Herring recruitment and SSB analyses for paper

03-28-2016

This is supplementary information for the Ward et al. paper

Data Processing

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

Read in the data. We'll primarily use data from brood years 1981 - 2011, because those are the span of years from the ASA model with R/S and covariates known (hatchery releases before 1980 incomplete).

```
pwsher = read_excel("../../data/herring/PWS_herring_final.xlsx")
```

Plot the response, log(Recruits/Spawners).

```
subset = which(pwsher$BroodYear%in%seq(1981,2011))
Y = log(as.numeric(pwsher$RecPerSpawn[subset])) # log(R/S)

par(mfrow = c(2,2),mgp=c(2,1,0),mai=c(0.8,0.6,0.2,0.05))
plot(1981:2011,Y, xlab="Year",ylab="log(Age.3 Recruits/Spawner)",main="PWS",type="b")
plot(1981:2011, pwsher$Rec3Obs[subset], xlab="Year",ylab="Recruits",main="PWS",type="b")
plot(1981:2011, pwsher$BroodYearSB[subset], xlab="Year",ylab="Spawners",main="PWS",type="b")
```

Plot the data, as log(Recruits/Spawners) versus Spawners over the period we're using, 1981-2011. This is the same formulation as the Ricker model assumes (below).

```
subset = which(pwsher$BroodYear%in%seq(1981,2011))
Y = log(as.numeric(pwsher$RecPerSpawn[subset])) # log(R/S)
X = as.numeric(pwsher$BroodYearSB[subset]) # number of spawners

par(mfrow = c(2,2),mgp=c(2,1,0),mai=c(0.8,0.6,0.2,0.05))
plot(X,Y, xlab="Spawners",ylab="log(Recruits/Spawner)",main="",type="b")
# fit linear model
lines(X, predict.lm(lm(Y~X),newdata=data.frame(X)), col="blue",lwd=3)
mod = lm(Y~X)
plot(1981:2011,mod$residuals, xlab="Year",ylab="Residuals",main="",type="b")
```

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.

