

Valuing Offshore Habitat to Recreational Anglers Using Cellphone Location Data

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Abstract

Offshore structures, including operational and reefed energy platforms, strengthen marine habitats and generate economic value, motivating interest in quantifying their net benefits. We combine a Random Utility Model with Murdock's (2006) site-choice approach to estimate the nonmarket value of offshore structures to recreational anglers in the Western Gulf of Mexicoⁱ (2019-2022). Recreational fishing trips are identified in cellphone location data using a machine learning classifier trained on Automatic Identification System data. Location choices indicate that anglers value destinations farther offshore, particularly those with operating and reefed energy platforms, while other artificial reefs generate smaller and spatially variable benefits.

Keywords: Random Utility Model, Site Choice Model, Mobility Data, Machine Learning, Offshore Structures

1. Introduction

The recreational site choice model based on the theoretical model of Random Utility (RUM) (McFadden, 1973), has long been used to better understand individuals' decisions to select a site as a recreational destination. Among all the recreational activities, recreational fishing is one of the most studied choice models, dating back to the 1980s (Milon, 1988; Bockstael et al., 1989).

While extensive research has addressed a large number of questions in this field focusing on

fishing launch sites (e.g., Hunt, 2005; Melstrom & Lupi, 2013; Dundas & von Haefen, 2020; Backstrom & Woodward, 2025), the value of conditions at different site locations in marine waters remains understudied due to lack of data on angler choices on the water. This occurs due to multiple obstacles in collecting desired data. First, the costly nature of intercept data collection and the large number of on-water sites available to offshore anglers, make the collection of such data at offshore sites nearly impossible. Previous studies of on-water choices in offshore recreational fishing have relied on surveys (Thomas & Stratis, 2002; Haab et al., 2008; Lew & Larson, 2015; Alvarez et al., 2019). However, the geographical scope of these studies is limited to a relatively small number of offshore destinations. Data of this kind are also subject to survey biases, such as recall bias and measurement errors, including human precision errors in converting geolocations. In addition, unlike on land, where there are typically a finite number of well-defined destinations, the number of on-water destinations is large, possibly infinite, and their boundaries are ambiguous. These limitations make it more difficult to comprehensively assess the desirability of offshore locations and their associated characteristics, especially in comparison to the extensive research conducted on on-land fishing locations.

In this study, we estimate the value of offshore fishing destinations using mobility data, which anonymously and passively tracks individuals over time and space. We contribute to the travel cost literature in two key dimensions. First, we use the most granular type of mobility data (also known as device-level data, which shows the time-stamped trajectory of movements) to accurately identify recreational behavior. Second, we couple these data to a standard discrete choice model based on the RUM to value offshore fishing locations, overcoming the fact that there are no well-defined fishing locations in marine waters.

Mobility data are increasingly being applied to a wide range of issues to study the mobility patterns of people in different communities. These studies combine advanced computational techniques (see Connolly et al. 2024) and include empirical studies of consumer choices and recreational visitations (Athey et al., 2018; Wood et al., 2020; Newbold et al., 2022), homogeneous and heterogeneous preferences for amenities (Merrill et al., 2020; Sevtsuk et al., 2021; Cook, 2022; Sparks et al., 2022; Zhang et al., 2024), and even susceptibility to wildfires (Lee & Beatty, 2025). While high-frequency location data of geospatial vessel tracking technologies (known as Vessel Monitoring Systems or VMS) have been used to classify and analyze diverse commercial fishing behavior (O’Farrell et al., 2017; O’Farrell, Chollett, et al., 2019; O’Farrell, Sanchirico, et al., 2019; Baeg & Hammond, 2023), such data have not been utilized to investigate on-water choices during recreational fishing trips. In addition, while citizen science apps that record location details of recreational users of different ecosystems have been used in recreational use value studies (Melstrom et al., 2024), such data are not available for recreational fishing activity that can accurately track the trajectory of movements and determine the value of selected sites.

This paper provides policy-relevant insights into the value of the many changes that have occurred and will occur in human-made structures in the Gulf of Mexico (GOM). First, there have been significant changes in the number of oil and gas rigs in the GOM in the last few decades. Based on the Bureau of Safety and Environmental Enforcement (BSEE) data, the number of standing energy rigs in the GOM peaked at over 4,000 in the early 2000s but had fallen to less than half that number by 2021. Interestingly, these structures actually benefit recreational fishing by providing underwater structures that support marine ecosystems and create desirable fishing locations for recreational anglers (Shipp & Bortone, 2009; Gardner et al.,

2022; DePiper et al., 2023). While some of the decommissioned rigs have been converted to artificial reefs under Rigs-to-Reefs (RtR) programs, there are limits to how many such projects can occur due to engineering and environmental limitations. Looking forward, with the potential for offshore wind energy in the GOM on the horizon (NCCOS, NOAA, 2024ⁱⁱ), it is important to identify desirable fishing locations and understand their value to the recreational anglers who are likely to benefit from the underwater structure that wind turbines will provide, just as they value oil and gas rigs. Our study specifically informs decisions related to these changes, helping to understand the value of programs like RtR and highlighting secondary benefits or costs of installing wind energy structures in areas that lack other types of structures. Our findings can also guide Bureau of Ocean Energy Management (BOEM)'s future offshore energy leasing, helping to ensure that they support sustainable fishing practices while balancing ecological and recreational needs. Such policy implications underscore the importance of our research in shaping effective marine resource management strategies.

Our findings indicate that, on average, both reefed rigs (RRs) and operating energy rigs (ERs) are desirable fishing structures in the GOM, whereas other types of artificial reefs (ORs) reduce the likelihood that an angler will choose a site. RRs and ERs are more strongly preferred in shallow than in deep waters, reflecting heterogeneity in preferences. We also find that younger RRs are favored, while older ERs are more likely to be selected. Fishing sites vary substantially in value: among those chosen by at least one angler, offshore sites have higher intrinsic value than those closer to shore. However, when considering the marginal value of structural changes—such as adding an RR or removing an ER—after accounting for travel costs, locations nearer to shore tend to yield higher value.

The paper progresses as follows: We begin with a detailed introduction of the datasets used, entailing the method used to identify recreational anglers among activities in GOM. This is followed by an explanation of the methodology and the econometric model. We then discuss the findings in the results section and conclude with a summary of key insights and their implications for policy and fishery management.

2. Data

2.1 *Mobility Data*

Our mobility data were provided by Cuebiq (formerly known as Spectus), which provides access to anonymized data collected from smartphones that are using an app from one of Cuebiq's partners. Individuals who provide data have opted in to share their locations through a General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA) compliant framework.ⁱⁱⁱ While the number of devices in Cuebiq's database varies over time, in the period of our study, January 2019 to April 2022, at least 16.8 million devices were included every day, with a high of 40 million devices (representing between 5 and 12% of the U.S. population). Cuebiq's data are considered to be representative of the U.S. population (Hsu et al., 2024). We use data from devices that were observed offshore in the Gulf of Mexico (GOM), shown in Figure 1.

[Figure 1 about here]

The unit of analysis in this study is a recreational fishing trip. In Ahmadiani & Woodward (2025) we describe in detail the approach used to identify recreational fishing trips; here, we briefly summarize that process, which is presented graphically in Figure 2. We make use of two main data sets in this process, both of which consist of pings (timestamp, latitude, and longitude) and

device identifiers. First, we use Automatic Information System (AIS) ^{iv} data that tracks (mostly commercial) vessels around the world. While the AIS data does have a category for *Pleasure Craft*, we use queries of the website *MarineTraffic.com* to create two sub-categories for this class: one for the main group of *Pleasure Craft*, which is the class for possible recreational fishing vessels, and one for *Sailing Vessels*. We break each vessel's pings into a series of trips, consisting of a sequence of at least 20 pings, with each trip ending when the device stops transmitting within the Gulf polygon (Figure 1) for at least 10 hours. We develop 37 features for each trip and train a machine learning (ML) classifier using vessel-class labels, which are included in the AIS data. The features include variables that describe a trip on the water such as speed, distance, duration, etc. (Ahmadiani & Woodward, 2025). We intentionally exclude destinations from the list of features to avoid biasing our identification process.

