

# Cost-effectiveness of stunning intervention

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2024-02-06

## Generic prep

Open libraries

```
rm(list=ls())
library(tidyverse)
options(dplyr.summarise.inform = FALSE)
library(scales)
library(rlang)
library(gt)
library(RColorBrewer)
library(forcats)
library(magrittr)
library(webshot2)
```

Run code with assumptions

```
#Useful monte carlo functions
source("0a Useful functions.R")
#Take on board assumptions for seabream, seabass and trout
source("0b Assumptions for seabream, seabass and trout.R")
#Modelling assumptions
source("0c Modelling assumptions.R")
```

## Helper functions

Write helper functions to call object/vectors

```

consumption <- function(country,species) obtain(species,country,"tons")
mshare <- function(scenario,country) obtain("mshare",scenario,country)
psuccess <- function(scenario) obtain("psuccess",scenario)
weight <- function(species) obtain("weight",species)
slaughter_minutes <- function(species) obtain("slaughter_minutes",species)
stun_share <- function(species) obtain(species,"stunned")
cost <- function(scenario) obtain("cost",scenario)

```

## Calculations

### Impact per dollar

#### Core calculation function

```

# Number of fish affected per year
no_fish_affected_per_year <- function(country,species,scenario) {
  consumption(country,species)*1E3/
    weight(species)*
    (1-stun_share(species))*
    mshare(scenario,country)*
    psuccess(scenario)*
    implementation_discount*
    fish_grocery
}

# Fish affected across all years of credit
no_fish_affected <- function(country,species,scenario) {
  no_fish_affected_per_year(country,species,scenario)*years_credit
}

# Fish minutes affected
fish_hours_affected <- function(country,species,scenario) {
  no_fish_affected(country,species,scenario)*slaughter_minutes(species)/60
}

```

#### Functions to apply calculations across countries, species and scenarios

I now produce a table that produces a possible combination of country and species

```
no_of_countries <- length(country_list)
combo <- expand_grid(country=country_list,species=species_list) %>%
  mutate(country_species=str_c(country,"_",species))
```

I now write a function that:

- Works out the total number of fish (or fish minutes) affected in a given scenario, country and species
- Sums the result for all species and countries
- Divides by the total program costs for a specific scenario

```
output_per_dollar <- function(fish_function,program) {

temp_output<- map2(                                # Allows repeated calcs across different input vectors
  combo$country,                                   # Input vector 1: countries to run function over
  combo$species,                                   # Input vector 2: species to run function over
  get(fish_function),                             # Calculation function (no of fish or minutes)
  scenario=program                                # Scenario (pilot or scale)
) %>%
  as.data.frame() %>%                             # Convert to data.frame
  mutate(
    total=rowSums(.))

return(
  temp_output$total/(no_of_countries*cost(program))
)
}
```

Generate table for combinations of output and scenario

```
results_combination <- expand_grid(
  measure=c("fish_hours_affected","no_fish_affected","no_fish_affected_per_year"),
  program=c("pilot","scale")) %>%
  mutate(description=str_c(program,"___",measure))
```

## Run calculations

I now write a function that works out the number of fish minutes affected and total number of fish affected per dollar across both the pilot and scale scenarios. The results of the montecarlo simulation are in a single table called “impact\_per\_dollar”.

```

impact_per_dollar <- map2(                                     # Function to iterate over vectors
  results_combination$measure, # Vector of different measures
  results_combination$program, # Vector of different scenarios
  output_per_dollar) %>% # Function to repeat
  as.data.frame()

# Assign names to data.frame
names(impact_per_dollar) <- results_combination$description

# Convert to long format
impact_per_dollar %<>%
  pivot_longer(
    cols=1:nrow(results_combination),
    names_to="description",
    values_to="number"
  ) %>%
  separate_wider_delim(description,delim="___",names=c("scenario","measure"))

```

## \$/DALY “welfare range” calculations

### Prep

I first produce estimates of fish years affected per dollar in both scenarios.

```

fypd_pilot <- output_per_dollar("fish_hours_affected","pilot")*hours_to_years
fypd_scale <- output_per_dollar("fish_hours_affected","scale")*hours_to_years
fypd <- function(scenario) obtain("fypd",scenario)

```

### Core calculation functions

```

wr_dollar_per_daly <- function(scenario) {
  1/(
    fypd(scenario)*
    salmon_wr*
    duration_share*
    fish_welfarerange_impact_stun/
    DALY_share_of_welfare_range)
}

