Reducing Income Variability in Natural Resource Portfolios via Integer Programming

Laura Greenstreet[1](✉), Qinru Shi[1], Marc Grimson[1], Franz W. Simon[2,3], Suresh A. Sethi[2,4], Carla P. Gomes[1], Andrea Lodi[5], and David B. Shmoys[1,6]

[1] Department of Computer Science, Cornell University, Ithaca, NY, USA
leg86@cornell.edu
[2] Department of Natural Resources and the Environment, Cornell University, Ithaca, NY, USA
[3] Department of Biology, University of Kentucky, Lexington, USA
[4] Aquatic Research and Environmental Assessment Center, Department of Earth and Environmental Sciences, Brooklyn College, Brooklyn, NY, USA
[5] Jacobs Technion-Cornell Institute, Cornell Tech, New York, NY, USA
[6] School of Operations Research and Info Engineering, Cornell University, Ithaca, NY, USA

Abstract. Alaskan fishing communities are heavily impacted by income variability, where studies suggest benefits to individuals and communities through diversification by participating in multiple fisheries. However, Alaska uses a limited entry permit system, allowing only a fixed number of individuals to participate in each fishery. This motivates a resource allocation problem to determine how to allocate fishing permits to minimize a global measure of income variability. Further, experts and policy makers are interested in what interventions are most effective for enabling diversification. In collaboration with Alaskan fisheries experts, we developed a quadratic constrained resource allocation problem to reduce community-level income variability and model financial and vocational training interventions. Using over 20 years of fisheries data, we demonstrate an integer programming approach can solve instances up to the state level, involving over 10,000 permits and 170 communities. The model shows the potential for a 30–75% reduction in community-level average fishery income variance and provides a flexible framework for resource managers to explore the impacts of financial and vocational training interventions to support natural resource portfolio adaptation.

Keywords: resource allocation · discrete optimization · quadratic integer programming · Alaskan fisheries · resource management

1 Introduction

Fisheries play important economic and social roles worldwide, including being responsible for more than 250 million primary livelihoods and being the main source of protein for over 20% of the global population [5,10,24]. In Alaska,

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seafood is the largest private sector employer, where for many communities, fisheries are the primary contributor to the local economy [14]. However, fishery incomes can be highly variable, where low-income years can be devastating for small communities. For example, in 2022 a crash in the snow crab fishery led the island of St. Paul to declare a 'cultural, economic, and social emergency', with tax revenue no longer able to cover emergency medical services [18]. As some fisheries are negatively correlated, income variance can be reduced through participation in multiple fisheries. However, obtaining new permits, gear, and vocational skills pose a significant barrier to entry. In this work, we explore the potential to reduce community-level revenue variance for over 170 fishing communities in Alaska, formulating a new constrained resource allocation problem and modeling the potential benefits of the interventions of permit financing and vocational skills training. The problem was studied working closely with fisheries experts in both academia and the Alaskan fisheries management community.

Alaska is the largest seafood producer in the United States, accounting for over a third of the revenue from the $5.9 billion industry [8]. Alaskan fisheries are also extremely diverse, with over 50 active commercial fisheries and operations ranging from individual owner-operated businesses to large vertically integrated catcher-processor enterprises [14]. Beyond economic impacts, income variability can have negative effects on community structures and populations' physical and mental health [8]. While prior work suggests income variability can be reduced through diversification by participating in multiple fisheries [15,23], this has not considered the problem at the system-level, taking into account that Alaska's limited entry commercial permit system only allows a fixed amount of participation in each fishery. Further, experts and policy makers want to understand how to maximize the benefits of potential interventions, such as financing to help fisherman with limited collateral receive loans to purchase new permits and equipment or vocational training to develop the skills to participate in new fisheries.

In addition to being the largest fisheries system in the United States, Alaskan fisheries are extremely data-rich, with over 40 years of data on fishing permit ownership, sales, and revenue. This provides a unique opportunity to understand economic patterns and study the potential for interventions through data-driven approaches.

Prior Work. While prior work suggests that income variability can be reduced through fishery diversification, to our knowledge, we are the first work to optimize at the system-level. Retrospective analyses have found that fishery income volatility decreases with portfolio diversity at both the individual and community-level [15,23]. A number of strategies have been investigated to mitigate fisheries risk [12,22] and several recent papers have characterized the risk-return frontier for fishery portfolios [17,25]. However, these works do not optimize over the full system and thus do not take into account that there is a limited amount of catch that can be sustainably caught from each fishery. Such efforts are critical for both understanding the potential benefits of diversification as a practical fisheries risk management strategy and for identifying policy levers to support diversification.

Although the permits owned by each community can be seen as a portfolio, this problem differs from standard portfolio optimization problems in that we are optimizing portfolios for multiple individuals with constraints ensuring that all permits are allocated [16]. Thus, the problem is more closely related to resource allocation problems, in which a fixed amount of resources must be divided among groups or tasks to minimize a cost function [9]. Integer and mathematical programming methods have been applied to a variety of discrete resource allocation problems including proportional division for parliamentary systems, virtual machine placement in cloud infrastructure, and in multi-carrier communication systems [11,19,21]. However, minimizing a measure of variance complicates our problem by introducing a quadratic objective, where non-linear resource allocation problems have received less attention [6].

