# AGEPRO Reference Manual 

Jon Brodziak<br>NOAA Fisheries<br>Pacific Islands Fisheries Science Center<br>Email: Jon.Brodziak@NOAA.GOV

Version 4.2
March 2018


#### Abstract

The AGEPRO reference manual describes the new version 4.2 model and software to perform stochastic age-structured projections for an exploited age-structured fish stock. The AGEPRO model can be used to quantify the probable effects of alternative harvest scenarios by multiple fleets on an age-structured population over a given time horizon. Primary outputs include the projected distribution of spawning biomass, fishing mortality, recruitment, and landings by time period. This new version allows for multiple recruitment models to account for alternative hypotheses about recruitment dynamics and applies model-averaging to predict the distribution of realized recruitment given estimates of recruitment model probabilities. The reference manual also describes the logical structure of the projection model, including program inputs, outputs, structure and usage. This includes three examples, which illustrate standard projection analyses, projection analyses for stock rebuilding, and projection analyses to calculate annual catch limits with specific probabilities of exceeding an overfishing level. Although all reasonable efforts have been taken to ensure the accuracy and reliability of the AGEPRO software and data, the National Oceanic and Atmospheric Administration and the U.S. Government do not and cannot warrant the performance or results that may be obtained by using this software or data.


## Introduction

The AGEPRO model was initially developed in 1994 to determine optimal strategies to rebuild a depleted fish stock. The model was reviewed at the May 1994 meeting of the Northeast Fisheries Science Center Methods Working Group (Brodziak and Rago, 1994; Brodziak et al. 1998). Subsequently, the model was applied to groundfish stocks at the 18th SARC (NEFSC 1994) to evaluate Amendment 5 harvest scenarios (NEFMC 1994) and was applied again in 1995 to assist with Amendment 7 (NEFMC 1996). The reference manual was prepared in 1997 to provide documentation and has been updated since then to describe modifications to the model and software. The current program is written in the C language to allow for dynamic array allocation and to achieve rapid processing speeds.

The AGEPRO program can be used to perform stochastic projections of the abundance of an exploited age-structured population over a given time horizon. The primary purpose of the AGEPRO model is to produce management strategy projections that characterize the sampling distribution of key fishery system outputs such as landings, spawning stock biomass, population age structure, and fishing mortality from one or more fleets, accounting for uncertainty in initial population estimates, future recruitment, and natural mortality (Figure 1). The acronym "AGEPRO" derives from age-structured projections, in contrast to size- or biomass-based projections for size- or biomass-structured models. The user can evaluate alternative harvest scenarios by setting quotas or fishing mortality rates in each year of the time horizon.

Three elements of uncertainty can be included in an AGEPRO projection: recruitment, initial population size, and process error for population and fishery processes. Recruitment is the primary stochastic element in the population model, where recruitment is typically defined as the number of age- 0 or age- 1 fish entering the modeled population at the beginning of each year in the time horizon. There are a total of fifteen stochastic recruitment models that can be used for population projection. It is also possible to simulate a deterministic recruitment trajectory (see recruitment model 3 below).

Initial population size is the second potential element of uncertainty for population projection (Figure 1). To include this element, a distribution of initial population sizes must be calculated a priori. This is typically done using bootstrapping, Markov chain Monte carlo simulation, or other techniques in most age-structured assessments. Alternatively, projections can be based on a single best point estimate with no uncertainty in the initial population size.

The third element of uncertainty is process error in population and fishery processes. The user can choose to simulate the following population and fishery processes at age through time with a multiplicative lognormal process error with mean value equal to unity and a constant coefficient of variation:

1. Natural mortality at age
2. Maturation fraction at age
3. Stock weight on January $1^{\text {st }}$ at age
4. Spawning stock weight at age
5. Mean population weight at age
6. Fishery selectivity at age
7. Discard fraction at age
8. Catch weight at age
9. Discard weight at age

The simulated values of each of these processes can be stored in auxiliary data files for the purpose of documenting projection results.

## Age-Structured Population Model

A pooled-sex, age-structured population model is the basis for the AGEPRO model and software. This model represents an iteroparous fish population whose abundance changes due to fluctuations in recruitment and natural mortality as well as fishing mortality from one or more fishing fleets. Population size at age changes continuously throughout the year due to the concurrent forces of natural and fishing mortality. Recruitment ( $R$, number of age-r fish) to the population occurs at the beginning of each year (January $1^{\text {st }}$ ) and is the first element in the population size at age vector (Table 1).

## Population Abundance, Survival, and Spawning Biomass

The AGEPRO model calculates the number of fish alive within each age class of the population through time. Let $Y$ denote the number of years in a projection where $t$ indexes time for $t=1,2, \ldots Y$. The maximum number of years in the projection is a dynamic variable specified by the user and constrained by the amount of computer memory. The minimum or youngest age class comprises the recruits and the age of recruitment is age $r \geq 0$. The oldest age class is a plus-group which consists of all fish that are at least as old as the plus group age ( $A$ ). The maximum number of age classes is 100, including the plus group. For each age class, the number of fish alive at the beginning of each calendar year (January $1^{\text {st }}$ ) is $N_{j}(t)$ where $j$ indexes age class and $t$ indexes year. The number of fish in the plus group is $N_{A}(t)$ which accounts for the number of fish that are age-A or older at the beginning of year $t$. Given this, the population abundance at the beginning of year $t$ is the vector $\underline{N}(t)$ with $R(t)$ used as an alternate notation to emphasize that a recruitment submodel is needed to stochastically generate recruitment through time horizon

$$
\underline{N}(t)=\left[\begin{array}{c}
R(t)  \tag{1}\\
N_{r+1}(t) \\
N_{r+2}(t) \\
\vdots \\
N_{A}(t)
\end{array}\right]
$$

Population survival at age from year $t-1$ to year $t$ is calculated using instantaneous fishing and mortality rates at age. To describe annual survival through mortality, let $M_{a}(t)$ denote the instantaneous natural mortality rate on age group a and let $F_{a}(t)$ denote the instantaneous fishing mortality rate for age- $a$ fish in year $t$ where $F_{a}(t)$ is the sum of fleet-specific fishing mortalities at age $a$. Population size at age in year $t$ for age classes indexed by $a=r$ to $A-1$ is given by

$$
\begin{equation*}
N_{a}(t)=N_{a-1}(t-1) \cdot e^{-M_{a-1}(t-1)-F_{a-1}(t-1)} \tag{2}
\end{equation*}
$$

Similarly, population size at age in year $t$ for the plus group of fish age- $A$ and older is given by

$$
\begin{equation*}
N_{A}(t)=N_{A}(t-1) \cdot e^{-M_{A}(t-1)-F_{A}(t-1)}+N_{A-1}(t-1) \cdot e^{-M_{A-1}(t-1)-F_{A-1}(t-1)} \tag{3}
\end{equation*}
$$

where survival for the plus-group involves an age- $A$ and an age-( $A-1$ ) component. Incoming recruitment is determined through a stochastic process that is either dependent or independent of spawning biomass in year $t$ (see Stock-Recruitment Relationship below).

Annual spawning biomass $B_{S}(t)$ is calculated from the population size vector $\underline{N}(t)$ and total mortality rates as well as information on sexual maturity and weight at age. The age-specific natural mortality rate is $M_{a}(t)$. To describe annual survival, let $F_{a}(t)$ be the instantaneous fishing mortality rate for age- $a$ fish in year $t$ where $F_{a}(t)$ is the sum of fleet-specific fishing mortalities at age $F_{a}(t)=\sum_{v} F_{v, a}(t)$. Further, let $P_{\text {mature }, a}(t)$ denote the average fraction of age- $a$ fish that are sexually mature in year $t$ and let $W_{s, a}(t)$ denote the average spawning weight of an age- $a$ fish in year $t$. Last, let $Z_{\text {Frac }}(t)$ denote the proportion of total mortality that occurs from January $1^{\text {st }}$ to the midpoint of the spawning season in year $t$. Given this, population size at the midpoint of the spawning season in year $t \underline{N}_{S}(t)$ is obtained by applying instantaneous natural and fishing mortality rates that occur prior to the spawning season to the population vector at the beginning of the year, $\underline{N}(t)$.

$$
\underline{N}_{S}(t)=\left[\begin{array}{c}
N_{r}(t) \cdot e^{-Z_{\text {Frac }}(t)\left[M_{r}(t)+F_{r}(t)\right]}  \tag{4}\\
N_{r+1}(t) \cdot e^{-Z_{\text {Frac }}(t)\left[M_{2}(t)+F_{2}(t)\right]} \\
N_{r+2}(t) \cdot e^{-Z_{\text {Frac }}(t)\left[M_{3}(t)+F_{3}(t)\right]} \\
\vdots \\
N_{A}(t) \cdot e^{-Z_{\text {Frac }}(t)\left[M_{A}(t)+F_{A}(t)\right]}
\end{array}\right]
$$

As a result, the amount of spawning biomass in year $t$ is the sum of the weight of the mature fish alive at the midpoint of the spawning season

$$
\begin{equation*}
B_{S}(t)=\sum_{a=r}^{A} W_{S, a}(t) \cdot P_{\text {mature }, a}(t) \cdot N_{a}(t) \cdot e^{-Z_{\text {Frac }}(t)\left[M_{a}(t)+F_{a}(t)\right]} \tag{5}
\end{equation*}
$$

## Catch, Landings, and Discards

The fishery catch depends on the fraction of the population that is vulnerable to harvest or the exploitable stock size. Catch at age by fleet (fleets are indexed by $v$ ) is determined by the Baranov catch equation (e.g., Quinn and Deriso 1999). The catch of age-a fish in year $t$ by fleet $v$ is $C_{v, a}(t)$

$$
\begin{equation*}
C_{v, a}(t)=\frac{F_{v, a}(t)}{M_{a}(t)+F_{v, a}(t)}\left[1-e^{-M_{a}(t)-F_{v, a}(t)}\right] \cdot N_{a}(t) \tag{6}
\end{equation*}
$$

To account for age-specific discarding of fish, let $P_{v, D, a}(t)$ be the proportion of age- $a$ fish that are discarded by fleet $v$ in year $t$, and let $W_{v, L, a}(t)$ and $W_{v, D, a}(t)$ be the average weight at age- $a$ in year $t$ for landed and discarded fish, respectively. Then, if discarding is included in the projections, the total landed weight of fish caught by fleet $v$ in year $t$, denoted by $L_{v}(t)$, is

$$
\begin{equation*}
L_{v}(t)=\sum_{a=r}^{A} C_{v, a}(t) \cdot\left[1-P_{v, D, a}(t)\right] \cdot W_{v, L, a}(t) \tag{7}
\end{equation*}
$$

Similarly, the total weight of discarded fish in year $t$, denoted by $D_{v}(t)$, is

$$
\begin{equation*}
D_{v}(t)=\sum_{a=r}^{A} C_{v, a}(t) \cdot P_{v, D, a}(t) \cdot W_{v, D, a}(t) \tag{8}
\end{equation*}
$$

## Population Harvest

Population harvest is set in each year in the projection time horizon by setting the harvest index $I(t)$. There are two options for determining the level of population harvest in each year of the time horizon: these are the fishing mortality and the quota options. Under the fishing mortality option, the user-input fishing mortality rate determines the harvest level (i.e., effort-based management). Under the quota option, the user-input landings quota (i.e., catch-based management). These two harvest options can be combined in any order within a given projection time horizon where, for example, effort-based management is applied in some years and quota-based management in the other years. In this case, the user sets a binary harvest index $I(t)$ to determine the harvest option for each year in the
projection time horizon. If $I(t)=1$, quota-based harvest control is applied in year $t$; else if $I(t)=0$, effort-based harvest control is applied. A mixture of quotas and effort-based harvest can be useful when projecting forward from a previous assessment to the present when only catch is available for the intervening years.

When effort-based management is applied, catch at age is determined by setting $F_{v, a}(t)$ by fleet for each age class. In this case, the fishing mortality rate on age- $a$ fish in year $t$ is the product of the fully-selected fishing mortality rate by fleet, denoted by $F_{v}(t)$, and the fleet- and age-specific fishery selectivity of age- $a$ fish, denoted by $S_{v, a}(t)$ as

$$
\begin{equation*}
F_{v, a}(t)=F_{v}(t) \cdot S_{v, a}(t) \tag{9}
\end{equation*}
$$

Landings and discards, if applicable, are then determined from $F_{v, a}(t)$. When quotabased management is applied, however, the $F_{v}(t)$ that would yield the landings quota must be determined numerically.

Under quota-based management, the landings quota by fleet in year $t$, denoted by $Q_{v}(t)$, will translate into a variety of effective fishing mortality rates depending on population size, fishery selectivity, and discarding, if applicable.

Ignoring the fleet index and time dimension for simplicity, a landings quota $Q$ can be expressed as a function of $F, Q=L(F)$, where $F$ is the fully-selected fishing mortality and $L$ is the landings expressed as a function of $F$. To see this result, observe that the catch of age-a fish can be expressed as a function of $F$

$$
\begin{equation*}
C_{a}(F)=\frac{F \cdot S_{a}(t)}{M_{a}(t)+F \cdot S_{a}(t)}\left[1-e^{-M_{a}(t)-F \cdot S_{a}(t)}\right] \cdot N_{a}(t) \tag{10}
\end{equation*}
$$

As a result, landings can also be expressed as a function of F

$$
\begin{equation*}
L(F)=\sum_{a=r}^{A} C_{a}(F) \cdot\left[1-P_{D, a}(t)\right] \cdot W_{L, a}(t) \tag{11}
\end{equation*}
$$

The fully-selected fishing mortality which satisfies the equation $Q=L(F)$ can be found using a robust root-finding algorithm and we apply the bisection method, that previous versions applied Newton's method. Quotas which exceed the exploitable biomass of the population are defined as being infeasible and simulations with infeasible quotas are also infeasible.

## Initial Population Abundance

There are two ways to set the initial population abundance, defined as the vector of the absolute number of fish alive on January $1^{\text {st }}$ of the first year $(t=1)$ of the projection time horizon $\underline{N}(1)$. The primary option is to use a set of samples from the distribution of the estimator of $\underline{N}(1)$. This approach explicitly incorporates uncertainty in the estimate of initial population abundance into the projections. Under this option, either frequentist methods such as bootstrapping or Bayesian methods such as Markov Chain Monte Carlo simulation can be applied to determine the sampling distribution of the estimator of $\underline{N}(1)$. The secondary option is to ignore uncertainty in the estimator of initial population abundance and use a single best estimate for the value of $\underline{N}(1)$. In this case, there is no uncertainty in the point estimate of $\underline{N}(1)$ used in the projections.

The primary option uses a set of $B$ initial population vectors, denoted by $\underline{N}^{(*)}(1)=\left\{\underline{N}^{(1)}(1), \underline{N}^{(2)}(1), \ldots, \underline{N}^{(B)}(1)\right\}$, for stochastic projections. In this case, the set of $B$ values are random samples from the distribution of the estimator of $\underline{N}(1)$ generated by the assessment model or other means. Given this, stochastic projection can be used to characterize the sampling distribution of key fishery outputs accounting for the uncertainty in the estimate of the initial population size. For each initial condition $\underline{N}^{(b)}(1)$, a set of simulations will be performed using the specified harvest strategy. Since dynamic array allocation is used to dimension the set of initial population vectors, the user may choose to input a large number of initial population vectors $\left(B>10^{3}\right)$ within the practical constraint of available computer memory.

The secondary option is to use a single point estimate of $\underline{N}(1)$ for projection. In this case, one estimate of population abundance is assumed to characterize the initial state of the population. Since there is no uncertainty in the initial state of the population this option allows one to characterize the sampling distribution of key fishery outputs due to uncertainty in recruitment or other variables subject to process errors.

Regardless of which initial population abundance option is used, the user must also specify the units of the initial population size vector taken from the assessment model. In particular, the initial population abundance vector is specified and input in relative abundance units along with a conversion coefficient $k_{N}$ to compute from relative units to absolute numbers, where the initial population abundance replicate is calculated as the conversion coefficient times the relative abundance vector via

$$
\underline{N}^{(b)}(1)=\left(N_{r}^{(b)}(1), \ldots, N_{A}^{(b)}(1)\right)=k_{N} \cdot \underline{n}^{(b)}(1)=\left(k_{N} \cdot n_{r}^{(b)}(1), \ldots, k_{N} \cdot n_{A}^{(b)}(1)\right)
$$

## Retrospective Adjustment

One can adjust the initial population numbers at age vector $\underline{N}(1)$ to reflect a retrospective pattern in calculating these estimates. In this case, the user must determine an appropriate vector of retrospective bias-correction coefficients, denoted by $\underline{\mathbb{C}}$, to apply to the vector
$\underline{\mathrm{N}}(1)$. These multiplicative bias-correction coefficients may be age-specific or constant across age classes. The bias-corrected initial population vector $\underline{\mathrm{N}}^{*}(1)$ is calculated from the element-wise product of $\underline{N}(1)$ and $\underline{C}$ as

$$
\begin{equation*}
\underline{N}^{*}(1)=\left(C_{r} \cdot N_{r}(1), \ldots, C_{a} \cdot N_{a}(1), \ldots, C_{A} \cdot N_{A}(1)\right)^{T} \tag{12}
\end{equation*}
$$

Note that the bias-correction coefficients are applied to all initial population vectors. If the bias-correction coefficients are determined to be constant across age classes then $\underline{\mathrm{C}}=$ (C, C, ... C) ${ }^{\mathrm{T}}$ and the bias-corrected initial population vector is

$$
\begin{equation*}
\underline{N}^{*}(1)=\left(C \cdot N_{r}(1), \ldots, C \cdot N_{a}(1), \ldots, C \cdot N_{A}(1)\right)^{T}=C \cdot \underline{N}(1) \tag{13}
\end{equation*}
$$

The bias-correction coefficients are only applied in the first time period of the projection time horizon to reflect uncertainty in the estimated population size at age. Mohn (1999) provides an informative presentation of the retrospective problem in sequential population analysis.

## Stock-Recruitment Relationship

In general, the relationship between spawning stock $B_{S}$ and recruitment $R$ is highly variable owing to intrinsic variability in factors governing early life history survival and to measurement error in the estimates of recruitment and the spawning biomass that generated it. The stock-recruitment relationship ultimately defines the sustainable yield curve and its expected variability assuming that the stochastic processes of growth, maturation, and natural mortality are density-independent and stationary throughout the time horizon. Quinn and Deriso (1999) provide a useful discussion of stock-recruitment models, renewal processes, and sustainable yield. Note that the assumed stockrecruitment relationship does not affect the initial population abundance at the beginning of the time horizon (see Initial Population Abundance).

A total of twenty stochastic recruitment models are available for population projection in the AGEPRO software. Thirteen of the recruitment models are functionally dependent on $B_{S}$ while seven do not depend on spawning biomass. Five of the recruitment models have time-dependent parameters, eleven are time-invariant, and four may include time as a predictor, or not. The user is responsible for the choice and parameterization of the recruitment models. A description of each of the recruitment models follows. Important: note that the absolute units for recruitment $R$ are numbers of age- $r$ fish, while for spawning biomass $B_{s}$, the absolute units are kilograms of spawning biomass in each of the recruitment models below.

## Model 1. Markov Matrix

A Markov matrix approach to modeling recruitment may be useful when there is uncertainty about the functional form of the stock-recruitment relationship. A Markov matrix contains transition probabilities that define the probability of obtaining a given level of recruitment given that $B_{S}$ was within a defined interval range. In particular, the distribution of recruitment is assumed to follow a multinomial distribution conditioned on the spawning biomass interval or spawning state of the stock. The Markov matrix model depends on spawning biomass and is time-invariant.

An empirical approach to estimate a Markov matrix uses stock-recruitment data to determine the parameters of a multinomial distribution for each spawning biomass state. In this case, matrix elements can be empirically determined by counting the number of times that a recruitment observation interval lies within a given spawning biomass state, defined by an interval of spawning biomass, and normalizing over all spawning states. To do this, assume that there are $K$ recruitment values and $J$ spawning biomass states. The spawning biomass states are defined by disjoint intervals on the spawning biomass axis

$$
\begin{equation*}
I_{1}=\left[0, B_{S, 1}\right) \text { and for } j=1, \ldots, J-2 I_{j}=\left[B_{S, j-1}, B_{S, j}\right) \text { and } I_{J}=\left[B_{S, J-1}, \infty\right) \tag{14}
\end{equation*}
$$

where the spawning biomass values $B_{S, j}$ are the input endpoints of the disjoint intervals of categories of spawning biomass (e.g., high, medium, low). Note that the spawning biomass intervals are defined by the cut points $B_{s, j}$. The conditional probability of realizing the $k^{\text {th }}$ recruitment value given that observed spawning biomass $B_{S, \text { Observed }}$ is in the $j^{\text {th }}$ interval is $P_{j, k}$. Here $P_{j, k}$ is the element in the $j^{\text {th }}$ row and $k^{\text {th }}$ column of the Markov matrix $\underline{\underline{P}}=\left[P_{j, k}\right]$ of conditional recruitment probabilities with elements

$$
\begin{equation*}
P_{j, k}=\operatorname{Pr}\left(R_{k} \mid B_{S, \text { observed }} \in I_{j}\right) \tag{15}
\end{equation*}
$$

These individual conditional probabilities can be estimated by the computing the number of points in the stock recruitment data set that fall within a selected recruitment [ $O_{k-1}, O_{k}$ ] range conditioned on the spawning biomass interval $I_{j}$. If $x_{j, k}$ represents the number of stock-recruitment observations in cell $I_{j} \times O_{k}$ and there is at least one observation in spawning state $j$, then the empirical maximum likelihood estimate of $P_{j, k}$ is

$$
\begin{equation*}
\operatorname{Pr}\left(R=O_{k} \mid B_{s} \in I_{j}\right)=\frac{x_{j, k}}{\sum_{k} x_{j, k}} \tag{16}
\end{equation*}
$$

Here $P_{j, k} \geq 0$ and $\sum_{k=1} P_{j, k}=1$.

Up to 25 recruitment values and up to 10 spawning biomass states can be used in the Markov matrix model. For each spawning biomass interval, the user needs to specify the conditional probabilities of realizing the expected recruitment level, e.g., the $P_{j, k}$. Given the conditional probabilities $P_{j, k}$, simulated values of $\hat{R}$ are generated by randomly sampling the conditional distribution $\hat{R}(t)=\operatorname{Pr}\left(R=O_{k} \mid B_{S}(t) \in I_{j}\right)$ through time.

## Model 2. Empirical Recruits Per Spawning Biomass Distribution

For some stocks, the distribution of recruits per spawner may be independent of the number of spawners over the range of observed data. The recruitment per spawning biomass $\left(R / B_{S}\right)$ model randomly generates recruitment under the assumption that the distribution of the $R / B_{S}$ ratio is stationary and independent of stock size. The empirical recruits per spawning biomass distribution model depends on spawning biomass and is time-invariant.