```

## Apply calculations

Calculate results and place into data frame

```
results_dollar_per_daly <-  
tibble(  
  # core calculations  
  pilot=wr_dollar_per_daly("pilot"),  
  scale=wr_dollar_per_daly("scale")) %>%  
  # pivot to long format  
  pivot_longer(  
    cols=1:2,  
    values_to="dollars_per_daly",  
    names_to="scenario"  
  ) %>%  
  # reformat for table production  
  mutate(scenario=str_to_sentence(scenario))
```

## Share of simulations beating \$/DALY benchmark

### Core calculation functions

```
#Moral value approach  
share_mv <- function(xvar,scenario,bar) {  
  mean(bar>(1/(fypd(scenario)*xvar)))  
}  
  
# Welfare range approach  
share_wr <- function(xvar,scenario,bar) {  
  mean(bar>  
    (1/  
      (xvar*  
        fypd(scenario)*  
        salmon_wr/  
        DALY_share_of_welfare_range  
      )))  
}
```

Define parameters over which to calculate results. Definition of xvar provided in the table below.

Approach	Meaning of 'xvar' variable means in context of calculations
Moral Value	Moral value of improving fish welfare for 1 year through intervention relative to gaining 1 DALY
Welfare Range	Welfare gain from intervention - expressed as % of entire fish welfare range (negative to positive)

## Run calculations

```
mv_table_values <- c(0.01,0.1,0.25,0.5,0.75,1,5,10,25,50,75,100,500,1000,5000)
wr_table_values <- c(0.01,0.05,0.1,0.25,0.5,0.75,0.9,0.95,0.99,1)
chart_values<- 10^seq(-4,4,0.01)
xvar_values <- c(chart_values,mv_table_values,wr_table_values)
scenario_list <- c("pilot","scale")
```

Calculate results

```
share_sims_results_table <-
# Generate one row for unique combination of xvar_values and scenario lists
expand_grid(
  xvar=xvar_values,
  scenario=scenario_list,
  bar=bar_values) %>%
# Core calculations using share_mv and share_wr calculation functions
rowwise() %>%
mutate(
  moral_value=share_mv(xvar,scenario,bar),
  welfare_range=share_wr(xvar,scenario,bar)
) %>%
# Convert pivot into longer format to make results easier to plot
pivot_longer(
  cols=c(moral_value,welfare_range),
  names_to="approach",
  values_to="share_of_simulations") %>%
# Change descriptions of variables to make results easier to interpret
mutate(
  scenario=str_to_sentence(scenario),
  approach=str_to_sentence(str_replace_all(approach,"_"," ")),
  bar_factor=
    factor(bar,levels=bar_values,labels=c("50","1K","70K")),
  bar_description=case_when(
```

```

    bar==50 ~ "50 - Open Philanthropy GHW bar",
    bar==1000 ~ "1K - Low HDI country HE av.",
    bar==70000 ~ "70K - Very high HDI country HE av.",
    TRUE ~ "ERROR")
)

```

## Results tables/charts

### Impact per dollar

```

# Code to create impact per dollar density plot

impact_density_plot <- function(desired_filter,description) {
  impact_per_dollar %>%
  filter(measure==desired_filter) %>%
  ggplot(
    aes(
      x=number,
      color=str_to_sentence(scenario)
    )
  ) +
  geom_density() +
  theme_light() +
  scale_x_log10(labels = scales::comma_format(drop0trailing = TRUE),n.breaks=8) +
  labs(
    title=description,
    y="Probability density",
    x=paste0(description," (log scale)",
    color="Scenario")
  )
}

# Code to create impact per dollar summary table

impact_table <- function(desired_filter,description) {
  impact_per_dollar %>%
  filter(measure==desired_filter) %>%
  mutate(scenario=str_to_sentence(scenario)) %>%
  group_by(scenario) %>%
  summarise(

```

```

    Mean=mean(number),
    p5=quantile(number,0.05),
    Median=median(number),
    p95=quantile(number,0.95)
  ) %>%
  pivot_longer(cols=2:5,names_to="Statistic",values_to="Value") %>%
  pivot_wider(names_from = "scenario",values_from = "Value") %>%
  gt() %>%
  fmt_number(decimals = 1) %>%
  tab_header(
    title = description) %>%
  tab_spanner(
    label = "Scenario",
    columns = c(Pilot,Scale))
}

# Generate results

fig9_fish_pd <- impact_density_plot("no_fish_affected","Number of fish affected per dollar")
tab8_fish_pd<- impact_table("no_fish_affected","Number of fish affected per dollar")
tab9_fish_pdpy <- impact_table("no_fish_affected_per_year","Number of fish affected per dollar per year")
fig10_fish_hours_pd <- impact_density_plot("fish_hours_affected","Fish hours affected per dollar")
tab10_fish_hours_pd <- impact_table("fish_hours_affected","Fish hours affected per dollar")

