Sockeye salmon analyses for paper

03-28-2016

This represents an outline / summary of the sockeye salmon analyses for the Ward et al. paper.

Data Processing

```
## Warning: package 'readxl' was built under R version 3.2.4
```

```
## Warning: package 'knitr' was built under R version 3.2.5
```

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
```

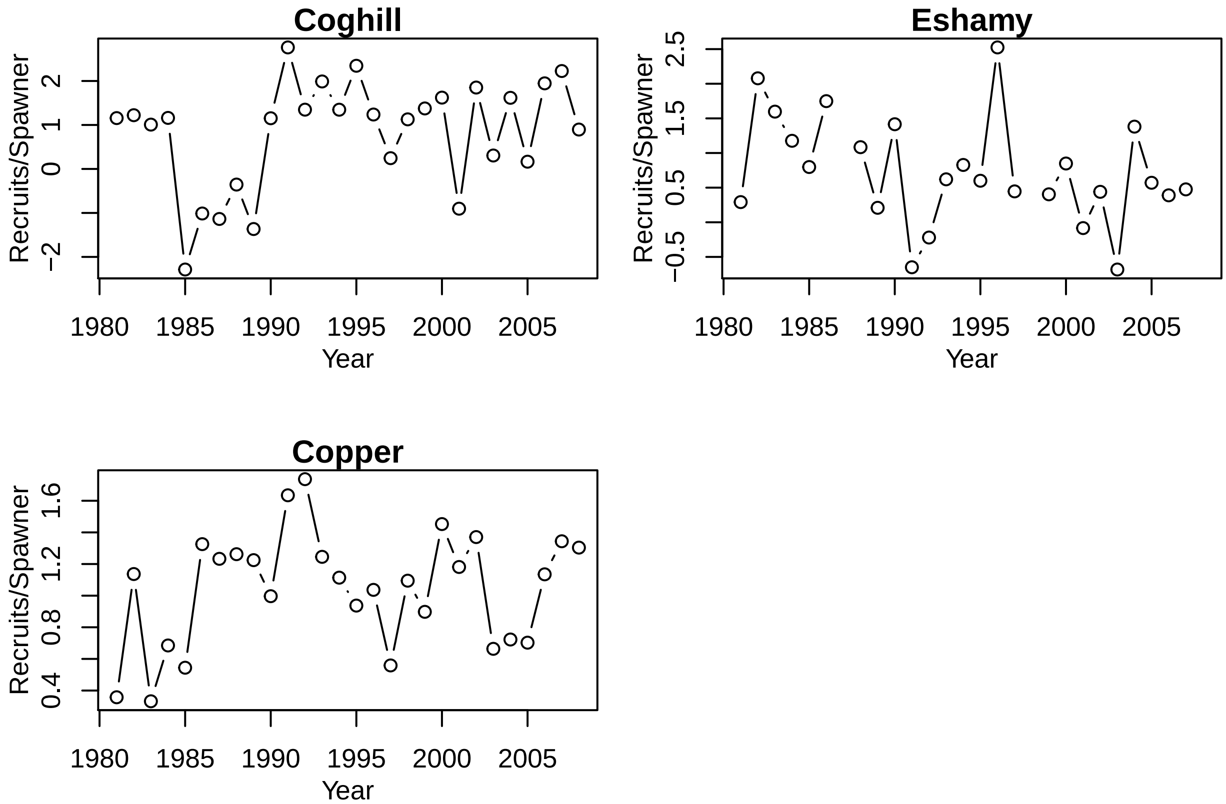


Figure 1: log(Recruits / Spawner) over time, 1981-2008

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).

```
## Warning: NAs introduced by coercion

## Warning: NAs introduced by coercion
```

Plot the residuals from the regression of log(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
```

