Conclusions and Recommendations from GSI Modelling and Sampling Workgroup

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The workgroup recommends that catch composition (incidental and legal) determined from GSI data be compared to predictions from the PSC Chinook Model for major fisheries. The model was not originally intended to estimate total catch composition for the fisheries that are simulated, and has a number of shortcomings due to incomplete representation of stocks, use of potentially inappropriate CWT indicator stocks, and other factors (see Section 2.1.2). Given these issues, model- and GSI-based estimates of stock composition in the Southeast Alaska all-gear fishery were surprisingly similar. However, there were some consistent biases for several stock groups. The Fraser, Lower Columbia and Puget Sound stock groups were consistently underestimated and the Mid/Upper Columbia stock group was consistently over-estimated by the PSC Chinook Model.

GSI data can be used in conjunction with estimated cohort vital rates based on CWTs and some very strong assumptions to estimate terminal run size for natural stocks (see Section 2.9). The workgroup felt that direct estimates of escapement (e.g. mark-recapture) would be much preferred over GSI-based indirect ones because direct estimates do not depend on assumptions about similar exploitation and maturation rates of natural and hatchery indicator stocks. However, given the costs of measuring escapement, the indirect method was considered to have promise. It was considered to be more useful for coho than Chinook, because direct estimates of coho escapement are more difficult, and because most coho stocks return at a single age. The workgroup recommends continued refinement of GSI-based methods, such as development of a hybrid approach to estimate regional escapement by incorporating information from wild escapement measurements of index stocks.

The workgroup recommends that collection of GSI data for in season management be done judiciously in cases where the benefits are well justified (see Section 1.5). While successful inseason programs have been undertaken using other technologies (e.g. scales) and in more spatially limited fisheries using GSI (e.g. Fraser sockeye) in the past, a coastwide application to evaluate inseason stock composition would be a very significant effort. There is also a need to investigate the cumulative impacts of using GSI for in season management if applied to a large number of fisheries. Given that resources are finite and management conflicts may be difficult to resolve, the benefits of such a program are likely difficult to justify.

The workgroup recommends that evaluation of the stock proportions of incidental fish based on GSI be compared to estimates from the CTC model on a limited scale to evaluate CTC model assumptions. Incidental morality is the sum of release mortality as well as mortality due to drop-off/drop-out (see Section 2.3). Only release mortality can be estimated, and it depends on the product of the release mortality rate, the encounter rate, and the proportion of each stock that cannot be retained. GSI data could be used to estimate the latter component, which would be an improvement relative to the current approach based on the CTC model. However, the estimate of release mortality may still be highly uncertain because of large variability in the release mortality rate and encounter rate, and the program would be costly and would require on-board observers to take samples and measure encounter rates.

Sample size requirements for GSI data depend on the objectives for estimation and the desired precision and bias (see Section 2.8). There are a number of statistical tools that can be used to estimate sample size, but the PSC will first have to identify and prioritize objectives and their risk tolerances that determine required levels of precision and bias. Sample sizes for estimating presence/absence are considerably more modest than estimation of stock proportions in the catch. For many stock assessment purposes, estimates of stock-age-specific fishery encounters are required, and this will typically require estimation of total catch, proportion legal-size, and possibly fishing effort, as well as age-specific stock proportions using GSI and scale data. The variance of such a compound statistics depends on the variance components, and reducing variance in just one component (e.g. stock proportions) does not necessarily lead to substantive gains in precision of the compound statistic. Under the optimistic assumption of random sampling and binomial or multinomial variation, achieving reasonable relative variance (CV=0.2) for stocks that constitute a very minor component of the catch (e.g., p=0.03) requires very large within-strata sample size (ca. 800). Misclassification error and clumping of stocks over space and time increase sample size requirements substantially. It is therefore not realistic to expect to be able to estimate the probability of occurrence or the fishery encounters of weak stocks that make up a very minor component (e.g. p<2%) of a particular fishery, regardless of sample size. Given this reality, a new approach to management of weak stocks is required (see Section 2.5.2).

Regarding sample size, the workgroup recommends: 1) prioritization of objectives for sampling; 2) sample representatively and continuously check that sampling protocols are being followed; 3) oversample the catch and process GSI data from a random sample of the larger sample to ensure that the data are representative; 4) coordinate GSI and CWT sampling programs; 5) aggregate the data as much as possible to improve precision and minimize misclassification error; and 6) recognize that a stock can be too small to be effectively sampled by GSI given sampling and misclassification error. More work needs to be done to define the parameters that determine this situation.

