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Estimating lentic recreational fisheries catch and effort across the United States

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Abstract

Recreational fisheries represent a socially, ecologically, and economically significant component of global fisheries. The U.S. Inland Creel and Angler Survey Catalog (CreelCat) database includes inland recreational fisheries survey data across the United States to facilitate large-scale analyses. However, because survey methods differ, a statistical method capable of integrating these surveys is necessary to assess patterns and relationships across regions. Here, we developed a hierarchical generalized linear mixed modeling approach to estimate the relationship between daily recreational fisheries catch and effort based on waterbody, socio-economic, and ecological covariates. We applied this approach to CreelCat data on lentic waterbodies and found that recreational fisheries catch and effort were non-linearly related (i.e., catch per unit of effort declined as effort increased), where effort varied regionally and by waterbody area, median county age, and distance to nearest primary road. This modeling approach could be used to inform data-poor regions or waterbodies, make comparisons across spatial scales, and, with the inclusion of socio-economic and ecological factors, inform management techniques in an era of shifting demographics and landscapes.

KEYWORDS
angling, creel surveys, fisheries management, freshwater fisheries, inland fisheries, socio-economic drivers

1 | INTRODUCTION

Recreational fishing is an important social and economic activity in many countries worldwide with an average global participation rate of approximately 10% (Arlinghaus et al., 2015). Given this high rate of participation, recreational fisheries have a substantial macroeconomic impact. For example, marine recreational fishers in Europe are estimated to have annual expenditures of €5.9 billion (Hyder et al., 2018) and the total economic impact of fishing in the U.S. is estimated at US$129 billion and 826,000 U.S. jobs when service industry jobs and other angling-associated expenditures are included (ASA, 2020). From a social perspective, recreational fishing can be enjoyed across ages, genders, races, and socio-economic statuses to provide a variety of angling opportunities to a diverse angling population (Connelly et al., 2001). Recreational fishing also strengthens social values and connections to provide a link to the outdoors and a sense of place and belonging in challenging times (Hailu et al., 2005; Hunt, 2008). During the COVID-19 pandemic, anglers viewed fishing as a safe activity by "Social fishtancing," (i.e., fishing alone or with friends and family at a safe distance; Midway et al., 2021) that benefits both physical and mental health (Howarth et al., 2021). Therefore, the importance of recreational angling goes beyond just catching fish and providing a valuable social and economic activity. Recreational fisheries in the U.S. are generally managed at the state level, using variable techniques that yield non-uniform metrics, which challenges understanding of the social-ecological implications and sustainability of recreational fishing at the landscape, regional, and national scales.

Social and physical environments surrounding recreational fisheries are constantly changing. Recreational fisheries increasingly face threats (e.g., climate change, overexploitation), meanwhile angler communities are becoming more urban and diverse in language and culture (Arlinghaus et al., 2002; Murdock et al., 1996). Managing inland fisheries to meet the needs of a changing angling public under new conditions will require an understanding of how large-scale changes affect local systems (Hunt et al., 2016). Despite the growing recognition that recreational fisheries are complex social–ecological systems, which operate across large scales and a variety of disciplines (Nieman et al., 2021), regional and national scale analyses have been mostly limited to extrapolations of angler expenditures (e.g., ASA, 2020). While expenditure reports are valuable for highlighting the economic and conservation importance of inland recreational fishing, they reveal little about the true scope of national catch, harvest, and fishing effort, among other metrics important for management. Now, more than ever, in an age of "big data" (Whittier et al., 2016), demand for regional and national integration of recreational inland fisheries data is growing. Cross-state comparisons can inform larger-scale research efforts and facilitate coordinated management practices (Midway et al., 2016).

Angler (creel) surveys are frequently used by natural resource management agencies to collect recreational angling data via on-site angler interviews, dockside intercept surveys, and angler counts at waterbodies. Interviews with anglers collect information related to catch and harvest, angler characteristics, and effort, while angler counts are used to estimate fishing pressure (Pollock et al., 1994). The information collected via angler interviews can be expanded based on estimates of fishing pressure to generate waterbody-specific estimates of recreational angling effort and catch for an entire survey period. Although information captured by creel surveys is often used to address local management concerns, the ability to identify patterns among waterbodies at broader spatial and temporal scales is critical to advancing understanding of these systems. Recently, data from creel surveys across the U.S. were made publicly available in a database known as the U.S. Inland Creel and Angler Survey Catalog (CreelCat; Lynch et al., 2021; Sievert et al., 2023; Sievert & Lynch, 2023). The CreelCat database provides access to detailed information characterizing angler catch and effort at the waterbody level. However, because creel survey methods often differ among surveying agencies, a method capable of integrating surveys is necessary to assess patterns and relationships across regions.

Our objective was to determine if creel surveys of differing designs could be integrated to estimate the relationship between angling catch and effort, along with the external factors driving angling effort, across multiple U.S. state jurisdictions. We used a hierarchical generalized linear mixed model to estimate the relationship between daily recreational fisheries catch and effort at a national scale. Our model accounted for survey design by including regional, latent random effects and tested the influence of waterbody, socio-economic, and ecological covariates on fishing effort. The model was developed using 2103 creel surveys from 18 states in six of seven U.S. National Climate Assessment-designated regions (USGCRP, 2019) that represented the largest integration of the U.S. creel surveys to date.

