# Sockeye salmon analyses for paper

09-01-2015

This represents an outline / summary of the analyses for the paper. For salmon, we're only digging into recruitment. For example with sockeye, there's been other studies on individual growth – see Ruggerone & Rogers (1998), "Historical Analysis of Sockeye Salmon Growth Among Populations Affected by the Exxon Valdez Oil Spill and Large Spawning Escapements"

# **Data Processing**

## Brief descriptions of each sockeye dataset are as follows:

### 1. Coghill Lake sockeye

Brood year returns are taken from the column 'AI' in the 'BroodTab' sheet. Return year escapement is taken from column 'AK' in the 'BroodTab' sheet.

#### 2. Eshamy Lake sockeye

R/S is calculated as brood year returns / escapement. This calculation is in column 'S' of the 'broodtab' sheet. Total brood year return is in column 'R', and total escapement is in column 'B' of the same sheet. Several values are missing, corresponding to years where the weir was not up and running.

### 3. Copper River sockeye

R/S is calculated as brood year returns / escapement. Escapement by calendar year is in column 'B' of the 'Brd Tbl' sheet, total brood year return is given in column 'AN'.

Read in the data. All datasets have been trimmed to start at Brood Year 1968. We'll primarily use data 1980 or 1981 - 2008, because those are the span of years with R/S and covariates known (hatchery releases before 1980 incomplete).

```
coghill = read_excel("../../data/salmon data/data for analysis/Coghill_Wild_Sockeye_final.xlsx")
eshamy = read_excel("../../data/salmon data/data for analysis/Eshamy_Wild_Sockeye_final.xlsx")
copper = read_excel("../../data/salmon data/data for analysis/Copper Wild_Sockeye_final.xlsx")
```

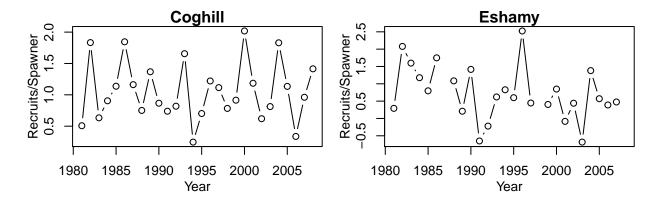
Plot the response, log(Recruits/Spawners).

## Warning: NAs introduced by coercion

Plot the predictor, number of spawners.

## Warning: NAs introduced by coercion

Plot the data, as log(Recruits/Spawners) versus Spawners over the period we're using, 1981-2008. This is the same formulation as the Ricker model assumes (below).



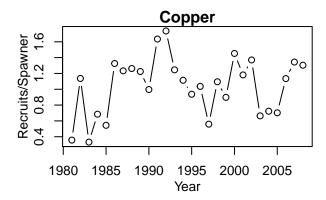


Figure 1: log(Recruits / Spawner) over time, 1981-2008

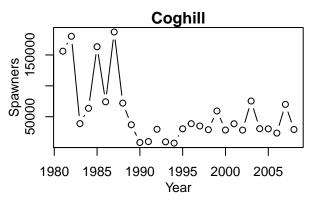
## Warning: NAs introduced by coercion

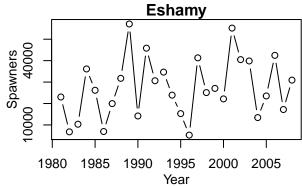
## Warning: NAs introduced by coercion

Plot the residuals from the regression of  $\log(\text{Recruits/Spawners})$  versus Spawners over the period we're using, 1981-2008. This is the same formulation as the Ricker model assumes (below).