The workgroup recommended development of a multi-stock synthesis model (see Section 2.7). This model would estimate biological and observation parameters by fitting to multiple sources of information, including stock-specific catch and escapement based on GSI and CWT data. This modeling approach has the advantages of replacing CTC model assumptions with estimated parameters, therefore providing a more realistic assessment of uncertainty and a better understanding of the data.

The workgroup recommends that a demonstration project be used to explore the utility of small area estimation statistical methods. The current Chinook and coho management approach requires estimation of many more parameters than can be supported by the data. As a result, many of these parameters cannot be estimated but are assumed and treated as known in the CTC model. Small area estimation (see Section 2.8) offers a statistical alternative to this dilemma, by pooling data across neighboring strata, where strata can be defined by area (stocks geographically close together), time (stocks that pass through a fishery near the same time), or based on other criteria. The extent of pooling is flexible and will depend on the amount of information in the data.

The modeling and sampling workgroup unanimously agreed that current GSI data cannot replace the function of CWT program. Thus funding to resurrect the CWT program should still be a top priority. GSI provides useful additional information (e.g. may permit estimation of terminal run size for natural stocks) and can be used to test specific hypotheses. GSI may provide a more substantive contribution under a different management paradigm. The workgroup recommends evaluation of the cost of a coastwide GSI ocean sampling and escapement program that allows run reconstruction based on GSI and ageing (for GSI reporting groups). The costs and benefits of this program should be compared to the CWT program.

Report of Discussions from GSI Modelling and Sampling Workgroup, May 16-17, 2007 (Portland),

and

Compilation of Workshop Reports

Presented at the September 11-13, 2007 Workshop (Vancouver)

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The overall objective of the PSC workshop series on GSI data is to develop recommendations for integration of GSI information into a coordinated coast-wide management system to improve the ability of ocean Chinook and coho fisheries to access abundant stocks within impact constraints established for other specific stocks. This draft report summarizes discussions of the GSI modeling and sampling workgroup that occurred during the May 2007 workshop, and compiles the reports provided by workgroup members following the May workshop. These reports address the key questions identified during the May workshop, and will be presented at the September 2007 workshop in Vancouver.

This report is organized into two major sections. Section 1.0 summarizes the May workshop discussions and the key questions that were identified. Section 2.0 compiles the individual reports addressing these specific questions. The final report will provide updated versions of individual reports and an additional section containing recommendations and synthesis developed during the September workshop.

1.0 Summary of May Workshop Discussions and Key Questions

Two issues were common to many of the GSI-modelling and sampling discussions during the May 2007 workshop. First, given the key role of models in coast-wide management decisions for chinook, there was much discussion about how GSI data could be incorporated into the models or used to evaluate model assumptions and predictions. There was some debate among workgroup members about the utility of the CTC model to address current and future management issues (e.g. operation of fisheries to avoid weak stocks), as well as wide range in understanding about how this model and other management models work. As a result, conversations related to GSI and the CTC model and other models were sometimes complex, and there was not always agreement among workgroup members concerning the utility and application of GSI data with respect to the CTC model. Second, it was recognized that the utility of GSI data to address some modeling and sampling questions very much depends on the temporal and spatial scale of management objectives. Because the scale of management objectives is broad and was not well defined at the workshop, workgroup responses to particular questions were variable and often depended on the scales assumed by individual participants.

The workgroup identified 10 key GSI-modeling and sampling questions. In summarizing discussions here, it was apparent that issues associated with question 4 (How can GSI be used in a post-season assessment of CTC model predictions?) were covered in discussions associated with questions 1 (How can GSI data be used to improve stock representation in the CTC model?) and 8 (Can a stock synthesis modeling approach be used…). Question 4 was therefore removed from this summary, and discussions associated with a total of 9 questions are summarized below.

1.1 How can GSI data be used to improve stock representation in the CTC model?

Issues: The CTC model simulates the dynamics of only a small proportion of the total number of Chinook stocks on a coast-wide basis. GSI data could be used to estimate the proportion of the catch that is comprised of stocks that are not associated with CTC Model stocks, potentially reducing uncertainty associated with the assumption that the currently modeled stocks adequately represent the dynamics of the many stocks that are not modeled. As well, the CTC model provides no representation for Chinook stock groups in the northern transboundary area or for Southern spring Chinook stocks. These stock groupings could potentially be included in the model if GSI data, and other supporting information, such as CWT data, were available.

