Modeling Recreational Effort in Wisconsin's Walleye Lakes

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Abstract

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Recreational angling is a popular pastime that, when under-regulated, has contributed to the overharvest of natural fish populations. However, recreational fisheries throughout the world are regulated less extensively than commercial fisheries. When no data for a recreational fishing site exists, managers frequently rely on models of effort or harvest to regulate human consumption. In the lakes of Wisconsin's Ceded Territories, the Wisconsin Department of Natural Resources (WiDNR) manages recreational harvest of walleye, one of the most commonly targeted recreational species in North America. The WiDNR sets annual harvest limits for lakes in this fishery, using population models of the walleye stock to determine harvest limits and creel survey data to estimate effort and harvest rates. Non-creeled lakes are thus regulated without information on effort or total harvest. This thesis examines the potential to improve estimates of effort for creeled and non-creeled lakes in the Wisconsin walleye fisheries. Specifically, to examine whether angler residency information could improve effort estimates, I investigate whether effort by anglers who reside on the lake - constituting 32% of lake effort on average - responds differently to lake attributes than effort by anglers with an associated travel cost. To further investigate how each group of anglers makes effort decisions, walleye population size, catch per unit effort (CPUE), and a measure of walleye catch posted to the smartphone application Fishbrain are compared as regressors. Using multivariate linear regressions, I estimate models of walleye effort for 229 lakes from 1995 to 2019, exploring the ability of key variables to explain effort patterns by driving and non-driving anglers. Other site attributes, including the number of concrete boat ramps and parking spots, were also included, improving models to varying degrees. The results indicate that key variables including the walleye population estimate and CPUE impact effort differently between driving and non-driving anglers, demonstrating that these two groups react differently to lake attributes in the Ceded Territories. I conclude that lake effort in this system is determined in part by the home locations of anglers, as indicated by the travel cost model. This information could potentially improve effort estimates for walleye in the Ceded Territories and in other recreational fisheries, particularly at sites that are regulated without effort data.

I. *Introduction*

Each year, almost one billion recreational anglers around the globe catch an estimated 47 billion fish, about half of which are harvested (Kelleher et al., 2012; Cooke & Cowx, 2004). Recreational fisheries provide the principal use of wild fish populations across inland temperate waters (FAO, 2012). Recreational angling has also become a significant source of harvest in marine and coastal environments, as well as in areas traditionally dominated by commercial fishing (Coleman et al., 2004; Radford et al., 2018). Despite a worldwide valuation of $190 billion (Kelleher et al., 2012) and yearly angler numbers quintupling those of industrial fisheries (FAO 2018), recreational fisheries have traditionally been a lower priority for scientists and governing bodies than their commercial counterparts (Arlinghaus et al., 2019; Cooke & Cowx, 2004; Post et al., 2002). This may be partially due to the higher global harvest by commercial fisheries each year in terms of total biomass (Cooke & Cowx, 2004) or due to commercial harvesters having more clear incentives to avoid overfishing their stocks (i.e, preservation of livelihood). However, recent studies have identified recreational angling's contribution to habitat and wildlife disturbances in high-effort areas, making fisheries more vulnerable to overharvest and collapse (Lewin et al., 2006; Post et al. 2002; Cox et al., 2002; Allen et al., 2013; Cooke & Cowx, 2006).

Recreational fisheries are frequently decentralized and relatively small in scale, exhibiting great spatial and temporal variability both between and within sites (McCluskey & Lewison, 2008). While this heterogeneity characterizes most recreational fisheries, inland settings such as lakes often develop fisheries that differ widely within a region due to the disconnected, nonuniform nature of angling sites and the irregular diffusion of users (Rypel et al., 2019). This poses a challenge for managers operating under budget constraints, since accurate effort and harvest estimates are integral to maintaining the sustainable use of recreational angling sites (McCluskey & Lewison, 2008), yet the continuous monitoring of all sites within a region is often prohibitively resource-intensive. To solve this problem, a representative subset of sites and anglers is surveyed, either through in-person angler counts and interviews or via phone or mail-in surveys, and extrapolated upon. When on-site (creel) surveys are conducted, the random sampling of sites and times allows for managers to estimate consumption across years and sites that were unsampled. The accuracy of these estimates depends on the representativeness of the sample design, as well as the method by which information is extrapolated to unsampled sites (Rypel et al., 2019). While most recreational fisheries are open access or regulated open access, survey data informs regional or site-specific regulations such as limits placed on the minimum size for harvest or anglers' maximum daily harvest (Arlinghaus et al., 2019; Beard et al., 2011). This means that for many recreational angling sites, policies governing harvest are set without site-level data on effort, harvest rates, and/or stock population levels (Rypel et al., 2019; US DOI, 1991). To regulate unmonitored sites, managers depend on site classification frameworks and/or statistical models of effort and harvest, which are often based on a limited set of fixed effects and unchanging site attributes such as surface area or maximum depth (Rypel et al., 2019; Hansen et al., 2015). Given the range of dynamic and static factors affecting fish populations and the increased awareness of recreational fishing's impacts, recent work has aimed to improve predictive models of angler effort by incorporating additional variables and data sources **(**Rypel et al., 2019; Hunt et al., 2019B; Papenfus et al., 2015; Embke et al., 2019**)**.

