# Optimizing aquaculture management using POMDPs

Olivia Beyer Bruvik[1]
oliviabb@stanford.edu

Duncan Eddy[2]
deddy@stanford.edu

Mykel Kochenderfer[2]
mykel@stanford.edu

[1]Computer Science Department
[2]Aeronautics and Astronautics Department
Stanford University, Stanford, CA.

## Problem

Sea lice (Lepeophtheirus salmonis) infestations are a persistent threat to salmon aquaculture, contributing to fish mortality, economic loss, and environmental harm. While treatments such as mechanical removal and chemical baths can reduce parasite load, they are costly, stressful to fish, and risk fostering resistance. Selecting optimal treatment strategies remains challenging due to uncertain infestation dynamics and noisy monitoring data. We want to improve production outcomes by posing managment strategy as a sequential decision problem, formulated as a POMDP and solved using optimization methods.

**Problem.** Solve medical treatment of salmon as a **partially observable Markov decision process** (POMDP) to **increase farm profitability**, **improve fish health**, and **reduce infection of wild fish**.

## Background

**Sea lice management.** Sea lice is currently managed by the expertise of farmers based on their observations of prevalence, understood through noisy population counts.

**Partially observable Markov decision process (POMDP).** Sequential decision making framework where the true state is unobservable. Defined by the tuple $\langle \mathcal{S}, \mathcal{A}, \mathcal{O}, T, O, R \rangle$ [1].

## Motivation

Can we accurately represent *population dynamics* and find *optimal treatment strategies* to **lower treatment costs**, **reduce regulatory penalties**, **increase harvest biomass**, and **improve fish health**?

## Methodology

We present a POMDP framework that adaptively recommends optimal aquaculture management strategies. A POMDP is defined as the tuple $\langle \mathcal{S}, \mathcal{A}, \mathcal{O}, T, O, R \rangle$ containing the model's state, action, and observation spaces along with transition, observation, and reward functions.

1. **States**: We define an 8-dimensional POMDP state vector as $s = [s_A, s_M, s_S, s_T, s_W, s_F, s$

WEIGHT, s_SAL], $whereweaccountfortheaverageadultfemalesealicepe$

2. **Actions**: We define several actions $a$ that farmers can perform after each observation $o$. These are

$$\mathcal{A} = \begin{cases} a_1 & \text{No treatment} \\ a_2 & \text{Mechanical treatment} \\ a_3 & \text{Thermal treatment.} \end{cases}$$

3. **Observations**: At every time step, we observe sea lice levels across life stages using negative binomial distributions with under-counting corrections, plus Gaussian noise for other observations. We observe

$$T_i \sim \text{NegativeBinomial}(r_i, p_i)$$

where $T_i$ is the total lice count for stage $i$ (adult, motile, sessile), $r_i = n \cdot \rho_i$ (dispersion parameter), and $p_i = \frac{r_i}{r_i + \mu_i}$ (success probability). The observed levels is then $o_i = \frac{T_i}{n}$.

