Assessment Working Paper 5

APPLICATION AND UPDATE OF A CATCH, MULTIPLE SURVEY MODEL TO THE CHESAPEAKE BAY BLUE CRAB FISHERY

Thomas J. Miller

Chesapeake Biological Laboratory
University of Maryland Center for Environmental Science
P. O. Box 38
Solomons, MD 20688

Introduction

Fisheries managers are increasingly tasked with developing fisheries policies that ensure that biological limits to either abundance or exploitation are not exceeded. To support these policies, assessment scientists have to develop reliable estimates of stock abundance and fishing pressure even in stocks for which the biological or fisheries data are not well developed. Several assessment approaches have been developed for these "data poor" fisheries including surplus production models (Prager 1994), delay difference models (Deriso 1980) and length-based approaches (Gallucci et al. 1996).

One approach to developing estimates of stock size and exploitation in data poor situations is the "Catch-Survey Analysis" (Mesnil 2003). The approach, originally developed by Collie and Sissenwine (1983) for yellow tail flounder, represents the population into two stages: pre-recruited and fully-recruited. CSA uses time series of catch and estimates of the relative abundances of both population stages from a fishery-independent survey to estimate the absolute abundance of both the pre-recruit and fully-recruited stages. A common practice is to partition a single survey time series of relative abundances into a pre-recruit and a fully-recruited indices using size or age composition information (Cadrin et al. 1999). In reviewing the application of CSA, Mesnil (2003) concluded that the approach can be valuable in supporting management advice, but noted concerns regarding catachability assumptions, natural mortality and accurate assignment to the stage of the population. In particular, Mesnil (2003) commented on the importance of correctly assigning the contribution of observation and process error in determining the reliability of CSA.

While attractive, CSA does have limitations. In many fisheries, no single fishery-independent survey fully indexes population abundance. Often surveys are of limited geographic or temporal coverage. Yet, for many of these same fisheries, multiple fishery-independent surveys are available. However, taken together, these surveys may integrate a sufficient spatial or temporal domain to adequately index the entire population. Thus, expansion of CSA to permit multiple surveys would offer substantial advantages. However, no analytical approach yet exists to include additional survey time series. There are two obvious ways in which to combine all sources of information into the catch-survey estimation. First, if the data from the two independent studies are in the same units and of the same length, then the data could simply be combined as the average over the two data sets. This approach, however, may introduce additional bias or uncertainty in estimated parameters as the method assumes that the coefficients of variation in the two independent surveys are equal. A second approach may be to carry out two independent assessment models using each independent data set, then average the outputs from each assessment model. Again this may also introduce the same bias for the same reasons as averaging the data. An alternative approach, developed herein, is to fit a single population dynamics model to the data, where the relative contribution of each data set to the objective function is properly weighted by the inverse of the observation errors in, this may also introduce the same bias for the same reasons as averaging the data.

METHODS

Full details of the development of the CMSA are given in Miller et al.(2005) and are only summarized here. The CMSA requires annual estimates of total removals (C_t) and survey indices for fully recruited individuals (n_t) and individuals that will recruit within the coming fishing season, or prerecruits (r_t). The abundance indices are assumed to be proportional to the total population via the following equations:

$$\boldsymbol{n_t = q_n N_t e^{v_t}} \quad \text{Eq. 1}$$
$$\boldsymbol{r_t = q_r R_t e^{\delta_t}} \quad \text{Eq. 2}$$

where q_n and q_r are scalers for recruits and prerecruits, respectively and assumed to be constant over time. N_t and R_t are the absolute abundances of recruits and pre-recruits, respectively. It is usually not practical to measure q_n and q_r in the field, and normally the scaling parameters are treated as unknown constants to be estimated from the data. There must be sufficient contrast in the relative abundance data to reliably estimate q_n, as these parameters are often confounded with other estimated parameters. In their original paper, Collie and Sissenwine (1983) assume that $q_n = q_r$, which simplifies the problem of parameter estimation. However, rarely is it safe to assume that the capture probabilities for younger–smaller individuals are the same for older–larger individuals. An alternative is to specify a ratio of capture probabilities (i.e., $\lambda = q_r/q_n$) based on differences in selectivities between pre-recruits and recruits (e.g., Cadrin et al., 1999). Thus, λ is an input parameter and Mesnil (2003) demonstrated that the results of the assessment can be somewhat sensitive assumed values of λ.

Assuming the fishery occurs at the end of each year, recruit abundance next year is predicted as:

$$\boldsymbol{N_{t+1} = [(N_t + R_t)e^{-M} - c_t]e^{\varepsilon_t}} \quad \text{Eq. 6.3}$$

where M is the instantaneous natural mortality rate and is assumed to be known or estimated from independent data. Process errors ($e^{\varepsilon t}$) were assumed to be lognormal and independent. The unknown parameters (denoted by θ for brevity) to be estimated are θ = (N_1, . . . ,N_T ,R_1, . . . ,R_T and q_n), and the input parameters thus far are M and λ.