This thesis uses angler count and interview data from 229 lakes governed by the Wisconsin Department of Natural Resources (WiDNR) in the Ceded Territories region of northern Wisconsin to assess determinants of walleye-directed effort by driving and non-driving anglers during the hook and line seasons from 1995 to 2019. I estimate numerous regressions of effort using variables from a range of confidential and publicly available datasets. In addition to variables used by the WiDNR to set target harvest levels, I identify novel variables as potential effort motivators based on support from literature (Hunt et al., 2019A; Parsons, 2003; Jiorle et al., 2016). By modeling effort by drivers and non-drivers separately, I examine how travel distance impacts effort decisions by each group, as travel distance has been identified as a primary determinant of effort by the travel cost literature (Parsons, 2003; Hunt et al., 2019B). Second, I evaluate the relative ability of catch per unit effort (CPUE) to explain driver and non-driver effort. I then test whether data from an angler diary smartphone application can explain additional variation in effort. Many recreational anglers have begun using smartphone applications to record and share their catch, and these data have the potential to improve predictions of effort in certain settings (Jiorle et al., 2016). The results of this thesis suggest there is potential for angler travel cost (residency) information to be used to set annual bag or size limits at lakes without effort data. Findings also highlight the diversity of factors impacting recreational resource consumption rates across lakes, ultimately underscoring the need for continued model development to improve the governance of heterogeneous, dynamic recreational fisheries.

II. *Background*

Wisconsin's Ceded Territories

Wisconsin waters draw over one million recreational anglers each year, approximately 27% of whom permanently reside outside of the state (US DOI, 2011). As the most commonly targeted gamefish in much of North America (Post et al., 2015), walleye (*Sander vitreus*) are among the most popular and economically significant of the nine sportfish species sought by anglers in Wisconsin (US DOI, 2019). Most walleye in Wisconsin inhabit lakes located within the Ceded Territories (Staggs et al., 1990). Fisheries in this region have been jointly managed by the WiDNR and the Great Lakes Indian Fish and Wildlife Commission since 1990 (US DOI, 1991). These agencies cooperate to develop and enforce policy in accordance with the 1983 Voigt Decision's reaffirmation of the hunting and fishing rights held by the Chippewa and Superior tribes of Wisconsin on lands ceded to the United States by two treaties during 1837 and 1842. The WiDNR therefore oversees walleye harvest in both the tribal fishery and the hook and line sport fishery.

Annual tribal spearing and netting of walleye takes place on an average of 149 lakes from late April to early May and is entirely monitored via a nightly permitting system (US DOI, 2019). The comparatively vast walleye hook and line fishery includes over 720 lakes and lasts from the end of May into March, with dates that occasionally overlap with the tribal fishery. No angling occurs in November, marking the transition to ice fishing season (US DOI, 2019). To track non-tribal harvest, the WiDNR has conducted angler creel surveys on a random sample of 16-25 lakes each year since 1990 (US DOI, 2019). Around 3% of walleye lakes are sampled annually, so extrapolation upon data depends on the representativeness of the random sample. This means WiDNR creel survey data include roving counts of all anglers on a waterbody as well as end-of-trip interviews with anglers at lake access points (US DOI, 1991; WI Lakes Partnership, 2016). Interviews record detailed catch, party, and trip information, while instantaneous angler counts are used to estimate effort levels. Surveys are designed to cover each lake for 40 hours per week, including at least two instantaneous angler counts on each randomly selected survey date. Business days and holidays are designated as separate strata before dates are selected so that sampling is maximally representative (McCluskey & Lewison, 2008). In addition to the random set of lakes that are creeled each year, 15 lakes have been sampled between four and seven times since 1995 in order to track trends more closely through time.

To prevent overharvest, the WiDNR sets a lake-level Total Allowable Catch (target TAC) each season, aiming to limit annual harvest of individual walleye stocks to 35% (US DOI, 2019). The target TAC is based on population estimates taken on select lakes each spring using the Chapman modification of the Peterson mark and recapture method (Ricker, 1975; Hansen et al., 2015). Estimates are typically recorded during all years that a lake is creeled (US DOI, 2019). For lakes without recent population surveys, abundance estimates are calculated using a regression (Eq. 1) of stock abundance (N_{ij}) on lake surface area and an error term (ε_{ij}), with a lake (b_{0i}) and year fixed effect (β_2) included in the operational model in 2015 (Hansen et al., 2015).

Equation 1: $\ln(N_{ij}) = \beta_0 + \beta_1 \ln(lake\ area_i) + \beta_2 centered\ year_t + b_{0i} + \epsilon_{it}$

The target TAC is set at 35% of the lower 95% prediction interval of this regression. The target TAC, the year's tribal harvest declaration, and prior years of creel data are then used to inform annual bag and size limits. For the small minority of lakes that have been creeled,[1] harvest and effort data is used in conjunction with population size and distribution data to inform the limits for each lake (WI Lakes Partnership, 2016). For lakes that are not creeled, these limits are set without information on consumption rates. Although significant regulatory changes were made in 2015 to reduce variability in bag limits and enact stricter size limits (Hansen et al.,

[1] Ten percent of walleye lakes have both abundance and creel surveys more recent than 2015.

2015), fishing regulations have always been set largely based on lake area for lakes without recent creel or population data (Eq. 1). This implies that two unsampled lakes – identically sized, but one receiving twice the effort – would be subject to the same regulations. Thus, the ability to develop predictive models of fishing effort has the potential to improve management when monitoring data are limited. Below, I develop models of effort for walleye fisheries in Wisconsin's Ceded Territories.