Paper Contribution. The contributions of our paper are as follows:

1. In collaboration with fisheries experts, we formulate a resource allocation problem to study the potential for reducing community-level income variability across Alaska through fishery diversification and model permit financing and vocational training interventions.
2. Using integer programming approaches, we are able to optimize over instances as large as the full state, including over 170 communities and over 10,000 individual permits from over 50 fisheries.
3. Our results show that an overall 30% average variance reduction is possible through financial incentives alone and this variance can be further reduced by over 75% by combining financial and vocational training interventions, revealing new opportunities for fisheries and optimization research.

Paper Organization. The remainder of the paper is organized as follows. Section 2 formally defines the optimization problem and presents a quadratic integer programming formulation and its linearization. Section 3 describes data processing and instance generation, the experimental setup, and experimental results. Section 4 discusses the optimization performance and implications of the solutions. Finally, Sect. 5 summarizes our contribution and outlines future research directions.

2 Modeling Framework

We now provide a more detailed description of the Alaska's commercial fishery permit system and then formally define the optimization problem. This analysis considers all commercial limited entry permits managed by the Alaskan Commercial Fisheries Entry Commission. Limited entry permits are owned by individuals and allow them to fish for a specific {species, location, and gear type} triplet combination. For example, a permit may allow an individual to fish for salmon in Cook Inlet using a drift gillnet, while different permits would be needed to fish for salmon in the same location using a set gillnet or in Prince

William Sound using the same gear. Permits of the same type are interchangeable, with the same potential for revenue. However, quotas vary from year to year, which – combined with factors such as changes in market price – can create highly variable revenue.

We define portfolios at the community-level using geographic locations, where a permit is considered part of a community's portfolio if it is registered to an address in that geographic location. While permits are owned by individuals, diversification and interventions often have impacts at the community-level. For example, fishing income is often reinvested into the community through the purchase of goods and services, leading to multiple individuals and businesses being impacted by low-income years. Communities are also an important source of knowledge, where skills can be transferred within a community.

Our goal is to determine an allocation of permits that minimizes community-level revenue variance, subject to feasibility constraints. First, we want to ensure that expected community revenues do not vary too much from their initial values. Second, Alaska is geographically vast, where the travel burden to use a permit can range from being able to fish within a community to requiring over 2,000 km of travel. Thus, we characterize a travel cost associated with each permit based on the location of fishing grounds and its community of origin. Finally, we want to understand the impact of two potential interventions: (i) financing, to allow the purchase of new permits and (ii) vocational training, to allow the usage of new permit types. While permit prices can be obtained from historical sales data, it is difficult to assign a financial cost to vocational skills training. Instead, we assign skills acquisition costs for the relative difficulty of acquiring the skills to use a permit assuming one previously fished another permit, which is then generalized to a community-level skills acquisition cost by taking the minimum skills acquisition cost across all permit types initially owned by a community. By assigning a vocational training budget, we can compare the relative impact of permit financing and vocational training investments.

2.1 Mixed Integer Quadratic Program Formulation

Let C and P be the sets of communities and permit types respectively, where a permit type is defined by a species-location-gear triplet (see Table 1 for all parameter definitions). For each permit $p \in P$, let $\mathrm{Price}(p)$ denote its price, $\mathrm{Rev}(p)$ denote its expected annual revenue, $\mathrm{Var}(p)$ denote its variance, and $\mathrm{Cov}(p, p')$ denote its covariance with $p' \in P$. For a community $c \in C$, and permit $p \in P$, let d_{cp} denote the distance that community c must travel to use permit p. Let $s : p_1, p_2 \to \mathbb{R}$ be a function representing the difficulty of obtaining the skills to transition from fishing permit p_1 to permit p_2 and P_c denote the set of permits initially owned by community c. We can then define the community-level vocational skills transition function, $t : c, p \to \mathbb{R}$ as

$$t(c, p) = \min_{p' \in P_c} s(p, p'). \tag{1}$$

Further, let x_{pc} be an integer decision variable representing the number of permits of type p in community c and x^0_{pc} be a constant for the number of permits of type p initially in community c. We can define the community level expected revenue and variance as

$$\mathrm{Rev}(c) = \sum_{p \in P} \mathrm{Rev}(p) \cdot x_{cp}, \tag{2}$$

$$\mathrm{Var}(c) = \sum_{p \in P} \Big[\mathrm{Var}(p) \cdot x_{cp}^2 + \sum_{p' \in P, p \neq p'} \mathrm{Cov}(p, p') \cdot x_{cp} x_{cp'} \Big]. \tag{3}$$

where $\mathrm{Var}(c^0)$ and $\mathrm{Rev}(c^0)$ denote the values for the initial permit configurations defined by the x^0_{pc} values. Finally, let v_c be a non-negative continuous decision variable used to enforce the permit financing constraint. By bounding these variables below by the cost difference between a community's initial and optimized portfolios, we can limit the total value of permit purchases that need to be supported by financing.

