GREAT LAKES FISHERY COMMISSION

2001 Project Completion Report[1]

Application of Decision Analysis to Great Lakes sea lamprey management

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Application of Decision Analysis to Great Lakes sea lamprey management

Project Completion Report

March 31, 2001

To

Great Lakes Fishery Commission

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Introduction

This report documents the completion of a two-year project funded by the Great Lakes Fishery Commission to investigate the importance of uncertainty to decision-making for the Commission's sea lamprey control program. This study is closely linked to another research project under the direction of the principal investigator for this study, funded by the Michigan Sea Grant College Program. Together these two projects comprise an examination of the application of decision analysis to two Great Lakes fishery management case studies. The first of these case studies concerns the sea lamprey control program on the St Marys River, and is the subject of this completion report.

Case Study Overview

The objective of this project was to develop a decision model for the St Marys River sea lamprey control program. We have completed the development of this model and will be holding a workshop April 24-25, 2001 to present and discuss the findings of our analysis. This work has been the subject of MSU PhD Student Steven Haeseker's dissertation research, which is scheduled for completion in August 2001. Haeseker has recently completed a manuscript to be submitted to the SLIS II proceedings that describes one component of our analysis – the estimation of a stock-recruitment relationship for the St Marys River lamprey population. He has presented the findings of a second component of the analysis – uncertainty concerning the spatial distribution of lamprey ammocoetes in the St Marys River – at a national fisheries conference in Toronto and a sea lamprey research meeting in Traverse City. We have also used annual estimates of trapping effectiveness and egg viability in lamprey nests to assess uncertainty in the trapping and sterile male release components of the control program. Finally, Jones and Haeseker have been working with Research Assistant and Programmer John Netto to develop a modeling tool to incorporate these uncertainty analyses into a formal decision analysis. Each of these components is described in more detail below.

Background

In 1998 and 1999 the Great Lakes Fishery Commission implemented a program to achieve an unprecedented level of control of the sea lamprey in the St. Marys River. Continued high rates of wounding of lake trout in northern Lakes Huron and Michigan motivated this extraordinary action. The St Marys River Control Program uses three control methods to achieve it's goals: (1) trapping adult lamprey as they return to spawn; (2) releasing sterilized males into the spawning population to interfere with normal reproduction; and (3) treatment of areas of the St. Marys River believed to contain the majority of the larval lamprey population with a bottom-release lampricide (Bayluscide). During 1998 and 1999 approximately 850 ha of the St. Marys River was treated. It has been estimated that this treatment resulted in the removal of nearly 50% of the extant larval population from the river.

The St. Marys River Control Task Force recommended that the Commission embark on this program of control based on an exhaustive analysis of information gathered during 1992-1997. These analyses allowed the task force to make model-based forecasts of the effects on parasitic lamprey abundance and lake trout recruitment of various control options, and to determine the optimal spatial allocation of Bayluscide treatments. The Task Force acknowledged, however, that considerable uncertainty remains regarding the accuracy of their model forecasts. Because of this the Task Force recommended, and the Commission supported, a comprehensive St. Marys River Assessment Plan that will allow measurement of the actual effects of the control actions on lamprey abundance and lake trout populations.

The Commission will be faced with future decisions regarding sea lamprey control in the St. Marys River (e.g. whether to continue to use Bayluscide treatments), and the uncertainty surrounding those decisions will continue to be large. As a result, the Commission, together with the Michigan Sea Grant College Program, sponsored this research project to examine the application of decision analysis methods to the St. Marys River control program.

What is decision analysis?

Decision analysis has been defined in a variety of ways. As the words suggest, the goal of a decision analysis is to analyze the expected consequences of a range of alternative decisions with a view towards choosing the preferred alternative. This implies that any decision analysis must include (1) decision alternatives to compare; (2) a basis for judging which alternative is best (i.e., objectives); and (3) a means for forecasting the consequences of each decision alternative (i.e., a model). Our approach to decision analysis originated in the field of business management (Raiffa 1968, Clemen 1996)) but has been recently applied to many resource management situations (e.g., Sainsbury *et al.* 1997, Robb and Peterman 1998)). In addition to the three components above, this approach can explicitly account for uncertainty, or risk, in the decision process by allowing for *alternative states of nature* that may lead to different possible consequences from the same set of decisions. Alternative states of nature can be characterized in a variety of different ways, including alternative parameter estimates for a particular model, or two entirely different models to explain the same phenomenon. An important conclusion that has emerged from applications of decision analysis is that *if one explicitly accounts for alternative possible outcomes, the preferred decision option can be different than if one assumes that the most likely outcome will occur.* In other words, accounting for uncertainty can affect decision choices.

Problem Bounding

To apply the method of decision analysis, we needed to complete the following tasks:

1. select a set of decision options to consider;

2. agree upon management objectives against which the performance of alternative decision options can be compared;
3. decide on the critical uncertainties that will define our alternative states of nature;
4. determine how to assign probabilities to these alternative states of nature;
5. develop a model or set of models that allows us to forecast the consequences of each decision option for each alternative state of nature;
6. use the model to rank each decision option in terms of its performance relative to the stated management objectives.

We began by holding a workshop in Detroit on April 21-22, 1999, attended by members of the St. Marys River Control Task Force, other sea lamprey experts and Great Lakes fishery managers. At the workshop we addressed the first three tasks:

<u>Decision options:</u>

- no future treatment
- trapping
- sterile male release
- Bayluscide
- TFM

We will consider both individual options and combinations of options. The no treatment and TFM options were included for comparative purposes and are not the focus of our analysis.

<u>Management objectives:</u>

- achieve target parasitic sea lamprey abundance levels (as per Lake Huron fish community objective);
- achieve lake trout rehabilitation objectives (various spawning stock biomass indicators);

- maximize economic values of fisheries and non-consumptive uses.

Fishery managers at the workshop advised that we focus on the first of these as our objective of primary interest because of: (a) the potentially confounding influence of other factors, such as commercial exploitation, on lake trout indicators, and (b) the difficulty of deriving credible forecasts or estimates of the latter two measures.

Critical uncertainties:

We identified a variety of critical uncertainties during workshop discussions, but there was broad consensus that the most important uncertainties to consider were:

- sea lamprey larval distribution and its effect on Bayluscide treatment effectiveness;
- larval demographics (i.e., uncertainties in growth, survival and transformation rates of larvae); and
- adult to age 1 stock-recruitment relationship.

Many other uncertainties were noted – we plan to consider these as part of a sensitivity analysis of the decision model. That is, we will examine whether the conclusions of our decision analysis depend on assumptions about uncertainties not explicitly included in the decision model.