The Travel Cost Model

To develop an empirical model of fishing effort, it is important to understand theoretical drivers of fishing effort. Recreational site use has been modeled using variations of the travel cost method for decades (Bockstael et al., 1987; Parsons, 2003). Often used to compute the use value of sites or site attributes, the Random Utility Maximization (RUM) model is the most widespread application of the travel cost method used to model fishing location choice across multiple potential sites (Breffle & Morey, 2000; Lupi, 2001). For each individual, the utility offered by a trip to each site is determined by angler travel costs and site attributes. Angler characteristics can also be incorporated by varying utility's relationships with site attributes and travel cost. Site attributes may include catch rates, available amenities, or environmental qualities. Utility (*v*) provided by site *i* on a given choice occasion, or opportunity for a recreational trip, is expressed as:

Equation 2: $v_i = \beta_{tc} tc_i + \beta_q q_i + \epsilon_i$

where tc_i is the travel cost associated with site *i*, q_i is a vector of site attributes, *βs* are coefficients relating site characteristics to utility, and random error term ε_i represents unobserved sources of angler utility (Parsons, 2003). Site selection is modeled by comparing utility across all sites in the choice set (S) and with the maximum utility that could be gained by doing something other than visiting one of the sites in S (v_0). The probability that an individual selects a site equals the probability that the site provides a higher utility than v_0 and all sites in S. The method of calculating this probability depends on assumptions about the distribution of ε_i, but substitute sites are always accounted for by using data from every site in S to calculate the probability for a single site. The multinomial logit form of this probability is the most basic, for which the probability of selecting site i takes the following form (Parsons, 2003):

Equation 3: $pr(i) = \frac{\exp\,(\beta_{tc}tc_i+\beta_q q_i)}{\exp\,(a_0+a_1 z)+\sum_{j=1}^{S}\exp\,(\beta_{tc}tc_j+\beta_q q_j)}$

Attributes in q_k ideally capture all catch-related and non-catch-related features of sites upon which anglers base decisions. Non-catch-related attributes often describe lake accessibility or environmental quality (Hunt et al., 2019A; Hunt et al., 2019B). Depending on the fishery in question and available data, the catch-related attribute(s) may take the form of catch rates, stock size estimates, or binary indicators of species presence (Melstrom et al., 2014; Pendleton & Mendelsohn, 1998). The variable that is closest to measuring the signal(s) anglers care about is expected to be the best predictor of site choice (Parsons, 2003). For a data-rich system in which anglers gain utility from high catch rates and have imperfect knowledge of stock abundance, CPUE may be the best predictor of utility. CPUE has been established as a key predictor of the behavior of commercial fishing vessels aiming to maximize profit (Branch et al., 2006; Abbott and Haynie, 2012). However, freshwater recreational anglers seeking to maximize their own utility may prioritize other signals over CPUE.

In some cases, the RUM model is effective in estimating choice across thousands of sites (Parsons, 2003). However, estimating the parameters of such a model generally requires detailed behavioral information for hundreds or thousands of anglers, usually including the point of origin, destination, cost, and other variables associated with each trip during the study window. Additionally, to precisely estimate site demand for hundreds of distinct recreational fishing sites in a managerial unit, attribute data for every substitute site is necessary. These requirements often exceed the data collected by managers using creel surveys in larger systems. In particular, access point interviews may not be designed to capture trip information with sufficient detail for RUM estimation, while attribute data such as abundance levels may only be available for a portion of sites.

Accessibility Metrics

Despite these data limitations, recent research has incorporated concepts from the travel cost method into models of recreational fishing effort with more similar data requirements and specifications to those used by managers. Variables capturing distance from sites to one or more major cities (Post & Parkinson, 2012; Martin, 2017) as well as more nuanced metrics of site accessibility **(**Reed-Andersen et al., 2000) have successfully acted as determinants of angler effort in various models that technically diverge from the standard random utility framework. In a model of site-level effort, Hunt et al. (2019B) developed an accessibility metric that captured the distribution of travel distances between angler population centers and each site, and then compared this distribution across all sites in the system (Eq. 4). This metric was not derived directly from the multinomial logit expression for probability of site selection according to the RUM model (Eq. 3) but considered the home locations of anglers and travel distances to all substitute sites. By using fishing license data to associate angler trips with home counties, a weighted average of travel distance with a similar structure to the RUM probability was statistically useful in modelling effort across hundreds of recreational angling sites. Equation 4 denotes accessibility (ACC_i) for lake *i* within choice set *J* and given *M* population centers acting as the origin for P_m annual angler trips. TD_{mi} denotes travel distance from population center *m* and lake *i*. λ is a parameter representing the negative effect of travel distance.

Equation 4: $ACC_i = \sum_{m=1}^{M}(\frac{P_m \lambda * \exp(-\lambda TD_{mi})}{\sum_{j=1}^{J} \lambda * \exp(-\lambda TD_{mj})}$

Creel surveys in the Ceded Territories do not record angler home locations, license numbers, or travel cost information, and abundance estimates do not exist for many sites in the walleye fishery. Therefore, the estimation of a RUM model to predict site-level effort is not feasible for lakes in this fishery without further data collection; neither is using some other metric of travel cost that utilizes the number of trips taken to each site by anglers originating from a specific location. However, the demonstrated benefits of incorporating travel cost data into non-RUM effort models in similar settings indicates that effort estimates in the Ceded Territories may also benefit from using angler home locations.

Resident versus Non-resident Status

Instead of an accessibility metric, I explore the importance of the lake resident or non-resident status of anglers. The RUM model implies that resident (*ND*) anglers - those residing on a lake and with no associated travel cost - would have a different response to signals of stock abundance than non-residents who drive to the lake (*D*). This can be seen by differentiating a standard site choice probability (Eq. 4) with respect to abundance. The simple example below represents the probability of selecting two sites: one that does not require travel (Eq. 5) and one that does (Eq. 6). The derivatives show that while the sign of the difference is theoretically ambiguous and depends on site attributes, anglers with no associated cost have a different response to abundance than traveling anglers (Eq. 7; Eq. 8).