To describe this nonparametric approach, let $S_{t}$ be the $R / B_{S}$ ratio for the $t^{\text {th }}$ stock recruitment data point assuming age-1 recruitment

$$
\begin{equation*}
S_{t}=\frac{R(t)}{B_{S}(t-1)} \tag{17}
\end{equation*}
$$

and let $R_{S}$ be the $S^{t h}$ element in the ordered set of $S_{t}$. The empirical probability density function for $R_{S}$, denoted as $g\left(R_{S}\right)$, assigns a probability of $1 / T$ to each value of $R / B_{S}$ where $T$ is the number of stock-recruitment data points. Let $G\left(R_{S}\right)$ denote the cumulative distribution function (cdf) for $R_{S}$. Set the values of G at the minimum and maximum observed $R_{S}$ to be $G\left(R_{\min }\right)=0$ and $G\left(R_{\max }\right)=0$ so that the cdf of $R_{S}$ can be written as

$$
\begin{equation*}
G\left(R_{S}\right)=\frac{s-1}{T-1} \tag{18}
\end{equation*}
$$

Random values of $R_{S}$ can be generated by applying the probability integral transform to the empirical cdf. To do this, let $U$ be a uniformly distributed random variable on the interval $[0,1]$. The value of $\widehat{R_{S}}$ corresponding to a randomly chosen value of $U$ is determined by applying the inverse function of the cdf $G\left(R_{S}\right)$. In particular, if $U$ is an integer multiple of $1 /(T-1)$ so that $U=s /(T-1)$ then $\widehat{R_{S}}=G^{-1}(U)$. Otherwise $\widehat{R_{S}}$ can be obtained by linear interpolation when $U$ is not a multiple of $1 /(T-1)$.

In particular, if $(s-1) /(T-1)<U<s /(T-1)$, then $\widehat{R_{S}}$ is interpolated between $R_{S}$ and $R_{S+1}$ as

$$
\begin{equation*}
U=\left(\frac{\frac{s}{T-1}-\frac{s-1}{T-1}}{R_{S+1}-R_{S}}\right)\left(\widehat{R_{S}}-R_{S}\right)+\frac{s-1}{T-1} \tag{19}
\end{equation*}
$$

Solving for $\widehat{R_{S}}$ as a function of $U$ yields

$$
\begin{equation*}
\widehat{R_{S}}=(T-1)\left(R_{S+1}-R_{S}\right)\left(U-\frac{s-1}{T-1}\right)+R_{S} \tag{20}
\end{equation*}
$$

where the interpolation index $s$ is determined as the greatest integer in $1+U(T-1)$. Given the value of $\widehat{R_{S}}$, recruitment is generated as

$$
\begin{equation*}
R(t)=N_{1}(t)=B_{S}(t-1) \cdot \widehat{R_{S}} \tag{21}
\end{equation*}
$$

The AGEPRO program can generate stochastic recruitments using model 2 with up to 100 stock-recruitment data points.

## Model 3. Empirical Recruitment Distribution

Another simple model for generating recruitment is to draw randomly from the observed set of recruitments $\underline{R}=\{R(1), R(2), \ldots, R(T)\}$.This may be a useful approach when the recruitment has randomly fluctuated about its mean and appears to be independent of spawning biomass over the observed range of data. In this case, the recruitment distribution may be modeled as a multinomial random variable where the probability of randomly choosing a particular recruitment is $1 / T$ given $T$ observed recruitments. The empirical recruitment distribution model does not depend on spawning biomass and is time-invariant.

In this model, realized recruitment $\hat{R}$ is simulated from the empirical recruitment distribution as

$$
\begin{equation*}
\operatorname{Pr}(\hat{R}=R(t))=\frac{1}{T}, \quad \text { for } t \in\{1,2, \ldots, T\} \tag{22}
\end{equation*}
$$

The empirical recruitment distribution approach is nonparametric and assumes that future recruitment is totally independent of spawning stock biomass. When current levels of $B_{S}$ are near the midrange of historical values this assumption seems reasonable. However, if contemporary $B_{S}$ values are near the bottom of the range, then this approach could be overly optimistic, for it assumes that all historically observed recruitment levels are
possible, regardless of $B_{S}$. The AGEPRO program allows up to 100 observed recruitments for random sampling. Note that the empirical recruitment distribution model can be used to make deterministic projections by specifying a single observed recruitment.

## Model 4. Two-Stage Empirical Recruits Per Spawning Biomass Distribution

The two-stage recruits per spawning biomass model is a direct generalization of the $\mathrm{R} / \mathrm{B}_{\mathrm{S}}$ model where the spawning stock of the population is categorized into "low" and "high" states. The two-stage empirical recruits per spawning biomass distribution model depends on spawning biomass and is time-invariant.

In this model, there is an $R / B_{S}$ distribution for the low spawning biomass state and an $R / B_{S}$ distribution for the high spawning biomass state. Let $G_{\text {Low }}$ be the cdf and let $T_{\text {Low }}$ be the number of $R / B_{S}$ values for the low $B_{S}$ state. Similarly, let $G_{\text {High }}$ be the cdf and let $T_{\text {High }}$ be the number of $R / B_{S}$ values for the high $B_{S}$ state. Further, let $B_{S}^{*}$ denote the cutoff level of $B_{S}$ such that, if $B_{S}>B_{S}^{*}$, then $B_{S}$ falls in the high state. Conversely if $B_{S}<B_{S}^{*}$ then $B_{s}$ falls in the low state. Recruitment is stochastically generated from $G_{\text {Low }}$ or $G_{\text {High }}$ using equations (20) and (21) dependent on the $B_{S}$ state. The AGEPRO program can generate stochastic recruitments using the two-stage model with up to 100 stockrecruitment data points per $B_{S}$ state.

## Model 5. Beverton-Holt Curve with Lognormal Error

The Beverton-Holt curve (Beverton and Holt 1957) with lognormal errors is a parametric model of recruitment generation where survival to recruitment age is density dependent and subject to stochastic variation. The Beverton-Holt curve with lognormal error model depends on spawning biomass and is time-invariant.

The Beverton-Holt curve with lognormal error generates recruitment as

$$
\hat{r}(t)=\frac{\alpha \cdot b_{S}(t-1)}{\beta+b_{S}(t-1)} \cdot e^{w}
$$

$$
\begin{equation*}
\text { where } w \sim N\left(0, \sigma_{w}^{2}\right), \hat{R}(t)=c_{R} \cdot \hat{r}(t) \text {, and } B_{S}(t)=c_{B} \cdot b_{S}(t) \tag{23}
\end{equation*}
$$

The stock-recruitment parameters $\alpha, \beta$, and $\sigma_{w}^{2}$ and the conversion coefficients for recruitment $c_{R}$ and spawning stock biomass $c_{B}$ are specified by the user. Here it is assumed that the parameter estimates for the Beverton-Holt curve have been estimated in relative units of recruitment $r(t)$ and spawning biomass $b_{s}(t)$ which are converted to absolute values using the conversion coefficients. Note that the absolute value of recruitment is expressed as numbers of fish, while for spawning biomass, the absolute value is expressed as kilograms of $B_{S}$. For example, if the stock-recruitment curve was
estimated with stock-recruitment data that were measured in millions of fish and thousands of metric tons of $B_{S}$, then $c_{R}=10^{6}$ and $c_{B}=10^{6}$. It may be important to estimate the parameters of the stock-recruitment curve in relative units to reduce the potential effects of roundoff error on parameter estimates. It is important to note that the expected value of the lognormal error term is not unity but is $\exp \left(\frac{1}{2} \sigma_{w}^{2}\right)$. Therefore, in order to generate a recruitment model that has a lognormal error term that is equal to 1 , one needs to multiply the parameter $\alpha$ by $\exp \left(-\frac{1}{2} \sigma_{w}^{2}\right)$. This bias correction applies when the lognormal error used to fit the Beverton-Holt curve has a log-scale error term $w$ with zero mean.

The Beverton-Holt curve is often reparameterized in a modified form with parameters for steepness $h$, unfished recruitment $R_{0}$, and unfished spawning biomass $B_{0}$. The modified Beverton-Holt curve produces $h \cdot R_{0}$ recruits when $B_{S}=0.2 B_{0}$ and has the form

$$
\begin{equation*}
\hat{R}=\frac{4 h R_{0} B_{S}}{B_{0}(1-h)+B_{S}(5 h-1)} \tag{24}
\end{equation*}
$$

The parameters $\alpha$ and $\beta$ can be expressed as functions of the parameters of the modified Beverton-Holt curve as

$$
\begin{equation*}
\alpha=\frac{4 h R_{0}}{5 h-1}=4 B_{0} \frac{h}{\left(\frac{B_{0}}{R_{0}}\right)(5 h-1)} \tag{25}
\end{equation*}
$$

and

$$
\begin{equation*}
\beta=\frac{B_{0}(1-h)}{(5 h-1)}=\frac{\alpha\left(\frac{B_{0}}{R_{0}}\right)\left(h^{-1}-1\right)}{4} \tag{26}
\end{equation*}
$$

Thus, parameter estimates for the modified curve can be used to determine the BevertonHolt parameters for the AGEPRO program.

## Model 6. Ricker Curve with Lognormal Error

The Ricker curve (Ricker 1954) with lognormal error is a parametric model of recruitment generation where survival to recruitment age is density dependent and subject to stochastic variation. The Ricker curve with lognormal error model depends on spawning biomass and is time invariant.

The Ricker curve with lognormal error generates recruitment as

$$
\begin{align*}
& \hat{r}(t)=\alpha \cdot b_{S}(t-1) \cdot e^{-\beta \cdot b_{s}(t-1)} \cdot e^{w} \\
& \text { where } w \sim N\left(0, \sigma_{w}^{2}\right), \hat{R}(t)=c_{R} \cdot \hat{r}(t), \text { and } B_{S}(t)=c_{B} \cdot b_{S}(t) \tag{27}
\end{align*}
$$

The stock-recruitment parameters $\alpha, \beta$, and $\sigma_{w}^{2}$ and the conversion coefficients for recruitment $c_{R}$ and spawning stock biomass $c_{B}$ are specified by the user. Here it is assumed that the parameter estimates for the Beverton-Holt curve have been estimated in relative units of recruitment $r(t)$ and spawning biomass $b_{s}(t)$ which are converted to absolute values using the conversion coefficients. It is important to note that the expected value of the lognormal error term is not unity but is $\exp \left(\frac{1}{2} \sigma_{w}^{2}\right)$. To generate a recruitment model that has a lognormal error term that is equal to 1 , premultiply the parameter $\alpha$ by $\exp \left(-\frac{1}{2} \sigma_{w}^{2}\right)$; this mean correction applies when the lognormal error used to fit the Ricker curve has a log-scale error term $w$ with zero mean.

## Model 7. Shepherd Curve with Lognormal Error

The Shepherd curve (Shepherd 1982) with lognormal error is a parametric model of recruitment generation where survival to recruitment age is density dependent and subject to stochastic variation. The Shepherd curve with lognormal error model depends on spawning biomass and is time-invariant.

The Shepherd curve with lognormal error generates recruitment as

$$
\hat{r}(t)=\frac{\alpha \cdot b_{S}(t-1)}{1+\left(\frac{b_{S}(t-1)}{k}\right)^{\beta}} \cdot e^{w}
$$

$$
\begin{equation*}
\text { where } w \sim N\left(0, \sigma_{w}^{2}\right), \hat{R}(t)=c_{R} \cdot \hat{r}(t) \text {, and } B_{S}(t)=c_{B} \cdot b_{S}(t) \tag{28}
\end{equation*}
$$

The stock-recruitment parameters $\alpha, \beta, k$, and $\sigma_{w}^{2}$ and the conversion coefficients for recruitment $c_{R}$ and spawning stock biomass $c_{B}$ are specified by the user. Here it is assumed that the parameter estimates for the Beverton-Holt curve have been estimated in relative units of recruitment $r(t)$ and spawning biomass $b_{s}(t)$ which are converted to absolute values using the conversion coefficients. It is important to note that the expected value of the lognormal error term is not unity but is $\exp \left(\frac{1}{2} \sigma_{w}^{2}\right)$. To generate a recruitment model that has a lognormal error term that is equal to 1 , premultiply the
parameter $\alpha$ by exp $\left(-\frac{1}{2} \sigma_{w}^{2}\right)$; this mean correction applies when the lognormal error used to fit the Ricker curve has a log-scale error term $w$ with zero mean.

## Model 8. Lognormal Distribution

The lognormal distribution provides a parametric model for stochastic recruitment generation. The lognormal distribution model does not depend on spawning biomass and is time-invariant.

The lognormal distribution generates recruitment as

$$
\hat{r}(t)=e^{w}
$$

$$
\begin{equation*}
\text { where } w \sim N\left(\mu_{\log (r)}, \sigma_{\log (r)}^{2}\right) \text { and } \hat{R}(t)=c_{R} \cdot \hat{r}(t) \tag{29}
\end{equation*}
$$

The lognormal distribution parameters $\mu_{\log (r)}$ and $\sigma_{\log (r)}^{2}$ as well as the conversion coefficient for recruitment $c_{R}$ are specified by the user. It is assumed that the parameters of the lognormal distribution have been estimated in relative units $r(t)$ and then converted to absolute values with the conversion coefficients.

## Model 9. Time-Varying Empirical Recruitment Distribution

This model has been deprecated. The time-varying empirical recruitment can be fully implemented using model 3.

## Model 10. Beverton-Holt Curve with Autocorrelated Lognormal Error

The Beverton-Holt curve with autocorrelated lognormal errors is a parametric model of recruitment generation where survival to recruitment age is density dependent and subject to serially-correlated stochastic variation. The Beverton-Holt curve with autocorrelated lognormal error model depends on spawning biomass and is time-dependent.

The Beverton-Holt curve with autocorrelated lognormal error generates recruitment as

$$
\hat{r}(t)=\frac{\alpha \cdot b_{S}(t-1)}{\beta+b_{S}(t-1)} \cdot e^{\varepsilon_{t}}
$$

$$
\begin{align*}
& \text { where } \varepsilon_{t}=\phi \varepsilon_{t-1}+w_{t} \text { with } w_{t} \sim N\left(0, \sigma_{w}^{2}\right) \text {, }  \tag{30}\\
& \hat{R}(t)=c_{R} \cdot \hat{r}(t) \text {, and } B_{S}(t)=c_{B} \cdot b_{S}(t)
\end{align*}
$$

The stock-recruitment parameters $\alpha, \beta, \phi, \varepsilon_{0}$, and $\sigma_{w}^{2}$ and the conversion coefficients for recruitment $c_{R}$ and spawning stock biomass $c_{B}$ are specified by the user. The parameter $\varepsilon_{0}$ is the log-scale residual for the stock-recruitment fit in the time period prior to the projection. If this value is not known, the default is to set $\varepsilon_{0}=0$.

## Model 11. Ricker Curve with Autocorrelated Lognormal Error

The Ricker curve with autocorrelated lognormal error is a parametric model of recruitment generation where survival to recruitment age is density dependent and subject to serially correlated stochastic variation. The Ricker curve with autocorrelated lognormal error model depends on spawning biomass and is time-dependent.

The Ricker curve with autocorrelated lognormal error generates recruitment as

$$
\hat{r}(t)=\alpha \cdot b_{s}(t-1) \cdot e^{-\beta \cdot b_{s}(t-1)} \cdot e^{\varepsilon_{t}}
$$

$$
\begin{align*}
& \text { where } \varepsilon_{t}=\phi \varepsilon_{t-1}+w_{t} \text { with } w_{t} \sim N\left(0, \sigma_{w}^{2}\right),  \tag{31}\\
& \hat{R}(t)=c_{R} \cdot \hat{r}(t) \text {, and } B_{S}(t)=c_{B} \cdot b_{S}(t)
\end{align*}
$$

The stock-recruitment parameters $\alpha, \beta, \phi, \varepsilon_{0}$, and $\sigma_{w}^{2}$ and the conversion coefficients for recruitment $c_{R}$ and spawning stock biomass $c_{B}$ are specified by the user. The parameter $\varepsilon_{0}$ is the log-scale residual for the stock-recruitment fit in the time period prior to the projection. If this value is not known, the default is to set $\varepsilon_{0}=0$.

## Model 12. Shepherd Curve with Autocorrelated Lognormal Error

The Shepherd curve with autocorrelated lognormal error is a parametric model of recruitment generation where survival to recruitment age is density dependent and subject to serially-correlated stochastic variation. The Shepherd curve with autocorrelated lognormal error model depends on spawning biomass and is time-dependent.

The Shepherd curve with autocorrelated lognormal error generates recruitment as

$$
\begin{equation*}
\hat{r}(t)=\frac{\alpha \cdot b_{S}(t-1)}{1+\left(\frac{b_{S}(t-1)}{k}\right)^{\beta}} \cdot e^{\varepsilon_{t}} \tag{32}
\end{equation*}
$$

$$
\begin{aligned}
& \text { where } \varepsilon_{t}=\phi \varepsilon_{t-1}+w_{t} \text { with } w_{t} \sim N\left(0, \sigma_{w}^{2}\right) \text {, } \\
& \hat{R}(t)=c_{R} \cdot \hat{r}(t) \text {, and } B_{S}(t)=c_{B} \cdot b_{S}(t)
\end{aligned}
$$

The stock-recruitment parameters $\alpha, \beta, k, \phi, \varepsilon_{0}$, and $\sigma_{w}^{2}$ and the conversion coefficients for recruitment $c_{R}$ and spawning stock biomass $c_{B}$ are specified by the user. The parameter $\varepsilon_{0}$ is the log-scale residual for the stock-recruitment fit in the time period prior to the projection. If this value is not known, the default is to set $\varepsilon_{0}=0$.

## Model 13. Autocorrelated Lognormal Distribution

The autocorrelated lognormal distribution provides a parametric model for stochastic recruitment generation with serial correlation. The autocorrelated lognormal distribution model does not depend on spawning biomass and is time-dependent.

The autocorrelated lognormal distribution is

$$
n_{r}(t)=e^{\varepsilon_{t}}
$$

$$
\begin{align*}
& \text { where } \varepsilon_{t}=\phi \varepsilon_{t-1}+w_{t} \text { with } w_{t} \sim N\left(\mu_{\log (r)}, \sigma_{\log (r)}^{2}\right) \text {, }  \tag{33}\\
& \text { and } R(t)=c_{R} \cdot n_{r}(t)
\end{align*}
$$

The lognormal distribution parameters $\mu_{\log (r)}, \sigma_{\log (r)}^{2}, \phi$, and $\varepsilon_{0}$ as well as the conversion coefficient for recruitment $c_{R}$ are specified by the user. It is assumed that the parameters of the lognormal distribution have been estimated in relative units $r(t)$ and then converted to absolute values with the conversion coefficient.

## Model 14. Empirical Cumulative Distribution Function of Recruitment

The empirical cumulative distribution function of recruitment can be used to randomly generates recruitment under the assumption that the distribution of $R$ is stationary and independent of stock size. The empirical cumulative distribution function of recruitment model does not depend on spawning biomass and is time-invariant.

To describe this nonparametric approach, let $R_{S}$ denote the $S^{\text {th }}$ element in the ordered set of observed recruitment values. The empirical probability density function for $R_{S}$, denoted as $g\left(R_{S}\right)$, assigns a probability of $1 / \mathrm{T}$ to each value of $R(t)$ where $T$ is the number of stock-recruitment data points. Let $G\left(R_{S}\right)$ denote the cumulative distribution function (cdf) for $R_{S}$. Set the values of G at the minimum and maximum observed $R_{S}$ to be $G\left(R_{\min }\right)=0$ and $G\left(R_{\max }\right)=0$ so that the cdf of $R_{S}$ can be written as

$$
\begin{equation*}
G\left(R_{S}\right)=\frac{s-1}{T-1} \tag{34}
\end{equation*}
$$

Random values of $R_{S}$ can be generated by applying the probability integral transform to the empirical cdf. To do this, let $U$ be a uniformly distributed random variable on the interval [0,1]. The value of $\widehat{R_{S}}$ corresponding to a randomly chosen value of $U$ is determined by applying the inverse function of the $\operatorname{cdf} G\left(R_{S}\right)$. In particular, if $U$ is an integer multiple of $1 /(T-1)$ so that $U=s /(T-1)$ then $\widehat{R_{S}}=G^{-1}(U)$. Otherwise $\widehat{R_{S}}$ can be obtained by linear interpolation when $U$ is not a multiple of $1 /(T-1)$.

In particular, if $(s-1) /(T-1)<U<s /(T-1)$, then $\widehat{R_{S}}$ is interpolated between $R_{S}$ and $R_{S+1}$ as

$$
\begin{equation*}
U=\left(\frac{\frac{s}{T-1}-\frac{s-1}{T-1}}{R_{S+1}-R_{S}}\right)\left(\widehat{R_{S}}-R_{S}\right)+\frac{s-1}{T-1} \tag{35}
\end{equation*}
$$

Solving for $\widehat{R_{S}}$ as a function of $U$ yields

$$
\begin{equation*}
\widehat{R_{S}}=(T-1)\left(R_{S+1}-R_{S}\right)\left(U-\frac{s-1}{T-1}\right)+R_{S} \tag{36}
\end{equation*}
$$

where the interpolation index $s$ is determined as the greatest integer in $1+U(T-1)$. Given the value of $\widehat{R_{S}}$, recruitment is set to be

$$
\begin{equation*}
\widehat{R}(t)=\widehat{R_{S}} \tag{37}
\end{equation*}
$$

The AGEPRO program can generate stochastic recruitments using model 14 with up to 100 recruitment data points.

Model 15. Two-Stage Empirical Cumulative Distribution Function of Recruitment
The two-stage empirical cumulative distribution function of recruitment model is an extension of Model 14 where the spawning stock of the population is categorized into low and high states. The two-stage empirical cumulative distribution function of recruitment model depends on spawning biomass and is time-invariant.

In this model, there is an empirical recruitment distribution $\underline{R}_{\text {Low }}$ for the low spawning biomass state and an empirical recruitment distribution $\underline{R}_{\text {High }}$ for the high spawning biomass state. Let $G_{\text {Low }}$ be the cdf and let $T_{\text {Low }}$ be the number of $R$ values for the low $B_{S}$ state. Similarly, let $G_{\text {High }}$ be the cdf and let $T_{\text {High }}$ be the number of $R$ values for the high $B_{S}$ state. Further, let $B_{s}^{*}$ denote the cutoff level of $B_{s}$ such that, if $B_{s}>B_{s}^{*}$, then $B_{s}$
falls in the high state. Conversely if $B_{S}<B_{S}^{*}$ then $B_{S}$ falls in the low state. Recruitment is stochastically generated from $G_{\text {Low }}$ or $G_{\text {High }}$ using equations (36) and (37) dependent on the $B_{S}$ state. The AGEPRO program can generate stochastic recruitments using model 15 with up to 100 stock-recruitment data points.

## Model 16. Linear Recruits Per Spawning Biomass Predictor with Normal Error

 The linear recruits per spawning biomass predictor with normal error is a parametric model to simulate random values of recruits per spawning biomass $\frac{R}{B_{S}}$ and realized recruitment values. The predictors in the linear model $X_{p}(t)$ can be any continuous variable and may typically be survey indices of cohort abundance or environmental covariates that are correlated with recruitment strength. Input values of each predictor are required for each time period. If a value of a predictor is missing or not known for one or more periods, the missing values can be imputed using appropriate measures of central tendency, e.g., mean or median values. Similarly, if this model has zero probability in a given time period (e.g., is not a member of the set of probable models), then dummy values can be input for each predictor. For each time period and simulation, a random value of $\frac{R}{B_{S}}$ is generated using the linear model$$
\begin{equation*}
\frac{R}{B_{S}}=\beta_{0}+\sum_{p=1}^{N_{p}} \beta_{p} \cdot X_{p}(t)+\varepsilon \tag{38}
\end{equation*}
$$

where $N_{p}$ is the number of predictors, $\beta_{0}$ is the intercept, $\beta_{p}$ is the linear coefficient of the $p^{\text {th }}$ predictor and $\varepsilon$ is a normal distribution with zero mean and constant variance $\sigma^{2}$. It is possible negative values of $\frac{R}{B_{S}}$ to be generated using this formulation; such values are excluded from the set of simulated values of $\frac{R}{B_{S}}$ from equation (35) by testing if $\frac{R}{B_{S}} \leq 0$ repeating the random sampling until an feasible positive value of $\frac{R}{B_{S}}$ is obtained.
This model randomly generates $\frac{R}{B_{S}}$ values under the assumption that the linear predictor of the $\frac{R}{B_{S}}$ ratio is stationary and independent of stock size. Random values of $\frac{R}{B_{S}}$ are multiplied by realized spawning biomass to generate recruitment in each time period. The linear recruits per spawning biomass predictor with normal error depends on spawning biomass and is time-invariant unless time is used as a predictor.