The parameter estimation procedure was as follows: initial guesses for θ were specified, then the following residual observation errors are calculated:

$$\boldsymbol{v_t = ln(n_t) - \ ln(q_n N_t)} \quad \text{Eq. 4}$$
$$\boldsymbol{\delta_t = ln(r_t) - \ ln(q_r R_t)} \quad \text{Eq. 5}$$

and the residual process errors were calculated by substituting expected values for eqs. 1 and 2 into eq. 3 and solving for ε_t:

$$\epsilon_t = ln[n_{t+1}] - ln\left[\left(n_t + {r_t}/_{\lambda}\right)e^{-M} - q_n c_t\right] \qquad \text{Eq. 6}$$

A non-linear search routine was then used to find the appropriate values of θ that minimized the following weighted sum of squared residuals

$$SS(\theta) = K_v \sum_{t=1}^{T} v_t^2 + K_\delta \sum_{t=1}^{T} \delta_t^2 + K_\varepsilon \sum_{t=1}^{T} \varepsilon_t^2 \qquad \text{Eq. 7}$$

The weighting terms (K's) define the relative magnitude observation and process errors, higher values of K imply lower coefficient of variation. Ideally, these terms should be proportional to the inverse of the variance of the observation errors and process error, but are often chosen subjectively through iterative procedures that examine the residual distributions post estimation. Note that it is not necessary to specify K terms for all 3 components of eq. 7; setting (user defined) values for K_δ and Kε and fixing Kv = 1 specifies the observation errors on pre-recruits and process errors relative to the observation errors on the recruited individuals.

To account for multiple fishery-independent surveys, we treated each of the j surveys series as independent, calculate the appropriate $q_{n,j}$ and $q_{r,j}$ values for each survey, and weight each data series by the inverse of the variance in observation errors. In this case, the same residuals calculations were used, but indexed by each data set j, (i.e.: $v_{t,j}$, $\delta_{t,j}$, and $\varepsilon_{t,j}$) and the weighted sum of squares now contained 3J components:

$$SS(\theta) = \sum_{j=1}^{J} \left(K_{v,j} \sum_{t=1}^{T} v_{t,j}^2 + K_{\delta.j} \sum_{t=1}^{T} \delta_{t,j}^2 + K_{\varepsilon,j} \sum_{t=1}^{T} \varepsilon_{t,j}^2 \right)_v \qquad \text{Eq. 8}$$

Estimated parameters obtained by minimizing eq. 8 were very sensitive to the weighting terms (K) specified by the user. In the case of having multiple surveys, it is no longer appropriate to weight the δ and ε terms relative to the ν terms unless the observation errors between the different data series are assumed to be equal. An alternative to the subjective weighting we estimated the total variance for each survey series and specify a ratio of observation error to process error for each series.

The CMSA model was fit to time series of fishery-independent survey data and catch data. We used fishery-independent data from three surveys: the VIMS trawl survey (1968-2009), the Maryland sumer trawl survey (1977-2009) and the winter dredge survey (1990-2009). The time series of age-0 ages in the winter dredge survey was modified to account for the value of survey catchability, q_0=0.4, calculated by Miller et al. (2011). We used reconstructed commercial catch data for the period 1968-2009 as taken from Miller et al. (2011). These data were converted from catch in weight to catch in number using jurisdiction-specific and sex-specific allometric relationships.

We conducted two runs of the model. In Model 1, we used the Virginia fall trawl survey index. This made this run directly comparable to runs of this model reported in Miller et al. (2005), but with updated time series. We also ran a second formulation – Model 2, in which we used the Virginia spring trawl survey indices. This model uses the same data as used in the SSCMSA in Miller et al. (2011)

RESULTS AND DISCUSSION

The results from the Model 1, which used the Virginia fall survey indices, provided an adequate fit to the observed survey time series (Fig. 1). The time series of pre-recruit abundance predicted by the model is highly variable, and does not fully capture the variability evident in the fishery-independent surveys (Fig. 1a). However, it does appear that recent recruitments have been lower than those observed 1980 – 1990. In contrast, the abundance of fully-recruited crabs predicted by the model agreed well with the observed trends in the fishery-independent indices of abundance of fully-recruited crabs (Fig. 1b). For example, the decline in abundance of fully-recruited crabs evident in all three surveys since 1990 is evident in the predicted abundance time series. Reflecting the trends in the trawl survey indices, the predicted abundances of fully-recruited crabs indicate a period of low abundance in the mid to late 1970's, followed by a population recovery by the early 1980s. Subsequently, there is a period of relative stability until 1990, from which point the time series exhibits a steady decline. The predicted time series shows the quick rebound following the decline in the 1970's, whereas the abundance has remained consistently low since 1993. Although, the predicted abundances of fully-recruited crabs have generally increased for the last four years, compelling signs of population recovery are yet to be apparent in the predictions.