Equation 5: $pr(i_{ND}) = \frac{\exp(\beta_N N_i)}{1+\exp(\beta_N N_i)+\exp(\beta_N N_j+\beta_{tc} tc_j^{ND})}$

Equation 6: $pr(i_D) = \frac{\exp(\beta_N N_i+\beta_{tc} tc_i)}{1+\exp(\beta_N N_i+\beta_{tc} tc_i^{D})+\exp(\beta_N N_j+\beta_{tc} tc_j^{D})}$

Equation 7: $\frac{d(pr(i_{ND}))}{d(N_i)} = \frac{\beta_N * \exp(\beta_N N_i) * (1+\exp(\beta_N N_j)+\beta_{tc} tc_j^{ND}))}{(1+\exp(\beta_N N_i)+\exp(\beta_N N_j+\beta_{tc} tc_j^{ND}))^2}$

Equation 8: $\frac{d(pr(i_D))}{d(N_i)} = \frac{\beta_N * \exp(\beta_N N_i+\beta_{tc} tc_i^{D}) * (1+\exp(\beta_N N_j+\beta_{tc} tc_j^{D}))}{\left(1+\exp(\beta_N N_i+\beta_{tc} tc_i^{D}\right)+\exp(\beta_N N_j+\beta_{tc} tc_j^{D}))^2}$

The RUM model therefore implies that a change in abundance causes a different unit change in the probability of site selection for resident versus nonresident anglers, and the magnitude and direction of this difference depends on the attributes of the lakes being compared. Thus, I explore how residency status can inform regressions of angler effort by separately modeling effort for drivers (non-residents) and non-drivers (residents). While unable to accommodate a continuous distribution of travel distances, this method is compatible with WiDNR creel data, since interviews record whether parties drove to the lake using a 0-1 indicator. Furthermore, given knowledge of the relative number of driving and non-driving anglers at a lake, the WiDNR could potentially use angler residency information to gain insight into effort levels, particularly where creel data is lacking.

Angler Diary Smartphone Apps: Fishbrain

While physical angler diaries have been historically employed as a high-resolution, narrow-scope approach to monitor angler behavior (McCluskey & Lewison, 2008), recent work has explored smartphone applications as a potential substitute (Venturelli et al., 2017). There are dozens, if not hundreds, of smartphone applications designed to assist anglers with recording, tracking, and/or sharing trip information. When many anglers in a system self-report detailed trip information to apps, data can potentially be collected on a broader scale than is possible using traditional methods. A few studies have successfully modeled effort or harvest using data from angler diary apps, either alongside or in place of traditional variables (Papenfus et al., 2015; Martin, 2017; Jiorle et al., 2016). The mobile app Fishbrain has over 5 million users and has provided data for two studies in Sweden (Wikstrom, 2015; Sundstedt & Rytterlund, 2017) but also has large user bases in the United States, Brazil, and Australia. The app associates unique user IDs with detailed data on each catch (species, size, geotagged location, etc.), but it does not record trips without catch since it primarily functions as a social platform to share images and/or records of caught fish. Although datasets including no-catch trips are more useful for fisheries managers (Venturelli et al., 2017), Fishbrain records of walleye catch in Ceded Territories lakes could potentially either increase resolution at lakes with recent creel data or contribute to estimates of effort at lakes without recent creel data. Fishbrain users may differ from the typical angler captured in a WiDNR creel - e.g., in avidity, skill, or demographics - which may allow app catch records to predict novel patterns in effort. I therefore investigate the ability of walleye catch posted to Fishbrain per unit time, alongside abundance and CPUE, to explain variation in effort by drivers and non-drivers.

III. *Methods and Data*

To assess how key variables capturing stock size, CPUE, and catch posted to Fishbrain affect walleye-directed effort by lake residents and non-residents in the Ceded Territories, I estimate multiple pairs of regressions of effort using lake attributes as regressors. Each pair includes a regression of effort by drivers and non-drivers on the same set of attributes. Model data was informed by two distinct creel datasets - angler counts and angler interviews - as well as a population estimate dataset provided by the WiDNR, publicly available lake attribute and access point datasets, and the confidential Fishbrain catch dataset. Analyses were performed in R 1.2.1335 (R Core Team, 2019). Creel data and population estimates provided by the WiDNR ranged from 1995-2019, and data for 229 lakes (415 lake-year combinations, 1993 lake-month combinations, 6.9% of the possible lake-month combinations for included lakes) were used to estimate models. Annual population estimates were used without manipulation, aside from singular instances during 1998 and 2000 in which lakes were surveyed twice within the year, for which the mean was used. Lake-years with population estimates of zero (n=1, 6 lake-months) were removed from the dataset. Creel interview data was aggregated to the monthly level to calculate CPUE, the average number of anglers per boat, the percentage of effort by non-drivers, and the percentage of effort directed toward walleye. To maximize available data, interview metrics other than CPUE were calculated using interviewed parties targeting all species. Only months from May to October were used to maximize relevance to the May abundance estimates. This includes the full duration of the boat and shore fishing season, while the absence of effort in November and late March/early April precedes shifts to and from ice-fishing, respectively, making May and October sensible cutoff points for the model. For lakes with sufficient creel data, walleye-directed effort was calculated for all six months of the sport fishing season before ice-fishing begins in December.

