

## **Wikiprint Book**

**Title: EwEugFitToTimeSeries**

**Subject: Ecopath Developer Site - EwEugFitToTimeSeries**

**Version: 3**

**Date: 2020-08-05 06:05:51**

## Table of Contents

9.11 Fit to time series

3

## 9.11 Fit to time series

When an Ecosim model is loaded, you can load time series reference data on relative and absolute biomasses of various pools over a particular historical period, along with estimates of changes in fishing impacts over that period. After such data have been loaded and applied (see [Time series](#)), a statistical measure of goodness of fit to these data is generated each time Ecosim is run. This goodness of fit measure is a weighted sum of squared deviations (SS) of log biomasses from log predicted biomasses, scaled in the case of relative abundance data by the maximum likelihood estimate of the relative abundance scaling factor  $q$  in the equation  $y = qB$  ( $y$  = relative abundance,  $B$  = absolute abundance). Each reference data series can be assigned a relative weight using a simple spreadsheet in the search interface, representing a prior assessment by the user about relatively how variable or reliable that type of data is compared to the other reference time series (low weights imply relatively high variance, unreliable data).

The *Fit to time series* search interface (*Time dynamic (Ecosim) > Outputs > Tools > Fit to time series*; Figure 9.9) allows users to do four types of analysis with the SS measure:

- i. Determine sensitivity of SS to the critical Ecosim vulnerability parameters ([Vulnerabilities](#) form), by changing each one slightly (1%) then rerunning the model to see how much SS is changed (i.e., how sensitive the time series predictions supported by data are to the vulnerabilities). See Option (1) below;
- ii. Search for vulnerability estimates that give better fits of Ecosim to the time series data (lower SS), with vulnerabilities blocked by the user into sets that are expected to be similar, (i.e., user can search for just one best overall vulnerability, or for better estimates for up to 15 blocks of predator-prey vulnerabilities). See Option (2) and/or (3) below;
- iii. Search for time series values of annual relative primary productivity that may represent historical productivity regime shifts impacting biomasses throughout the ecosystem (for this search, the user must have linked a time forcing function to primary production using the [Apply forcing function to primary production](#) form and setting the  $i,i$  element of the forcing table for  $i$  = primary producers to the number of the forcing function). See Option (2) and/or (3) below;
- iv. Estimate a probability distribution for the null hypothesis that all of the deviations between model and predicted abundances are due to chance alone, i.e. under the hypothesis that there are no real productivity anomalies. See Option (4) below.

### 1. Option (1)

Option 1 is invoked by clicking one of the two **Sensitivities of SS to V** button at the bottom of the screen. You can choose whether to determine sensitivity of SS to vulnerabilities associated with individual predator-prey interactions (i.e., by predator-prey cell) or to vulnerability settings for all of a predator's foraging arena (i.e., by predator column).

Progress in this assessment is shown by placing an X in the vulnerability layout grid (on the right of the form) as the sensitivity to each vulnerability is computed. When all tests are completed, relative sensitivities are shown on a colour code scale on the vulnerability grid. A grid cell shown in red (for prey type in row  $i$ , predator type in column  $j$  of the grid) is one for which SS was most sensitive (among those tested) to changing that vulnerability, while a grid cell shown in blue is one for which SS was not sensitive to changing that vulnerability. Note that the colours shown on the vulnerability grid after this search are purely to help the user identify vulnerability blocks for the parameter search, and are NOT used by the interface to define vulnerability blocks for estimation.

It is, however, possible to transfer the information from the sensitivity table to the search table using one of the three transfer buttons on the form. We recommend that you use the transfer some pred/prey or transfer by pred column rather than the transfer by prey row, which biologically makes less sense.

### 2/3. Options (2) and/or (3)

Options 2 and/or 3 are invoked by pressing the **Search** button on the search interface, after deciding which parameters to include in the search by setting nonzero variance values for one or both of Vulnerability search and Anomaly search:

#### Vulnerability search

Checking the **Vulnerability search** box and setting its variance  $> 0$  causes the search to include parameter blocks that have been sketched as non-black in the vulnerability layout grid on the right side of the search interface.

#### Anomaly search

Check the **Anomaly search box** and click on the **Anomaly search tab** on the right of the form. You must also select an applied time series forcing shape from the thumbnails at the bottom of the form (see [Apply forcing function for primary production](#)). You must also set the **First year** and **Last year** for the search, the **PP Variance** ( $> 0$ ) and the **Spline points** for smoothing.

The variance values are then treated as Bayesian prior variances for the parameters included in the search. Large variance values allow the search procedure to vary the parameters more widely in search of lower SS parameter combinations.