## Warning: NAs introduced by coercion

## Warning: NAs introduced by coercion





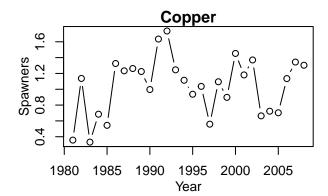
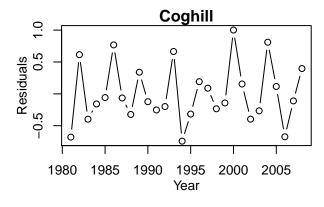
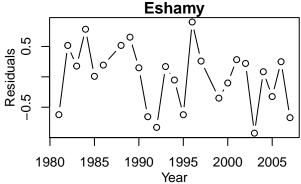
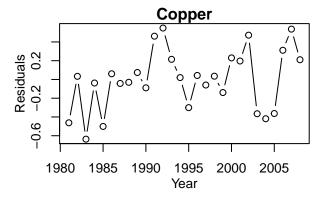


Figure 2: Spawners over time, 1981-2008







#

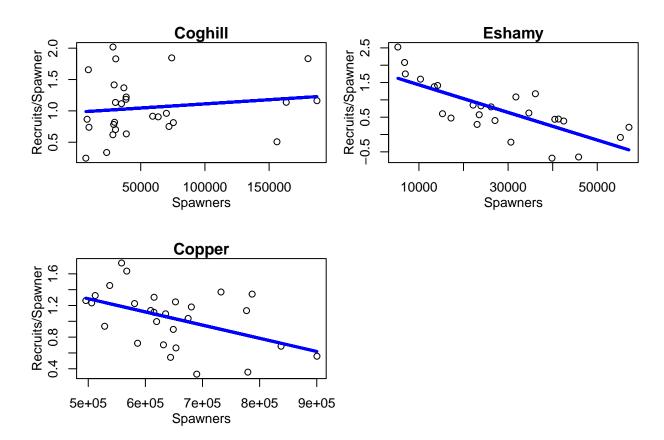


Figure 3: Raw data plot of log(R/S) on Spawners, 1981-2008

Modeling recruiutment

We'll conduct this analysis using the Ricker stock-recruit model, which is equivalent to a linear regression model,

```
log(R/S)_t = a_i + b_i * S_t + c_i * X_t + e_i
```

where  $a_i$  represents the population-specific intercept,  $b_i$  is a density-dependent parameter (generally negative),  $c_i$  is an optional coefficient(s) incorporating a time-varying covariate  $X_t$ , and  $e_i$  is an error term. Simple models for the error are IID white noise, which we'll adopt here.

# Constructing the basic (null) model with no covariates.

We'll start with just using data 1981-2008, and spawners as a predictor of recruitment. Each population (Coghill, Eshamy, Copper) is assumed to be an independent 'process', but have shared observation errors. Recruits / spawner is not modeled as an autoregressive state-space process, but all uncertainty is assumed to have arisen from measurement and observation error. Hypotheses for mechanistic relationships are discussed and evaluated below.

```
subset = which(coghill$BroodYear%in%seq(1981,2008))

Y = log(as.numeric(coghill$RecPerSpawn[subset])) # log(R/S)

X = as.numeric(coghill$Escapement[subset]) # number of spawners

nT = length(Y)

Y2 = log(as.numeric(eshamy$RecPerSpawn[subset])) # log(R/S)

X2 = as.numeric(eshamy$Escapement[subset]) # number of spawners
```

```
X2[which(is.na(X2))]= exp(fit[which(is.na(X2))])
Y3 = log(as.numeric(copper$RecPerSpawn[subset])) # log(R/S)
X3 = as.numeric(copper$Escapement[subset]) # number of spawners

# fit in initial Ricker S-R state space model
cMat = matrix(NA, nrow=3, ncol = nT)
cMat[1,] = X
cMat[2,] = X2
cMat[2,] = X2
cMat[3,] = X3

Yall = rbind(Y,Y2,Y3) # log(R/S)

Covar = matrix(list(0),3,3)
Covar[1,1] = "Spawn.Cog"
Covar[2,2] = "Spawn.Esh"
Covar[3,3] = "Spawn.Cop"

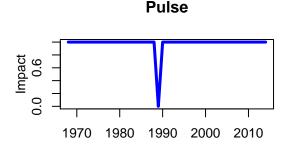
models = list()
```