2 | MATERIALS AND METHODS

2.1 | Modeling approach

A hierarchical generalized linear mixed modeling approach was developed to estimate recreational fisheries catch and effort based on local waterbody, socio-economic, and ecological covariates. The model used catch and effort data and was formulated based on the catch-per-unit-effort equation to estimate survey abundance,

$$C = qEN, \tag{1}$$

where C is catch, q is catchability, E is effort, and N is abundance (see review in Maunder & Punt, 2004). Often, catch-per-unit-effort is used to estimate waterbody-specific fish abundance based on estimates of catch, effort, and catchability. However, given that quantifying abundance was not the goal of this study, nor were fish abundance estimates available for the catch and effort data that were analyzed, Equation 1 was simplified to,

$$\log(C) = \log(q) + \log(E) + \varepsilon_C. \tag{2}$$

This formulation assumes a linear relationship on a natural log-scale between catch and effort that is modified by catchability and observation error of the catch (ε_C). Although $\log(N)$ was dropped, variability contributed by abundance to the relationship between catch and effort would be included in ε_C. To test and account for uncertainty in linearity of the relationship between catch and effort in original measurement scales, Equation 2 was modified as,

$$\log(C) = \log(q) + b\log(E) + \varepsilon_C, \tag{3}$$

where $b = 1$ quantified linearity, $b < 1$ would indicate saturation in catch with effort, and $b > 1$ would indicate a disproportionate increase in catch with effort (i.e., facilitation).

The log of waterbody-level fishing effort could be described by a linear combination of local covariates,

$$\log(E) = \beta_0 + \beta_{i \ldots n} X_{i \ldots n} + \varepsilon_E, \quad (4)$$

where β_0 is an intercept, $\beta_{i \ldots n}$ are slopes of relationships with covariates i, $X_{i \ldots n}$ are covariates, and ε_E is effort observation error. This equation was the first level of a hierarchical model, where effort estimates were used to estimate catch in the second level of the model via Equation 3. Observation errors from Equations 3 and 4 were both assumed to be independent random variables from normal distributions with mean 0. By estimating both log(C) and log(E) and propagating uncertainty from both variables into final model estimates, the hierarchical model was an errors-in-variables approach, with uncertainty in response and predictor variables (Aljafary et al., 2019; Hilborn & Walters, 1992). This approach should be less biased for estimating the relationship between catch and effort than if all variation was attributed to the response variable.

The relationship between catch and effort may vary among regions, which was accounted for by estimating b as a latent random effect (r),

$$\log(C) = \log(q) + b_r \log(E) + \varepsilon_C. \quad (5)$$

This parameterization would examine whether the shape of the relationship between catch and effort varied as a result of regional fish population characteristics and fishing strategies. Regional variability was incorporated into effort estimates by estimating an intercept as a latent random effect,

$$\log(E) = \beta_{0,r} + \beta_{i \ldots n} X_{i \ldots n} + \varepsilon_{E.} \quad (6)$$

This parameterization estimated a variable base level of fishing for each region where fishing occurred. This equation could be parameterized to allow regional variation in effects of covariates, but these parameters would likely be more difficult to estimate and could lead to erroneous values based on small waterbody sample sizes in some regions. The base level of fishing and shape of the relationship between catch and effort could also both vary regionally, although attempts to model both of these parameters as latent random effects failed due to convergence problems. Regions examined were based on regions defined in the U.S. National Climate Assessment (USGCRP, 2019), to represent social and environmental differences and to provide a framework for future modeling climate effects on recreational fisheries (Table 1; Figure 1). Multiple comparisons testing with Bonferroni corrections was used to quantify differences between latent regional random effects (Midway et al., 2020).

The Template Model Builder (TMB, Kristensen et al., 2016) package in R (R Core Team, 2022) was used to evaluate negative logarithms of marginal likelihoods (nll) simultaneously for both models (Equations 3–6) and the data, and to evaluate nll gradients. Further, the R function nlminb() was used to find maximum likelihood estimates of all parameter values.

2.2 | Recreational fisheries data

Recreational fisheries catch and effort data from lentic waterbodies (e.g., lakes, ponds, impoundments) were from the CreelCat database (Lynch et al., 2021; Sievert et al., 2023; Sievert & Lynch, 2023). Data consisted of creel survey data collected by state agencies throughout the U.S. Creel surveys used angler counts and interviews to estimate waterbody-level catch and effort for a survey period. Regions were included if they had at least 10 creel surveys, which resulted in 18 states being included (see Table 1; Figure 1). For simplicity and comparability, catch and effort data were aggregated across taxa and catch and effort were divided by survey duration to obtain daily estimates. Surveys varied in their duration (minimum survey length = 14 days, maximum survey length = 395 days), timing (e.g., summer, winter), and occurred across a range of years (earliest year = 2000, latest year = 2022). These temporal characteristics may introduce non-random variation in catch and effort both within and across surveys, however, for the purposes of this study, mean daily catch and effort were assumed to be representative across survey periods and years. Surveys that targeted a specific species were removed because such surveys could bias estimates of total catch and effort on a waterbody by anglers. To minimize autocorrelation between the samples and the risk of one waterbody characterizing a larger region, the number of surveys that could be included from a single surveyed area was limited to five. If more than five surveys from a surveyed area were in the database, the five most recent surveys were retained. Furthermore, any surveys conducted prior to the year 2000 were removed to minimize overweighting model estimates with states possessing disproportionately long time-series.

2.3 | Covariate data

To quantify the influence of local, waterbody-level covariates on effort, surveys were connected to associated waterbodies as polygons. Most waterbodies could be attributed to polygons within the National Hydrography Dataset (NHD; Stachelek, 2019; USGS, 2021). In some cases, surveyed waterbodies were not delineated within the NHD, and therefore, needed to be created manually. Manual waterbody delineation was accomplished using aerial imagery acquired from the ESRI World Imagery Map Service (https://services.arcgisonline.com/ArcGIS/rest/services/World_Imagery/MapServer; accessed 2021–2022) to draw a polygon approximating the extent of a surveyed waterbody. For some surveys, the extent of a creel survey did not match the extent of a waterbody. When the extent of a survey and waterbody were mismatched, the boundary of the polygon was corrected to match the surveyed extent (i.e., polygon represented a partial waterbody that corresponded to the area included in the survey). Some surveys were attributed to multiple waterbodies, such as clusters of ponds (typically found in public parks) or chains of lakes in which anglers moved among them. When surveys occurred across multiple waterbodies, surveyed waterbodies were

TABLE 1 Number of surveys (Survey *N*), number of waterbodies (Waterbody *N*), number of years (year *N*), average number of surveys per year (Annual *N*), and average number of waterbodies per year (Annual Waterbody *N*) used to model the relationship between angling catch and effort in 18 states within the U.S.