Using these definitions, we can state the problem by the mixed integer quadratic program (MIQP)

$$\min \quad \frac{1}{|C|} \sum_{c \in C} \frac{\mathrm{Var}(c)}{\mathrm{Rev}^2(c^0)} \tag{4}$$

$$\text{s.t.} \quad \sum_{c \in C} x_{pc} = \sum_{c \in C} x^0_{pc} \qquad \forall p \in P \tag{5}$$

$$\sum_{p \in P} x_{pc} = \sum_{p \in P} x^0_{pc} \qquad \forall c \in C \tag{6}$$

$$\sum_{p \in P} \mathrm{Rev}(p) \cdot x_{pc} \geq (1 - \phi) \cdot \mathrm{Rev}(c^0) \qquad \forall c \in C \tag{7}$$

$$\sum_{p \in P} d_{pc} x_{pc} \leq (1 + \eta) \cdot \sum_{p \in P} d_{pc} x^0_{pc} \qquad \forall c \in C \tag{8}$$

$$\sum_{p \in P} \mathrm{Price}(p) \cdot (x^0_{pc} - x_{pc}) \leq v_c \qquad \forall c \in C \tag{9}$$

$$\sum_{c \in C} v_c \leq \psi \tag{10}$$

$$\sum_{p \in P} \sum_{c \in C} t_{pc} x_{pc} \leq \rho \tag{11}$$

$$v_c \geq 0 \qquad \forall c \in C \tag{12}$$

$$x_{pc} \in \mathbb{Z}_{\geq 0} \qquad \forall p \in P, c \in C \tag{13}$$

We minimize the average community variance over squared revenue ratio as an approximation of the coefficient of variation (CV), which is preferable to the total variance as the impact of revenue variance is relative to a community's income. For example, a standard deviation in revenue of \$100,000/year is much more impactful for a community with an expected annual revenue of \$100,000 than one of \$1 million. Constraints (5) and (6) capture that the number of permits per fishery and community is fixed. Fixing the number of permits per community ensures roughly the same number of livelihoods remain in each community. However, we test relaxing this constraint. Constraints (7) and (8) ensure that community-level revenue and travel distance remain within fixed proportions of their initial values (ϕ and η, respectively). Constraints (9) and (10) ensure the total community-level change in permit portfolios requiring financing does not exceed ψ. Constraint (11) ensures that the total vocational skills training costs do not exceed ρ. Finally, constraints (12) and (13) define variables' characteristics.

2.2 Linearized Formulation

To avoid a quadratic objective, we can test a straight-forward linearization by considering each individual permit instead of permit type and introduce binary variables tracking whether pairs of permits are in the same community. Let P' be the set of all individual permits and extend the definitions of $\text{Price}(p), \text{Rev}(p), \text{Var}(p)$, and $\text{Cov}(p, p')$ to individual permits. Let y_{pc} be a binary decision variable for whether permit p is owned by community c and $w_{pp'c}$ be a binary decision variable for whether permits p and p' are both owned by community c. Further, extend the definitions of $\text{Rev}(c)$ and $\text{Var}(c)$ to individual permits, namely

$$\text{Rev}(c) = \textstyle\sum_{p \in P'} \text{Rev}(p) \cdot y_{pc}, \tag{14}$$

$$\text{Var}(c) = \textstyle\sum_{p \in P'} \Big[\text{Var}(p) \cdot y_{pc} + \sum_{p' \in P', p' \neq p} \text{Cov}(p, p') \cdot w_{pp'c}\Big]. \tag{15}$$

We can state the resulting mixed binary linear program (MBLP) as

$$\min \quad \frac{1}{|C|} \sum_{c \in C} \frac{\text{Var}(c)}{\text{Rev}^2(c^0)} \tag{16}$$

$$\begin{aligned}
\text{s.t.} \quad & w_{pp'c} \geq y_{pc} + y_{p'c} - 1 && \forall c \in C, p, p' \in P' && (17)\\
& \textstyle\sum_{c \in C} y_{pc} = \sum_{c \in C} y^0_{pc} && \forall p \in P && (18)\\
& \textstyle\sum_{p \in P'} y_{pc} = \sum_{p \in P'} y^0_{pc} && \forall c \in C && (19)\\
& \textstyle\sum_{p \in P'} \text{Rev}(p) \cdot y_{pc} \geq (1 - \phi) \cdot \text{Rev}(c^0) && \forall c \in C && (20)\\
& \textstyle\sum_{p \in P'} d_{pc} y_{pc} \leq (1 + \eta) \cdot \sum_{p \in P'} d_{pc} y^0_{pc} && \forall c \in C && (21)\\
& \textstyle\sum_{p \in P'} \text{Price}(p) \cdot (y^0_{pc} - y_{pc}) \leq v_c && \forall c \in C && (22)\\
& \textstyle\sum_{c \in C} v_c \leq \psi && && (23)\\
& \textstyle\sum_{p \in P'} \sum_{c \in C} t_{pc} y_{pc} \leq \rho && && (24)\\
& v_c \geq 0 && \forall c \in C && (25)\\
& y_{pc}, w_{pp'c} \in \{0, 1\} && \forall p, p' \in P, c \in C && (26)
\end{aligned}$$