When the **Search** button is pressed, progress of the SS minimization procedure is shown in the **Iterations** panel (a Marquardt nonlinear search algorithm with trust region modification of the Marquardt steps). For each step in the search, the algorithm must run the Ecosim model at least  $N + 1$  times, where  $N$  is the number of parameters with nonzero variances ( $N$  can be up to Last year - First year + 16). For most runs, the algorithm incrementing one PP annual value or one vulnerability block value slightly, so as to calculate the Jacobian matrix of sensitivities of each of the predicted time series observations to each of the parameters. After  $N+1$  such checks, the Jacobian matrix is used to estimate an initial best step change for each parameter and a few more runs are used to further improve the step. The algorithm stops when these changes become very small (or a numerical error occurs in the search calculations, if the search results in unrealistic values for some parameters). If no numerical error occurs during the search, the best estimates found during the search will be displayed in the *Forcing function* form (for PP time series) and/or the *Vulnerabilities* form (for vulnerabilities). These new values will be saved with the Ecosim scenario if the user answers yes to the save scenario message on exit from Ecosim.

See Option 4 for important notes about obtaining spurious fits.

#### 4. Option (4)

##### Time series random effects

Option 4 is necessary because, when you use the search interface to estimate time series values of a forcing function, e.g., to obtain a temporal pattern of apparent primary production anomalies for the ecosystem, you need to be careful about the risk of obtaining a spurious anomaly sequence that just represents measurement errors in the fitting data. Generally, if you are fitting the data to  $n$  independent time series of relative abundance, (i.e., for  $n$  of the groups), you can expect the fitting procedure to reduce the sum of squares (SS) by the proportion  $(n-1)/n$  by varying time forcing values even if there is no real time forcing effect. So if  $n=1$ , the fitting procedure can usually find a sequence of forcing values that make  $SS=0$ , but this sequence is meaningless (could be either real productivity anomalies or just spurious way of explaining measurement errors in the single abundance time series).

The Null hypothesis distribution  $SS_{red}/SS_{o}$  button allows you to estimate a probability distribution for the F statistic  $SS_{reduced}/SS_{base}$  under the null hypothesis that all of the deviations between model and predicted abundances are due to chance alone, i.e. under the hypothesis that there are no real productivity anomalies. The calculation of this F statistic requires a Monte-Carlo simulation procedure in order to account for autocorrelation in the model residuals that is expected even under the null hypothesis. Be warned that even if you do find a statistically significant reduction in SS by using the search procedure, this does not mean that the estimated sequence of relative primary production values is in fact real. All that you can say is this: assuming that primary production was in fact variable and that this did cause changes in relative abundance throughout the food web, then our best estimate of the historical pattern of variation is the one obtained by the fitting procedure.

Use the *Time series weight* box to set relative weights. This represents a prior assessment by the user about relatively how variable or reliable that type of data is compared to the other reference time series (low weights imply relatively high variance or unreliable data; higher weights imply low variance or reliable data). This grid will/will not overwrite weights that were set on the *Time series* form.

For users familiar with nonlinear estimation procedures used in single-species stock assessment, e.g., for fitting production models to time series CPUE data, searches on the vulnerability parameters should look quite familiar. In essence, the Ecosim search procedure for vulnerabilities is just an observation error fitting procedure where vulnerability changes usually have effects quite similar to changes in population  $r$  parameters in single-species models. Allowing the search to also include historical primary production anomalies corresponds to searching also for nuisance parameter estimates of what we usually call the process errors in single species assessment.

Ecosim users are cautioned that the search procedure in no way guarantees finding better Ecosim parameter estimates. Better fits to data can easily be obtained for the wrong reasons (some time series, particularly CPUE data, can be misleading in the first place, as can historical estimates of changes in fishing mortality rates; many parameter combinations may equally well explain patterns in the data). Nonlinear search procedures can become lost or trapped at local parameter combinations where there are local minima in the SS function far from the combinations that would actually fit the data best.

The best way to insure against the technical problems of searching a complex SS function is to use multiple shooting: start the search from a variety of initial parameter combinations (patterns sketched in time forcing function and/or vulnerability settings in flow control interface) and check whether it keeps coming back to the same final estimates. Look very closely at the time series data for possible violations of the assumption that  $y = qB$ , due to progressive changes in the methods of measuring relative abundance ( $y$ ) or nonlinearities caused by factors such as density-dependent catchability. If  $y$  is a biomass reconstruction from methods such as VPA that assume constant natural mortality rate  $M$ , watch out for spurious trends in  $y$  caused by the sort of changes in  $M$  that Ecosim predicts, particularly for younger animals. Look for alternative combinations of Ecosim parameters that appear to fit the data equally well but would imply quite different responses to policy changes such as increases in fishing rates.

Search procedures are most useful in diagnosing problems with both the model and data. That is, the greatest value of doing some formal estimation is while it seems not to be working, when it cannot find good fits to data. Poor fits can be informative about both the model and the data. For example, in a study on impact of lobster fishing on Hawaiian monk seals, it seemed initially that Ecosim could explain monk seal decline as a consequence of fishing down one of their foods, the lobster. But this hypothesis never really fit the monk seal population trend data well: Ecosim predicted a monk seal decline with development of the lobster fishery, but nowhere as severe or persistent as the observed decline. This lack of fit told us we needed to look for some other factor that hit the monk seals well after the lobster fishery had its impacts, and this factor turned out to be an oceanographic regime shift (decrease in primary productivity) that apparently impacted the availability of fish prey as well as lobsters.