Creel interviews and counts were used to calculate monthly effort levels for drivers and non-drivers according to Equation 9:

Equation 9: $E_{imt}^{ND} = ND_{it} * W_{it} * A_{it} * (D_{H_{mt}} * \sum_{p=1}^{S_{H_{imt}}} \frac{12*avg\left(C_{H_{imt_p}}\right)}{S_{H_{imt}}} + D_{B_{mt}} * \sum_{q=1}^{S_{B_{imt}}} \frac{12*avg\left(C_{B_{imt_q}}\right)}{S_{B_{imt}}})$

where (E_{NDimt}) denotes effort by non-drivers on lake *i* during month *m* of year *t*, ND_{itm} is the percent of effort by non-drivers during lake-year-month *it*, W_{itm} is the average percent of walleye-directed effort during lake-year-month *itm*, A_{itm} is the average number of anglers per boat during lake-year *itm*, D_x is the number of days of type *x*, *H* denotes holidays (including weekends), *B* denotes business days, S_x is the number of surveyed days of type *x*, and C_y is the average count on day *y* (McCormick & Meyer, 2017). To calculate effort by drivers, ND_{it} was replaced with (1-ND_{it}). Average count was multiplied by twelve to factor in twelve fishable hours each day. Importantly, average count is the key variable tracking effort, as it is informed by creel counts - the interview dataset informs the other metrics. Interview data was also used to calculate CPUE by dividing the total monthly catch by the total walleye-directed effort at each lake. For all lake-month combinations with sufficient data, a time-lagged CPUE from the previous month was calculated. May lake-month combinations therefore had no associated lagged CPUE and were not included in models, as no lakes were surveyed in successive years. The 68 additional lake-months with zero walleye effort had undefined CPUEs and were similarly dropped. Descriptive statistics for model data are outlined in Table 1.

Fishbrain catches were linked to lakes by geospatially matching the longitude and latitude of catches in the application dataset with publicly available lake shapefiles (WiDNR, 2017; Pebesma, 2018). Shapefiles were identified by Water Body Index Code (WBIC), and catches falling within 20m of the shapefile boundary were attached to a lake unless the site names in each dataset clearly indicated a mismatch. Five lakes were not present in the spatial dataset, so a 1000m buffer around their centroids was used, and catches were matched using lake names from the Fishbrain dataset (Figure 1). Fishbrain catch was subdivided by lake-year after early analysis indicated that monthly subdivision was too fine for use.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Monthly Effort (hours)	1,993	1,278.5	1,668.8	0	222.807	696.824	1,673.863	16,795.650
% Walleye Effort	1,993	0.283	0.205	0	0.118	0.247	0.408	1
Abundance	1,993	2,312.4	2,622.8	4	516	1,411	3,172	16,450
Month	1,993	7.981	1.412	6	7	8	9	10
Year	1,993	2,006.7	7.204	1,995	2,000	2,006	2,013	2,019
Area (acres)	1,993	899.58	973.13	84	305	534	1,014	6,148
Max Depth (ft.)	1,993	45.109	24.229	8	26	41	60	117
# Concrete Ramps	1,993	1.002	0.861	0	0	1	1	4
# Parking Spots	1,993	22.910	21.693	0	10	20	30	110
Annual FB Catch	1,993	0.042	0.224	0	0	0	0	2
Lagged CPUE	1,993	0.306	0.393	0	0.055	0.187	0.408	5
% ND Effort	1,993	0.324	0.270	0	0.084	0.279	0.508	1
ND Effort	1,993	440.28	827.74	0	20.76	130.824	508.018	11,796.6
D Effort	1,993	838.23	1,237.06	0	125.21	387.59	1,064	13,190.6
Lakes per Year	25	16.619	3.106	10	14	17	19	21
Lakes per Month	5	397.8	6.702	388	395	398	404	404

Table 1: Descriptive statistics of all variables informing regressions.

In addition to these variables of interest, four supplemental lake attributes expected to impact effort were derived from publicly available WiDNR lake attribute data: area, maximum depth, the number of parking spots, and the number of concrete boat ramps. Size-related attributes like area and maximum depth have been historically identified as effort motivators due to their relationship with capacity, the likelihood of site knowledge or recognition by anglers, and angler expectations of target species presence/behavior (Hunt et al., 2019A; Martin et al., 2017; Fayram et al., 2006; Reed-Andersen et al., 2000). Presence and quality of access points has also been useful in modeling effort, as these attributes facilitate site use, particularly by boating anglers. Since some lake names are duplicated several times within the Ceded Territories, area and maximum depth were determined using Water Body Index Code (WBIC) to match lakes with creel data. The access point dataset, which informed parking space and boat ramp variables, lacked associated WBICs, and data points were instead tagged with latitude and longitude. Access points were therefore geospatially matched to lakes using the same technique as was used for the Fishbrain catches.