Constraint (17) connects the binary variables for whether pairs of permits are in each community, $w_{pp'c}$, to the binary variables for each permit being in each community, y_{pc}. The objective and other constraints remain the same, adapted to the binary variables. As discussed further in Sect. 4, this straight-forward linearization significantly increases the number of variables and constraints (with negative effects on the solvability of the model).

3 Experiments

The goal of the experiments is to both evaluate the optimization performance of the integer programming methods, in terms of both the optimality gap and objective, and to test that our modeling assumptions and interpretations are supported by the historical data. We test the following assumptions and hypotheses:

Table 1. Model parameters and sets

Sets	
P	Set of all permit types
P'	Set of all individual permits
C	Set of all communities
Parameters	
$\text{Price}(p)$	Purchase price of permit p
$\text{Rev}(p)$	Expected annual revenue of permit p
$\text{Var}(p)$	Annual variance of permit p
$\text{Cov}(p, p')$	Annual covariance between permits p and p'
$\text{Rev}(c)$	Expected annual revenue of community c, defined in (2)
$\text{Var}(c)$	Variance of community c, defined in (3)
d_{cp}	Travel distance for community c to use permit p
t_{cp}	Transition cost for community c to acquire permit p
ϕ	Maximum proportion of community expected revenue change
η	Maximum proportion of community travel distance change
ψ	Maximum cost of permit purchases requiring financing
ρ	Maximum value for vocational training costs across all communities

1. We assume vocational skill transition values capture the difficulty in transitioning between fisheries, so permit acquisitions with a high transition cost occur rarely in practice.
2. We hypothesize permit acquisitions have historically occurred that would incur a vocational skills cost in our model. We are interested in the number and magnitude of historical actions and how they compare to the distribution in the optimized solutions.
3. We hypothesize all combinations of revenue and variance increase and decrease occur in the historical data, including communities experiencing a year-to-year decrease in expected revenue and increase in variability.[1] We are interested in the distribution of expected revenue and variance changes in the historical data and how they compare to the optimized solutions.

3.1 Data and Instance Generation

Historical data for 2000–2023 was obtained from the Alaska Commercial Fisheries Entry Commission [3,4]. While over 450 permit types were issued over these

[1] For example, decreased community level income and increased variability could occur if an individual chose to sell a permit, decreasing revenue, while a lower cost permit was purchased that increased variance.

years, many have low levels of commercial activity or are not exclusively for commercial purposes, such as trials of new permit types and educational permits. To focus on active commercial fisheries, each year we included permits where at least 25% of all permit owners and a minimum of 10 permit holders reported revenue each year over the past five years. This reduced the average number of permit types to 52 per year while retaining an average of 96% of revenue.

Permit sale prices and expected revenue were obtained from CFEC Basic Information Tables (BIT), which provide aggregated financial information at the permit-level [3]. To maintain confidentiality, values are not reported if fewer than five permit owners report revenue for a given year. In the rare cases where values were needed for a permit with anonymized data, we imputed the missing values with the average revenue across all reported years. The raw data provide us with a time series to calculate expected revenue and variance.

As recent performance is of more importance to fisherman than long-term trends, we used exponentially weighted calculations for mean revenue and variance. These calculations require a single parameter, α, for kernel width which determines the amount of weight placed at the start of the time series. For $\alpha = 0$, we recover the mean and variance of the time series while for $\alpha = 1$ the expected revenue becomes that of the previous year with no variance. Consulting with fisheries experts, we chose $\alpha = 0.25$ to place $\sim$95% of weight on the previous five years.

We define communities as any geographic location with at least three registered permits in a given year, resulting in an average of 170 communities per year. Initial community portfolios were determined using the annual records in the CFEC's permit registration database [4]. Spatial layers were used to determine centroids for each community and fisheries region, and travel distances were calculated as the distance between centroids. Finally, quantitative transition difficulty scores in $\{0, \ldots, 10\}$ were assigned to pairs of permits using fishery expert ratings of the difficulty of transitioning between each component of the species, gear, and location attributes that define a fishing permit type.

In addition to creating instances based on all communities, we defined 14 small instances of 4–45 communities based on fishing regions and intermediate instances with 6–88 communities based on four larger geographic regions (see Fig. 1). Running the model without the vocational skills budget constraint, we found the optimal transition cost to be $\sim 10^6$. To understand the impact of different orders of magnitude of vocational skills budget, we tested vocational training budgets of 0 and 10^i for $i = 2, \ldots, 6$. We ran initial feasibility tests on the 14 small instances using the 2023 data and a vocational skills budget of 1000. For the larger regions, we tested instances for the five regions for six vocational skills budgets across 24 years, resulting in 720 unique instances.