Uncertainties: Estimates of catch proportions based on GSI data will be highly uncertain in cases where: 1) stocks are very small; 2) stocks are of moderate-size, but rarely caught in distant fisheries; 3) genetic classification error for stocks is large (in some cases it may not be possible to segregate stocks that need to be segregated for management purposes). Uncertainties associated with 1) and 2) are not unique to GSI data, but apply to any tagging program with sparse recoveries. This issue is of particular concern for weak ESA-listed stocks.

Discrepancies between CTC model-based catch composition and that derived from GSI data will depend on the spatial and temporal scale of the analysis. It is uncertain what scale is appropriate and how to integrate GSI-based catch proportion estimates into the CTC model.

GSI data could be used to estimate the proportion of the catch that is comprised of stocks which are represented in the base period and which are not represented in the CTC Model. However, the correspondence between Model stocks, CWT indicator stocks, and the GSI baseline is not at all clear. A number of other issues could enter into this type of evaluation, such as stocks that are genetically related to CTC Model stocks, but which are not represented in the CTC Model, and the methods employed to estimate the stock composition (e.g., assignment error, cut-off criteria, proportion unassigned). The evaluation of the distribution of individual stocks will require GSI estimates wherever individual stocks are impacted by fisheries; consequently, unless methods are standardized and baseline discrimination power is consistent, these results will not be comparable and hence cannot be readily combined. Further, GSI methods would need to be capable of distinguishing between hatchery and wild fish if artificial production alters migratory or maturation behavior (e.g., yearling production of fall Chinook), and would be affected by stock/age assignment error.

Regarding northern transboundary area and Southern stocks not represented in the CTC model, GSI data alone would not constitute a sufficient information basis to include these stocks in the model. CWT data would be required since the current model is based on stock-age-fishery specific exploitation rates. The reason why some Southern US stocks are not included in the CTC Model is that available CWT data indicated little evidence of significant impact by ocean fisheries on these stocks.

Discussion needs to be expanded to Chinook models in general, rather than limited to just the CTC Model. Most of the detailed fishery management planning is actually done using other models such as Chinook FRAM, Klamath Ocean Harvest Model, and terminal fishery models.

Workgroup Tasks:

i. Provide brief and clear descriptions of Chinook management models to facilitate future workgroup discussions about GSI-model linkages. See Section 2.1.1 for descriptions of Chinook management models.

ii. Compare GSI- and CTC model-based catch composition of Chinook in South East Alaskan troll fishery across range of spatial and temporal scales. See Section 2.1.2.

iii. Compare list of stock groupings in CTC model with genetic reporting groups. See Section 5 of genetics workgroup report.

1.2 The CTC model assumes that exploitation rates estimated from CWT data for hatchery stocks adequately represent the exploitation rates on wild stocks. How can GSI data be used to evaluate or avoid this assumption?

Issues: GSI data could be used to estimate the proportion of the catch comprised of specific wild stocks. For wild stocks where escapement and age composition in catch and escapement is reasonably well determined, these data could be combined to estimate exploitation rates.

Uncertainties: GSI data cannot discriminate between hatchery stocks and progeny of hatchery fish that spawn in the wild in the same system. Relatively accurate escapement estimates are required to calculate exploitation rates and there are few accurate escapement estimates for wild stocks.

Workgroup Tasks: None identified.

1.3 How can GSI data to better account for incidental mortalities of sub-legal fish that are released?

Issues: With increases in mark-selective fisheries, the magnitude of errors in predicted harvest impacts on sub-legal fish will likely increase. GSI data could be collected from sub-legal fish prior to improve estimates of sub-legal mortality rates for wild stocks.

