Appendix A. Bayesian Surplus Production Model using WinBugs.

Due to the high dependence of ASPIC results upon the parameter constraints, an alternative production model was applied to the gray triggerfish data. This alternative model is the Bayesian Surplus Production (BSP) model of Meyer and Millar (1999) modified to emulate the ASPIC calculations. The modification consisted of adding a variable to account for the ratio of biomass in the first year of the simulation to biomass at maximum sustainable yield. The software used for the Gibbs sampling is WinBugs (freeware available at http://www.mrc-bsu.cam.ac.uk/bugs/winbugs/contents.shtml). The code and data for the BSP is given at the end of this appendix.

When Bayesian models are run with non-informative priors the posterior distributions should approximate bootstrap confidence intervals from equivalent maximum likelihood approaches, as seen in the most recent Georges Bank yellowtail flounder assessment. However, this equivalence holds true only when the data is sufficient to estimate parameters in the model. In the case of gray triggerfish, the data available do not seem sufficient to adequately estimate model parameters with non-informative priors. This is seen both in ASPIC and BSP when no constraints are placed upon the parameters, the estimate of r is near zero and the model interprets the fishery as a "mining" operation. Thus, prior information must be incorporated into the assessment. This was done using ASPIC by fixing parameter values or placing tight constraints on the searched parameter space. In BSP, prior information can quantitatively be incorporated, with the posterior distributions directly reflecting the prior assumptions. This appendix contains three examples of prior assumptions applied to the gray triggerfish data. These three examples do not represent actual prior beliefs but rather are shown to demonstrate the dependence of the posteriors upon the priors. If this approach is chosen to provide management advice for gray triggerfish, then appropriate priors will need to be used in the model.

The three examples change only the prior assumption on the r parameter of the BSP from non-informative to highly informative. The other prior distributions are all non-informative. The prior distribution for r is a uniform distribution in all three cases: U(0.01,1.99), U(0.5,1.5) and U(0.9,1,1). Summary statistics for the posteriors of r, K and MSY related parameters for the three examples are given in Table A1 and the phase plots for the three examples are given in Figure A1. As expected, r and K are highly negatively correlated over the three examples and MSY increases with increasing r. Not as expected is the high degree of skewness in the r posterior distributions (Figure A2) in all three cases. This skewness, even with tight priors, means that the lower bound for r has more influence on the posterior than the upper bound. Thus, if true priors for r are to be created, more attention should be paid to the lower bound than the upper bound.

Reference
Meyer, R. and R.B. Millar. 1999. BUGS in Bayesian stock assessments. Can. J. Fish. Aquat. Sci. 56: 1078-1086.

(A1)

Table A1. Summary of posterior distributions under three different priors for r based on 2 chains of 50,000 samples after a 1000 sample burn in.

| node	mean	sd	MC error	10%	median	90%
r ~ U(0.01,1.99)						
r	0.1455	0.1374	0.005594	0.02811	0.1105	0.2883
K	24.97	9.977	0.4106	14.3	22.28	40.93
MSY	0.8148	0.7069	0.03028	0.1775	0.6175	1.713
BMSY	12.48	4.989	0.2053	7.149	11.14	20.47
FMSY	0.07276	0.06872	0.002797	0.01405	0.05526	0.1442
r ~ U(0.5,1.5)						
r	0.6354	0.146	0.005476	0.5129	0.5874	0.817
K	17.75	9.693	0.4454	9.585	14.14	33.18
MSY	2.83	1.84	0.08574	1.429	2.227	5.104
BMSY	8.875	4.846	0.2227	4.793	7.07	16.59
FMSY	0.3177	0.07299	0.002738	0.2565	0.2937	0.4085
r ~ U(0.9,1.1)						
r	0.9804	0.0556	0.000861	0.9121	0.9718	1.065
K	16.53	9.681	0.4472	8.06	12.94	31.81
MSY	4.048	2.374	0.1098	1.976	3.169	7.789
BMSY	8.266	4.841	0.2236	4.03	6.472	15.91
FMSY	0.4902	0.0278	0.000431	0.456	0.4859	0.5325
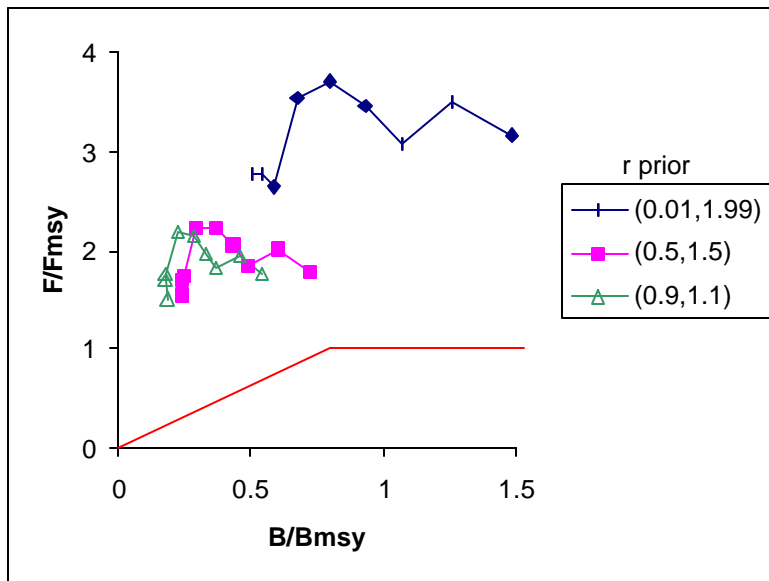
Figure A1. Phase plot from Bayesian surplus production model under three different priors for r.
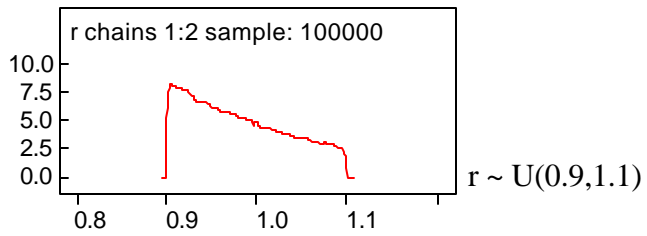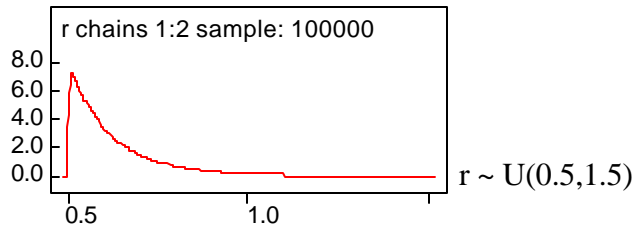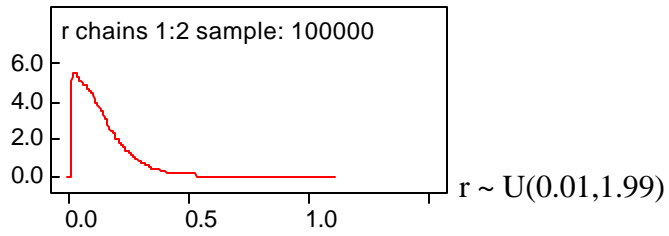
Figure A2. Posterior distributions for parameter r in the Bayesian surplus production model under different priors (denoted to the right of each posterior distribution).