3.2 Experimental Configuration

Both the MIQP and linearized BIP were implemented in Gurobi using gurobipy 11.0.3. Instances were given a 5 min time limit and an optimality tolerance of 10^{-3} on an Apple M1 processor with 8 GB or RAM running on macOS Sonoma

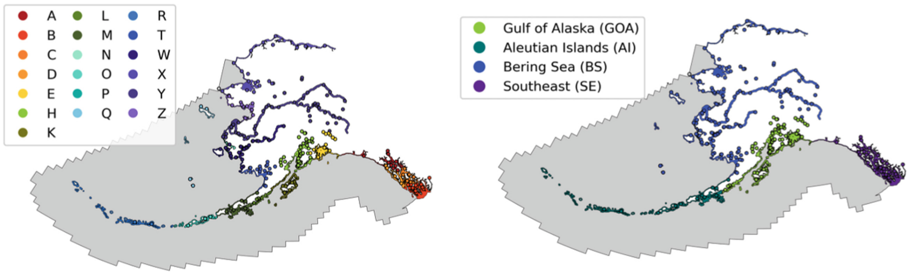

Fig. 1. Spatial visualization of instances, where colored polygons indicate regions and colored dots indicate communities associated with that instance. Left: Small spatial instances where communities are grouped based on fishing permit regions, where instances are defined by a set of communities and their initial permits. Right: Intermediate spatial instances based on geographic regions of Alaska.

14.5. Additional hour long runs were performed for vocational skills budgets of 0, 10^3, and 10^6 for the years of 2003, 2013, and 2023. For these runs, we used a maximum community-level travel distance increase of 50%, $\eta = 0.5$, maximum community-level revenue decrease of 15%, $\phi = 0.15$, and an exponential scaling with base four for the transition scaling function and relaxed the financing constraint, $\phi = \infty$. Additionally, we tested the sensitivity of the results to the maximum-community level distance and revenue change parameters (η and ϕ) and the vocational scaling function.

3.3 Results

On the small instances, the MIQP significantly outperformed the MBLP. The MIQP was able to solve all instances to optimality in under a minute, while the MBLP was only able to solve 6/14 in the 5 min time limit (see Table 2). On the remaining instances, the MBLP had multiple optimality gaps over 10% and was not able to instantiate the largest instance due to exceeding the 8GB of RAM allotted. Due to the poor performance of the MBLP, only the MIQP was tested on the larger instances.

For the larger instances, the MIQP was able to solve 50% of instances in the 5 min time limit, increasing to 64% with a 30 min time limit (see Table 3). For the five minute time limit, the average optimality gap ranged from 0.7 to 5.7% by region, generally increasing with instance size. As expected, the optimality gap also increased with the vocational training budget, increasing from 0.0% to 7.0%. Performance also varied by year, with instances increasing in difficulty in the 2010s from an average gap of around 3% up to 10%. Increasing to a 30 min limit, nearly two-thirds of instances were solved to optimality, including over half of the statewide instances, and reduced the average optimality gap by over 60% (see Table 3).

The optimization was able to reduce the average coefficient of variation by 34% without any vocational training investment (see Fig. 2). While there was

Table 2. Instance parameters and comparison of the MIQP and MBLP on the small spatial instances, where bold values indicate the best value when comparing the models. The MIQP was able to solve all instances to optimality in under a minute. In comparison, the MBLP was only able to solve 6/14 instances to optimality, with gaps as large as 19% on the remaining instances. Further, the MBLP was unable to instantiate the instance with the largest number of ternary variables due to reaching the memory limit. $|C|$: number of communities, $|P|$: number of permit types, $|P'|$: number of individual permits.

Instance	$\|C\|$	$\|P\|$	$\|P'\|$	$\|C\|\|P\|\|P\|$	Runtime (min)		Optimality Gap (%)	
					MIQP	MBLP	MIQP	MBLP
W	4	5	25	2.5×10^3	**0.00**	**0.00**	**0.0**	**0.0**
L	4	4	46	8.5×10^3	**0.00**	**0.00**	**0.0**	**0.0**
X	8	7	191	2.9×10^5	**0.00**	0.03	**0.0**	**0.0**
P	21	7	128	3.4×10^5	**0.00**	5.00	**0.0**	**0.0**
Z	7	7	226	3.5×10^5	**0.00**	5.00	**0.0**	**0.0**
M	9	5	237	5.0×10^5	**0.00**	4.09	**0.0**	**0.0**
T	8	7	636	3.2×10^6	**0.00**	5.00	**0.0**	1.1
E	26	5	485	6.1×10^6	**0.00**	5.00	**0.0**	10.8
K	28	7	698	1.4×10^7	**0.00**	5.00	**0.0**	19.0
B	26	7	806	1.7×10^7	**0.01**	5.00	**0.0**	7.2
D	33	4	858	2.4×10^7	**0.00**	5.00	**0.0**	2.9
A	35	8	840	2.5×10^7	**0.02**	5.00	**0.0**	10.0
C	32	5	1053	3.4×10^8	**0.65**	5.00	**0.0**	2.0
H	45	26	2762	3.5×10^8	**0.00**	–	**0.0**	–