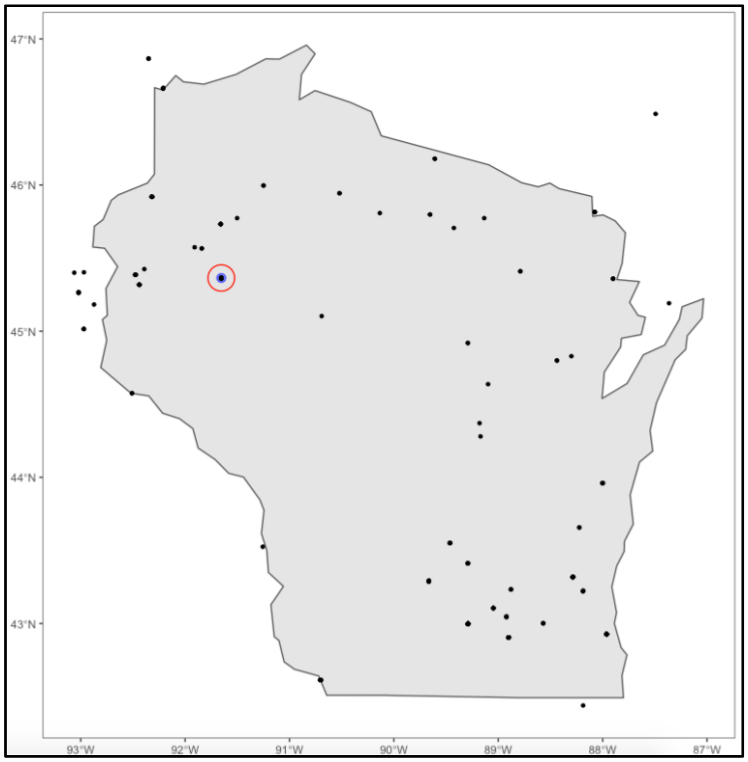

Figure 1: A map of Wisconsin showing the 10,000m boundary (red) around the centroid of Mud Lake (blue) used to match the lake with Fishbrain catches (black) and discriminate between shared names.

Model specifications were estimated in pairs (Table 2). A log-log regression of monthly effort on lake area, month and year indicators, and other lake attributes unrelated to the walleye stock was estimated first for drivers and non-drivers. The increase in adjusted R^2 gained from including abundance, CPUE, and Fishbrain catch was then compared. To avoid losing data points with undefined natural logarithms, CPUE and monthly effort were increased by one prior to the log transformation.[2] The next pair of models added log(abundance + 1) as an explanatory

2 Fishbrain catch was not logged as the log transformation did not improve model performance.

variable. In the following two pairs of models, log(abundance + 1) was replaced by log(CPUE + 1) and Fishbrain catch, respectively, to compare the ability of these three variables to explain effort variation. As mentioned above, since May lake-months and those with zero lagged walleye-directed effort had no associated CPUE, these data points were omitted from models.

$$1_D:\ (1\text{-}ND_{it})*log(E_{imt}+1) = \beta_0+\boldsymbol{X_i'\delta}+\beta_{3t}*\boldsymbol{year}_t+\beta_{4m}*\boldsymbol{month}_{mi}+\varepsilon_{imt}$$
$$1_{ND}:\ ND_{it}*log(E_{imt}+1) = \beta_0+\boldsymbol{X_i'\delta}+\beta_{3t}*\boldsymbol{year}_t+\beta_{4m}*\boldsymbol{month}_{mi}+\varepsilon_{imt}$$

$$2_D:\ (1\text{-}ND_{it})*log(E_{imt}+1) = \beta_0+\beta_1*log(N_{it}+1)+\boldsymbol{X_i'\delta}+\beta_{3t}*\boldsymbol{year}_t+\beta_{4m}*\boldsymbol{month}_{mi}+\varepsilon_{imt}$$
$$2_{ND}:\ ND_{it}*log(E_{imt}+1) = \beta_0+\beta_1*log(N_{it}+1)+\boldsymbol{X_i'\delta}+\beta_{3t}*\boldsymbol{year}_t+\beta_{4m}*\boldsymbol{month}_{mi}+\varepsilon_{imt}$$

$$3_D:\ (1\text{-}ND_{it})*log(E_{imt}+1) = \beta_0+\beta_1*log(CPUE_{imt})+\boldsymbol{X_i'\delta}+\beta_{3t}*\boldsymbol{year}_t+\beta_{4m}*\boldsymbol{month}_{mi}+\varepsilon_{imt}$$
$$3_{ND}:\ ND_{it}*log(E_{imt}+1) = \beta_0+\beta_1*log(CPUE_{imt})+\boldsymbol{X_i'\delta}+\beta_{3t}*\boldsymbol{year}_t+\beta_{4m}*\boldsymbol{month}_{mi}+\varepsilon_{imt}$$

$$4_D:\ (1\text{-}ND_{it})*log(E_{imt}+1) = \beta_0+\beta_1*log(FishbrainCatch_{imt})+\boldsymbol{X_i'\delta}+\beta_{3t}*\boldsymbol{year}_t+\beta_{4m}*\boldsymbol{month}_{mi}+\varepsilon_{imt}$$
$$4_{ND}:\ ND_{it}*log(E_{imt}+1) = \beta_0+\beta_1*log(FishbrainCatch_{imt})+\boldsymbol{X_i'\delta}+\beta_{3t}*\boldsymbol{year}_t+\beta_{4m}*\boldsymbol{month}_{mi}+\varepsilon_{imt}$$

Table 2: Four pairs of models to assess drivers of walleye-directed effort in the Ceded Territories. $\boldsymbol{X_i'\delta}$ represents a vector of coefficients and the corresponding vector of lake attributes. Attributes include the lake area, maximum depth, number of parking spots, and number of concrete ramps.

IV. *Results*

The outputs of all models are detailed in Tables 3 and 4. Interestingly, lake attributes often had coefficients that differed in sign between driver and non-driver models. Coefficients were much more consistent within these two groups. A notable exception is the log(area) term, which lacked significance in Model 2_D but had a significant, positive effect in all other models. Each attribute coefficient was statistically significant in either all driver or all non-driver models. The regression of driver effort on abundance (Model 2_D) had the highest adjusted R^2 of all models (0.280).[3] The fixed effects exhibited a range of significance, but their inclusion improved the R^2

[3] Modeling summed driver and non-driver effort yielded an R^2 near 0.5 but did not allow inter-group comparison between driving and non-driving anglers.

