Spatial-dynamic model of commercial fishing trip decision-making [*]

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Abstract

Innovative sources of high-resolution mobility data are enabling new approaches to modeling and measurement of human behavior. With the advent of global positioning data in fisheries, now more than ever we can empirically model fishers' decision-making. In the short-run, after choosing the fishing gear, fishers decide where to fish, how much to fish and when to return to the port on a given trip. Most of the research investigating these decisions has focused on one aspect of the decision at a time (e.g., choosing a fishing location), treating other aspects exogenous. These decisions, however, are interconnected and conditional on the underlying vessel capital stock (e.g., hold and fuel capacity). This research constructs a novel spatial dynamic model of an individual fisher's trip level decision-making that incorporates simultaneous decisions on location choice, fishing effort to allocate at each location, and travel route. It is motivated by the observations on fishing trips from the Gulf of Mexico's bottom longline fishery. We demonstrate the model using numerical simulations. Simulation results show that technology constraints endogenously determine the trip length. These constraints also impose a shadow price that affects the individual fisher's choice of location and effort from the outset of a trip. We compare these optimal spatial patterns with those from a myopic fisher and a partially myopic fisher, where the former makes one choice ahead decisions and for the latter we consider different levels of forward-looking choices (2, 3, and 6 decisions ahead). The myopic fisher does not optimize route planning or consider the technological constraints until it is time to return to port. Both factors result in large reductions in trip profit even though, for example, catches can be the same across the myopic and dynamic fisher. For the partially myopic

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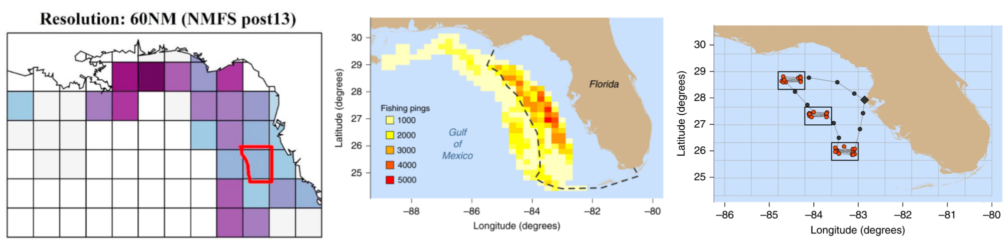
fisher, the degree of route planning and consideration of technological constraints depends on the level of forward-looking. Not surprisingly, the more forward looking the partially myopic the closer it approaches the dynamic optimal. Building more refined models of trip level spatial decision-making is important for the design and assessment of spatial and aspatial fishery management instruments.

1 Introduction

The existence of high frequency space-time data on human activities and movements is permitting the exploration and prediction of behavior in unprecedented ways. Cellphone data has been used to understand the differential abilities of income groups to respond to COVID-19 emergency declarations (Weill et al., 2020), to better predict traffic patterns (Wang et al., 2013), and to understand global mobility patterns (Kraemer et al., 2020). Economists are employing these data to measure/predict poverty and wealth (Blumenstock et al., 2015; Steele et al., 2017), measure consumer preferences (Athey et al., 2018), spatial concentration of urban economic activity and value of transportation infrastructure (Gupta et al., 2020; Miyauchi et al., 2021; Kreindler and Miyauchi, 2021), social networks and social connections (Björkegren, 2019; Athey et al., 2020; Büchel et al., 2020; Couture et al., 2021)

Satellite tracking data of vessels that report GPS coordinates throughout their voyage have been used to map patterns of fishing effort across the globe (Kroodsma et al., 2018), assess the effectiveness of the 200-nautical mile exclusive economic zone in limiting foreign vessels intruding into a coastal nations waters (Englander, 2019), investigate the explore-exploit tradeoff (OFarrell et al., 2019b), identify behavioral typologies of fishing vessels (OFarrell et al., 2019a) and the behavioral changes post the introduction of catch shares (Watson et al., 2018).

These data are also permitting researchers to revisit methodologies developed to explore space-time behavior to better understand their potential strengths and weaknesses. For example, Dépalle et al. (2021) use vessel monitoring system (VMS) data matched with logbook data on catches and effort to demonstrate potential biases in discrete choice random utility models of fishing location choices due to spatial aggregation. Figure 1 contrasts the traditional data used in modeling fishing choices (Figure 1a) with the vessel level tracking data that is available (Figure 1b and 1c). While the historical data had trip-level data on whether a vessel visited a site and catch, the VMS data includes finer spatial information on the vessel's path, site choice, and time spent in each location.



(a) Trip-level logbook data (b) Fishing heatmap using hourly VMS data (c) Simulated track plotted using VMS and Observer data

Figure 1: Data of longline fishing in the Gulf of Mexico. Figure 1a shows the 60NM-long statistical areas used by the U.S. National Marine Fisheries Service (NMFS) after 2013 for trip-level logbook reporting(Dépalle et al., 2021). Figure 1b is heatmap of fishing activity by longline vessels using the hourly Vessel Monitoring System (VMS) positions. Figure 1c is a simulated vessel track with VMS pings classified into fishing (red circles), transiting (black dots) or in port (black diamonds) using a supervised learning algorithm trained by onboard observer data. Figure 1b and 1b comes from OFarrell et al. (2019b).

Motivated by the existence of this data, we develop a more refined trip level model of spatial-temporal decision-making of vessels to inform the design of spatial and aspatial management measures (Bockstael and Opaluch, 1983). On any trip, skippers decide where to fish, how to navigate to the sites, how much to fish, and when to return to the port conditional on vessel capital, labor, target species, and gear. The decisions are influenced by economic opportunities, technology (e.g., vessel hold and fuel capacity), and regulations (e.g., closed areas and seasons, gear restrictions).

On each trip, the short-run decision of location choice for commercial fishers is a dynamic spatial problem. Spatial patchiness of marine resources with different population levels and economic characteristics generates discontinuities in the spatial structure (Sanchirico and Wilen, 1999). Spatial decisions are therefore modelled as discrete choices among a finite set of fishing sites in commercial fisheries. Since the original Bockstael and Opaluch (1983) work, most of the empirical studies use a static random utility model (RUM) to investigate trip-level location choice under stock-induced uncertainty (see, e.g., Eales and Wilen (1986); Abbott and Wilen (2011)). For fisheries consisting of multiple day trips (e.g., tuna, groundfish), researches have incorporated dynamic behavior into the static RUM with state dependence, evolving information, and changing choice sets. While these advances capture some aspects of the decision-making calculus, they are still simplifications of the full dynamic choice problem. Mostly, as a means to maintain computational tractability, they fail to incorporate the interconnections between location choice, trip duration, and vessel characteristics. The studies that are more dynamic in fishers decision-making for multi-day trips[1], however, often assume an exogenous trip length for identification purpose (see, e.g., Hicks and Schnier (2006, 2008); Hutniczak and Münch (2018)). A notable exception is a recent paper by Abe and Anderson (2022) that models endogenous trip length resulting from freshness loss in a dynamic discrete choice model. However, the study does not include trip-level location choice analysis.

This research constructs a dynamic spatial model of an individual fisher's location choice (extensive margin), cruise trajectory, and effort allocation at each site (intensive margin) within a trip. The Gulf of Mexico's reef-fish bottom longline fishery provides the motivation

[1] Instead of maximizing current period utility in the static RUM, these studies consider the optimal trajectory of forward-looking fishing decisions and maximize the sum of expected utility from the multi-period cruise.

and application of the method for numerical analysis. A key feature of the model is the explicit incorporation of route planning and trip-level production constraints on vessel hold capacity and/or fuel consumption. The binding technology constraints introduce a shadow price[2] into the decision-making of where to fish, how much to fish, and when to return to port. Route planning consists of finding the shortest path connecting the chosen locations. Both the shadow price and route planning are missing in the previous discrete choice modeling of fisher trip decisions. We illustrate the utility of modeling the spatial-dynamic decisions of fishers under binding technology constraints and route planning using numerical simulations.

At the same time that high frequency data are becoming available, advances in computational abilities and algorithms in operations research enable us to solve this complex spatial-dynamic problem. The fishing trip decision-making is very similar to the orienteering problem (OP), which is a routing problem with profits in the operation research literature (Gunawan et al., 2016; Vansteenwegen and Gunawan, 2019). Solving the OP corresponds to solving two well-known combinatorial optimization problems in an integrated way: the knapsack problem (KP) and the traveling salesman problem (TSP). The individual fisher's location choice problem modifies the OP to account for the effort allocated at each location and is formulated as a mixed integer quadratically constrained problem (MIQCP). It is solved by the off-the-shelf solver Gurobi using a branch-and-bound algorithm.

To understand how optimal spatial effort allocation decisions differ from the approaches often utilized in the literature, we also develop a myopic model where the individual fisher chooses a location at each decision point within a trip and the effort to allocate at each site. This stands in contrast to the dynamic optimal fisher that chooses a sequence of locations.

[2]The shadow price could be on fuel capacity or hold capacity depending on which constraint is binding.

The myopic model mimics the assumption in the discrete choice literature on fishing location decisions. We also consider cases of a partially myopic fisher that considers multiple forward decisions but is not optimizing the entire trip (e.g., 2 decisions ahead, 3 decisions, and 6 decisions).

Previous empirical studies find evidence that fishers are more likely to choose locations with high expected rewards, low travel distance and low risk. Our simulation results are consistent with the previous literature. Sites with high fish stock and low travel distance are visited. Simulation results also show that technology constraints such as fuel constraint and hold capacity constraint endogenously determine the trip length. The fuel constraint and the hold capacity constraint limit the number of fishing sites to go and the amount of fishing effort applied by constraining the total fuel usage and/or the total fish harvest. These technology constraints impose shadow prices that affect the decision of fishing effort and location choice from the outset of a trip. Comparing the results from the optimal trip decision-making with the myopic, we demonstrate how the prior research is subject to misspecification, as researchers have ignored the role of vessel capacity, fuel constraints and route planning in their estimations of fishers' location choice. We decompose the profit loss from ignoring route planning and technology constraint by modeling a partially myopic fisher who considers multiple choices at a time. The more sites the partially myopic fisher considers in the trip decision making, the higher the profit realized from better route planning and distribution of fishing effort.

The paper is organized as follows. Section 2 reviews the literature in the short run location choice in commercial fishery. Section 3 presents the model of the short run decision on location choice and effort allocation by the dynamic fisher, the myopic fisher, and the partially myopic fisher. Section 4 describes the Gulf of Mexico demersal longline fishery and parameterization.

Section 5 presents the simulation results. Section 6 concludes.

2 Literature Review

The short-run decision of location choice for commercial fishers at the trip level is a dynamic spatial problem. The individual fisher's problem is cast as choosing fishing sites to maximize the overall trip profits. Spatial patchiness of marine resources with different population levels and economic characteristics generate discontinuities in the spatial structure(Sanchirico and Wilen, 1999). Spatial decisions are therefore modelled as discrete choices among a finite set of fishing sites in commercial fisheries.