Region	State	Survey *N*	Waterbody *N*	Year *N*	Annual *N*	Annual waterbody *N*
Midwest	Michigan	623	199	22	28.32 ± 19.58	27.70 ± 19.50
	Minnesota	377	209	18	20.94 ± 14.48	18.80 ± 12.90
	Wisconsin	414	270	23	18.00 ± 5.27	18.00 ± 5.27
	Total	1414	678	23	61.48 ± 20.14	59.20 ± 19.40
Northeast	Connecticut	85	40	16	5.31 ± 4.13	4.81 ± 3.29
	Massachusetts	3	1	3	1.00 ± 0.00	1.00 ± 0.00
	Vermont	12	6	4	3.00 ± 0.82	2.50 ± 1.29
	Total	100	47	17	5.88 ± 5.05	5.29 ± 4.27
Northern Great Plains	Nebraska	45	14	6	7.50 ± 1.87	7.50 ± 1.87
	North Dakota	32	9	11	2.91 ± 1.64	2.18 ± 0.98
	South Dakota	77	35	7	11.00 ± 6.08	9.71 ± 5.25
	Wyoming	4	4	3	1.33 ± 0.58	1.33 ± 0.58
	Total	158	62	17	9.29 ± 9.76	8.29 ± 8.85
Southeast	Arkansas	18	11	10	1.80 ± 1.03	1.80 ± 1.03
	Florida	157	43	15	10.46 ± 7.06	10.10 ± 6.86
	Kentucky	46	28	8	5.75 ± 1.91	5.25 ± 1.75
	Tennessee	67	29	4	16.75 ± 0.50	16.80 ± 0.50
	South Carolina	4	1	4	1.00 ± 0.00	1.00 ± 0.00
	Total	288	112	17	17.18 ± 17.22	16.60 ± 16.90
Southwest	Utah	27	23	10	2.70 ± 1.25	2.70 ± 1.25
Southern Great Plains	Texas	10	4	8	1.25 ± 0.46	1.25 ± 0.46
	Kansas	102	73	17	6.00 ± 4.08	5.88 ± 4.04
	Total	112	77	18	6.22 ± 4.57	6.11 ± 4.51
Total		2103	999	23	91.43 ± 39.23	87.50 ± 38.50

Note: Mean ± standard deviation are shown for numbers of surveys per year and numbers of waterbodies surveyed per year.

combined into multipart polygons to create a single record for multiple waterbodies. Total area of each spatial polygon was calculated to use as a covariate in the model. During model testing, relationships between waterbody area and fishing effort differed between Great Lakes creel surveys and non-Great Lakes creel surveys, which were explored using separate β_i between Great Lakes surveys and non-Great Lakes surveys.

Creel surveys were connected to the 2019 American Community Survey (ACS) census five-year dataset, which collects demographic data throughout the U.S., to examine socio-economic drivers of recreational fishing effort (Walker & Herman, 2021). Specific covariates were selected based on past evidence of their influence on recreational fishing effort (see Adams et al., 1993; Arlinghaus, 2006; Arlinghaus et al., 2015; Floyd et al., 2006, 2010). To quantify relationships between census covariates and recreational fishing effort, each survey waterbody was intersected with every overlapping county. The mean of census variables (Table 2) was then estimated for all overlapping counties for each waterbody to ensure that each surveyed waterbody had a single value for each associated census variable.

Land cover near waterbodies was also included as a covariate in the model. Land cover could affect fishing effort through a variety of mechanisms, by influencing the number of anglers (e.g., waterbodies within urban areas) or access to waterbodies (e.g., waterbodies surrounded by wetlands). Land cover data were acquired from the 2019 National Land Cover Database (NLCD) (https://www.mrlc.gov/data?f%5B0%5D=year%3A2019). The NLCD database provided 15 land cover classes for areas with CreelCat data: open water, developed open space, developed low intensity, developed medium intensity, developed high intensity, barren land, deciduous forest, evergreen forest, mixed forest, shrub-scrub, grasslands-herbaceous, pasture-hay, cultivated crops, woody wetlands, and emergent herbaceous wetlands. The proportion of land cover was calculated for each class within buffers around each waterbody. Buffers at two scales (100 m and 5000 m) represented how land cover affected fishing effort based on access (100 m) or broader socio-economic surroundings (5000 m). Due to the relatively large number of land cover classes, four cumulative land cover types reflected overall hypotheses: development (developed low intensity, developed medium intensity, developed high intensity), farms (pasture/hay, cultivated