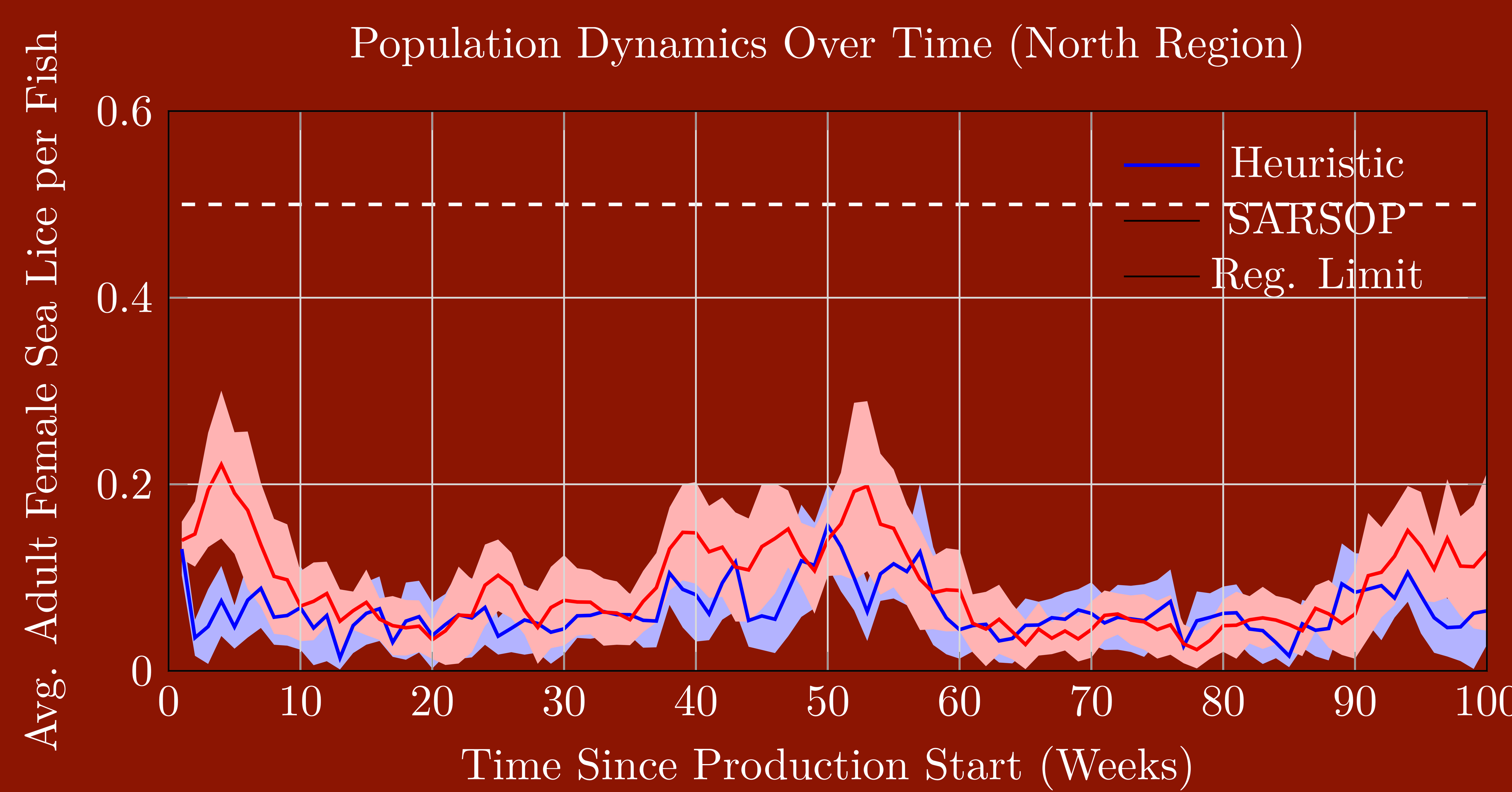
4. **Transition Function**: We implement a stage-structured sea lice population model with temperature-dependent development rates, along with a seasonal temperature model, and fish growth and mortality dynamics. To overcome the curse of dimensionality, we integrate a population growth prediction model $f$ inspired by Stige *et al.* [2] to reduce the state space as follows:

$$s_{A,t+1} \stackrel{\text{def}}{=} f([s_{A,t}, s_{M,t}, s_{s,t}, s_{T,t}])$$

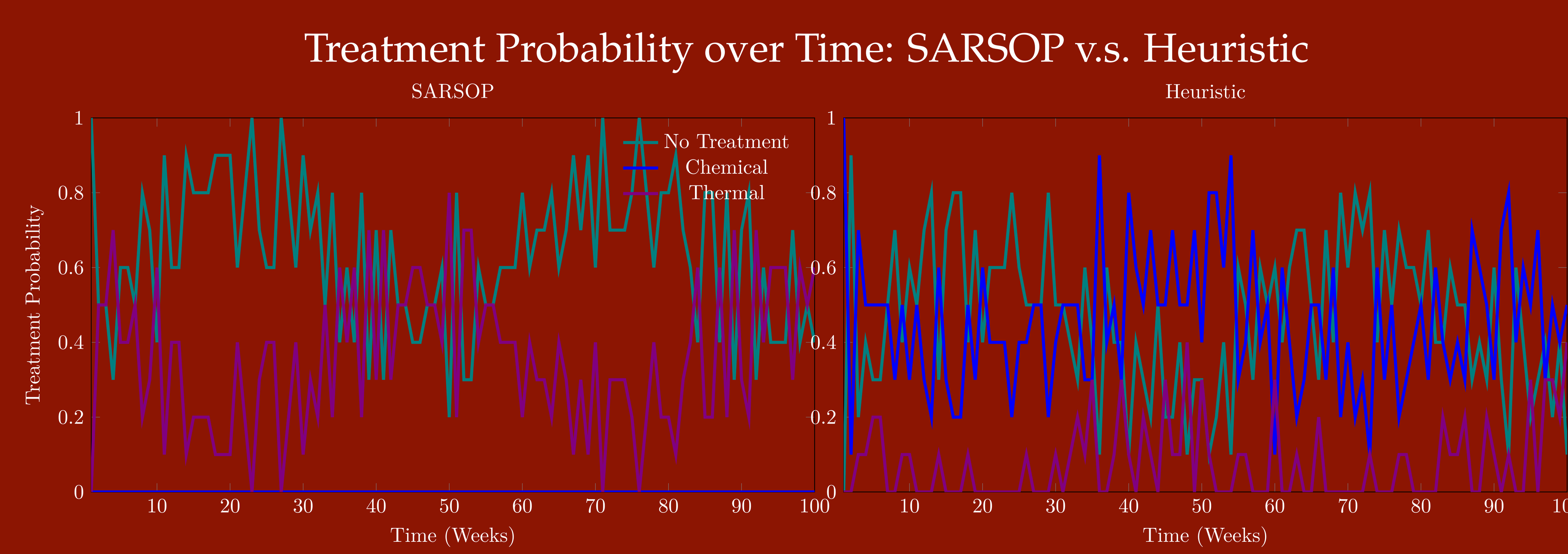
5. **Reward function**: Our reward function is a multi-objective function balancing different outcome objectives.