Table 3. Instance parameters and performance of the MIQP on the large instances with runtimes of 5 (total of 720 instances) and 30 min (total of 45 instances). Gurobi was able to solve half of all instances in 5 min, increasing to nearly two-thirds in 30 min. For unsolved instances, gaps ranged from 0.6–4.0% increasing with instance size and vocational training budget. $|C|$: number of communities, $|P|$: number of permit types, $|P'|$: number of individual permits.

Region	$\|C\|$	$\|P\|$	$\|P'\|$	Solved Ratio		Runtime Ratio		Avg. Gap (%)	
				5	30	5	30	5	30
AI	6	9	139	1.00	1.00	0.00	0.00	0.0	0.0
BS	88	33	3597	0.54	0.67	0.44	0.38	1.0	0.6
GOA	47	45	3673	0.42	0.56	0.68	0.47	3.3	2.3
SE	28	41	4946	0.33	0.44	0.76	0.77	0.7	0.4
ALL	170	52	12378	0.22	0.56	0.92	0.90	5.7	4.0

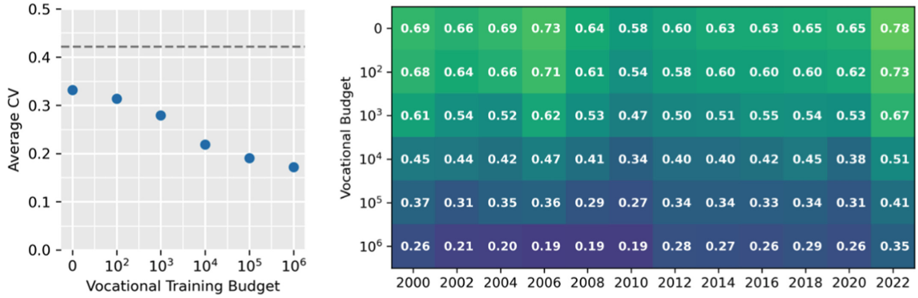

Fig. 2. Analysis of variance reduction. Left: Average community-level coefficient of variation (CV) in the optimized solutions for 2023 (blue points) compared to the average CV before optimization (gray line). Right: Matrix visualizing the proportion of the initial average CV of the optimized solutions by transition budget for even years from 2000–2023. Across years, with virtually no vocational skill investment the average CV can be reduced by over 30%. With moderate or intensive vocational skills interventions the average CV can be reduced by an average of 50% or 75% respectively. (Color figure online)

some variability across years, 19/24 years experienced at least a 30% reduction and all years achieved at least a 22% improvement. For the highest vocational skills budget, the average coefficient of variation was reduced by more than 75% of its initial value, with a 35–60% improvement for intermediate vocational training budgets.

We compared the historical data and the optimized solutions to test our hypotheses and modeling assumptions. First, we analyzed community-level revenue and variance changes to understand the distribution of impacts on communities. For the historical data, we considered year-to-year changes, while for the optimization we considered the difference between the initial and optimized solutions. Plotting the ratio of expected revenue versus the standard deviation in revenue by community, we can visualize the distribution of community outcomes (see Fig. 3). Averaging from 2001–2023, the optimized solutions increased the number of communities experiencing a variance decrease from 41% to 83–90%, increasing with the vocational skills budget, and increase the average magnitude of decrease from under 10% to 45–55%. Further, the optimization increased the number of communities experiencing the best outcome of increased expected revenue and decreased expected variability from 6% to 11–13% and decreased the proportion of communities experiencing the worst outcome of decreased expected revenue and increased variability from 3% to 1%. However, while historically the most wealthy communities remained near the origin in the optimized solutions they tend to end up in the first quadrant, experiencing an increase in revenue and variability.

Second, we analyzed the actions taken by each intervention. For the vocational skills budget, we can assign transition costs to historic data based on year-to-year permits transfers, determining a budget for historical actions. On