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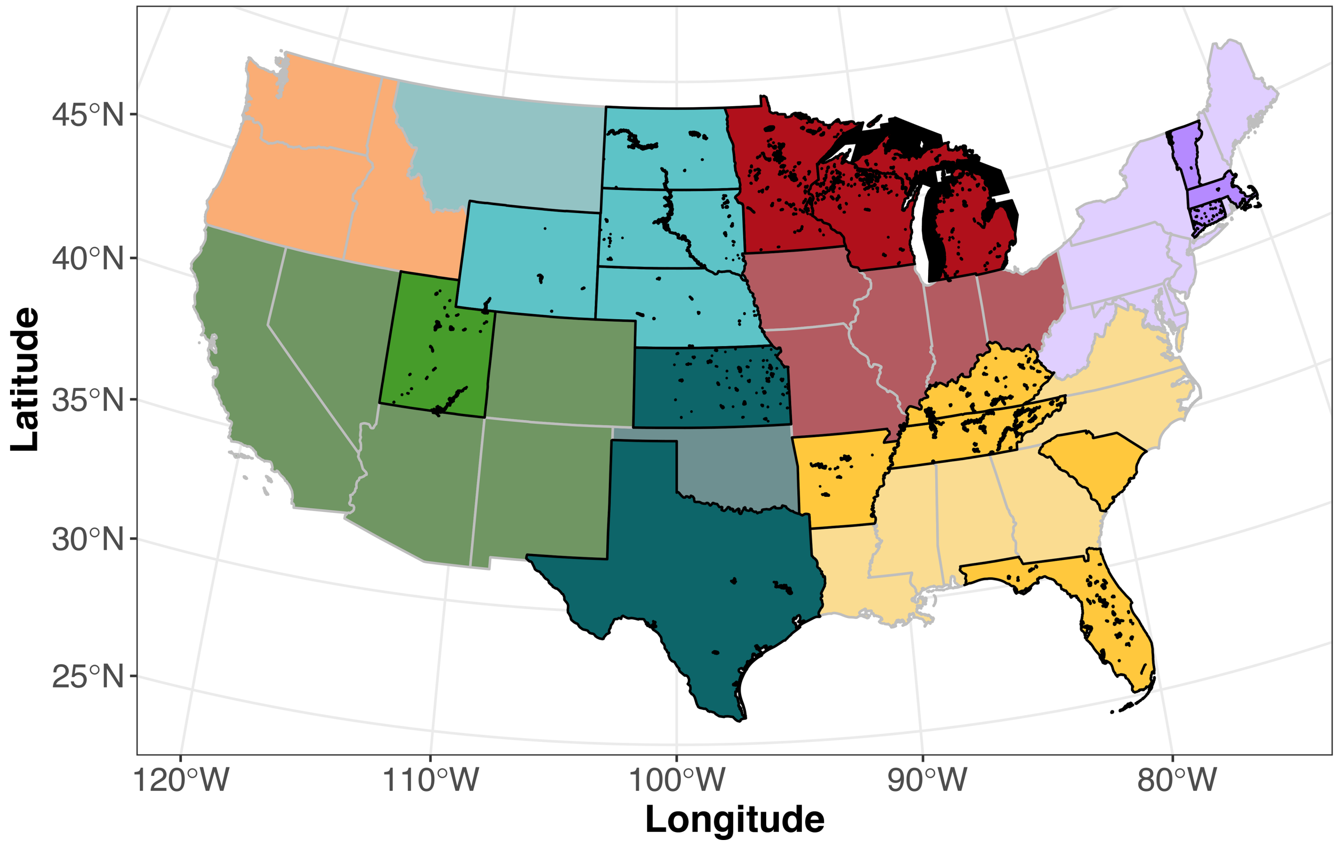

FIGURE 1 Map of states and waterbodies where creel surveys were used to model the relationship between angling catch and effort in 18 states within the U.S. Colors represent regions defined by the U.S. National Climate Assessment. States with faded colors had no data, while states with bright colors had data. Waterbodies with creel survey data are shown in black.

TABLE 2 Waterbody and socio-economic covariates used to model the relationship between angling catch and effort in 18 states within the U.S.

Symbol	Name	Description	Data source	Census code
A	Waterbody area (km^2)	Surveyed waterbody area	NHD	
PS	Population size	Total human population	ACS Census	B01003_001
MI	Median income	Median income in the past 12 months	ACS Census	B06011_001
MA	Median age	Median age	ACS Census	B01002_001
MH	Median household size	Average household size of occupied housing units	ACS Census	B25010_001
DS	Distance to road	Distance to nearest primary road	US Census Tiger	
DV	Development	Developed low, medium, and high intensity	NLCD	
FM	Farms	Pasture/hay and cultivated crops	NLCD	
FT	Forests	Deciduous, evergreen, and mixed forest	NLCD	
WT	Wetlands	Woody and emergent herbaceous wetlands	NLCD	

crops), forests (deciduous forest, evergreen forest, mixed forest), and wetlands (woody wetlands, emergent herbaceous wetlands). Distance from each waterbody boundary to the nearest primary road was used as a proxy for waterbody accessibility. The dataset for nearest main road was from the 2016 U.S. Census Tiger shapefiles dataset (https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html).

2.4 | Model selection

A stepwise model selection framework was used to identify the most parsimonious model. The framework was conducted in two steps, where model selection was based on Akaike information criterion (AIC), Bayesian information criterion (BIC), and model residuals to identify the most informative model for the observed data. BIC measured goodness-of-fit with specific emphasis on model simplicity, while AIC was a measure of prediction accuracy (Sober, 2002). A conservative cut-off of 10 AIC and BIC points was used to determine if the model criterion indicated improved fit (Richards, 2005). The first step sought to identify if including $\beta_{0,r}$ or b_r improved model fit. The second step used the best model from step one, in forward selection with 10 covariates (Table 2), with previously defined hypotheses (Section 2.3) to determine which covariates were most informative.

3 | RESULTS

The final dataset included 2103 surveys of 999 waterbodies from 18 states in six of seven U.S. regions from 2000 to 2022 (Table 1). The number of surveys and waterbodies surveyed differed among years (mean = 91.43 surveys per year, SD = 39.23; mean = 87.50 waterbodies per year, SD = 38.50). Survey duration varied, with 25 surveys of less than 30 days, 236 surveys of 31–90 days, 579 surveys of 90–180 days, 1157 surveys of 180–360 days, and 106 surveys longer than 360 days (Figure S1). The Midwest was the most surveyed region, with 1414 surveys from 678 waterbodies within three states across 23 years, while the Southwest was the least surveyed region, with 27 surveys from 23 waterbodies in one state (Utah) across 10 years. Surveyed waterbody areas ranged from 0.002 to 6579 km^2, with a high regional mean of 315.3 km^2 in the Midwest and a low regional mean of 20.4 km^2 in the Northeast. In the Midwest, 34.2% of surveys were in the Great Lakes.