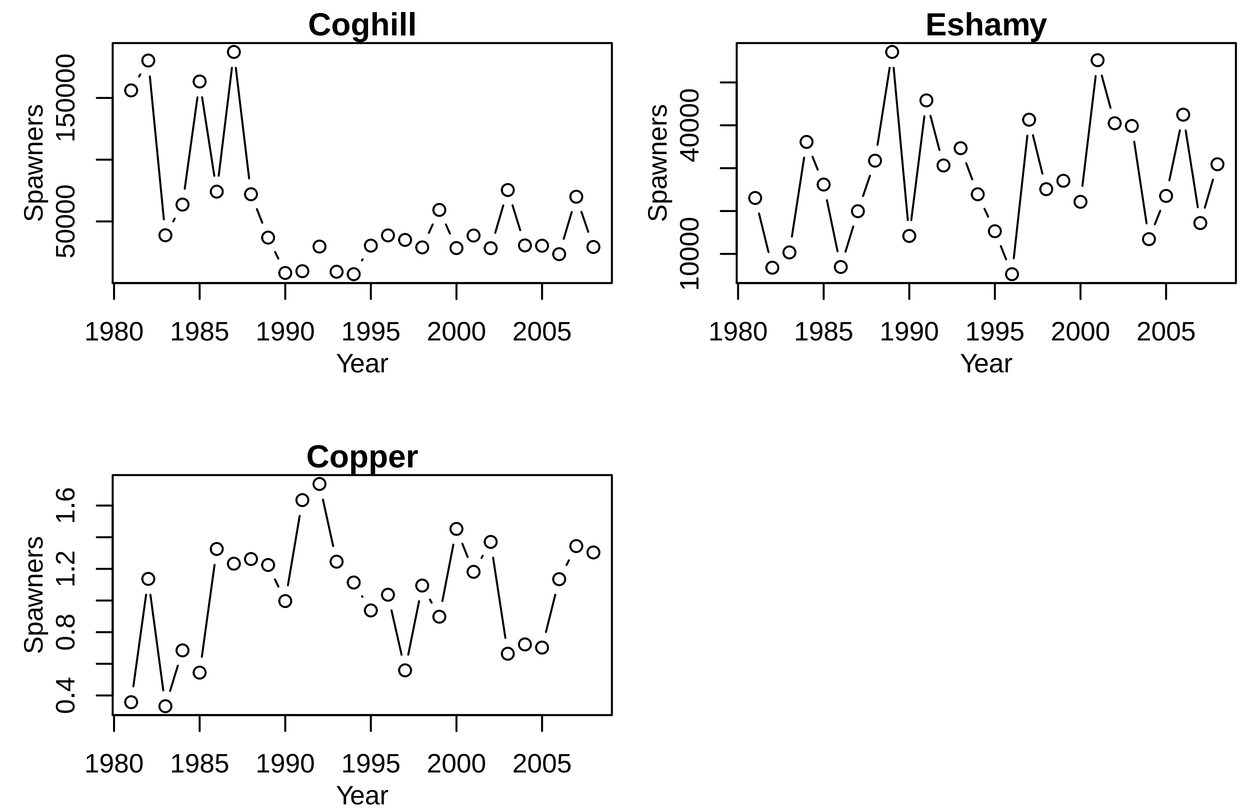
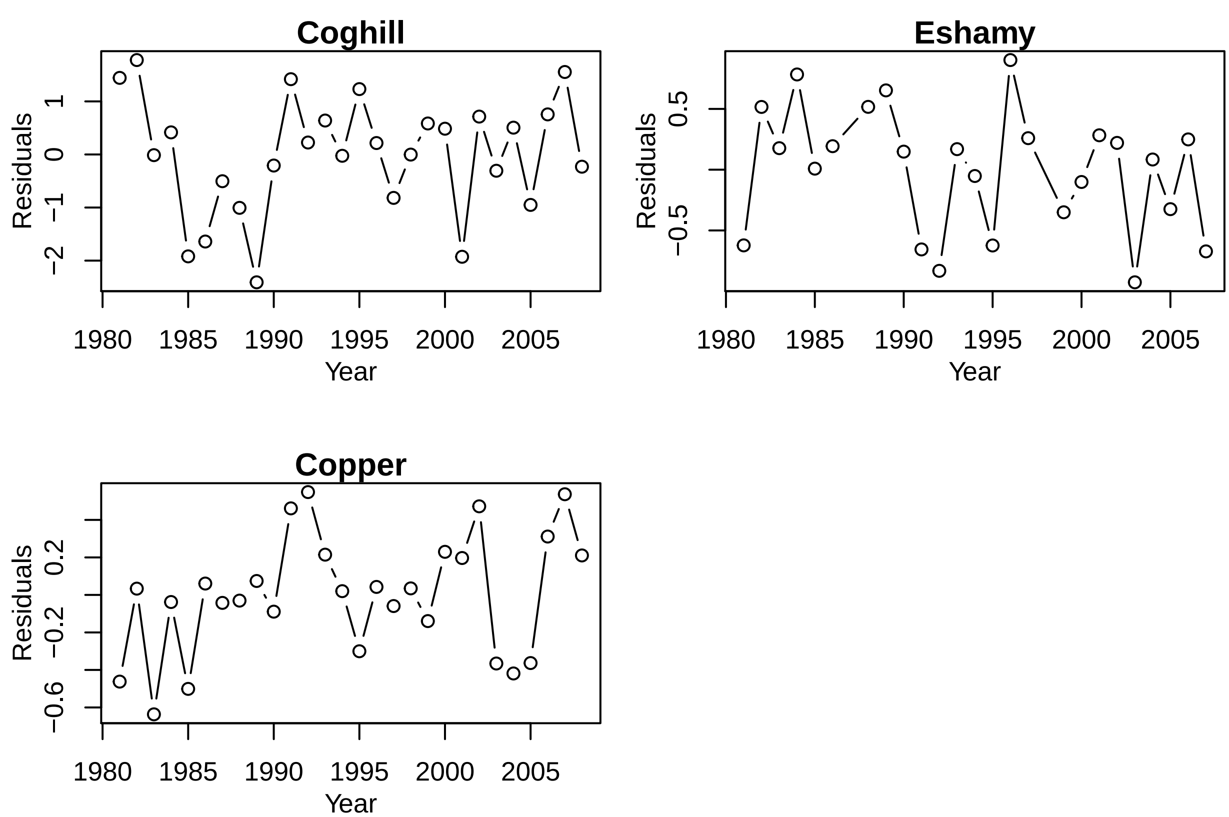