The CTC Model computes the stock composition of sub-legal sized fish based on the proportion of each stock-age that is non-vulnerable to a given fishery (< min size limit) and the stock-age cohort sizes for stocks that are caught at any age in the fishery. Thus, only stocks that are caught as legal-sized fish are presumed to be present as sub-legal fish. Note that the CTC Model does not directly represent "distribution" of either the legal or sub-legal sized fish, rather distributional inferences are drawn from model estimates of mortalities across fisheries. The total population of sub-legal sized fish is first computed based on cohort strengths and age-fishery specific proportions of non-vulnerable fish. The composition of the sub-legal mortalities is determined by the proportion of this aggregated sub-legal population that is comprised of individual stocks and ages. The stock composition of the legal sized fish will depend on stock-age cohort sizes and their associated stock-age exploitation rates. As the cohort sizes of different ages and stocks differ, the stock compositions of the legal and sub-legal sized fish will differ. The magnitude of the incidental mortalities estimated by the CTC Model is derived through a variety of methods, depending on the availability of data on the total number of sub-legal encounters observed in monitoring programs.

A related key assumption of the current CTC Model is that all fish of a given age in a specific fishery have the same size distribution, i.e., there are no stock-specific differences in growth functions; this also means that fish of a given age from a given stock have different size distributions depending on the fishery in which it is caught. This assumption is an artifact of the limited amount of size-at-age data that was available when the CTC Model was originally formulated.

A second issue is related to the use of different methods to compute incidental fishing mortalities and hence cohort sizes in the CTC Model and the CWT cohort analysis programs. The CTC Model computes incidental mortalities for all stocks and ages simultaneously while the cohort analysis is performed on each stock individually.

Uncertainties: GSI data could improve estimates of incidental mortality impacts on wild stocks, but these estimates may still very imprecise or biased due to the considerable uncertainty about the shaker-mortality rates. As for 1), it will be difficult to estimate sub-legal proportions for small stocks and due to other factors.

Workgroup Tasks: Provide more detail on issue and how GSI data would be collected and used in CTC model. See Section 2.3.

1.4 How can GSI data be used to improve estimates of the underlying stock distribution over space and time?

Issues: The CTC model assumes that the underlying distribution of stocks, in the absence of fishing, estimated from data collected during the base period, is consistent over time. Although GSI data could be used to estimate stock proportions by fishery, it is less evident how GSI could be used to evaluate the assumption about the temporal stability of the underlying distribution.

Uncertainties: The timing and location of fisheries will change, thus it will be difficult to determine whether observed changes in proportions of various stocks in the catch are due to changes in the underlying distribution over time, or due to differences in fishing patterns. The assessment is further complicated by the fact that recruitment rates to fisheries will be temporally variable due to changes in survival and maturity schedules that may differ among stocks. It may be difficult to evaluate changes in the underlying distribution without a non-fishery based sampling program where effort over space and time is consistent. The cost of such a monitoring program would be very large. In short, the ease at which the underlying stock distribution can be determined from GSI data given other sampling limitations has very likely been oversimplified.

Workgroup Tasks: Provide more detail on issue and use data from CROOS program to illustrate challenges. See Section 2.4.

1.5 How will stock distribution information provided by GSI data be used in fishery management decisions?

Issues: GSI data could contribute to a better understanding of the underlying distribution of stocks, as well as the catch composition of existing fisheries. This information could be used to make pre-season or in-season adjustments to time and area closures to protect weak stocks and optimize catches of more productive stocks. GSI data, in conjunction with effort information, could be used to track catch per unit effort (CPUE) for specific stocks, which could incorporated in the fitting procedure of a future stock assessment model, or for improved pre-season or in-season forecasts.

Uncertainties: Even if the underlying stock distribution, and stock-specific catch compositions for various fisheries could can be better defined from GSI data (see uncertainties associated with question 1.4), it may still be difficult to use this information to shape fisheries if many weak stocks are involved. In this situation it may be necessary to close most areas or openings in a management area. Prioritization of closures in these cases will also depend on the relatively productivity of weak stocks and their status, which may be poorly determined. How would rules for closures based on underlying stock distributions or catch-proportions within certain fisheries be formalized in the current institutional setting?

Workgroup Tasks.

i. Provide more detail on management issues. See Section 2.5.1.

ii. Write-up description of potential new management model that uses GSI data. The resolution at which stocks were represented in the model (i.e., the extent aggregations) would depend on the expected proportions of stocks of concern in a fishery. For example, where the proportions of stocks of concern are small, more aggregated reporting groups would be used. See Section 2.5.2.

