Herring recruitment and SSB analyses for paper

03-28-2016

This is supplementary information for the Ward et al. paper

Data Processing

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")
```

```
# Fit initial DLM with time-varying DD effects
# Example from MARSS manual
dat_mat = matrix(Y, nrow=1)
m = 2

# for observation eqn
Z = array(NA, c(1,m,length(Y)))
Z[1,1,] = rep(1,length(Y)) # intercept
Z[1,2,] = X # covariate

inits.list = list(x0=matrix(c(0, 0), nrow=m))
mod.list = list(B="identity", U="zero", Q="diagonal and unequal", Z=Z, A="zero")
dlm1 = MARSS(dat_mat, inits = inits.list, model=mod.list)
```

```
## Warning! Abstol convergence only. Maxit (=500) reached before log-log convergence.
```

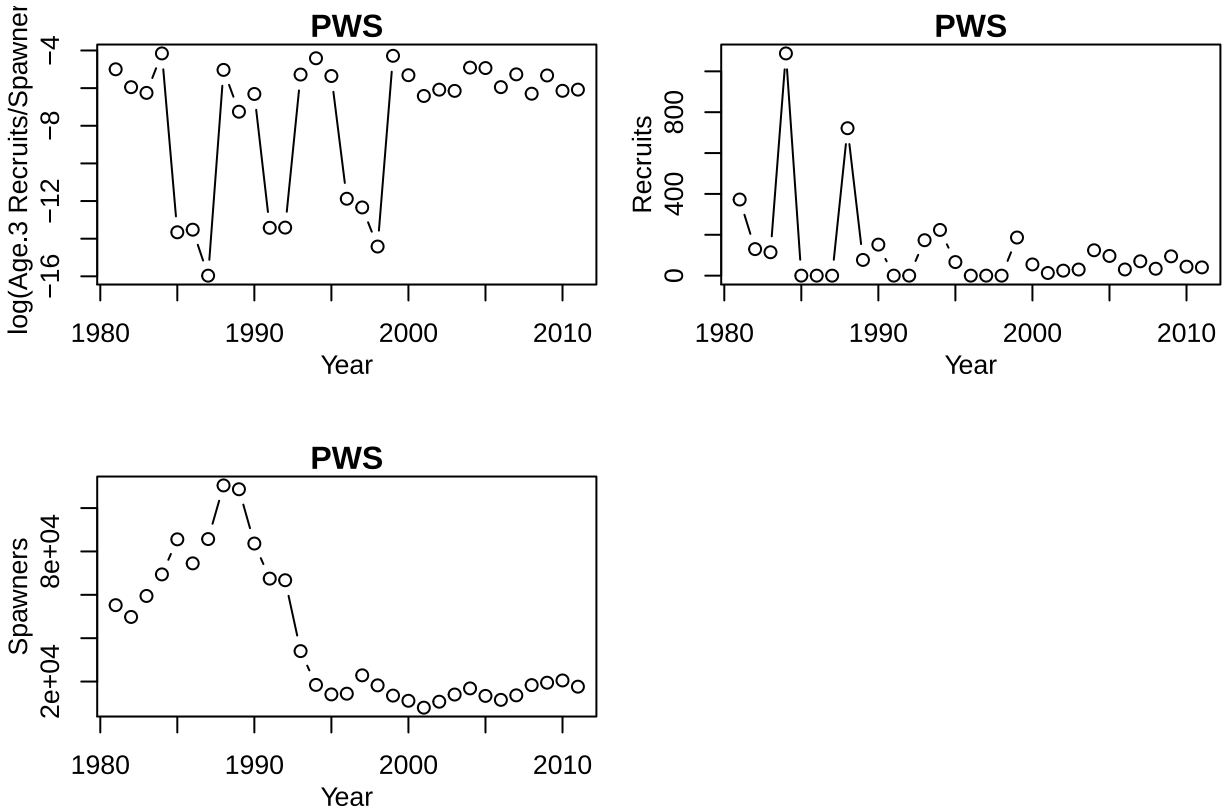

Figure 1: log(Recruits / Spawner) over time, 1981-2011

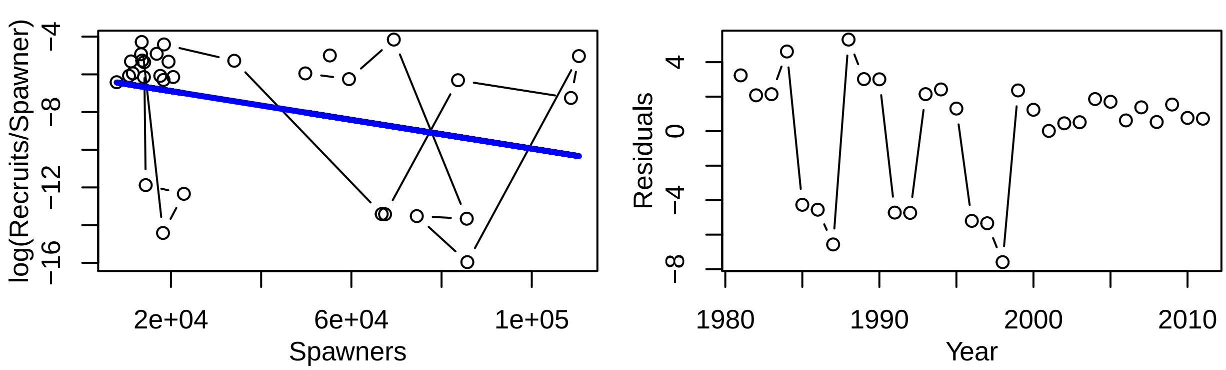

Figure 2: Raw data plot of log(R/S) on Spawners, 1981-2011