Model 17. Loglinear Recruits Per Spawning Biomass Predictor with Lognormal Error
The loglinear recruits per spawning biomass predictor with lognormal error is a parametric model to simulate random values of recruits per spawning biomass $\frac{R}{B_{S}}$ and associated random recruitments. Predictors for the loglinear model $X_{p}(t)$ can be any continuous variable and could include survey indices of cohort abundance or environmental covariates that are correlated with recruitment strength. Input values of each predictor are required for each time period. If a value of a predictor is missing or not known for one or more periods, the missing values can be imputed using appropriate measures of central tendency, e.g., mean or median values. If this model has zero probability in a given time period (e.g., is not a member of the set of probable models), then dummy values can be input for each predictor. For each time period and simulation, a random value of the natural logarithm of $\frac{R}{B_{S}}$ is generated using the loglinear model

$$
\begin{equation*}
\log \left(\frac{R}{B_{S}}\right)=\beta_{0}+\sum_{p=1}^{N_{p}} \beta_{p} \cdot X_{p}(t)+\varepsilon \tag{39}
\end{equation*}
$$

where $N_{p}$ is the number of predictors, $\beta_{0}$ is the intercept, $\beta_{p}$ is the linear coefficient of the $p^{\text {th }}$ predictor and $\varepsilon$ is a normal distribution with constant variance $\sigma^{2}$ and mean equal to $-0.5 \sigma^{2}$. In this case, the mean of $\varepsilon$ implies that the expected value of the lognormal error term is unity. This model generates positive random values of $\frac{R}{B_{S}}$ under the assumption that the linear predictor of the $\frac{R}{B_{S}}$ ratio is stationary and independent of stock size. Simulated values of $\frac{R}{B_{S}}$ are multiplied by realized spawning biomass to generate recruitment in each time period. The loglinear recruits per spawning biomass predictor with lognormal error depends on spawning biomass and is time-invariant unless time is used as a predictor.

## Model 18. Linear Recruitment Predictor with Normal Error

The linear recruitment predictor with normal error is a parametric model to simulate representative random values of recruitment. The predictors in the linear model $X_{p}(t)$ can be any continuous variable and could represent survey indices of cohort abundance or environmental covariates correlated with recruitment strength. Input values of each predictor are required for each time period. If a value of a predictor is missing or not known for one or more periods, the missing values can be imputed using appropriate measures of central tendency, e.g., mean or median values. Similarly, if this model has zero probability in a given time period (e.g., is not a member of the set of probable
models), then dummy values can be input for each predictor. For each time period and simulation, a random value of $R$ is generated using the linear model

$$
\begin{align*}
& n_{r}(t)=\beta_{0}+\sum_{p=1}^{N_{p}} \beta_{p} \cdot X_{p}(t)+\varepsilon  \tag{40}\\
& \text { with } R(t)=c_{R} \cdot n_{r}(t)
\end{align*}
$$

here $N_{p}$ is the number of predictors, $\beta_{0}$ is the intercept, $\beta_{p}$ is the linear coefficient of the $p^{\text {th }}$ predictor and $\varepsilon$ is a normal distribution with zero mean and constant variance $\sigma^{2}$ and the conversion coefficients for recruitment is $c_{R}$. It is possible that negative values of $R$ can be generated using this formulation; such values are excluded from the set of simulated values of $R$ from equation (37) by testing if $R$ repeating the random sampling until an feasible positive value of $R$ is obtained. This model randomly generates $R$ values under the assumption that the linear predictor of $R$ is stationary and independent of stock size. The linear recruitment predictor with normal error does not depend on spawning biomass and is time-invariant unless time is used as a predictor.

## Model 19. Loglinear Recruitment Predictor with Lognormal Error

The loglinear recruitment predictor with lognormal error is a parametric model to simulate random values of recruitment R. Predictors for the loglinear model $X_{p}(t)$ can be any continuous variable such as survey indices of cohort abundance or environmental covariates that are correlated with recruitment strength. Input values of each predictor are required for each time period. If a value of a predictor is missing or not known for one or more periods, the missing values can be imputed using appropriate measures of central tendency, e.g., mean or median values. If this model has zero probability in a given time period (e.g., is not a member of the set of probable models), then dummy values can be input for each predictor. For each time period and simulation, a random value of the natural logarithm of $R$ is generated using the loglinear model

$$
\begin{align*}
& \log \left(n_{r}(t)\right)=\beta_{0}+\sum_{p=1}^{N_{p}} \beta_{p} \cdot X_{p}(t)+\varepsilon  \tag{41}\\
& \text { with } R(t)=c_{R} \cdot n_{r}(t)
\end{align*}
$$

where $N_{p}$ is the number of predictors, $\beta_{0}$ is the intercept, $\beta_{p}$ is the linear coefficient of the $p^{\text {th }}$ predictor and $\varepsilon$ is a normal distribution with constant variance $\sigma^{2}$ and mean equal to $-0.5 \sigma^{2}$, and the conversion coefficients for recruitment is $c_{R}$. In this case, the mean of $\varepsilon$ implies that the expected value of the lognormal error term is unity. This model generates positive random values of R under the assumption that the linear predictor of the $R$ is stationary and independent of stock size. The loglinear recruitment predictor with lognormal error does not depend on spawning biomass and is time-invariant unless time is used as a predictor.

## Model 20. Fixed Recruitment

The fixed recruitment predictor applies a specified value of recruitment for each year of the time horizon. The vector of input recruitment values in relative units is $\underline{n}_{r}=\left[n_{r}(1), n_{r}(2), \ldots, n_{r}(Y)\right]$ for projections years 1 through Y. The fixed recruitment model predicts recruitment as

$$
\begin{equation*}
R(t)=c_{R} \cdot n_{r}(t) \tag{42}
\end{equation*}
$$

where the conversion coefficient for input recruitment to absolute numbers is $c_{R}$.
The fixed recruitment model does not depend on spawning biomass and is time-invariant.

## Model 21. Empirical Cumulative Distribution Function of Recruitment with Linear Decline to Zero

The empirical cumulative distribution function of recruitment with linear decline to zero model is an extension of the empirical cumulative distribution function of recruitment (Model 14) in which recruitment strength declines when the spawning stock biomass falls below a threshold $B_{S}^{*}$. The decline in recruitment randomly generated from the empirical cdf of the observed recruitment is proportional to the ratio of current spawning stock biomass to the threshold $\frac{B_{S}}{B_{S}^{*}}$ when $B_{S}<B_{S}^{*}$. In particular, predicted recruitment values are randomly generated using equation (37) given the input time series of observed recruitment. That is, if the current spawning biomass is at or above the threshold with $B_{S} \geq B_{S}^{*}$ then the predicted recruitment is

$$
\begin{equation*}
R=c_{R} \cdot\left[(T-1)\left(R_{S+1}-R_{S}\right)\left(U-\frac{s-1}{T-1}\right)+R_{S}\right] \tag{43}
\end{equation*}
$$

where the conversion coefficient for input recruitment to absolute numbers is $c_{R}$.

Otherwise, if the current spawning biomass falls below the threshold with $B_{S}<B_{S}^{*}$ then the predicted recruitment is reduced to be

$$
\begin{equation*}
R=c_{R} \cdot \frac{B_{S}}{B_{S}^{*}}\left[(T-1)\left(R_{S+1}-R_{S}\right)\left(U-\frac{s-1}{T-1}\right)+R_{S}\right] \tag{44}
\end{equation*}
$$

where the conversion coefficient for input recruitment to absolute numbers is $c_{R}$. The empirical cumulative distribution function of recruitment with linear decline to zero model depends on spawning biomass and is time-invariant.

## Recruitment Model Probabilities

Model uncertainty about the appropriate stock-recruitment model can be directly incorporated into AGEPRO projections. Using a set of recruitment models may be appropriate when each model provides a similar statistical fit to a set of stock-recruitment data, where similarity can be measured using Akaike information criterion, deviance information criterion, widely applicable information criterion, or other goodness-of-fit measures. Given a measure of a stock-recruitment model's relative likelihood compared to a set of alternative models, one can use information criteria to calculate an individual model's probability of best representing the true state of nature. Alternatively, one can assign model probabilities based on judgment of other measures of goodness of fit or use the principle of indifference to assign equal probabilities in the absence of compelling information.

Regardless of the approach used to estimate them, the recruitment model probabilities are used to generate stochastic recruitment dynamics in a straightforward manner. Suppose there are a total of $N_{M}$ probable recruitment models, as determined by the user. The probability that recruitment model $m$ is realized in year $t$ is denoted by $P_{R, m}(t)>0$. Conservation of total probability implies that the sum of model probabilities over the set of probable models in each year is unity

$$
\begin{equation*}
\sum_{m=1}^{N_{M}} P_{R, m}(t)=1 \tag{45}
\end{equation*}
$$

This gives a conditional probability distribution for randomly sampling recruitment submodels in each year of the projection time horizon. As in previous versions of AGEPRO, a single recruitment model can be used for the entire projection time horizon by setting $N_{M}=1$.

One advantage of including multiple recruitment models with time-varying probabilities is that one can use auxiliary information on recruitment strength, such as environmental covariates, to make short-term recruitment predictions (1-2 years) and then change to a less informative set of medium-term recruitment models for medium-term recruitment predictions (3-5 years). Another advantage of including multiple recruitment models is to account for model selection uncertainty, which can be a substantial source of uncertainty for some fishery systems.

## Process Errors for Population and Fishery Processes

Process errors to generate time-varying dynamics of population and fishery processes can be included in stock projections using AGEPRO. These process errors are defined as independent multiplicative lognormal error distributions for each life history and fishery process.

The general form for a lognormal multiplicative process error term in year $t$, denoted by $\varepsilon_{t}$, is

$$
\begin{align*}
& \varepsilon_{t} \sim \exp (w) \\
& \text { where } w \sim N\left(-0.5 \sigma^{2}, \sigma^{2}\right) \tag{46}
\end{align*}
$$

And where the user specifies the coefficient of variation of the lognormal process error as $C V=\sqrt{\exp \left(\sigma^{2}\right)-1}$ which sets the value of $\sigma$ as $\sigma=\sqrt{\log \left(C V^{2}+1\right)}$.

The five population processes and four fishery processes that can include process error along with the input file keyword to specify the process are (keyword):

- Natural mortality at age (NATMORT) $M_{a}(t)$
- Maturation fraction at age (MATURITY) $P_{\text {mature }, a}(t)$
- Stock weight on January $1^{\text {st }}$ at age (STOCK_WEIGHT) $W_{P, a}(t)$
- Spawning stock weight at age (SSB_WEIGHT) $W_{s, a}(t)$
- Midyear mean population weight at age (MEAN_WEIGHT) $W_{\text {midyear,a }}(t)$
- Fishery selectivity at age by fleet (FISHERY) $S_{v, a}(t)$
- Discard fraction at age by fleet (DISCARD) $P_{v, D, a}(t)$
- Landed catch weight at age by fleet (CATCH_WEIGHT) $W_{v, L, a}(t)$
- Discard weight at age by fleet (DISC_WEIGHT) $W_{v, D, a}(t)$

For detailed documentation of projection results, the user can choose to store individual simulated values of these processes through time in auxiliary data files by setting the value of the DataFlag=1 under the keyword OPTIONS (Table 3). The auxiliary file names are constructed from the AGEPRO input filename with file extensions ranging from .xxx1 to .xxx9 for the nine processes in the bullet list above, noting that not all processes may be used in a given projection, e.g., discarding. For processes that are used, the auxiliary file names are assigned in the order in which the process parameters are set in the AGEPRO input file. For example, if the spawning stock weight at age process parameters appeared fifth in the ordering of keywords to specify these nine processes in the AGEPRO input file, then the time series of simulated spawning stock weights at age would be store in the auxiliary output file name "input_filename.xxx5". Each row in this file would be the spawning weights at age for one year, in sequence, for each bootstrap replicate and simulation.

## Total Stock Biomass

Total stock biomass $B_{T}$ is the sum over the recruitment age $(r)$ to the plus-group age $(A)$ of stock biomass at age on January $1^{\text {st }}$. The computational formula for $B_{T}$ in year $t$ is

$$
\begin{equation*}
B_{T}(t)=\sum_{a=r}^{A} W_{P, a}(t) \cdot N_{a}(t) \tag{47}
\end{equation*}
$$

where $W_{P, a}(t)$ is the population mean weight of age-a fish on January $1^{\text {st }}$ in year $t$.

## Mean Biomass

Mean stock biomass $\bar{B}$ is the average biomass of the stock over a given year. In particular, mean stock biomass depends on the total mortality rate experienced by the stock in each year. In the AGEPRO model, the user selects the range of ages to be used for calculating mean biomass. One can choose the full range of ages in the model (age-r through age-A) or alternatively select a smaller age range if desired. In this case, the upper age $A_{v}$ for mean biomass calculations must be less than or equal to the plus group age $A$. Similarly the lower age $A_{L}$ must be greater than or equal to the recruitment age $r$. If $W_{\text {midyear }, a}(t)$ denotes the mean weight of age- $a$ fish at the mid-point of year $t$ then the computational formula for $\bar{B}$ in year $t$ is

$$
\begin{equation*}
\bar{B}(t)=\sum_{a=A_{L}}^{A_{\nu}} W_{\text {midyear }, a}(t) \cdot N_{a}(t) \cdot \frac{\left(1-\exp \left(-M_{a}(t)-F_{a}(t)\right)\right)}{\left(M_{a}(t)+F_{a}(t)\right)} \tag{48}
\end{equation*}
$$

where $F_{a}(t)$ is the total fishing mortality on age- $a$ fish calculated across all fleets.

## Fishing Mortality Weighted by Mean Biomass

Fishing mortality weighted by mean biomass $F_{\bar{B}}(t)$ in year $t$ is the mean-biomass weighted sum of fishing mortality at age over the age range of $A_{L}$ to $A_{U}$ (see Mean Biomass above). This quantity may be useful for equilibrium comparisons with fishing mortality reference points developed from surplus production models. The computational formula for fishing mortality weighted by mean biomass is

$$
\begin{align*}
& F_{\bar{B}}(t)=\frac{\sum_{a=A_{L}}^{A_{\mathcal{L}}} \bar{B}_{a}(t) \cdot F_{a}(t)}{\bar{B}(t)}  \tag{49}\\
& \text { where } \bar{B}_{a}(t)=W_{\text {midyear }, a}(t) N_{a}(t) \frac{\left(1-\exp \left(-M_{a}(t)-F_{a}(t)\right)\right)}{\left(M_{a}(t)+F_{a}(t)\right)}
\end{align*}
$$

where $F_{a}(t)$ is the total fishing mortality on age- $a$ fish calculated across all fleets.

## Feasible Simulations

A feasible simulation is defined as one where the all landings quotas by fleet can be harvested in each year of the projection time horizon. An infeasible simulation is one where the exploitable biomass is insufficient to harvest at least one landings quota in one or more years of the time horizon. All simulations are feasible for projections where population harvest is based solely on fishing mortality values. For projections that specify landings quotas by fleet in one or more years, the feasibility of harvesting the landings
quota is evaluated using an upper bound on $F$ that defines infeasible quotas relative to the exploitable biomass (Appendix). For purposes of summarizing projection results, the total number of simulations is denoted as $K_{\text {тотац }}$ and the total number of feasible simulations is denoted as $K_{\text {FEASIbLE }}$.

## Biomass Thresholds

The user can specify biomass thresholds for spawning biomass $\left(B_{S, \text { THRESHOLD }}\right)$, mean biomass $\left(\bar{B}_{\text {THRESHOLD }}\right)$, and total stock biomass $\left(B_{T, \text { THRESHOLD }}\right)$ for Sustainable Fisheries Act (SFA) policy evaluation. These biomass thresholds can be specified using the input keyword REFPOINT (Tables 2 and 3). If the REFPOINT keyword is used in an AGEPRO model, then projected biomass values are compared to the input thresholds through time. Probabilities that biomasses meet or exceed threshold values are computed for each year. In addition, the probability that biomass thresholds were exceeded in at least one year within a single simulated population trajectory is computed. If the user specifies fishing mortality-based harvesting with no landings quotas, then the SFAthreshold probabilities are computed over the entire set of simulations. Let $K_{B}(t)$ be the number of times that projected biomass $B(t)$ meets or exceeds a threshold biomass $B_{\text {THRESHoLD }}$ in year $t$. The counter $K_{B}(t)$ is evaluated for each year and biomass series (spawning, mean, or total stock). Given that $K_{\text {тотаL }}$ is the total number of feasible simulation runs, the estimate of the annual probability that $B_{\text {THRESHOLD }}$ would be met or exceeded in year $t$ is

$$
\begin{equation*}
\operatorname{Pr}\left(B(t) \geq B_{\text {THRESHOLD }}\right)=\frac{K_{B}(t)}{K_{\text {TOTAL }}} \tag{50}
\end{equation*}
$$

Note that this also provides an estimate of the probability of the complementary event that biomass does not exceed the threshold via

$$
\begin{equation*}
\operatorname{Pr}\left(B(t)<B_{\text {THRESHOLD }}\right)=1-\operatorname{Pr}\left(B(t) \geq B_{\text {THRESHOLD }}\right)=1-\frac{K_{B}(t)}{K_{\text {TOTAL }}} \tag{51}
\end{equation*}
$$

Next, if $K_{\text {threshold }}$ denotes the number of simulations where biomass exceeded its threshold at least once, then the probability that $B_{\text {THRESHOLD }}$ would be met or exceeded at least

$$
\begin{equation*}
\operatorname{Pr}\left(\exists t \in[1,2, \ldots, Y] \text { such that } B(t) \geq B_{\text {THRESHOLD }}\right)=\frac{K_{\text {THRESHOLD }}}{K_{\text {TOTAL }}} \tag{52}
\end{equation*}
$$

If the user specifies landings quota-based harvesting in one or more years, then the

SFA-threshold probabilities can be computed over the set of feasible simulations. In this case, the year-specific conditional probability that $B_{\text {THRESHOLD }}$ would be met or exceeded for feasible simulations is

$$
\begin{equation*}
\operatorname{Pr}\left(B(t) \geq B_{\text {THRESHOLD }}\right)=\frac{K_{B}(t)}{K_{\text {FEASIBLE }}} \tag{53}
\end{equation*}
$$

Note that the counter $K_{B}(t)$ can only be incremented in a feasible simulation. In contrast, the joint probability that $B_{\text {THRESHOLD }}$ would be met or exceeded for the entire set of simulations is given by Equation 54 and the probability that $B_{\text {THRESHOLD }}$ would be met or exceeded at least once during the projection time horizon is given by Equation 55.

## Fishing Mortality Thresholds

The user can specify the fishing mortality rate threshold for annual total fishing mortality ( $F_{\text {THRESHOLD }}$ ) calculated across all fleets using the keyword REFPOINT. In this case, projected total $F$ values are compared to the $F_{\text {THRESHOLD }}$ through time. Probabilities that fishing mortalities exceed threshold values are computed for each year in the same manner as for biomass thresholds (see Biomass Thresholds above). In particular, if $K_{F}(t)$ is the number of times that fishing mortality $F(t)$ exceeds the threshold fishing mortality $F_{\text {THRESHOLD }}$ in year $t$, then the annual probability that the fishing mortality threshold is exceeded is

$$
\begin{equation*}
\operatorname{Pr}\left(F(t)>F_{\text {THRESHOLD }}\right)=\frac{K_{F}(t)}{K_{\text {TOTAL }}} \tag{54}
\end{equation*}
$$

and the complementary probability that the fishing mortality threshold is not exceeded is

$$
\begin{equation*}
\operatorname{Pr}\left(F(t) \leq F_{\text {THRESHOLD }}\right)=1-\frac{K_{F}(t)}{K_{\text {TOTAL }}} \tag{55}
\end{equation*}
$$

## Types of Projection Analyses

The AGEPRO module can perform three types of projection analyses. These are: standard, rebuilding and PStar projection analyses.

## Standard Projection

The standard projection analysis is the most flexible and can be used to apply mixtures of quota and fishing mortality based harvest by multiple fleets to the age-structured population. For a standard projection, alternative models can be setup and evaluated using any of the keyword options (Tables 2 and 3) except the REBUILD keyword.

## Rebuilding Projection

The rebuilding type of projection analysis is focused on the calculation of the constant total fishing mortality calculated across all fleets that will rebuild the population, denoted as $F_{\text {Rebuild }}$. In this case, the user needs to specify the target year (TargetYear, see keyword REBUILD in Table 3) in which the population is to be rebuilt, the target biomass value (TargetType), the type of biomass being rebuilt (TargetType, e.g., spawning stock biomass), and the target percentage for achieving the rebuilding target expressed in terms of the fraction of simulations that achieve the rebuilding target (TargetPercent). Note that in cases where the rebuilding target is not achievable, the summary output of the rebuilding analysis will report that the combined catch, total fishing mortality and landings distributions are zero throughout the projection time horizon. For a rebuilding projection, the user needs to specify an initial harvest scenario of total fishing mortality values by year using the keyword HARVEST. The value of $F_{\text {REbuild }}$ will then be iteratively calculated and the model results will be reported for the projection using the calculated value of $F_{\text {REBUILD }}$. For a rebuilding projection, the model can be setup and evaluated using any of the keyword options (Tables 2 and 3 ) except the PSTAR keyword.

## PStar Projection

The acronym PStar stands for the probability of exceeding the overfishing threshold in a target year. The PStar type of projection analysis is focused on the calculation of the total allowable catch $T A C_{\text {PStar }}$ that will achieve the specified probability of overfishing in the target year. In this case, the user needs to specify the target year (TargetYear, see keyword PSTAR in Table 3) in which the total annual catch to achieve PStar is calculated, the number of PStar values to be evaluated (KPStar), the vector of probabilities of overfishing or PStar values to be used (PStar), and the fishing mortality rate that defines the overfishing level (PStarF). For a PSTAR projection, the model can be setup and evaluated using any of the keyword options (Tables 2 and 3) except the REBUILD keyword.

## Age-Structured Projection Software

This section covers operational details for using the AGEPRO software and is organized into four sections. First, input data requirements and projection options are covered and the structure of an input file is described. Second, projection model outputs are described in relation to keywords in the input file and the structure of the standard output file is described. Third, a set of examples are provided to illustrate projection options and features of the software.

## Input Data

There are four categories of input data for an AGEPRO projection run: system, simulation, biological, and fishery (Figure 2). The system data consists of the input filename and this information is read from standard input (e.g., from the command line or via the AGEPRO GUI). The simulation, biological and fishery data are read from the text input file and the associated text bootstrap file containing the initial population numbers at age data.

The AGEPRO input file is structured by keywords. Each keyword identifies a set of related inputs for the projection run in a single section of the input file (Table 2). The table of AGEPRO input keywords below lists the 23 possible keywords in the sequential order that the information is read into the program.

Each keyword specifies a projection model attribute and the associated set of inputs that are required to implement it (Table 3). This includes a detailed listing of the AGEPRO input file structure showing the sequence of inputs by keyword. Here the input data type is shown in parentheses, where the types are: $\mathrm{I}=$ integer, $\mathrm{S}=$ string, $\mathrm{F}=$ floating point (Table 3). For data that are input as an array, the array dimensions are listed in order as [0: Dimension1] [0: Dimension2] and so on (Table 3).