$$R(s,a) = -(\lambda_1 * \text{trt. cost} + \lambda_2 * \text{reg. penalties} + \lambda_3 * \text{biomass} + \lambda_4 * \text{health})$$

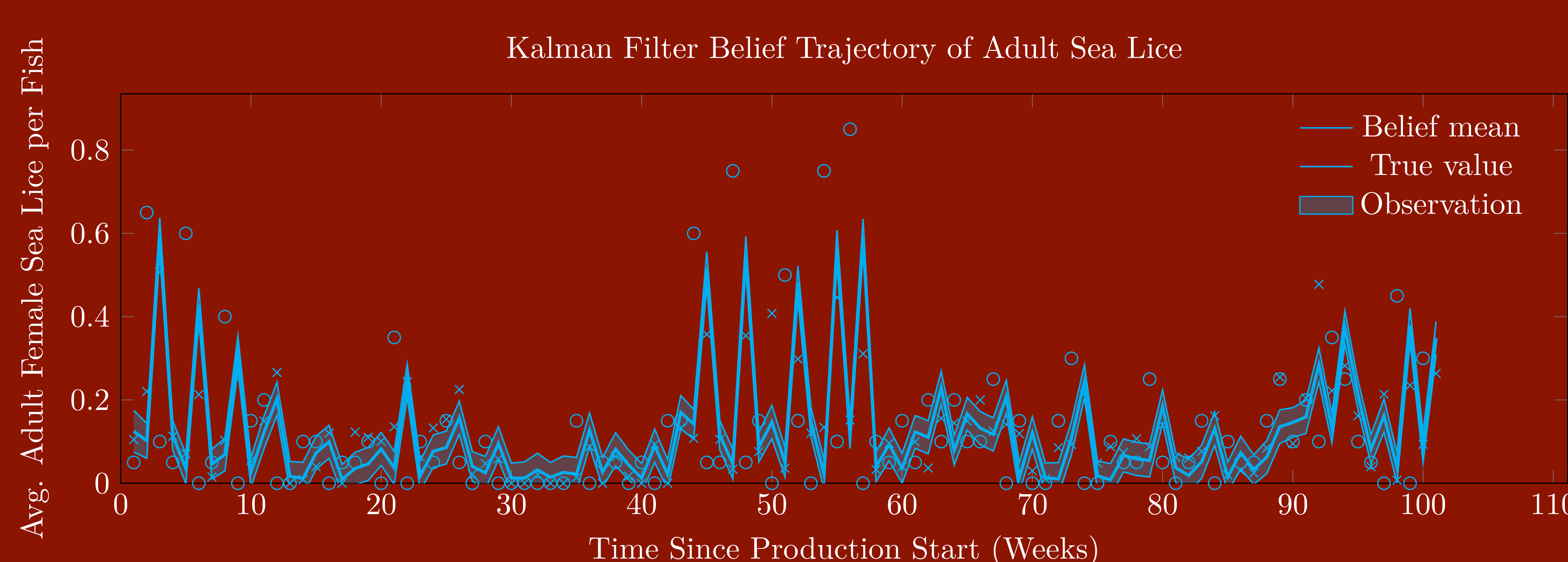
# Applying the **POMDP framework** to aquaculture can optimize **management strategies** to **reduce overtreatment**.




SARSOP minimizes harmful and expensive treatments while keeping sea lice levels under the regulatory limit.




The SARSOP policy relies more heavily on thermal treatments, while the heuristic favors mechanical treatments..