Model 1 also produced reasonable estimates of exploitation fractions for the period during which empirical estimates of exploitation rates are available from the witner dredge survey (Fig. 1c). For this period, model estimates of exploitation fraction are always < 1. However, for the earlier period (1968 – 1990) estimates of exploitation fraction are more variable and often > 1. We believe that these discrepancies early in the time series represent the high levels of observation errors in the VIMS and Maryland DNR surveys providing no constraint on population sizes or trends.

Finally, we examined the relationship between the abundance of fully-recruited crabs predicted by the model, and the predicted exploitation fraction in Model 1 (Fig. 1d). The model indicated that in 2009 the blue crab population was not overfished, nor was it experiencing overfishing. Moreover, Model 1 indicated that the crab population was above target abundance in 2009.

As noted in Miller et al. (2005), there was a strong negative relationship between predicted μ and predicted abundance of fully recruited crabs in Model 1(Fig. 1d). This pattern may indicate that the blue crab fisheries act in a depensatory fashion – that is as abundance declines, the exploitation on the crabs remaining increases. Such a pattern in exploitation is not conducive to sustainability. However, we also caution that the exploitation fraction in this model is calculated as catch / abundance. Thus the plot in Fig. 1d is effectively a plot of C/N vs N. Any plot of a random variable against a function of its inverse is likely to produce the strong negative, nonlinear relationship observed in figure 1d.

Model 2, which used the VIMS spring trawl index produced broadly similar patterns to Model 1. The results from Model 2 are presented in Figure 2. In general, adult stages were predicted more precisely than pre-recruits (Fig. 2b vs Fig 2b). However, we note that the adult time series predicted by Model 2, does not follow the abundance trend observed in the winter dredge survey as well as did predictions from Model 1. In particular, there is a periodicity in landings predicted by the model in the period 1990-2009 that is not present in the previous run. It appears that these periodicities are induced by peaks in the Virginia spring trawl index that were not present in the fall index.

The pattern in exploitation rates predicted in Model 2 does not fit the observed pattern particularly well (Fig. 1c). We presume that this mismatch between observed and predicted results from the decreased population abundances predicted by Model 2 compared to Model 1. Despite this difference, the pattern in the control rule predicted by Model 2 exhibits the same inverse relationship evident in Model 1.

We conclude that the CMSA is able to predict dynamics in the crab population that match those observed when configured exactly the same as in the Miller et al. (2005) assessment. However, model predictions appear to be sensitive to the switch from the VIMS fall to the VIMS spring index. It is not clear whether this reflects changes in the ratio of observation to process error between the two surveys, or whether they are providing different information to the model regarding the dynamics of blue crab.

LITERATURE CITED

Cadrin, S. X., S. H. Clark, D. F. Schick, M. P. Armstrong, D. M. McCarron, and B. Smith. 1999. Application of catch-survey models to the northern shrimp fishery in the Gulf of Maine. North American Journal of Fisheries Management **19**:551-568.

Collie, J. S. and M. P. Sissenwine. 1983. Estimating population size from relative abundance data measured with error. Canadian Journal of Fisheries and Aquatic Science **40**:1871-1879.

Deriso, R. B. 1980. Harvesting strategies and parameter estimation for an age-structured model. Canadian Journal of Fisheries and Aquatic Science **37**:268-282.

Gallucci, V. F., B. Amjoun, J. B. Hedgepeth, and H.-L. Lai. 1996. Size-based methods of stock assessment of small fisheries. Pages 9-81 *in* V. F. Gallucci, S. Saila, D. J. Gustafson, and B. J. Rothschild, editors. Stock Assessment: Quantitative Methods and Applications for Small-Scale Fisheries. CRC Press, Boca Raton, FL.

Mesnil, B. 2003. The Catch-Survey Analysis (CSA) method of fish stock assessment: an evaluation using simulated data. Fisheries Research **63**:193-212.

Miller, T. J., S. J. D. Martell, D. B. Bunnell, G. Davis, L. A. Fegley, A. F. Sharov, C. F. Bonzek, D. A. Hewitt, J. M. Hoenig, and R. N. Lipcius. 2005. Stock Assessment of Blue Crab in Chesapeake Bay: 2005. Final Report Ref: [UMCES]CBL 05-077. UMCES Tech. Ser. No. TS-487-05-CBL., University of Maryland Center for Environmental Science Chesapeake Biological Laboratory, Solomons, MD.

Miller, T. J., M. J. Wilberg, A. R. Colton, G. R. Davis, A. Sharov, R. N. Lipcius, G. M. Ralph, E. G. Johnson, and A. G. Kaufman. 2011. Stock assessment of blue crab in Chesapeake Bay, 2011. TS-XXX-11, University of Maryland Center for Environmental Science Chesapeake Biological Laboratory, Solomons, MD.

Prager, M. H. 1994. A Suite of Extensions to a Nonequilibrium Surplus-Production Model. Fishery Bulletin **92**:374-389.