[Figure 2 about here]

After calculating the same features for the 196,040 trips from the Cuebiq data, we apply the ML classifier to identify devices that are likely to be on a recreational vessel. This left 85,184 potential recreational fishing trips. While our classifier is useful for excluding non-recreational trips, it cannot alone be used to identify recreational fishing trips. Hence, we apply nine additional non-machine-learning (non-ML) criteria to identify recreational fishing trips (Figure 2 and Appendix A), which left us with 16,277 trips that we believe are involved in recreational fishing.

As described in Ahmadiani & Woodward (2025), to test the validity of our trip identification approach, we compare the spatial and temporal variation of the identified mobility-data trips with known recreational fishing data from Texas, Alabama, and Mississippi. As seen in Appendix Figure A1, there is a strong correlation between the mobility data trips and the recreational

fishing data used for effort estimation in those states. Hence, we conclude that there is strong evidence that at least the majority of the trips we identify are indeed involved in recreational fishing.

Finally, some of the trips that remained lacked sufficient pings throughout the trip to predict with confidence where fishing occurred. Hence, we excluded any trip that had interruptions in the pings of more than two hours, retained only fully-tracked trips that have enough data throughout the trip so that we can be confident that we are observing the fishing destination.^v The percentage of trips that are fully-tracked falls with the trip's duration (see Appendix Figure A2). For example, almost all trips that are two hours in duration were fully-tracked, while more than 60% of nine-hour trips were interrupted. Since a long trip that is fully-tracked is representative of more trips than a short one, we use the inverse of the percentages shown in Appendix Figure A2 as weights in our regressions. We are left with a total of 8,502 recreational fishing trips into the GOM that we use for the site choice model.^{vi}

2.2 *Offshore sites in the GOM*

A trip in our data consists of a sequence of pings, which may occur every few minutes or be irregular with long gaps between them. The device may stop for long periods along the way, or may speed out for many miles, stop, and then speed back to land. For our econometric analysis, we use a standard site-choice travel cost model in which we assume that an angler chooses a single destination from a large set of locations in the Gulf.^{vii} The single-destination specification is clearly an abstraction from the true data generating process behind many marine recreational fishing trips as an anglers' choice problem is a trip with stops at multiple locations. While compared to other data generating processes (e.g., portfolio and dynamic multiple-destination travel-cost models) the single-destination specification will tend to overestimate the marginal

cost to reach a selected destination, thus underestimating the marginal utility of income, on average, it may also underestimate the marginal utility of any given destination if a site is not often identified as a primary location and underrepresented in the choice set. Hence, the monetary value of a site or changes to a site may be over- or under-estimated by the single destination choice model. Hence, we follow standard practice (Lupi et al., 2020) by identifying a single destination for each trip and ignoring secondary destinations that might be visited along the way.

Each trip is defined as starting once a device enters the polygon portrayed in Figure 1, and we refer to that point as the origin. We consider three specifications to identify the primary destination for each trip: FP: the farthest point from the origin; FS: the farthest stop or trawl (movement less than 5 mph) from the origin; and LS: the location at which the device spent the longest time stopped or trawling.^{viii} Lacking data on the locations that anglers actually considered their primary location, we have no a priori reason to suspect that one of these specifications is more accurate than the others. Hence, we carry out analysis with all three destination specifications and focus on results that are consistent. The three destination specifications will affect the destinations identified, and will likely have differing consequences across regions. For instance, in Texas, structures tend to be located farther from shore, while structures tend to be closer to the Louisiana coast.

Since there is no boundary for selected destinations, offshore site alternatives in our analysis are defined by dividing the GOM into hexagons using Uber's Hexagonal Hierarchical Spatial Index.^{ix} The Uber H3 system allows for efficient and scalable division of any space. We use resolution 6 hexagons, which have an average side length of 3.7 km. Once an angler starts a trip, we define their set of options as the suite of hexagons in the Gulf that have been chosen on at

least one trip in our data, and that are less than 145 km from the origin hexagon for that trip.^x By excluding destination sites that are farther than 145 km from the origin, we form a realistic set of choices for each angler, corresponding to 10% farther than the furthest distance traveled by 99% of anglers. The number of hexagons that are chosen by anglers varies somewhat between the three alternatives: 1,063, 1,060, and 1,037 for FP, FS, and LS, respectively. The number of possible hexagons varies because changes in the destination specification will change the hexagons that overlap across anglers. For example, if two anglers' destinations are in the same hexagon in one specification and in different hexagons in another specification, this could lead to a change in the number of hexagons in the aggregate choice set. Appendix Table A1 reports summary statistics for trips under the tree specifications, including the number of hexagons identified under each of the three destination specifications.

2.3 *Offshore site characteristics*

To examine the features that attract anglers, we define a set of characteristics for each offshore site. We obtain the complete list and geolocation of artificial reefs in Texas, Louisiana, Mississippi, and Alabama from Gardner et al. (2022). The locations of active platforms are obtained from the Bureau of Safety and Environmental Enforcement (BSEE). As described in Appendix B, using these data, we determine if the hexagon contains any ERs, RRs, or ORs. We define a separate category (NOAA hereafter) for other artificial reefs tracked in datasets maintained by NOAA, which are not specifically intended for fish habitat conservation.

Distance from shore is calculated as Haversine distance from the coast. As described in Appendix B, for each hexagon, we estimate the water depth, the biological conditions using fishery-independent data on the weighted catch per unit of effort (cpue) for four species,^{xi} and

two measures of water quality, dissolved oxygen, and chlorophyll (Gulf of America Coastal Ocean Observing System).^{xii}

Table 1 presents summary statistics on offshore site characteristics that are used in our econometric models. On average, 12% of destination hexagons contain an RR, 40% contain an ER, and 28% contain ORs. Among all the sites, 64% have more than one type of structure. The distance to the coast variable, which averages 22.32 miles, is different from the distance traveled by an angler to that site, since anglers rarely travel exactly perpendicularly from coastline where they launch their boats.