```

## \$/DALY Range

Density plot

```

fig11_dolperdaly_density <-
  results_dollar_per_daly %>%
  ggplot(
    aes(
      x=dollars_per_daly,
      color=scenario
    )
  ) +
  geom_density() +
  theme_light() +
  scale_x_log10(
    breaks=10^seq(0,15,1),
  )

```



```

labels = scales::label_number(scale_cut = scales::cut_short_scale())) +
labs(
  title = "$/DALY Density Plot",
  y="Probability density",
  x="$/DALY (log-scale)",
  color="Scenario")

```

Summary stats table

```

tab11_dolperdaly_density <-
results_dollar_per_daly %>%
  group_by(scenario) %>%
  summarise(
    Mean=mean(dollars_per_daly),
    p1=quantile(dollars_per_daly,0.01),
    p5=quantile(dollars_per_daly,0.05),
    p10=quantile(dollars_per_daly,0.10),
    p25=quantile(dollars_per_daly,0.25),
    Median=median(dollars_per_daly),
    p75=quantile(dollars_per_daly,0.75),
    p90=quantile(dollars_per_daly,0.90),
    p95=quantile(dollars_per_daly,0.95),
    p99=quantile(dollars_per_daly,0.99)
  ) %>%
  pivot_longer(cols=2:11,names_to="Statistic",values_to="$/DALY") %>%
  pivot_wider(names_from = "scenario",values_from = "$/DALY") %>%
  gt() %>%
  tab_spanner(
    label = "Scenario",
    columns = c(Pilot,Scale)) %>%
  fmt_number(columns=2:3,suffixing=TRUE,n_sigfig =3)

```

**Share of simulations beating benchmark**

**Chart**

```

share_sims_chart <- function (
  chart_approach,
  xvar_lower_lim=0,

```

```

        xvar_upper_lim=max(xvar_values),
        xlab_des
    ) {

share_sims_results_table %>%
  filter(
    approach==chart_approach,
    xvar<=xvar_upper_lim,
    xvar>=xvar_lower_lim
  ) %>%
  ggplot(
    aes(
      x=xvar,
      y=share_of_simulations,
      color=as.factor(scenario),
      linetype=bar_factor)) +
  geom_line(lwd=0.8) +
  scale_linetype_manual(values=c("solid","dotted","twodash")) +
  scale_color_brewer(palette = "Dark2") +
  theme_light() +
  scale_y_continuous(limits=c(0,1),n.breaks=10,labels = scales::percent_format(accuracy =
  labs(
    subtitle = str_to_title(paste0(chart_approach," approach")),
    title="Share of simulations where intervention beats $/DALY benchmark",
    y="Share of simulations",
    x=xlab_des,
    linetype="$ / DALY Benchmark",
    color="Intervention",
    caption= "Note log scale on x-axis")

  }

xlab_wr="
  Welfare gain from intervention as a % of total fish welfare range"

xlab_mv="Moral value of improving a fish-life year via intervention
relative to gaining a human DALY"

```

Produce share of simulations charts

```
fig12_wr_benchmark <- share_sims_chart("Welfare range", xvar_upper_lim=1, xlab_des=xlab_wr)+
  scale_x_log10(limits=c(0.001,1), labels = scales::percent_format(drop0trailing = TRUE), n.
  scale_y_continuous(limits=c(0,0.6), n.breaks=10, labels = scales::percent_format(accuracy
```

Scale for y is already present.

Adding another scale for y, which will replace the existing scale.

```
fig13_mv_benchmark <- share_sims_chart("Moral value", xvar_lower_lim=0.003, xlab_des=xlab_mv)
  scale_x_log10(labels = scales::label_number_si(drop0trailing = TRUE), n.breaks=11)
```

Warning: `label\_number\_si()` was deprecated in scales 1.2.0.

i Please use the `scale\_cut` argument of `label\_number()` instead.

## Table

Share of simulations at various welfare range / moral value assumptions.

```
share_beating_bar_table <- function(values, chart_approach) {
  share_sims_results_table %>%
    filter(
      xvar %in% values,
      approach==chart_approach) %>%
    select(-approach) %>%
    distinct() %>%
    mutate(
      scenario_bar=paste(scenario, bar, sep="_") %>%
    pivot_wider(id_cols=xvar, names_from=scenario_bar, values_from=share_of_simulations) %>%
    arrange(xvar) %>%
    gt() %>%
    tab_header(title = "Share of simulations beating $DALY bar") %>%
    cols_label(xvar=chart_approach)
}

tab12_wr_benchmark <- share_beating_bar_table(wr_table_values, "Welfare range") %>%
  fmt_percent(columns=1, decimals=0) %>%
  fmt_percent(columns=2:7, decimals=1)

tab13_mv_benchmark <- share_beating_bar_table(mv_table_values, "Moral value") %>%
```

```
fmt_percent(columns=2:7,decimals=1)
```

Minimum moral value needed to achieve given share of simulations to beat \$/DALY bar.