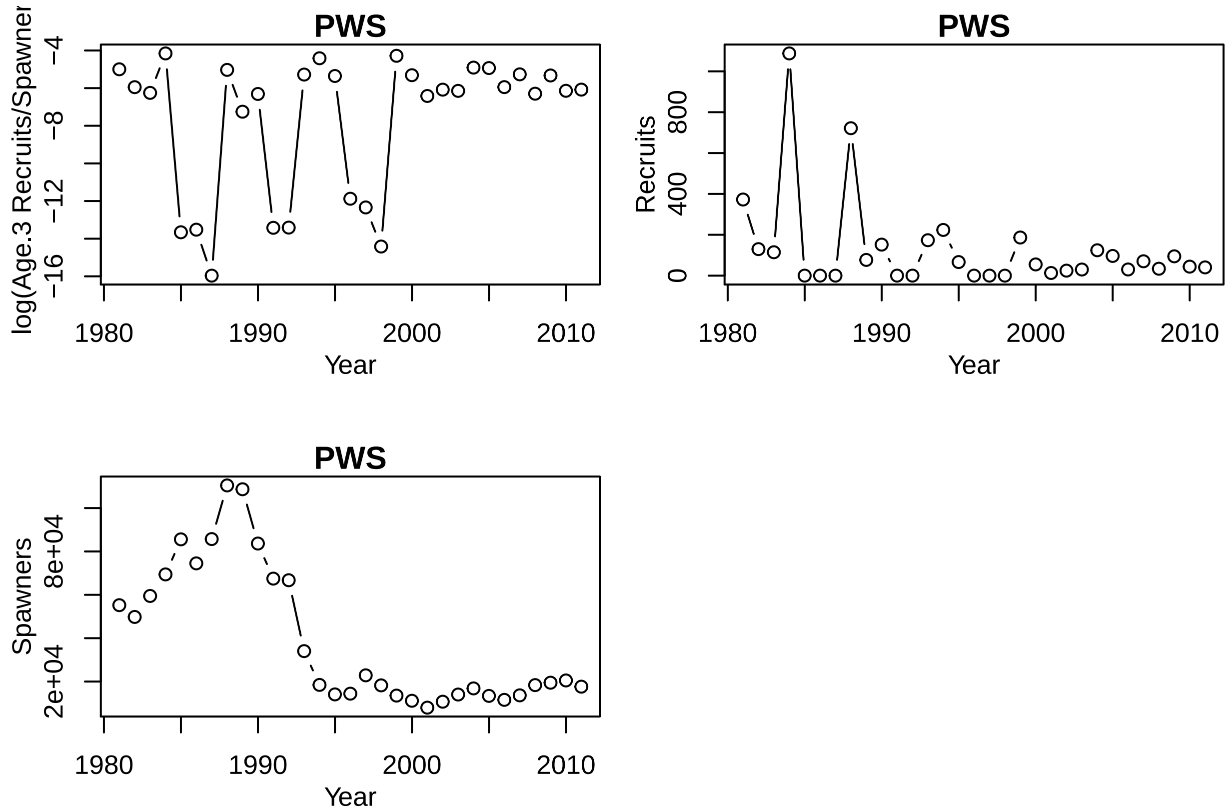

Figure 1: log(Recruits / Spawner) over time, 1981-2011

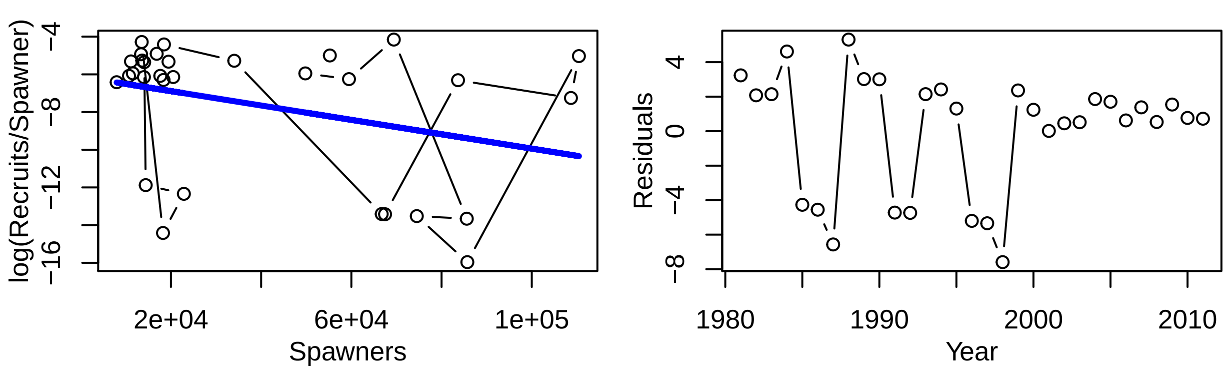

Figure 2: Raw data plot of log(R/S) on Spawners, 1981-2011

Constructing the basic (null) model with no covariates.

We'll start with just using data 1981-2011, and spawners as a predictor of recruitment. 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(pwsher$BroodYear%in%seq(1981,2011))

Y = log(as.numeric(pwsher$RecPerSpawn[subset])) # log(R/S)
X = as.numeric(pwsher$RecPerSpawn[subset]) # number of spawners
nT = length(Y)

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

models = list()
```

Model	AICc	Coef
Null model	171.821	NA
Density dependence	153.545	593.41662427

Hypothesis 2: EVOS had an impact on herring productivity

The EVOS spill occurred in 1989. Herring 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(pwsher$BroodYear, 1-pwsher$EVOS.pulse.lag0, xlab = "", ylab = "Impact",
     main = "Pulse",col="blue",lwd=3,type="l")
plot(pwsher$BroodYear, 1-pwsher$EVOS.press.lag0, xlab = "", ylab = "Impact",
     main = "Press",col="blue",lwd=3,type="l")
plot(pwsher$BroodYear, pwsher$EVOS.pulseRecovery.lag0, xlab = "", ylab = "Impact",
     main = "Pulse/Recovery",col="blue",lwd=3,type="l")
```

```
library(MARSS)
covar.names = c("EVOS.pulse.lag0", "EVOS.press.lag0", "EVOS.pulseRecovery.lag0",
    "EVOS.pulse.lag1", "EVOS.press.lag1", "EVOS.pulseRecovery.lag1",
"EVOS.pulse.lag2", "EVOS.press.lag2", "EVOS.pulseRecovery.lag2")
# fit in initial Ricker S-R state space model
```