Larval distribution uncertainty

Cost-effective treatment of the St Marys River with Bayluscide requires good information on the spatial distribution of larvae. During 1998-99, nearly 850 ha of river were treated, amounting to approximately 10% of the river channel. The treatment plots were delineated using data from a survey of the entire river conducted during 1993-96, as well as from a limited re-survey conducted in 1998.

Use of these data relies on the assumption that the spatial distribution of ammocoetes does not change from year to year. Otherwise, treatment maps created from a survey year may not accurately describe the optimal areas to treat in a different year. It seems likely that this assumption is generally true, because the spatial pattern of ammocoetes in a river probably reflects the distribution of preferred habitats (e.g., larvae are not found in areas of coarse substrate or bedrock, or where flow velocities are high), as well as the physical processes (currents) that govern dispersal of young ammocoetes. Both physical habitat and current patterns are unlikely to change greatly from one year to the next. Nevertheless, large areas of apparently suitable habitat in the St Marys River contain very few larvae, suggesting the possibility that some interannual variation occurs.

To quantify the magnitude of this variation, repeated surveys of the same areas are required. Aside from the limited re-survey in 1998, the whole-river mapping effort did not include surveys of the same areas of the river in more than one year. From 1995 to 2000, however, a set of nine index sites have been surveyed each year, using methods similar to those employed in the whole-river survey. These data can be used to examine inter-annual variation in larval distributions, and thereby develop an empirical basis for describing the uncertainty associated with Bayluscide treatments.

We used a direct approach to determine the effect of inter-annual variation on treatment effectiveness. First, the index site data from one year (the base year) were used to delineate the set of treatment areas that would target the greatest proportion of the larval population in the index sites, given that only a fraction of the entire area in the index sites could be treated. Then, this set of treatment areas was applied to the larval distributions observed in other years, and the proportion of that year's observed population lying within these areas was recorded. By comparing the proportion of the index site larval population targeted in the base year to the proportion targeted in the other years, we obtain an estimate of the effect of temporal variation in larval distributions on treatment effectiveness.

The index site data for 1995-1998 were imported into a GIS program for display and manipulation. We manually digitized polygon borders around the nine index sites to get an overall area. Then we delineated treatment areas by drawing polygons around areas with high concentrations of larvae. Consistent with the approach used to delineate treatment areas in the 98/99 control program (Roger Bergstedt, USGS, personal communication), the polygons were loosely drawn around the "hot spots" such that adjacent areas were also included (Figure 1). The smallest treatment polygons were greater than 7,000 m^2.

We then ranked the treatment area polygons according to the number of sampled larvae included, implicitly assuming that this is directly proportional to the abundance of larvae within each polygon. To simulate a treatment, we selected a sufficient number of polygons, in order of decreasing rank, to achieve a target level of control. We examined simulated treatments that represented target suppression levels of 28, 40, 50, and 58% in the base year.

Treatment areas developed in any given base year consistently performed less well when applied to other years (Figure 2). The mean performance was 77.2%, averaged across 60 cases (4 possible base years, 3 comparison years, and 5 target levels). To simulate Bayluscide treatments in our decision model we fitted a linear model to the data in Figure 2 ($y = -0.07 + 0.89x$, $\sigma^2 = 0.006$) and use this model together with the estimated variance to randomly choose an actual proportion targeted given a user-specified target level of control.

Future work on this area of uncertainty will involve developing Markov process models with transition probabilities derived from an analysis of the index site data. The Markov models will be used to simulate future possible larval distribution maps for the entire river, based on the 1993-96 survey. The principal challenges associated with developing these models are (1) accounting for the non-stationarity of the index site data (overall abundance declines during the 1996-2000 period), and (2) conditioning the transition probabilities for a specific location on the state of neighboring locations (to account for spatial autocorrelations, if they exist).

Demographics, stock and recruitment

The effectiveness of control methods that alter the number of effective spawners (e.g., adult trapping, releasing sterilized males) depends on the reproduction and recruitment dynamics of sea lamprey populations. Specifically, the shape of the stock-recruitment relationship and the variability around it (process error) will determine the degree to which reductions in spawner numbers will consistently result in reductions in recruitment. Conversely, control methods that target the larval population after year-class strength is determined (e.g., application of lampricides) are not affected by the stock-recruitment relationship. For this reason, knowledge of the stock-recruitment relationship is key to assessing the trade-off between these control strategies.

Although estimates of recent spawner abundance were available, estimates of larval recruitment are not. Without estimates of larval production it is impossible to directly estimate the parameters of a stock-recruitment relationship. On the other hand, several data sources exist that provide insight into the relative abundance and age-composition of lamprey at various stages during their life cycle. By combining these heterogeneous data sets within an age-structured population model describing the lamprey life cycle, using likelihood techniques, we were able to estimate a time series of historical recruitment and other demographic parameters consistent with the observed data. This approach is similar to that described by Fournier and Archibald (1982) and Methot (1989) whereby several sources of data are incorporated into a single, statistically based framework. To aid in the estimation of population parameters, six separate data sources were incorporated: parasitic lamprey CPUE data, mark-recapture spawning phase data, mark-recapture parasitic-phase data, Bayluscide survey larval age-composition data, deepwater electrofishing larval age-composition data, and metamorphosing larvae age-composition data.

The model describes the full lamprey life cycle from age-0 recruitment through spawning. We assume the larval population is restricted to ages 0 through 6 and is subject to natural mortality rates that are constant across ages and years. As the model larvae age, they undergo a process of metamorphosis from larvae to parasites. A step function was used to describe the probability of metamorphosis as an increasing function of age for larvae ages 4 though 6. The metamorphosed larvae enter the parasitic-phase population in Lake Huron. After 18 months in the parasitic form, a portion of the parasitic-phase population in Lake Huron returns to the St. Marys River to reproduce.

The overall model required 39 parameters to be estimated. These included the number of age-0 recruits from 1967 through 1996 ($N_{0,y},\ \ y = 1967,1970,...1996$), the initial numbers-at-age for ages 0 through 4 during 1966 ($N_{i,1966},\ \ i = 0,2,...4$), a natural mortality rate (M) assumed to be constant across years and ages in the larval population, two parameters describing the probability that larvae metamorphose given its age, and the proportion (S) of the parasitic-phase population in Lake Huron that migrates to the St. Marys River during spawning. The S parameter represents a combination of two processes: the survival from metamorphosed larvae to spawner and the fraction of parasites in Lake Huron that migrate into the St. Marys River.

Given the initial age- and year-specific abundance estimates, subsequent larval abundances were calculated using the equation

$$N_{i+1,y+1} = N_{i,y} * e^{-M} * [1 - P(met. | age = i)] \qquad (3)$$

where $P(met. | age = i)$ is a larvae's probability of transformation given that it is age i. This formulation of the equation essentially assumes that larvae undergo an instantaneous process of mortality and transformation with constant abundance over the rest of the year. The probability of metamorphosis given age was modeled using a monotonic step function, with

$$P(met. | age = 4) < P(met. | age = 5) < P(met. | age = 6).$$

All of the remaining age-6 larvae were assumed to metamorphose that year. Therefore $P(met. | age = 6) = 1$.