The system data consists of the input file name for the projection run (Figure 2). The input file name can be any text string with the file extension "inp". For example, a valid input file name is "GB cod 2017 FMSY projection.inp".

Within the input file, the simulation data are specified (Tables 2 and 3) within the keyword sections named: GENERAL, CASEID, BOOTSTRAP, RETROADJUST, BOUNDS, OPTIONS, SCALE, PERC, REFPOINT, REBUILD, and PSTAR.

The biological data are specified (Tables 2 and 3 ) within the keyword sections of the input file named: NATMORT, BIOLOGICAL, MATURITY, STOCK_WEIGHT, SSB_WEIGHT, MEAN_WEIGHT, and RECRUIT. The recruitment models are specified in the RECRUIT keyword section and the specific inputs needed for each recruitment model are listed in Table 4.

The fishery data are specified (Tables 2 and 3 ) within the keyword sections of the input file named: HARVEST, FISHERY, DISCARD, CATCH_WEIGHT, and DISC_WEIGHT.

To run the AGEPRO program using the AGEPRO GUI, do the following:

- Start the AGEPRO program (double left click on the program icon)
- Under the File menu tab, select either "Create a New Case" or "Select Existing AGEPRO Input Data File" to set the input data file
- For the selected input file, click on the Run menu tab and select "Launch AGEPRO model ...".
- When the projection run is completed, the AGEPRO output files are written to a new folder. The new folder is created in the folder
~/Username/Documents/AGEPRO/New_Folder_Name where the New_Folder_Name is the input data file name with the time stamp of the run appended to it.

To run the AGEPRO program from the DOS command line, enter "agepro42.exe inputfilename". The software first checks whether the input file exists and will stop if the
input file does not exist. If the input file exists and is successfully read, you will see the following output in the command line screen:
>agepro42.exe inputfilename
> Bootstrap Iteration: 1
> Bootstrap Iteration: 2
> Bootstrap Iteration: NBootstrap
> Summary Reports ...

## Model Outputs

An AGEPRO model run creates a standard output file that summarizes the projection analysis results (Figure 2). The model will also create a set of files containing the raw output results for key quantities of interest. The user also has the option of creating output files for the simulated process error data for documentation and the option of creating an R export file that stores the projections results in an R language dataframe.

There are nine categories of output in the standard output file. The first output describes the setup of the AGEPRO model and lists the input and bootstrap file names and the recruitment models and associated model probabilities. The second output shows the input harvest scenario in terms of quotas or fishing mortality rates by year and fleet. The third output shows the realized distribution of recruitment through time. The fourth output shows the realized distribution of spawning stock biomass through time. The fifth output shows the realized distribution of total stock biomass on January $1^{\text {st }}$ through time. The sixth output shows the realized distribution of mean biomass through time. The seventh output shows the realized distribution of combined catch biomass across fleets through time. The eighth output shows the realized distribution of landings through time. The ninth output shows the realized distribution of total fishing mortality through time. In addition, if the user has setup REBUILD or PSTAR projection analyses, then the results of those analyses will also be listed in the standard output file.

The user may also select to produce summaries of the distribution of population size at age by year. This is done by setting the StockSummaryFlag=1 under the keyword OPTIONS in the input file (Table 3). The summaries are output to a new file with the name inputfilename.xx1, where inputfilename is the name of the AGEPRO input file for the model. Note choosing this option will typically produce a large file inputfilename.xx1 requiring on the order of 100 Mb of storage.

The user may also select to produce a percentile summary of the key results in the outputfile. This is done by using the keyword PERC in the input file (Tables 2 and 3).

The user may also select to store age-specific population and fisheries process error simulation results in auxiliary output files. This is done by setting the DataFlag=1 under the keyword OPTIONS in the input file (Table 3). The simulated process error data can include the following age-specific information, depending on the projection model setup:
natural mortality at age, maturity fraction at age, stock weight on January $1^{\text {st }}$ at age, spawning stock weight at age, mean population weight at age, fishery selectivity at age, discard fraction at age, catch weight at age and discard weight at age

The AGEPRO model will automatically create auxiliary raw output data files to record simulated trajectories of recruitment, spawning biomass, total stock biomass on January $1^{\text {st }}$, mean biomass, combined catch biomass, landings, discards, and fishing mortality. This raw output data can be used to characterize the distribution of these key outputs through time. One auxiliary file is created for each the outputs used in the projection model. The raw output data file names are:

1. Stock numbers at age summary: inputfilename.xx1 (Note that this file is created only if StockSummaryFlag=1)
2. Recruitment: inputfilename.xx2
3. Spawning Stock Biomass: inputfilename.xx3
4. Total Stock Biomass on January $1^{\text {st }}$ : inputfilename.xx4
5. Mean Biomass: inputfilename.xx5
6. Combined Catch Biomass: inputfilename.xx6
7. Landings: inputfilename.xx7
8. Discards: inputfilename.xx8
9. Fishing Mortality: inputfilename.xx9

The raw output data files have the same structure. In each output file, a single row represents a single simulated time trajectory with Y entries ordered from time $t=1$ to time $t=Y$. Within the file, trajectories are ordered by initial population vector (bootstrap) and then simulation for that initial vector. For example, if $B_{S}^{[b, k]}(t)$ denotes the spawning biomass in year $t$ simulated from the $b^{\text {th }}$ initial population vector and the $k^{\text {th }}$ simulation for that vector, then the output file for spawning biomass with $B$ initial vectors and $K$ simulations would have $B \cdot K$ rows that were ordered as

$$
\left[\begin{array}{cccc}
B_{S}^{[1,1]}(1) & B_{S}^{[1,1]}(2) & \ldots & B_{S}^{[1,1]}(Y)  \tag{56}\\
B_{S}^{[1,2]}(1) & B_{S}^{[1,2]}(2) & \ldots & B_{S}^{[1,2]}(Y) \\
\vdots & \vdots & \vdots & \vdots \\
B_{S}^{[B, K]}(1) & B_{S}^{[B, K]}(2) & \ldots & B_{S}^{[B, K]}(Y)
\end{array}\right]
$$

The output units of recruitment are numbers of fish. The output units of spawning biomass, total stock biomass, mean biomass, combined catch biomass, landings, and discards are kilograms. The units of F are the total annual fishing mortality rate calculated across all fleets.

## AGEPRO Projection Examples

The following set of examples is provided to illustrate projection options and features of the software. These projections use actual fishery data but are for the purposes of illustration only.

Example 1: The first example is a fishing mortality and landings quota projection for Acadian redfish. The time horizon is 2004-2009. The fishery is comprised of two fleets that have identical fishing mortality rates in 2004, identical quotas in 2005, and fishing mortality rates that differ by 2 -fold during 2006-2009. This is standard projection analysis with 1000 bootstraps and 100 simulations per bootstrap based on an ADAPTVPA stock assessment analysis. The model also outputs an R dataframe.

Running example 1 (see Appendix for input file) produces the following output:


```
2009
```

Spawning Stock Biomass x 1000 MT

| Year | Average | StdDev |
| :---: | :---: | ---: |
| 2004 | 175.6964 | 4.2235 |
| 2005 | 192.3968 | 5.2539 |
| 2006 | 201.4634 | 6.0700 |
| 2007 | 207.9323 | 6.4531 |
| 2008 | 213.1455 | 6.8011 |
| 2009 | 215.0860 | 7.3413 |

Spawning Stock Biomass Distribution

| Year | $1 \%$ | $5 \%$ | $10 \%$ | $25 \%$ | $50 \%$ | $75 \%$ | $90 \%$ | $95 \%$ | $99 \%$ |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 2004 | 165.8676 | 168.7638 | 170.1585 | 172.7614 | 175.8218 | 178.5690 | 180.8508 | 182.8573 | 185.5046 |  |
| 2005 | 179.8766 | 183.7197 | 185.6327 | 188.7590 | 192.5027 | 195.8383 | 198.9160 | 201.2237 | 204.6554 |  |
| 2006 | 187.0135 | 191.4990 | 193.8062 | 197.3170 | 201.4796 | 205.3871 | 209.1779 | 211.8179 | 215.7972 |  |
| 2007 | 192.7856 | 197.3545 | 199.8073 | 203.5527 | 207.8812 | 212.1478 | 216.2523 | 218.9945 | 223.3188 |  |
| 2008 | 197.3263 | 201.9852 | 204.6063 | 208.5499 | 213.0613 | 217.5741 | 221.9399 | 224.8047 | 229.3702 |  |
| 2009 | 198.4668 | 203.2224 | 205.9017 | 210.1353 | 214.9276 | 219.7958 | 224.6939 | 227.6763 | 232.7305 |  |
|  |  |  |  |  |  |  |  |  |  |  |


| Year | Average | StdDev |
| :---: | :---: | :---: |
| 2004 | 200.4105 | 5.4728 |
| 2005 | 211.6190 | 6.0268 |
| 2006 | 219.0101 | 6.6628 |
| 2007 | 224.8245 | 7.3809 |
| 2008 | 230.5534 | 8.6653 |
| 2009 | 233.1329 | 10.5266 |

JAN-1 Stock Biomass Distribution

| Year | $1 \%$ | $5 \%$ | $10 \%$ | $25 \%$ | $50 \%$ | $75 \%$ | $90 \%$ | $95 \%$ | $99 \%$ |  |
| :--- | :---: | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 2004 | 187.3186 | 191.4205 | 193.6011 | 196.6419 | 200.3894 | 203.9891 | 207.4034 | 209.8751 | 213.3976 |  |
| 2005 | 197.4892 | 201.7822 | 204.0521 | 207.4953 | 211.5906 | 215.5423 | 219.3350 | 222.0173 | 226.0517 |  |
| 2006 | 203.4717 | 208.0624 | 210.6302 | 214.5143 | 218.9420 | 223.3492 | 227.6193 | 230.4027 | 234.8197 |  |
| 2007 | 208.3844 | 213.0947 | 215.5979 | 219.8570 | 224.5975 | 229.4958 | 234.4669 | 237.6307 | 242.8859 |  |
| 2008 | 212.2717 | 217.3223 | 220.0521 | 224.7293 | 230.0136 | 235.7004 | 241.6218 | 245.6423 | 254.4127 |  |
| 2009 | 212.1537 | 217.8630 | 220.8943 | 226.1200 | 232.1722 | 238.8682 | 246.3096 | 251.9540 | 265.1036 |  |
|  |  |  |  |  |  |  |  |  |  |  |


| Year | Average | StdDev |
| :---: | :---: | :---: |
| 2004 | 195.1458 | 5.3333 |
| 2005 | 206.0696 | 5.8806 |
| 2006 | 211.4024 | 6.4287 |
| 2007 | 216.9493 | 7.1218 |
| 2008 | 222.4861 | 8.3790 |
| 2009 | 225.0471 | 10.1991 |

Mean Biomass Distribution

| Year | 1\% | 5\% | 10\% 25\% | \% 50\% | 75\% | 90\% | 95\% | 99\% |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 2004 | 182.4411 | 186.3680 | 188.4693 | 191.4729 | 195.1343 | 198.6408 | 201.9259 | 204.3602 | 207.8469 |
| 2005 | 192.2976 | 196.4658 | 198.6699 | 202.0527 | 206.0414 | 209.8959 | 213.5926 | 216.1956 | 220.1596 |
| 2006 | 196.4374 | 200.8584 | 203.3081 | 207.0736 | 211.3400 | 215.5932 | 219.6988 | 222.4009 | 226.6468 |
| 2007 | 201.0939 | 205.6560 | 208.0465 | 212.1518 | 216.7343 | 221.4392 | 226.2450 | 229.2876 | 234.3949 |
| 2008 | 204.8011 | 209.7117 | 212.3378 | 216.8668 | 221.9600 | 227.4532 | 233.1969 | 237.0978 | 245.6776 |
| 2009 | 204.7867 | 210.2699 | 213.1971 | 218.2598 | 224.1077 | 230.5910 | 237.8015 | 243.2913 | 256.1328 |
| Comb | ed Catc | omass x | $\mathrm{X} \quad 1000$ |  |  |  |  |  |  |


| Year | Average | StdDev |
| :---: | :---: | :---: |
| 2004 | 0.6798 | 0.0165 |
| 2005 | 0.7000 | 0.0000 |
| 2006 | 4.4690 | 0.1527 |
| 2007 | 4.7193 | 0.1773 |
| 2008 | 4.8199 | 0.1837 |

Combined Catch Distribution

| Year | 1\% | 5\% | 10\% | 25\% | 50\% | 75\% | 90\% | 95\% 9 | 99\% |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 2004 | 0.6412 | 0.6528 | 0.6582 | 0.6686 | 0.6804 | 0.6910 | 0.6998 | 0.7076 | 0.7181 |
| 2005 | 0.7000 | 0.7000 | 0.7000 | 0.7000 | 0.7000 | 0.7000 | 0.7000 | 0.7000 | 0.7000 |
| 2006 | 4.1055 | 4.2163 | 4.2773 | 4.3641 | 4.4707 | 4.5678 | 4.6673 | 4.7226 | 4.8303 |
| 2007 | 4.2937 | 4.4271 | 4.4985 | 4.5986 | 4.7187 | 4.8331 | 4.9489 | 5.0200 | 5.1365 |
| 2008 | 4.4001 | 4.5202 | 4.5918 | 4.6971 | 4.8173 | 4.9389 | 5.0572 | 5.1349 | 5.2584 |
| 2009 | 4.3327 | 4.4380 | 4.5063 | 4.6087 | 4.7229 | 4.8433 | 4.9632 | 5.0356 | 5.1588 |

Landings x 1000 MT

| Year | Average | StdDev |
| :---: | :---: | :---: |
| 2004 | 0.6798 | 0.0165 |
| 2005 | 0.7000 | 0.0000 |
| 2006 | 4.4690 | 0.1527 |
| 2007 | 4.7193 | 0.1773 |
| 2008 | 4.8199 | 0.1837 |
| 2009 | 4.7281 | 0.1781 |

Landings Distribution

| Year | $1 \%$ | $5 \%$ | $10 \%$ | $25 \%$ | $50 \%$ | $75 \%$ | $90 \%$ | 95 | 9 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 2004 | 0.6412 | 0.6528 | 0.6582 | 0.6686 | 0.6804 | 0.6910 | 0.6998 | 0.7076 | 0.7181 |
| 2005 | 0.7000 | 0.7000 | 0.7000 | 0.7000 | 0.7000 | 0.7000 | 0.7000 | 0.7000 | 0.7000 |
| 2006 | 4.1055 | 4.2163 | 4.2773 | 4.3641 | 4.4707 | 4.5678 | 4.6673 | 4.7226 | 4.8303 |
| 2007 | 4.2937 | 4.4271 | 4.4985 | 4.5986 | 4.7187 | 4.8331 | 4.9489 | 5.0200 | 5.1365 |
| 2008 | 4.4001 | 4.5202 | 4.5918 | 4.6971 | 4.8173 | 4.9389 | 5.0572 | 5.1349 | 5.2584 |
| 2009 | 4.3327 | 4.4380 | 4.5063 | 4.6087 | 4.7229 | 4.8433 | 4.9632 | 5.0356 | 5.1588 |

Total Fishing Mortality

| Year | Average | StdDev |
| :---: | :---: | :---: |
| 2004 | 0.0048 | 0.0000 |
| 2005 | 0.0048 | 0.0001 |
| 2006 | 0.0300 | 0.0000 |
| 2007 | 0.0300 | 0.0000 |
| 2008 | 0.0300 | 0.0000 |
| 2009 | 0.0300 | 0.0000 |

Total Fishing Mortality Distribution

| Year | $1 \%$ | $5 \%$ | $10 \%$ | $25 \%$ | $50 \%$ | $75 \%$ | $90 \%$ | $95 \%$ |  |  | $99 \%$ |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :---: | :---: | :---: |
| 2004 | 0.0048 | 0.0048 | 0.0048 | 0.0048 | 0.0048 | 0.0048 | 0.0048 | 0.0048 | 0.0048 |  |  |  |
| 2005 | 0.0045 | 0.0046 | 0.0047 | 0.0047 | 0.0048 | 0.0049 | 0.0050 | 0.0051 | 0.0052 |  |  |  |
| 2006 | 0.0300 | 0.0300 | 0.0300 | 0.0300 | 0.0300 | 0.0300 | 0.0300 | 0.0300 | 0.0300 |  |  |  |
| 2007 | 0.0300 | 0.0300 | 0.0300 | 0.0300 | 0.0300 | 0.0300 | 0.0300 | 0.0300 | 0.0300 |  |  |  |
| 2008 | 0.0300 | 0.0300 | 0.0300 | 0.0300 | 0.0300 | 0.0300 | 0.0300 | 0.0300 | 0.0300 |  |  |  |
| 2009 | 0.0300 | 0.0300 | 0.0300 | 0.0300 | 0.0300 | 0.0300 | 0.0300 | 0.0300 | 0.0300 |  |  |  |

Probability Spawning Stock Biomass Exceeds Threshold 236.700 (1000 MT)
Year Probability
$2004 \quad 0.000000$
20050.000000
20060.000000
20070.000000
20080.000010
20090.001950

Probability Threshold Exceeded at Least Once $=0.0019$
Probability Total Fishing Mortality Exceeds Threshold 0.0400
Year Probability
$2004 \quad 0.000000$

```
2005 0.000000
2006 0.000000
2007 0.000000
2008 0.000000
2009 0.000000
```

Probability Threshold Exceeded at Least Once $=0.0000$

Example 2: The second example is a fishing mortality and landings quota projection for Gulf of Maine haddock with a PStar analysis in 2018. The time horizon is 2014-2020. The fishery is comprised of one fleet. This is PStar projection analysis with 1000 bootstraps and 10 simulations per bootstrap based on an ASAP stock assessment analysis. The model output shows that total allowable catch amounts in 2018 to produce probabilities of overfishing of $10 \%, 20 \%, 30 \%, 40 \%$ and $50 \%$ at the overfishing level of $F=0.35$. The total allowable catches to produce overfishing probabilities of $10 \%, 20 \%$, $30 \%, 40 \%$ and $50 \%$ are calculated to be $1780,1998,2176,2332$, and 2497 mt , respectively. The model output includes a stock summary of numbers at age and also outputs a percentile analysis for key outputs at the $90^{\text {th }}$ percentile.

Running example 2 (see Appendix for input file) produces the following output:
AGEPRO VERSION 4.2

GoM haddock ASAP_final (1977-2011 recruitment)
Date \& Time of Run: 29 Dec 2017 14:19

Number of Feasible Solutions: 10000 of 10000 Realizations


| 2018 | 2141.7581 | 2406.3266 |
| :--- | :--- | :--- |
| 2019 | 2156.4185 | 2450.1039 |
| 2020 | 2183.0481 | 2465.0965 |

Recruits Distribution
$\begin{array}{lllllllll}\text { Year Class } 1 \% & 5 \% & 10 \% & 25 \% & 50 \% & 75 \% & 90 \% & 95 \% & 99 \%\end{array}$
$2014150.1671205 .1791 \quad 227.5903 \quad 331.14521120 .8200 \quad 2542.19906162 .88106484 .111011028 .6100$ $2015 \quad 149.3512 \quad 204.6887 \quad 228.6934 \quad 334.46831120 .1820 \quad 2541.2640 \quad 6152.7080 \quad 6487.611011048 .1000$ 2016154.2960203 .8387225 .7294361 .41241129 .39052545 .18906212 .65206501 .735010886 .1000 $2017 \quad 152.0371 \quad 210.7372 \quad 232.7332 \quad 359.05381129 .9945 \quad 2544.15106190 .17106506 .016011309 .1700$ 2018 153.6666 204.7484227 .5898 349.5553 1122.89352544 .31306203 .13906499 .257011243 .7600 $2019 \quad 152.0957 \quad 209.2503 \quad 231.1399 \quad 342.58361125 .14452543 .90006212 .27906536 .652011337 .6800$ $2020150.5870206 .1237 \quad 230.0479360 .46501132 .44352544 .98906226 .10506535 .536011422 .0900$

Spawning Stock Biomass $\mathrm{x} \quad 1000$ MT

| Year | Average | StdDev |
| :---: | :---: | :---: |
| 2014 | 6.6153 | 1.5860 |
| 2015 | 11.0899 | 2.9220 |
| 2016 | 12.8636 | 3.4163 |
| 2017 | 12.6038 | 3.2662 |
| 2018 | 11.3916 | 3.0953 |
| 2019 | 9.7421 | 3.0356 |
| 2020 | 9.0292 | 2.7831 |

Spawning Stock Biomass Distribution

| Year | $1 \%$ | $5 \%$ | $10 \%$ | $25 \%$ | $50 \%$ | $75 \%$ | $90 \%$ | $95 \%$ |  |  |
| :--- | :--- | :--- | :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 2014 | 3.5200 | 4.3275 | 4.7137 | 5.4851 | 6.4722 | 7.5894 | 8.7222 | 9.4729 | 10.9446 |  |
| 2015 | 5.4666 | 6.9514 | 7.6632 | 8.9364 | 10.7412 | 12.9279 | 14.9858 | 16.4572 | 19.3031 |  |
| 2016 | 6.4490 | 8.0138 | 8.8712 | 10.3627 | 12.4238 | 15.0340 | 17.4631 | 19.0611 | 22.6196 |  |
| 2017 | 6.5380 | 7.9215 | 8.7276 | 10.2139 | 12.2223 | 14.6496 | 17.0540 | 18.4992 | 21.5570 |  |
| 2018 | 5.6092 | 6.9035 | 7.6665 | 9.1293 | 11.0387 | 13.3430 | 15.5845 | 16.9557 | 19.8974 |  |
| 2019 | 4.0236 | 5.3269 | 6.0556 | 7.5435 | 9.4281 | 11.6586 | 13.8259 | 15.2291 | 17.8403 |  |
| 2020 | 3.8158 | 4.9913 | 5.6425 | 6.9951 | 8.7759 | 10.8012 | 12.7350 | 14.0313 | 16.5065 |  |

JAN-1 Stock Biomass x 1000 MT

| Year | Average | StdDev |
| :--- | :--- | :--- |
| 2014 | 11.4167 | 2.9021 |
| 2015 | 13.9657 | 3.6246 |
| 2016 | 14.8968 | 3.8103 |
| 2017 | 14.6414 | 3.6817 |
| 2018 | 13.7025 | 3.4096 |
| 2019 | 11.6265 | 3.4733 |
| 2020 | 10.8758 | 3.2285 |

JAN-1 Stock Biomass Distribution


| Year | Average | StdDev |
| :--- | :--- | :--- |
| 2014 | 13.5594 | 3.5654 |
| 2015 | 15.0921 | 4.0054 |
| 2016 | 15.3716 | 3.9588 |
| 2017 | 14.6866 | 3.7276 |
| 2018 | 12.9499 | 3.5927 |
| 2019 | 11.4205 | 3.4391 |
| 2020 | 10.7213 | 3.2607 |