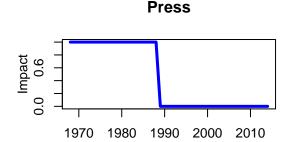
Model	AICc
Unequal density dependence (Ricker b)	110.236
Equal density dependence (Ricker b)	138.758
Null model	140.096

# Hypothesis 1: EVOS had a negative impact on sockeye productivity

The EVOS spill occurred in 1989. Sockeye typically migrate to the ocean 2 years after spawning, so the immediate impacts of the spill may have impacted recruitment from brood years 1987, 1988, and 1989.

We'll include the impacts of the EVOS spill. We'll do this 3 ways: creating a pulse impact, a press impact, and a press impact followed by a recovery back to the original state. The form of the recovery was assumed to be linear over a 20 - year period.





# Pulse/Recovery

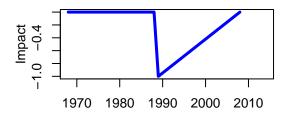


Figure 4: Illustration of covariates representing EVOS impacts

```
library(MARSS)
covar.names = c("EVOS.pulse.lag0","EVOS.press.lag0","EVOS.pulseRecovery.lag0",
"EVOS.pulse.lag2","EVOS.press.lag2","EVOS.pulseRecovery.lag2")
# fit in initial Ricker S-R state space model

cMat = matrix(NA, nrow=4, ncol = nT)
cMat[1,] = X
cMat[2,] = X2
cMat[3,] = X3
Yall = rbind(Y,Y2,Y3)
```

```
# Coefficients matrix. cMat Matrix is dimensioned
# cmat.row x cmat.col, and Covar needs to be dimensioned
# cmat.row x n.responses
Covar = matrix(list(0),3,3)
Covar[1,1] = "Spawn.Cog"
Covar[2,2] = "Spawn.Esh"
Covar[3,3] = "Spawn.Cop"
Covar = rbind(Covar,c("EVOS","EVOS","EVOS"))
```

Model	AICc	Coef
EVOS.pulse.lag0	110.544	0.39952299
EVOS.press.lag0	112.881	0.04859224
EVOS.pulseRecovery.lag0	112.698	-0.08068823
EVOS.pulse.lag2	112.466	-0.16163056
EVOS.press.lag2	112.193	-0.14517433
EVOS.pulseRecovery.lag2	112.686	0.06548589

These results show that in general, adding EVOS as an impact increases AICc.

# Hypothesis 2: Sockeye productivity in PWS has been negatively impacted by predation and competition from juvenile pink or chum salmon

```
library(MARSS)
covar.names = c("juv.hatchRelPink.lag2","juv.hatchRelChum.lag2",
"juv.wildPinkRun.lag1", "juv.wildChumRun.lag1")
# fit in initial Ricker S-R state space model
cMat = matrix(NA, nrow=4, ncol = nT)
cMat[1,] = X
cMat[2,] = X2
cMat[3,] = X3
Yall = rbind(Y, Y2, Y3)
# Coefficients matrix. cMat Matrix is dimensioned
# cmat.row x cmat.col, and Covar needs to be dimensioned
# cmat.row x n.responses
Covar = matrix(list(0), 3, 3)
Covar[1,1] = "Spawn.Cog"
Covar[2,2] = "Spawn.Esh"
Covar[3,3] = "Spawn.Cop"
Covar = rbind(Covar,c("Competition","Competition","Competition"))
juvComp.models = list()
```

AICc	Coef
112.855	0
111.29	0
112.482	1e-08
109.472	7.1e-07
	112.855 111.29 112.482

These results show that in these indices of pink and chum salmon juvenile competion with juvenile sockeye increases AICc.