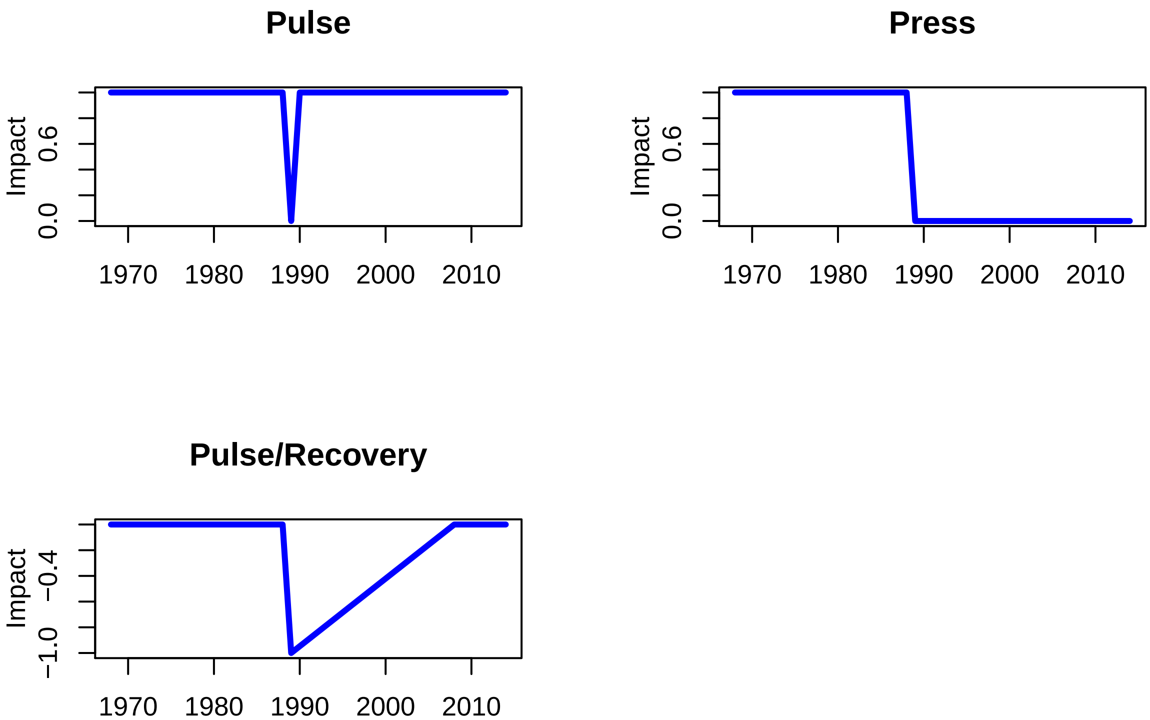

Figure 3: Illustration of covariates representing EVOS impacts

```
cMat = matrix(NA, nrow=2, ncol = nT)
cMat[1,] = X

evos.models = list()
```

Model	AICc	Coef
EVOS.pulse.lag0	154.744	3.20957037
EVOS.press.lag0	156.402	-0.27799353
EVOS.pulseRecovery.lag0	156.201	0.66390167
EVOS.pulse.lag1	155.766	2.01321987
EVOS.press.lag1	156.265	0.45434887
EVOS.pulseRecovery.lag1	156.409	0.08514066
EVOS.pulse.lag2	151.47	-5.59004114
EVOS.press.lag2	155.611	-1.53496175
EVOS.pulseRecovery.lag2	155.081	1.66102237

These results show that most of the EVOS models do worse than the null model, maybe with the exception of the lag.0 model.

Hypothesis 4: Herring productivity in PWS has been affected by predation and competition from juvenile pink salmon.

Age-1 herring in 1969 may be affected by pink salmon released in 1969 (BY 1968), competing in the later summer or fall months.

```
library(MARSS)
covar.names = c("juv.hatchRelPink.lag2","juv.hatchRelChum.lag2",
"juv.wildPinkRun.lag1","juv.wildChumRun.lag2")
# fit in initial Ricker S-R state space model

cMat = matrix(NA, nrow=2, ncol = nT)
cMat[1,] = X

juvComp.models = list()
```

Model	AICc	Coef
juv.hatchRelPink.lag2	156.427	0
juv.hatchRelChum.lag2	150.072	-5e-08
juv.wildPinkRun.lag1	156.386	-4e-08
juv.wildChumRun.lag2	151.674	7.39e-06

These results show that there isn't much support for including pink or chum competion with herring as a predictor for the decline (AICc worse than null model).