[Table 1 about here]

2.4 *Estimation of the travel cost*

Calculation of travel cost in our model is more complicated than in a standard case on land, and involves several steps and data sets. The estimated travel cost should reflect the opportunity cost of each potential trip, including the out-of-pocket and time lost. In most travel-cost models, this means that analysts assume that the shortest distance is used and that drivers travel at the speed limit. Unlike travel with cars, however, the speed of a boat is not constrained by a speed limit. Hence, assuming a constrained speed is not necessarily appropriate (see Wolff (2014) for examples of such studies). Moreover, while its fuel consumption per hour may vary little if the boat is operating efficiently, a boat's speed will be affected by the weather conditions on a given day. Hence, in our estimate of fuel cost, FC , and the value of travel time, $VOTT$, we assume that the least-cost way to reach a destination is to travel at the speed at which a boat is operating at its optimal RPM.^{xiii}

A prototypical single-destination trip would be one in which the captain brings the boat up to a planing speed (typically 20-35 mph) while traveling to and from their fishing location. While we do not observe in the mobility data the factors related to the boats' characteristics, we do observe the boats' speeds and can estimate the weather conditions during each trip. To estimate the fuel-efficient speed for a given trip, \hat{s}_{it} (for individual i and recreational trip at time t), we first identify the apparent efficient speed observed on each trip, s_{ijt} (for individual i , recreational trip to site j at time t). Appendix Figure C1 illustrates a representative trip from our data. The map shows the trajectory of the boat during its four-hour, 23-mile trip, with the speeds indicated by the color scale. As seen in the inset graph, for about 20 of the 23 miles of the trip, the boat's speed was between 22 and 25 mph. For this trip, therefore, we assume that the efficient speed is 23.5 mph. While not all trips have a clear fuel-efficient speed like the one presented in the figure, we define s_{ijt} as the speed (± 2 mph) at which the boat traveled the greatest distance during the trip. Using data from thousands of trips, we estimate \hat{s}_{it} as a function of weather conditions at the trip's origin on the day of the trip (Appendix Table C1). Weather data are derived from daily averages and interpolated linearly using data from six weather buoys maintained by the National Data Buoy Center.^{xiv} As a robustness test, we also estimate models in which \hat{s}_{it} is set at the average optimal speed (21.5 mph) for all trips.

With a predicted efficient speed for a trip, we are able to calculate the $VOTT$ and FC for each trip and each possible destination. The duration of a trip from individual i 's origin to destination j on day t , a trip for D_{ijt} miles, would be D_{ijt}/\hat{s}_{ijt} . We can, therefore, estimate the value of travel time of this trip as

$$VOTT_{ij} = \left(\frac{1}{3} \cdot w_i \cdot \frac{D_{ijt}}{\hat{s}_{it}} \right), \quad (1)$$

where w_i is the hourly wage of individual i , and we assume that individuals' opportunity cost of their time is 1/3 the monetary cost of their time as is commonly done in this literature (Cesario, 1976; Lupi et al., 2020). To estimate the fuel cost of the trip, FC_{ijt} , we assume that the gallons of fuel per hour while operating at the efficient speed is constant at g :

$$FC_{ijt} = \left(p_t \cdot g \cdot \frac{D_{ijt}}{\hat{s}_{it}} \right), \quad (2)$$

where g is the gallons per hour when running the motor at an efficient speed, and p_t is price per gallon.

Boat fuel consumption depends on unobserved boat characteristics such as size, engine horsepower, and speed efficiency. Using data from the Boating Magazine database and a sample of 25- to 40-foot boats, which are typical for offshore recreational fishing, we estimate an average of $g=26.3$.^{xv} The monthly price of gasoline, p_t , used to estimate the cost of travel over our study period in the Gulf region, is obtained from the Energy Information Administration (EIA). Finally, the wage rate, w_i , is calculated using the median income at the census block group level based on the American Community Survey (ACS) and merged with census block groups for each device.^{xvi}

Table 2 shows the characteristics of identified complete recreational fishing trips in our study.

[Table 2 about here]

3. Methods

3.1 *Theoretical model*

The analytical objective of this project is to estimate the recreational fishing demand for offshore fishing trips with a focus on on-water fishing destinations. A choice occasion in our model is the decision about where to go fishing in the GOM, conditional on being on the water within the polygon indicated in Figure 1. While one may reasonably consider the full trip of an angler from their home to the on-water destination, the pragmatic decision to narrow the commodity of interest to offshore sites offers multiple benefits. First, it avoids aggregating diverse behaviors arising from multi-destination and multi-purpose trips (Lupi et al., 2020). Second, unlike previous studies on recreational fishing that account for launch site attributes and combine on-land and on-water travel using nested logit or conditional logit (Haab et al., 2008; Alvarez et al., 2019), a portion of our trips originates from private access points, preventing us from incorporating their on-land characteristics. On the other hand, by estimating the model conditional on being on the water in the Gulf, we somewhat narrow the meaning of our estimates. We do not estimate the full value of the recreational fishing trip, which would require data for the land-based portion of the trip, nor do we estimate the value of a trip occasion, which would require a decision on the extensive margin, i.e., when anglers choose not to fish.^{xvii} Nonetheless, for the population of anglers who took trips in the region, our model is able to estimate the relative marginal value to them of different site attributes.

We use a discrete choice model in which we estimate the probability that a recreational angler makes an offshore fishing trip to an on-water site. The discrete choice model (commonly known as the Random Utility Model-RUM) assesses the value of choice by assuming that individuals

choose the alternatives with the highest utility. In a site-choice setting, the utility of individual i visiting site j is presented in equation (3):

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt}, \quad (3)$$

where V_{ijt} is a function of site characteristics, including travel distance and ε_{ijt} accounts for unobserved taste preferences of the individual, which are unknown to researchers. In this study, i represents a device held by an angler on a recreational fishing trip on day t in the study area. If ε_{ijt} has an i.i.d. Type I extreme value distribution, the probability that angler i selects offshore site j over all other sites ($k \in K$) is defined by equation (4):

$$P_{ijt} = \frac{e^{V_{ijt}}}{\sum_{k \in K} e^{V_{ikt}}} = \frac{e^{\delta_j + \beta \cdot TC_{ijt}}}{\sum_{k \in K} e^{\delta_k + \beta \cdot TC_{ikt}}} \quad (4)$$

where TC_{ijt} is the total cost of travel on water and δ_j represents the site (alternative) specific constant (ASC) that accounts for time-invariant site characteristics (both observed and unobserved). The travel cost is calculated as

$$TC_{ijt} = FC_{ijt} + VOTT_{ijt}. \quad (5)$$

3.2 Empirical approach

We estimate the value of site-specific factors on the value of offshore fishing locations using a two-stage regression method (Murdock, 2006). In this approach, a first-stage conditional-logit model is estimated (equation 4) to recover an estimate of the travel-cost parameter, β , and the vector of ASCs, $\hat{\delta}_j$. We then carry out a second-stage model in which we regress the estimated

$\hat{\delta}_j$ on observable time-invariant characteristics, X_j , using ordinary least squares:

$$\hat{\delta}_j = \alpha X_j + \xi_j. \quad (6)$$

As explained in Murdock (2006), this allows us to estimate robust standard errors for the coefficients capturing the marginal value of site characteristics. The vector, X_j in equation (6), is the vector of site characteristics, which are obtained by overlaying the H3 hexagons with geolocations of ERs, RRs, and ORs, and other site characteristics (i.e., water depth, shortest distance to coast, average cpue, and water quality). We use dummy variables to indicate the presence of structures, while the total number of structures captures the impact of the abundance of such structures on site desirability. The coefficients from the second-stage regression are estimates of the marginal value of that feature (e.g., presence of an ER) to an angler who has reached that site.

To account for the sampling bias of interrupted trips (e.g., pings are not observable during some part of the trip), we estimate the regressions with a corrective sampling weight that varies based on trip duration, giving greater weight to trips with a higher percentage of interruptions (Appendix A).

3.3 Measures of welfare change

We first estimate the WTP for each offshore site j as the ratio of the ASC to the travel cost coefficient:

$$WTP_j = \frac{\hat{\delta}_j}{|\hat{\beta}|}, \quad (7)$$

which captures the intrinsic value of each site, including both observable and unobservable characteristics.