The number of metamorphosed lamprey produced in a particular year was calculated using the equation

$$n_{metamorphosed,y} = \sum_{i=4}^{6} P(met. | age = i) * N_{i,y} \qquad (4)$$

Because of the timing of the metamorphosis process relative to the operation of the commercial fishery, the metamorphosed larvae produced in the fall and early winter of year y would not show up in the commercial catch until year $y+1$. Similarly, parasitic lamprey in the Lake Huron in the summer of year y do not spawn until the spring and summer of year $y+1$.

The St. Marys River is not the only river producing parasitic lamprey in Lake Huron. At this time the river-specific contribution to the Lake Huron parasitic-phase lamprey population is largely unknown. The parasitic-phase CPUE and the parasitic-phase mark-recapture data sets can only be used to provide information on the relative abundance of lamprey in Lake Huron, not on how much the St. Marys River population contributes to the overall population. To properly describe the overall system, we needed an estimate of the contribution of the St. Marys River to the Lake Huron parasitic-phase population.

The St. Marys River Assessment Plan (Bergstedt et al. 1998) estimated that the St. Marys River produces 88% of the total parasites in Lake Huron. We used this estimate in our model to scale the production of the St. Marys River relative to the other sources in Lake Huron. By using this estimate we are essentially assuming that number of lamprey in Lake Huron is a function of the amount of larval habitat, the number of spawners, and the number of hosts available. Of these three factors, we assume that only the amount and quality of larval habitat remains constant over time. The number of spawners and hosts is assumed to vary over time, causing the observed variability in recruitment and parasite densities. Young et al. (1996) concluded that habitat quantity and quality have remained relatively constant in the St. Marys River and that host availability was likely a more important factor in determining parasite abundance. Therefore using this estimate essentially means that the St. Marys River contains 88% of the total larval habitat available to larvae that eventually enter Lake Huron.

To estimate parameters, the overall model was fit to the six data sets by specifying the statistical distribution of each data set and then constructing likelihood for each data set. For the parasitic-phase CPUE data set, a lognormal distribution was assumed and the corresponding log-likelihood (ignoring constants) was

$$L_1 = -\sum_y 0.5\left[\left(\log_e\left(\frac{n_y}{n_{1999}}\right) - \log_e(a_y)\right)\Big/ s_y\right]^2 \qquad (5)$$

where n_y is the estimated number of parasitic-phase lamprey in year y, n_{1999} is the estimated number of parasitic-phase lamprey in year 1999, a_y is the parasitic-phase CPUE in year y, s_y is the standard error estimate associated with each a_y. The a_y and s_y

were estimated using a general linear model. This form for the likelihood was used because it mirrored the CPUE outputs from the general linear model.

The parasitic-phase mark-recapture data set and the spawning-phase mark-recapture data set were assumed to be described by lognormal distributions. The log-likelihoods (ignoring constants) for these data sets were of the form

$$L_i = -\sum_y 0.5\left[\left(\log_e(x_{i,y}) - \log_e(x'_{i,y})\right)/\hat{s}_{i,y}\right]^2 \qquad (6)$$

where L_i is the log-likelihood for data set i, $x_{i,y}$ is the empirical estimate of the population size for data set i in year y, $x'_{i,y}$ is the model prediction of population size for data set i in year y, and $\hat{s}_{i,y}$ is the estimated standard deviation for data set i in year y.

For the Bayer survey data set, the deepwater electrofishing data set, and the transforming larvae data set, a multinomial distribution was assumed to describe the proportions-at-age. The corresponding log-likelihoods (ignoring constants) were of the form

$$L_i = \sum_y J_{i,y} \sum_a P'_{i,a,y} \log_e(P_{i,a,y}) \qquad (7)$$

where L_i is the log-likelihood for data set i, $J_{i,y}$ is the sample size in year y for data set i, $P_{i,a,y}$ is the model prediction of the proportion age-a in year y, and $P'_{i,a,y}$ is the empirical estimate of the proportion age-a in year y. To prevent large sample sizes from overwhelming the log-likelihood, a maximum effective sample size for the combined Bayluscide and deepwater electrofishing data sets was determined using the iterative method outlined in the appendix of McAllister and Ianelli (1997). If the number sampled in a year was greater than the maximum sample size calculated, then $J_{i,y}$ was set to the calculated maximum effective sample size. For the Bayluscide and deepwater electrofishing data sets, $J_{\max} = 80$. Because the number of samples in the metamorphosing larvae data set were only 34 in 1995 and 43 in 1996, a maximum effective sample size was not estimated and instead the observed number of samples were used for the $J_{i,y}$.

Combining the six log-likelihoods, the overall log-likelihood objective function used to estimate model parameters was

$$L = L_1 + L_2 + L_3 + L_4 + L_5 + L_6 \qquad (8)$$

We used AD Model Builder software (Otter Research Ltd. 1994) to estimate model parameters.

Estimating Stock-Recruit Function Uncertainty

The primary objective of this study was to estimate the stock-recruit function for St. Marys River sea lamprey and its associated uncertainty. An additional objective was to estimate the larval abundance-at-age for 1998 and the demographic parameters (M, S, and $P(met. | age = i)$) for forecasting future population dynamics.

We assumed that lamprey recruitment was governed by a Ricker-type stock-recruit function of the form

$$R = aSe^{-bS} \cdot e \qquad (9)$$

where R is the number of age-0 larvae produced, S is the number of female spawners that produced R, α and β are parameters determining the productivity and compensation, respectively, and log(ε) is distributed N (0, σ^2). Let θ be a vector of the 39 parameters estimated in the population model. θ contains the initial numbers-at-age for 1966, the number of age-0 larvae from 1967-1996, M, S, and the two parameters describing $P(met. | age = i)$. If we denote the information contained in the six data sets as *Z*, then our primary objective is to approximate the posterior density

$$p\left(a, b, s^{2}, q \mid Z\right)$$

We accomplished this objective using a two-stage approach. For the first stage we utilized the Monte Carlo Markov Chain (MCMC) procedure within AD Model Builder to obtain 10,000 samples from the posterior density of θ. That is, samples from $p(q \mid Z)$. Each sample (θ_i, *i* = 1…10,000) determines a data set of estimated stock sizes and the estimated number of age-0 recruits that were produced. This is possible because once the initial recruitments and demographic parameters are specified, the historical stock and recruit sizes are completely determined. We denote these stock-recruit data sets as Y_i, *i* = 1…10,000.