Figure 1. Results of the catch-multiple survey updated to include recent data. The model configuration was exactly that used in the Miller et al. (2005) assessment base run. Data were updated to reflect increases in available time series to cover the period 1968-2009.

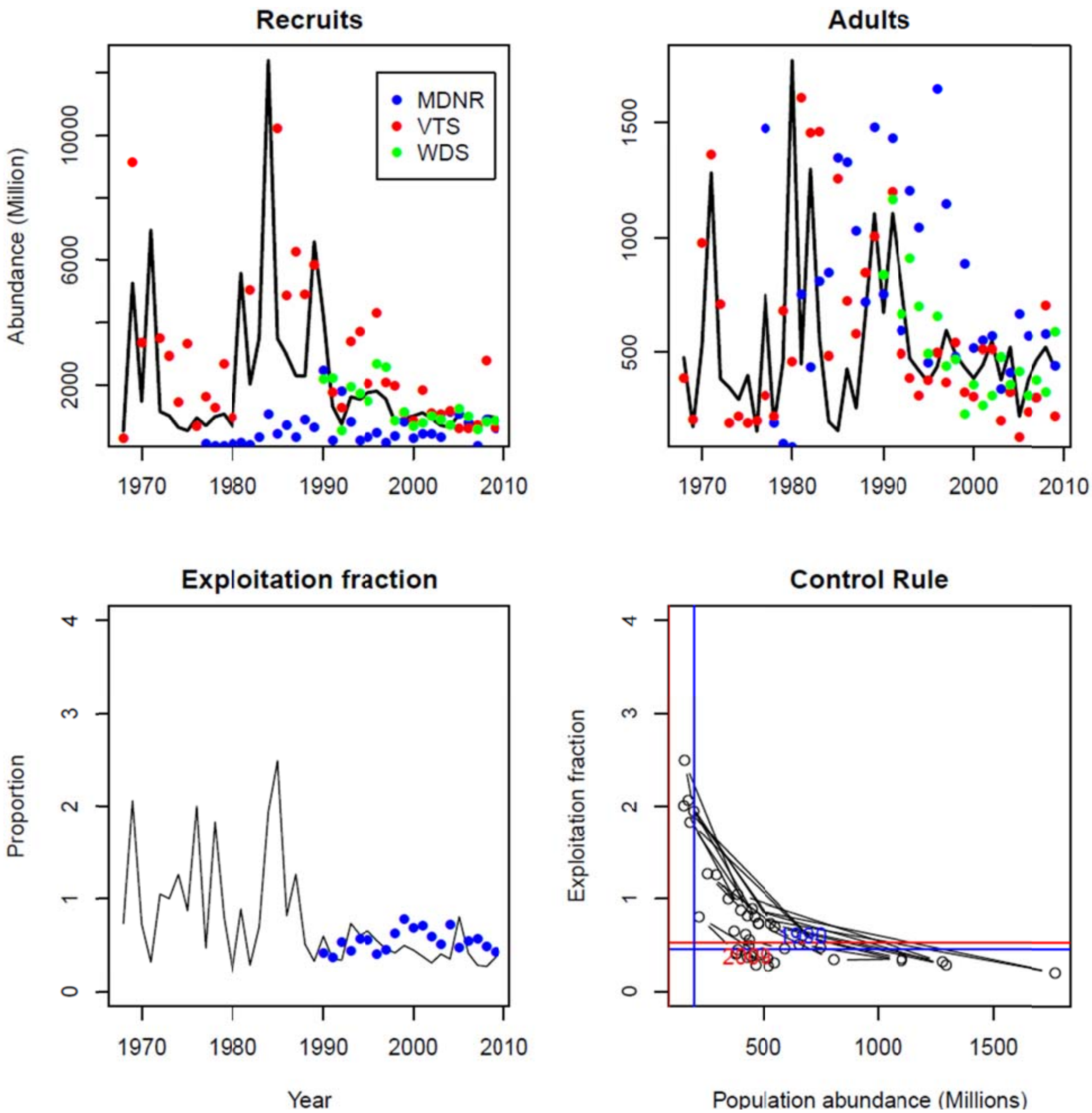
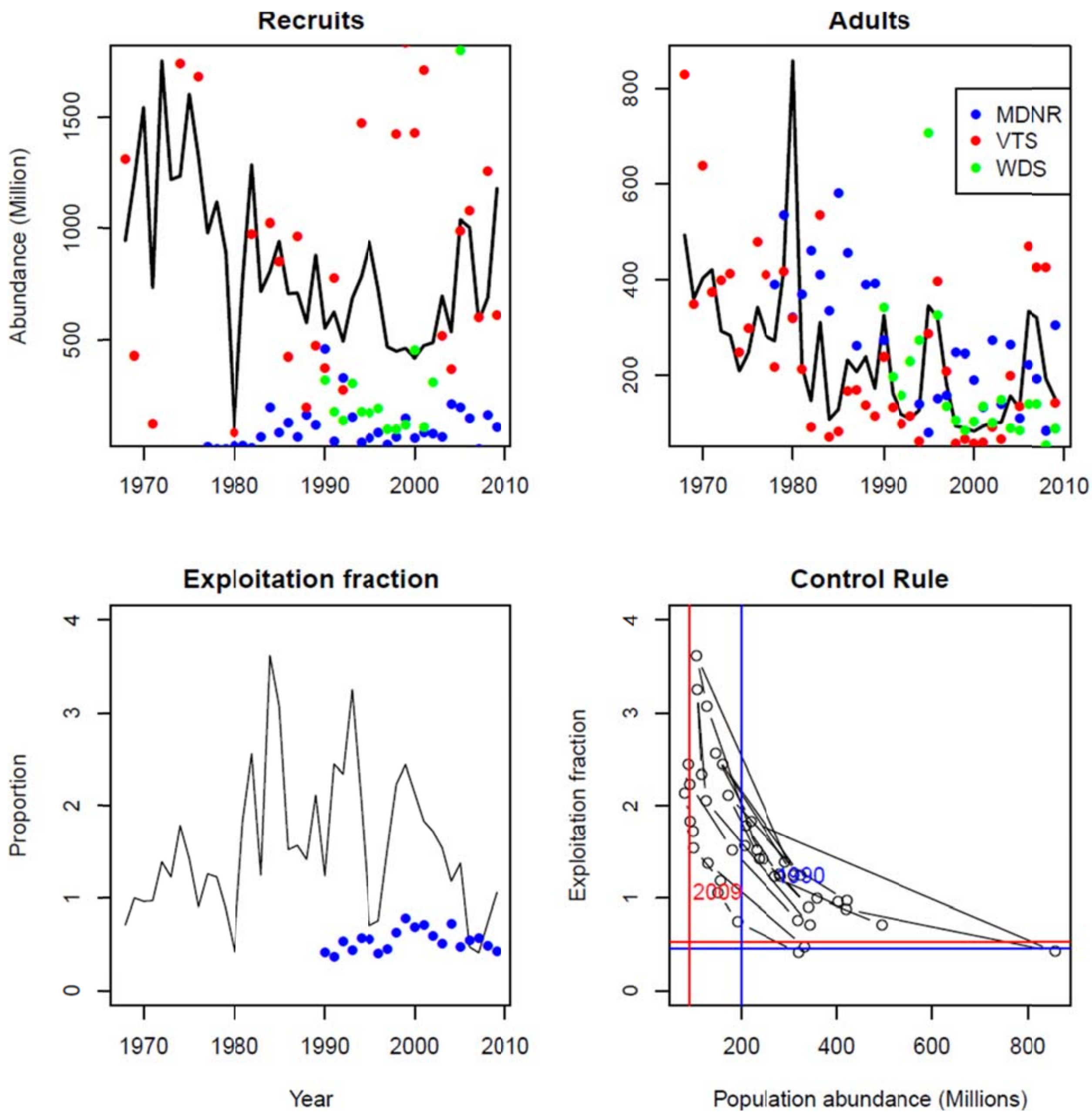