The discrete choice random utility model (noted as RUM) was first used in Bockstael and Opaluch (1983) to model the medium-run decision[3] of fishery choice in New England trawling fishery. Since then, the RUM has been utilized to model the short-run margin of the fishery production process, trip-level location choice in single and multispecies fisheries (Eales and Wilen, 1986; Dupont, 1993; Mistiaen and Strand, 2000; Smith, 2005; Abbott and Wilen, 2011; Sun et al., 2016), and trip-level fishery and location-choice in multi-species fisheries (Holland and Sutinen, 2000; Curtis and Hicks, 2000; Curtis and McConnell, 2004). Eales and Wilen (1986) and Sun et al. (2016) modeled the location choice of the first set, which is a very short-run decision.

The static RUM is usually formed as the following: fishers, conditional on taking a fishing trip, make a decision of where to fish to maximize the current period utility in time period t

[3] In the fishing production, medium run decisions include between fishing trip decisions such as switching ports, switching target species, and switching gear.

that is affected by travel costs and expected rewards linearly.

$$U_{ijt} = \beta_{dist} \times \text{Dist}_{ijt} + \beta_{rewards} \times E[\text{Rewards}_{ijt}] + \varepsilon_{ijt} \tag{1}$$

where i represents the vessel, j is the site and t is the decision point (usually in temporal dimension). ε_{ijt} is the random shock. Dist_{ijt} denotes the distance to a given location. These studies show that fishers tend to visit a site with a high expected revenue and a short travel distance. Extensions of the static RUM include variables such as variance of the rewards (Dupont, 1993; Mistiaen and Strand, 2000; Hutniczak and Münch, 2018), preference heterogeneity (Smith, 2005), state dependence (your past experience affects future choice) (Holland and Sutinen, 2000; Smith, 2005), evolving information and information sharing (Curtis and McConnell, 2004; Abbott and Wilen, 2011; Dépalle et al., 2021), spatial correlation and learning (Marcoul and Weninger, 2008; Hutniczak and Münch, 2018), and bycatch avoidance (Haynie et al., 2009; Abbott and Wilen, 2011).

Applied studies of location choice spanned a diverse range of fisheries from sedentary species (Smith, 2002, 2005; Marcoul and Weninger, 2008) to pelagic species (Curtis and Hicks, 2000; Mistiaen and Strand, 2000; Curtis and McConnell, 2004). For sedentary species, most vessels fish single-day trips choosing 1-2 fishing grounds (Eales and Wilen, 1986; Smith, 2005; Marcoul and Weninger, 2008). For finfish species like groundfishes or tunas, vessels make multi-day trips (Curtis and Hicks, 2000; Curtis and McConnell, 2004; Hicks and Schnier, 2008; Abbott and Wilen, 2011; Hutniczak and Münch, 2018). This adds a layer of dynamic complexity to the problem. On a multiday cruise, spatial location choices may be made in a dynamic context instead of myopic day-to-day strategies. A set of papers incorporate skipper's forward-looking behavior in the RUM by adding expected future payoffs to the objective function (Curtis and Hicks, 2000; Curtis and McConnell, 2004; Hicks et al., 2004; Hicks and Schnier, 2008). The dynamic random utility model (DRUM), a static RUM entrenched in dynamic optimization developed and used in Hicks and Schnier (2006, 2008), is a middle ground approach[4] to include dynamic choices and remain computationally tractable.

Even in the pseudo-dynamic models, trip length for multi-day trips is usually assumed exogenous. For example, Curtis and Hicks (2000); Curtis and McConnell (2004); Hicks and Schnier (2006, 2008); Hutniczak and Münch (2018) assume the length of the trip is known before leaving port. Trip duration, as an input of the short-run fishery production process, is endogenously determined during a trip. (Curtis and Hicks, 2000) and (Curtis and McConnell, 2004) suggest that catch deterioration affects location choice through the impact on produc-
1 tion horizon. A recent paper by Abe and Anderson (2022) models the dynamic choices of endogenous trip length due to freshness deterioration. However, the paper doesn't include the spatial margin of the trip level production process.

Fuel and hold capacity are mainly discussed in the literature of capacity measures and capacity utilization[5]. Little attention has been paid to the role of fuel capacity and hold capacity in location and trip duration choice. One reason could be that few trips land a full load (Smith and Hanna, 1990; Abe and Anderson, 2022) or appear to use up all the fuel on a given trip. Although the ex-post constraints may not be binding, these constraints are

[4]It is a middle-ground approach as stated in (Hicks and Schnier, 2006) because the state space is deterministic, rather than stochastic and path dependent, to avoid the curse of dimentionality. The individual fisher formulates the expectation about the site conditions at the port and uses the deterministic information to calculate the value function for future periods. There is no information processing and expectation updating by vessels during the cruise.

[5]Fishing capacity measures the capability of a vessel or fleet of vessels to catch fish (Smith and Hanna, 1990; Gréboval, 2003). Fuel consumption is an input measure to represent the effective effort applied to existing capital stock, usually not captured in the capacity analysis (Kirkley et al., 2002; Dupont et al., 2002; Felthoven and Morrison Paul, 2004). Hold capacity is the most widely used output-based physical measure of fishing capacity (Gréboval, 1999).

likely to impact the ex-ante decision-making given that there is a risk violating them on any given trip[6]. Running out of fuel at sea also could have devastating consequences for the vessel capital and crew.

Up to now, the literature on trip-level location choice addresses portions of the full dynamic spatial problem faced by commercial fishers on a trip most likely due to model and computation complexity. As far as we are aware, no paper in the fishery economics literature on location choice captures the interlinked decision on location choice, fishing effort, travel route, and trip length with the technology constraints of fuel and hold capacity[7].

3 Methodology

To address the gap in the literature, we develop a structural model for the dynamic within-trip
1 decision process of location choice, effort allocation and the path in a multi-day trip, while the trip duration is endogenously determined by fuel or hold capacity constraints. Although uncertainty is a key part of the problem, the paper starts with a deterministic fish stock setting to disentangle the complex spatial dynamic problem. In ongoing work, we are incorporating uncertainty and passive learning over trip on the stock levels in each site.

The spatial dynamic fishing production problem of an individual vessel can be modeled as a single vehicle routing problem with profits (VRPP) or a traveling salesman problem with profits (TSPs with profits) in the operation research literature. In the routing problem with profits, all nodes of interest have a certain profit and not all of them need to be visited, but

[6]An analogy could be range anxiety which is a well-known phenomena with the use of electrical vehicles (EV) (Li et al., 2017). EV owners worry about running out of electricity before reaching the destination given the limited driving range, even though many do not run out of a charge on any given trip.

[7]Haynie and Layton (2010) jointly estimated the expected catch value and location choice. However, the continuous catch is treated as a random variable instead of a choice variable after the location is chosen. There is no assumption about the fishers effort allocation rule.

a selection has to be made. According to the way the two payoffs, profits and travel costs (mostly distance or time), are addressed, the single vehicle routing problem with profits could be categorized into three types of problems. In the profitable tour problem (PTP) (Dell'Amico et al., 1995), the objective function is to visit a subset of customers that maximizes the total collected profit minus travel cost. In the prize-collecting traveling salesman problem (PCTSP) (Balas, 1989), the objective is to minimize the total travel cost to collect a minimum amount of profit by visiting a subset of the customers. In the orienteering problem (OP) (Tsiligirides, 1984; Golden et al., 1987), the objective is to find a route that maximizes the total collected profit from the subset of nodes while not exceeding a given travel cost constraint (typically a time constraint).

The OP setting fits the spatial dynamic fishing production problem of an individual vessel the best. Because the individual vessel tries to maximize the total collected fishing profit from a subset of fishing locations and avoid violating two travel cost constraints: the hold capacity constraint and fuel capacity constraint. The OP actually integrates the difficulties of two complex combinatorial optimization problems: the knapsack problem (KP)[8] and the regular traveling salesman problem (TSP)[9]/the vehicle routing problem (VRP)[10] (Vansteenwegen and Gunawan, 2019).

The OP can be formulated as an integer programming model with the following binary decision variables: $y_i = 1$ if node i is visited, and $x_{ij} = 1$ if a visit to node i is followed by a visit to node j. We modify the OP for individual fisher's location choice problem by introducing a

[8] In the KP, each item has a profit and requires some volume. The goal is to determine the combination of items that maximizes the total profit and that fits in a given volume. In the fishing production context, fish catch requires storage space.

[9] The objective of the TSP is to find the shortest single route visitng all customers.

[10] The objective of the VRP with a single vehicle is to minimize the total distance required to visit a fixed set of customers starting from a depot.

continuous decision variable, fishing effort, and rewriting the profit at each node as a function of fishing effort using a generalized Schaefer harvest function (Zhang and Smith, 2011). With the binary and continuous decision variables, this discrete-continuous problem is formulated as a mixed integer programming (MIP) problem. In the formulation of the routing problem, time is implicit and endogenous to the explicit spatial choice.

$$\begin{aligned} \text{profit}_i &= p \times \text{harvest}_i - \text{cost}(\text{harvest}_i) \\ &= p \times q\text{Effort}_i^{\gamma}\text{Stock}_i^{\beta} - \text{cost}(\text{Effort}_i) \end{aligned} \tag{2}$$

3.1 Model for the location choice problem

3.1.1 Assumptions

1 The model features a vessel with a finite amount of fishing sites and a single port. The vessel starts and ends at the port (Node 1) in a fishing trip. Each fishing site $i \in N$ is associated with a non-negative fish stock, Stock_i. Fish stock is 0 at the port. In the deterministic case, the fisher has perfect information about the fish stock at each fishing site.

Since the distance from fishing site i to j is assumed to equal the distance from fishing j to i ($d_{ij} = d_{ji}$), we can model the problem as an undirected graph $G = (N, E)$, consisting of the set N of nodes and the set E of edges. In the undirected graph G, all the edges (i, j) are bidirectional, $x_{ij} = x_{ji}$. A brief explanation of the terms used in operation research is in Table 1.

Table 1: Terms used in fishery operation research

Node	A fishing site or a port. Nodes in the problem are numbered 1 to N
Edge	A connection between any two nodes representing movement
Tour	A fishing trip. It involves departure from a port, a sequence of fishing site visits and the return to the port.

The vessel is assumed to maximize profit. The profits from fishing at each site are aggregated into a trip-level return and each site can be visited at most once.