The second stage consisted of obtaining samples from the posterior density,

$$p(a, b, s^2 \mid Y)$$

To accomplish this, first we converted the Ricker model above into its linear form,

$$\ln(R/S) = \ln(a) - bS + e = b_0 + b_1 S + e \qquad (10)$$

Then for each stock-recruit data set (Y_i), we used Result 2.1.1 from Tanner (1996) to draw a single sample from $p(b_0, b_1, s^2 \mid Y_i)$. Because $\exp(\hat{b}_0)$ is only a median-unbiased estimate of α, we report $\exp(\hat{b}_0 + s^2/2)$, a nearly unbiased estimate of α, where s^2 is the residual variance of the best-fit line to Y_i (Quinn and Deriso 1999).

Combining the results from the two stages resulted in samples from an approximation to the posterior density,

$$p(a, b, s^2, q \mid Z).$$

This two stage approach is not unique, as our approach is analogous to sampling from the posterior predictive distribution as described in Gelman et al. (1995) and Tanner (1996). We were able to use this approach to quantify the joint uncertainty in the parameters of the stock-recruit function together with the recent larval population age-composition and demographic parameters. We use samples from this joint probability distribution to simulate uncertainty in population dynamics in our decision model.

We were able to estimate a maximum log-likelihood data set of historical stock sizes and the number of age-0 recruits that were produced (Figure 3). The variation in recruitment is substantial across stock sizes. The least squares fit of the Ricker stock-recruit function to these data resulted in estimates of α = 5684, β = 0.00018, and $\hat{s}^2$ = 1.16. The posterior distributions for these parameters can be seen in Figures 4, 5, and 6, respectively. Although the modes of the posteriors for each of the parameters closely match their maximum log-likelihood estimates, there is considerable uncertainty in each of the parameters. Positive values for β imply that compensation exists in the stock-recruit function.

However, the values for β are relatively small, with some samples even taking on negative values, suggesting that compensatory forces are weak. Values for α were generally below 40,000, but a long, thin tail of samples runs out to over 120,000. The posterior density for s^2 has most of its mass in the 0 to 10 range, suggesting that there is considerable variation in recruitment.

The results of this analysis suggest that recruitment variation, after accounting for the effect of stock size, is considerable. The recruitment estimates shown in Figure 3 represent a process error variance estimate of 1.16. The posterior density plot for this parameter (Figure 6) indicates that substantially higher process error variances (and thus recruitment variation levels) are plausible. Second, the β parameter estimates do not suggest that compensatory mechanisms are likely to exert a strong influence on the effectiveness of control measures that act to reduce reproduction.

Uncertainty in Trapping and Sterile Male Release Technique Effectiveness

The stock-recruitment relationship is not the only source of uncertainty governing the performance of trapping and sterile male releases. Both techniques rely on the achievement of target levels of reduction in the effective number of female spawners each year. Traps have been operated since 1991 with an operating efficiency, on average, of 38.6%. The sterile male release technique uses an estimate of the ratio of sterile to non-sterilized males in the spawning population to describe the level of control applied. Additional data have been collected, however, on the average proportion of viable eggs observed in nests. Year-to-year differences in trapping efficiency and in the observed versus the expected proportion of viable eggs give an indication of variability (i.e., uncertainty) in the performance of these two control methods that is not governed by uncertainty in lamprey stock and recruitment.

Trap efficiency has varied fairly uniformly from 20-54% since 1991 (Figure 7). We will simulate this uncertainty by drawing values for trap efficiency from a uniform distribution with a range of 20-54%. Estimates of sterile:non-sterile male ratios varied from 0.25 to 5.36 during 1993-2000. These estimates are based on known releases of sterilized males and mark-recapture estimates of the abundance of non-sterilized males in the spawning population. During the same period, egg viability in surveyed nests ranged from 7.8-47.8%. Observations of egg viability in nests where non-sterilized males were observed averaged 43.4% from 1993-1997. Using this figure as a estimate of expected egg viability in the absence of sterile male releases, we estimated the sterile:non-sterile male ratio that would have led to the observed average egg viability during 1993-2000, and compared that to the estimates obtained from the release and population estimate data (Figure 8). The results suggest large variation between the expected (from release numbers) and observed (from nest observations) reductions in reproductive output, and a tendency towards a negative bias, particularly at higher release ratios.

The Decision Model

The preceding sections describe our analysis of the key uncertainties identified at the March 1999 workshop. The next step in the decision analysis process is to develop a model that can be used to forecast the outcomes of alternative decision options, while accounting for the uncertainties described above. We are in the final stages of developing this decision model, which will be used to explore decision options at the April 23-24 workshop. Here we briefly describe the structure of the model.

The model is specifically designed to forecast future trends in parasitic lamprey production from the St Marys River, given a set of control actions. We use an age-structured, dynamic simulation model, whose structure mirrors that of the stock-assessment model described earlier (stock-recruitment uncertainty section). Simulations begin in 2000 and run for thirty years. Our principal indicator of model performance is the average abundance of parasitic lamprey over the entire 30-year time horizon. The model also records the number of years during the simulation where parasitic abundance is below a user-specified target level of abundance.

To carry out the decision analysis, the model has to be repeated for a representative range of “alternative states of nature”, after which the results are summarized, weighting the outcome for each “state” by its relative likelihood, or probability. As well, we need to consider alternative decision choices, in order to rank their relative performance. We have constructed an interface for the model that allows users to specify the set of decision alternatives they wish to compare, and that allows determination of which uncertainties are included in the simulations (Figure 9). The decision alternatives include: (1) adult trapping (specify target percentage removed); (2) sterile male releases (specify target ratio); and Bayluscide application (specify frequency and percent of larval population targeted). For each of these decision options, the model user can include uncertainty in the option’s effectiveness, based on the analyses presented above. As well, the simulations are repeated for a large number (default: 1000) of realizations of the estimated joint probability distribution of lamprey demographic parameters, and for several (default: 100) realizations of the process error uncertainty (i.e., recruitment variability) in the stock-recruitment relationship (Figure 9).

This decision model will be used to examine a range of control alternatives, including tradeoffs among control methods (trapping versus SMRT versus Bayluscide) operating at different levels. We will also define the most effective combination of control methods for a range of overall annual expenditures on control. Finally, we have also developed a variation of the decision model that allows examination of the contribution that alternative control strategies can make to reducing our uncertainty about the stock-recruitment relationship. This will allow us to determine the potential for adopting an active adaptive management strategy for the St Marys River.