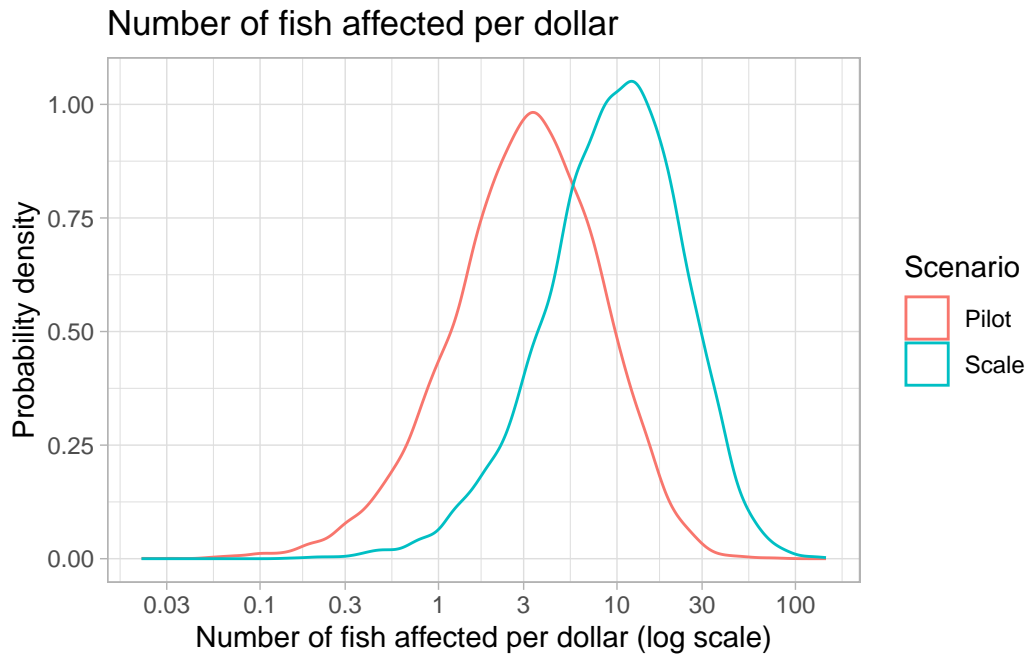
```
sim_cuts<- c(0,0.01,0.1,0.25,0.5,0.75,0.90,0.95,0.99,1,1.01)

tab14_min_mv <- share_sims_results_table %>%
filter(approach=="Moral value") %>%
  mutate(
    sims_bin=
      cut(share_of_simulations,breaks=sim_cuts,right=FALSE,labels=head(sim_cuts,-1))) %>%
group_by(scenario,bar,sims_bin) %>%
summarise(min_moral_value=min(xvar)) %>%
mutate(scenario_bar=str_c(scenario,bar,sep="_")) %>%
pivot_wider(id_cols=sims_bin,names_from=scenario_bar,values_from=min_moral_value) %>%
mutate(sims_bin=head(sim_cuts,-1)) %>%
gt() %>%
fmt_percent(columns=1,decimals=0) %>%
fmt_number(columns=2:7,decimals=1) %>%
tab_header(title = "Minimum moral value assumption needed for to achieve share of simula
```

## Print charts and tables

Impact per dollar charts and tables

```
fig9_fish_pd
```



tab8\_fish\_pd

Number of fish affected per dollar

Statistic	Scenario	
	Pilot	Scale
Mean	4.6	13.3
p5	0.6	1.9
Median	3.2	9.9
p95	13.5	36.0

