state conditions, unless otherwise specified by the user, for mixing behavior, as well as turbulent mixing conditions (e.g., sufficiently large Reynolds number) (Doneker and Jirka, 2007).

A3. Population data

Fish population and water temperature data, at the Shawnee Fossil Plant, from the Electric Power Research Institute's (EPRI) Ohio River Ecological Research Program (ORERP) were used. ORERP produces yearly studies at power plant locations, with particular interest in thermal pollution and fish populations. Years in which the SFP was studied include 2005, 2006, 2007, 2009, 2012, 2014, and 2015 (Electric Power Research Institute, 2007; 2008; 2009a; 2012; 2014; 2016; 2017).

Within each yearly ORERP study, three upstream and downstream sampling events were completed, typically in June, August, and October (though in 2009, the sampling months were June, August, and November for certain data at the SFP) (Electric Power Research Institute, 2012). Using data from June to October is consistent with past work on the Ohio River by Thomas et al. (2004). To avoid complication from inclusion of two cold-water data points in the analysis, the data from November for 2009 were removed for the meta-analysis completed in this work. Additionally, only electrofishing data were used, which were collected in 500 m sections. For consistency in data analysis, only the catch events that were conducted using boat electrofishing were analyzed.

Population data in the EPRI reports are presented in a variety of ways, with catch per effort (CPE, # /km) presented for upstream and downstream sampling. In the results section, values for plume and ambient conditions were reported. As CPE values were reported as number of individuals per km, the TDCs presented in this work are for a 1000 m (1 km) downstream distance.

A4. Additional population information from literature

The Shawnee Fossil Plant is located in Ohio River navigational Pool 53 (Illinois Department of Natural Resources, 2017), informing additional fish population information. A report by Henley (1995), using 1978-1987 data, noted that Pool 53 had one of the largest fish biomass estimates, due to suitable flood plain and channel topography. Mean creel survey values per pool in the Ohio River, reported by Henley (1995), varied in range depending on the species. Fish per acre values are also reported by Henley (1995), and specific to Pool 53, the most common species is Gizzard Shad at over 14,000 fish/acre, and Bluegill and Drum are also abundant at 170 and 207 fish/acre, respectively. In the EPRI meta-analysis, Gizzard Shad, Threadfin Shad, and Emerald Shiner were removed from total population counts, as the young-of-year (YOY) for those species appear as relative population boons, unrelated to the overall community composition and makeup of the remaining fish community. EPRI provides such normal community level population counts as CPE, and the ORERP analyses include data with and without Gizzard Shad, Threadfin Shad, and Emerald Shiner. In Henley (1995), species of interest like Largemouth Bass and Black Crappie have expected populations of 22 and 63 fish/acre, which is much smaller than the expected value for Gizzard Shad. As such, the removal of the three YOY populations is justifiable when concerned with stable, economically viable populations of fishes of interest.

Converting the study site area of 1000 m downstream distance (length of river) with a river width of 1,220 m (width of river) gives a total study area of approximately 1,220,000 m^2. A study of fish abundance on the Ohio River using hydroacoustic estimates by Hartman et al. (2000) found that total fish populations ranged from 11,543 to 14,962 fish per 6,130.5 m^2 lock chamber. Scaling these values to the total study site (1,220,000 m^2), the population range is 2,297,000 to 2,977,000 total fish. A Preston and White (1978) study reports 181,000 total fish for the lower reach of the Ohio River (using the Smithland, no. 50, and no. 52 locks), providing further insight into expected population ranges for fish. Note that the numbers reported in Hartman et al. (2000) were for lock chambers on the upper Ohio River, not at Pool 53. Overall, literature values for expected fish populations vary widely, presumably due to sampling methods, timing, and other factors. The literature values reported above are merely presented as additional information, with the potential for incorporation into future population assessments and/or as scaling factors.

A5. Temperature and other biological/physicochemical data

In addition to temperature readings upstream and downstream of power plant outfalls, data collected for ORERP studies included habitat characteristics (e.g., percent boulder, cobble, gravel, and sand), specific conductance (μS/cm), mean monthly flow (cfs), water clarity (mm), and dissolved oxygen (ppm). In each year, correlation analysis was completed between CPE as well as biomass and temperature, habitat characteristics, and river flow. Individually, some years show positive, neutral, or negative correlation between fish population and temperature. In completing the meta-analysis, the linear regression of population as a function of temperature was significant ($p = 0.02$). Thus interannual data might be capturing large-scale trends over time, whereas intrannual sampling might be more dependent on specific seasonal influences within the habitat.