Other decision/uncertainty analysis work

In addition to the St. Marys River case study, we have been formally examining the significance of uncertainty to sea lamprey management in two other areas. First, we have developed a methodology for estimating the overall uncertainty in the assesement of potential production of parasitic lamprey from streams being considered for treatment. The method was developed as part of the Masters thesis project of MSU student Todd Steeves, and uses a numerical simulation to propagate the uncertainty associated with each component of the larval assessment process into an overall estimate of uncertainty (Figure 10). We have shown (M.L. Jones, unpublished data) that the ranking of streams in order of priority for treatement (based on the estimated lamprey population relative to the cost of treatment for each stream) can be quite different when uncertainty is included, as opposed to the currently employed method, which uses point estimates of lamprey abundance in each stream.

Second, we have examined the general significance of uncertainty about the lamprey stock-recruitment relationship to trade-offs between lampricide and alternative controls. We have collected stock-recruitment data from over 30 Great Lakes tributary streams as part of a research project on compensatory mechanisms, and have used these data to describe the process uncertainty associated with the estimated stock-recruitment relationship. We then developed a model that simulated a whole-lake lamprey control problem and compared the performance of lampricide and alternative controls in the presence of this process uncertainty. The results indicate that the large amount of process uncertainty (year-to-year variability) in recruitment, even at low spawning stock sizes, greatly reduces the effectiveness of alternative control methods, such as sterile male releases, that target reproduction. The results of this work will be published in a compensatory mechanisms synthesis paper for SLIS II.

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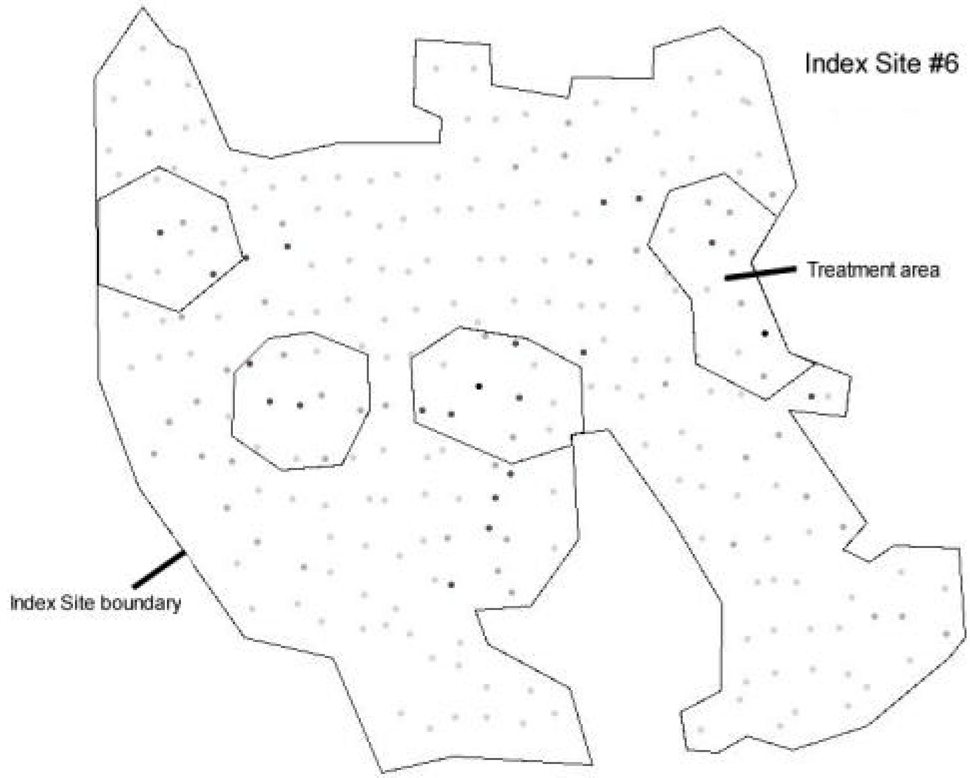

Figure 1. Map of St Marys River index site #6, showing the lamprey catches for 1995. Each point represents a sample; darker shaded points represent samples with higher catches. Treatment area polygons were drawn around the six samples where the largest catches were obtained. This example depicts a case in which 15% of the index site area (for all nine index sites) was selected for treatment.

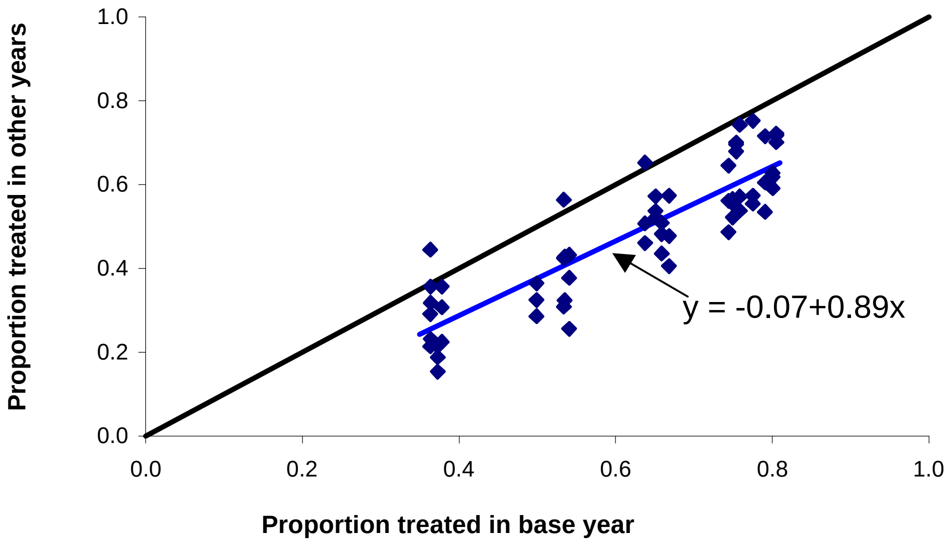

Figure 2. Comparisons of the proportion of larvae included in treatment areas in index sites in a year other than the year for which the treatment area was defined (base year) versus the proportion included in the treatment areas in the base year. The lower line represents the linear least-squares fit to the data.