We then estimate the marginal value of ER and RR structures at relevant location in the Gulf. In this case, we estimate the willingness to pay for the presence of structure k in each H3 hexagon, j , WTP_i^k using the log-sum formula (Small & Rosen, 1981; Hanemann, 1999):

$$.WTP_i^k = \frac{1}{\beta} \left[\ln \left(\sum_j \exp(V_{ij}^*) \right) - \ln \left(\sum_j \exp(V_{ij}) \right) \right]. \quad (8)$$

When evaluating destination k , V_{ik}^* is calculated by predicting the value at that site using the estimated coefficients from the second-stage regression and assuming the structure type is present, and V_{ik} is calculated assuming the structure is absent. For all hexagons $j \neq k$, $V_{ik}^* = V_{ik}$, i.e., the existing conditions. We simulate the marginal effect of the structures in each destination hexagon using the estimated travel-cost coefficient, β , from the first-stage regression, and the marginal effects of the site characteristics, α , from the second-stage regression.

4. Results

4.1 Two-stage estimation of conditional logit

Table 3 shows the first-stage regression results based on equation (4), where the estimated total travel cost variable is the only observed independent variable that varies across trips on different days and sites. Columns (1), (2), and (3) present the specification where anglers' chosen site is defined by the FP, FS and LS destination specifications, respectively, and travel cost is estimated using for predicted optimal speed. The results of models using the average optimal speed are presented in Appendix Table C2. As expected, the estimated coefficients on total travel cost are negative and statistically significant across all the models—all else equal anglers would prefer to go to a closer site.

[Table 3 about here]

Table 4 summarizes the results of our second-stage regressions, where we regress the ASCs estimated in Table 3 on observable site characteristics. These models present the base model without any interaction effects, including only dummy variables for the presence of the four structure types, the total number of structures in each hexagon, a dummy variable for shallow water, distance to coast in miles, average weighted catch per unit of effort, and measures of water quality (dissolved oxygen and chlorophyll). Across all three models, ERs have a strongly positive effect on the desirability of a given destination in all destination specifications, though the effect is much larger in column 2. RRs are also found to positively impact choice probability in FP and LS specifications.

Interestingly, the estimated coefficients for ORs and NOAA structures are negative and statistically significant. That is, having the presence of these structures reduces the probability that a site is chosen compared to sites that are in the choice set but lack any structures at all. The positive coefficient of *Distance to coast* and negative coefficient of *Shallow water* suggest that sites that are farther from the coast and in deeper water tend to have a greater intrinsic value.

As a robustness test, we also estimate the conditional logit models using only trips taken outside working hours (weekends and holidays), assuming these are more likely to be true recreational trips. While the travel cost coefficients are very similar to those using all trips (Appendix Table C3), the estimated second-stage coefficients (Appendix Table C4) vary somewhat in both signs and significance. While the positive value of energy rigs, and negative value of shallow water are consistent, our conclusions regarding some of the other factors that affect recreation demand are not as robust and certainly merit further research.

It should be noted that the placement of RRs and ORs is not random, which raises concerns about endogeneity. Depth, structure type, and distance to shore may be jointly determined with unobserved aspects of site quality—such as water quality, habitat richness, or expected catch. Therefore, we attempt to control for this by including biological and water quality controls in our models, reducing the risk of misattributing the value of favorable ecological conditions to the presence of certain structures. We find that estimated coefficient of average weighted cpue is positive and weakly significant for specification (1) and (2), suggesting catch opportunities matter but not strongly. Negative and significant coefficients of average chlorophyll in columns (1) and (3) also indicate that water quality is correlated with anglers' destination choice.^{xviii}

[Table 4 about here]

Table 5 reports more comprehensive models with interaction terms between structure type and (i) structure age (column 2), (ii) water depth at placement (column 3), (iii) distance to the coast (column 4), and (iv) the presence of other structure types (columns 5) to assess heterogeneous effects in the FP specification. Column (1) is the base model, and (6) is the model with all interactions. The heterogeneity analysis based on age in column (2) shows that older RRs reduce site attractiveness, while older ERs become more valuable for site attractiveness. These age effects suggest that RRs placed more recently are more attractive than the older sites, perhaps because planners have learned over time about where to place these structures. Older ERs are particularly desirable, and this supports the notion that the habitat under the platforms improves over time. Column 3 allows us to compare the value of structures in shallow and deep water. Taking into account the interaction effect, while OR structures are unattractive in both shallow and deep water (-1.56, $p < 0.001$; -0.35, $p < 0.001$), NOAA structures are unattractive in shallow water (-0.22 $p < 0.098$). In contrast, RRs and ERs are more attractive in shallow water (0.84,

$p < 0.000$ and $0.57, p < 0.000$), but only RRs are less attractive in deeper water ($-0.68, p < 0.077$). Column 4 shows a significant negative interaction between distance to coast and ORs and ERs, indicating that holding all else equal, the marginal value of these structures is lower the farther they are from coast. The estimated interactions for RR and NOAA structures are not statistically significant. No comparable distance effect is observed for RRs. Column 5 examines whether different structures interact with each other. We find no evidence of complementarities or substitution effects between structure types. Finally, column 6 includes all interaction terms simultaneously; as expected, multicollinearity reduces the precision of some coefficient estimates, leading to weaker statistical significance. Results corresponding to the two other destination specifications (FS and LS) are reported in Appendix Tables C5 and C6. The results are generally consistent with those in Table 5, though there are some differences, with the most noticeable differences being in the FP specification.^{xix}

[Table 5 about here]

As an additional robustness test, we estimate a model in which we limit the anglers to those residing in the same state as the one where they launch their trip. Results in Appendix Table C7 show that for the subset of respondents who launched their trips from their state of residence (73% of the sample), the findings remain robust. The most notable difference arises in the coefficient on shallow water – when focusing only on in-state anglers, we find no evidence of a preference for shallow- relative to deep-water destinations.

4.2 *The intrinsic value of offshore destinations*

Using the estimated ASCs and the travel cost coefficient, we estimate the intrinsic value of each site across the Gulf using equation 7.^{xx} Figure 3 presents the heatmap of estimated WTPs for H3 hexagons in FP specification. Dark grey hexagons represent the most valued sites, and light grey

depicts the least valued ones. The map shows that destinations farther out in the GOM tend to be valued more highly, with values declining uniformly as we approach the coastline (fading from dark grey to light grey). This makes sense – despite the fact that sites near the coast tend to be chosen more often – the only reason an angler would travel far out, and some anglers do that, would be to reach a highly desirable location. We note that the WTP is estimated from ASCs, which are expressed relative to a reference destination. As such, the resulting values reflect relative desirability rather than absolute magnitudes. To facilitate interpretation, we normalize the WTP values in Figure 3 to range between 0 and 100. Appendix Figure C2, panels A and B, present the WTP maps for the FS and LS specifications, respectively, using the same interval scale as Figure 3, with ASCs measured relative to the same reference destination (the H3 hexagon depicted as reference). Although there are differences between the three destination specifications, the correlations are extremely high, exceeding 92% for all comparisons (Appendix Figure C3).

[Figure 3 about here]

4.3 *Policy-relevant Marginal value of ERs and RRs*

In Figure 4 we present the estimated mean willingness to pay for the presence of RR and ER structures in select destination hexagons. To estimate the marginal value of a structure, we apply equation (8), calculating the difference marginal value of the structure's presence at a site using parameter estimates from model 3 from Table 5.^{xxi} The estimates reflect the average marginal value per trip of adding or removing a structure at a location, calculated for anglers who included that location in their choice set on a given day.

We map the WTP for two policy-relevant changes. In Figure 4 panel A, we present the value of RRs in hexagons where there are currently no ERs or RRs. This provides an estimate of the

locations where placement of an RR would be particularly valuable. Because the value of adding an RR falls as the cost to reach the site increases, the locations near favored launch sites tend to be those locations where we predict the highest value. It is clear that if it were possible to choose any place to put the next RR, there is substantial variation in terms of where that would be valuable to anglers.