Mean Biomass Distribution

| Year | $1 \%$ | $5 \%$ | $10 \%$ | $25 \%$ | $50 \%$ | $75 \%$ | $90 \%$ | $95 \%$ | $99 \%$ |  |
| :--- | :--- | :--- | :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 2014 | 6.7743 | 8.5594 | 9.4054 | 10.9301 | 13.1275 | 15.7951 | 18.3751 | 20.0235 | 23.4287 |  |
| 2015 | 7.5738 | 9.4465 | 10.3652 | 12.1587 | 14.5926 | 17.5658 | 20.4590 | 22.3897 | 26.2371 |  |
| 2016 | 7.9903 | 9.7496 | 10.6488 | 12.4953 | 14.9115 | 17.8132 | 20.7241 | 22.5648 | 26.2661 |  |
| 2017 | 7.6799 | 9.2810 | 10.1779 | 11.9493 | 14.2831 | 17.0375 | 19.6923 | 21.2855 | 24.9087 |  |
| 2018 | 6.1034 | 7.6719 | 8.5812 | 10.3214 | 12.6155 | 15.2101 | 17.6818 | 19.3861 | 22.5858 |  |
| 2019 | 4.9062 | 6.3754 | 7.2373 | 8.9247 | 11.0836 | 13.6122 | 15.9977 | 17.5320 | 20.7117 |  |
| 2020 | 4.6255 | 5.9719 | 6.7819 | 8.3407 | 10.4020 | 12.7506 | 15.0877 | 16.4991 | 19.5794 |  |

Combined Catch Biomass x 1000 MT

| Year | Average | StdDev |
| :---: | :---: | :---: |
| 2014 | 0.5000 | 0.0000 |
| 2015 | 0.8803 | 0.2338 |
| 2016 | 1.1420 | 0.3043 |
| 2017 | 1.4560 | 0.3947 |
| 2018 | 2.4966 | 0.0000 |
| 2019 | 1.3033 | 0.4176 |
| 2020 | 1.2978 | 0.4060 |

Combined Catch Distribution

| Year | $1 \%$ | $5 \%$ | $10 \%$ | $25 \%$ | $50 \%$ | $75 \%$ | $90 \%$ |  |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| $95 \%$ |  | $99 \%$ |  |  |  |  |  |  |  |
| 2014 | 0.5000 | 0.5000 | 0.5000 | 0.5000 | 0.5000 | 0.5000 | 0.5000 | 0.5000 | 0.5000 |
| 2015 | 0.4340 | 0.5427 | 0.6046 | 0.7113 | 0.8555 | 1.0264 | 1.1884 | 1.3045 | 1.5357 |
| 2016 | 0.5651 | 0.7098 | 0.7834 | 0.9215 | 1.1052 | 1.3265 | 1.5480 | 1.6929 | 1.9909 |
| 2017 | 0.7298 | 0.9039 | 0.9911 | 1.1700 | 1.4071 | 1.6944 | 1.9823 | 2.1726 | 2.6016 |
| 2018 | 2.4966 | 2.4966 | 2.4966 | 2.4966 | 2.4966 | 2.4966 | 2.4966 | 2.4966 | 2.4966 |
| 2019 | 0.5368 | 0.7012 | 0.8076 | 0.9984 | 1.2549 | 1.5584 | 1.8669 | 2.0601 | 2.4484 |
| 2020 | 0.5392 | 0.7114 | 0.8088 | 1.0025 | 1.2569 | 1.5518 | 1.8438 | 2.0309 | 2.3896 |

Landings x 1000 MT

| Year | Average | StdDev |
| :---: | :---: | :---: |
| 2014 | 0.5000 | 0.0000 |
| 2015 | 0.8803 | 0.2338 |
| 2016 | 1.1420 | 0.3043 |
| 2017 | 1.4560 | 0.3947 |
| 2018 | 2.4966 | 0.0000 |
| 2019 | 1.3033 | 0.4176 |
| 2020 | 1.2978 | 0.4060 |

Landings Distribution

| Year | $1 \%$ | $5 \%$ | $10 \%$ | $25 \%$ | $50 \%$ | $75 \%$ | $90 \%$ |  |  | 9 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 2014 | 0.5000 | 0.5000 | 0.5000 | 0.5000 | 0.5000 | 0.5000 | 0.5000 | 0.5000 | 0.5000 |  |
| 2015 | 0.4340 | 0.5427 | 0.6046 | 0.7113 | 0.8555 | 1.0264 | 1.1884 | 1.3045 | 1.5357 |  |
| 2016 | 0.5651 | 0.7098 | 0.7834 | 0.9215 | 1.1052 | 1.3265 | 1.5480 | 1.6929 | 1.9909 |  |
| 2017 | 0.7298 | 0.9039 | 0.9911 | 1.1700 | 1.4071 | 1.6944 | 1.9823 | 2.1726 | 2.6016 |  |
| 2018 | 2.4966 | 2.4966 | 2.4966 | 2.4966 | 2.4966 | 2.4966 | 2.4966 | 2.4966 | 2.4966 |  |
| 2019 | 0.5368 | 0.7012 | 0.8076 | 0.9984 | 1.2549 | 1.5584 | 1.8669 | 2.0601 | 2.4484 |  |
| 2020 | 0.5392 | 0.7114 | 0.8088 | 1.0025 | 1.2569 | 1.5518 | 1.8438 | 2.0309 | 2.3896 |  |

Total Fishing Mortality

| Year | Average | StdDev |
| :---: | :---: | :---: |
| 2014 | 0.2105 | 0.0583 |
| 2015 | 0.2000 | 0.0000 |
| 2016 | 0.2000 | 0.0000 |
| 2017 | 0.2000 | 0.0000 |
| 2018 | 0.3687 | 0.1159 |
| 2019 | 0.2000 | 0.0000 |
| 2020 | 0.2000 | 0.0000 |

Total Fishing Mortality Distribution
Year $1 \% \quad 5 \% \quad 10 \% \quad 25 \% \quad 50 \% \quad 75 \% \quad 90 \% \quad 95 \% \quad 99 \%$ $\begin{array}{llllllllll}2014 & 0.1148 & 0.1340 & 0.1461 & 0.1696 & 0.2014 & 0.2412 & 0.2857 & 0.3139 & 0.3952\end{array}$

| 2015 | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 2016 | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 |
| 2017 | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 |
| 2018 | 0.1825 | 0.2189 | 0.2408 | 0.2860 | 0.3500 | 0.4296 | 0.5190 | 0.5799 | 0.7405 |
| 2019 | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 |
| 2020 | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 |

JAN-1 Stock Numbers at Age - 1000 Fish
2014
Age $1 \% \quad 5 \% \quad 10 \% \quad 25 \% \quad 50 \% \quad 75 \% \quad 90 \% \quad 95 \% \quad 99 \%$
$1 \quad 1095.74001126 .82001157 .67001199 .90001247 .39001293 .21001339 .05001360 .06001404 .8700$
5815.73007232 .07008377 .470010215 .800012906 .850016274 .700019489 .500022076 .300026764 .3000 $605.2860742 .5500 \quad 868.77901068 .18001346 .63001645 .24002021 .11002259 .37002788 .3600$
1901.02002180 .25002400 .84002791 .00003321 .58003853 .17004463 .83004836 .62005563 .4700 $\begin{array}{lllllllllll}176.1790 & 213.9540 & 241.0530 & 284.5670 & 342.7900 & 418.2160 & 477.3430 & 529.6300 & 634.5340\end{array}$ $\begin{array}{lllllllll}32.9855 & 41.5396 & 46.7232 & 56.6142 & 69.9137 & 88.1928 & 104.1120 & 118.6870 & 136.1660\end{array}$ $\begin{array}{lllllllll}12.9987 & 16.9683 & 19.9008 & 24.6551 & 31.1685 & 38.9058 & 47.6952 & 55.4722 & 66.0063\end{array}$ $\begin{array}{llllllllll}50.5496 & 64.3146 & 72.2744 & 89.3943 & 110.0280 & 133.9590 & 157.0870 & 170.5340 & 207.6260\end{array}$ $\begin{array}{lllllllllll}103.9710 & 159.1740 & 182.0530 & 225.6940 & 284.1005 & 356.5180 & 433.8950 & 482.1760 & 567.9220\end{array}$

2015
$\begin{array}{llllllllll}\text { Age } & 1 \% & 5 \% & 10 \% & 25 \% & 50 \% & 75 \% & 90 \% & 95 \% & 99 \%\end{array}$
$1 \begin{array}{lllllllllllllllll}1 & 150.1671 & 205.1791 & 227.5903 & 331.1452 & 1120.8200 & 2542.1990 & 6162.8810 & 6484.1110 & 11028.6100\end{array}$ 887.8562922 .5597942 .9964979 .34311019 .94001061 .28901100 .21701123 .07701160 .5660 4724.36705884 .96006798 .61908276 .997010469 .330013189 .730015985 .880018030 .010021786 .0300 $458.6349579 .8621 \quad 677.1247 \quad 832.97861056 .43551303 .77601602 .36101814 .0020 \quad 2236.2140$ $1388.88501636 .08701812 .6300 \quad 2132.5230 \quad 2555.2555 \quad 2996.30003495 .62303824 .34604417 .0360$ $\begin{array}{llllllllll}120.7904 & 150.2547 & 172.1194 & 206.6085 & 252.4803 & 312.3292 & 361.4383 & 400.4779 & 498.4812\end{array}$ $\begin{array}{lllllllll}21.3308 & 27.8132 & 31.8572 & 39.5234 & 50.0190 & 63.7509 & 76.3860 & 88.3243 & 102.9572\end{array}$ $\begin{array}{lllllllll}8.1611 & 11.0643 & 12.9375 & 16.8231 & 21.5830 & 27.4805 & 34.0739 & 39.6238 & 48.4185\end{array}$ $+\begin{array}{lllllllll}99.1900 & 142.4742 & 166.3174 & 212.3172 & 272.2853 & 345.9320 & 425.8746 & 468.2724 & 564.1196\end{array}$

2016

| Age | $1 \%$ | $5 \%$ | $10 \%$ | $25 \%$ | $50 \%$ | $75 \%$ | $90 \%$ | $95 \%$ | $99 \%$ |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 149.3512 | 204.6887 | 228.6934 | 334.4683 | 1120.1820 | 2541.2640 | 6152.7080 | 6487.6110 | 11048.1000 |
| 2 | 122.6079 | 167.5320 | 186.7238 | 270.6380 | 932.5010 | 2086.0260 | 5051.1580 | 5326.5060 | 9020.4290 |
| 3 | 710.6238 | 743.4937 | 762.5140 | 792.6984 | 826.6821 | 862.4630 | 895.3975 | 913.9427 | 949.1091 |
| 4 | 3699.5560 | 4632.8560 | 5342.0500 | 6523.0780 | 8265.4655 | 10393.9500 | 12573.6900 | 14252.8300 | 17146.8600 |
| 5 | 353.6407 | 447.9320 | 522.2761 | 642.1836 | 814.4617 | 1004.5240 | 1234.6130 | 1397.6710 | 1723.4520 |
| 6 | 1022.0040 | 1210.2630 | 1332.3580 | 1574.6600 | 1884.6520 | 2212.1540 | 2583.8580 | 2825.5160 | 3269.6370 |
| 7 | 85.6311 | 107.2060 | 122.3344 | 147.0802 | 180.6755 | 222.8392 | 258.5840 | 286.6373 | 358.1803 |
| 8 | 14.7620 | 19.2894 | 22.1592 | 27.4605 | 34.8072 | 44.3394 | 53.2656 | 61.4762 | 71.9711 |
| $9+$ | 76.3752 | 107.4038 | 125.3629 | 160.6426 | 205.1725 | 259.9684 | 318.5978 | 352.4900 | 422.2210 |

2017
Age $1 \% \quad 5 \% \quad 10 \% \quad 25 \% \quad 50 \% \quad 75 \% \quad 90 \% \quad 95 \% \quad 99 \%$ 154.2960203 .8387225 .7294361 .41241129 .39052545 .18906212 .65206501 .735010886 .1000 $\begin{array}{lllllllllllll}122.4453 & 166.9060 & 186.5583 & 273.5268 & 924.9599 & 2074.8450 & 5058.8330 & 5326.8450 & 9059.0880\end{array}$ $\begin{array}{lllllllllllll}98.6721 & 135.7598 & 151.5422 & 218.5243 & 758.2042 & 1695.3800 & 4090.3880 & 4320.9590 & 7276.3590\end{array}$ $\begin{array}{lllllllll}555.9447 & 583.0513 & 598.1129 & 623.8630 & 651.9622 & 681.2245 & 708.2104 & 724.4374 & 754.6333\end{array}$ 2851.89903580 .10504117 .68505024 .59306371 .60708004 .35909689 .658010972 .100013239 .3800 $261.0618 \quad 330.7912384 .8489473 .6005 \quad 600.6945 \quad 742.7213913 .83291037 .54101277 .2900$ $\begin{array}{llllllllllllllllllllllll}726.6373 & 861.8317 & 950.5333 & 1123.4050 & 1341.5895 & 1577.9470 & 1845.7470 & 2020.5990 & 2342.8860\end{array}$ $\begin{array}{llllllllll}59.3449 & 74.6039 & 85.0226 & 102.4041 & 125.6241 & 155.1049 & 180.6077 & 200.1796 & 252.7425\end{array}$ $\begin{array}{llllllllll}65.8990 & 89.2369 & 103.3606 & 131.8739 & 167.2694 & 209.3213 & 257.1538 & 283.2395 & 341.7310\end{array}$

2018
Age $1 \% \quad 5 \% \quad 10 \% \quad 25 \% \quad 50 \% \quad 75 \% \quad 90 \% \quad 95 \% \quad 99 \%$
$1 \quad 152.0371 \quad 210.7372 \quad 232.7332 \quad 359.05381129 .99452544 .15106190 .17106506 .016011309 .1700$ $\begin{array}{llllllllllllll}125.9985 & 167.1557 & 185.6035 & 295.5600 & 935.4454 & 2097.9120 & 5084.9840 & 5334.7680 & 8852.2650\end{array}$ $99.7584134 .7766152 .1943 \quad 222.3991751 .90131685 .25004105 .33004336 .85707370 .9580$ $\begin{array}{llllllllllll}78.4004 & 106.8737 & 119.8788 & 172.1859 & 597.7342 & 1338.5740 & 3226.9110 & 3417.3480 & 5798.7450\end{array}$ $\begin{array}{lllllllllll}424.1483 & 447.3210 & 459.3271 & 479.6160 & 502.7516 & 526.7769 & 548.9252 & 561.7752 & 586.3748\end{array}$ 2089.68002644 .40203036 .45503710 .96304707 .01405923 .21007170 .13808083 .27909706 .0750

```
7 187.2364 235.6444 273.3657}3037.6416 428.3732 530.8136 653.5985 742.1140 910.3953
502.6856 601.8133 660.8785 780.8261 935.3516 1100.4240}1284.5000 1409.9500 1644.4540
9+
2019
Age 1% 5% 10% 25% 50% 75% 90% 95% 99%
    153.6666 204.7484 227.5898 349.5553 1122.8935 2544.3130 6203.1390 6499.2570 11243.7600
    125.6385}171.2869 191.4572 293.4845 936.8988 2101.1120 5065.3120 5337.1690 9282.9010
    100.6454 133.9611 149.4112 239.4418 755.7065 1695.1120 4083.9320 4302.3260 7124.3410
    75.9471 101.6247 116.3168 169.1645
    56.9325 77.0244 87.8735 126.1823 438.8362 990.5278 2389.8910 2567.0220 4265.1580
    241.0660 274.4351 290.0872 315.9705 342.6452 368.9478
    1088.2510 1459.0940 1752.8150 2264.1170 3022.4015 3969.4200 4952.0780 5644.7680 6985.5020
    92.5160}1126.7009 153.4395 200.6431 262.7260 334.9452 427.0272 493.7872 614.5672
    249.7404 360.1757 416.3782 521.9749 661.7476 821.6150 987.4303 1108.2670 1319.1460
2020
Age \(1 \% \quad 5 \% \quad 10 \% \quad 25 \% \quad 50 \% \quad 75 \% \quad 90 \% \quad 95 \% \quad 99 \%\)
152.0957 209.2503 231.1399 342.5836 1125.1445 2543.9000 6212.2790 6536.6520 11337.6800
    125.4417 168.1045 186.3815 286.0352 934.1904 2103.3390 5072.6260 5335.4040 9113.0580
    101.2067 138.5952 155.5509 238.0804 764.2864 1702.1790 4113.1280 4342.2010 7582.7920
    79.8333 105.2166 118.2490 189.0875 597.1814 1343.2180}3222.5690 3401.1950 5652.6620
    58.6316
    41.8457 56.4963 64.9800 93.3839 324.2153 733.5625}17663.0560 1905.3330 3168.3210
    171.4524 195.2795 206.3613 224.8976 244.1048 263.1188 280.4399 289.7867 308.1276
    749.8229 1020.1310 1215.3620 1577.0540 2104.9460 2770.4520 3463.9650 3924.7230 4854.7490
    + 244.0270 346.8155 405.7743 507.1333 642.8957 794.1324 959.9258 1070.2010 1260.2230
```

Requested Percentile Report
Percentile $=90.00 \%$
$2014 \quad 2015 \quad 2016 \quad 2017 \quad 2018 \quad 2019 \quad 2020$

| Recruits | 6162.8810 | 6152.7080 | 6212.6520 | 6190.1710 | 6203.1390 | 6212.2790 | 6226.1050 |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Spawning Stock Biomass | 8.7222 | 14.9858 | 17.4631 | 17.0540 | 15.5845 | 13.8259 | 12.7350 |  |
| Jan-1 Stock Biomass | 15.2749 | 18.8028 | 20.0188 | 19.6778 | 18.2481 | 16.3219 | 15.2091 |  |
| Mean Biomass | 18.3751 | 20.4590 | 20.7241 | 19.6923 | 17.6818 | 15.9977 | 15.0877 |  |
| Combined Catch Biomass | 0.5000 | 1.1884 | 1.5480 | 1.9823 | 2.4966 | 1.8669 | 1.8438 |  |
| Landings | 0.5000 | 1.1884 | 1.5480 | 1.9823 | 2.4966 | 1.8669 | 1.8438 |  |
| FMort | 0.2857 | 0.2000 | 0.2000 | 0.2000 | 0.5190 | 0.2000 | 0.2000 |  |

Stock Numbers at Age
Age $1 \quad 1339.05006162 .88106152 .70806212 .65206190 .17106203 .13906212 .2790$
Age $2 \quad 19489.50001100 .21705051 .15805058 .83305084 .98405065 .31205072 .6260$
$\begin{array}{llllllllllll}\text { Age } 3 & 2021.1100 & 15985.8800 & 895.3975 & 4090.3880 & 4105.3300 & 4083.9320 & 4113.1280\end{array}$
Age $4 \quad 4463.83001602 .361012573 .6900 \quad 708.21043226 .91103151 .60903222 .5690$
$\begin{array}{llllllllllllll}\text { Age } 5 & 477.3430 & 3495.6230 & 1234.6130 & 9689.6580 & 548.9252 & 2389.8910 & 2427.3970\end{array}$
$\begin{array}{llllllllll}\text { Age } 6 & 104.1120 & 361.4383 & 2583.8580 & 913.8329 & 7170.1380 & 392.5774 & 1763.0560\end{array}$
$\begin{array}{llllllllll}\text { Age } 7 & 47.6952 & 76.3860 & 258.5840 & 1845.7470 & 653.5985 & 4952.0780 & 280.4399\end{array}$
$\begin{array}{lllllllllll}\text { Age } 8 & 157.0870 & 34.0739 & 53.2656 & 180.6077 & 1284.5000 & 427.0272 & 3463.9650\end{array}$
$\begin{array}{llllllllll}\text { Age } 9 & 433.8950 & 425.8746 & 318.5978 & 257.1538 & 296.8760 & 987.4303 & 959.9258\end{array}$
PStar Summary Report
Overfishing F $=0.3500$ Target Year $=2018$

| PStar | TAC |
| :--- | :--- |
|  |  |
| 0.1000 | 1780 |
| 0.2000 | 1998 |
| 0.3000 | 2176 |
| 0.4000 | 2332 |
| 0.5000 | 2497 |

Example 3: The third example is a fishing mortality and landings quota projection for Gulf of Maine haddock with a rebuilding analysis for 2014-2020. The fishery is comprised of one fleet with process error in fishery selectivity. This is rebuilding projection with 1000 bootstraps and 10 simulations per bootstrap based on an ASAP stock assessment analysis. The model output shows the constant fishing mortality to rebuild the stock is $F_{\text {REBuILD }}=0.045$. The model output includes a stock summary of numbers at age and also outputs a percentile analysis for key outputs at the $90^{\text {th }}$ percentile.