The Kalman filter facilitates policy actions based on the true sea lice levels as opposed to noisy observations..

## Optimization

We use proven off the shelf solvers to compute policies that map the predicted average adult female lice levels a week ahead to the optimal treatment action for that wee. We compare a handful of solvers and focus on the performance of SARSOP [3], an approximate offline POMDP solver, and QMDP [4] against a heuristic policy that applies treatment when the cumulative belief that the next week's predicted lice levels approaches the regulatory limit exceeds a parametric threshold.

## Evaluation

We evaluate the policies based on a number of metrics that affect the profitability and environmental burdens of a production cycle, including the total treatment cost in millions of NOK (MNOK) across a production cycle, the number of regulatory penalties incurred as a result of the weekly average adult female lice per fish exceeding the limit of 0.5, the lice burden, lost biomass and fish disease related to treatments and sea lice.

## Experiments

**Table 1:** Comparison of Methods Across Regions

| Region | Method | Reward | Treatment Cost (MNOK) |
|---|---|---|---|
| North | SARSOP | $\mathbf{-5.20 \pm 2.76}$ | $\mathbf{15.60 \pm 7.10}$ |
| | Heuristic | −19.71 ± 3.05 | 72.4 ± 10.6 |
| West | SARSOP | $\mathbf{-26.13 \pm 5.32}$ | $\mathbf{135.60 \pm 15.30}$ |
| | Heuristic | −42.02 ± 3.59 | 218.80 ± 14.00 |
| South | SARSOP | $\mathbf{-78.16 \pm 4.47}$ | $\mathbf{427.20 \pm 14.10}$ |
| | Heuristic | −96.80 ± 4.76 | 552.80 ± 15.40 |

**Table 2:** Deep-dive on SARSOP and Heuristic for the South Region

| | SARSOP | Heuristic |
|---|---|---|
| Expected Reward | $\mathbf{-78.16 \pm 4.47}$ | $-96.80 \pm 4.76$ |
| Total Treatment Cost (MNOK) | $\mathbf{427.20 \pm 14.10}$ | $552.80 \pm 15.40$ |
| Number of Regulatory Penalties | $1.40 \pm 0.50$ | $\mathbf{0.00 \pm 0.00}$ |
| Mean Adult Female Lice per Fish | $0.13 \pm 0.01$ | $\mathbf{0.07 \pm 0.01}$ |
| Mean Biomass Loss (tons) | $\mathbf{710.12 \pm 0.17}$ | $710.15 \pm 0.16$ |
| Fish Disease | $1815.40 \pm 44.10$ | $\mathbf{1300.00 \pm 46.9}$ |

## Policy Analysis

Treatment becomes more dominant as temperature and the average number of adult female sea lice per fish increase. SARSOP treats less than the heuristic policy, thereby minimizing treatment costs and fish harm while staying under the regulatory limit (see fig 4).

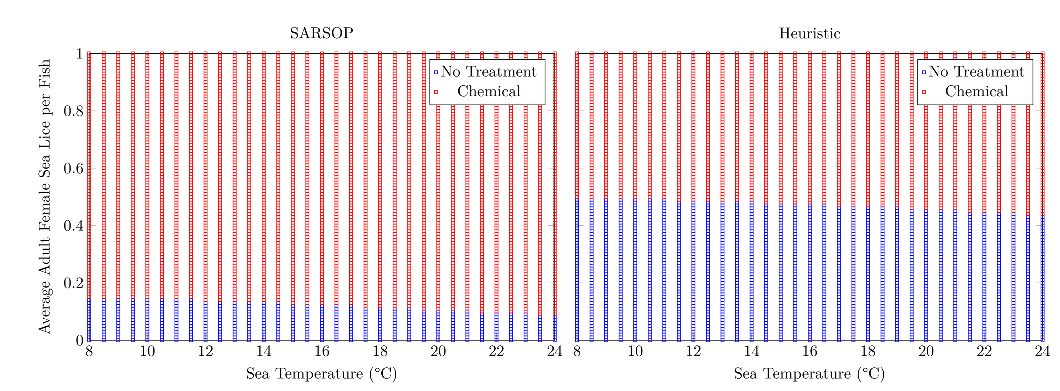



**Figure 4:** Dominant actions of the SARSOP and heuristic policies in the South Region across sea temperatures and average adult female sea lice per fish.

## Acknowledgments

I would like to thank Isaac Waard for his mentorship and guidance with code debugging, Dylan Asmr for sharing valuable insights on state space decomposition, and Arec Jamgochian for assistance with troubleshooting the Kalman filter. I am also grateful to everyone in SISL for their engaging conversations and continual support.

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