In Figure 4B we calculate the WTP for ERs at locations where those structures already exist. This shows us the locations where the removal of a rig will impose the greatest cost on anglers. As in Panel A, ERs are most valuable where access is least costly. While the value to anglers is probably given relatively little consideration when choosing to decommission an ER, it is clear that there are some rigs that are particularly valued. In those cases, the estimated value to anglers may help prioritize where rigs should be retained.^{xxii}

[Figure 4 about here]

5. Discussion and Conclusion

In this study, we use mobility data to identify recreational fishing activities in the GOM among various activities using machine learning methods. We identify a sample of 8,502 recreational fishing trips from January 2019 to April 2022 and provide evidence that the data are valid recreational fishing trips (Appendix Figure A1). We then estimate the value of offshore fishing sites in the GOM and the marginal value of structures within those sites.

Our analysis shows that anglers' site choices are strongly influenced by travel costs and site characteristics. As expected, anglers prefer closer destinations, but even after accounting for travel costs, structural features and environmental conditions significantly shape site desirability. Our findings indicate that Energy rigs (ERs) and reef reefs (RRs) are valued and

increase the probability that a site is chosen, while other artificial reefs (ORs) and NOAA structures generally reduce attractiveness. Depth and distance matter as well, such that regardless of the presence and type of structures, destinations in deeper waters and farther offshore are more highly valued, while shallow water locations are less desirable. However, further analysis reveals heterogeneity in these estimates—something that was previously impossible to investigate—suggesting that preferences for RRs vary by location. Specifically, while both RRs and ERs appear to be most valuable when placed in shallow waters (<250 feet), newer RRs are preferred while older ERs are more valued. The sites with the highest intrinsic value are far from the coast. Site-specific estimates of WTP for policy-relevant changes in structure composition reveal substantial variation in WTP across both structure types and location, such that while the marginal value of an RR or ER at some destinations provides only limited benefits, other destinations generate WTP values as high as \$8 per trip. Notably, the locations where structures are most valued are concentrated near popular launch sites. Because we lack exact information on how anglers determine their primary fishing location or where most fishing occurs, we defined three alternative measures of destination and, consequently, three corresponding definitions of each individual's choice set. Our results remain robust in terms of the sign of effects across most specifications, and where differences arise, they point to meaningful heterogeneity in preferences across individuals.

In addition to providing valuable insights regarding manmade infrastructure in the Gulf, this study demonstrates the power of mobility data and this analytical approach in the absence of traditional data sources. For instance, while many previous studies have emphasized and estimated the value of artificial reefs for water-based recreational activities, including recreational fishing, using stated preferences and stated revealed preference methods (Oh et al.,

2008; Polak & Shashar, 2013; Chen et al., 2013; Smith et al., 2016; Hindsley et al., 2023; Tunca et al., 2016), no study has been able to place a monetary value on a large number of offshore locations visited in marine waters. This limitation was largely due to the high cost of data collection and data constraints. Mobility data has changed this landscape.

The use of mobility data is particularly valuable in applications like ours, which cover large geographical areas such as the GOM, where thousands of energy structures are installed and operated, with many more potentially retained through Rigs-to-Reefs programs. Compared to many of the previous studies that investigated value of a site or resource commodity on land using mobility data based on visitation (or foot traffic) to points of interest such as stores, restaurants, or parks, we use data at the device level and smallest resolution of time (each ping), to study a specific activity and movement, not simply location choice. Data at this level allows us to look at behavior that reveals a site's choice. There is virtually no other data type that can capture the geographic and temporal scope of recreational fishing at a similar level of granularity.

However, we acknowledge some of the limitations of mobility data that need to be considered. For instance, data coverage varies across mobility data sources and, therefore, analysis of consistency of results across data sources is important (Hsu et al., 2024) and is a subject for future research. Also, it must be acknowledged that access to the data is not cheap and the computational burden to analyze the data is substantial. Researchers without access to funding and/or advanced computational power will face significant barriers. On the other hand, surveys are the most common approach for studying recreational behavior and they too can be quite expensive.

Another fundamental difference between mobility data and traditional data sources—one that can be both empowering and challenging—is that to better understand individual behavior and make the data useful for economic modeling, it must be supplemented with satellite surveys or expert opinions from anglers. For instance, in this study, assumptions about speed, boat movement, and other underlying factors used in building the machine learning model are derived from both formal and informal surveys of experts, including anglers and other scientists working with this type of data.

The ability to observe complete trip behavior suggests multiple avenues for future research. We might treat trips as single-destination events, but as a sequence of dynamic choices as in Provencher & Bishop (1997) or as a collection of fishing destinations as in Parsons et al. (2021). Both of these approaches are beyond the scope of this paper but offer appealing options for future work.

Overall, this study demonstrates the potential to use mobility to study the value of environmental amenities associated with an activity that must be identified separately from other activities that occupy the same space. Even in the absence of easily defined points of interest, mobility data can help us value amenities. Traditionally, valuation has been limited to focus on behaviors that are exhibited through the choice of a set of well-defined destinations. Mobility data can expand the range of activities that infer environmental value and the types of environmental services that can be valued. The scope to study new problems is vast.

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Tables

Table 1: Summary Statistics for Offshore Sites Characteristics

	Mean	Median	SD	Min	Max
Reefed rigs (RR)	0.123	0	0.328	0	1
Other artificial reefs (OR)	0.279	0	0.449	0	1
NOAA structures (NOAA) ^(a)	0.611	1	0.488	0	1
Energy rigs (ER)	0.404	0	0.491	0	1
All structures counts	11.19	2	29.21	0	381
% of destination with different type of structure	0.646	1	0.479	0	1
Shortest distance to coast (mi)	22.32	15.95	20.02	0.01	92.408
Shallow water (< 250 feet)	0.885	1	0.320	0	1
Average weighted catch per unit of effort (cpue)	0.225	0.037	0.425	0	4.11
Average dissolved oxygen (mg/L)	5.776	5.867	1.221	1.8	12.3
Average chlorophyll ($\mu\text{g/L}$)	3.435	2.439	3.001	0.05	13
Maximum age of RRs in a destination ^(b)	2.764	0	8.267	0	57
Maximum age of OR in a destination	7.61	0	16.762	0	117
Maximum age of ER in a destination	17.874	0	24.013	0	73.325

Note: (a) NOAA structures are not specifically intended for fish habitat conservation; therefore, they are categorized separately and excluded from the aggregate variables (i.e., *Total number of all structure types* and *Percentage of destinations with different structure types*). (b) The maximum age variable is only available when at least one structure has a non-missing age value. The calculations of depth, cpue, dissolved oxygen, and chlorophyll are described in Appendix B.

Table 2: Summary Statistics for Trips Used in Site-Choice Model

	Mean	Median	SD	Min	Max
Trip duration (hrs)	5.2	4.8	2.4	2.0	69.1
Total distance traveled (mi)	38.5	30.4	31.7	0.7	735.5
Max distance from origin (mi)	25.2	20.7	20.5	0.5	144.5
Weekend trip (%)	0.6	1.0	0.5	0	1
Number of stops	4.7	4	2.4	1	26
Max distance from coast (mi)	7.4	6.0	6.3	0.2	57.2
Wind speed (m/s)	4.3	4.2	1.3	1.4	11.6
Gust speed (m/s)	5.5	5.4	1.5	2.1	14.8
Wave height (m)	0.6	0.6	0.3	0.1	2.8
Air temperature (°C)	26.8	27.9	3.4	6.7	31.5
Optimal speed (mph)	21.3	21.7	10.6	2.0	59.8
N (Total trips)	8502				

Table 3: First-Stage Regression: Conditional Logit Model Results

	FP	FS	LS
	(1)	(2)	(3)
Travel cost	-0.0253*** (0.0004)	-0.0257*** (0.0005)	-0.0300*** (0.0005)
ASCs	Yes	Yes	Yes
Interruption weight	Yes	Yes	Yes
# of Trips	8,502	8,498	8,499
# of sites	1,063	1,060	1,037
Log-likelihood	-17839.467	-17523.709	-17134.178
BIC	51283	50590	49470

Note: * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors in parentheses.