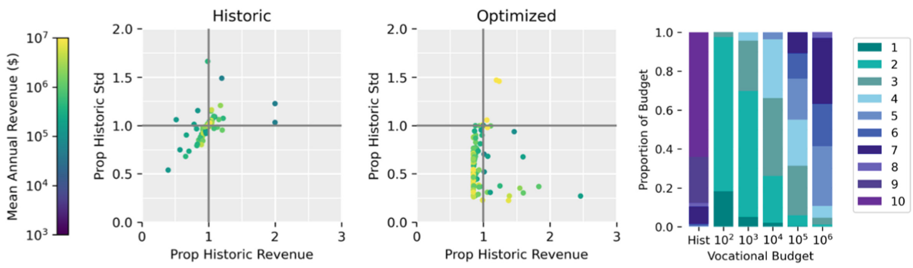

Fig. 3. Analysis of the optimized solutions. Left and center: Change in expected revenue and standard deviation in revenue by community from the historical data from 2022 to 2023 (left) and from the 2023 historical data to the optimized solution for a transition budget of 1,000 (center). The optimized solution results in more communities experiencing a variance decrease and larger magnitude decreases. Additionally, more communities experience higher revenue and lower variance and fewer experience lower revenue and higher variance. Right: Assigning vocational skills costs to historical transitions, we can compare the vocational skills budget that would have been required for historical actions to the optimization results. Historically, few high cost actions occurred but they dominated the vocational training budget. In contrast, the optimized solutions consist almost entirely of low (level 1–3) or mid-cost actions (level 4–6) which dominate both the number and cost of actions.

average, the transition budget needed for historical year-to-year changes was 37,000 units but only consisted of 41 actions, i.e., cases where permits were acquired at a transition cost. In contrast, the optimized solutions with a transition budget of 100 units resulted in an average of 12 actions and a transition budget of 10,000 units resulted in an average of 344 actions. While historically, only an average of 6 actions occurred per year of transition levels 5–10, due to the small number of total actions and exponential scaling of the transition scaling function, they dominate the transition budget (see Fig. 3). For the optimized solutions, at all budget levels over 70% of actions are level 1–3 (see Fig. 3). However, the cost is slowly dominated by the small proportion of higher level transitions. For permit financing, we looked at the magnitude and number of communities that would require some level of financing. While the total value of permits does not change with the optimization, we see community level changes to portfolio values. Communities with decreased portfolio value would obtain additional one-time revenue through the sale of their permits, while communities with increased portfolio value would require financing to help purchase new permits. In the optimization results, the total value of permits requiring financing ranged from $92–106 million, increasing with vocational training budget, with 28–40% of communities requiring some level of financing.

Finally, we tested the sensitivity of the results to the community-level revenue change and distance change constraints and the vocational skills scaling function. Fully relaxing the distance constraint only resulted in benefits at the highest vocational training budgets (see Fig. 4). Increasing or decreasing the maximum

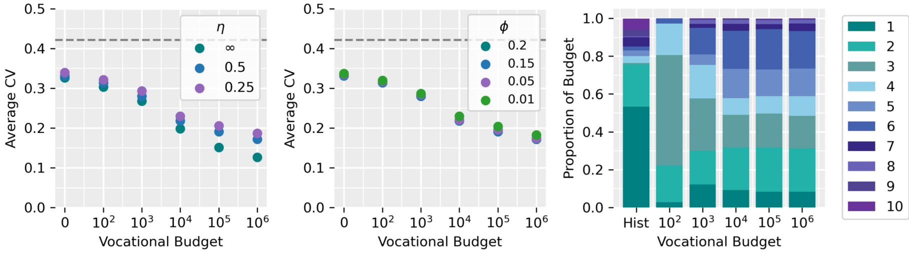

Fig. 4. Tests of model sensitivity. Results are shown for 2023, where parameters for main runs are shown in blue and the grey line shows the pre-optimization objective. Left: The model is not highly sensitive to maximum increase in travel distance (η), where fully relaxing the constraint only results in moderate improvements for the largest transition budgets. Center: The model is insensitive to the maximum community-level revenue decrease (ϕ), where objectives are nearly identical for the constraint varying from 20% to 1%. Right: Distribution of actions in the vocational budget with a quadratic scaling function. Changing the vocational scaling function does not change the distribution of actions for extreme budgets, but results in more mid-level (level 4–6) actions for intermediate budgets. (Color figure online)

community-level revenue change up to 20% or as low as 1% only resulted in very small changes to the objective, often within the optimality gap (see Fig. 4). Finally, changing the vocational skills scaling function does not change the objective value for the extreme budgets, it does change the distribution of actions. Namely, due to the slower scaling of the quadratic function, we see more intermediate level actions (level 4–6), however we continue to see very few of the highest cost actions (levels 8–10) (see Fig. 4).

4 Discussion

The poor performance and high memory demands of the MBLP arise from the ternary variables and corresponding constraints for every individual permit-permit-community combination. This leads to millions of variables and constraints even in small instances due to hundreds of individual permits and tens of communities. In contrast, the MIQP could solve some statewide instances with over 10,000 permits and 170 communities to optimality.

The MIQP was able to solve half the larger instances in 5 min and nearly two-thirds of instances in 30 min, with an average remaining gap of 1.5%. In practice, a runtime of 30 min would not be an issue, as a limited number of configurations would be tested to inform decision makers for periods of years. Further, gaps of a few percent would be tolerable, as solutions would not be implemented exactly but instead would be used by decision makers to understand the types and magnitudes of changes that could be most effective in lowering community-level variance and the potential magnitude of benefit from combinations of permit financing and vocational training interventions. The results are promising for this application, showing potential community-level reduction of coefficient of variation of over 30% with permit financing interventions alone and improvements over 75% with combined financing and vocational skills investments. The consistent results across reference years suggests that the model is robust to initial conditions within the historical range and that Gurobi is able to provide good solutions. Further, the sensitivity analyses suggests the results of the model are relatively robust to changes in constraint thresholds and the vocational scaling function.