1.6 Can GSI data be used in cohort reconstruction?

Issues: Cohort reconstruction requires reliable estimates of catch, escapement, marine survival, and age proportions in the escapement and catch. Currently, cohort reconstruction can only be done on CWT-tagged indicator stocks. GSI could potentially be used to estimate the catch for wild untagged stocks and increase the number of stocks where reconstruction could be applied.

Uncertainties: The workgroup felt that GSI data has little to no potential for reconstruction of Chinook stocks due to errors in ageing, and limited ability to assign fish to individual groups due to stock assignment error. Most coho stocks show little variation in age-at-maturity so ageing error is less of an issue, but escapement estimates for wild coho stocks are generally poor, the genetic baseline for coho is less well developed, and coho generally show less genetic differentiation making increasing the uncertainty in stock proportion estimates. Thus, cohort reconstruction for coho based on GSI data was also viewed rather pessimistically by the subgroup. Uncertainties associated with other questions, such as difficulty in separating key stock groupings from GSI data (e.g. fall and spring Klamath Chinook) also apply to cohort reconstruction.

Workgroup Tasks:

i. Investigate the effects of both stock assignment error and aging error on estimates generated by cohort reconstruction methods and try to devise methods for correcting for stock/age assignment error. See Sections 2.6.1 and 2.6.2

ii. Describe small area estimation approaches in GSI setting when aging data is not available. See Section 2.6.3.

1.7 Can a stock synthesis modeling approach be used to integrate multiple sources of data, including GSI data, to provide improved estimates of harvest rate impacts and better account for uncertainty?

Issues: The CTC model has been successful in helping to make difficult coast-wide decisions on chinook management, but the modeling framework has a number of deficiencies that could be improved by using a stock synthesis approach. For example, the underlying distribution of stocks is estimated using data only from the base period, and uncertainty in escapement data, estimates of harvest rates, marine survival rates, and age composition from index stocks based on CWT data are not considered in the CTC model. GSI data could be used to improve understanding of the underlying stock distribution and the proportion of the catch of various fisheries made up by specific wild stocks. If this information was integrated in a stock synthesis framework it could lead to improved estimates of harvest impacts, and would certainly lead to more realistic estimates of uncertainty due to variations or trends in underlying stock distribution patterns from those implicitly assumed in the CTC model. The improved model would take full advantage of GSI data, and be useful in prioritizing and designing future sampling programs. To some extent, the workgroups ability to assess the utility of GSI data for coast-wide chinook management was limited by not having such a modeling framework.

Uncertainties: Stock synthesis modeling approaches are widely applied in fisheries management, but there are few examples where they have been applied in multi-stock and multi-fishery settings. A coast-wide stock synthesis model may not be feasible given the large number of chinook and coho stocks and fisheries. GSI data, while potentially providing a better accounting of wild untagged stocks, also increases the complexity of the model. Depending on the extent of stock and fishery aggregation, a coast-wide stock synthesis model for coho or chinook could have thousands of parameters. It may not be computationally feasible to estimate these parameters and their uncertainty, and would likely be very difficult to understand and hence trust the model output. Considering these potential difficulties, and the institutional challenges in chinook and coho management, it is highly uncertain whether a more complex model will aid the decision making process.

Workgroup Tasks: Provide a conceptual overview of a multi-stock, multi-fishery, Bayesian stock synthesis model applied in a chinook or coho management setting with emphasis on how GSI data would be integrated. See Section 2.7.

1.8 What are the sample size requirements for GSI data?

Issues and Uncertainties: The workgroup spent little time discussing this issue due to time limitations. It was recognized that required levels of precision and accuracy vary for different components of the fishery. For example, in large mixed-stock ocean fisheries it may be sufficient to be able to identify stock aggregates, while in terminal fisheries it may be necessary to identify the component stocks within the aggregates The adequacy of the CWT sampling approach in relation to GSI requirements was briefly discussed. For example, the CWT program currently samples 20% of the catch. This may be sufficient to determine catch composition for stocks of interest in cases where the catch is large and where a substantial proportion of the catch is made up of these stocks, but inadequate when these conditions are not met. The number of GSI samples required for various levels of precision, accuracy, and reporting aggregation, needs to be determined and compared to the costs of sampling and processing to determine the feasibility of using GSI data on a coast-wide basis. Finally, as for any sampling program, the problem of lack of independence among fish within a sample must be recognized when evaluating the precision associated with alternate sample sizes.