```
## Alert: Numerical warnings were generated. Print the $errors element of output to see the warnings.
##
## MARSS fit is
## Estimation method: kem
## Convergence test: conv.test.slope.tol = 0.5, abstol = 0.001
## WARNING: Abstol convergence only no log-log convergence.
##  maxit (=500) reached before log-log convergence.
##  The likelihood and params might not be at the ML values.
##  Try setting control$maxit higher.
## Log-likelihood: -81.4806
## AIC: 172.9612   AICc: 175.3612
##
##            Estimate
## R.R        4.38e+00
## Q.(X1,X1)  1.43e-02
## Q.(X2,X2)  3.17e-09
## x0.X1     -4.31e+00
## x0.X2     -1.73e-05
## Initial states (x0) defined at t=0
##
## Standard errors have not been calculated.
## Use MARSSparamCIs to compute CIs and bias estimates.
##
## Convergence warnings
## 454 warnings. First 10 shown.  Type cat(object$errors) to see the full list.
##  Warning: the  Q.(X1,X1)  parameter value has not converged.
##  Type MARSSinfo("convergence") for more info on this warning.
##
## MARSSkem warnings. Type MARSSinfo() for help.
##  iter=51 Setting diagonal to 0 blocked. logLik was lower in attempt to set 0 diagonals on Q logLik o
##  iter=52 Setting diagonal to 0 blocked. logLik was lower in attempt to set 0 diagonals on Q logLik o
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##  iter=56 Setting diagonal to 0 blocked. logLik was lower in attempt to set 0 diagonals on Q logLik o
##  iter=57 Setting diagonal to 0 blocked. logLik was lower in attempt to set 0 diagonals on Q logLik o
```
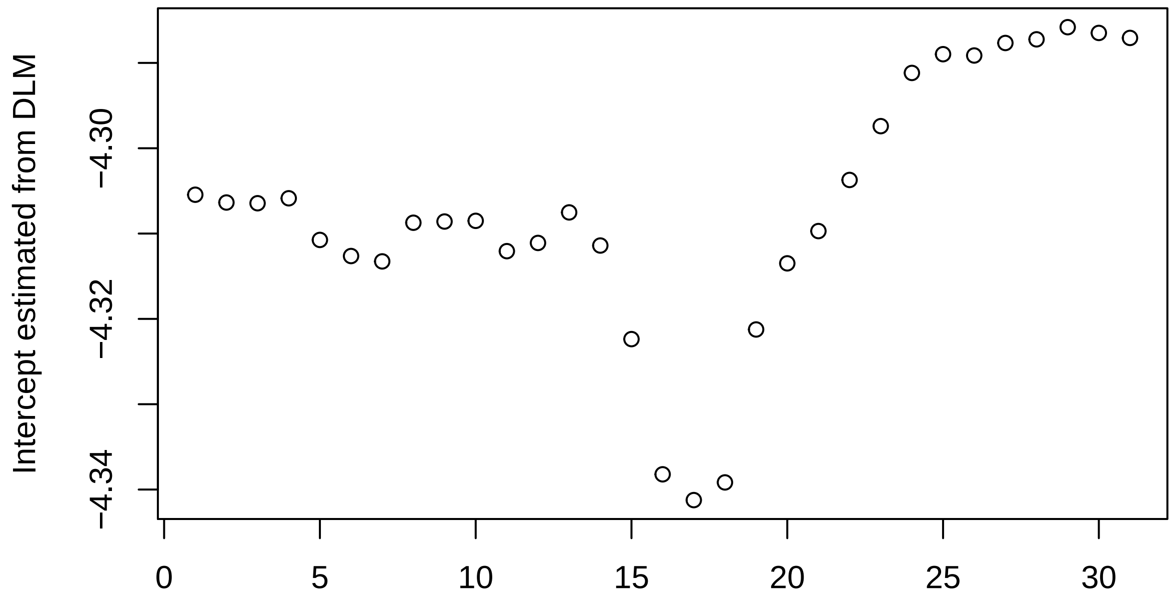