3.1.2 Formulation

The goal of the individual vessel is to find a route that visits a subset of N fishing sites and to choose the fishing effort at each site to maximize the total profit subject to technology constraints imposed by fuel and hold capacity constraints. The problem of the individual vessel is

$$
\begin{array}{rlll}
\max\limits_{x_{ij},y_i,A_i} & \sum_{i\in N}(p_i q A_i^{\gamma} Stock_i y_i - afc_{fuel}A_i) - \sum_{(i,j)\in E} d_{ij}x_{ij}bfc_{fuel} & & \\
\text{s.t.} & \sum_{(i,j)\in E} d_{ij}x_{ij}bf + \sum_{i\in N} A_i af \leq & F_{max} & \text{Fuel constraint} \\
& \sum_{i\in N} qA_i^{\gamma} Stock_i y_i \leq & C_{max} & \text{Hold capacity constraint} \\
& \sum_{j=2}^{N} x_{1j} = & 2y_1 & \text{Entering and Leaving 1} \\
& \sum_{i=1}^{N-1} x_{ik} = & 2y_k, x_{ik} = x_{ki} \text{ if } i > k, i \neq k, k = 2,\cdots,|N|^{11} & \text{Entering and Leaving } k \\
& y_1 = & 1 & \text{Visit Node 1} \\
& \sum_{i\in S}\sum_{j\in S} x_{ij} \leq & \sum_{i\in S\setminus\{k\}} y_i, \forall S \subset N\setminus\{1\}, |S|\geq 3, k\in S & \text{Subtour elimination} \\
& x_{ij}, y_i \in & \{0,1\} &
\end{array}
\tag{3}
$$

Table 2 summarizes the model variables and parameters that will appear repeatedly in the paper. Each constraint in (3) isexplained in turn below.

Objective function The vessel chooses the fishing site y_i, path x_{ij} and fishing effort A_i at each fishing site to maximize the total trip profit. Fishing profit equals to harvest revenue

[11] Edge $x_{ik} = x_{ki}$ in the undirected graph.

Table 2: Variable and parameter definitions

Decision Variables	Label	Range
x_{ij}	$=1$ if the edge ij is visited, 0 otherwise. $x_{ij} = x_{ji}$ in the undirected case.	(0,1)
y_i	$=1$ if the node i is visited, 0 otherwise	(0,1)
A_i	fishing effort (hook number $\times$ fishing hour) at node i	continuous
Parameters	**description**	**Value**
N	the set of nodes in the network (the port and fishing sites)	15
E	the set of edges in the network	
S	the set of subtours	
k	an index representing the node	
d_{ij}	travel distance in nm between node i and j. $d_{ij} = d_{ji}$ in the undirected case	
Stock_i	fish stock at node i	
p_i	price of harvest at node i	300
q	catchability coefficient	$9.4 \times 10^{-6\dagger}$
f	fuel usage, gallon per hour	5
c_{fuel}	$ per gallon, unit cost of fuel usage	2
a	fishing effort fuel consumption coefficient	0.002
speed	traveling speed, knots (nautical mile per hour)	5
b	traveling fuel consumption coefficient, 1/speed,	0.2
F_{max}	fuel capacity	
C_{max}	hold capacity	
γ	output elasticity of fishing effort	0.7
β	output elasticity of fish stock	1

- †: See derivation in Appendix Section D

minus fishing cost and traveling cost.

$$\max_{x_{ij}, y_i, A_i} \quad \text{Profit} = \textstyle\sum_{i \in N} (p_i \text{harvest}_i y_i - afc_{fuel} A_i) - \textstyle\sum_{(i,j) \in E} d_{ij} x_{ij} bfc_{fuel} \tag{4}$$

The price per node is allowed to be different across fishing sites and we assume that the harvest function is a Cobb-Douglas production function.

$$\text{harvest}_i = q \text{Stock}_i^{\beta} A_i^{\gamma} \tag{5}$$

where q is catchability coefficient, defined as the fraction of the population fished by an effort unit (Gulland, 1983). The Schaefer harvest function is a special case when $\gamma = 1, \beta = 1$ (Schaefer, 1954) .

Constraints The individual fisher faces the following constraints.

Fuel constraint limits the total fuel usage of fishing ($\sum_{i \in N} A_i a f$) and traveling between sites ($\sum_{(i,j) \in E} d_{ij} x_{ij} b f$) given the fuel capacity of the vessel F_{max}:

$$\sum_{(i,j) \in E} d_{ij} x_{ij} b f + \sum_{i \in N} A_i a f \leq F_{max}. \tag{6}$$

The total trip harvest must be less than or eqaul to the available hold capacity C_{max}:

$$\sum_{i \in N} q Stock_i A_i^{\gamma} y_i \leq C_{max}. \tag{7}$$

The set of port constraints ensure the vessel starts from and ends at the port (Node 1).

$$\sum_{k=2}^{N} x_{1k} = 2 y_1. \tag{8}$$

$$y_1 = 1. \tag{9}$$

The connectivity constraint ensures connectivity at node k in terms of entering and exiting the location. The vessel arrives at Node k via edge (i, k) and leaves Node k via edge (k, j). Edge $x_{kj} = x_{jk}$ because edges are bidirectional.

$$\sum_{i=1}^{N-1} x_{ik} = 2 y_k, x_{ik} = x_{ki} \text{ if } i > k, i \neq k, k = 2, \cdots, |N|. \tag{10}$$

Suppose $N = 3$, we can rewrite the connectivity constraint as the following. If the vessel visits Node 3 ($y_3 = 1$), then the travel path is either 1-3-2 ($x_{13} = x_{32} = 1$) or 2-3-1 ($x_{23} = x_{31} = 1$). Because the edge is bidirectional, edge $x_{13} = x_{31}$, $x_{12} = x_{21}$. Then the equation

$x_{12}+x_{13}=2y_2$ describes the two possible paths that the individual vessel visits Node 3.

$$\begin{aligned} x_{12}+x_{13} &= 2y_1 \\ x_{12}+x_{23} &= 2y_2 \\ x_{13}+x_{23} &= 2y_3 \end{aligned} \tag{11}$$

Subtour elimination constraints eliminate possible subtours[12]. For every subset of nodes (port excluded), the number of visited edges inside the subset (x_{ij}-values equal to 1) should be strictly smaller than the number of nodes in the subset. Dantzig et al. (1954) proposed the following subtour elimination constraints for the travelling salesman problem (Equation 12). It is the strongest known linear relaxation for the travelling salesman problem but the exponential number of constraints makes the implementation impractical (Palomo-Martínez et al., 2017). The set of subtours is $|S|=\sum_{i\in S} y_i$.

$$\sum_{i,j\in S} x_{ij} \leq |S|-1; \forall S \subset N \setminus \{1\}, S \neq \varnothing. \tag{12}$$

Since not all nodes are visited in the solution of the orienteering problem, Feillet et al. (2005) defined a stronger formulation[13] (see Equation 13) (Palomo-Martínez et al., 2017). The bidirection setting of x_{ij} naturally deleted subtours with only two nodes[14] .

$$\sum_{i,j\in S: i\neq j} x_{ij} \leq \sum_{i\in S\setminus\{k\}} y_i; \forall S \subset N \setminus \{1\}, |S| \geq 3, k \in S. \tag{13}$$

[12]Subtours: The optimal solution found doesn't give one continuous path through all the points, but instead has several disconnected loops (subtours). Appendix Section B includes an example of TSP solution with subtours.

[13]The formulation is stronger for the orienteering problem where only a subset of nodes is visited. In the traveling salesmen problem, the formulation is different because all nodes are visited.

[14]A subtour of two nodes i and j requires both $x_{ij}=1$ and $x_{ji}=1$. But the bidirectional edge $x_{ij}=1$ represents either the edge from i to j is taken or the edge of j to i is taken but not both. Therefore there are no subtours of two nodes with the bidirectional edge x_{ij}.

The edge choice variable x_{ij} and node choice variable y_i are both binary variables: $x_{ij} \in (0, 1)$ and $y_i \in (0, 1)$. Fishing effort (fishing hour × hook number), A_i, is continuous.

Solution We solve for an open-loop solution that does not account for the strategic interaction between players through the evolution of state variables over time and the associated control adjustments (aka feedback rule). The player chooses the plan for the whole trip at the beginning and commits to it (Cellini and Lambertini, 2004).

3.2 1-site Ahead Myopic Fisher

3.2.1 Assumptions and Setup

Period-by-period static random utility model for location decisions depicts a myopic fisher. Using the similar formulation of the dynamic fisher, the individual fisher does a rolling maximization by choosing only one site at each decision point.

Because time is implicit and endogenous to spatial location in this framework, the decision point is in the spatial dimension. At the initial decision point one, the fisher is at the port (Node 1) and chooses to go to site k. Then the fisher is at site k, the decision point two where the second site is chosen. The time between two decision points (chosen locations) equals to the fishing time at the previous decision point (location) plus travelling time from the previous decision point (location) to the current decision point (location). It is endogenously determined by the location choice and effort allocation. The temporal dimension can be constructed using the model solution of location choice, effort allocation and path.

If the available storage is used up, the fisher has to return to the port. Moreover, if the fuel cannot support the trip from the current site to any next site and then back to the port, the fisher will return to the port immediately[15]. Otherwise, the vessel will be adrift at sea after fishing at the next site due to insufficient fuel.

In this setting, we modify the fuel constraint as Equation 14 since the fisher considers the distance between the next site and the port in addition to the distance between current site and the next site. The bidirectional edge x_{ij} used in the dynamic fisher's problem (Equation 3) doesn't capture the difference between travel distance back to the port of edge (i, j) and that of edge (j, i). The distance from site i to site j to the port (Node 1) is not equal to the distance from site j to site i to the port because the distance from the site to port depends on the current site ($d_{ij} + d_{j1} \neq d_{ji} + d_{i1}$ because $d_{i1} \neq d_{j1}$ given $i \neq j$).

The myopic 1-step ahead fisher problem is a directed graph with directional edges.

$$\sum_{(i,j) \in E} (\mathrm{d}_{ij} + d_{j,1}) x_{ij} b f + \sum_{(i) \in N} a A_i f \leq F^t_{max} \tag{14}$$

[15]Going back to the port results in negative profit because there is no fish stock at the port. Negative profit is allowed in the rolling maximization to make this happen.