Workgroup Tasks:

i. Outline issues and statistical methods for sample size computations. See sections 2.8.1-2.8.4.

1.9 How can GSI data be used to improve escapement estimates, and would it be better to invest in direct estimates of escapement rather than improving estimates of stock composition via GSI data?

Issues: Escapement data is the most important information to evaluate the success of harvest management decisions for conserving weak stocks. There are two separate and somewhat conflicting issues associated with estimating escapement and GSI data. In cases where it is very difficult or expensive to estimate escapement of wild non-index stocks directly, GSI data could be used to calculate escapements based on the proportion of CWTs represented in terminal fisheries for the index stock relative to the total number of CWTs for that stock that were released, and the proportion of the catch represented by the wild stock (production-expansion estimation method). Direct estimates of escapement would be preferred, and large investments in GSI data potentially reduce funding to directly estimate escapement in cases where it is feasible.

Uncertainties: This issue is not unique to GSI data, and has been well described in PSC's expert panel report on the CWT program.

Workgroup Tasks:

i. The management workgroup will be preparing a brief summary of how escapement estimates generated from GSI and CWT data might be compared with estimates generated by other means. See Section 2.9.

1.10 Alternate Monitoring and Assessment Approaches

Much of the GSI-modeling and sampling discussions were to some extent constrained by existing management and stock assessment frameworks. Some workgroup members felt strongly that a broader and more open-minded approach should be used in discussions concerning GSI data to fully explore its potential to help meet PSC management objectives. Two relatively significant and alternate monitoring and stock assessment approaches were briefly discussed and are reviewed below.

Coast-wide fishery independent juvenile trawl survey. Catch per effort from trawl-based surveys of juveniles could be used in conjunction with stock composition estimates of the surveyed populations from GSI data to improve the accuracy of pre-season forecasts.

Systematic fishery sampling program. As reviewed in question 4), changes in the timing and location of fisheries since the model base period, as well as potential changes in the underlying distribution of stocks, have compromised the ability of the CTC Chinook model to characterize fishery impacts. Considering that the shape of future fisheries may change, a systematic sampling program will be more efficient at estimating the underlying stock distribution and the extent to which it changes due to factors like climate change.

2.0 Individual Modelling and Sampling Workgroup Reports

2.1.1 Overview of Chinook Management Models

Overviews of PSC Chinook Model and the Chinook Fram Model were provided by Gary Morishima

DRAFT MODEL DESCRIPTION
Pacific Salmon Commission Chinook Model
August 8, 2000

Primary Use:

The Pacific Salmon Commission (PSC) Chinook Model is used annually by the PSC to set catch levels of southeast Alaskan and some British Columbia Chinook fisheries tat are driven by model estimates of aggregate chinook abundance in those fisheries (Aggregate Abundance Based Management). Some outputs of the PSC Chinook model are used as inputs to the Chinook FRAM for Alaskan and BC fisheries. The model is also used to generate a portion of the Snake River Fall Index and to compute the Individual Stock Based Management (ISBM) indices for PFMC and inside fisheries as required by the new Pacific Salmon Treaty.

Brief History of Development:

The PSC Chinook model, unlike other models used in the PFMC process, is a multiple year, annual time step model that predicts future stock abundance and fishery catches given historic data on catches, stock abundances, and stock productivity.

Development of the PSC Chinook model began with a single stock model designed to estimate the effects of catch restrictions on stock rebuilding over a number of years. In 1984 a 4 stock, 9 fishery model was used for the Pacific Salmon Treaty negotiations. In 1986 the model was recoded in QuickBasic. Over the years the model has been expanded and revised in important ways.

- Model resolutions has increased to 25 fisheries and 30 stocks
- Ability to evaluate effects of Chinook non-retention and size limit changes were developed
- Stock enhancement (hatchery releases) and supplementation strategies can be evaluated.
- Chinook abundance by fishery can be calculated

- Special reports allow flexibility in post processing of model data (eg ISBM indices).

Stratification:

Stocks:

There are 30 stocks represented in the PSC Chinook model. In some cases, stocks have been combined for purposes of ocean fishery assessments (e.g., Puget Sound Fingerling, Cowlitz/Kalama/Lewis).