The analysis also supports our assumptions and hypotheses. The vocational skills budget analysis found that high transition cost actions occur rarely in practice and few transitions occur historically where there has not been concerted investment in vocational skills training. It makes sense that there is a background level of actions occurring that would incur a transition cost in our model, as there is limited capacity in the existing system to overcome these costs. For example, permit owners can move between communities or an individual working for an existing business can eventually acquire enough skills and capital to start their own business. However, the results of the optimization suggest that significant benefits could be achieved by facilitating additional vocational training. Key differences between the historical and optimized vocational skills budgets are the number and kinds of actions. Historically, there were very few cases in which permits were acquired at a vocational skill cost, though transitions occurred at all cost levels. In contrast, the optimized solutions resulted in significantly more actions but at lower budget levels. This suggests that significant diversification benefits can be achieved without the need for drastic changes in the fisheries that communities participate in.

The community-level analysis found that historically the distribution of year-to-year changes includes all outcomes of changes in revenue and variance, with the majority of communities experiencing a small improvement to one at the cost of the other. In addition to lowering income variation overall, the optimized solutions resulted in significantly more communities experiencing a variance reduction, with larger magnitude reductions, more communities experiencing the best outcome, and fewer communities experiencing the worst outcome. This is an appealing result for potential policy, as the vast majority of communities have the potential to benefit from diversification. While the distribution for the wealthiest communities shifted to experiencing higher expected revenue and income variability, this may be tolerated or even perceived as a benefit, as the larger annual revenue and diversification of income outside of fisheries not captured in this analysis may make the wealthiest communities more tolerant of income variability for the benefit of higher expected revenue.

As the first analysis at the system-level, we show there is not only potential for benefit to individuals or communities from diversification, but potential significant benefits for the entire system. The analysis suggests that over a 30% reduction in average income variability is possible through permit financing alone, with improved outcomes realized across the distribution of communities. While financing is an important management lever to facilitate fisheries adaptation, fishers' access to financing is limited because conventional commercial banks typically do not provide loans for fishing permits, gear, or boats. Available financing in Alaska is insufficient and restricted to niche lending programs including the public-private Alaska Commercial Fishing and Agriculture Bank and small community-based programs such as the non-profit Alaska Local Fish Fund program [1,2]. It is important to note that the cost of this intervention could be significantly smaller than the \$92–106 community-level increase in portfolio values in the optimized solutions, as the interventions could include offering loans at reduced interest rates or with reduced collateral. Further, interventions of the magnitude of tens of millions are not unprecedented. For example, the US Department of Commerce allocated \$40 million in financial disaster relief in response to the 2024 snow crab fishery crisis [13]. To date, vocational training has not commonly been viewed as a key policy lever in natural resource sustainability science, however the results of the optimization show that combining vocational training with permit financing can more than double the potential reduction in income variability. While the instances presented in this paper fully relax the permit financing constraint, the optimization approach presented here provides a flexible framework for decision makers to quantify cost-benefit trade-offs in financing and vocational training investments.

The results of the optimization motivate several directions for future work. First, the amount of permit financing and vocational skills training proposed by the optimized solutions suggests further research into the potential cost and scalability of these interventions. This information could be incorporated into future iterations of the optimization as constraints or allowing for a single financial budget to be allocated between permit financing and vocational skills interventions. However, the magnitude of the interventions in the optimized solutions also suggest that changes would realistically be implemented over time, motivating an alternative formulation with yearly intervention budgets. Further, ecosystems in Alaska have already began to undergo significant shifts due to climate change [7,20]. While these changes are captured retrospectively through the revenue and variance calculations, as we optimize over longer time periods, incorporating climate trends will be key to accurately characterizing income variability.

5 Conclusion

High income variability from fisheries has many negative impacts on Alaskan communities. Previous work suggests that community-level income variability can be reduced through diversification in fisheries participation, though prior work had not considered the effects at the system level. In collaboration with fisheries experts, we formulate a new constrained resource allocation problem to determine how to optimally allocate permits to minimize the average community-level coefficient of variation and model financing and vocational skills interventions. Testing integer programming methods on multiple regions over 20 years, we find that the model can solve instances up to the state-level to optimality, with over 170 communities and 10,000 permits.

The optimization reduced the average community-level coefficient of variation by over 30% through permit financing alone and up to 75% with both financing and vocational skills training interventions. Comparing to historical changes, the optimization not only resulted in better average values but improved the proportion of communities experiencing a variation reduction from 41% to up to 90% with both interventions, and increased the magnitude of the reduction from 10% to up to 55%. However, the level of permit financing and vocational training required for the optimized solutions significantly exceeds the capacity of the current system, motivating future work into optimization overtime and incorporating climate trends to accurately capture future income variability.

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