The best-fitting model without covariates was the model with the effort intercept ($\beta_{0,r}$) estimated as a latent random effect (Effort intercept model; Table 3). The second-best fitting model estimated the linearity term as a latent random effect, *b* (Linearity-term model; ΔAIC = 281, ΔBIC = 280). Improved model fit for the effort intercept model, indicated by better fitting residuals by region (Figures S2–S4 and S5–S7), suggested that regional differences in the base level of fishing effort were more important than regional differences in the shape of the relationship between catch and effort. The Effort intercept model estimated a linearity term (*b*) that did not differ significantly from 1 ($b = 0.87$, 95% CI = 0.70–1.04).

The best-fitting model with covariates (Model C24) included log(waterbody area), with separate slopes for Great Lakes and non-Great Lakes surveys, median household age, and distance from the nearest primary road (Table 4). Model C24 had a substantially lower AIC and BIC (Table S1) and residuals than all other models (Figures S8–S11). Log(waterbody area) was positively related to fishing effort on non-Great Lakes waterbodies ($\beta = 0.537$, 95% CI = 0.515–0.559) and Great Lakes waterbodies ($\beta = 0.123$, 95% CI = 0.107–0.139; Figure 2), whereas median household age ($\beta = -0.040$, 95% CI = −0.046 to −0.034) and distance to primary roads ($\beta = -0.0023$, 95% CI = −0.0018 to −0.0028) were both negatively related to fishing effort.

The best-fitting model with covariates (Model C24) also fit the relationship between log(Catch numbers per day) and log(Effort hours per day) well, with an estimate of *b* that was significantly less than 1 ($b = 0.927$, 95% CI = 0.862–0.992; Figure 3), which indicated that catch saturated with increasing effort (Figure 4). The largest residuals from the relationship were for surveys with fewer effort hours per day that resulted in fewer catches than expected. The latent random regional effects for β also indicated that the Northeast ($\beta = 5.37$, 95% CI = 4.88–5.86) was the only region that differed significantly from another region (the Northern Great Plains, $\beta = 6.37$, 95% CI = 5.90–6.83; Figure 5).

TABLE 3 Comparison of models without covariates used to model the relationship between angling catch and effort in 18 states within the U.S. using Akaike information criterion (AIC) and Bayesian information criterion (BIC).

Model name	β_0	*b*	k	ΔAIC	ΔBIC
Effort intercept	**Latent**	**Fixed**	**4**	**0**	**0**
Linearity term	Fixed	Latent	4	281	280
Basic	Fixed	Fixed	5	394	400

Note: β_0 and *b* columns indicate whether those parameters were estimated a fixed effect or as a latent random effect, k is the number of fixed effects model parameters and Δ represents the difference in criterion score for a particular model from the model with the lowest criterion score. Table ordered from smallest ΔAIC to largest. Bolded text indicates the best fitting model (i.e., lowest AIC and BIC scores). Basic model refers to the model when no latent random effects were included.

TABLE 4 Comparison of models with covariates used to model the relationship between angling catch and effort in 18 states within the U.S. using Akaike information criterion (AIC) and Bayesian information criterion (BIC).

Model name	X_1	X_2	X_3	k	ΔAIC	ΔBIC
Effort intercept				4	2317	2295
C1	*A*			5	1426	1409
C2	A_{GL}			6	347	336
C6	MA			5	2135	2118
C15	A_{GL}	MA		7	76	71
C24	$\mathbf{A_{GL}}$	**MA**	**DS**	**8**	**0**	**0**
C22	A_{GL}	MA	MH	8	65	66
C21	A_{GL}	MA	PS	8	78	78
C26	A_{GL}	MA	FM	8	67	67

Note: All models use the same formulation as the Effort intercept model from Table 3. X_i represents the covariate included (see Table 2 for abbreviations; A_{GL} indicates a model with separate β estimates for waterbody area between Great Lakes and non-Great Lakes surveys), k is the number of fixed effects model parameters and Δ represents the difference in criterion score for a particular model from the model with the lowest criterion score. Bolded text indicates the best fitting model (i.e., lowest AIC and BIC scores). Results with land cover are only shown for the 100 m buffer because results were not substantially different with the 5000 m buffer. Models shown are meant to represent a range of model complexities and the magnitude of associated model criterion scores. Full results shown in Table S1.