Alaska/Canada	**Puget Sound/Wash Coast**	**Columbia River/Oregon**
Alaska South SE Northern/Central B.C. Fraser Early Fraser Late WCVI Hatchery WCVI Wild Upper Strait of Georgia Lower Strait of Georgia Natural Lower Strait of Georgia Hatchery	Nooksack Fall Puget Sound Fingerling Puget Sound Natural Fingerling Puget Sound Yearling Nooksack Spring Skagit Wild Stillaguamish Wild Snohomish Wild Washington Coastal Hatchery Washington Coastal Wild	Columbia River Upriver Bright Spring Creek Hatchery Lower Bonneville Hatchery Cowlitz Fall Hatchery Lewis River Wild Willamette River Spring Hatchery Cowlitz Spring Hatchery Columbia River Summer Snake River Wild Fall Mid Columbia Bright Fall Hatchery Oregon Coastal

Fisheries:

There are 25 fisheries represented in the PSC model. Fisheries can be considered preterminal or terminal, for each stock.

Troll	Sport	Net
Southeast Alaska North BC Central BC WCVI Strait of Georgia Washington/Oregon	Southeast Alaska North/Central BC WCVI Outside Washington Ocean North Puget Sound South Puget Sound Strait of Georgia Freshwater	Southeast Alaska North BC Central BC WCVI Juan de Fuca North Puget Sound South Puget Sound Johnstone Strait Washington Coast Fraser Freshwater

Time Periods:

The PSC Chinook Model uses one time step per year, over multiple years. Model simulations are usually run from catch year 1979 through 2005. Data projected beyond the upcoming fishing year is seldom used, however.

Base Period:

The PSC Chinook Model relies upon escapement, catch, and CWT recovery data collected during the 1979-1981 base period. Data from this period represent fishery reflect exploitation patterns over an extensive geographic area during an extended period of time. This is important to permit evaluation of fishery impacts under a wide variety of season structures. Base period exploitation rates for preterminal fisheries, harvest rates for terminal fisheries, and maturation rates are estimated through cohort analysis procedures.

Not all stocks represented in Chinook FRAM have CWT data directly available from the 1979 –1981 base. (e.g. Snake River Fall Chinook). These stocks are known as ‘Out of Base’ stocks. For these stocks, time series of available CWT derived exploitation rates (harvest rates in terminal fisheries) by fishery are used to estimate what the base period recoveries would have been had the stock been CWTed. These generated recoveries are then used in cohort analysis procedures to estimate base period exploitation rates for the stock.

Capacity to Evaluate Fishery Regulations:

The model has the capacity to simulate three general types of measures to constrain fishery impacts: (1) effort controls; (2) catch ceilings; and (3) catch quotas. These are the same types of measures evaluated by the Chinook FRAM, and the methods used are essentially the same for both models. More detail on the methods is available in the Chinook FRAM description.

Another primary used of the Chinook Model is to predict fishery abundance indices for Aggregate Abundance Based Management (AABM) fisheries and exploitation rate reduction indices for Individual Stock Based Management (ISBM) fisheries. Both types of fisheries are defined by the new Pacific Salmon Treaty agreementModel Structure:

The PSC Chinook model is a deterministic model that essentially performs book-keeping functions to track the progress of individual stock/brood year groups as they are exploited by various fisheries over a number of years.

Individual stock/brood groups are exploited as a single pool; that is, each year, all pre-terminal fisheries operate on the entire cohort and all terminal fisheries operate on the mature run. This structure poses the potential problem thatSAME CHANGE AS IN CHINOOK FRAM HERE since each fishery is modeled independently, it is possible for all fisheries combined to catch more fish than exist in the entire cohort or mature run.

The PSC Chinook model does not contain an explicit migration mechanism, other than the movement of fish from preterminal fishing areas to terminal fishing areas upon maturation. Migration is otherwise implied by base period exploitation rates that vary by time,age, and fishery strata.