	Dependent variable:			
	1_D	1_{ND}	2_D	2_{ND}
	Log(D Effort+1)	Log(NDEffort+1)	Log(D Effort+1)	Log(ND Effort+1)
Log(Abundance)			0.517***	0.040
			(0.043)	(0.041)
Log(Area)	0.504***	0.642***	-0.019	0.601***
	(0.060)	(0.054)	(0.073)	(0.068)
# Parking Spots	0.020***	-0.024***	0.021***	-0.023***
	(0.003)	(0.003)	(0.003)	(0.003)
# Concrete Ramps	0.043	0.161***	0.011	0.159***
	(0.066)	(0.060)	(0.064)	(0.060)
Max Depth (ft.)	0.003	-0.004**	0.003*	-0.004**
	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.248	-0.307	-0.212	-0.343
	(0.408)	(0.371)	(0.396)	(0.372)
Year?	Yes	Yes	Yes	Yes
Month?	Yes	Yes	Yes	Yes
Observations	1,993	1,993	1,993	1,993
R^2	0.240	0.251	0.291	0.251
Adjusted R^2	0.228	0.239	0.280	0.239
Res. Std. Error	1.810	1.644	1.748	1.644
	(df=1960)	(df=1960)	(df=1959)	(df=1959)
F Statistic	19.368***	20.532***	24.420***	19.938***
	(df=32;1960)	(df=32;1960)	(df=33;1959)	(df=33;1959)
Note:				*p**p***p<0.01

Table 3: Outputs of model pairs 1 and 2, including coefficients, (standard errors), adjusted R^2.

of all tested models.[4] Replacing the abundance variable with CPUE resulted in a lower adjusted R^2 value for non-drivers (0.245), while using the Fishbrain catch resulted in a still lower value (0.231). On the other hand, models of driver effort exhibited little variation in their ability to explain effort, remaining at an adjusted R^2 of about 0.239. While abundance and CPUE both

[4] When both fixed effects were dropped from models, the adjust R^2 value decreased by about 0.1.

	Dependent variable:			
	3_D	3_{ND}	4_D	4_{ND}
	Log(D Effort+1)	Log(ND Effort+1)	Log(D Effort+1)	Log(ND Effort+1)
Log(Lag CPUE+1)	1.188***	0.165		
	(0.178)	(0.163)		
Annual FB Catch			0.597***	-0.186
			(0.208)	(0.189)
Log(Area)	0.457***	0.635***	0.508***	0.640***
	(0.060)	(0.055)	(0.060)	(0.054)
# Parking Spots	0.021***	-0.023***	0.019***	-0.023***
	(0.003)	(0.003)	(0.003)	(0.003)
# Concrete Ramps	0.053	0.163***	0.050	0.159***
	(0.065)	(0.060)	(0.066)	(0.060)
Max Depth (ft.)	0.004**	-0.004**	0.002	-0.004**
	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.117	-0.325	0.246	-0.306
	(0.404)	(0.371)	(0.407)	(0.371)
Year?	Yes	Yes	Yes	Yes
Month?	Yes	Yes	Yes	Yes
Observations	1,993	1,993	1,993	1,993
R^2	0.257	0.251	0.243	0.251
Adjusted R^2	0.245	0.239	0.231	0.239
Res. Std. Error (df=1959)	1.790	1.644	1.807	1.644
F Statistic (df=33;1960)	20.553***	19.941***	19.100***	19.939***
Note:				*p**p***p<0.01

Table 4: Outputs of model pairs 3 and 4, including coefficients, (standard errors), adjusted R^2.

explained significant variation in driver effort, neither was significant in the regressions of non-driver effort. The R^2 values indicate that ability to predict driver or non-driver effort within the sample was fairly low, and models were not tested on out of sample data points. Annual

Fishbrain catch also exhibited a significant coefficient in model 4_D, but lent almost no improvement to the R^2 (+0.003).

V. *Discussion*

The results of the four model pairs indicate that drivers and non-drivers reacted differently to lake attributes. Although effort by non-drivers was lower than driver effort at most lakes, a few lakes with very high angler counts also had high annual percentages of non-driving effort recorded in their interviews (Table 1). Assuming the representativeness of interviews, effort on these lakes would likely react differently to a changing set of site attributes than it would on lakes with mostly driving anglers. The different reactions by these two groups to lake attributes indicates that lake residency information may be useful to managers modeling effort. Abundance and CPUE estimates have a positive ability to explain walleye-directed effort by driving anglers in this system, while effort by non-drivers did not appear to be similarly influenced. This further indicates that total effort by each group is not driven by identical factors. This difference in responsiveness suggests that modeling the combined effort by drivers and non-drivers as one variable may understate average effort at some sites. Since total effort at one site by a group equals the product of angler responsiveness to site attributes times the number of anglers in the group, future models may more precisely measure differences in individual responsiveness by controlling for the size of the driving and non-driving angler populations.

Abundance had the highest ability to explain driver effort compared to time-lagged CPUE and Fishbrain catch. The abundance coefficient was expectedly positive for drivers, while this coefficient was not significant for non-drivers. A subset of anglers may seek out population estimates for surveyed lakes, as these are made public by the WiDNR, but estimates would be outdated as they are not made available for the current year. Thus, most anglers do not experience this abundance metric directly. Nonetheless, the higher R^2 stemming from WiDNR population estimates indicates that CPUE had less influence on effort allocation by drivers. Since CPUE is experienced somewhat directly by all anglers, the relatively high responsiveness of drivers to abundance provides nontrivial insight into the determinants of effort in this recreational fishery. To calculate CPUE, interviews including walleye-directed effort were necessary; CPUE was therefore based on 35% of monthly interviews on average and may perform better in more data-rich settings. However, Model 3_D performed better than Models 1_D and 4_D, indicating that CPUE explained some portion of effort patterns by drivers. CPUE could therefore be useful in modeling driver effort, especially if it is more readily available than alternative abundance indexes such as WiDNR population estimates. The near-constant adjusted R^2 across non-driver models suggests that effort by resident anglers may be less responsive to abundance signals. If this portrays the true behavior of residents, lakes with many residents may be less inclined to self-regulate, as decreases in abundance or CPUE would be slower to deter effort. Fishbrain data was severely limited in its overlap with creel, and it performed unsurprisingly poorly in the absence of other variables pertinent to the walleye stock. In more data-rich settings, smartphone application data may be more useful, as user-recorded trip information could alleviate the cost associated with on-site surveys or reveal novel trends among specific user groups.