Hypothesis 5: Herring productivity in PWS has been affected by predation and competition from adult pink (and chum) salmon

```
library(MARSS)
pwsher$ad.totalPinkRun.lag1 = pwsher$ad.wildPinkRun.lag1 + pwsher$ad.hatchPinkRun.lag1
covar.names = c("ad.hatchPinkRun.lag1","ad.hatchRelChum.lag2",
"ad.wildPinkRun.lag1","ad.wildChumRun.lag1",
"ad.totalPinkRun.lag1")
# fit in initial Ricker S-R state space model

cMat = matrix(NA, nrow=2, ncol = nT)
cMat[1,] = X

adComp.models = list()
```

Model	AICc	Coef
ad.hatchPinkRun.lag1	156.199	2e-08
ad.hatchRelChum.lag2	152.458	-5e-08
ad.wildPinkRun.lag1	153.205	1.2e-07
ad.wildChumRun.lag1	155.646	-1.16e-06
ad.totalPinkRun.lag1	155.211	3e-08

These results show that adult runs of chum or pink salmon may have a negative impact on PWS herring recruitment.

Hypothesis 3: Herring productivity in PWS has been shaped by changing ocean

```
library(MARSS)
covar.names = c("humpbacks","Upwelling.summerBefore",
"Upwelling.summerAfter","discharge.lag0","discharge.lag1",
"win.sst.lag1","win.sst.lag0")
# fit in initial Ricker S-R state space model

cMat = matrix(NA, nrow=2, ncol = nT)
cMat[1,] = X

enviro.models = list()
```

Model	AICc	Coef
humpbacks	154.957	-0.03538012
Upwelling.summerBefore	154.426	-0.1956743
Upwelling.summerAfter	156.301	0.04565842
discharge.lag0	147.106	-3.913e-05
discharge.lag1	156.554	-3.61e-06
win.sst.lag1	155.79	-0.80434565
win.sst.lag0	150.021	-2.4536092

These results show that most of the environmental indices (or humpbacks) doesn't appear to have a strong impact on PWS herring recruitment. The exception is discharge, which has a huge improvement as a predictor (- 8 log likelihood units)

Using this best model, let's look at including some of the EVOS or pink/chum covariates with discharge.

```
library(MARSS)
covar.names = c("EVOS.press.lag2","EVOS.pulseRecovery.lag2",
"ad.hatchRelPink.lag2","ad.hatchRelChum.lag2")

cMat = matrix(NA, nrow=3, ncol = nT)
cMat[1,] = X
cMat[2,] = pwsher[subset,"discharge.lag0"]

combo.models = list()
```

Model	AICc	Coef
Discharge+ EVOS.press.lag2	150.155	0
Discharge+ EVOS.pulseRecovery.lag2	150.206	0
Discharge+ ad.hatchRelPink.lag2	150.009	0
Discharge+ ad.hatchRelChum.lag2	147.399	0

What this shows is that once all of these predictors to the model with discharge, they do roughly equally well, so the model with discharge alone is still best.

The R^2 from this model is about ~ 0.55, and we can look at the plot of observed and predicted values.

```
cMat = matrix(NA, nrow=2, ncol = nT)
cMat[1,] = X
cMat[2,] = pwsher[subset,"discharge.lag0"]
mod = lm(Y~cMat[1,]+cMat[2,])
```

```
pdf("Figure 3 herring.pdf")
expr = expression(paste("Total discharge ", m^3, " ", s^-1, sep=""))
par(mfrow=c(2,1),mgp=c(2,1,0),mai=c(0.7,0.7,0.3,0.1))
plot(pwsher$BroodYear[which(pwsher$BroodYear%in%seq(1981,2011))],pwsher$discharge.lag0[which(pwsher$Bro
     type="b", lwd=3, xlim=c(1981,2011))
legend('topleft',"(a)", bty='n')
plot(1981:2011, lm(Y~cMat[1,]+cMat[2,])$fitted.values, xlab="", ylim=c(-16,1),type="l",lwd=3,ylab="log(
legend('topleft',"(b)", bty='n')
points(1981:2011, Y, col="grey30",lwd=2,cex=1.2)
dev.off()
```

```
## pdf
##   2
```