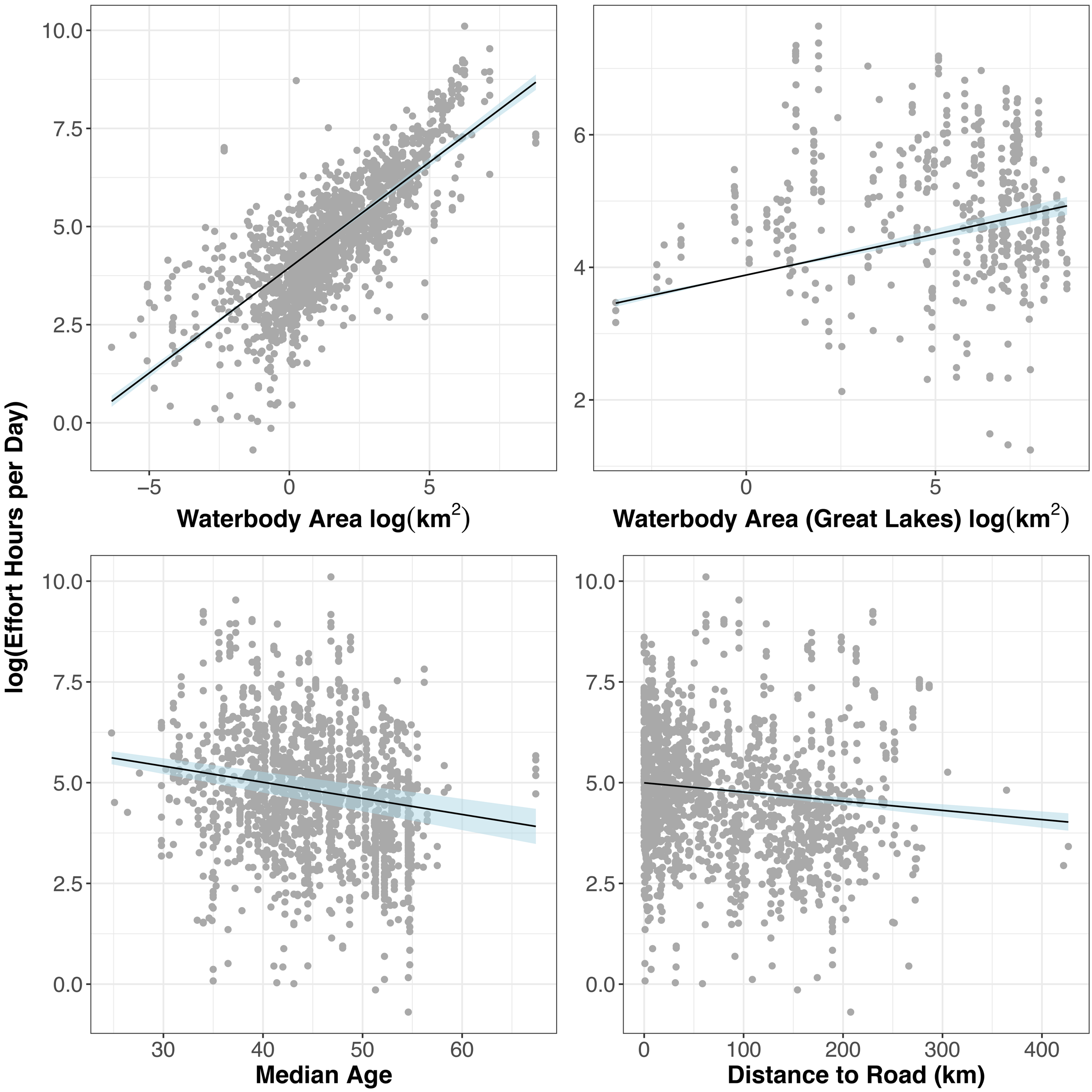

FIGURE 2 Relationships between log-transformed effort hours per day and waterbody area (non-Great Lakes and Great Lakes) median age, and distance to road, from model C24 in 18 states within the United States. Points represent data, black lines represent modeled relationships, and light blue polygons represent 95% confidence intervals around those estimates. Due to the larger number of samples from non-Great Lakes, represented data and model estimates for distance to road, median age, and log waterbody area do not include Great Lakes data.

4 | DISCUSSION

Despite differing creel survey methods (Pollock et al., 1994) and a wide geographic scale, we found that estimated catch did not increase linearly with fishing effort, but rather, catch per unit of effort declined as fishing effort increased. Recreational angling can substantially impact fish stocks and supporting ecosystems (Cooke & Cowx, 2004; Schafft et al., 2021), so assessing the magnitude of fishing effort and catch is important for developing sustainable fisheries management plans (FAO, 2012). However, the magnitude of fishing effort is simpler to quantify than catch, especially given recent technological advances that permit remote and automated angler counts (Dainys et al., 2022; van Poorten et al., 2015). We found that catch per unit of effort decreased as effort increased, like other studies (Aljafary et al., 2019). Therefore, catch-effort models that assume a linear relationship between macro-scale recreational

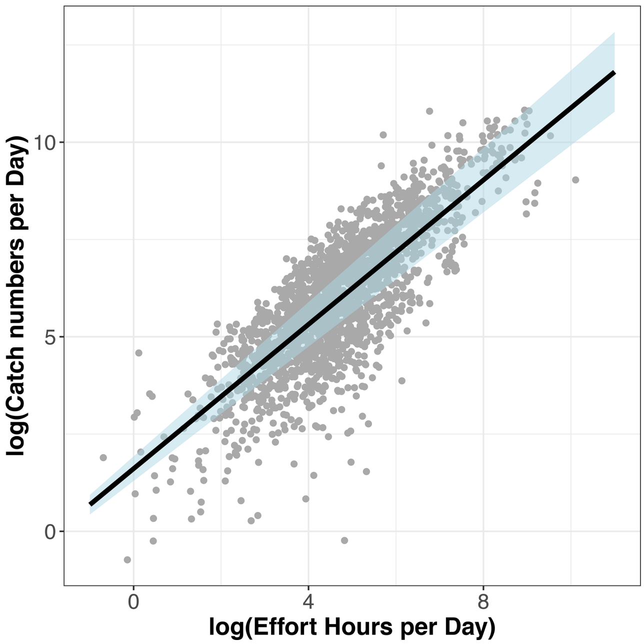

FIGURE 3 Relationship between log-transformed effort hours and catch numbers per day (Model C24) in 18 states within the United States. Gray dots represent individual data points, the black line represents the predicted relationship, and the blue polygon represents 95% confidence intervals around the relationship.