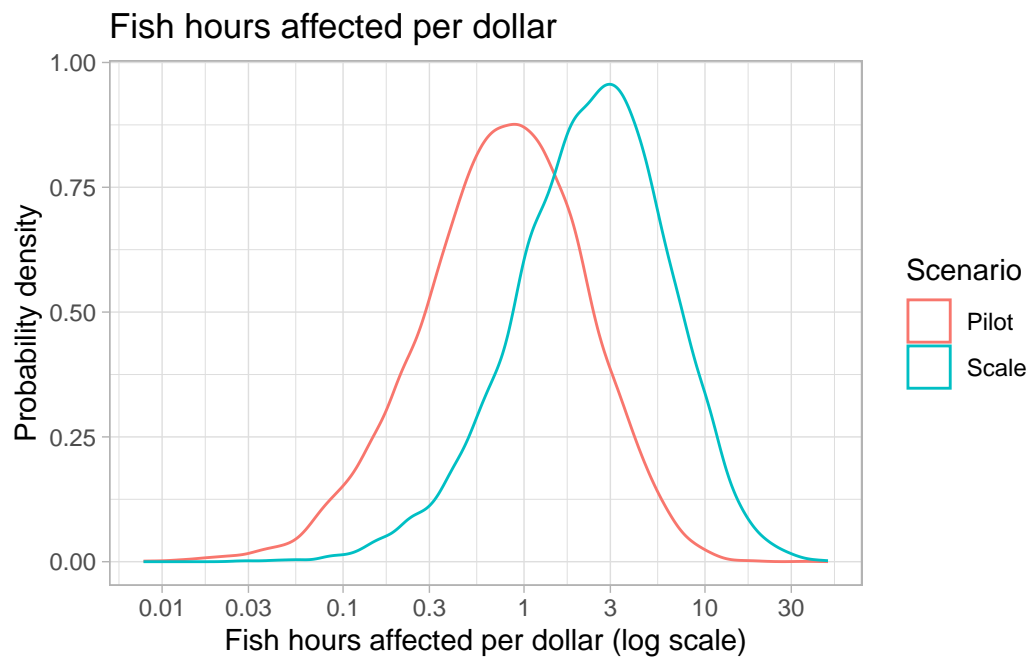
tab9\_fish\_pdpv

Number of fish affected per dollar per year

Statistic	Scenario	
	Pilot	Scale
Mean	0.4	1.2
p5	0.1	0.2
Median	0.3	1.0

p95	1.1	2.8
-----	-----	-----

fig10\_fish\_hours\_pd



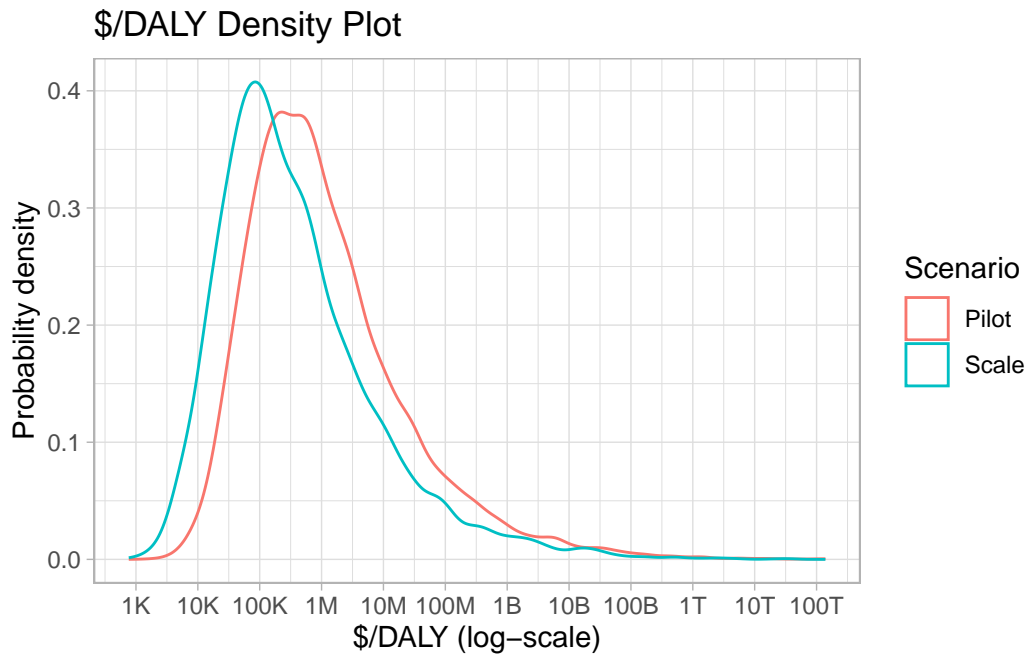
tab10\_fish\_hours\_pd

Fish hours affected per dollar

Statistic	Scenario	
	Pilot	Scale
Mean	1.2	3.6
p5	0.1	0.4
Median	0.8	2.5
p95	3.8	10.4