Figure 2. Results of the catch-multiple survey analysis using the VIMS trawl spring index of abundance. With this exception, the model configuration was exactly that used in the Miller et al. (2005) assessment base run. Data were updated to reflect increases in available time series to cover the period 1968-2009.



Appendix I. Catch Multiple Survey Analysis

The code for the catch-multiple survey model given as 1) The input data file and 2) The ADMB code for the catch-multiple survey model.

Appendix I.1 Input Data File

```
#MCS_04_2005.dat


#M

0.9


#Fishery Month

6

#Catch Years

1968        2009

#Observed Catches (numbers millions - converted to numbers using survey weights   -UPDATED)

#   1968        1969     970       1971       1972       1973       1974       1975      1976       1977       1978       1979        1980
1981      1982       1983       1984       1985       1986       1987       1988       1989      1990       1991      1992       1993       1994
1995       1996       997       1998       999       2000       2001       2002       2003       2004       2005       2006       2007       2008
09

353.2649993          359.9548462          389.573118          409.4467322          406.0101668          346.970454
            372.4924462          350.9267686          310.4507618          354.8006154          332.690882          370.8803657
            362.8139262          402.3281932          373.1398442          387.4893563          385.7836057          393.8614898
            353.5517168          325.0414361          337.1333044          363.8055438          403.9210756          393.8681015
            274.801405           350.9034322          259.2563982          244.290027          242.5932991          275.2581305
            207.2059382          217.9344792          175.0880675          170.220234          171.3021589          155.0371594
            184.702237           179.032453           158.9912147          133.1260409          143.1395714          159.8375029

#########################################################################################################

# f_switch  == 1 use just adults in mu, ==2 use both adults and recruits in mu

01


########################################################################################################

#Observed exploitation fractions

#mu_switch - mu_switch =1 includes mu in obj function, mu_switch=0 does not include
```