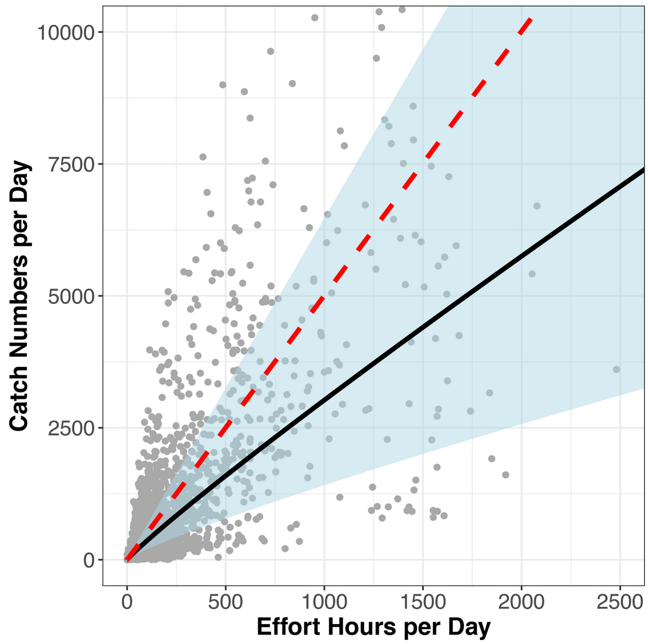

FIGURE 4 Relationship between effort hours and catch numbers per day (Model C24) in 18 states within the United States. Gray dots represent individual data points, the black line represents the predicted relationship, the dashed red line represents a linear relationship (i.e., $b = 1$), and the blue polygon represents 95% confidence intervals around the relationship. The *x* and *y*-axis ranges were reduced to include most of the data.

fishing effort and catch would overestimate catch, except when effort is small. Although local recreational fisheries can be dynamic due to local environmental and social conditions (Dundas & von Haefen, 2020; Fedler & Ditton, 1994; Midway et al., 2021), we found that when viewed across large scales, each hour of recreational fishing effort produced a relatively consistent catch [e.g., 1 h of fishing after 100 h of effort produces a catch of approximately 3.32 fish (95% CI = 1.67–6.54) and 2.82 fish (95% CI = 1.22–6.41) after 1000 hours of effort].

The non-linear relationship between recreational fishing effort and catch indicated that angling efficiency decreased with increasing angling effort, perhaps because of fish population characteristics or fishing effort dynamics (Harley et al., 2001). Catch-per-unit-effort is ideally proportional to fish density or abundance (Maunder & Punt, 2004), although many factors can invalidate this assumption (see Harley et al., 2001). Nonetheless, fish abundance estimates were not available for catch and effort data that we analyzed, and we assumed that the effect of fish abundance would be included in observation error. Alternatively, if the effect of fish abundance was not fully reflected in observation error (i.e., its effect is not normally distributed around zero), the shape of the relationship we found between catch and effort (e.g., increased effort reduces catch per unit of effort) may not have been accurate. Competition among anglers can cause catch per unit of effort to decline with increasing effort (Aljafary et al., 2019), usually when fish aggregate in ideal habitat that fishers target (Dassow et al., 2020). Increased fishing effort can cause congestion in such locations, and thereby lead fishers to target other locations where catchability is lower (Hunt et al., 2019; Parkinson et al., 2004). Finally, although the effect is likely not large enough to fully explain the pattern we observed, fish can avoid fishing gear after capture (Lennox et al., 2017), causing catch rates to decline in response to learning at high levels of effort in catch and release fisheries.

We found that fishing effort varied among regions and was driven by local socio-ecological covariates, perhaps in response to local culture, demographics, and urbanization (Arlinghaus et al., 2012, 2021; Fedler & Ditton, 2001). We found significant differences in angling effort among regions, with the lowest fishing effort in the Northeast. This finding is similar to previous analyses that showed Connecticut and Massachusetts had below average resident and non-resident angling rates (Adams et al., 1993). It is also possible that inland fishing pressure was lowest in the Northeast and Southeast because most surveys in those regions were from states along the coast, where residents also fished recreationally in coastal marine ecosystems.

Waterbody size was exponentially related to fishing effort in our study, similar to many other studies that found fishing effort was positively related to waterbody size (Hunt, 2005; Kane et al., 2022). The relationship between fishing effort and waterbody size may be the result of angler preference. For example, large waterbodies may yield higher catches because of more productive (Downing & Plante, 1993) and diverse fish populations (Amarasinghe & Welcomme, 2002), while simultaneously being less congested due to larger fishing area (Hunt et al., 2019). In contrast, recent research

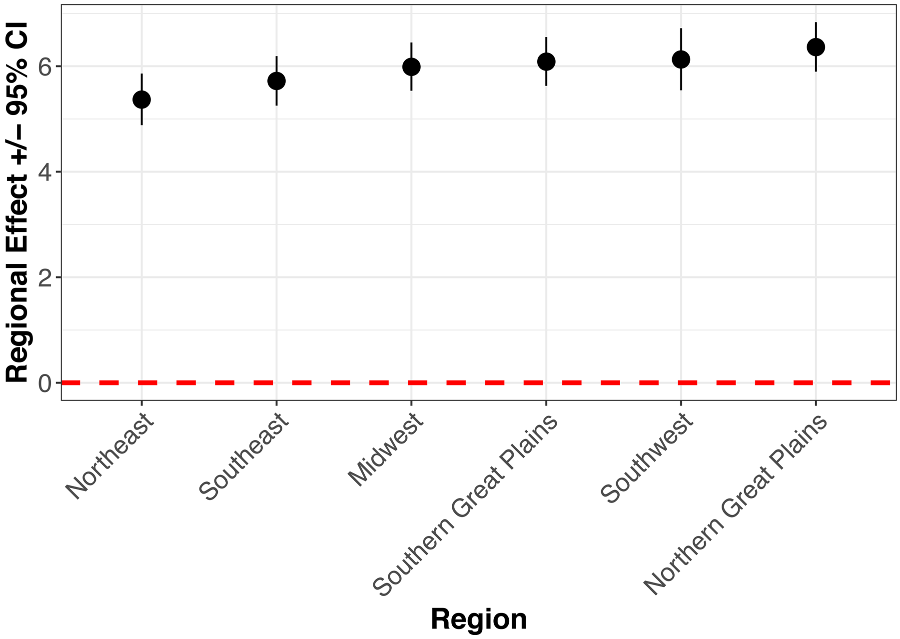

FIGURE 5 Latent effect of region of creel surveys on logarithmically transformed effort hours per day (Model C24) in 18 states within the United States. Points represent the model estimate of the effect, lines represent Bonferroni corrected 95% confidence interval around estimates, and the dashed red line represents zero.