Figure 2: Spawners over time, 1981-2008



#

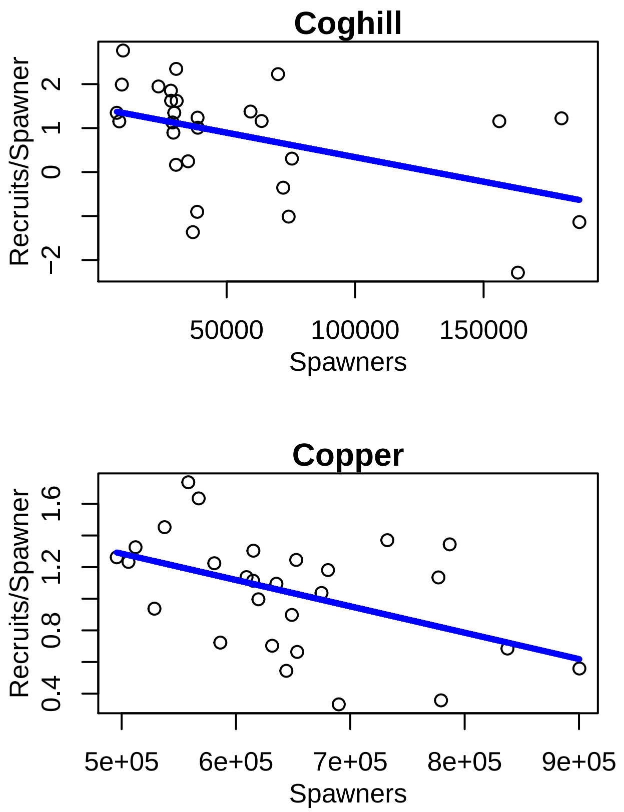


Figure 3: Raw data plot of log(R/S) on Spawners, 1981-2008

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.

```r
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
```

```r
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)	197.278
Equal density dependence (Ricker b)	208.102
Null model	212.593

Hypothesis 2: Sockeye productivity was affected by EVOS

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.

[Note: a negative coefficient on the press or pulse corresponds to a negative impact; because of how we coded the dummy covariate, a negative coefficient on the pulse-recovery change translates into a positive perturbation]