The significance of the terms capturing area, maximum depth, parking spots, and concrete boat ramps supports the consideration of lake size and access data in setting lake regulations. Lake area had a strong influence on effort in all models except Model 2_D, reinforcing expectations from literature (Hunt et al., 2019A). The lack of significance of the area term in

Model 2_D and its significance in other driver models may indicate that population estimates and lake area had a strongly correlated impact on effort by non-drivers. In other words, lake size may be picking up variation in Models 1_D, 3_D, and 4_Dthat is explained by abundance but not by CPUE, Fishbrain catch, or other lake attributes. Area therefore appears to positively impact non-driver effort while acting as a proxy for abundance in driver models. This positive impact on non-driver effort may indicate that it is serving as a proxy for the number of lakeside homes. Area is regarded as a key predictor by Ceded Territory managers and in the recreational fishing literature. If lake area impacts effort decisions by driving and non-driving anglers separately, as results suggest, managers could use lake residency or travel cost information to improve effort estimates that currently rely on lake area and/or other site attributes. Unexpectedly, the number of concrete boat ramps did not affect effort by drivers; possibly this relationship was obscured by the positive impact of parking spots, which are found at most boat ramps. Resident anglers often own private docks, but public boat ramps still facilitate the entry and exit of boats from water bodies. Therefore, the positive effect of concrete boat ramps on non-driver effort likely captures the responsiveness of individual resident anglers to boat ramps and/or the higher number of resident anglers at lakes with boat ramps. The impact of parking spots on effort by both groups of anglers was consistent and strongly significant, indicating that public parking spots increased driver effort while decreasing effort by non-drivers. For a given number of concrete ramps, the negative effect of parking spots on non-driver effort may result from crowding impacts associated with an increase in drivers, or from lakes with large parking lots having fewer lakeside homes. Maximum depth negatively affected effort by non-drivers while not impacting driver effort - this variable was on average the least strongly significant, indicating that maximum depth may not be a strong signal to anglers and that lake area is the better-performing attribute related to lake size. Maximum depth's negative impact on non-driver effort may capture patterns in the size of resident populations (fewer residents at deeper lakes, all else constant) or a true resident preference for more shallow lakes.

If effort can be modeled more precisely for sampled and unsampled lakes, regulations will become better informed and will more accurately reflect the target TAC for their lake. While theory has been developed regarding models of individual choice in recreational fisheries, aggregate effort models remain more ad-hoc, as exemplified by their steps toward the incorporation of travel cost. Since aggregate effort models have the potential to inform critical steps in regulation, further development of theory surrounding aggregate choice in recreational systems is needed. While models did not exceed an adjusted R^2 of 0.28 and were not used to predict out of sample, results consistently indicated that effort by drivers and non-drivers had different responses to regressors. Based on the comparatively high performance of a combined (driver plus non-driver) effort model, more precise estimates of the percentage of driver and non-driver effort may increase the R^2 of models and improve out of sample prediction. Equations 8 and 9 did not necessarily imply an insignificant coefficient on abundance for Model 2_{ND}, but this finding may indicate a high variability in responsiveness or a true lack of responsiveness to abundance by resident anglers, which differs significantly from the positive coefficient on abundance in Model 2_{D}. While estimating separate models for drivers and non-drivers is a limited incorporation of travel cost, being based on a binary indicator of driver status, the results demonstrate that travel cost affects how anglers make effort decisions in the Ceded Territories. This makes travel cost data potentially useful to managers in setting target size and bag limits for a given target TAC, since effort for a given lake depends on the residency (travel cost) of the angler population. Ultimately, this reinforces current work toward integrating travel cost variables into models used by managers. The lower ability of Fishbrain catch to explain effort patterns highlights the importance of recording of no-catch trips, as their inclusion in app data may have increased the variable's range and benefit to the R^2. That said, it should be noted that as smartphones and angler diary applications become more commonly used, their datasets may continue to become increasingly rich and informative to managers. Additionally, given the limitations of model data, additional testing of the relationship between CPUE and effort variables in recreational fisheries is recommended. While CPUE data may be immediately unavailable to managers regulating unsurveyed lakes in regions like the Ceded Territories, CPUE from sources like angler diary apps may be available for these lakes, and CPUE from surveyed lakes may also inform other steps in regulation. Finally, given the cost-effectiveness of collection and potential for high-resolution data, further comparisons of smartphone app data and traditional data sources are recommended. Programs to incentivize the sharing of catch through such apps may facilitate their usefulness to managers. Given the current management status of the planet's recreational fisheries and the potential for overharvest and other outcomes threatening their sustainability, novel data sources may provide insight that protects the longevity of recreational fishing systems. The results of this thesis support further research into the usefulness of novel factors such as travel cost metrics and smartphone app data to managers of recreational fisheries in creating effective policy where traditional data is limited, which is almost universally the case.

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