has indicated that smaller waterbodies can receive greater angler effort (h/ha) and biomass stocked (kg/ha) than larger waterbodies per unit area (Kaemingk et al., 2022). We also found that the relationship between waterbody area and fishing effort differed between Great Lakes and other lakes, perhaps because Great Lakes anglers tend to target a relatively small number of taxa (Melstrom & Lupi, 2013). These highly targeted species (e.g., walleye *Sander vitreus*, Chinook salmon *Oncorhynchus tshawytscha*) tend to be spatially restricted (Dippold et al., 2020; Simpson et al., 2016), so the ratio between fished area and total area may be smaller than in non-Great Lakes fisheries. Further, accessibility to Great Lakes fisheries is more limited than non-Great Lakes waterbodies because of fewer available shore fishing opportunities or boat launches than other waterbodies. Finally, the different effect of waterbody area for Great Lakes creel surveys may also be related to differences in resources needed to engage in off-shore angling on the Great Lakes, where larger boats and specialized expensive gear is needed (Tanner & Tody, 2002).

We found that distance to primary road and median age were negatively related to recreational fishing effort, as we expected, because access and geographic proximity positively influence the likelihood of recreational fishing engagement (Arlinghaus, 2006; Hunt et al., 2019), along with participation in outdoor recreational activities (Hendee, 1969). Prior observations of a similar relationship between fishing effort and median age were hypothesized to be driven by reduced physical ability of old-aged anglers to spend time fishing (Walsh et al., 1989). In contrast, the relationship between age and fishing effort may not be straightforward, because life-style changes associated with aging could positively or negatively affect recreational behavior (see Arlinghaus, 2006).

Creel surveys are often used to gather information related to waterbody-specific management concerns, so the timing and location of creel surveys are often non-random (Lynch et al., 2021). Targeting specific waterbodies, possibly with unique management challenges, can bias estimates of recreational fishing effort and catch in relation to their applicability to other random waterbodies elsewhere. Furthermore, differences in sampling protocols (e.g., frequency of interviews, timing of surveys) likely affected our model estimates, which we attempted to account for as regional latent random effects, although other sampling effects would be worth examining at smaller spatial scales. Given the hierarchical structure of our approach, with uncertainty around both catch and effort, our estimates could be biased (Aljafary et al., 2019). If the approach we used were applied to smaller scale analyses, different relationships between catch and effort could be explored, where catchability may be more substantially impacted by target species (Mosley et al., 2022), angler skills and gear (Heermann et al., 2013), or by interference among anglers (Lewin et al., 2006).

The availability of spatial data for each CreelCat survey allowed integration with other large-scale spatiotemporal datasets, which also provides an avenue for further research on socio-ecological system dynamics outside the scope of what is typically collected by creel surveys (e.g., as discussed in Nieman et al., 2021). Although we found no evidence of relationships between fishing effort and land cover data, such relationships may be evident at finer spatial scales (e.g., regional, state). Furthermore, similar approaches could be extended to include many other types of spatially referenced data (e.g., climate projections) to understand the influence of many drivers on recreational fisheries dynamics. Integrating climate data could help to understand how climate change influences recreational fishers. For example, climate change will likely affect fish habitats and populations, environmental conditions that directly affect fishing effort, and mitigation and adaptation policies that could affect fishing effort (e.g., fuel prices; Hunt et al., 2016). Additionally, heat stress contributes to higher rates of post-release mortality (Gale et al., 2013), so integrated climate and creel data could be used to identify fisheries in need of supplemental management policies to protect against synergistic effects of high fishing effort and warming temperatures (Hunt et al., 2016).

Limited inland fishery data pose a challenge to creating effective, sustainable management regimes. A modeling approach with the predictive power to estimate inland recreational fishing catch and effort across local, regional, and national levels could be a powerful tool for informing management efforts, especially in data-poor scenarios, by leveraging regional angling similarities and socio-economic and ecological covariates to predict catch or effort in waterbodies with limited data. Currently, global inland recreational fisheries tend to be data-poor due to monitoring challenges associated with their seasonal and diverse nature (FAO, 2010). Poorly informed management regimes may result in adverse life history effects, high mortality rates, and even fishery collapse due to overfishing (Allan et al., 2005; Embke et al., 2019; Lewin et al., 2006; Post et al., 2002; Robertson et al., 2018). Herein, we used a framework for integrating creel survey data to assess the relationship between inland recreational catch and effort across multiple spatial scales. Such a tool could be used to inform data-poor regions or waterbodies, compare angling catch and effort across broad spatial scales, and inform management actions by predicting changes in catch and effort via the effects of shifting demographics and landscapes.

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CONFLICT OF INTEREST STATEMENT

Abigail J. Lynch is an author on this manuscript and an editor for Fisheries Management and Ecology and therefore her acting as an editor for this manuscript would be a conflict of interest. We declare no other conflicts of interest.

DATA AVAILABILITY STATEMENT

The data analyzed here, along with a variety of other Creel survey data, can be accessed through the publically available U.S. Inland Creel and Angler Survey Catalog (CreelCat). The dataset is described in Lynch et al. (2021), is directly accessible at: https://doi.org/10.5066/P9DSOPHD, and is accessible through the CreelCat software at: https://doi.org/10.5066/P9E45TNJ. The model described here has been developed into an R package, "CreelCatch," to allow future use and it is available at: https://doi.org/10.5066/P9E45TNJ.

ETHICS STATEMENT

Our work involved statistical modeling of fisheries data that do not require ethical approval.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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