Table 4: Second-Stage Regression of ASC on Site Characteristics

	(1)	(2)	(3)
	FP:	FS:	LS:
	Table 4, column 1	Table 4, column 2	Table 4, column 3
RR	0.422** (0.170)	0.322 (0.214)	0.433** (0.196)
OR	-1.720*** (0.140)	-1.097*** (0.145)	-1.967*** (0.152)
NOAA	-0.219* (0.133)	-0.623*** (0.143)	-0.392** (0.152)
ER	0.369*** (0.123)	1.366*** (0.148)	0.514*** (0.136)
All structures counts	-0.000 (0.001)	0.008*** (0.002)	0.000 (0.001)
Shallow water (=1 if <250 ft)	-2.121*** (0.204)	-3.083*** (0.260)	-2.577*** (0.255)
Distance to coast (mi)	0.081*** (0.004)	0.083*** (0.004)	0.095*** (0.005)
Avg. weighted cpue	0.224* (0.126)	0.264* (0.143)	0.199 (0.134)
Average dissolved oxygen	-0.073 (0.052)	-0.116* (0.064)	-0.088 (0.058)
Average chlorophyll	-0.086*** (0.021)	-0.006 (0.025)	-0.091*** (0.023)
Constant	-2.418*** (0.404)	-3.235*** (0.517)	-3.027*** (0.463)
BIC	4278.730	4524.813	4399.803
R-squared	0.683	0.664	0.691
Observations	1063	1060	1037

Note: * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors in parentheses.

Table 5: Second-Stage Regression (Heterogeneous Effects)

	(1)	(2)	(3)	(4)	(5)	(6)
	Base	Age	Depth	Distance	Structure types	All
RR	0.422** (0.170)	0.947** (0.379)	-0.682* (0.385)	0.454 (0.313)	0.401 (0.385)	-0.952 (0.645)
OR	-1.720*** (0.140)	-1.584*** (0.191)	-3.498*** (0.533)	-1.189*** (0.199)	-1.727*** (0.165)	-2.856*** (0.676)
NOAA	-0.219* (0.133)	-0.235* (0.136)	-0.544 (0.453)	-0.240 (0.207)	-0.219 (0.134)	-0.456 (0.498)
ER	0.369*** (0.123)	-0.614** (0.262)	-0.704* (0.401)	0.822*** (0.177)	0.332** (0.147)	-1.094** (0.528)
All structures counts	-0.000 (0.001)	-0.001 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)
Shallow water (=1 if <250 ft)	-2.121*** (0.204)	-2.159*** (0.202)	-3.526*** (0.339)	-2.050*** (0.197)	-2.115*** (0.204)	-3.250*** (0.339)
Distance to coast	0.081*** (0.004)	0.084*** (0.004)	0.076*** (0.004)	0.093*** (0.006)	0.081*** (0.004)	0.083*** (0.006)
Avg. cpue	0.224* (0.126)	0.229* (0.126)	0.283** (0.126)	0.237* (0.126)	0.222* (0.126)	0.276** (0.125)
Avg dissolved oxygen	-0.073 (0.052)	-0.055 (0.052)	-0.067 (0.053)	-0.085 (0.053)	-0.076 (0.052)	-0.061 (0.054)
Avg chlorophyll	-0.086*** (0.021)	-0.087*** (0.022)	-0.088*** (0.021)	-0.090*** (0.022)	-0.085*** (0.021)	-0.090*** (0.022)
Max. age of RRs		-0.027** (0.014)				-0.032** (0.012)
Max. age of ORs		-0.002 (0.004)				-0.003 (0.004)
Max. age of ERs		0.023*** (0.005)				0.020*** (0.005)
RR × Shallow			1.525*** (0.424)			1.831*** (0.402)
OR × Shallow			1.939*** (0.559)			1.567** (0.609)
NOAA × Shallow			0.319 (0.465)			0.191 (0.469)
ER × Shallow			1.279*** (0.420)			0.753* (0.427)
RR × Dist.to coast				0.002 (0.008)		0.007 (0.008)
OR × Dist. to coast.				-0.028*** (0.007)		-0.014* (0.008)

NOAA × Dist to coast				-0.003 (0.007)		-0.001 (0.007)
ER × Dist. to coast				-0.018 ^{***} (0.006)		-0.008 (0.007)
RR × OR					-0.317 (0.570)	0.108 (0.602)
RR × ER					0.100 (0.409)	0.625 (0.416)
OR × ER					0.112 (0.290)	0.484 (0.302)
Constant	-2.418 ^{***} (0.404)	-2.553 ^{***} (0.401)	-1.132 ^{**} (0.450)	-2.660 ^{***} (0.433)	-2.397 ^{***} (0.411)	-1.484 ^{***} (0.498)
BIC	4278.7	4254.5	4257.4	4282.1	4299.0	4277.6
R-squared	0.683	0.688	0.698	0.690	0.683	0.703
Observations	1063	1055	1063	1063	1063	1055

Note: * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors in parentheses. Dependent variable is the ASC estimated from first step with travel cost using the predicted optimal speed specification for FP, destination of farthest point from origin.