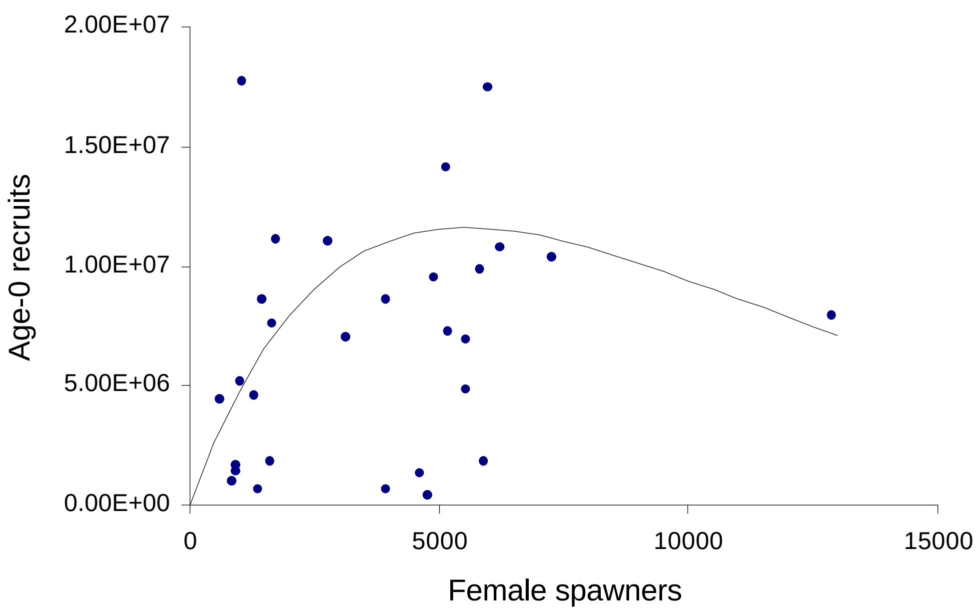

Figure 3. Maximum log-likelihood estimates of the number of female spawners and age-0 recruits for the St. Marys River sea lamprey population, 1968-1996. The least-squares fit of a Ricker stock-recruit function is also plotted.

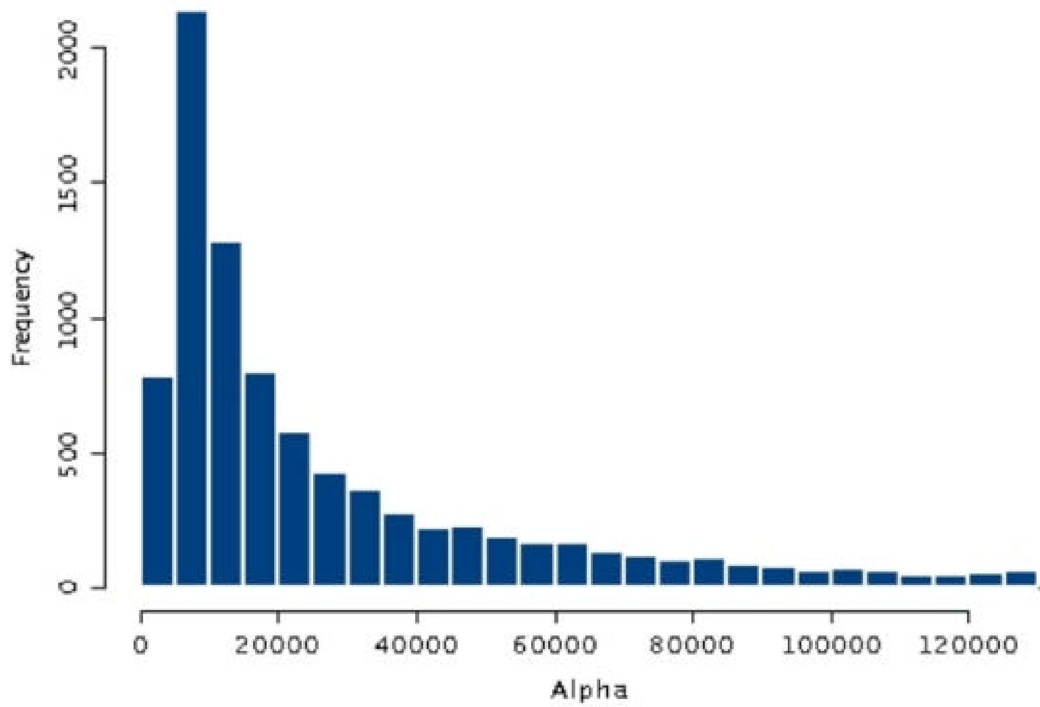

Figure 4. Frequency histogram of 10,000 estimates of the α (alpha) parameter from a Ricker stock-recruit function.

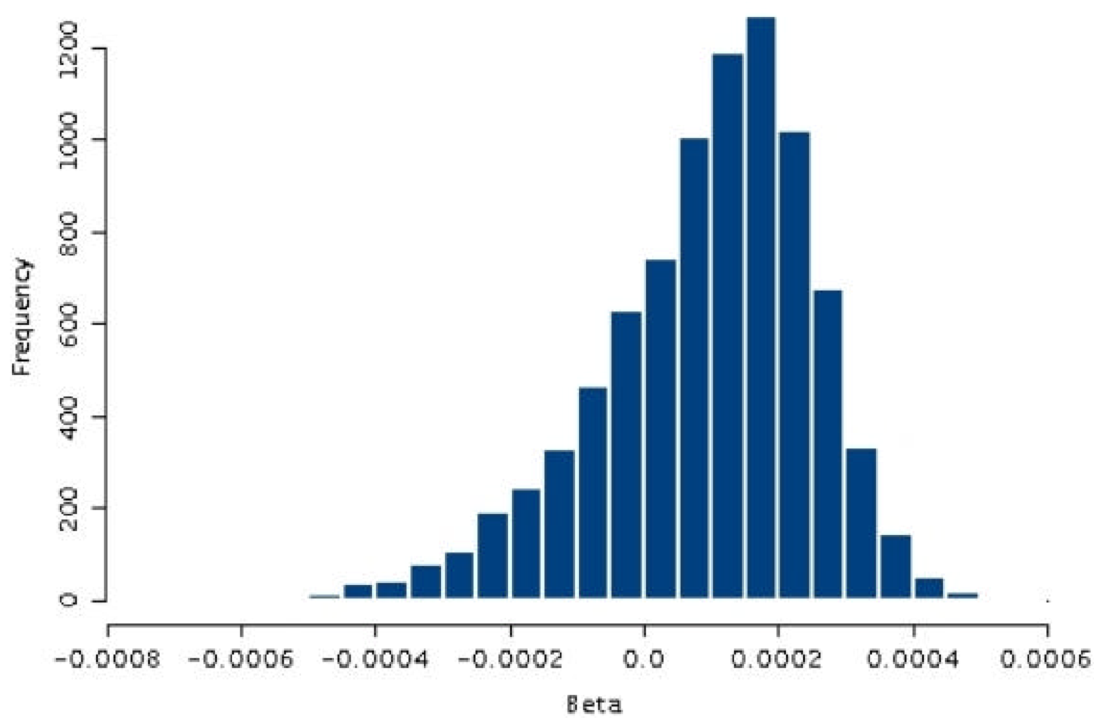

Figure 5. Frequency histogram of 10,000 estimates of the β (beta) parameter from a Ricker stock-recruit function.