Running example 3 (see Appendix for input file) produces the following output:


Spawning Stock Biomass x 1000 MT

| Year | Average | StdDev |
| :---: | :---: | :---: |
| 2014 | 6.6170 | 1.5864 |
| 2015 | 11.2472 | 2.9734 |
| 2016 | 13.6893 | 3.6225 |
| 2017 | 14.2545 | 3.6743 |
| 2018 | 14.2000 | 3.5843 |
| 2019 | 13.8474 | 3.4929 |
| 2020 | 13.5056 | 3.3958 |

Spawning Stock Biomass Distribution

| Year | 1\% | 5\% | 10\% | 25\% | 50\% | 75\% 9 | 90\% 95 | 95\% 99\% |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 2014 | 3.5078 | 4.3130 | 4.7139 | 5.4741 | 6.4677 | 7.5996 | 8.7246 | 9.50791 | 10.8959 |
| 2015 | 5.5792 | 7.0419 | 7.7295 | 9.0558 | 10.8637 | 13.1038 | 15.2164 | 16.6561 | 19.6792 |
| 2016 | 6.8389 | 8.5537 | 9.4430 | 11.0420 | 13.2202 | 15.9565 | 18.5612 | 220.2245 | 23.9665 |
| 2017 | 7.3671 | 8.9936 | 9.9199 | 11.6008 | 13.8159 | 16.5604 | 19.2488 | 20.9204 | 24.5266 |
| 2018 | 7.4340 | 9.0080 | 9.8747 | 11.5974 | 13.8368 | 16.4445 | 18.9478 | 820.6655 | 24.1175 |
| 2019 | 7.2135 | 8.7442 | 9.6034 | 11.3116 | 13.5319 | 16.0556 | 18.4609 | 20.0106 | 23.2609 |
| 2020 | 7.1247 | 8.5118 | 9.3369 | 11.0000 | 13.2158 | 15.6735 | 18.0730 | 19.5799 | 22.4662 |
| JAN- | tock Bi | nass x | 1000 M |  |  |  |  |  |  |


| Year | Average | StdDev |
| :--- | :--- | :--- |
| 2014 | 11.4174 | 2.8996 |
| 2015 | 13.9853 | 3.6385 |
| 2016 | 15.5776 | 3.9671 |
| 2017 | 16.1162 | 4.0252 |
| 2018 | 16.0743 | 3.9486 |
| 2019 | 15.7028 | 3.8651 |
| 2020 | 15.3638 | 3.7809 |

JAN-1 Stock Biomass Distribution

| Year | $1 \%$ | $5 \%$ | $10 \%$ | $25 \%$ | $50 \%$ | $75 \%$ | $90 \%$ | $95 \%$ | $99 \%$ |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 2014 | 5.9561 | 7.3305 | 8.0160 | 9.3127 | 11.0570 | 13.2145 | 15.2783 | 16.6890 | 19.4895 |  |
| 2015 | 7.0768 | 8.8151 | 9.7325 | 11.3215 | 13.5287 | 16.2558 | 18.8747 | 20.6014 | 24.4138 |  |
| 2016 | 8.1564 | 9.8810 | 10.8909 | 12.7070 | 15.0950 | 18.1127 | 20.8555 | 22.7520 | 26.5054 |  |
| 2017 | 8.5564 | 10.2829 | 11.2717 | 13.1921 | 15.6896 | 18.6290 | 21.5091 | 23.3583 | 27.0562 |  |
| 2018 | 8.5860 | 10.3039 | 11.2642 | 13.1568 | 15.7288 | 18.5593 | 21.3129 | 23.1065 | 26.8372 |  |
| 2019 | 8.3366 | 10.0510 | 10.9747 | 12.8914 | 15.3734 | 18.1349 | 20.8302 | 22.5606 | 26.1722 |  |
| 2020 | 8.1237 | 9.7586 | 10.7283 | 12.5950 | 15.0481 | 17.7564 | 20.3938 | 22.0870 | 25.1322 |  |

Mean Biomass x 1000 MT

| Year | Average | StdDev |
| :--- | :--- | :--- |
| 2014 | 13.5499 | 3.5542 |
| 2015 | 15.4331 | 4.0737 |
| 2016 | 16.4904 | 4.2029 |
| 2017 | 16.6939 | 4.1849 |
| 2018 | 16.3128 | 4.0289 |
| 2019 | 15.7412 | 3.9122 |
| 2020 | 15.4252 | 3.8993 |

Mean Biomass Distribution

| Year | $1 \%$ | $5 \%$ | $10 \%$ | $25 \%$ | $50 \%$ | $75 \%$ | $90 \%$ | $95 \%$ | $99 \%$ |  |
| :--- | :--- | :--- | :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 2014 | 6.8296 | 8.5113 | 9.3948 | 10.9509 | 13.0968 | 15.7592 | 18.2887 | 20.0230 | 23.4237 |  |
| 2015 | 7.8519 | 9.6342 | 10.6250 | 12.5018 | 14.9013 | 17.9378 | 20.8969 | 22.8972 | 27.2031 |  |
| 2016 | 8.6093 | 10.4184 | 11.4735 | 13.4336 | 16.0525 | 19.1332 | 22.1543 | 24.0733 | 28.1761 |  |
| 2017 | 8.7683 | 10.6194 | 11.6720 | 13.6335 | 16.2788 | 19.3000 | 22.2328 | 24.2065 | 28.2042 |  |
| 2018 | 8.6469 | 10.3838 | 11.3612 | 13.3676 | 15.9913 | 18.8559 | 21.6646 | 23.4338 | 27.1640 |  |
| 2019 | 8.3179 | 9.9544 | 10.9414 | 12.8538 | 15.4182 | 18.2748 | 20.9306 | 22.6906 | 26.1512 |  |
| 2020 | 7.9700 | 9.6937 | 10.6649 | 12.5609 | 15.0972 | 17.9037 | 20.6399 | 22.3327 | 25.8592 |  |

Combined Catch Biomass x 1000 MT
Year Average StdDev

| 2014 | 0.5000 | 0.0000 |
| :--- | :--- | :--- |
| 2015 | 0.2016 | 0.0350 |
| 2016 | 0.2789 | 0.0737 |
| 2017 | 0.3796 | 0.1018 |
| 2018 | 0.4419 | 0.1161 |
| 2019 | 0.4422 | 0.1156 |
| 2020 | 0.4748 | 0.1232 |

Combined Catch Distribution

| Year | $1 \%$ | $5 \%$ | $10 \%$ | $25 \%$ | $50 \%$ | $75 \%$ | $90 \%$ | 95 | $95 \%$ |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 2014 | 0.5000 | 0.5000 | 0.5000 | 0.5000 | 0.5000 | 0.5000 | 0.5000 | 0.5000 | 0.5000 |
| 2015 | 0.1003 | 0.1249 | 0.1392 | 0.1633 | 0.1963 | 0.2339 | 0.2728 | 0.2977 | 0.3469 |
| 2016 | 0.1394 | 0.1741 | 0.1925 | 0.2250 | 0.2708 | 0.3237 | 0.3775 | 0.4135 | 0.4824 |
| 2017 | 0.1914 | 0.2364 | 0.2608 | 0.3046 | 0.3669 | 0.4417 | 0.5168 | 0.5646 | 0.6686 |
| 2018 | 0.2283 | 0.2769 | 0.3047 | 0.3575 | 0.4290 | 0.5124 | 0.5971 | 0.6567 | 0.7565 |
| 2019 | 0.2287 | 0.2767 | 0.3051 | 0.3569 | 0.4295 | 0.5137 | 0.5978 | 0.6517 | 0.7612 |
| 2020 | 0.2444 | 0.2973 | 0.3263 | 0.3852 | 0.4629 | 0.5511 | 0.6407 | 0.6968 | 0.8046 |
|  |  |  |  |  |  |  |  |  |  |


| Year | Average | StdDev |
| :---: | :---: | :---: |
| 2014 | 0.5000 | 0.0000 |
| 2015 | 0.2016 | 0.0530 |
| 2016 | 0.2789 | 0.0737 |
| 2017 | 0.3796 | 0.1018 |
| 2018 | 0.4419 | 0.1161 |
| 2019 | 0.4422 | 0.1156 |
| 2020 | 0.4748 | 0.1232 |

Landings Distribution

| Year | $1 \%$ | $5 \%$ | $10 \%$ | $25 \%$ | $50 \%$ | $75 \%$ | $90 \%$ |  |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| $25 \%$ | $95 \%$ | $99 \%$ |  |  |  |  |  |  |  |
| 2014 | 0.5000 | 0.5000 | 0.5000 | 0.5000 | 0.5000 | 0.5000 | 0.5000 | 0.5000 | 0.5000 |
| 2015 | 0.1003 | 0.1249 | 0.1392 | 0.1633 | 0.1963 | 0.2339 | 0.2728 | 0.2977 | 0.3469 |
| 2016 | 0.1394 | 0.1741 | 0.1925 | 0.2250 | 0.2708 | 0.3237 | 0.3775 | 0.4135 | 0.4824 |
| 2017 | 0.1914 | 0.2364 | 0.2608 | 0.3046 | 0.3669 | 0.4417 | 0.5168 | 0.5646 | 0.6686 |
| 2018 | 0.2283 | 0.2769 | 0.3047 | 0.3575 | 0.4290 | 0.5124 | 0.5971 | 0.6567 | 0.7565 |
| 2019 | 0.2287 | 0.2767 | 0.3051 | 0.3569 | 0.4295 | 0.5137 | 0.5978 | 0.6517 | 0.7612 |
| 2020 | 0.2444 | 0.2973 | 0.3263 | 0.3852 | 0.4629 | 0.5511 | 0.6407 | 0.6968 | 0.8046 |

Total Fishing Mortality

| Year | Average | StdDev |
| :---: | :---: | :---: |
| 2014 | 0.2102 | 0.0578 |
| 2015 | 0.0445 | 0.0000 |
| 2016 | 0.0445 | 0.0000 |
| 2017 | 0.0445 | 0.0000 |
| 2018 | 0.0445 | 0.0000 |
| 2019 | 0.0445 | 0.0000 |
| 2020 | 0.0445 | 0.0000 |

Total Fishing Mortality Distribution

| Year | $1 \%$ | $5 \%$ | $10 \%$ | $25 \%$ | $50 \%$ | $75 \%$ | $90 \%$ | $95 \%$ | $99 \%$ |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 2014 | 0.1162 | 0.1334 | 0.1462 | 0.1696 | 0.2015 | 0.2408 | 0.2839 | 0.3145 | 0.3851 |
| 2015 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 |
| 2016 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 |
| 2017 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 |
| 2018 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 |
| 2019 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 |
| 2020 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 | 0.0445 |
|  |  |  |  |  |  |  |  |  |  |

## 2014

Age $1 \% \quad 5 \% \quad 10 \% \quad 25 \% \quad 50 \% \quad 75 \% \quad 90 \% \quad 95 \% \quad 99 \%$
$1 \quad 1095.74001126 .82001157 .67001199 .90001247 .39001293 .21001339 .05001360 .06001404 .8700$
$2 \quad 5815.73007232 .07008377 .470010215 .800012906 .850016274 .700019489 .500022076 .300026764 .3000$
$\begin{array}{llllllllll}176.1790 & 213.9540 & 241.0530 & 284.5670 & 342.7900 & 418.2160 & 477.3430 & 529.6300 & 634.5340\end{array}$
$\begin{array}{llllllllll}32.9855 & 41.5396 & 46.7232 & 56.6142 & 69.9137 & 88.1928 & 104.1120 & 118.6870 & 136.1660\end{array}$
$\begin{array}{llllllllll}12.9987 & 16.9683 & 19.9008 & 24.6551 & 31.1685 & 38.9058 & 47.6952 & 55.4722 & 66.0063\end{array}$
$\begin{array}{llllllllll}50.5496 & 64.3146 & 72.2744 & 89.3943 & 110.0280 & 133.9590 & 157.0870 & 170.5340 & 207.6260\end{array}$
$\begin{array}{llllllllll}103.9710 & 159.1740 & 182.0530 & 225.6940 & 284.1005 & 356.5180 & 433.8950 & 482.1760 & 567.9220\end{array}$
2015
Age $1 \% \quad 5 \% \quad 10 \% \quad 25 \% \quad 50 \% \quad 75 \% \quad 90 \% \quad 95 \% \quad 99 \%$
153.7521208 .0085229 .3621347 .06161132 .09552545 .34706225 .63206522 .298011133 .4100
$\begin{array}{lllllllllll}886.9999 & 920.9055 & 944.3435 & 979.9522 & 1020.1620 & 1060.7430 & 1100.8560 & 1122.0680 & 1162.0630\end{array}$
4740.63505881 .51806788 .08908280 .253010437 .900013190 .600015924 .290017940 .130021772 .2100
$\begin{array}{llllllllll}462.1501 & 579.5480 & 678.5247 & 836.1118 & 1057.6295 & 1300.8420 & 1601.9910 & 1805.4510 & 2228.2810\end{array}$
1402.68701632 .07301811 .38602130 .75702557 .11403001 .14903490 .78503797 .37504431 .1560
$\begin{array}{lllllllll}121.0333 & 150.3102 & 172.2205 & 206.2701 & 252.2545 & 312.3252 & 361.8990 & 399.4688 & 500.4583\end{array}$
$\begin{array}{lllllllll}21.2549 & 27.8869 & 31.7288 & 39.5810 & 50.0350 & 63.4947 & 76.4838 & 88.1371 & 102.7191\end{array}$
$\begin{array}{lllllllll}8.1178 & 11.0340 & 12.9066 & 16.8518 & 21.5642 & 27.4360 & 34.0090 & 39.6686 & 48.5591\end{array}$
$\begin{array}{lllllllll}99.6480 & 143.0746 & 165.8811 & 212.3056 & 272.7287 & 345.4891 & 426.8521 & 469.6036 & 565.7290\end{array}$

2016
Age $1 \% \quad 5 \% \quad 10 \% \quad 25 \% \quad 50 \% \quad 75 \% \quad 90 \% \quad 95 \% \quad 99 \%$
$\begin{array}{lllllllllllll}152.8537 & 207.5118 & 228.9794 & 352.4027 & 1126.1215 & 2542.6540 & 6181.5870 & 6500.1300 & 11200.0900\end{array}$ $\begin{array}{llllllllllll}125.6120 & 169.9832 & 187.3362 & 285.8009 & 935.7087 & 2106.8640 & 5088.4640 & 5358.8910 & 9065.7230\end{array}$ $\begin{array}{llllllllll}717.8408 & 749.2020 & 767.2159 & 798.8983 & 833.9748 & 868.6385 & 901.6998 & 920.6849 & 957.7862\end{array}$ 3849.55804772 .20305517 .53506713 .56708486 .435010724 .060012954 .930014583 .390017684 .0800 368.8452470 .1688546 .3981674 .9982854 .92531053 .69401296 .10801465 .79401812 .3090
1112.43401304 .31601447 .64101703 .72002044 .26002402 .50002796 .62803037 .71403551 .5220
$\begin{array}{llllllllllll}95.8425 & 119.3594 & 136.5312 & 163.6895 & 200.5233 & 247.8007 & 287.8207 & 317.0682 & 397.7311\end{array}$ $\begin{array}{lllllllll}16.6931 & 22.0278 & 25.0771 & 31.2594 & 39.5369 & 50.2574 & 60.4657 & 69.4576 & 81.1850\end{array}$ $\begin{array}{llllllllll}87.9257 & 122.3541 & 142.6734 & 181.7372 & 232.7070 & 294.7329 & 361.5172 & 399.8996 & 479.7186\end{array}$
Age $1 \% \quad 5 \% \quad 10 \% \quad 25 \% \quad 50 \% \quad 75 \% \quad 90 \% \quad 95 \% \quad 99 \%$ $\begin{array}{llllllllllll}152.0864 & 205.9702 & 227.0639 & 334.5421 & 1120.9140 & 2544.0470 & 6196.3710 & 6505.2510 & 10864.6400\end{array}$ $\begin{array}{llllllllllllll}124.9328 & 169.5370 & 187.5875 & 289.2126 & 936.7591 & 2082.4200 & 5059.7310 & 5330.1260 & 9139.4520\end{array}$ $\begin{array}{lllllllllllllllll}102.7604 & 138.0878 & 153.3027 & 233.9465 & 767.8980 & 1732.9510 & 4159.4080 & 4386.5270 & 7358.2990\end{array}$ $\begin{array}{lllllllll}578.2827 & 604.7967 & 621.0119 & 646.7345 & 676.8689 & 707.3514 & 734.5654 & 751.9041 & 781.6806\end{array}$ 3091.67503845 .17004440 .20805421 .13206866 .77008644 .612010492 .010011781 .010014283 .2900 $\begin{array}{llllllllll}296.0683 & 374.3265 & 437.9340 & 540.8164 & 682.1429 & 842.5300 & 1037.5380 & 1173.8450 & 1454.1730\end{array}$ 879.95751036 .52601146 .00001352 .41001621 .88851915 .97802223 .34202419 .69702822 .7990 $\begin{array}{lllllllll}75.7144 & 94.2965 & 107.6556 & 129.2856 & 158.5479 & 195.8338 & 227.5058 & 250.5553 & 316.8310\end{array}$ $\begin{array}{llllllllll}86.1764 & 115.7229 & 134.3767 & 170.3536 & 216.4243 & 270.1949 & 329.6626 & 363.0636 & 442.1880\end{array}$

2018
$\begin{array}{lllllllll}\text { Age } & 1 \% & 5 \% & 10 \% & 25 \% & 50 \% & 75 \% & 90 \% & 95 \%\end{array}$
$\begin{array}{lllllllllllll}153.9306 & 204.6065 & 223.9934 & 335.6253 & 1120.2075 & 2541.6660 & 6154.7360 & 6491.9800 & 10947.3800\end{array}$ $124.3599168 .1019186 .5384274 .1155 \quad 933.74312097 .51505068 .91505351 .93008980 .8960$ $\begin{array}{lllllllllll}102.6584 & 138.0619 & 153.2109 & 234.4648 & 768.2888 & 1705.2570 & 4137.6920 & 4376.4240 & 7491.3740\end{array}$ $\begin{array}{lllllllllll}83.0630 & 111.7923 & 125.1747 & 190.0386 & 624.9189 & 1406.8860 & 3375.8670 & 3580.8130 & 5996.0150\end{array}$ $\begin{array}{llllllllll}463.1497 & 486.4656 & 499.5535 & 521.4975 & 546.8899 & 572.8059 & 596.2554 & 610.6294 & 636.2804\end{array}$ 2458.21103074 .00403543 .97204341 .75105493 .74806912 .79108409 .31409431 .287011449 .5100 $232.8949297 .6859348 .1032429 .2734541 .3385 \quad 669.5108 \quad 824.7090 \quad 932.74571149 .7860$ $\begin{array}{lllllllllllllllllllll}693.9673 & 815.9270 & 903.8471 & 1069.8840 & 1279.5850 & 1510.4820 & 1752.6630 & 1913.4760 & 2242.3930\end{array}$ $\begin{array}{llllllllll}131.7504 & 172.7009 & 195.3063 & 239.6761 & 298.3704 & 363.7684 & 430.1583 & 479.6413 & 576.7128\end{array}$

2019
$\begin{array}{llllllllll}\text { Age } & 1 \% & 5 \% & 10 \% & 25 \% & 50 \% & 75 \% & 90 \% & 95 \% & 99 \%\end{array}$
$1 \begin{array}{llllllllllllll}1 & 151.7663 & 206.4086 & 227.8564 & 353.3611 & 1136.3925 & 2544.5000 & 6227.9310 & 6534.0640 & 11412.9500\end{array}$ $126.1664166 .8946184 .0337 \quad 273.6497926 .28802074 .87405060 .77005321 .24409009 .6770$ $101.1790 \quad 137.3052 \quad 152.7485 \quad 223.9679 \quad 764.13671718 .87104145 .21704387 .62307300 .6000$ $83.1064111 .7158 \quad 124.8275190 .8343 \quad 624.49401389 .56403365 .45103567 .18506061 .0810$ $\begin{array}{lllllllllll}67.4937 & 90.0772 & 101.2675 & 154.1486 & 505.3076 & 1142.8570 & 2726.6630 & 2894.6220 & 4833.3090\end{array}$ $367.9427 \quad 387.4575 \quad 398.0623416 .4294 \quad 437.2194459 .0043478 .4960491 .2420 \quad 512.2461$ $1965.46402431 .67802821 .03703445 .31304364 .2560 \quad 5494.9360 \quad 6693.26507529 .1950 \quad 9091.8490$

```
8
9+ 645.5298 785.3057 869.6136 1034.7050 1242.1625 1464.2670 1703.0170 1862.6330 2167.4780
2020
\begin{tabular}{lcccccccccc} 
Age & \(1 \%\) & \(5 \%\) & \(10 \%\) & \(25 \%\) & \(50 \%\) & \(75 \%\) & \(90 \%\) & \(95 \%\) & \(99 \%\) \\
1 & 150.6260 & 205.4969 & 229.0507 & 342.5477 & 1120.8380 & 2543.5260 & 6205.1600 & 6521.0480 & 11515.9200 \\
2 & 123.8571 & 167.9808 & 187.1525 & 289.8989 & 937.2894 & 2106.1880 & 5097.7430 & 5374.9480 & 9313.5090 \\
3 & 102.3573 & 135.9500 & 150.7452 & 222.9596 & 759.5409 & 1692.0840 & 4135.9360 & 4364.2630 & 7376.7490 \\
4 & 81.7678 & 111.0348 & 123.6390 & 182.1238 & 620.7917 & 1400.0710 & 3356.1290 & 3576.1200 & 5956.0300 \\
5 & 67.0329 & 89.8906 & 100.9146 & 154.5096 & 504.2604 & 1124.6640 & 2720.8110 & 2890.6500 & 4865.1570 \\
6 & 54.1054 & 71.9035 & 81.1756 & 123.2250 & 405.4597 & 915.6747 & 2177.4730 & 2329.5830 & 3886.8050 \\
7 & 290.4778 & 305.5871 & 315.3789 & 330.0894 & 347.1659 & 365.1161 & 381.6304 & 391.7124 & 410.2046 \\
8 & 1534.5130 & 1921.6320 & 2227.5890 & 2721.7010 & 3447.9955 & 4331.5540 & 5284.6800 & 5929.2270 & 7222.0580 \\
\(9+\) & 695.9149 & 838.0460 & 934.9111 & 1101.1280 & 1328.9345 & 1555.9650 & 1818.6410 & 1978.0690 & 2310.0400
\end{tabular}
```

Requested Percentile Report
Percentile $=90.00 \%$
$\begin{array}{lllllll}2014 & 2015 & 2016 & 2017 & 2018 & 2019 & 2020\end{array}$


Stock Numbers at Age
Age $1 \quad 1339.05006225 .63206181 .58706196 .37106154 .73606227 .93106205 .1600$
$\begin{array}{lllllllllll}\text { Age } 2 & 19489.5000 & 1100.8560 & 5088.4640 & 5059.7310 & 5068.9150 & 5060.7700 & 5097.7430\end{array}$
$\begin{array}{lllllllllllll}\text { Age } 3 & 2021.1100 & 15924.2900 & 901.6998 & 4159.4080 & 4137.6920 & 4145.2170 & 4135.9360\end{array}$
$\begin{array}{llllllllllll}\text { Age } 4 & 4463.8300 & 1601.9910 & 12954.9300 & 734.5654 & 3375.8670 & 3365.4510 & 3356.1290\end{array}$
$\begin{array}{llllllllllll}\text { Age } 5 & 477.3430 & 3490.7850 & 1296.1080 & 10492.0100 & 596.2554 & 2726.6630 & 2720.8110\end{array}$
$\begin{array}{llllllllll}\text { Age } 6 & 104.1120 & 361.8990 & 2796.6280 & 1037.5380 & 8409.3140 & 478.4960 & 2177.4730\end{array}$
$\begin{array}{lllllllll}\text { Age } 7 & 47.6952 & 76.4838 & 287.8207 & 2223.3420 & 824.7090 & 6693.2650 & 381.6304\end{array}$
$\begin{array}{llllllll}\text { Age } 8 & 157.0870 & 34.0090 & 60.4657 & 227.5058 & 1752.6630 & 651.1502 & 5284.6800\end{array}$
$\begin{array}{llllllllll}\text { Age } 9 & 433.8950 & 426.8521 & 361.5172 & 329.6626 & 430.1583 & 1703.0170 & 1818.6410\end{array}$

## Acknowledgments

Special thanks to Paul Rago and Chris Legault for their help in developing this modeling framework and software. Thanks also to Eric Fletcher for programming the graphical user interface, Alan Seaver for rewriting the AGEPRO module in the C language, and Laura Shulman for Fortran support.

## References

Beverton, R.J.H., and Holt, S.J. 1957. On the dynamics of exploited fish populations. Chapman and Hall, London. Fascimile reprint, 1993.

Brodziak, J. and P. Rago. Manuscript 1994. A general approach for short-term stochastic projections in age-structured fisheries assessment models. Methods working group, Population dynamics branch. Northeast Fisheries Science Center. Woods Hole, Massachusetts, 02543.

Brodziak, J., P. Rago, and R. Conser. 1998. A general approach for making short-term stochastic projections from an age-structured fisheries assessment model. In F. Funk, T. Quinn II, J. Heifetz, J. Ianelli, J. Powers, J. Schweigert, P. Sullivan, and C.-I. Zhang (Eds.), Proceedings of the International Symposium on Fishery Stock Assessment Models for the 21st Century. Alaska Sea Grant College Program, Univ. of Alaska, Fairbanks.

Brodziak, J., Traver, M., Col, L., and Sutherland, S. 2006. Stock assessment of Georges Bank haddock, 1931-2004. NEFSC Ref. Doc. 06-11. Available at: http://www.nefsc.noaa.gov/nefsc/publications/crd/crd0611/

Mayo, R.K. and Terceiro, M., editors. 2005. Assessment of 19 Northeast groundfish stocks through 2004. 2005 Groundfish Assessment Review Meeting (2005 GARM), Northeast Fisheries Science Center, Woods Hole, Massachusetts, 15-19 August 2005. U.S. Dep. Commer., Northeast Fish. Sci. Cent. Ref. Doc. 05-13, 499 p.

Mohn, R. 1999. The retrospective problem in sequential population analysis: An investigation using cod fishery and simulated data. ICES J. Mar. Sci. 56,473-488.

New England Fishery Management Council [NEFMC]. 1994. Amendment 5 to the Northeast Multispecies Fishery Management Plan. NEFMC, Newburyport, MA.

NEFMC. 1996. Amendment 7 to the Northeast Multispecies Fishery Management Plan. NEFMC, Newburyport, MA.

Northeast Fisheries Science Center [NEFSC]. 1994. Report of the 18th Northeast Regional Stock Assessment Workshop: Stock Assessment Review Committee Consensus Summary of Assessments. NEFSC Ref. Doc. 94-22, Woods Hole, MA 02543, 199 p.