1

#muyrs

1990

2009

estimates of mu from winter dredge   UPDATED

1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009

0.48 0.37 0.66 0.38 0.33 0.35 0.24 0.24 0.44 0.40 0.50 0.47 0.37 0.42 0.48 0.27 0.32 0.39 0.26 0.25

###

#nsets (1=MD Trawl, 2=VA Trawl, 3=Winter Dredge)

3

#relative selectivity

.3 .3 .5

#Survey Years (Start)

1977 1968 1990

#Survey Years (end - UPDATED)

2009 2009 2009

#Survey months

7 1 1

#Proportion of total error due to measurement errors

0.65 0.65 0.35

#Juvenile index

#MD Trawl Age-0   UPDATED

1977 1978 1979 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009

0.6 0.21 0.29 0.7 0.78 0.36 1.94 6.27 2.57 4.13 1.92 5.23 3.79 14.73 1.32 10.62 4.92 1.16 1.88 2.7 0.93 2.02 4.75 1.78 2.62 2.53 1.93 6.77 6.34 4.67 0.24 5.25 3.48

#VA Trawl Age-0 UPDATED

1968 1969 1970 1971 1972 1973 1974 1975 1976 1977 1978 1979 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009

fall

#0.67 22.01 8.04 84.52 8.42 7.03 3.49 7.96 1.61 3.9 3.07 6.42 2.26 37.77 12.15 45.6 49.35 24.66 11.72 15.09 11.78 14.1 40.24 4.26 3.04 8.14 8.88 4.94 10.35 5.04 4.72 2.6 2 4.46 2.61 2.54 2.8 1.43 1.43 1.69 6.69 1.54

#spring

10.79 3.51 26.36 1 28.49 27.24 14.33 15.28 13.83 31.89 15.67 17.44 0.67 22.01 8.04 84.52 8.42 7.03 3.49 7.96 1.61 3.9 3.07 6.42 2.26 37.77 12.15 45.6 49.35 24.66 11.72 15.09 11.78 14.1 40.24 4.26 3.04 8.14 8.88 4.94 10.35 5.04 4.72 2.6 2 4.46 2.61 2.54 2.8 1.43 1.43 1.69 6.69 1.54 4.58

#WDS Age-0 UPDATED

1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009

111.65 111.75 26.575 97.675 87.725 75.125 136 130.2 42.1 57.475 34.6 39.8 49.6 44.15 36.15 62.55 49.175 28.2 41.9 42.25

#Adult index

#MD Trawl age-1+ UPDATED

1977 1978 1979 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009

29.29 3.83 2.01 1.76 14.96 8.62 16.08 16.84 26.69 26.34 20.48 14.24 29.35 14.93 28.42 11.84 23.88 20.77 9.05 32.73 22.75 9.55 17.56 10.27 10.93 11.35 6.79 8.2 13.2 11.3 5.98 11.48 8.72

#VA Trawl age-1+ UPDATED

1968 1969 1970 1971 1972 1973 1974 1975 1976 1977 1978 1979 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009

fall

#3.12	1.65	7.85	10.91	5.7	1.54	1.77	1.55	1.61	2.49	1.79	5.47	3.68
	12.93	11.7	11.73	3.9	10.09	5.81	4.67	6.79	8.07	20.9	9.62	3.97
	3.1	2.49	3.03	4	2.98	4.35	2.62	2.46	4.12	4.1	1.61	2.61
	1.03	1.93	2.42	5.64	1.77							

spring

5.82	2.51	14.66	1.94	2.22	4.55	4.63	3.77	3.11	6.54	3.6	2.69	3.12
	1.65	7.85	10.91	5.7	1.54	1.77	1.55	1.61	2.49	1.79	5.47	3.68
	12.93	11.7	11.73	3.9	10.09	5.81	4.67	6.79	8.07	20.9	9.62	3.97
	3.1	2.49	3.03	4	2.98	4.35	2.62	2.46	4.12	4.1	1.61	2.61
	1.03	1.93	2.42	5.64	1.77	2.79						

#WDS age-1+ TO BE UPDATED

1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009

84.775	118.05	67.3	92.075	70.65	49.875	66.275	44.7	47.675	23.25	36.65	26.975	31.4
	48.75	36.45	42.3	31.45	38.5	32.85	59.9					