3.2.2 Formulation

The myopic problem at each decision point t can be formulated as

$$
\begin{aligned}
\max_{x_{ij},y_i,A_i} \quad & \textstyle\sum_{i\in N}(p_i q A_i^{\gamma} Stock_i y_i - afc_{fuel}A_i) - \sum_{(i,j)\in E} d_{ij}x_{ij}fc_{fuel} && \\
\text{s.t.} \quad \textstyle\sum_{(i,j)\in E}(\mathrm{d}_{ij}+d_{j,1})x_{ij}bf + \sum_{(i)\in N} A_i af \leq \; & F_{max}^t && \text{Fuel constraints} \\
\textstyle\sum_{i\in N} qStock_i A_i^{\gamma} y_i \leq \; & C_{max}^t && \text{Hold capacity constraints} \\
\textstyle\sum_i^N x_{ik} + \sum_i^N x_{ki} = \; & y_k, i \neq k && \text{Entering and Leaving k} \\
y_k = \; & 1 && \text{Starting from Node k} \\
\textstyle\sum_i^N x_{ki} = \; & 1, i \neq k && \text{Starting from Node k} \\
\textstyle\sum_{i,j} x_{ij} = \; & 1 && \text{One edge is visited} \\
\textstyle\sum_{i=1}^N y_i = \; & 2 && \text{Two nodes are visited} \\
A_k = \; & 0, k \in \text{visited nodes} && \text{No harvest at previously visited nodes} \\
y_k = \; & 0, k \in \text{visited nodes} \setminus \text{starting node} && \text{Visited nodes in previous trip exclusion} \\
x_{ij}, y_i \in \; & \{0,1\} &&
\end{aligned}
\tag{15}
$$

F_{max}^t (C_{max}^t) is the available fuel capacity (hold capacity) at decision point t, equal to the available fuel capacity (hold capacity) subtracted by realized fuel consumption (harvest) at the previous decision point $t-1$.

$$
\begin{aligned}
F_{max}^t = \; & F_{max}^{t-1} - d_{ij}x_{ij}^{t-1}bf - A_i^{t-1}af \\
C_{max}^t = \; & C_{max}^{t-1} - qStock_i(A_i^{t-1})^{\gamma} y_i^{t-1}
\end{aligned}
\tag{16}
$$

3.3 M-site Ahead Partially Myopic Fisher

3.3.1 Assumption and Setup

Instead of site-by-site choice, the m-site ahead partially myopic fisher chooses a sequence of up to m sites before returning to the port at every decision point. The fisher follows the sequence to visit the chosen fishing sites. The degree of forward looking m is between 1 and $N-1$, while N denotes the total number of sites including the port[16]. At the first chosen site, the fisher re-optimizes the trip by choosing another sequence of up to m sites before returning to the port. The whole choice set includes no more than $m+1$ sites because at some decision point t, the remaining fuel constraint and/or capacity may not be sufficient to support travelling and fishing to another m sites and returning to the port. This process repeats until the fisher arrives at the port.

Specifically, the modeling for the m-site ahead partially myopic fisher is:

1. At the port (the first decision point, $n_1^0 = 1$), the myopic fisher chooses the first set of $m+1 \leq N$ sites (n_1^1, n_2^1, $\cdots$, n_m^1, port) before going back to the port, subject to fuel constraint $F_{max}^1 = F_{max}$ and capacity constraint $C_{max}^1 = C_{max}$. The superscript 1 of choice n_m^1 and technology constraints F_{max}^1 and C_{max}^1 denotes the choice is made at the first decision point. The subscript m of choice n_m^1 denotes it is the mth chosen location in the choice set.

2. After fishing at the chosen site n_1^1 (the second decision point), the fisher makes the second choice set of m sites before returning to the port (n_1^2, n_2^2, $\cdots$, n_m^2, port), subject to fuel constraint F_{max}^2 and hold capacity constraint C_{max}^2. F_{max}^2 equals to fuel constraint at

[16]When $m = 1$, the m-site ahead fisher is the pure myopic fisher described in the previous section. When $m = N$, the m-site ahead fisher is the pur dynamic fisher.

the first decision point F_{max}^1 minus the fuel usage from the port (the first decision point) to site n_1^1 (the second decision point) and fishing fuel usage at site n_1^1. C_{max}^2 equals to hold capacity constraint at the first decision point C_{max}^1 minus the fish catch at the second decision point site n_1^1.

3. After fishing at Site n_1^t (the $t+1$th decision point), the fisher chooses the $t+1$th sequence of sites (n_1^{t+1}, n_2^{t+1}, $\cdots$, n_m^{t+1}= port) subject to constraints of fuel F_{max}^{t+1} and hold capacity C_{max}^{t+1}.

4. This repeats T times until the fisher chooses the port ($n_1^T = port$) at Site n_1^{T-1} (the Tth decision point). The travel path of the fisher is (port, n_1^1, n_1^2, $\ldots$, n_1^t,$\ldots$,n_1^T =port). See Appendix Section F for the choice sets, fuel capacity constraints and hold capacity constraints at each decision point.

3.4 Formulation

At the tth decision point, Site n_1^{t-1}, the partially myopic fisher chooses a sequence of sites, travel routes and fishing efforts to maximize the profit. Decision point t ranges from 1 to T. The m-site ahead partially myopic fisher's problem is an undirected graph.

$$
\begin{aligned}
\max_{x_{ij},y_i,A_i} \quad & \textstyle\sum_{i\in N}(p_i q A_i^{\gamma} Stock_i y_i - afc_{fuel}A_i) - \sum_{(i,j)\in E} d_{ij}x_{ij}bfc_{fuel} & & \\
\text{s.t.} \quad \textstyle\sum_{(i,j)\in E} d_{ij}x_{ij}bf + \sum_{i\in N} A_i af \leq \; & F^t_{max} & & \text{Fuel constraint} \\
\textstyle\sum_{i\in N} qA_i^{\gamma} Stock_i y_i \leq \; & C^t_{max} & & \text{Hold capacity constraint} \\
\textstyle\sum_{j=2}^{N} x_{1j} = \; & y_1 + 1\{t=1\}y_1 \text{ [17]} & & \text{Entering and Leaving 1} \\
\textstyle\sum_{j=2}^{N} x_{n_1^{t-1}j} = \; & y_{n_1^{t-1}}, \text{ if } t \geq 2 \text{ [18]} & & \text{Entering and Leaving } n_1^{t-1} \\
\textstyle\sum_{i=1}^{N-1} x_{ik} = \; & 2y_k, x_{ik} = x_{ki} \text{ if } i > k, i \neq k, k = 2, \cdots, |N| \text{ [19]} & & \text{Entering and Leaving } k \\
y_1 = \; & 1 & & \text{Visit Node 1} \\
y_{n_1^{t-1}} = \; & 1 \text{ [20]} & & \text{Visit Node } n_1^{t-1} \\
\textstyle\sum_{i\in S}\sum_{j\in S} x_{ij} \leq \; & \textstyle\sum_{i\in S\setminus\{k\}} y_i, \forall S \subset N \setminus \{1\}, |S| \geq 3, k \in S & & \text{Subtour elimination} \\
\textstyle\sum_{i\in N} y_i \leq \; & m + 1 + 1\{t \geq 2\} \text{ [21]} & & \text{Node Visit constraint} \\
x_{ij}, y_i \in \; & \{0,1\} & &
\end{aligned}
\tag{17}
$$

4 Setting

The model and analysis in the paper are motivated and parameterized to the extent possible by the Gulf of Mexico grouper-tilefish demersal longline fishery (Figure 2). OFarrell et al. (2019b) integrated three datasets (Vessel Monitoring System (VMS) data, observer data,

[17] If the fisher is at the port (the first decision point), $\sum_{j=2}^{N} x_{1j} = 2y_1$ because the fisher leaves and returns to the port. If the fisher is at another site other than port, $\sum_{j=2}^{N} x_{1j} = y_1$ because the fisher has to return to the port.

[18] If the fisher is at another site n_1^{t-1} other than the port (the tth choice set , $t \geq 2$), this constraint denotes that fisher departures from Site n_1^{t-1}.

[19] Edge $x_{ik} = x_{ki}$ in the undirected graph.

[20] When the fisher is at the port,$n_1^{t-1} = 1$, this constraint duplicates $y_1 = 1$ and becomes redundant. When the fisher is at Site n_1^{t-1} other than the port, the constraint ensures that site is chosen.

[21] At the port (the first decision point), the fisher chooses m sites and port so in total $m+1$ sites. However, at Site n_1^t other than the port (the tth decision point, $t \geq 2$), the fisher chooses $m+2$ sites. The extra 2 sites include the current site and the port.

logbook data) to capture the fine spatial behavior of the fleet. The dataset consists of more than one million hourly GPS positions (VMS pings) from the bottom longline fishery tracking 5508 trips made by 133 vessels from 2007 to 2014. Figure 1b is the fishing heat map plotted using 587,204 VMS pins from 106 vessels from 2007 to 2009.

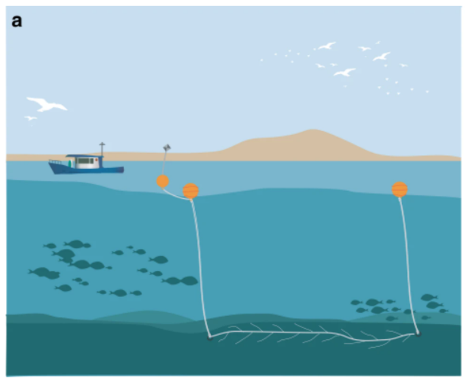


Figure 2: Bottom longlines fishing in Gulf of Mexico (OFarrell et al., 2019b)

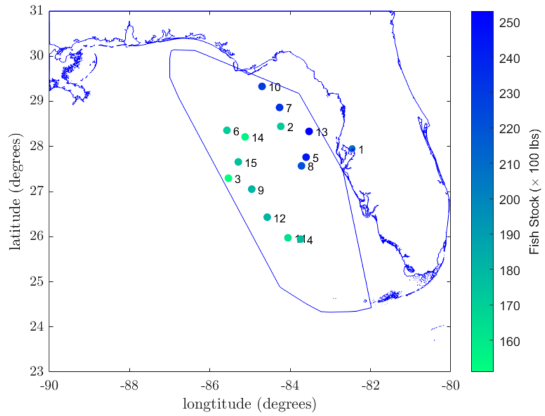
1 At present, the paper demonstrates the model on a 15-node problem (See Figure 3), where the port (Node 1) is set at Tampa, FL. The simulated vessel path in Figure 1c forms the basis for modeling a vessel leaving and returning to the same port.

The fishing ground modeled in the paper is based on the eastern Gulf of Mexico and is created as a convex hull of the VMS pings classified as fishing using a supervised learning algorithm trained by the observer data (OFarrell et al., 2019b)[22]. The fourteen nodes representing fourteen fishing sites are randomly generated within the polygon. The inter-site distances are calculated in nautical miles as the great-circle distance based on the fishing site coordinates using Haversine formula. The fish stocks are random draws following a spatial pattern that stock is higher for inshore sites[23]. Fishing effort is defined as fishing hour (longline set, soak

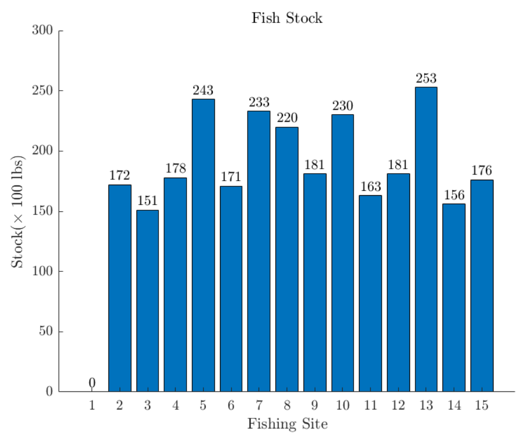
[22]VMS records east to the 87th meridian west are used in this version of the paper. The convex hull is created using `chull` function in R.

[23]At a close-to-shore site, stock (lbs) is a random draw from the uniform distribution [20000, 30000]. Stock at an offshore site is a random number that is uniformly distributed in [15000, 20000]. A site is considered as close-to-shore if the point-to-polygon (site-to-shore) distance is below a threshold. The Euclidean distance of

and retrieve time) times the number of hooks. The number of hooks is set to be 1000 to simplify the analysis[24]. In the harvest function, we set the output elasticity of fishing effort $\gamma = 0.7$ and the catch stock elasticity $\beta = 1$ as Zhang and Smith (2011) estimate the output elasticity of fishing effort γ to be less than 1 (diminishing harvests in fishing effort) regardless of whether the catch stock elasticity β is restricted to 1 for all gears in the reef-fish fishery in the Gulf of Mexico[25].