Dollar per daly distribution

fig11\_dolperdaly\_density



```
tab11_dolperdaly_density
```

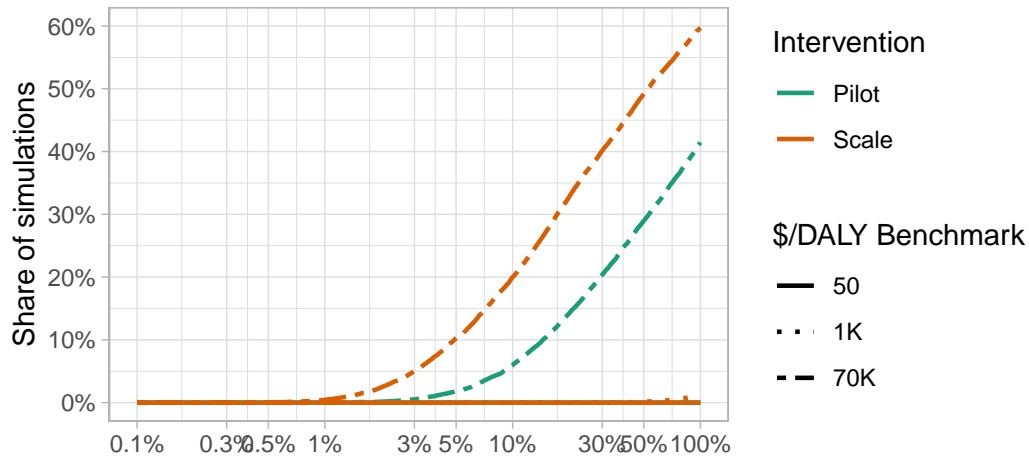
Statistic	Scenario	
	Pilot	Scale
Mean	41.1 <i>B</i>	12.3 <i>B</i>
p1	11.8 <i>K</i>	4.11 <i>K</i>
p5	29.9 <i>K</i>	10.4 <i>K</i>
p10	52.3 <i>K</i>	17.8 <i>K</i>
p25	151 <i>K</i>	51.0 <i>K</i>
Median	680 <i>K</i>	216 <i>K</i>
p75	4.92 <i>M</i>	1.61 <i>M</i>
p90	61.0 <i>M</i>	18.1 <i>M</i>
p95	366 <i>M</i>	114 <i>M</i>
p99	26.9 <i>B</i>	9.98 <i>B</i>

Welfare range benchmarks

```
fig12_wr_benchmark
```

Warning: Removed 600 rows containing missing values (`geom\_line()`).

## Share of simulations where intervention beats \$/DALY benchr Welfare Range Approach



Welfare gain from intervention as a % of total fish welfare range

Note log scale on x-axis

tab12\_wr\_benchmark

## Share of simulations beating \$DALY bar

Welfare range	Pilot_50	Pilot_1000	Pilot_70000	Scale_50	Scale_1000	Scale_70000
1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.4%
5%	0.0%	0.0%	1.8%	0.0%	0.0%	10.3%
10%	0.0%	0.0%	5.9%	0.0%	0.0%	20.0%
25%	0.0%	0.0%	17.5%	0.0%	0.0%	37.0%
50%	0.0%	0.0%	29.0%	0.0%	0.2%	49.2%
75%	0.0%	0.0%	36.1%	0.0%	0.5%	55.5%
90%	0.0%	0.0%	39.4%	0.0%	0.9%	58.2%
95%	0.0%	0.0%	40.4%	0.0%	1.0%	59.1%
99%	0.0%	0.0%	41.2%	0.0%	1.1%	59.6%
100%	0.0%	0.0%	41.4%	0.0%	1.2%	59.8%