NEFSC. 2002. Final Report of the Working Group on Re Evaluation of Biological Reference Points for New England Groundfish. NEFSC Ref. Doc. 02 04, p. 254. Available at: http://www.nefsc.noaa.gov/nefsc/publications/crd/crd0204/

NEFSC. 2008a. Assessment of 19 Northeast Groundfish Stocks through 2007: Report of the 3rd Groundfish Assessment Review Meeting (GARM III), Northeast Fisheries

Science Center, Woods Hole, Massachusetts, August 4-8, 2008. US Dep Commer, NOAA Fisheries, Northeast Fish Sci Cent Ref Doc. 08-15; 884 p + xvii.

NEFSC. 2008b. Appendix to the Report of the 3rd Groundfish Assessment Review Meeting (GARM III): Assessment of 19 Northeast Groundfish Stocks through 2007, Northeast Fisheries Science Center, Woods Hole, Massachusetts, August 48, 2008. US Dep Commer, NOAA Fisheries, Northeast Fish Sci Cent Ref Doc. 08-16; 1056 p.

Quinn, T.J., II, and R. B. Deriso. 1999. Quantitative fish dynamics. Oxford University Press, New York, 542 p.

Ricker, W.E. 1954. Stock and recruitment. J. Fish. Res. Board. Can. 11:559-623.
Shepherd, J.G. 1982. A versatile new stock-recruitment relationship for fisheries and the construction of sustainable yield curves. J. Cons. Int. Explor. Mer 40:67-75.

Table 1. Glossary of variables in the AGEPRO module.

| Variable | Description |
| :---: | :---: |
| A | Age of plus-group (fish age-A and older) and last index value for $\underline{N}$ |
| $B_{S}(t)$ | Spawning biomass in year $t$ |
| $\bar{B}(t)$ | Mean stock biomass in year $t$ |
| $B_{T}(t)$ | Total stock biomass on January $1^{\text {st }}$ of year $t$ |
| B | Number of input initial population vectors $\underline{N}(t)$ |
| $C_{a}(t)$ | Total catch number of age-a fish that are caught in year $t$ |
| $C_{v, a}(t)$ | Number of age- $a$ fish caught by fleet $v$ in year $t$ |
| $D(t)$ | Total weight of fish discarded fish in year $t$ |
| $F(t)$ | Instantaneous fully-selected fishing mortality rate in year $t$ |
| $F_{a}(t)$ | Total fishing mortality rate for age- $a$ fish in year $t$ |
| $F_{v, a}(t)$ | Fishing mortality rate on age-a fish by fleet $v$ in year $t$ |
| $F_{B}(t)$ | Instantaneous fishing mortality weighted by mean biomass in year $t$ |
| $I(t)$ | Harvest index for year $t$. <br> If the harvest index has value $I(t)=1$, then fishery harvest is based on a specified landings quota $Q(t)$ <br> Else if $I(t)=0$, then fishery harvest is based on a fishing mortality rate $F(t)$ |
| $L(t)$ | Total weight of fish landed in year $t$ |
| $M_{a}(t)$ | Instantaneous natural mortality rate of age-a fish in year $t$ |
| $N_{a}(t)$ | Number of age-a fish alive on January $1^{\text {st }}$ of year $t$ |
| $N_{M}$ | Number of recruitment models used in the projection |
| $P_{v, D, a}(t)$ | Proportion of age- $a$ fish caught and discarded in year $t$ |
| $S_{v, a}(t)$ | Fishery selectivity for age- $a$ fish by fleet $v$ in year $t$ |
| $P_{R, i}(t)$ | Probability that the $i^{\text {th }}$ recruitment model is applied in year $t$ |
| $P_{\text {mature,a }}(t)$ | Proportion of age-a fish that are sexually mature in year $t$ |
| $Z_{\text {Frac }}(t)$ | Proportion of total mortality occurring prior to spawning in year $t$ |
| $Q_{v}(t)$ | Landings quota for fleet $v$ in year $t$ |
| $R(t)$ | Recruitment (number of age-1 fish on January $1^{\text {st }}$ ) in year $t$ |
| $W_{P, a}(t)$ | Average population weight of an age-a fish on January $1^{\text {st }}$ in year $t$ |

Table 1. Glossary, continued.
Variable Description
$W_{v, L, a}(t) \quad$ Average landed (catch) weight of an age-a fish by fleet $v$ in year $t$
$W_{\text {S.a }}(t) \quad$ Average spawning weight of an age-a fish in year $t$
$W_{\text {midyear }, a}(t) \quad$ Average mid-year, or mean population weight of an age-a fish in year $t$
$W_{v, D, a}(t) \quad$ Average weight of an age- $a$ fish discarded by fleet $v$ in year $t$
$Y \quad$ Number of years in projection time horizon where $t=1,2, \ldots, Y$

Table 2. Table of AGEPRO input keywords.

| KEYWORD | PURPOSE |
| :---: | :---: |
| GENERAL | Input general model parameters |
| CASEID | Input title identifying model attributes |
| BOOTSTRAP | Input information for bootstrap numbers at age file |
| HARVEST | Input information for harvest intensity (F or Q) by fleet |
| RETROADJUST | Input information for retrospective bias adjustment |
| NATMORT | Input information for natural mortality rate (M) at age |
| BIOLOGICAL | Input information on seasonal spawning timing |
| for $F$ and $M$ |  |

Table 2. Table of AGEPRO input keywords, continued.

| KEYWORD | PURPOSE |
| :---: | :---: |
| SCALE | Input information on scaling factors for biomass, <br> recruitment, and stock size |
| PERC | Input information for setting a specific percentile for <br> the distributions of outputs |
| REFPOINT | Input information for reference points |
| REBUILD | Input information for calculating F to rebuild spawning <br> biomass <br> which is the probability of overfishing in the target <br> projection year |
| PSTAR |  |

Table 3. Structure of an AGEPRO version 4.2 input file by keyword. Inputs are space delimited.

| KEYWORD | INPUT VARIABLE |
| :---: | :---: |
| GENERAL | 1. NFyear (I) - this is the first year of the projection <br> 2. NXYear (I) - this is the last year of the projection <br> 3. NFAge (I) - this is the first age in the population model <br> 4. NXAge (I) - this is the plus-group age in the population model <br> 5. NSims (I) - this is the number of simulations to conduct for each bootstrap replicate of initial population size <br> 6. NFleet (I) - this is the number of fleets in the harvest model <br> 7. NRecModel (I) - this is the number of recruitment submodels in the population model <br> 8. DiscFlag (I) - this is a logical flag to indicate whether discards are included in the harvest model (1=true, $0=$ false) <br> 9. ISeed (I) - this is a positive integer seed to initialize the random number generator |
| CASEID | 1. Model (S) - this is a string that describes the projection model run |
| BOOTSTRAP | 1. NBoot (I)- this is the number of bootstrap replicates of initial population size <br> 2. BootFac ( F ) - this is the multiplicative factor to convert the relative bootstrap population numbers at age to absolute numbers at age <br> 3. BootFile (S) - this is the name of the bootstrap filename including the file path |
| HARVEST | 1. HarvestSpec[0:NYears-1] (F) - this is the harvest specification by year vector where an input of zero indicates an F-based harvest rate and any positive input indicates a quota-based harvest rate (that is, input $=0$ for $F$ and input $>0$ for catch biomass) <br> 2. HarvestValue[0:NYears-1][0:Nfleet-1] (F) - this is the harvest amount by year and fleet array where an input row is the set of annual F values or catches (in metric tons) depending on the harvest specification by year. |

Table 3. Structure of an AGEPRO version 4.2 input file by keyword, continued.

| KEYWORD | INPUT VARIABLE |
| :---: | :---: |
| RETROADJUST | 1. RetroAdjust[0:NAges-1] (F) - this is the vector of age-specific numbers at age multipliers for an initial population size at age vector if retrospective bias adjustment is applied |
| NATMORT | 1. NatMortFlag (I) - this is the logical flag that indicates if the average natural mortality rate at age vector is to be read from an existing data file (input $=1$ ) or not (input !=1) <br> 2. NatMortTimeFlag (I) - this is the logical flag that indicates if the average natural mortality rate at age vector is a time-varying array (input $=1$ ) ordered by year (row) and age (column); otherwise the average natural mortality rate at age vector does not vary by year <br> 3. If (NatMortFlag = 1) then read DataFiles[*] (S) Else if (NatMortTimeFlag = 1) then Read AvgNatMort[0:NAges-1][0:NYears-1] (F) Else Read AvgNatMort[0:NAges-1][0] (F) - this is the logic for the average natural mortality rate at age vector inputs <br> 4. NatMortErr[0:NAges-1] (F) - this is the vector of age-specific CVs for sampling the natural mortality rate at age vector with lognormal process error |
| BIOLOGICAL | 1. ZFracTimeFlag (I) - this is the logical flag that indicates if the fractions of fishing and natural mortality that occur before spawning are a timevarying array (input $=1$ ) or constant values <br> 2. If (ZFracTimeFlag $=1$ ) then read TF[0:NYears-1] ( F ) and read $\mathbf{T M}[0: \mathrm{NYears}-1](\mathrm{F})$ Else read TF[0] (F) and read TM[0] (F) - this is the logic for the fractions of fishing and natural mortality that occur before spawning |

Table 3. Structure of an AGEPRO version 4.2 input file by keyword, continued.

| KEYWORD | INPUT VARIABLE |
| :---: | :---: |
| MATURITY | 1. MaturityFlag (I) - this is the logical flag that indicates if the average fraction mature at age vector is to be read from an existing data file (input $=1$ ) or not (input !=1) <br> 2. MaturityTimeFlag (I) - this is the logical flag that indicates if the average fraction mature at age vector is a time-varying array (input =1) ordered by year (row) and age (column); otherwise the average fraction mature at age vector does not vary by year <br> 3. If (MaturityFlag = 1) then read DataFiles[*] (S) Else if (MaturityTimeFlag = 1) then read AvgMaturity [0:NAges-1][0:NYears-1] (F) Else read AvgMaturity[0:NAges-1][0] (F) ) - this is the logic for the average fraction mature at age vector inputs <br> 4. MaturityErr[0:NAges-1] (F) - this is the vector of age-specific CVs for sampling the fraction mature at age vector with lognormal process error |
| STOCK_WEIGHT | 1. StockWtFlag (I) - this is the logical flag that indicates if the average stock weight at age vector is to be read from an existing data file (input $=1$ ) or not (input $!=1$ ) <br> 2. StockWtTimeFlag (I) - this is the logical flag that indicates if the average stock weight at age vector is a time-varying array (input $=1$ ) ordered by year (row) and age (column); otherwise the average stock weight at age vector does not vary by year <br> 3. If (StockWtFlag $=1$ ) then read DataFiles[*] (S) Else if (StockWtTimeFlag = 1) then read AvgStockWeight [0:NAges-1][0:NYears-1] (F) Else read AvgStockWeight [0:NAges-1][0] (F) ) this is the logic for the average stock weight at age vector inputs <br> 4. StockWtErr[0:NAges-1] (F) - this is the vector of age-specific CVs for sampling the stock weight at age vector with lognormal process error |

Table 3. Structure of an AGEPRO version 4.2 input file by keyword, continued.

| KEYWORD | INPUT VARIABLE |
| :---: | :---: |
| SSB_WEIGHT | 1. SpawnWtFlag (I) - this is the logical flag that indicates if the average spawning weight at age vector is to be read from an existing data file (input $>0$ ) or to be read from the input file (input $=0$ ) or to be set equal to the average stock weight at age vector (input=-1) <br> 2. SpawnWtTimeFlag (I) - this is the logical flag that indicates if the average spawning weight at age vector is a time-varying array (input $=1$ ) ordered by year (row) and age (column); otherwise the average spawning weight at age vector does not vary by year <br> 3. If (SpawnWtFlag $>0$ ) then read DataFiles[*] (S) Else if (SpawnWtFlag $=-1$ ) then set average spawning weight at age vector to equal the average stock weight at age vector Else if (SpawnWtTimeFlag =1) then read AvgSpawnWeight [0:NAges-1][0:NYears-1] (F) Else read AvgSpawnWeight [0:NAges-1][0] (F) this is the logic for the average spawning weight at age vector inputs <br> 4. SpawnWtErr[0:NAges-1] (F) - this is the vector of age-specific CVs for sampling the spawning weight at age vector with lognormal process error |
| MEAN_WEIGHT | 1. MeanStockWtFlag (I) - this is the logical flag that indicates if the average mean weight at age vector is to be read from an existing data file (input $>0$ ) or not (input $=0$ ) <br> 2. MeanStockWtTimeFlag (I) - this is the logical flag that indicates if the average mean weight at age vector is a time-varying array (input $=1$ ) ordered by year (row) and age (column); otherwise the average mean weight at age vector does not vary by year <br> 3. If (MeanStockWtFlag >0) then read DataFiles[*] (S) Else if (MeanStockWtTimeFlag $=0$ ) then read AvgMeanStockWeight [0:NAges-1][0:NYears-1] (F) Else read AvgMeanStockWeight [0:NAges-1][0] (F) - this is the logic for the average mean weight at age vector inputs <br> 4. MeanStockWtErr[0:NAges-1] (F) - this is the vector of age-specific CVs for sampling the mean weight at age vector with lognormal process error |

Table 3. Structure of an AGEPRO version 4.2 input file by keyword, continued.

| KEYWORD | INPUT VARIABLE |
| :---: | :---: |
| FISHERY | 1. FSelecFlag (I) - this is the logical flag that indicates if the average fishery selectivity at age vectors by fleet are to be read from an existing data file (input $=1$ ) or not (input !=1) <br> 2. FSelecTimeFlag (I) - this is the logical flag that indicates if the average fishery selectivity at age vectors by fleet are a time-varying array (input =1) ordered by fleet (index 1), year (index 2), and age (index 3); otherwise the average fishery selectivity at age vectors by fleet do not vary by year <br> 3. If (FSelecFlag $=1$ ) then read DataFiles [*] (S) Else if (FSelecTimeFlag = 1) then read AvgFSelec [0:NAges-1][0:NYears-1][0:NFleets-1] (F) Else read AvgFSelec[0:NAges-1][0][0:NFleets-1] (F) - this is the logic for the average fishery selectivity at age vectors by fleet inputs <br> 4. FSelecErr[0:NAges-1][0:NFleets-1] (F) - this is the array of age-specific and fleet-specific CVs for sampling the fishery selectivity at age vectors by fleet with lognormal process error |
| DISCARD | 1. DiscFracFlag (I) - this is the logical flag that indicates if the average discard fraction at age vectors by fleet are to be read from an existing data file (input =1) or not (input !=1) <br> 2. DiscFracTimeFlag (I) - this is the logical flag that indicates if the average discard fraction at age vectors by fleet are a time-varying array (input $=1$ ) ordered by fleet (index 1), year (index 2), and age (index 3); otherwise the average discard fraction at age vectors by fleet do not vary by year <br> 3. If (DiscFracFlag $=1$ ) then read DataFiles [*] (S) Else if (DiscFracTimeFlag $=1$ ) then read AvgDiscFrac [0:NAges-1][0:NYears-1][0:NFleets-1] (F) <br> Else read AvgDiscFrac[0:NAges-1][0][0:NFleets-1] ( F ) - this is the logic for the average discard fraction at age vectors by fleet inputs <br> 4. DiscFracErr[0:NAges-1][0:NFleets-1] (F) - this is the array of age-specific and fleet-specific CVs for sampling the discard fraction at age vectors by fleet with lognormal process error |

Table 3. Structure of an AGEPRO version 4.2 input file by keyword, continued.

| KEYWORD | INPUT VARIABLE |
| :---: | :---: |
| CATCH_WEIGHT | 1. CatchWtFlag (I) - this is the logical flag that indicates if the average catch weight at age vectors by fleet are to be read from an existing data file (input $>0$ ) or to be read from the input file (input $=0$ ) or to be set equal to the average stock weight at age vector (input=-1) or to be set equal to the average spawning weight at age vector (input=-2) or to be set equal to the average mean weight at age vector (input=-3) <br> 2. CatchWtTimeFlag (I) - this is the logical flag that indicates if the average catch weight at age vectors by fleet are a time-varying array (input $=1$ ) ordered by fleet (index 1), year (index 2), and age (index 3 ); otherwise the average catch weight at age vectors by fleet do not vary by year <br> 3. If (CatchWtFlag >0) then read DataFiles[*] (S) Else if (CatchWtFlag $=-1$ ) then set average catch weight at age vector to equal the average stock weight at age vector <br> Else if (CatchWtFlag = -2) then set average catch weight at age vector to equal the average spawning weight at age vector <br> Else if (CatchWtFlag $=-3$ ) then set average catch weight at age vector to equal the average mean weight at age vector Else if (CatchWtTimeFlag $=0$ ) then read AvgCatchWeight [0:NAges-1][0:NYears-1][0:NFleets-1] (F) Else read AvgCatchWeight[0:NAges-1][0][0:NFleets-1] (F) - this is the logic for the average catch weight at age vector inputs <br> 4. CatchWtErr[0:NAges-1][0:NFleets-1] (F) - this is the array of age-specific and fleet-specific CVs for sampling the catch weight at age vectors by fleet with lognormal process error |

Table 3. Structure of an AGEPRO version 4.2 input file by keyword, continued.

| KEYWORD | INPUT VARIABLE |
| :---: | :---: |
| DISC_WEIGHT | 1. DiscWtFlag (I) - this is the logical flag that indicates if the average discard weight at age vectors by fleet are to be read from an existing data file (input $>0$ ) or to be read from the input file (input $=0$ ) or to be set equal to the average stock weight at age vector (input=-1) or to be set equal to the average spawning weight at age vector (input=-2) or to be set equal to the average mean weight at age vector (input=-3) or to be set equal to the average catch weight at age vector (input=-4) <br> 2. DiscWtTimeFlag (I) ) - this is the logical flag that indicates if the average discard weight at age vectors by fleet are a time-varying array (input $=1$ ) ordered by fleet (index 1), year (index 2), and age (index 3); otherwise the average discard weight at age vectors by fleet do not vary by year <br> 3. If (DiscWtFlag $=1$ ) then read DataFiles[*] (S) Else if (DiscWtFlag $=-1$ ) then set average discard weight at age vector to equal the average stock weight at age vector <br> Else if (DiscWtFlag $=-2$ ) then set average discard weight at age vector to equal the average spawning weight at age vector <br> Else if (DiscWtFlag $=-3$ ) then set average discard weight at age vector to equal the average mean weight at age vector <br> Else if (DiscWtFlag $=-4$ ) then set average discard weight at age vector to equal the average catch weight at age vector <br> Else if (DiscWtTimeFlag $=1$ ) then read <br> AvgDiscWeight [0:NAges-1][0:NYears-1][0:NFleets1] (F) <br> Else read AvgDiscWeight[0:NAges-1][0][0:NFleets- <br> 1] ( F ) - this is the logic for the average discard weight at age vector inputs <br> 4. DiscWtErr[0:NAges-1][0:NFleets-1] (F) - this is the array of age-specific and fleet-specific CVs for sampling the discard weight at age vectors by fleet with lognormal process error |

Table 3. Structure of an AGEPRO version 4.2 input file by keyword, continued.

| KEYWORD | INPUT VARIABLE |
| :---: | :---: |
| RECRUIT | 1. RecFac ( F ) - this is the multiplier to convert recruitment submodel units for recruitment to absolute numbers of fish <br> 2. SSBFac ( F ) - this is the multiplier to convert recruitment submodel units for spawning biomass to absolute spawning weight of fish in kilograms <br> 3. MaxRecObs (I) - this is the maximum number of recruitment observations for an empirical recruitment submodel <br> 4. RecruitType[0:NRecModel-1] (I) - this is the vector of recruitment submodel types included in the projection <br> 5. RecruitProb[0:NYears-1][0:NRecModel-1] (F) - this is the array of recruitment submodel probabilities ordered by year (row) and submodel (column) with row sums equal to unity <br> 6. For $\mathrm{J}=0$ to (NRecModel - 1) Call ReadRecruitModelInput(J,[RecruitType[J]) this is the set of function calls to read in the input data needed for each recruitment submodel in the order they are specified in RecruitType where the required input data for each submodel are listed in Table 4. |
| BOUNDS | 1. MaxWeight $(\mathrm{F})$ - this is the maximum value of an fish weight, noting that there is lognormal sampling variation for weight at age values <br> 2. MaxNatMort ( F ) - this is the maximum natural mortality rate, noting that there is lognormal sampling variation for natural mortality at age values |
| OPTIONS | 1. StockSummaryFlag (I) - this is the logical flag to output stock summary information <br> 2. DataFlag (I) - this is the logical flag to output population and fishery processes simulated with lognormal process error to auxiliary output files <br> 3. ExportRFlag (I) - this is the logical flag to output projection results to an R dataframe |
| SCALE | 1. scalebio ( F ) - the output units of biomass expressed in thousand metric tons <br> 2. scalerec ( F ) - the output units of recruitment numbers <br> 3. scalestk (F) - the output units of stock size numbers |

Table 3. Structure of an AGEPRO version 4.2 input file by keyword, continued.

| KEYWORD | INPUT VARIABLE |
| :---: | :---: |
| PERC | 1. PercReportValue ( F ) - this is the user-selected percentile for reporting the percentile of the projected distribution of the following quantities of interest by year: spawning stock biomass, stock biomass on January $1^{\text {st }}$, mean biomass, combined catch biomass, landings, fishing mortality, and stock numbers at age |
| REFPOINT | 1. SSBThresh ( F ) - this is the spawning biomass threshold expressed in biomass output units <br> 2. StockBioThresh (F) - this is the stock biomass threshold expressed in biomass output units <br> 3. MeanBioThresh ( F ) - this is the mean biomass threshold expressed in biomass output units <br> 4. FMortThresh ( F ) - this is the fishing mortality threshold |
| REBUILD | 1. TargetYear (I) - this is the user-selected target year for rebuilding to the target value <br> 2. TargetValue ( F ) - this is the target biomass value in units of thousands of metric tons <br> 3. TargetType (I) - this is the index for the type of population biomass as the target where $0=$ spawning stock biomass, $1=$ stock biomass on January $1^{\text {st }}$, else $=$ mean biomass <br> 4. TargetPercent ( F ) - this is the percent frequency of achieving the target value by the target year where the percent frequency is a value between 0 (indicating zero chance of achieving target) and 100 (indicating 100 percent chance of achieving target). |
| PSTAR | 1. KPStar (I) - this is the user-selected number of PStar values to be evaluated in the target year <br> 2. PStar[0:KPStar-1] (F) - these are the PStar values to evaluate where PStar is the probability of exceeding the overfishing level <br> 3. PStarF (F) - this is the fishing mortality rate that defines the overfishing level <br> 4. TargetYear (I) - this is the user-selected target year for which the total annual catch to produce the userselected PStar values is calculated |

Table 4. Required input data for AGEPRO recruitment models, where spawning biomass and recruitment inputs are measured in units of the conversion factors SSBFac and RecFac respectively, which typically have units of SSBFac=RecFac=1000.