Figures

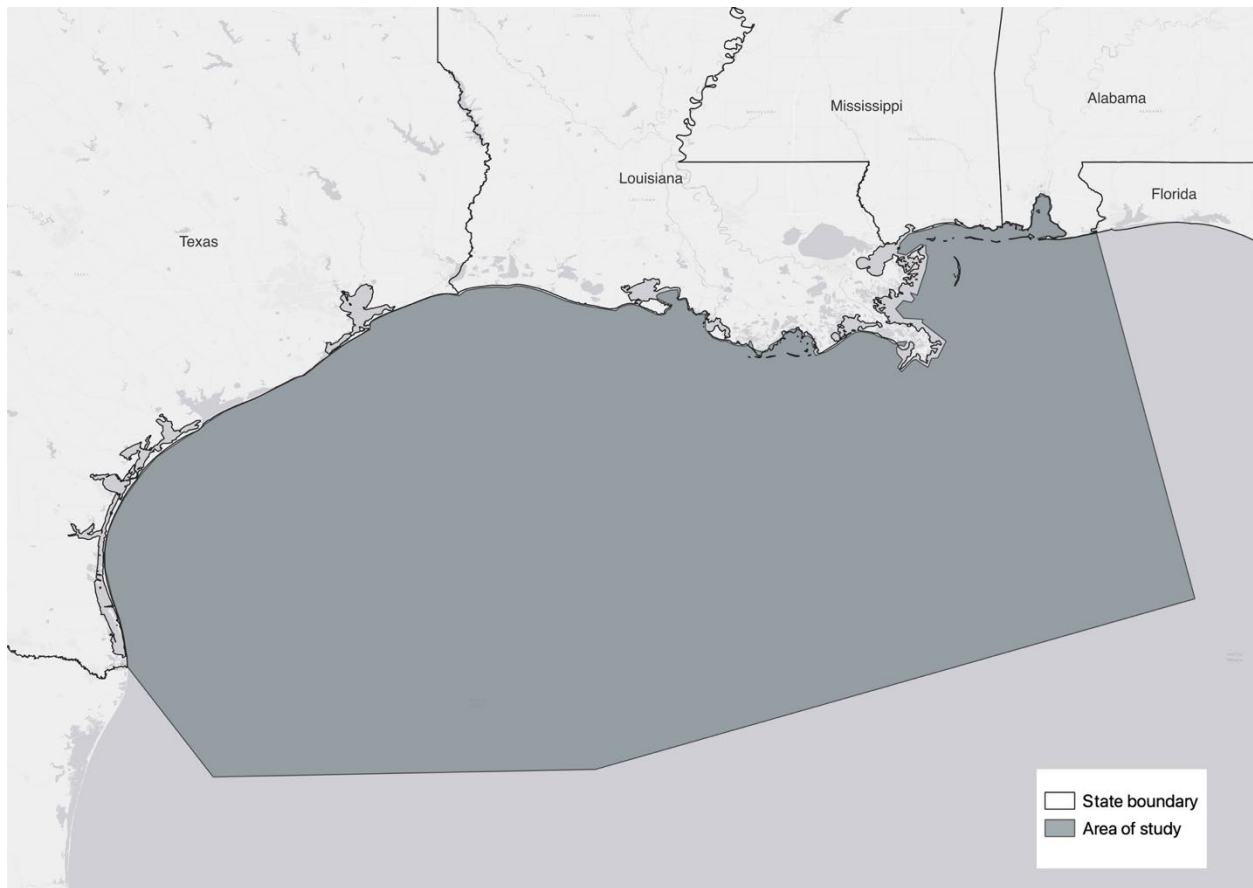


Figure 1: Area of Study Where Trip Pings Are Retrieved from The AIS and Cuebiq Data Sets

Source: Modified from Ahmadiani and Woodward (2025, fig. 2).

Note: The depicted polygon contains all GPS pings in trips in both AIS and Cuebiq data. Land is excluded from this polygon except for islands, which are excluded when processing the data.

Data Cleaning & Feature Extraction

AIS data

- Labeled – vessel class is known
- Time-stamped geolocations of 144,512 trips
- Calculated 37 trip features

Cuebiq Mobility Data

- Unlabeled – no indication of type of user
- 300,000 devices that were observed in the Gulf
- Time-stamped geolocations of 196,040 trips (at least 20 pings)
- Calculated 37 trip features

Exclusion criteria

- 1) Transportation trips
- 2) Excessively long trips (> 72 hours)
- 3) Trips starting ≥ 5 km from the coast
- 4) Very short trips (< 2 hours)
- 5) Long-duration short-distance trips
- 6) Trips that never left land
- 7) Trips without data before & after
- 8) Trips with substantial time on land
- 9) Trips with time at industrial sites

Recreational Fishing Identification

Train machine learning classifier

Apply classifier to mobility data

Potential recreational trips in mobility data

(85,184 trips)

Apply 9 non-ML exclusion criteria

All identified recreational fishing trips

(16,277 trips)

Separate fully-tracked trips

Fully-tracked recreational fishing trips with destinations

(8,284 trips)

Figure 2: Identification Processes for Recreational Fishing Trips

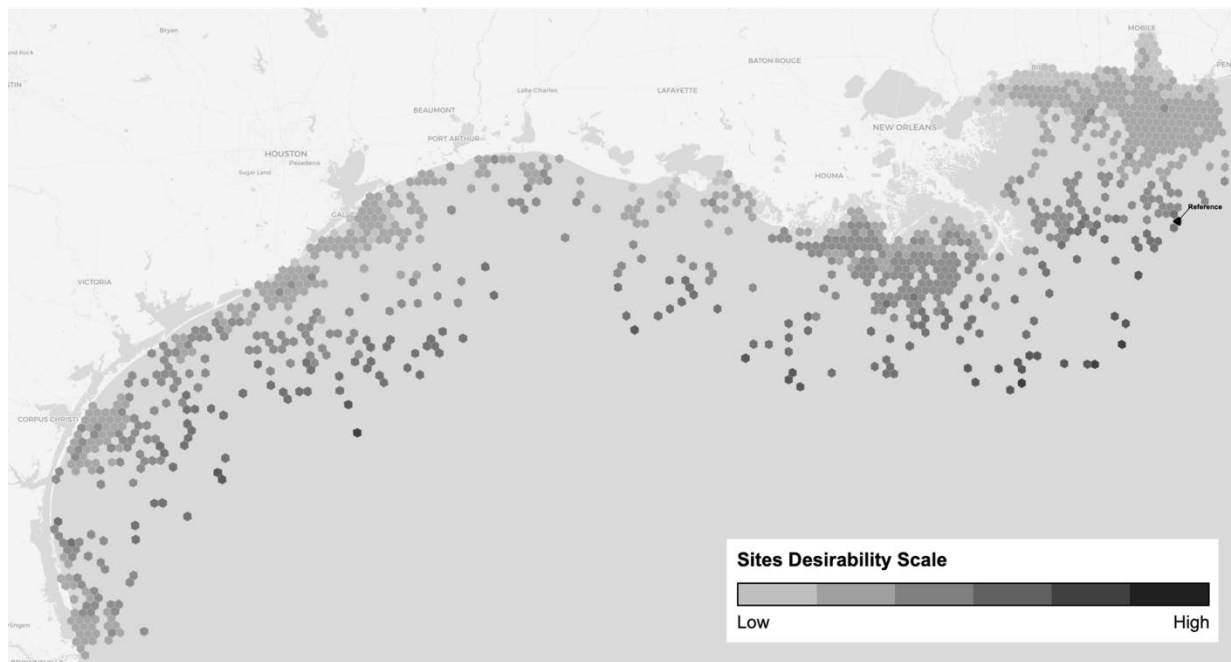


Figure 3: Sites' Relative Desirability Based on Their Intrinsic Values (FP)

Note: The heatmap uses a color spectrum ranging from light grey to dark grey, where light grey represents less desirability in terms of intrinsic values, and dark grey indicates higher values. All values are expressed relative to a reference H3 hexagon off the Alabama coast, which is depicted as the reference in the map.