As an example of learning things about the data as well as the model, attempts to fit Ecosim to historical abundance estimates (from VPA) for Pacific herring in the Georgia Strait, British Columbia, Canada, have consistently led to Ecosim predicting lower juvenile herring abundances than observed during peak periods of historical fishing, and lower recent biomass of adult herring than observed. It looks in this case like the problem is with the data, not Ecosim: VPA likely resulted in overestimates of juvenile herring abundance during a period when we would expect juvenile herring to have had higher natural mortality rate than assumed in the VPA, and overestimates of adult biomass due to not correcting the VPA estimates for observed changes in growth rates (lower conditions factors observed) during the period where Ecosim predicts lower biomass.

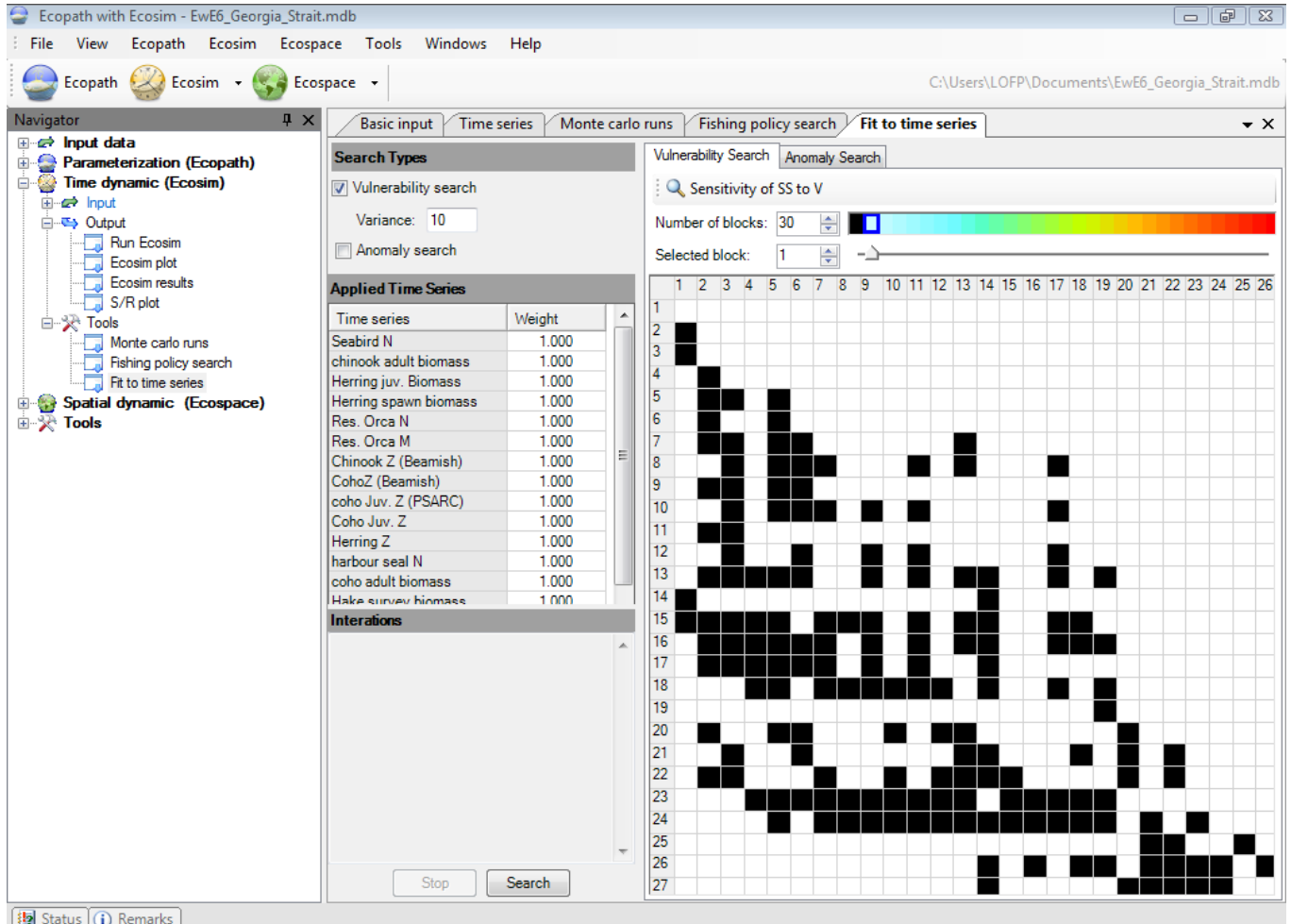


Figure 9.9 The *Fit to time series* form.