| Model <br> Number | Recruitment Model | Recruitment Model Input Description |
| :---: | :---: | :---: |
| 1 | Markov Matrix | Input the number of recruitment states: $K$ <br> On the next line input the recruitment values: $R_{1}, R_{2}, \ldots, R_{K}$ <br> On the next line input number of spawning biomass states: $J$ <br> On the next line input $J-1$ cut points: $B_{S, 1}, B_{S, 2}, \ldots, B_{S, J-1}$ <br> On the next $J$ lines input the conditional recruitment probabilities for the spawning biomass states: $\begin{aligned} & p_{1,1}, p_{1,2}, \ldots, p_{1, K} \\ & p_{2,1}, p_{2,2}, \ldots, p_{2, K} \\ & \vdots \\ & p_{J, 1}, p_{J, 2}, \ldots, p_{J, K} \end{aligned}$ |
| 2 | Empirical Recruits Per Spawning Biomass Distribution | Input the number of stock recruitment data points: $T$ On the next line input the recruitments: $R_{1}, R_{2}, \ldots, R_{T}$ <br> On the next line input the spawning biomasses: $B_{S, 1}, B_{S, 2}, \ldots, B_{S, T}$ |
| 3 | Empirical Recruitment Distribution | Input the number of recruitment data points: $T$ On the next line input the recruitments: $R_{1}, R_{2}, \ldots, R_{T}$ |
| 4 | Two-Stage Empirical Recruits Per Spawning Biomass Distribution | Input the number of low and high recruits per spawning biomass data points: $T_{\text {Low }}, T_{\text {High }}$ <br> On the next line input the cutoff level of spawning biomass: $B_{S}^{*}$ <br> On the next line input the low state recruitments: $R_{1}, R_{2}, \ldots, R_{T_{\text {Low }}}$ <br> On the next line input the low state spawning biomasses: $B_{S, 1}, B_{S, 2}, \ldots, B_{S, T_{\text {Low }}}$ <br> On the next line input the high state recruitments: $R_{1}, R_{2}, \ldots, R_{T_{\text {High }}}$ <br> On the next line input the high state spawning biomasses: $B_{S, 1}, B_{S, 2}, \ldots, B_{S, T_{\text {Hgh }}}$ |

Table 4. Required input data for AGEPRO recruitment models, continued.

| Model <br> Number | Recruitment <br> Model | Recruitment Model <br> Input Description |
| :---: | :---: | :--- |
| 5 | Beverton-Holt Curve with <br> Lognormal Error | Input the stock-recruitment parameters: $\alpha, \beta, \sigma_{w}^{2}$ |
| 6 | Ricker Curve with <br> Lognormal Error | Input the stock-recruitment parameters: $\alpha, \beta, \sigma_{w}^{2}$ |
| 7 | Shepherd Curve with <br> Lognormal Error | Input the stock-recruitment parameters: $\alpha, \beta, k, \sigma_{w}^{2}$ |
| 10 | Lognormal Distribution <br> Beverton-Holt Curve with <br> Autocorrelated Lognormal <br> Error | Input the log-scale mean and standard deviation: $\mu_{\text {log }(r)}, \sigma_{\log (r)}$ <br> On the next line input the autoregressive parameters: $\phi, \varepsilon_{0}$ |
| 11 | Ricker Curve with <br> Autocorrelated Lognormal <br> Error | Input the stock-recruitment parameters: $\alpha, \beta, \sigma_{w}^{2}$ <br> On the next line input the autoregressive parameters: $\phi, \varepsilon_{0}$ |
| 12 | Shepherd Curve with <br> Autocorrelated Lognormal <br> Error | Input the stock-recruitment parameters: $\alpha, \beta, k, \sigma_{w}^{2}$ <br> On the next line input the autoregressive parameters: $\phi, \varepsilon_{0}$ |

Table 4. Required input data for AGEPRO recruitment models, continued.

| Model <br> Number | Recruitment <br> Model | Recruitment Model <br> Input Description |
| :---: | :---: | :--- |
| 13 | Autocorrelated Lognormal <br> Distribution | Input the log-scale mean and standard deviation: $\mu_{\text {log(r) }}, \sigma_{\text {log(r) }}$ <br> On the next line input the autoregressive parameters: $\phi, \varepsilon_{0}$ |
| 14 | Empirical Cumulative <br> Distribution Function of <br> Recruitment | Input the number of recruitment data points: $T$ <br> On the next line input the recruitments: $R_{1}, R_{2}, \ldots, R_{T}$ |
| 15 | Two-Stage Empirical <br> Cumulative Distribution <br> Function of Recruitment | Input the number of low and high recruits per spawning biomass data points: $T_{\text {Low }}, T_{\text {High }}$ <br> On the next line input the cutoff level of spawning biomass: $B_{S}^{*}$ <br> On the next line input the low state recruitments: $R_{1}, R_{2}, \ldots, R_{T_{\text {Low }}}$ <br> On the next line input the high state recruitments: $R_{1}, R_{2}, \ldots, R_{T_{\text {High }}}$ |
| 16 | Linear Recruits Per <br> Spawning Biomass | Input the number of predictors: $N_{p}$ <br> On the next line input the intercept coefficient: $\beta_{0}$ <br> On the next line input the slope coefficient for each predictor: $\beta_{1}, \beta_{2}, \ldots, \beta_{N_{p}}$ <br> On the next line input the error variance: $\sigma^{2}$ <br> On the next $N_{p}$ lines input the expected value of the predictor through the projection time horizon: <br> $X_{1}(1), \ldots, X_{1}(Y)$ <br> $X_{2}(1), \ldots, X_{2}(Y)$ <br> $\vdots$ <br> $X_{p}(1), \ldots, X_{p}(Y)$ |

Table 4. Required input data for AGEPRO recruitment models, continued.

| Model Number | Recruitment Model | Recruitment Model Input Description |
| :---: | :---: | :---: |
| 17 | Linear Recruits Per Spawning Biomass Predictor with Lognormal Error | Input the number of predictors: $N_{p}$ <br> On the next line input the intercept: $\beta_{0}$ <br> On the next line input the linear coefficient for each predictor: $\beta_{1}, \beta_{2}, \ldots, \beta_{N_{p}}$ <br> On the next line input the log-scale error variance: $\sigma^{2}$ <br> And on the next $N_{p}$ lines input the expected predictor values over the forecast time horizon $1, \ldots, Y$ : $\begin{array}{cccc} X_{1}(1) & X_{1}(2) & \ldots & X_{1}(Y) \\ X_{2}(1) & X_{2}(2) & \ldots & X_{2}(Y) \\ \vdots & \vdots & \vdots & \vdots \\ X_{p}(1) & X_{p}(2) & \ldots & X_{p}(Y) \\ \hline \end{array}$ |
| 18 | Linear Recruitment <br> Predictor with Normal Error | Input the number of predictors: $N_{p}$ <br> On the next line input the intercept: $\beta_{0}$ <br> On the next line input the linear coefficient for each predictor: $\beta_{1}, \beta_{2}, \ldots, \beta_{N_{p}}$ <br> On the next line input the error variance: $\sigma^{2}$ <br> And on the next $N_{p}$ lines input the expected predictor values over the forecast time horizon $1, \ldots, Y$ : $\begin{array}{cccc} X_{1}(1) & X_{1}(2) & \ldots & X_{1}(Y) \\ X_{2}(1) & X_{2}(2) & \ldots & X_{2}(Y) \\ \vdots & \vdots & \vdots & \vdots \\ X_{p}(1) & X_{p}(2) & \ldots & X_{p}(Y) \\ \hline \end{array}$ |

Table 4. Required input data for AGEPRO recruitment models, continued.

| Model Number | Recruitment Model | Recruitment Model Input Description |
| :---: | :---: | :---: |
| 19 | Loglinear Recruitment Predictor with Lognormal Error | Input the number of predictors: $N_{p}$ <br> On the next line input the intercept: $\beta_{0}$ <br> On the next line input the linear coefficient for each predictor: $\beta_{1}, \beta_{2}, \ldots, \beta_{N_{p}}$ <br> On the next line input the log-scale error variance: $\sigma^{2}$ <br> And on the next $N_{p}$ lines input the expected predictor values over the forecast time horizon $1, \ldots, Y$ : $\begin{array}{cccc} X_{1}(1) & X_{1}(2) & \ldots & X_{1}(Y) \\ X_{2}(1) & X_{2}(2) & \ldots & X_{2}(Y) \\ \vdots & \vdots & \vdots & \vdots \\ X_{p}(1) & X_{p}(2) & \ldots & X_{p}(Y) \end{array}$ |
| 20 | Fixed Recruitment | Input the number of recruitment data points: $Y$ On the next line input the recruitments: $R_{1}, R_{2}, \ldots, R_{Y}$ |
| 21 | Empirical Cumulative Distribution Function of Recruitment with Linear Decline to Zero | Input the number of observed recruitment values: $T$ On the next line input the recruitment values: $R_{1}, R_{2}, \ldots, R_{T}$ And on the next line input spawning biomass threshold: $B_{S}^{*}$ |



Figure 2. AGEPRO input/output diagram

SYSTEM DATA


INPUT FILE
KEYWORDS FOR

## Appendix

## Example 1 Input File

## AGEPRO VERSION 4.0

[CASEID]
REDFISH - RECRUITMENT MODEL 14
[GENERAL]
2004200912610021049667890
[BOOTSTRAP]
10001000
C:IUsers\Jon.Brodziak\Documents\AGEPRO\Example1_2017-12-29_13-58-58\Example1.BSN
[STOCK_WEIGHT]
01
$\begin{array}{lllllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 & 0.558\end{array}$ 0.5650 .5810 .5950 .5830 .5820 .637
$\begin{array}{lllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 \\ 0.558\end{array}$ $\begin{array}{llllll}0.565 & 0.581 & 0.595 & 0.583 & 0.582 & 0.637\end{array}$
$\begin{array}{llllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 \\ 0.548 & 0.558\end{array}$ 0.5650 .5810 .5950 .5830 .5820 .637
$\begin{array}{lllllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 & 0.558\end{array}$ 0.5650 .5810 .5950 .5830 .5820 .637
$\begin{array}{llllllllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 & 0.558\end{array}$ 0.5650 .5810 .5950 .5830 .5820 .637
 0.5650 .5810 .5950 .5830 .5820 .637
0.0010 .0010 .0010 .0010 .0010 .0010 .0010 .0010 .0010 .0010 .0010 .0010 .0010 .0010 .001000 .0010 .0010 .0010 .001 0.0010 .0010 .0010 .0010 .0010 .001
[SSB_WEIGHT]
01
$\begin{array}{llllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 & 0.558\end{array}$ $\begin{array}{lllllll}0.565 & 0.581 & 0.595 & 0.583 & 0.582 & 0.637\end{array}$
$\begin{array}{llllllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 & 0.558\end{array}$ $\begin{array}{llllll}0.565 & 0.581 & 0.595 & 0.583 & 0.582 & 0.637\end{array}$
 $\begin{array}{llllll}0.565 & 0.581 & 0.595 & 0.583 & 0.582 & 0.637\end{array}$
$\begin{array}{llllllllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 & 0.558\end{array}$ $\begin{array}{llllll}0.565 & 0.581 & 0.595 & 0.583 & 0.582 & 0.637\end{array}$
 $\begin{array}{lllllll}0.565 & 0.581 & 0.595 & 0.583 & 0.582 & 0.637\end{array}$
$\begin{array}{lllllllllllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 & 0.558\end{array}$ $\begin{array}{lllllll}0.565 & 0.581 & 0.595 & 0.583 & 0.582 & 0.637\end{array}$
$\begin{array}{lllllllllllllllllllllllllllllllllll}0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0 & 0.001 & 0.001 & 0.001 & 0.001\end{array}$ $\begin{array}{llllllllllll}0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001\end{array}$

## [MEAN_WEIGHT]

01
$\begin{array}{lllllllllllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 & 0.558\end{array}$ $\begin{array}{llllll}0.565 & 0.581 & 0.595 & 0.583 & 0.582 & 0.637\end{array}$
$\begin{array}{lllllllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 & 0.558\end{array}$ $\begin{array}{llllll}0.565 & 0.581 & 0.595 & 0.583 & 0.582 & 0.637\end{array}$
$\begin{array}{llllllllllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 & 0.558\end{array}$ $\begin{array}{llllll}0.565 & 0.581 & 0.595 & 0.583 & 0.582 & 0.637\end{array}$
$\begin{array}{llllllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 & 0.558\end{array}$ $\begin{array}{lllllll}0.565 & 0.581 & 0.595 & 0.583 & 0.582 & 0.637\end{array}$
$\begin{array}{lllllllllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 & 0.558\end{array}$ $\begin{array}{lllll}0.565 & 0.581 & 0.595 & 0.583 & 0.582\end{array} 0.637$
$\begin{array}{lllllllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 & 0.558\end{array}$ 0.5650 .5810 .5950 .5830 .5820 .637
$\begin{array}{lllllllllllllllllllllllllllllll}0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0 & 0.001 & 0.001 & 0.001 & 0.001\end{array}$ $\begin{array}{lllllllll}0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001\end{array}$
[CATCH_WEIGHT]
01
$\begin{array}{lllllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 & 0.558\end{array}$ $\begin{array}{lllll}0.565 & 0.581 & 0.595 & 0.583 & 0.582\end{array} 0.637$
$\begin{array}{llllllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 & 0.558\end{array}$ $\begin{array}{llllll}0.565 & 0.581 & 0.595 & 0.583 & 0.582 & 0.637\end{array}$
$\begin{array}{lllllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 & 0.558\end{array}$ $\begin{array}{lllll}0.565 & 0.581 & 0.595 & 0.583 & 0.582\end{array} 0.637$
$\begin{array}{llllllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 & 0.558\end{array}$ $\begin{array}{lllll}0.565 & 0.581 & 0.595 & 0.583 & 0.582\end{array} 0.637$
$\begin{array}{lllllllllllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 & 0.558\end{array}$ $\begin{array}{lllllll}0.565 & 0.581 & 0.595 & 0.583 & 0.582 & 0.637\end{array}$
$\begin{array}{lllllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 & 0.558\end{array}$ $\begin{array}{llllllll}0.565 & 0.581 & 0.595 & 0.583 & 0.582 & 0.637\end{array}$
$\begin{array}{llllllllllllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 & 0.558\end{array}$ $\begin{array}{llllll}0.565 & 0.581 & 0.595 & 0.583 & 0.582 & 0.637\end{array}$
$\begin{array}{lllllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 & 0.558\end{array}$ 0.5650 .5810 .5950 .5830 .5820 .637
$\begin{array}{lllllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 & 0.558\end{array}$ 0.5650 .5810 .5950 .5830 .5820 .637
$\begin{array}{lllllllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 & 0.558\end{array}$ 0.5650 .5810 .5950 .5830 .5820 .637
$\begin{array}{llllllllllllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 & 0.558\end{array}$ $\begin{array}{lllll}0.565 & 0.581 & 0.595 & 0.583 & 0.582\end{array} 0.637$
$\begin{array}{lllllllllllllllllllll}0.01 & 0.02 & 0.059 & 0.099 & 0.145 & 0.178 & 0.201 & 0.25 & 0.272 & 0.31 & 0.348 & 0.391 & 0.423 & 0.429 & 0.463 & 0.495 & 0.503 & 0.508 & 0.548 & 0.558\end{array}$ $\begin{array}{llllll}0.565 & 0.581 & 0.595 & 0.583 & 0.582 & 0.637\end{array}$
$\begin{array}{llllllllllllllllllllllllllll}0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0 & 0.001 & 0.001 & 0.001 & 0.001\end{array}$ $\begin{array}{lllllll}0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001\end{array}$
$\begin{array}{lllllllllllllllllllllllllllllllllll}0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0 & 0.001 & 0.001 & 0.001 & 0.001\end{array}$ $\begin{array}{llllllll}0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001\end{array}$
[NATMORT]
01
$\begin{array}{lllllllllllllllllllllllllllllllll}0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05\end{array}$ 0.050 .05
$\begin{array}{llllllllllllllllllllllllllllllllllll}0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05\end{array}$ 0.050 .05
$\begin{array}{lllllllllllllllllllllllllllllllllllll}0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05\end{array}$ 0.050 .05
 0.050 .05
$\begin{array}{llllllllllllllllllllllllllllllllll}0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05\end{array}$ 0.050 .05
$\begin{array}{lllllllllllllllllllllllllllll}0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05 & 0.05\end{array}$ 0.050 .05
$\begin{array}{lllllllllllllllllllllllll}0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1\end{array} 0.1$
[BIOLOGICAL]
0
0.4
0.4
[MATURITY]
01
0.010 .020 .050 .150 .360 .640 .850 .950 .980 .991111111111111111111
$\begin{array}{lllllllllllllllllllllll}0.01 & 0.02 & 0.05 & 0.15 & 0.36 & 0.64 & 0.85 & 0.95 & 0.98 & 0.99 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1\end{array} 111$
0.010 .020 .050 .150 .360 .640 .850 .950 .980 .9911111111111111111111
0.010 .020 .050 .150 .360 .640 .850 .950 .98
0.010 .020 .050 .150 .360 .640 .850 .950 .980 .9911111111111111111111
0.010 .020 .050 .150 .360 .640 .850 .950 .98
$\begin{array}{lllllllllllllllllllllllllllllllll}0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001\end{array}$ $\begin{array}{lllllllll}0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001\end{array}$
[FISHERY]
01
00.0020 .0110 .0540 .2230 .5220 .6560 .78311111111111111111111111
00.0020 .0110 .0540 .2230 .5220 .6560 .78311111111111111111111111
00.0020 .0110 .0540 .2230 .5220 .6560 .78311111111111111111111111111
00.0020 .0110 .0540 .2230 .5220 .6560 .783111111111111111111111111
00.0020 .0110 .0540 .2230 .5220 .6560 .7831111111111111111111111
00.0020 .0110 .0540 .2230 .5220 .6560 .783111111111111111111111111
$\begin{array}{lllllllllllllllllllllllllll}0 & 0.002 & 0.011 & 0.054 & 0.223 & 0.522 & 0.656 & 0.783 & 1 & 1 & 0.783 & 0.656 & 0.522 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5\end{array}$
$\begin{array}{lllllllllllllllllllllllllllllllllllll}0 & 0.002 & 0.011 & 0.054 & 0.223 & 0.522 & 0.656 & 0.783 & 1 & 1 & 0.783 & 0.656 & 0.522 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5\end{array}$
$\begin{array}{lllllllllllllllllllllllllll}0 & 0.002 & 0.011 & 0.054 & 0.223 & 0.522 & 0.656 & 0.783 & 1 & 1 & 0.783 & 0.656 & 0.522 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5\end{array}$
$\begin{array}{llllllllllllllllllllllllllllllllllll}0 & 0.002 & 0.011 & 0.054 & 0.223 & 0.522 & 0.656 & 0.783 & 1 & 1 & 0.783 & 0.656 & 0.522 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5\end{array}$
$\begin{array}{llllllllllllllllllllllllll}0 & 0.002 & 0.011 & 0.054 & 0.223 & 0.522 & 0.656 & 0.783 & 1 & 1 & 0.783 & 0.656 & 0.522 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5\end{array}$
 $\begin{array}{lllllllllllllllllllllllllllll}0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001\end{array}$
$\begin{array}{llllllll}0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001\end{array}$
$\begin{array}{llllllllllllllllllllll}0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001\end{array}$
$\begin{array}{llllllll}0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001\end{array}$
[RECRUIT]

1000000175
14
1
1
1
1
1
53
73.593978 .184570 .600462 .126766 .088669 .981449 .944570 .402242 .673185 .297748 .288798 .136476 .86733 .8211
$\begin{array}{lllllllllllllllllllllllllllll}7.8195 & 4.3288 & 2.6275 & 2.7917 & 4.2174 & 249.227 & 6.5051 & 2.5329 & 1.9038 & 1.7011 & 1.5596 & 2.2002 & 52.7585 & 2.4754 & 2.8037 & 10.179\end{array}$

$\begin{array}{lllllllllllllllllllll}32.1726 & 34.4703 & 29.245 & 81.7098 & 30.5807 & 25.3895 & 26.28 & 30.1793\end{array}$
[HARVEST]
010000
$0.002393500 .010 .01 \quad 0.010 .01$
$\begin{array}{llllllll}0.00239 & 350 & 0.02 & 0.02 & 0.02 & 0.02\end{array}$
[REFPOINT]
236700000.04
[OPTIONS]
001

## Example 2 Input File

```
AGEPRO VERSION 4.0
[CASEID]
GoM haddock ASAP_final (1977-2011 recruitment)
[GENERAL]
20142020 1 9 10 1 1 0 854236
[BOOTSTRAP]
1000 1000
C:\Users\Jon.Brodziak\Documents\AGEPRO\Example2_2017-12-29_14-19-44\Example2.BSN
[STOCK_WEIGHT]
0}
0.15 0.4 0.71 1 1.24 1.43 1.59 1.82 2.04
0.14}0.1
[SSB_WEIGHT]
-1 0
[MEAN_WEIGHT]
0
0.3 0.6 0.89}1.171.4 1.55 1.7 1.96 2.04
0.14}00.1
[CATCH_WEIGHT]
-3 0
[NATMORT]
0
0.2}00.
0.1
[BIOLOGICAL]
0
0.25
0.25
[MATURITY]
0}
0.04}00.2
0.23}00.08\quad0.020.001 0.001 0.001 0.001 0.001 0.001
[FISHERY]
0 0
0}0.050.19 0.3 0.52 0.69 0.82 1 0.83
0.36}00.190.14 0.15 0.13 0.13 0.12 0.001 0.16
[RECRUIT]
1000 1000 50
14
1
1
1
1
1
1
35
5997 1476 6048 6435 4612 774 2445 1043 282 265 134 443 187 244 267 711 1318 2903 2540 1080 2179 2276 13429
2547 1121 1216 219 6281 386 1118 1218 215 301 966 6659
[HARVEST]
1 0 0 0 2 0 0
500}00.20.20.2 0.2 500 0.2 0.2
[PSTAR]
5
0.1}00.20.3 0.4 0.5
0.35
2018
[BOUNDS]
100.6
[OPTIONS]
1 0 0
[SCALE]
1000 1000 1000
[PERC]
90
```


## Example 3 Input File

```
AGEPRO VERSION 4.0
[CASEID]
GoM haddock ASAP_final FREBUILD Projection
[GENERAL]
2014 2020 1 9 10 1 1 0 30076
[BOOTSTRAP]
1000 1000
C:\Users\Jon.Brodziak\Documents\AGEPRO\Example3_2017-12-29_14-49-07\Example3.BSN
[STOCK_WEIGHT]
0}
0.15 0.4 0.71 1 1.24 1.43 1.591.82 2.04
0.14}00.130.07 0.05 0.03 0.03 0.08 0.03 0.04
[SSB_WEIGHT]
-1 0
[MEAN_WEIGHT]
0
0.3 0.6 0.89 1.17 1.4 1.55 1.7 1.96 2.04
0.14}00.11 0.11 0.06 0.05 0.05 0.05 0.07 0.04
[CATCH_WEIGHT]
-3 0
[NATMORT]
0
0.2}00.20.2 0.2 0.2 0.2 0.2 0.2 0.2
0.1
[BIOLOGICAL]
0
0.25
0.25
[MATURITY]
0 0
0.04}00.28 0.81 0.98 1 1 1 1 1
0.23}00.08\quad0.020.001 0.001 0.001 0.001 0.001 0.001
[FISHERY]
0}
0}0.050.190.30.520.69 0.82 1 0.83
llllllllll
[RECRUIT]
1000 1000 50
14
1
1
1
1
1
1
35
5997 1476 6048 6435 4612 774 2445 1043 282 265 134 443 187 244 267 711 1318 2903 2540 1080 2179 2276 13429
2547 1121 1216 219 6281 386 1118 1218 215 301 966 6659
[HARVEST]
1 0 0 0 0 0 0
500}00.
[REBUILD]
2020 11000 0 75
[BOUNDS]
100.6
[OPTIONS]
1 0 0
[SCALE]
1000 1000 1000
[PERC]
90
```