```
par(mfrow = c(2,2),mgp=c(2,1,0))
plot(coghill$BroodYear, 1-coghill$EVOS.pulse.lag0, xlab = "", ylab = "Impact",
     main = "Pulse",col="blue",lwd=3,type="l")
plot(coghill$BroodYear, 1-coghill$EVOS.press.lag0, xlab = "", ylab = "Impact",
     main = "Press",col="blue",lwd=3,type="l")
plot(coghill$BroodYear, coghill$EVOS.pulseRecovery.lag0, xlab = "", ylab = "Impact",
     main = "Pulse/Recovery",col="blue",lwd=3,type="l")
```

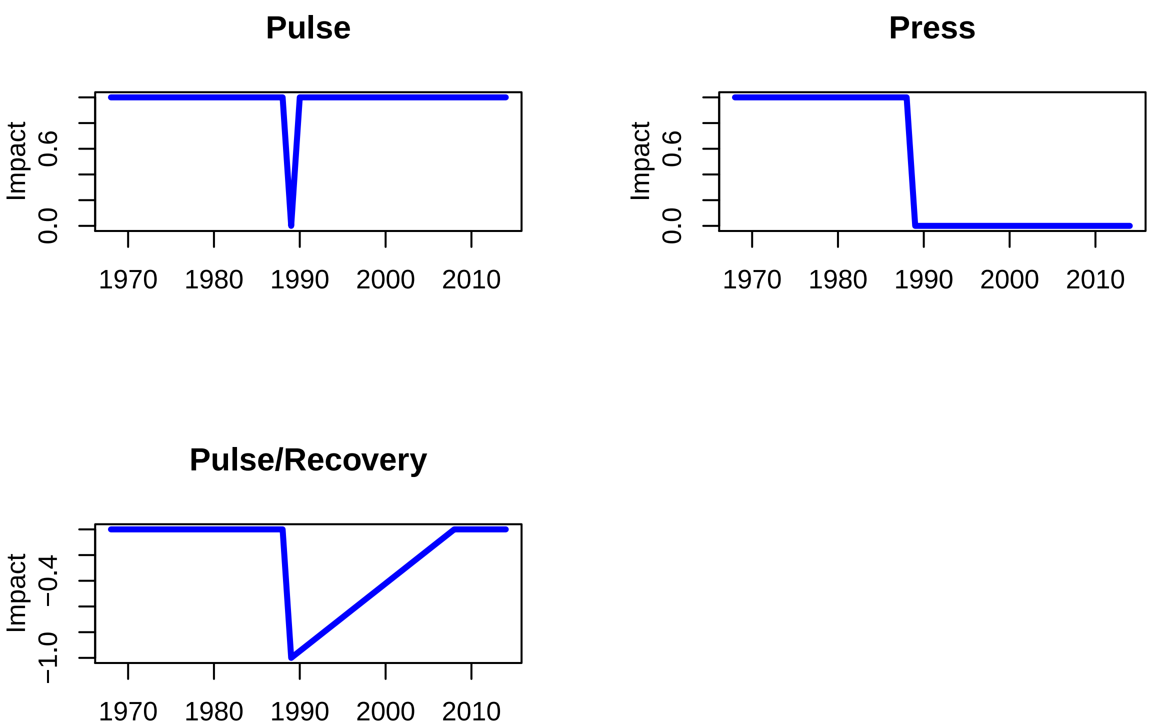


Figure 4: Illustration of covariates representing EVOS impacts

```
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
```

```r
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"))

evos.models = list()
```

Model	AICc	Coef
EVOS.pulse.lag0	197.784	-0.63237089
EVOS.press.lag0	199.514	0.21591469
EVOS.pulseRecovery.lag0	199.876	-0.09323786
EVOS.pulse.lag2	199.632	-0.28607022
EVOS.press.lag2	199.977	0.04650402
EVOS.pulseRecovery.lag2	199.914	0.03198866

These results show that in general, adding EVOS as an impact increases AICc. # Hypothesis 3: Sockeye productivity in PWS has been affected by changing ocean conditions

```r
library(MARSS)
covar.names = c("SST.sock.lag2","Upwelling.winter.lag1",
"Upwelling.winter.lag2", "discharge.lag0", "discharge.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("Enviro","Enviro","Enviro"))

enviro.models = list()
```

Model	AICc	Coef
SST.sock.lag2	199.572	0.13842369

Model	AICc	Coef
Upwelling.winter.lag1	199.715	-0.00141134
Upwelling.winter.lag2	199.889	0.00117947
discharge.lag0	199.279	-1.19e-06
discharge.lag1	200.132	8.2e-07

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

Hypothesis 4: 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()
```

Model	AICc	Coef
juv.hatchRelPink.lag2	199.837	0
juv.hatchRelChum.lag2	199.736	0
juv.wildPinkRun.lag1	199.962	0
juv.wildChumRun.lag1	198.653	-7.1e-07

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

Hypothesis 5: Sockeye productivity in PWS has been affected 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	199.912	0
ad.hatchRelChum.lag1	199.627	0
ad.wildPinkRun.lag2	198.569	-1e-08
ad.hatchPinkRun.lag2	186.697	-3e-08
ad.wildChumRun.lag2	199.215	-1.7e-07
ad.totalPinkRun.lag2	190.197	-2e-08

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

As an update to the climate hypotheses, 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)
```

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

```r
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)	286.093
Equal density dependence (Ricker b)	315.86

```r
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	285.345	0.22845471

Model	AICc	Coef
Upwelling.winter.lag1	287.064	-0.00330322
Upwelling.winter.lag2	287.438	-0.00288361

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)	286.093
Equal density dependence (Ricker b)	315.86

```
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)
```

```r
# 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()
```

```r
kable(m)
```

Model	AICc	Coef
SST.sock.lag2	285.345	0.22845471
Upwelling.winter.lag1	287.064	-0.00330322
Upwelling.winter.lag2	287.438	-0.00288361