# Hypothesis 3: Sockeye productivity in PWS has been negatively impacted by predation and competition from adult pink salmon

```
library(MARSS)
coghill$ad.totalPinkRun.lag2 = coghill$ad.wildPinkRun.lag2 + coghill$ad.hatchPinkRun.lag2
covar.names = c("ad.hatchRelPink.lag0", "ad.hatchRelChum.lag1",
"ad.wildPinkRun.lag2", "ad.hatchPinkRun.lag2", "ad.wildChumRun.lag2",
"ad.totalPinkRun.lag2")
# fit in initial Ricker S-R state space model
cMat = matrix(NA, nrow=4, ncol = nT)
cMat[1,] = X
cMat[2,] = X2
cMat[3,] = X3
Yall = rbind(Y, Y2, Y3)
# Coefficients matrix. cMat Matrix is dimensioned
# cmat.row x cmat.col, and Covar needs to be dimensioned
# cmat.row x n.responses
Covar = matrix(list(0), 3, 3)
Covar[1,1] = "Spawn.Cog"
Covar[2,2] = "Spawn.Esh"
Covar[3,3] = "Spawn.Cop"
Covar = rbind(Covar,c("Predation","Predation","Predation"))
adComp.models = list()
```

Model	AICc	Coef
ad.hatchRelPink.lag0	111.747	0
ad.hatch Rel Chum.lag 1	112.872	0
ad.wildPinkRun.lag2	109.853	-1e-08
ad.hatch Pink Run.lag 2	112.441	0
ad.wildChumRun.lag2	112.886	3e-08
ad.total Pink Run.lag 2	111.363	0

These results show that in these indices of pink and chum salmon adult predation with juvenile sockeye

# Hypothesis 4: Sockeye productivity in PWS has been largely shaped by changing ocean conditions (SST, PDO)

```
library(MARSS)
covar.names = c("SST.sock.lag2","Upwelling.winter.lag1",
"Upwelling.winter.lag2")
# fit in initial Ricker S-R state space model
cMat = matrix(NA, nrow=4, ncol = nT)
cMat[1,] = X
cMat[2,] = X2
cMat[3,] = X3
Yall = rbind(Y, Y2, Y3)
# Coefficients matrix. cMat Matrix is dimensioned
# cmat.row x cmat.col, and Covar needs to be dimensioned
# cmat.row x n.responses
Covar = matrix(list(0), 3, 3)
Covar[1,1] = "Spawn.Cog"
Covar[2,2] = "Spawn.Esh"
Covar[3,3] = "Spawn.Cop"
Covar = rbind(Covar,c("Enviro","Enviro","Enviro"))
enviro.models = list()
```

Model	AICc	Coef
SST.sock.lag2	113.464	0.05151739
Upwelling.winter.lag1	110.229	0.00345955
Upwelling.winter.lag2	111.427	0.00275928

These results show that in these indices of pink and chum salmon adult predation with juvenile sockeye increases AICc.

As an update, we can also explore whether these same correlations hold for the longer time series, going back to 1968.

```
subset = which(coghill$BroodYear%in%seq(1968,2008))

Y = log(as.numeric(coghill$RecPerSpawn[subset])) # log(R/S)

X = as.numeric(coghill$Escapement[subset]) # number of spawners

nT = length(Y)

Y2 = log(as.numeric(eshamy$RecPerSpawn[subset])) # log(R/S)

X2 = as.numeric(eshamy$Escapement[subset]) # number of spawners
```

```
X2[which(is.na(X2))]= exp(fit[which(is.na(X2))])
Y3 = log(as.numeric(copper$RecPerSpawn[subset])) # log(R/S)
X3 = as.numeric(copper$Escapement[subset]) # number of spawners

# fit in initial Ricker S-R state space model
cMat = matrix(NA, nrow=3, ncol = nT)
cMat[1,] = X
cMat[2,] = X2
cMat[3,] = X3

Yall = rbind(Y,Y2,Y3) # log(R/S)

Covar = matrix(list(0),3,3)
Covar[1,1] = "Spawn.Cog"
Covar[2,2] = "Spawn.Esh"
Covar[3,3] = "Spawn.Cop"

models = list()
```