(a) Map



(b) Simulated fish stock

Figure 3: Spatial distribution and fish stock of the port (Node 1) and 14 fishing sites in the Gulf of Mexico

We consider the trips of a dynamic fisher, a myopic fisher, and a partially myopic fisher in the presence of three sets of technology constraints: no binding technology constraints (sufficiently large fuel capacity $F_{max} = 20000$ gallons and hold capacity $C_{max} = 200 \times 100$ lbs), a binding fuel capacity constraint {fuel capacity $F_{max} = 3000$ gallons, hold capacity $C_{max} = 200 \times 100$ lbs}, and a binding hold capacity constraint { fuel capacity $F_{max} = 20000$

1 is used as the threshold.

[24]The observer data includes 8252 longline sets from 314 fishing trips by 83 vessels from 08/08/2006 to 04/24/2014.The hook number ranges from 150 to 3000 with a median of 1000 and a mean of 1019.

[25]The estimated catch effort elasticity for bottom longline is 0.3325 with standard error 0.0093 in Zhang and Smith (2011). However, the effort in Zhang and Smith (2011) is defined as number of crew times trip days while the effort in this paper is defined as number of hooks times fishing hour (longline set, soak and retrieve time).

gallons, hold capacity $C_{max} = 30 \times 100$ lbs}[26]. The problems are formulated as mixed-integer programming (MIP) problems and solved by the Gurobi solver.

The implicit temporal dimension can be constructed by the fishing and travelling times. Fishing effort reflects the fishing hours (longline set, soak, and retrieve time) spent at a fishing site. Travelling time can be calculated from the travel distance of the chosen edge with a given travel speed. Suppose the traveling speed is 5 knots (nautical mile per hour), traveling fuel consumption rate is 5 gallon per hour while fishing fuel consumption rate is 10 gallon per hour[27].

5 Results

Generally, we expect that the technology constraints affect the short-run decisions over fishing location, path, and fishing effort by imposing a trip level shadow price. Before reporting the simulation results that demonstrate those findings, we can analytically show the role that technology constraints play in determining the effort allocation at each site. Specifically, the trip level shadow price that holds across fishing sites either affects the marginal revenue $(p - \lambda_{hold})$ or the marginal cost $(c_{fuel} + \lambda_{fuel})$ depending on the constraint that is binding. Equation 19 shows the optimal effort allocation at site i.

[26] The logbook data includes hold capacity and fuel capacity for 145 vessels. The hold capacity in pounds ranges from 1000 to 200,000 with mean of 15787 and median 12000. The fuel capacity in gallons ranges from 200 to 6000 with mean of 1319 and median of 1000.

[27] Fuel consumption rate for fishing is assumed to be twice as large as steaming. Accurate information on fuel consumption rates for steaming and fishing were not available yet. We are exploring ways to improve this parameterization by developing methods more appropriate for longline fishing in the Gulf of Mexico.

$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial A_i} &= pq\text{Stock}_i y_i \gamma A_i^{\gamma-1} - afc_{fuel} - \lambda_{fuel} af - \lambda_{hold} q\text{Stock}_i y_i \gamma A_i^{\gamma-1} \\
&= (p-\lambda_{hold}) q\text{Stock}_i y_i \gamma A_i^{\gamma-1} - (c_{fuel}+\lambda_{fuel}) af \qquad (18) \\
&= 0
\end{aligned}$$

$$\Rightarrow A_i^* = [\frac{(p-\lambda_{hold}) q\text{Stock}_i y_i \gamma}{(c_{fuel}+\lambda_{fuel}) af}]^{\frac{1}{1-\gamma}} \qquad (19)$$

Regardless of the binding constraint, the shadow price reduces the effort allocation at each site relative to the case where the constraints are not binding. The latter is representative of the myopic fisher at sites that are not their last fishing sites. Having said that, eventually the constraints will bind even in the myopic case and at the last decision point where they bind, there is a revealed shadow price. For example, if the myopic fisher is making their 5th decision of where to go on a trip and how much effort to exert and they calculate that they can't go to another site as they will run out fuel, then that decision's optimal calculus includes the shadow price attached to the binding fuel constraint. But for all decisions before their 5th, the constraint did not bind and therefore their decision calculus was independent of the shadow price.

The presence of the shadow price impacts directly the effort exerted in each patch which also determines the fuel used for fishing in each patch and the catch. As such, it influences the path taken on the trip (and the fuel expended steaming to and from the fishing sites).

5.1 Dynamic fisher vs myopic fisher

Figure 4 shows the location choice,travel path and fishing effort of the dynamic fisher and the myopic fisher under three sets of technology constraints. Table 3 highlights the differences in key variables across the cases including the trip profit, fuel use, harvest, shadow price, and endogenous trip length.

Variable	Unconstrained $F_{max} = 20,000, C_{max} = 200$		Fuel $F_{max} = 3,000, C_{max} = 200$		Hold $F_{max} = 20,000, C_{max} = 30$	
Fisher Type	Dynamic	Myopic	Dynamic	Myopic	Dynamic	Myopic
Profit		$0.94\pi_{\text{dynamic}}$		$0.44\pi_{\text{dynamic}}$		$0.61\pi_{\text{dynamic}}$
Fuel Usage	17518.03	17916.41	3000	3000	2138.7	3064
Harvest	160.88	160.88	40.74	29.16	30	30
Shadow price		-	$\lambda_{\text{fuel}} = 1.6031$		$\lambda_{hold} = 142.3355$	
Travel%	6.9%	10.8%	34.5%	10%	36.9%	9.8%
Fishing%	93.1%	89.2%	65.5%	90%	63.1%	90.2%
Trip Length (day)	75	79	15	13	11	13

1. Travel% denotes percentage of travel time of the total trip length. Same for Fishing%.

Table 3: Fuel and Hold Usage, Binding Constraints, Shadow Price, Travel Route and Time

5.1.1 Nonbinding constraints

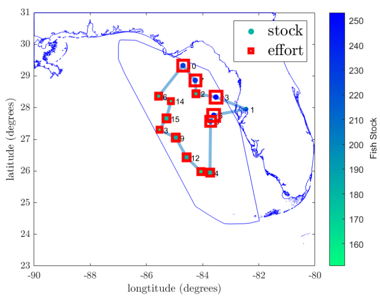
With sufficient fuel and hold capacity[28], the dynamic fisher and myopic fisher visit and harvest at all fishing sites and exert fishing effort at each site until the marginal profit equals 0 ($\frac{\partial \pi}{\partial \text{effort}_i} = 0$). While the two are identical in terms of sites visited, harvest, and effort exerted, the trip profits differ because the dynamic fisher optimizes their route while the myopic does not[29]. Figure 4a and 4b show the route planning by the dynamic fisher while the myopic fisher only considers the next best choice (mainly following the order of fish stock).

5.1.2 Binding fuel constraint

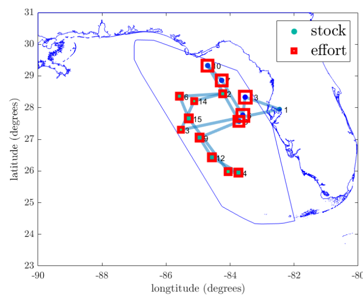
While the unconstrained case is valuable for highlighting the role and value of route planning, vessels are constrained in their fuel and hold capacity, especially when considering the large choice set of fishing sites. To investigate the role of these technological constraints, we reduce the fuel capacity to ensure that it is binding. Specifically, when we set the fuel constraint

[28]We set fuel capacity $F_{max} = 20,000$ gallons and hold capacity $C_{max} = 200 \times 100$ lbs so that neither constraints bind (Table 3).

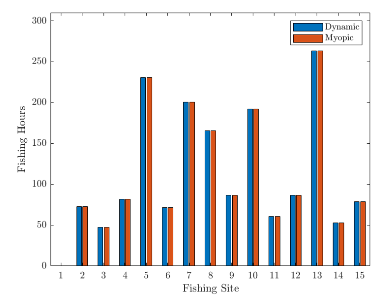
[29]The bidirectional route for the dynamic fisher:1-5-8-4-11-12-9-15-14-6-10-7-2-13-1. The directional route for the myopic fisher:1-13-5-7-10-8-9-12-4-11-15-6-2-14-3-1.



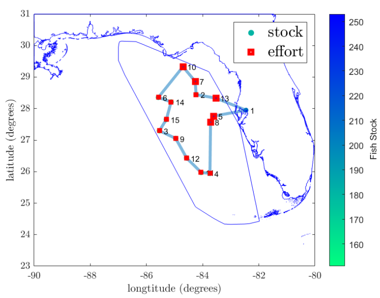
(a) Unconstrained, Dynamic



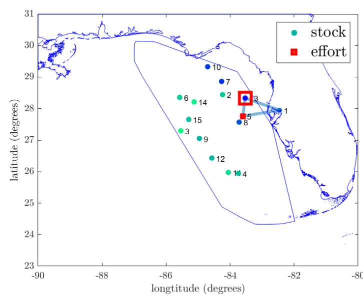
(b) Unconstrained, Myopic



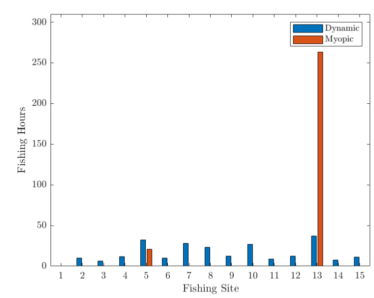
(c) Effort



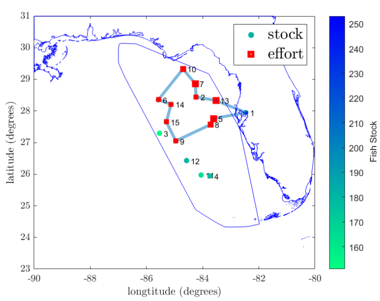
(d) Fuel, Dynamic,



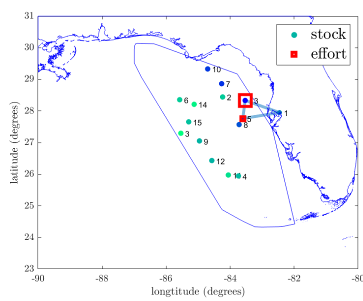
(e) Fuel, Myopic



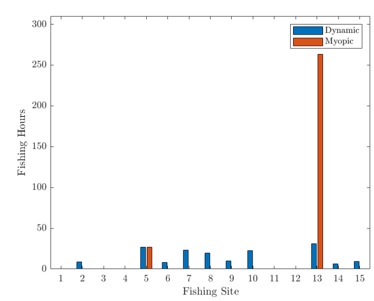
(f) Effort



(g) Hold, Dynamic



(h) Hold, Myopic



(i) Effort

Figure 4: Travel Path and Fishing Effort, Dynamic Fisher vs Myopic Fisher

to 3,000 gallons with the same hold capacity constraint of 200×100 lbs, we find that both fishers face a binding fuel constraint though it only appears in the last decision of the myopic fishers trip calculus[30].