(A3)

WinBugs Code

```
# Bayesian Surplus Production Model (Meyer and Millar 1999 CJFAS 56:1078-1086)
# note units are millions of pounds
# modified to include B1ratio as a parameter to emulate ASPIC

model bspb1ratio
{
# Prior distributions
K ~ dunif(1.0,50.0)
r ~ dunif(lowerbound,upperbound)
iqMRFSS ~ dgamma(0.001,0.001)I(0.1,1000)
qMRFSS <- 1/iqMRFSS
iqHB ~ dgamma(0.001,0.001)I(0.1,1000)
qHB <- 1/iqHB
iqCOMM ~ dgamma(0.001,0.001)I(0.1,1000)
qCOMM <- 1/iqCOMM
isigma2 ~ dgamma(4.0,0.01)
sigma2 <- 1/isigma2
itau2MRFSS ~ dgamma(2.0,0.1)
tau2MRFSS <- 1/itau2MRFSS
itau2HB ~ dgamma(2.0,0.1)
tau2HB <- 1/itau2HB
itau2COMM ~ dgamma(2.0,0.1)
tau2COMM <- 1/itau2COMM
B1ratio ~ dunif(0.1,3)

# compute B as proportions of K each year
Pmean[1] <- log(B1ratio/2.0)
P[1] ~ dlnorm(Pmean[1],isigma2)I(0.001,3)
for (i in 2:9){
        Pmean[i] <- log(max(P[i-1]+r*P[i-1]*(1-P[i-1])-C[i-1]/K,0.0001))
        P[i] ~ dlnorm(Pmean[i],isigma2)I(0.0001,3)
        }

# indices
# MRFSS
for (i in 1:9){
        ImeanMRFSS[i] <- log(qMRFSS*K*P[i])
        IMRFSS[i] ~ dlnorm(ImeanMRFSS[i],itau2MRFSS)
        residMRFSS[i] <- IMRFSS[i]-qMRFSS*K*P[i]
        }
# Headboat
for (i in 1:9){
        ImeanHB[i] <- log(qHB*K*P[i])
        IHB[i] ~ dlnorm(ImeanHB[i],itau2HB)
        residHB[i] <- IHB[i]-qHB*K*P[i]
        }
# Commercial (note offset to start in year 5)
for (i in 1:5){
        ImeanCOMM[i] <- log(qCOMM*K*P[i+4])
        ICOMM[i] ~ dlnorm(ImeanCOMM[i],itau2COMM)
        residCOMM[i] <- ICOMM[i]-qCOMM*K*P[i+4]
        }

# management parameters
MSY <- r*K/4
FMSY <- r/2
BMSY <- K/2
```

(A4)

```
for (i in 1:9){
        B[i] <- P[i]*K
        F[i] <- C[i]/B[i]
        Fratio[i] <- F[i]/FMSY
        Bratio[i] <- B[i]/BMSY
        }
}
# end model
```

Inits 1
```
list(
P=c(0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5),
r=1.0,
K=2.0,
iqMRFSS=10,iqHB=10,iqCOMM=10,
isigma2=100,
itau2MRFSS=100,itau2HB=100,itau2COMM=100,B1ratio=0.5)
```

Inits 2
```
list(
P=c(1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0),
r=1.0,
K=2.0,
iqMRFSS=10,iqHB=10,iqCOMM=10,
isigma2=100,
itau2MRFSS=100,itau2HB=100,itau2COMM=100,B1ratio=1)
```

Data
```
list(
C=c(2.879967,2.716294,2.034239,1.993541,1.834610,1.479484,0.951435,0.918420,0.854017),
IMRFSS=c(1,0.798686323,0.692725293,0.481591119,0.476903019,0.369144684,0.315112402,0.30990834,0.333967974),
IHB=c(1,0.876718967,0.89668334,0.869380228,0.716404616,0.507410188,0.546172301,0.413510912,0.379198522),
ICOMM=c(1,0.928154184,0.711026109,0.657762002,0.610113529),
lowerbound=0.9,upperbound=1.1)
```