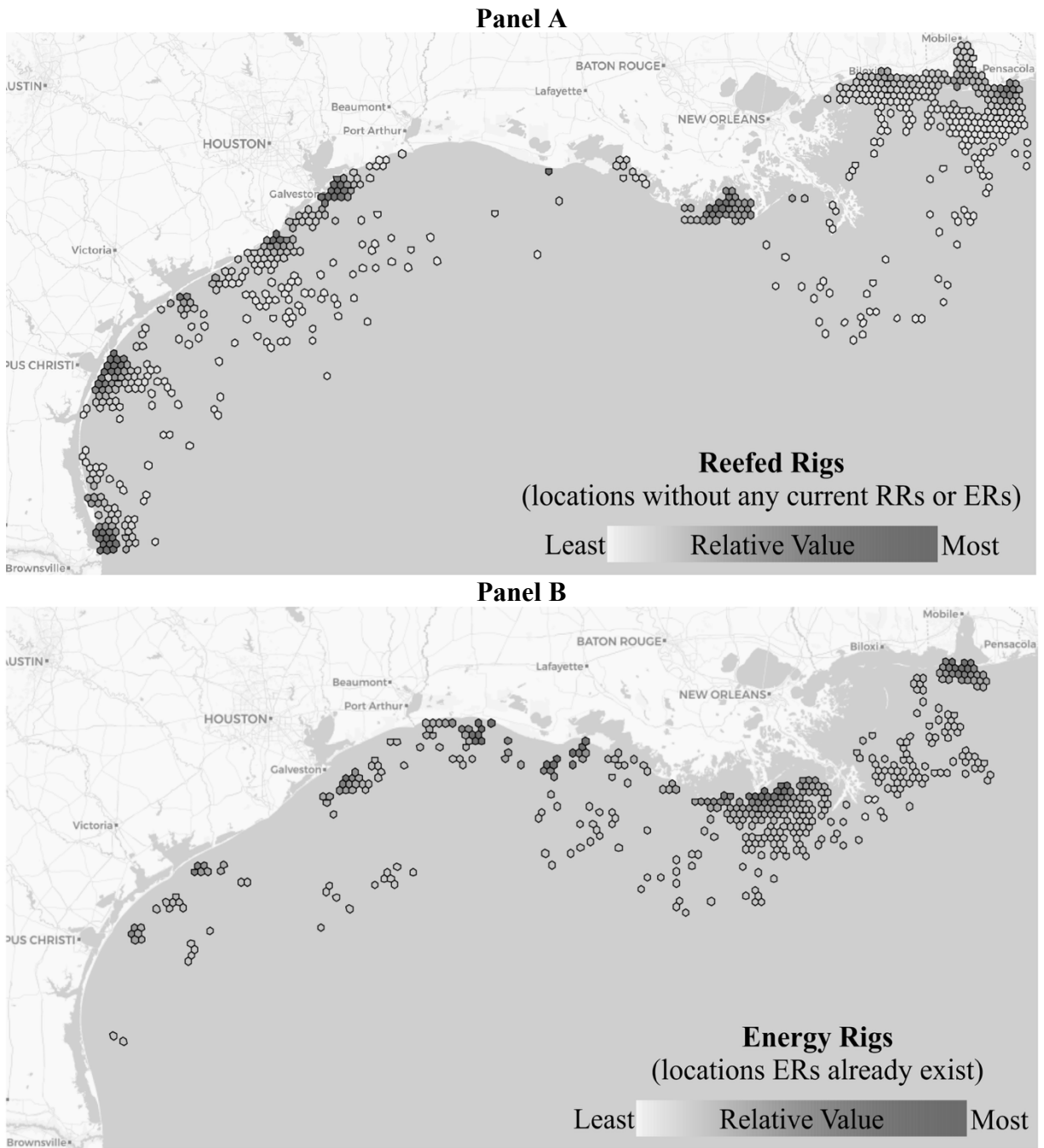


Figure 4: Relative Marginal Value of an RR and ER by Location

Note: Panel A presents the marginal value of RRs for locations without any RR or SR. Panel B presents ERs' values for locations where they exist. WTP is for the presence of each structure type by destination, per trip for anglers with that site in their choice set. Values are calculated using the FP specification and Model 3 in Table 5.

ⁱ The name of the Gulf of Mexico is referred to as the Gulf of America by the U.S. government. We retain the more traditional name in this paper.

ⁱⁱ Retrieved on July 16, 2024, from <https://coastalscience.noaa.gov/project/identifying-potential-wind-energy-areas-in-gulf-of-mexico/>.

ⁱⁱⁱ Through its Social Impact program, Cuebiq provides mobility insights for academic research and humanitarian initiatives. The Cuebiq responsible data sharing framework enables research partners to query anonymized and privacy-enhanced data, by providing access to an auditable, on-premise Data Cleanroom environment. To preserve privacy, the data provider obfuscates home locations in the dataset to the Census Block Group level. All final outputs provided to partners are aggregated in order to preserve privacy.

^{iv} Retrieved in September 2023 from <https://marinecadastre.gov/ais/>

^v Appendix A provides a detailed explanation of how we distinguish fully-tracked and interrupted trips.

^{vi} A total of 8,745 complete recreational fishing trips were identified based on ML and non-ML algorithms.

However, for site choice modeling in our specification with the largest number of trips, we excluded 243 trips due to either missing census block IDs for anglers or the defined destination being outside the feasible choice set.

^{vii} We acknowledge that an angler may have multiple destinations, stopping to fish at a variety of places during a trip. The consideration of a dynamic multiple-destination travel-cost model is beyond the scope of the current paper. The portfolio approach (Parsons et al., 2021) would not be feasible in this context due to the massive number of possible combinations when there are over 1,000 unique destinations in the Gulf. While excluding secondary fishing destinations from the analysis is certainly an abstraction from the true angler decision making process, it is not clear how this will bias our results. If some destination types are over-represented in secondary destinations relative to what we consider the primary destination, those types will be undervalued in our estimates. We note, however, that this problem affects all models in which only the primary destination is used. The difference is that secondary destinations are not available in most data sets.

^{viii} See Appendix Figure A3 for a map showing an example of the three destination specifications.

^{ix} For more information on H3 geospatial indexing see <https://www.uber.com/blog/h3/>

^x When using 150 km and 120 km thresholds as robustness instead of our baseline, the travel cost coefficients are statistically identical, and the ASC estimates differ only marginally, with no meaningful impact on the second-stage regressions. Results are available upon request.

^{xi} Retrieved in August 2025 from <https://apps-st.fisheries.noaa.gov/dismap/DisMAP.html>

^{xii} Retrieved in August 2025 from

https://gisdata.gcoos.org/search?source=jorge.brenner%2540tamu.edu_tamu&tags=Gulf%2520of%2520Mexico%20Cwater%2520quality

^{xiii} We appreciate the helpful input from Scott Hickman and Jinyuan Zhang, experienced recreational anglers, in the development of our speed and travel cost specifications.

^{xiv} Retrieved in November 2023 from <https://www.ndbc.noaa.gov>

^{xv} Retrieved in February 2025 from <https://www.boatingmag.com>.

^{xvi} When CBG-year income (ACS B19013_001E) is missing, we first use the closest available year for the same CBG; if still missing, we spatially impute from the five nearest CBGs in the same year (Haversine distance). Remaining gaps are filled with county-level income (2021 ACS), and, if needed, by averaging the five nearest counties.

^{xvii} The selection of a single-destination model, conditional on anglers already being on the water and therefore ignoring the land portion of the trip, is an informed decision made to avoid arbitrary assumptions that could bias

estimates in unpredictable ways. For example, the CBG assigned by Cuebiq reflects an individual's nighttime location based on a 90-day moving average, which may not represent the true origin of any given fishing trip. Moreover, offshore recreational trips can be multi-purpose or multi-day, and anglers, especially the 27% of our sample traveling from out of state, may stay in temporary accommodations near the coast for extended periods, leading to misidentification of the true home CBG. While this simplification may introduce some bias into absolute WTP estimates and is less likely to affect the relative value of offshore locations, it avoids much greater imprecision that would arise from attempting to model these ambiguous and highly variable land-based origins. However, exploring these differences in detail is better left to future work.

^{xviii} As a robustness test, Appendix Table C4 presents the second-stage regression of outside working hours (weekends and holidays). The results are consistent in terms of the signs of most coefficients, with the notable exception of the coefficient on ORs, where there are differences in the magnitudes and significance levels.

^{xix} Results for models using the average optimal speed are consistent with those based on predicted speed and are available upon request.

^{xx} Because one of the ASCs is not recovered in the analysis, we normalize all WTP values between 0 and 100. Hence, values are relative, not absolute.

^{xxi} Results are produced for results from alternative destination specifications and second-stage models are available upon request.

^{xxii} The average WTP estimates for off-hours trips and all trips are highly correlated, with a 98% correlation (p-value = 0.000) across all points in the two samples. For sites without ERs or RRs, the mean WTP for RRs is 0.29 for off-hours trips and 0.25 for all trips. For sites with ERs, the corresponding mean WTP for RRs is 0.19 and 0.17, respectively.