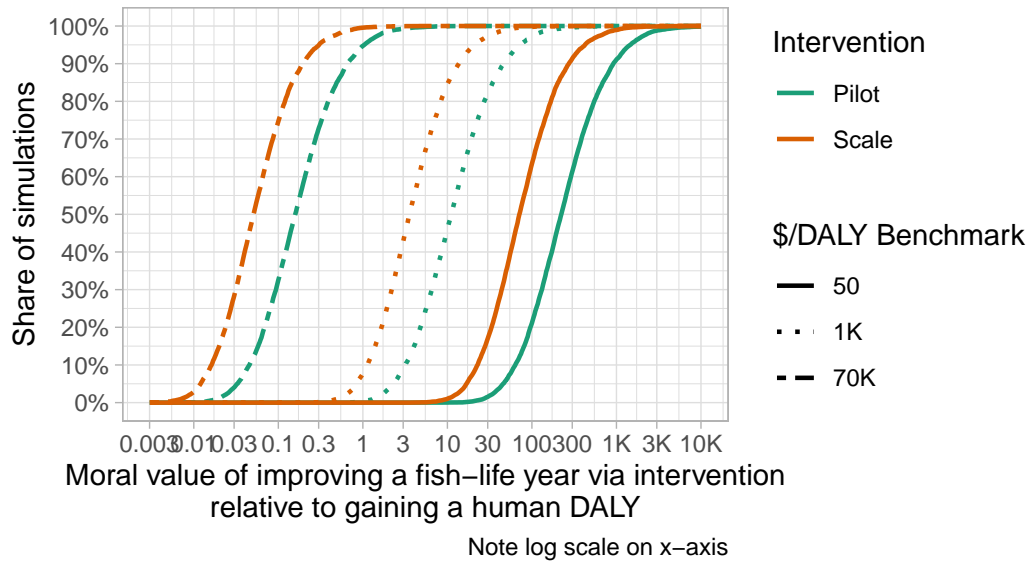
Moral value benchmarks

fig13\_mv\_benchmark



## Share of simulations where intervention beats \$/DALY benchmark

### Moral Value Approach



tab13\_mv\_benchmark

### Share of simulations beating \$DALY bar

Moral value	Pilot_50	Pilot_1000	Pilot_70000	Scale_50	Scale_1000	Scale_70000
0.01	0.0%	0.0%	0.1%	0.0%	0.0%	2.9%
0.10	0.0%	0.0%	32.6%	0.0%	0.0%	74.7%
0.25	0.0%	0.0%	66.8%	0.0%	0.1%	93.3%
0.50	0.0%	0.0%	85.3%	0.0%	1.0%	97.8%
0.75	0.0%	0.1%	91.5%	0.0%	3.5%	99.0%
1.00	0.0%	0.4%	94.7%	0.0%	7.6%	99.6%
5.00	0.0%	21.1%	99.7%	0.1%	63.4%	100.0%
10.00	0.0%	46.1%	100.0%	1.0%	84.6%	100.0%
25.00	0.8%	77.7%	100.0%	12.2%	96.3%	100.0%
50.00	6.1%	91.1%	100.0%	35.3%	98.9%	100.0%
75.00	13.2%	95.3%	100.0%	52.1%	99.6%	100.0%
100.00	21.1%	97.2%	100.0%	63.4%	99.8%	100.0%
500.00	77.7%	99.9%	100.0%	96.3%	100.0%	100.0%
1000.00	91.1%	100.0%	100.0%	98.9%	100.0%	100.0%
5000.00	99.5%	100.0%	100.0%	100.0%	100.0%	100.0%

```
tab14_min_mv
```

Minimum moral value assumption needed for to achieve share of simulations beating bar

sims_bin	Pilot_50	Pilot_1000	Pilot_70000	Scale_50	Scale_1000	Scale_70000
0%	0.0	0.0	0.0	0.0	0.0	0.0
1%	26.9	1.3	0.0	10.0	0.5	0.0
10%	64.6	3.2	0.0	22.9	1.1	0.0
25%	114.8	5.6	0.1	38.9	1.9	0.0
50%	223.9	11.2	0.2	72.4	3.6	0.1
75%	457.1	22.9	0.3	144.5	7.1	0.1
90%	933.3	46.8	0.7	275.4	13.8	0.2
95%	1,479.1	74.1	1.0	426.6	21.4	0.3
99%	3,467.4	173.8	2.5	1,023.3	51.3	0.7
100%	NA	1,122.0	16.2	6,456.5	323.6	4.7

## Export charts and tables

```
save_chart("fig9_fish_pd.png",fig9_fish_pd)
save_chart("fig10_fish_hours_pd.png",fig10_fish_hours_pd)
save_chart("fig11_dolperdaly_density.png",fig11_dolperdaly_density)
save_chart("fig12_wr_benchmark.png",fig12_wr_benchmark)
```

Warning: Removed 600 rows containing missing values (`geom\_line()`).

```
save_chart("fig13_mv_benchmark.png",fig13_mv_benchmark)
save_chart("fig13_mv_benchmark.png",fig13_mv_benchmark)
```

```
save_table(tab8_fish_pd,"tab8_fish_pd.html")
save_table(tab9_fish_pdpy,"tab9_fish_pdpy.html")
save_table(tab10_fish_hours_pd,"tab10_fish_hours_pd.html")
save_table(tab11_dolperdaly_density,"tab11_dolperdaly_density.html")
save_table(tab12_wr_benchmark,"tab12_wr_benchmark.html")
save_table(tab13_mv_benchmark ,"tab13_mv_benchmark.html")
save_table(tab14_min_mv,"tab14_min_mv.html")
```

```
saveRDS(fypd_scale, file= "../3_intermediate_data/fypd_scale.rds")
```

## Additional analyses

### Sensitivity to DALY as a share of human welfare range assumption

This section examines how the share of simulations beating various benchmarks under an assumption that an intervention that improves welfare by 10% of the human welfare range for a year is equivalent to averting a DALY, rather than 50%.