Appendix I.2 ADMB File for CMSA

```
//*******************************************************
//    Programmer: Steve Martell
//    Project Name: Blue crab CMS model
//    Date:
//    Version:  4
//    Comments:  Modified by Tom Miller to include N=N+R
//
//*******************************************************/
DATA_SECTION
      init_number m;

      init_number fm;               //Fishery month
      !!fm=fm/12;

      //Read in Catch data
      init_int scyr;
      init_int ecyr;
      init_vector ct(scyr,ecyr);
      int nobs;
      !!nobs=ecyr-scyr;
      //!!ct*=0;

      init_int f_switch             //swithc to include adults (1) or adults
and prerecruits in mu (2)
      // read in estimated exploitation fractions
      init_int mu_switch;                 // switch to include exploitation
fraction in fvec (1=in, 0=out)
      init_int smuyr;
      init_int emuyr;
      init_vector mu(smuyr,emuyr);
      int nmu;                      // number of obs of exploitaiton fraction

      !! nmu=(emuyr-smuyr);
      !!cout<<"Mu_switch "<<mu_switch<<endl;

      //read in paired survey data
      init_int nsets;                   // Number of sureveys
      init_vector relsel(1,nsets);
      init_ivector sSyr(1,nsets);
      init_ivector eSyr(1,nsets);
      init_vector sm(1,nsets);
      init_vector p(1,nsets);       //sigma/tau
      init_matrix yt_r(1,nsets,sSyr,eSyr);
      init_matrix yt_a(1,nsets,sSyr,eSyr);
      !!sm=sm/12;
      //!!cout<<"Survey start year"<<endl<<sSyr<<endl;
      //!!cout<<"End start year"<<endl<<eSyr<<endl;

      //read in unpaired adult survey data
      init_int ny;
      init_ivector syt(1,ny);
      init_ivector eyt(1,ny);
      init_vector usm(1,ny);
```

```
      init_vector mode_pry(1,ny);
      init_vector cv_pry(1,ny);
      init_matrix yt(1,ny,syt,eyt);
      !!usm=usm/12;




PARAMETER_SECTION
      init_bounded_number log_no(0.0001,10,1);
      //init_bounded_vector sel(1,nsets,0.0001,2,2);
      init_bounded_vector kappa(1,nsets,0.0001,3,1);        //total variance
      init_bounded_vector log_rt(scyr,ecyr+1,0.0001,10,1);
      init_bounded_vector nu(scyr+1,ecyr,-15,15,1);


      !!kappa=0.065;

      !!log_no=log(max(ct)/0.007);

      !!log_rt=log(exp(log_no)/exp(-m)-exp(log_no));


      sdreport_number sd_no;

      objective_function_value f;

      number tau;

      vector na(1,nsets);
      vector nr(1,nsets);
      vector ny(1,nsets);

      vector q_a(1,nsets);               // selectivity for adults in survey
      vector q_r(1,nsets);               // selectivity for recruits in
survey

      vector nt(scyr,ecyr+1);              // fully recruited abundance
      vector rt(scyr,ecyr+1);              // recruit abundance
      vector ft(scyr,ecyr);                // exploitation fraction
      vector ft2(scyr,ecyr);             // exploitation fraction based on
n+r
      vector mu_dev(smuyr,emuyr);          // expoitation fraction deviations
      vector Nt(scyr,ecyr+1);              // total population abundance

      matrix epsilon(1,nsets,sSyr,eSyr);      //adult observation errors
      matrix delta(1,nsets,sSyr,eSyr);    //recruit observation errors
      matrix p_nu(1,nsets,sSyr+1,eSyr);   //predicted process errors


PROCEDURE_SECTION
      //--------MAIN--------

      pop_dynamics();
      //cout<<"OK after pop_dynamics"<<endl;
      exp_dev();
```

```
	//cout<<"OK after exploitation deviations"<<endl;
	observation_errors();
	//cout<<"OK after observation_errors"<<endl;
	process_errors();
	//cout<<"OK after process_errors"<<endl;
	calc_objective_function3();
	//cout<<"OK after calc_objective_function3"<<endl;

	//____________________

FUNCTION pop_dynamics
	int i;
	nt.initialize();
	nt(scyr)=exp(log_no);
	rt=exp(log_rt);

	//process error var.
	tau=min(elem_prod((1.-p),kappa));
	sd_no=exp(tau);
	//cout<<"tau = "<<tau<<endl;

	for(i=scyr;i<=ecyr;i++)
		{