```r
plot(dlm1$states[1,], xlab="", ylab="Intercept estimated from DLM")
```



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 1981-2011, 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$RecPerSpawn[subset])) # log(R/S)
# This line was the source of the error / correction - it was:
# X = as.numeric(pwsher$RecPerSpawn[subset]) # number of spawners
# but should be:
X = as.numeric(pwsher$BroodYearSB[subset])
nT = length(Y)

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

models = list()
```

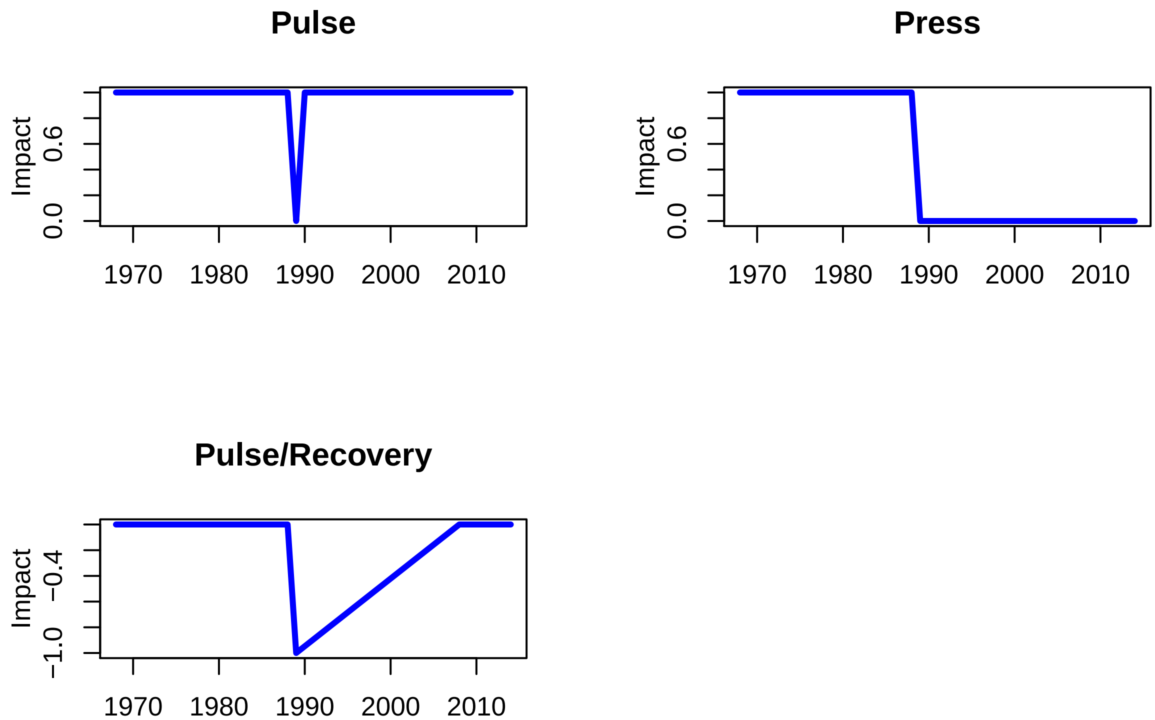


Figure 3: Illustration of covariates representing EVOS impacts

Model	AICc	Coef
Null model	171.821	NA
Density dependence	173.359	-3.074e-05

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

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

evos.models = list()
```

Model	AICc	Coef
EVOS.pulse.lag0	175.365	3.4316015
EVOS.press.lag0	175.888	-1.21518653
EVOS.pulseRecovery.lag0	175.522	1.43441656
EVOS.pulse.lag1	173.156	6.56276584
EVOS.press.lag1	176.094	0.73317426
EVOS.pulseRecovery.lag1	176.22	0.01951371
EVOS.pulse.lag2	171.726	-7.32022149
EVOS.press.lag2	175.445	-1.8396526
EVOS.pulseRecovery.lag2	174.893	2.2764401

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	176.099	0
juv.hatchRelChum.lag2	172.554	-5e-08
juv.wildPinkRun.lag1	174.317	3.2e-07
juv.wildChumRun.lag2	173.676	8.09e-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.wildPinkRun.lag1","ad.wildChumRun.lag1",
"ad.totalPinkRun.lag1","ad.hatchRelChum.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	175.844	3e-08
ad.wildPinkRun.lag1	171.129	2e-07
ad.wildChumRun.lag1	175.758	-1.07e-06
ad.totalPinkRun.lag1	174.235	5e-08
ad.hatchRelChum.lag1	175.301	2e-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	175.078	-0.02902948
Upwelling.summerBefore	175.929	-0.10831668
Upwelling.summerAfter	175.039	-0.19788951
discharge.lag0	171.501	-3.916e-05
discharge.lag1	175.977	5.01e-06
win.sst.lag1	174.417	-1.77711111
win.sst.lag0	174.509	-1.7621888

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

```
pdf("Figure 6 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
```