Model	AICc
Unequal density dependence (Ricker b)	194.758
Equal density dependence (Ricker b)	232.109

```
library(MARSS)
covar.names = c("SST.sock.lag2","Upwelling.winter.lag1",
"Upwelling.winter.lag2")
# fit in initial Ricker S-R state space model
cMat = matrix(NA, nrow=4, ncol = nT)
cMat[1,] = X
cMat[2,] = X2
cMat[3,] = X3
Yall = rbind(Y, Y2, Y3)
{\it \# Coefficients \ matrix. \ cMat\ Matrix \ is \ dimensioned}
# cmat.row x cmat.col, and Covar needs to be dimensioned
# cmat.row x n.responses
Covar = matrix(list(0), 3, 3)
Covar[1,1] = "Spawn.Cog"
Covar[2,2] = "Spawn.Esh"
Covar[3,3] = "Spawn.Cop"
Covar = rbind(Covar,c("Enviro","Enviro","Enviro"))
enviro.models = list()
```

Model	AICc	Coef
SST.sock.lag2	193.53	0.17134324
Upwelling.winter.lag1	196.642	0.00144245
Upwelling.winter.lag2	196.76	-0.00123668

As an update, we can also explore whether these same correlations hold for the longer time series, going back to 1968.

```
subset = which(coghill$BroodYear%in%seq(1968,2008))

Y = log(as.numeric(coghill$RecPerSpawn[subset])) # log(R/S)

X = as.numeric(coghill$Escapement[subset]) # number of spawners

nT = length(Y)

Y2 = log(as.numeric(eshamy$RecPerSpawn[subset])) # log(R/S)

X2 = as.numeric(eshamy$Escapement[subset]) # number of spawners
```

```
X2[which(is.na(X2))]= exp(fit[which(is.na(X2))])
Y3 = log(as.numeric(copper$RecPerSpawn[subset])) # log(R/S)
X3 = as.numeric(copper$Escapement[subset]) # number of spawners

# fit in initial Ricker S-R state space model
cMat = matrix(NA, nrow=3, ncol = nT)
cMat[1,] = X
cMat[2,] = X2
cMat[2,] = X2
cMat[3,] = X3

Yall = rbind(Y,Y2,Y3) # log(R/S)

Covar = matrix(list(0),3,3)
Covar[1,1] = "Spawn.Cog"
Covar[2,2] = "Spawn.Esh"
Covar[3,3] = "Spawn.Cop"

models = list()
```

Model	AICc
Unequal density dependence (Ricker b) Equal density dependence (Ricker b)	194.758 232.109

```
library(MARSS)
covar.names = c("SST.sock.lag2","Upwelling.winter.lag1",
"Upwelling.winter.lag2")
# fit in initial Ricker S-R state space model

cMat = matrix(NA, nrow=4, ncol = nT)
cMat[1,] = X
cMat[2,] = X2
cMat[3,] = X3
Yall = rbind(Y,Y2,Y3)

# Coefficients matrix. cMat Matrix is dimensioned
# cmat.row x cmat.col, and Covar needs to be dimensioned
# cmat.row x n.responses
Covar = matrix(list(0),3,3)
```

```
Covar[1,1] = "Spawn.Cog"
Covar[2,2] = "Spawn.Esh"
Covar[3,3] = "Spawn.Cop"
Covar = rbind(Covar,c("Enviro","Enviro"))
enviro.models = list()
```

# kable(m)

Model	AICc	Coef
SST.sock.lag2	193.53	0.17134324
Upwelling.winter.lag1	196.642	0.00144245
Upwelling.winter.lag2	196.76	-0.00123668