			nt(i+1)=((nt(i)+rt(i))*exp(-m*fm)-ct(i))*exp(-m*(1.-fm));

			if(i>scyr) {
				nt(i+1)*=exp(sqrt(tau)*nu(i));
			}

			Nt(i)=nt(i)+rt(i);
		}
		switch(f_switch)
			{
			     case 1:                  // use just adults
			            ft=elem_div(ct,nt(scyr,ecyr));
			     break;
			   case     2:                // use both adults and
recruits
			            ft=elem_div(ct,Nt(scyr,ecyr));
			   break;
		}

//_________________________________________
FUNCTION exp_dev
	int i;
	mu_dev.initialize();



	for(i=smuyr;i<=emuyr;i++)
	{

		mu_dev(i)=mu(i)-ft(i);
	}


FUNCTION dvariable get_q_MLE(dvector& y, dvar_vector& n)
```

```
	{
		//compute conditional MLE for q_a
		int i;
		dvariable q;
		dvariable xy;
		dvariable x2;

		xy=0.;
		x2=0.;

		for(i=y.indexmin();i<=y.indexmax();i++)
		{
			if(y(i)>0){
				xy+=y(i)*n(i);			// maintain running
totals
				x2+=n(i)*n(i);
			}
		}
		q=xy/x2;
		return(q);
	}

FUNCTION observation_errors
	int i,j;
	//Modify to accomodate missing data  DONE

	epsilon.initialize();
	delta.initialize();
	q_a.initialize();
	q_r.initialize();

	na.initialize();
	nr.initialize();

	for(j=1;j<=nsets;j++)
	{

		//MLE for q_a
		q_a(j)=get_q_MLE(yt_a(j),nt(sSyr(j),eSyr(j)));
		q_r(j)=q_a(j)*relsel(j);
		//q_r(j)=q_a(j)*sel(j);




		//do adult indices first


		for(i=sSyr(j);i<=eSyr(j);i++)

		{
			if(yt_a(j,i)>0){
				epsilon(j,i)=log(yt_a(j,i))-log(q_a(j))-
log(nt(i)*exp(-m*sm(j)));
				na(j)+=1.;
// sample size
```

```
			}
		}

		//now do juvenile indices


		for(i=sSyr(j);i<=eSyr(j);i++)

		{
			if(yt_r(j,i)>0){
				delta(j,i)=log(yt_r(j,i))-log(q_r(j))-log(rt(i)*exp(-
m*sm(j)));
				nr(j)+=1.;
// sample size
			}

			//if(yt_a(j,i)>0)epsilon(j,i)-=sum(epsilon(j))/na(j);
		}

	}

	//cout<<"e = "<<sum(epsilon)<<endl;
	//cout<<"d = "<<sum(delta)<<endl;


FUNCTION process_errors
	//For each index, calculate the expected process errors
	//based on relative abundance indices and pop dy model.

	//Modify to accomodate missing data  DONE

	int i,j;
	p_nu.initialize();
	ny.initialize();



	for(j=1;j<=nsets;j++)

	{
		for(i=sSyr(j);i<eSyr(j);i++)
		{
			if(yt_a(j,i+1)>0&&yt_a(j,i)>0&&yt_r(j,i)>0){
				p_nu(j,i+1)=log(yt_a(j,i+1)/q_a(j));
				p_nu(j,i+1)-=log(((nt(i)+rt(i))*exp(-m*fm)-
ct(i))*exp(-m*(1.-fm)));
				ny(j)+=1.;
			}
		}
		//cout<<p_nu(j)<<endl;
		//cout<<"p_nu = "<<sum(p_nu)<<endl;
	}
	//cout<<"p_nu = "<<sum(p_nu)<<endl;

FUNCTION calc_objective_function3
	//Modify to accomodate missing data DONE(changes in sample size na)
```

```
    int j;
    dvar_vector fvec(1,nsets+1);
    fvec.initialize();



    for(j=1;j<=nsets;j++)

    {
                fvec[j]=0.5*(na(j)+nr(j)+ny(j))*log(kappa(j))
                                  +0.5*(na(j)+nr(j))*log(p(j))
                                  +0.5*ny(j)*log((1-p(j)))
                                  +1./(2.*kappa(j))

    *(norm2(epsilon(j))/p(j)+norm2(delta(j))/p(j)+norm2(p_nu(j))/(1.-
p(j)));
    }

    if(mu_switch==1) {
                      fvec[nsets+1] =(1./(2*(nmu-1)))*log(norm2(mu_dev));
                }
    cout<<"fvec"<<fvec<<endl;
    f=sum(fvec);


REPORT_SECTION
    int i;
    report<<"Nt"<<endl<<nt<<endl;
    report<<"Rt"<<endl<<rt<<endl;
    report<<"nsets"<<endl<<nsets<<endl;
    report<<"sSyr & eSyr"<<endl<<sSyr<<endl<<eSyr<<endl;
    report<<"Adult Survey"<<endl;
    for(i=1;i<=nsets;i++){
          report<<yt_a(i)/q_a(i)<<endl;
    }
    report<<"Recruit Survey"<<endl;
    for(i=1;i<=nsets;i++){
                report<<yt_r(i)/q_r(i)<<endl;
    }

    //fishing mortality rate
    report<<"Ft"<<endl<<ft<<endl;
    report<<"Ct"<<endl<<ct<<endl;
    report<<"Ft2"<<endl<<ft2<<endl;
    report<<"Exp. Deviations"<<endl<<mu_dev<<endl;

    //residuals
    report<<"delta"<<endl<<(delta)<<endl;
    report<<"epsilon"<<endl<<(epsilon)<<endl;
    report<<"p_nu"<<endl<<(p_nu)<<endl;
    report<<"nu"<<endl<<nu<<endl;

    report<<"q_a"<<endl<<q_a<<endl;
```