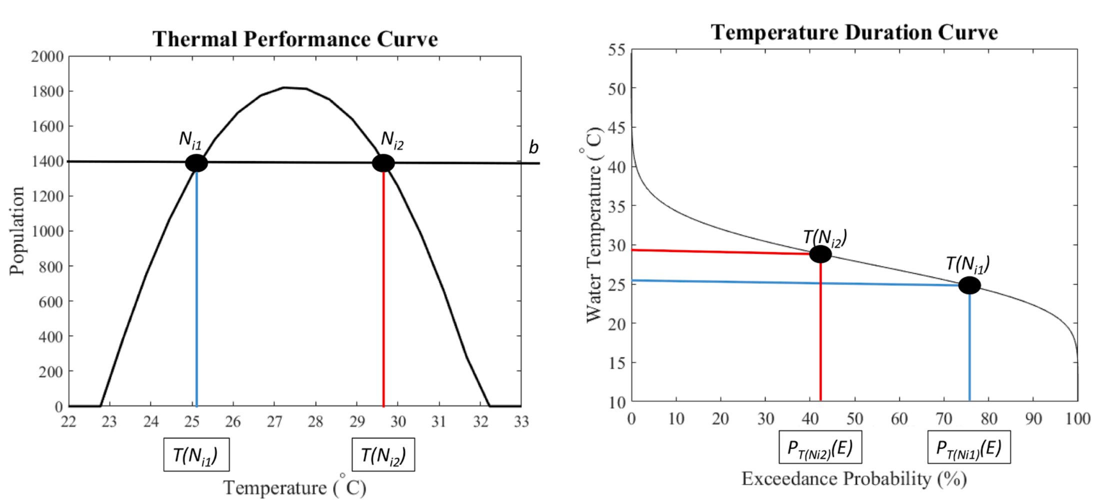
The significance of intrannual upstream versus downstream differences in dissolved oxygen, flow, water clarity, and specific conductance also varied year to year in the ORERP reports at the SFP. Completing a linear regression on dissolved oxygen, flow, clarity, and specific conductance versus population for all years of available data (less the November data points from 2009), following the same approach as for temperature versus population, the relationship between flow and population was found to be significant ($p = 0.03$, $R^2 = 0.11$). Water clarity did fit a second order polynomial (inverted parabola) trend ($R^2 = 0.11$), but the trend was not significant ($p = 0.12$). Thus flow and temperature were considered to be the most important factors affecting fish population at the SFP within the interannual meta-analysis conducted.

For the purposes of demonstrating the effect of temperature on population, temperature was isolated as the variable of interest for use in the creation of PHDCs from TPCs and TDCs. A study by Lessard and Hayes (2002) found temperature to be the most important predictor of fish species richness within Michigan waterways affected by small dams. Henley (1995) noted that for some species with lower thermal tolerances (e.g, Striped Bass), temperature appeared to impact the number of older individuals in sampling events during summer collection. Rijnsdorp et al. (2009) also discuss the effects of temperature on fish populations, but note that at the community level, changes in population as a result of temperature changes could be indicative of trophic interactions among species within the community.

A6. Thermal performance curves

The inclusion of Fig. A.6 is for reference for differently-shaped TPCs (such as an arbitrary parabolic TPC). In literature, TPCs can take many shapes, with a curve resembling an inverted parabola (with gentle upward trend toward the optimal temperature and rapid decline past the optimal temperature) being commonly reported (Schulte et al., 2011). In the main text, the TPC was linear in shape. It is possible that by including only the months of June, August, and October in the meta-analysis of population versus temperature, that the linear TPC is actually the trailing end of a larger, inverted parabola-shaped TPC. However, such conjecture is not warranted given the unavailability of winter-time population and temperature data for the study location, particularly given that summer (e.g., warm water temperatures) is the season of interest.

The TPC generated in this work is not necessarily indicative of mortality rates due to temperature, but rather relates the likelihood of finding fish. The meta-analysis of EPRI data reveals small population values for the location of interest, and could be an artifact of sampling methods or conditions. Note that in reality, many species coexist at the location of interest, with varied and overlapping species-specific TPCs, and potentially larger population values than were captured in EPRI data collection could be present. Additionally, care should be taken when using TPCs, particularly in climate change studies (as suggested in Section 5.1), with regard to the time scale of interest as well as the shape of the TPCs (Schulte et al., 2011). The meta-analysis in this work is intended to inform the generation of TPCs, but the focus is on the method development and usefulness of PHDCs in economic analyses.



(a) TPC (b) TDC

Fig. A1. Graphical representation of the creation of a population habitat duration curve (PHDC) from a a) parabolic thermal performance curve and b) temperature duration curve is shown, following Eqs. 3a and 3b. To find the $P(E)$ value associated with a given population threshold b (equivalent to population value at N_{i1} and N_{i2}), the probability of being between the temperature range $T(N_{i1})$ and $T(N_{i2})$ corresponding to N_{i1} and N_{i2} is found by solving Eqs. 3a and 3b. In this example, the population value $b = 1400$ is met or exceeded approximately 33% of the time ($P(N_{ij} \geq 1400) = 0.33$, or 33%).

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.ecolmodel.2020.109373

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