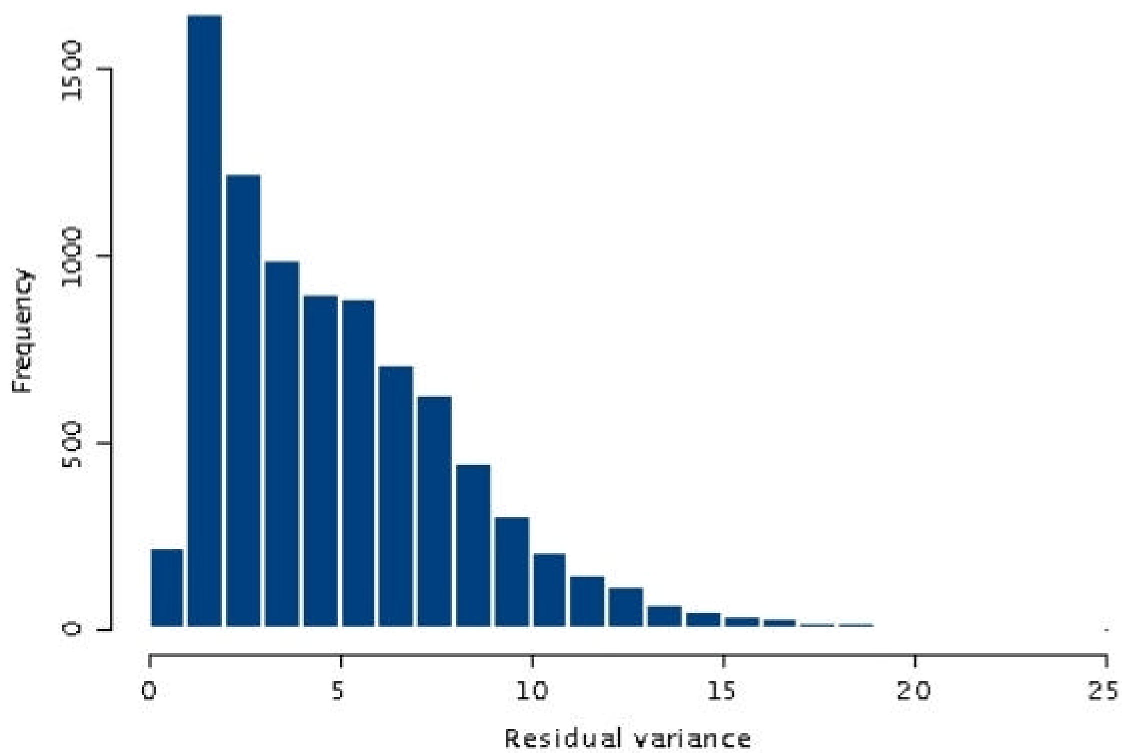

Figure 6. Frequency histogram of 10,000 estimates of σ^2 (residual variance) from Ricker stock-recruit functions estimated from the simulated data sets.

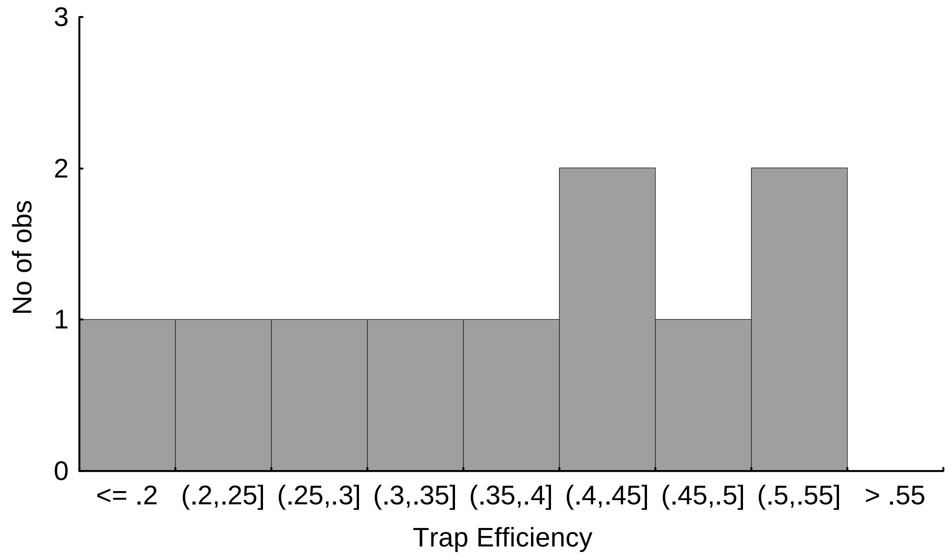

Figure 7. Histogram of trap efficiency estimates from 1991-2000 for all St Marys River traps combined. Trap efficiency is defined as the estimated proportion of the lamprey spawning run captured in traps each year.

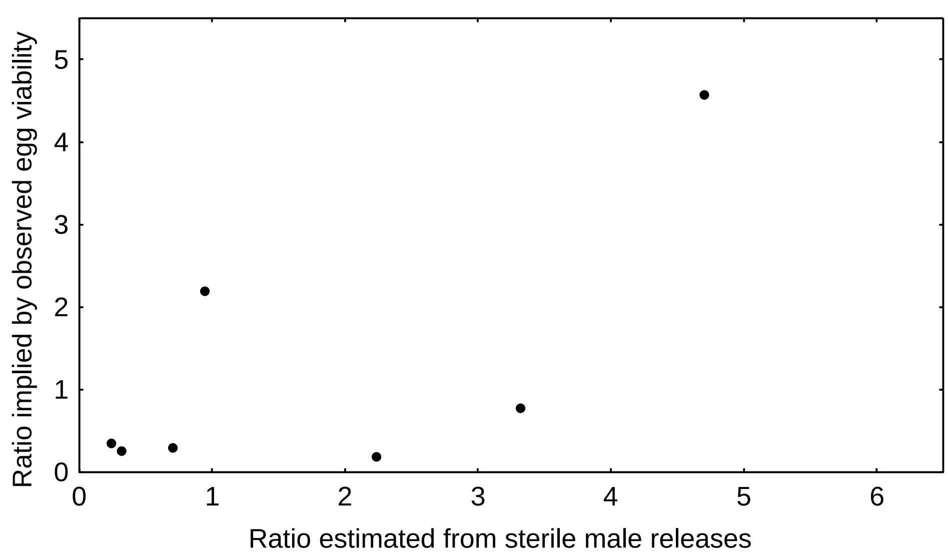

Figure 8. Comparison of the sterile:non-sterile male ratio implied by observed egg viability in nests to the ratio estimated from releases of sterilized males and the spawning population estimate. See the text for an explanation of how the implied ratio was calculated.