Calculation function

```
share_wr_alt <- function(xvar, scenario, bar) {
  mean(bar >
    (1/
      (xvar *
        fypd(scenario) *
        salmon_wr_alt /
        DALY_share_of_welfare_range_alt
      )))
}
```

Generate output table

```
# Generate one row for unique combination of xvar_values and scenario lists

alt_output_table <- expand_grid(
  xvar=wr_table_values,
  scenario="scale",
  bar=bar_values) %>%
# Core calculations using share_mv and share_wr calculation functions
rowwise() %>%
mutate(
  base=share_wr(xvar, scenario, bar),
  alt=share_wr_alt(xvar, scenario, bar)
) %>%
select(-scenario) %>%
pivot_longer(
  cols=c(base, alt),
  names_to="wr_assumptions",
```

```

    values_to="share_of_sims") %>%
mutate(
  bar_factor=
    factor(bar,levels=bar_values,labels=c("50","1K","70K")) %>%
pivot_wider(
  id_cols=xvar,
  names_from=c(wr_assumptions,bar_factor),
  values_from=share_of_sims) %>%
gt() %>%
fmt_percent(decimals =1) %>%
fmt_percent(columns=xvar,decimals =0) %>%
  cols_label(
    xvar = "Welfare range impact")

```

Output table is printed below. Overall conclusions do not appear overly sensitive to this assumption. If the stunning intervention improves fish welfare by an average 50% of the fish welfare range for the entire (non-stunning) slaughter duration, it will beat a benchmark of \$1K/DALY in only 6.6% of simulations.

alt\_output\_table

Welfare range impact	base_50	alt_50	base_1K	alt_1K	base_70K	alt_70K
1%	0.0%	0.0%	0.0%	0.0%	0.4%	10.3%
5%	0.0%	0.0%	0.0%	0.0%	10.3%	37.0%
10%	0.0%	0.0%	0.0%	0.2%	20.0%	49.2%
25%	0.0%	0.0%	0.0%	1.9%	37.0%	62.6%
50%	0.0%	0.0%	0.2%	6.6%	49.2%	71.1%
75%	0.0%	0.0%	0.5%	10.9%	55.5%	75.0%
90%	0.0%	0.0%	0.9%	13.3%	58.2%	76.6%
95%	0.0%	0.0%	1.0%	14.1%	59.1%	77.0%
99%	0.0%	0.0%	1.1%	14.8%	59.6%	77.2%
100%	0.0%	0.0%	1.2%	14.9%	59.8%	77.3%

### How might animals affected per dollar from the fish stunning intervention compare to marginal chicken grants

In this section I perform a quick BOTEK to see how the animals affected per dollar from the fish stunning intervention in the scale scenario might compare to marginal chicken grants.

I first import raw sample data (5000 simulations) for chickens affected per dollar from the Guesstimate model from Šimčíkas (2019).

```
# Import data on chickens affected per dollar from Guesstimate samples
chickens_per_dollar_historic <-
  read_csv("../1_input_data/chickens_per_dollar.csv",show_col_types=FALSE) %>%
  pull(chickens_per_dollar) %>%
  sample(sims,replace=TRUE)
```

I then work estimate marginal chickens affected per dollar, conditional on an assumption that marginal grants may impact 3.5 to 5 times fewer animals per dollar, then historic ones.

```
# Assumption about guesstimate samples
decrease_in_chicken_effectiveness <- runi(3.5,5)
chickens_per_dollar_marginal <- chickens_per_dollar_historic/decrease_in_chicken_effectiveness
```

I then work out the share of simulations where marginal chicken grants affect more animals per dollar then fish stunning grants in the scale scenario. About half the time.

```
# Assumption about guesstimate samples
mean(chickens_per_dollar_marginal>output_per_dollar("no_fish_affected","scale"))
```

```
[1] 0.4926
```

I then look at how the overall distributions compare.

```
summarystats(chickens_per_dollar_marginal,output_per_dollar("no_fish_affected","scale"))
```

statistic	chickens_per_dollar_marginal	output_per_dollar("no_fish_affected", "scale")
mean	15.0	13.3
sd	17.7	11.8
median	9.13	9.90
p5	2.14	1.89
p10	2.92	2.89
p25	4.96	5.37
p75	18.1	17.4
p90	33.6	27.9
p95	47.3	36.0