In Figure 4d, we see that the dynamic fisher goes to the same location choices, as the unconstrained case, but reduces the effort at every visited site. In the presence of the constraint and with diminishing marginal harvest to effort, we find that it is optimal to spread fishing effort across fishing sites instead of concentrating effort on one or two sites with the largest fish stock. The effort is reallocated such that marginal profit of effort equals to the the shadow cost of fuel times the fuel consumption per unit of effort ($\frac{\partial \pi}{\partial \text{effort}_i} = af\lambda_{\text{fuel}}$).

The myopic fisher on the other hand concentrates effort at Site 13 with the highest fish stock (Figure 4e). When the fisher makes the choice to visit Site 13, the fuel constraint is not binding, and as such the fishing effort at Site 13 is the unconstrained optimal effort. The fuel constraint, however, is binding and hence reduces the effort spent at Site 5, the last fishing site before the port. Since fishing and travelling consume fuel, we find that the relative shadow price of fuel for the myopic at site 5 is greater than the optimal shadow price ($\lambda_{fuel,5}^{myopic} = 2.1230 > \lambda_{fuel}^{dynamic} = 1.6031$). This results in the effort at Site 5 being smaller than the dynamic optimal level. The inefficient use of fuel[31] and concentrated levels of effort across fishing sites, limits the number of visited sites and leads to a much lower profit for the myopic fisher ($\pi_{\text{myopic}} \approx 0.44\pi_{\text{dynamic}}$).

[30] The bidirectional route for the dynamic fisher:1-5-8-4-11-12-9-15-14-6-10-7-2-13-1. The directional route for the myopic fisher:1-13-5-1.

[31] Because the myopic fisher visits the fishing sites following the order of fish stock, the first few visited fishing sites have the largest fish stock and therefore requires a lot of fishing effort/fuel to drive down the marginal profit of effort to zero.

5.1.3 Binding hold constraint

We now consider the case of reducing the hold capacity from 200×100 lbs to 30×100 lbs while using the unconstrained amount of fuel. Both fishers have a binding hold constraint but just as in the case with the binding fuel constraint, the dynamic fisher considers the constraint when deciding the trip and myopic only in their final decision point[32].

In Figure 4g, we see that the dynamic fisher no longer visits the relatively distant Sites 3, 4, 11 and 12 (a smaller circle), and reduces the effort at every visited site. The effort is reallocated such that marginal profit of harvest equals to the shadow cost of hold capacity ($\frac{\partial \pi}{\partial \text{harvest}_i} = \lambda_{\text{hold}}$). On the contrary, the myopic fisher concentrates effort at Site 13 with the highest fish stock (Figure 4h). The hold capacity constraint for the myopic fisher is binding at Site 5, the last decision point before returning to the port ($\lambda_{hold,5}^{myopic} = 154.47 > \lambda_{hold}^{dynamic} = 142.33$). Given the relative size of the shadow prices, we find that the effort at Site 5 is smaller in the myopic than the dynamic optimal level. The myopic fisher again has a much lower trip level profit ($\pi_{\text{myopic}} \approx 0.61\pi_{\text{dynamic}}$), even though both fishers have the same harvest. We also find that the endogenous trip length is longer and that most of their fuel is spent fishing (they fish longer and harder at each patch before moving on as they are fishing until the marginal profit goes to zero).

5.2 M-site ahead partially myopic fisher

From the previous results, the dynamic fisher and the myopic (1-site ahead) fisher behave differently in route planning and incorporating shadow price of the technology constraints into fishing effort. In the unconstrained case, the myopic fisher makes less profit because of

[32] The bidirectional route for the dynamic fisher:1-5-8-9-15-14-6-10-7-2-13-1. The directional route for the myopic fisher:1-13-5-1.

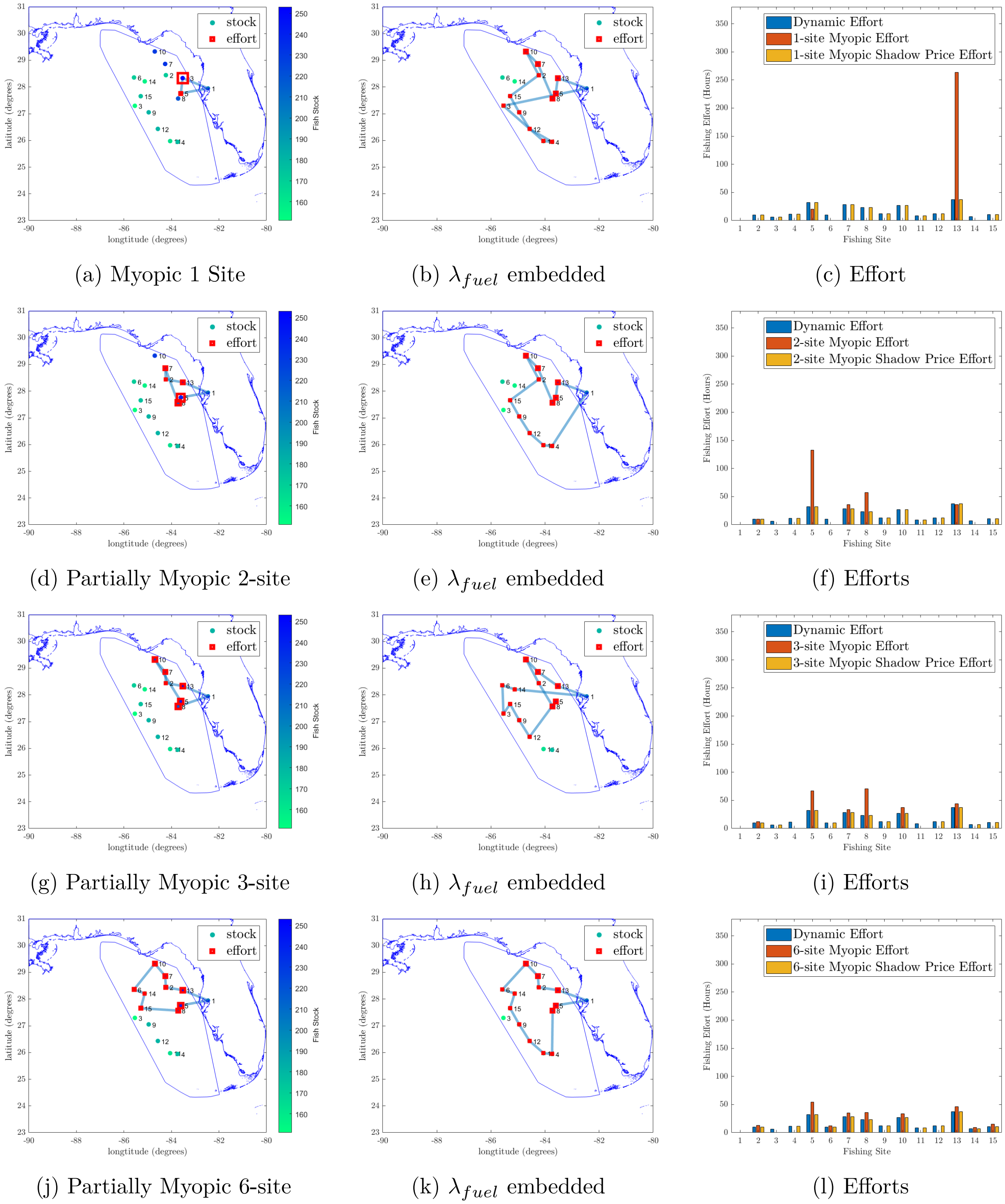
no route planning. In the fuel constrained case and hold constrained case, no route planning and ignoring the technology constraint before the last decision point lead to the smaller profit for the myopic fisher. This section decomposes the loss from route planing and the loss from ignoring the technology constraint shadow price in the fuel constrained case ($F_{max} = 3000$ gallons, $C_{max} = 200 \times 100$ lbs.).

The m-site ahead fisher is more forward looking with larger m, therefore the degree of route planning increases with m. To separate the impact of route planning from that of technology constraint shadow price, we consider an m-site ahead fisher who knows and incorporates the shadow price of the binding technology constraint. From Equation 19, the shadow price of fuel acts as extra fuel cost that affects the fishing effort at each fishing site when the fuel constraint is binding. Then the m-site ahead partially myopic fisher knowing λ_{fuel} faces the
1 cost of $c_{fuel} + \lambda_{fuel}$ in the decision-making process. Figure 5 shows the location choice, travel path and fishing effort of the m-site ahead fisher and the m-site ahead fisher knowing λ_{fuel}. Table 4 summarizes the deviation of profit from the dynamic optimal profit, total catch, travel and fishing time.

For the myopic fisher who makes period-by-period/site-by-site decision, $\pi_{myopic} = 0.44\pi_{dynamic}$. With the shadow price of fuel embedded in the decision making, the profit almost doubled ($\pi_{myopic,\lambda_{fuel}} = 0.86\pi_{dynamic}$). The profit increases largely because the myopic fisher chooses the dynamic optimal level of effort, knowing the shadow price of fuel. The myopic fisher, however, visits fewer sites than the dynamic fisher because of the lack of route planning (Figure 5b). When m increases from 1 to 2, 3 and 6, the profit increases from better route planning that leads to less fuel wasted allowing visiting and fishing at more sites. However, the fuel is not used up with constrained route planning. We find that the magnitude of profit increase from route planning is lower compared to the magnitude of profit increase from embedding the shadow price of fuel. That is, the efficiency loss from overfishing at each site is much greater than the efficiency loss from poor route planning. Whether this holds in general is unclear and is something we plan to explore with further sensitivity analysis. For example, we are currently assuming that the travel fuel consumption rate is half of the fishing fuel consumption rate and as such, improving travel efficiency may not increase much profit.

In general, profit increases with increasing m due to both better route planning and accounting for the shadow price of the technology constraints. That is, greater forward-looking behavior results in spreading effort across fishing sites by considering the binding technology constraints. Although the shadow price of fuel is not equal across all visited fishing sites, the difference among the shadow price of fuel decreases with m[33]. From the third column of graphs in Figure 5, we can see that fishing efforts (red column by the m-site ahead partially myopic fisher) are more concentrated at early visited sites with smaller m ($m = 1, 2$ Figure 5c and 5f). Fishing efforts between the dynamic and partially myopic fisher are more equal across the fishing sites with larger m ($m = 3, 6$ Figure 5i and 5l).