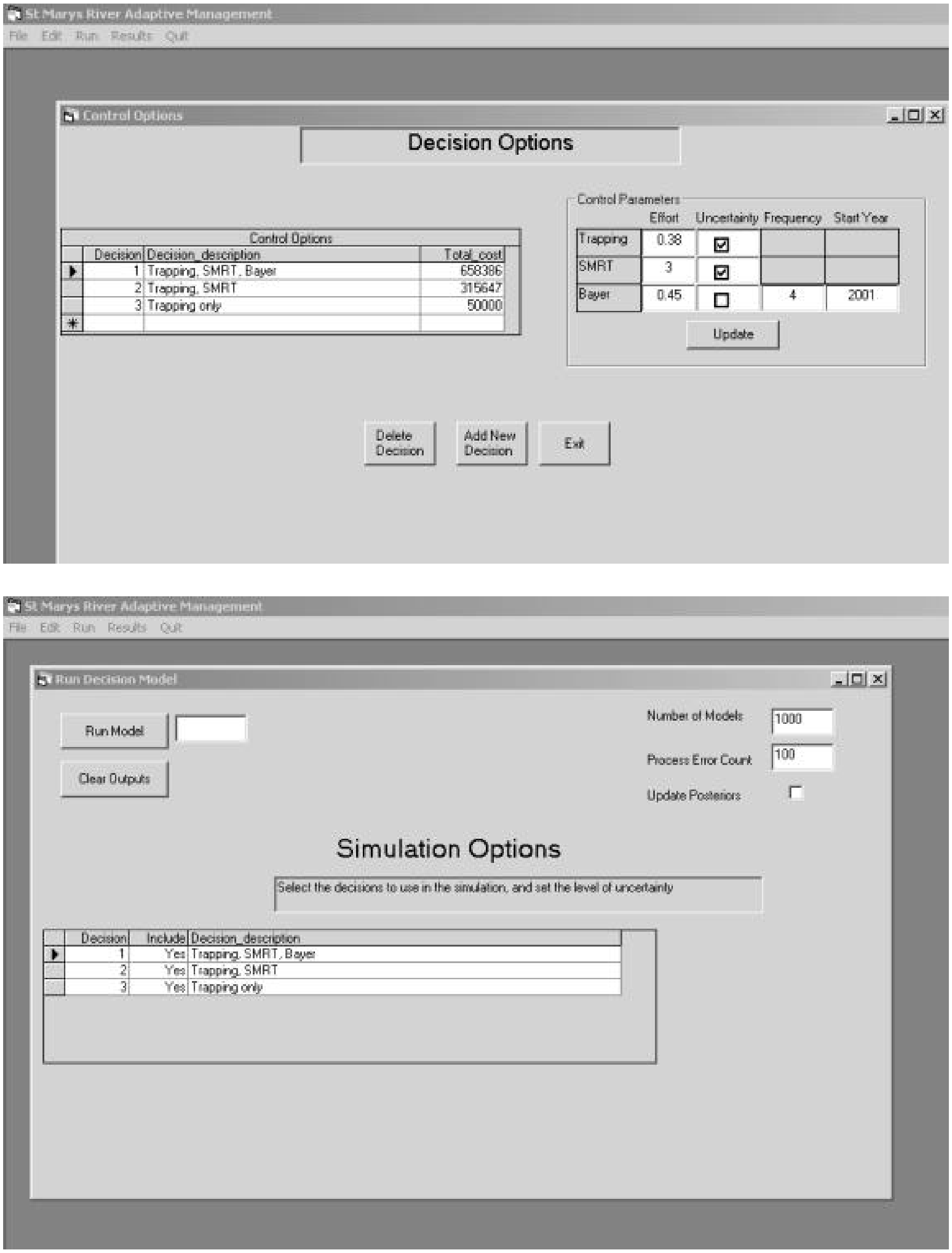

Figure 9. Examples of the user-interface for the St Marys River decision model. Top panel: Decision options specification sheet. Bottom panel: Simulation options specification sheet.

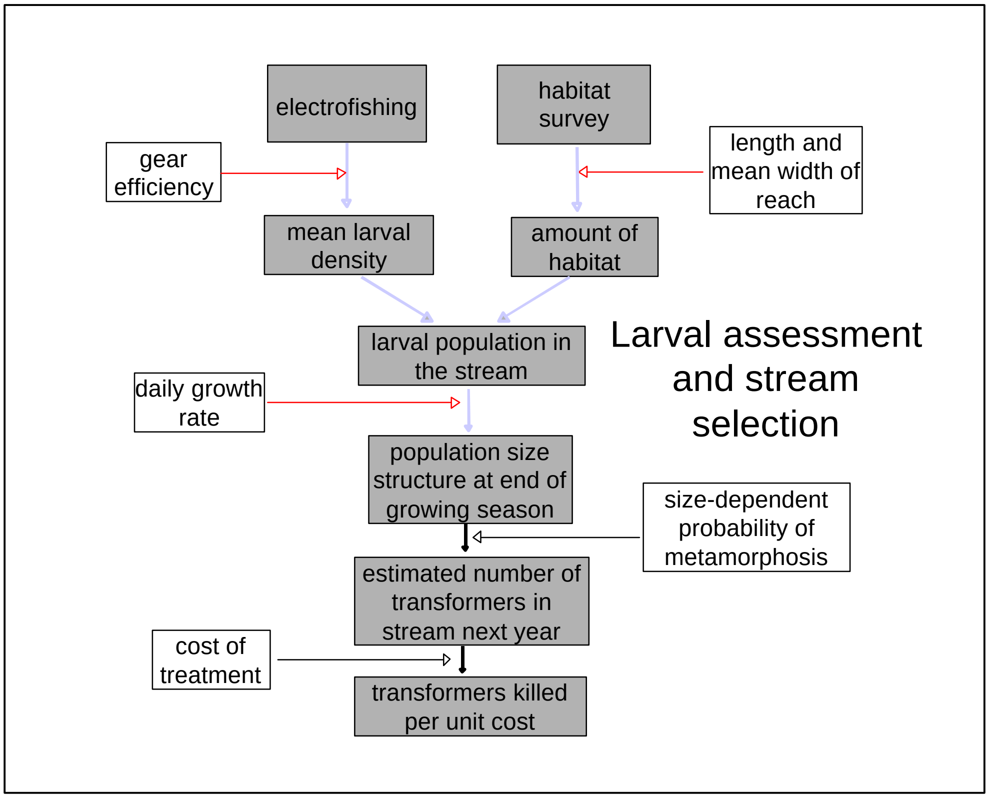

Figure 10. Steps involved in determining the rank of individual streams for lampricide treatment. Streams with the highest estimate of "transformers killed per unit cost" are giving the highest priority for treatment. Each of the steps shown in this figure includes an element of uncertainty.