[33] Here are the revealed shadow price for partially myopic fishers.
2-site ahead: $\lambda_{fuel,5} = 0.3607$, $\lambda_{fuel,8} = 0.7460$, $\lambda_{fuel,7} = 1.3513$, $\lambda_{fuel,i} = 1.6359, i = 2, 13$.
3-site ahead: $\lambda_{fuel,8} = 0.5804$, $\lambda_{fuel,5} = 0.8955$, $\lambda_{fuel,10} = 1.2654$, $\lambda_{fuel,i} = 1.4262, i = 7, 2, 13$.
6-site ahead: $\lambda_{fuel,5} = 1.0821$, $\lambda_{fuel,8} = 1.1579$, $\lambda_{fuel,15} = 1.2996$, $\lambda_{fuel,i} = 1.3735, i = 14, 6, 10, 7, 2, 13$.



(a) Myopic 1 Site

(b) λ_{fuel} embedded

(c) Effort

(d) Partially Myopic 2-site

(e) λ_{fuel} embedded

(f) Efforts

(g) Partially Myopic 3-site

(h) λ_{fuel} embedded

(i) Efforts

(j) Partially Myopic 6-site

(k) λ_{fuel} embedded

(l) Efforts

Figure 5: M-site ahead partially myopic fisher, binding fuel, $F_{max} = 3000$, $C_{max} = 200$

Variable	Dynamic	1-site ahead		2-site ahead		3-site ahead		6-site ahead	
		Myopic	w/λ_{fuel}	Partially Myopic	w/λ_{fuel}	Partially Myopic	w/λ_{fuel}	Partially Myopic	w/λ_{fuel}
Profit[1]	6221.2	0.44	0.86	0.78	0.87	0.88	0.87	0.95	0.97
Fuel Usage	3000	3000	2994.5	3000	2771.43	3000	2887.08	3000	2914.54
Harvest	40.74	29.16	37.75	36.08	36.61	38.32	37.30	39.73	39.6
λ_{fuel}	1.6031		1.6031		1.6031		1.6031		1.6031
Travel%[2]	34.5%	10%	41.9%	17.2%	37.4%	21.2%	39.6%	26.3%	34.5%
Fishing%	65.5%	90%	58.1%	82.8%	62.6%	78.8%	60.4%	73.7%	65.5%
Trip Length (day)	15	13	16	13.7	14.2	14	15	14.4	14.7
# Sites	14	2	12	5	11	6	12	9	13

1. Only the profit of the dynamic fisher is listed in the table. For the myopic and partially myopic fishers, the percentage of the dynamic profit $\frac{\pi}{\pi_{dynamic}}$ is listed.

2. Travel% denotes percentage of travel time of the total trip length. Same for Fishing%.

Table 4: Fuel and hold usage by m-site ahead partially myopic fisher with binding fuel, $F_{max} = 3000$, $C_{max} = 200$

6 Conclusions

Fishing production function is uniquely shaped by space. This paper constructs a spatial dynamic model of an individual fisher's decision on location choices, effort allocation, and a multi-day trip path with endogenous trip length. This structural behavioral model of ex-ante short run production decision-making is useful to fishery management and lays the foundation of a comprehensive model of the fishing production process. After estimation or calibration using the empirical data, the model can be used to predict fishers' responses to policies like area closure and access economic impacts for policy design or evaluation.

The individual fisher maximizes profit by choosing locations with high fish stock and low travel distance. Technology constraints such as fuel and hold capacity impose shadow prices affecting, from the outset of the trip, the interconnected decision on location choice, effort allocation, and travel path.

For this analysis we generate a random set of 14 fishing sites, each with a given fish stock following the spatial pattern that nearshore sites are higher in stock. Changes in the location of the sites or the spatial pattern of fish stock won't change the qualitative results. We may have another set of between-site distances with another draw of fishing sites or a different set of stock. Then the resulting chosen fishing sites, the fishing effort at each site, and the travel path for a specific type of fisher may change. However, the fisher has consistent behavior. The dynamic fisher always allocates effort at every visited site so that the marginal profit of harvest is equal to the shadow price of fuel or hold. The myopic fisher or the partially myopic tends to overfish at the early visited sites.

An implication of our findings is that in the traditional random utility model of fishing location (Equation 1) the coefficient of expected rewards is overestimated if the technology constraints are omitted. Route planning is also missing in the static RUM models. Considering one location choice at a time, the myopic fisher will not know all the chosen locations ahead and hence fail to find the shortest path. This will inversely restrict the fishing effort at each fishing site and the number of fishing sites that the fisher can visit. We conclude that the static RUM models are structurally misspecified but leave for future research an investigation into the empirical ramification of the incorrect specification.

The current version of the paper accounts only for the deterministic case in which the fisher has perfect information on the fish stock at each fishing site. Under a stochastic setting, the individual fisher cannot observe the fish stock and has beliefs on the mean and variance of the stock at each site. Under uncertainty, the vessel hold capacity constraint also becomes a probabilistic constraint. Decision making with uncertainty also requires cognitive operations, including information acquisition and information processing. In future work, we plan to incorporate these features of fishery production into the structural model of trip level decision-making.

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A Fishing Production Process

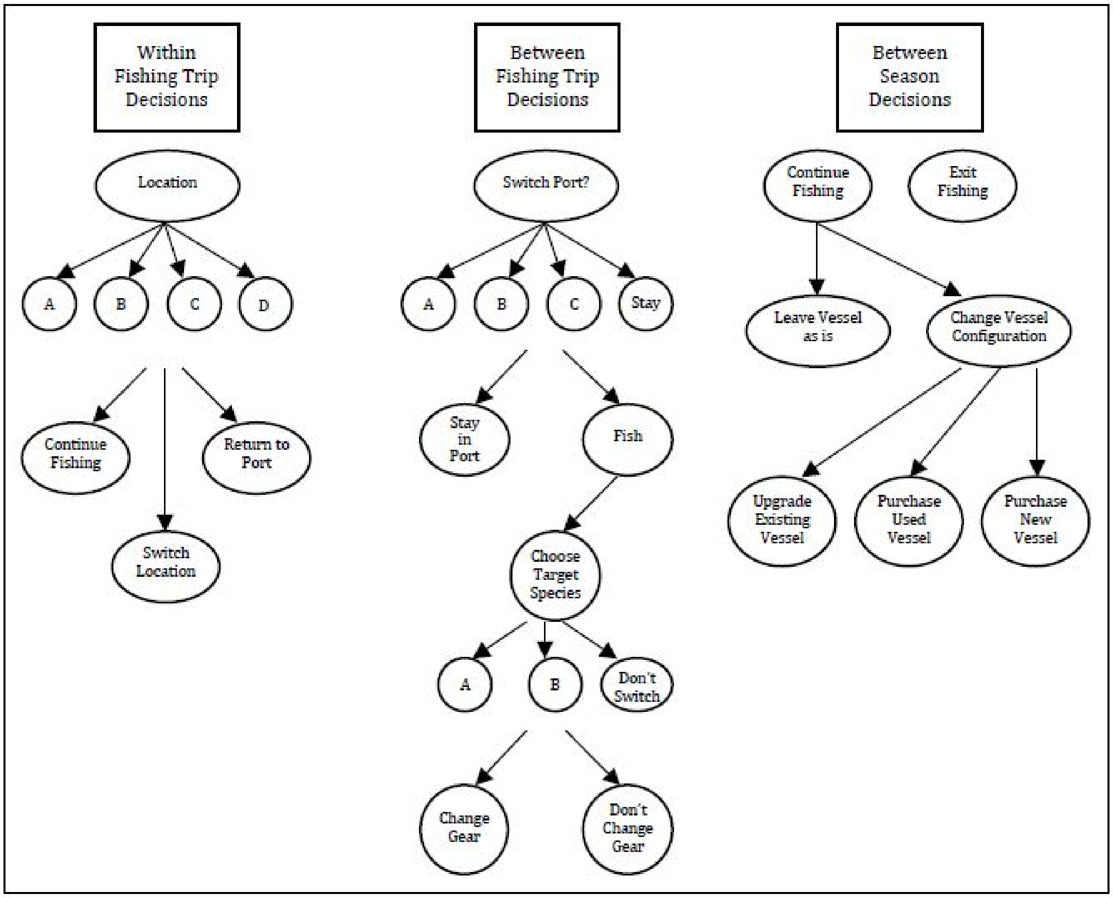
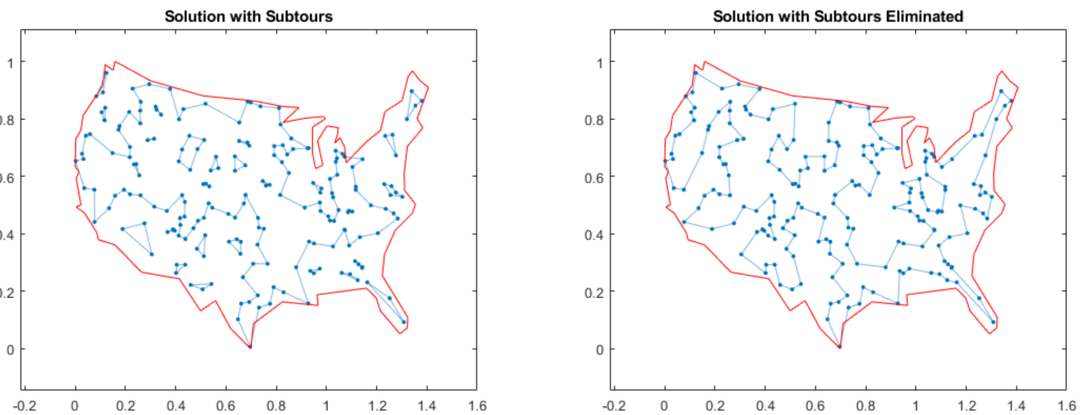


Figure 1.1: The fishing production process -

Figure 6: The Fishing Production Process (Reimer, 2012)

B Subtours in the Traveling Salesman Problem



(a) Solution with subtours (b) Solution with subtours eliminated

Figure 7: Example of subtours from Traveling Salesman Problem: Problem-Based MathWorks (2021)

C Optimal Unconstrained and Constrained Fishing Effort

The Lagrange function of the dynamic fisher optimization problem (Problem 3) is

$$
\begin{aligned}
\mathcal{L}(x_{ij}, y_i, A_i, \lambda) = \quad & \textstyle\sum_{i\in N}(pqA_i^{\gamma} Stock_i y_i - afc_{fuel}A_i) - \sum_{(i,j)\in E} d_{ij}x_{ij}bfc_{fuel} \\
& -\lambda_{fuel}(\textstyle\sum_{(i,j)\in E} d_{ij}x_{ij}bf + \sum_{(i)\in N} A_i af - F_{max}) \\
& -\lambda_{hold}(\textstyle\sum_{i\in N} qA_i^{\gamma} Stock_i y_i - C_{max})
\end{aligned} \tag{20}
$$

The first order condition of fishing effort at each site is

$$
\begin{aligned}
\tfrac{\partial \mathcal{L}}{\partial A_i} = \quad & pq\text{Stock}_i y_i \gamma A_i^{\gamma-1} - afc_{fuel} - \lambda_{fuel}af - \lambda_{hold}q\text{Stock}_i y_i \gamma A_i^{\gamma-1} \\
= \quad & (p-\lambda_{hold})q\text{Stock}_i y_i \gamma A_i^{\gamma-1} - (c_{fuel}+\lambda_{fuel})af \\
\Rightarrow A_i^* = \quad & (\tfrac{(p-\lambda_{hold})q\text{Stock}_i y_i \gamma}{(c_{fuel}+\lambda_{fuel})af})^{\frac{1}{1-\gamma}}
\end{aligned} \tag{21}
$$

1. If neither of the fuel and hold constraint binds, $\lambda_{fuel} = 0, \lambda_{hold} = 0$. $A_i^* = (\frac{pq\text{Stock}_i y_i \gamma}{c_{fuel}af})^{\frac{1}{1-\gamma}}$

2. If the fuel constraint binds while hold constraint doesn't. $\lambda_{fuel} > 0, \lambda_{hold} = 0$. From the

FOC, we can derive $A_i^*(\lambda_{fuel})$, the optimal fishing effort as a function of λ_{fuel}.

$$\begin{aligned} A_i^* = & \ (\tfrac{(p-\lambda_{hold})q\text{Stock}_i y_i \gamma}{(c_{fuel}+\lambda_{fuel})af})^{\frac{1}{1-\gamma}} \\ = & \ (\tfrac{pq\text{Stock}_i y_i \gamma}{(c_{fuel}+\lambda_{fuel})af})^{\frac{1}{1-\gamma}} \end{aligned} \tag{22}$$

Use the binding fuel constraint, we can solve λ_{fuel} and therefore A_i^*.

$$\begin{aligned} \textstyle\sum_{(i,j)\in E} d_{ij}x_{ij}bf + \sum_{(i)\in N} A_i af = & \ F_{max} \\ \Rightarrow \textstyle\sum_{(i,j)\in E} d_{ij}x_{ij}bf + \sum_{(i)\in N} (\tfrac{pq\text{Stock}_i y_i \gamma}{(c_{fuel}+\lambda_{fuel})af})^{\frac{1}{1-\gamma}} af = & \ F_{max} \\ \Rightarrow \lambda_{fuel} & \\ \Rightarrow A_i^* = (\tfrac{pq\text{Stock}_i y_i \gamma}{(c_{fuel}+\lambda_{fuel})af})^{\frac{1}{1-\gamma}} \text{ using derived } \lambda_{fuel} & \end{aligned} \tag{23}$$

3. If the fuel constraint doesn't bind while the hold constraint binds, $\lambda_{fuel} = 0, \lambda_{hold} > 0$.

   Similarly, we can derive $A_i^*(\lambda_{hold})$ from the FOC, the optimal fishing effort as a function of λ_{hold}.

$$\begin{aligned} A_i^* = & \ (\tfrac{(p-\lambda_{hold})q\text{Stock}_i y_i \gamma}{(c_{fuel}+\lambda_{fuel})af})^{\frac{1}{1-\gamma}} \\ = & \ (\tfrac{(p-\lambda_{hold})q\text{Stock}_i y_i \gamma}{c_{fuel}af})^{\frac{1}{1-\gamma}} \end{aligned} \tag{24}$$

   Using the binding hold constraint, we can solve λ_{hold} and therefore A_i^*.

$$\begin{aligned} \textstyle\sum_{i\in N} qA_i^{\gamma} Stock_i y_i = & \ C_{max} \\ \Rightarrow \textstyle\sum_{i\in N} q(\tfrac{(p-\lambda_{hold})q\text{Stock}_i y_i \gamma}{c_{fuel}af})^{\frac{\gamma}{1-\gamma}} Stock_i y_i = & \ C_{max} \\ \Rightarrow \lambda_{hold} & \\ \Rightarrow A_i^* = (\tfrac{(p-\lambda_{hold})q\text{Stock}_i y_i \gamma}{c_{fuel}af})^{\frac{1}{1-\gamma}} \text{ using derived } \lambda_{hold} & \end{aligned} \tag{25}$$

D Derivation of Catchability Coefficient q

The catchability coefficient q is chosen so that the harvest from the unconstrained optimal effort at each site is interior $q(A_i^*)^\gamma \text{Stock}_i y_i < \text{Stock}_i$. With no constraint on fuel and hold, $\lambda_{fuel} = \lambda_{hold} = 0$,

$$\begin{aligned} A_i^* = &\ (\tfrac{(p-\lambda_{hold})q\text{Stock}_i y_i \gamma}{(c_{fuel}+\lambda_{fuel})af})^{\frac{1}{1-\gamma}} \\ = &\ (\tfrac{pq\text{Stock}_i y_i \gamma}{c_{fuel}af})^{\frac{1}{1-\gamma}} \end{aligned} \tag{26}$$

The optimal harvest at each site should not exceed the available stock.

$$\begin{aligned} q(A_i^*)^\gamma \text{Stock}_i y_i &< \text{Stock}_i \\ q(A_i^*)^\gamma y_i &< 1 \\ q y_i (\tfrac{pq\text{Stock}_i y_i \gamma}{c_{fuel}af})^{\frac{\gamma}{1-\gamma}} &< 1 \\ q^{\frac{1}{1-\gamma}} y_i^{\frac{1}{1-\gamma}} (\tfrac{p\text{Stock}_i \gamma}{c_{fuel}af})^{\frac{\gamma}{1-\gamma}} &< 1 \\ q^{\frac{1}{1-\gamma}} y_i^{\frac{1}{1-\gamma}} &< (\tfrac{p\text{Stock}_i \gamma}{c_{fuel}af})^{\frac{-\gamma}{1-\gamma}} \\ q y_i &< (\tfrac{c_{fuel}af}{p\text{Stock}_i \gamma})^{\gamma} \end{aligned} \tag{27}$$

Given parameter values of Stock_i, a,p,c_{fuel}, q is chosen so that works for all site, $qy_i = \frac{1}{2} min[(\frac{c_{fuel}af}{p\text{Stock}_i \gamma})^\gamma]$.

E Scaling Fishing effort

Fishing effort is defined as hook number $\times$ fishing hour. Replace effort A_i with $A_i \eta \kappa$ as $\eta = 1000$ is the number of hooks, κ is the scaling parameter, then A_i is just fishing hour.

Fishing fuel consumption is $af\eta\kappa A_i$ while the traveling fuel consumption is $bfd_{ij}x_{ij}$ is .

Choose $a = 0.001$ so that $a \times \eta = 1$. A_i is the fishing hour, then $f \times \kappa$ is the fuel consumption per fishing hour. $d_{ij}x_{ij}$ is the traveling distance while b is $\frac{1}{\text{speed}}$, so $bd_{ij}x_{ij}$ is the travel hour. f is the fuel consumption per traveling hour. κ can be interpreted as scaling parameter for fuel consumption per fishing hour.

- $\kappa = 2$, fishing fuel consumption is twice of traveling fuel consumption per hour.
- $\kappa = 1$, fishing fuel consumption is the same as traveling fuel consumption per hour.
- $\kappa = 0.5$, fishing fuel consumption is half of traveling fuel consumption per hour.

So the Lagrange can be rewritten as

$$\begin{aligned}\mathcal{L}(x_{ij}, y_i, A_i, \lambda) = \quad & \textstyle\sum_{i\in N}(pqA_i^{\gamma}\eta^{\gamma}\kappa^{\gamma}Stock_i y_i - afc_{fuel}A_i\eta\kappa) - \sum_{(i,j)\in E} d_{ij}x_{ij}bfc_{fuel} \\ & -\lambda_{fuel}(\textstyle\sum_{(i,j)\in E} d_{ij}x_{ij}bf + \sum_{(i)\in N} A_i\eta\kappa af - F_{max}) \\ & -\lambda_{hold}(\textstyle\sum_{i\in N} qA_i^{\gamma}\eta^{\gamma}\kappa^{\gamma}Stock_i y_i - C_{max})\end{aligned} \tag{28}$$

The first order condition of fishing effort at each site is

$$\begin{aligned}\frac{\partial\mathcal{L}}{\partial A_i} &= pq\text{Stock}_i y_i\gamma A_i^{\gamma-1}\eta^{\gamma}\kappa^{\gamma} - af\eta\kappa c_{fuel} - \lambda_{fuel}af\eta\kappa - \lambda_{hold}q\text{Stock}_i y_i\gamma A_i^{\gamma-1}\eta^{\gamma}\kappa^{\gamma} \\ &= (p - \lambda_{hold})q\text{Stock}_i y_i\gamma A_i^{\gamma-1}\eta^{\gamma}\kappa^{\gamma} - (c_{fuel} + \lambda_{fuel})af\eta\kappa \\ \Rightarrow A_i^* &= \left(\frac{(p-\lambda_{hold})q\text{Stock}_i y_i\gamma\eta^{\gamma}\kappa^{\gamma}}{(c_{fuel}+\lambda_{fuel})af\eta\kappa}\right)^{\frac{1}{1-\gamma}}\end{aligned} \tag{29}$$

The moment condition can be rewritten as

$$\left(\frac{p-\lambda_{fuel}}{c_{fuel}+\lambda_{fuel}}\right)q_{vt}\text{Stock}_{ivt}y_{ivt}\gamma\text{Effort}_{ivt}^{\gamma-1}\eta^{\gamma}\kappa^{\gamma} = af\eta\kappa \tag{30}$$

F Timing of m-site ahead partially myopic fisher

Decision point t	Current Site	Choice set with order	Fuel Constraint	Capacity Constraint
t=1	$n_1^0 = 1$, port	$n_1^1, n_2^1, \cdots, n_m^1$, port	$F_{max}^1 = F_{max}$	$C_{max}^1 = C_{max}$
t=2	n_1^1	$\mathrm{n}_1^2, n_2^2, \cdots, n_m^2$, port	$F_{max}^2 = F_{max}^1 - d_{1n_1^1} bf - A_{n_1^1} af$	$C_{max}^2 = C_{max}^1 - qStock_{n_1^1} A_{n_1^1}^{\gamma}$
t=3	n_1^2	$\mathrm{n}_1^3, n_2^3, \cdots, n_m^3$, port	$F_{max}^3 = F_{max}^2 - d_{n_1^1 n_1^2} bf - A_{n_1^2} af$	$C_{max}^3 = C_{max}^2 - qStock_{n_1^2} A_{n_1^2}^{\gamma}$
t+1	n_1^t	$\mathrm{n}_1^{t+1}, n_2^{t+1}, \cdots, n_m^{t+1} =$ port	$F_{max}^{t+1} = F_{max}^t - d_{n_1^{t-1} n_1^t} bf - A_{n_1^t} af$	$C_{max}^{t+1} = C_{max}^t - qStock_{n_1^t} A_{n_1^t}^{\gamma}$
t=T	n_1^{T-1}	$n_1^T =$ port	$F_{max}^T = F_{max}^{T-1} - d_{n_1^{T-2} n_1^{T-1}} bf - A_{n_1^{T-1}} af$	$C_{max}^T = C_{max}^{T-1} - qStock_{n_1^{T-1}} A_{n_1^{T-1}}^{\gamma}$

Table 5: Timing of m-site ahead partially myopic fisher