Sequence of Computations:

For each year and fishery strata, the PSC Chinook model simulates fishery regulations and salmon population dynamics using the sequence of computations depicted in figure 1:

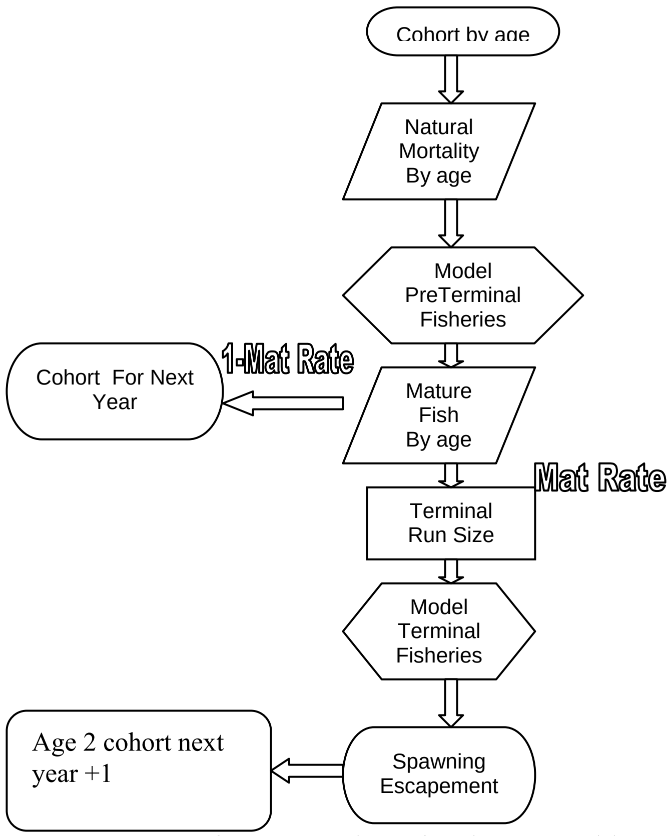


Figure 1. Sequence of Computations for the PSC Chinook Model.

Algorithms:

The PSC Chinook Model simulates fisheries through the use of simple linear equations. If all fish can be retained above a given size, the following general form is used:

$$C_{s,a,f} = BPER_{s,a,f} * N_{s,a} * PV_{s,a,f} * S_f$$

Where:

$C_{s,a,f}$	Catch for stock ***s*** of age **a** in fishery ***f***
$BPER_{s,a,f}$	Base Period Exploitation Rate (Harvest Rate for Terminal Fisheries) for stock ***s*** of age **a** in fishery ***f***. The BPER is derived from cohort analysis using CWT release and recovery data for 1979-1981.
$N_{s,a}$	Number of fish in cohort (for PreTerminal Fisheries; Terminal Run Size for Terminal Fisheries) for stock ***s*** of age **a**
$PV_{s,a,f}$	Proportion of Cohort of age **a** vulnerable to the gear employed in fishery ***f***.
S_f	Impact scalar for fishery ***f*** relative to the base period

The parameter ***S*** lies at the crux of the model's fishery simulation algorithms. The model can evaluate two general types of fisheries: (1) effort-based; or (2) catch-based. For effort-based fisheries, the parameter ***S*** is specified by the modeler to reflect expected effort relative to the effort observed during the model's base period. For catch-based fisheries, ***S*** is computed automatically so as to attain a specified catch level. If the catch level is to be modeled as a quota, then ***S*** is computed as:

$$S_f = \frac{QuotaLevel_f}{\sum_s C_{s,f}}$$

If the catch level is to be modeled as a ceiling or guideline, then ***S*** is computed in the same manner, but has a maximum value of 1.0.

Shaker mortalities are computed only for stocks with landed catch in a fishery.

The following steps are used to compute shaker mortalities:

1. For the stocks with landed catch in a fishery, compute the encounter rate as the ratio of the combined total of the sublegal populations to combined legal populations.

2. Compute the total sublegals encountered by multiplying the landed catch by the encounter rate.

3. Compute the incidental mortality by multiplying encounters by the sum of the release mortality rate and the drop off mortality rate.

4. Allocate the total incidental mortality to each stock and age in proportion to fraction of the total sublegal populations which is comprised of that stock and age.

An additional ‘dropoff’ mortality is also included as a percentage of the landed catch.

Reproduction for stocks with biologically based escapement goals is modeled through a simple Ricker Spawner-Recruit function of the form

$$\text{Recruits} = \text{Spawners} * \text{EXP}(\alpha * (1 - \text{Spawners} / \beta)$$

Annual Management Process:

The PSC Chinook model is calibrated annually by the bilateral Chinook Technical Committee (CTC) of the Pacific Salmon Commission. The calibration process involves updating historic data on fishery catch and effort scalers, stock ocean or spawning escapements, Chinook non-retention data, Interdam losses for Columbia river stocks, and hatchery releases. Abundance forecasts, in the form of predicted terminal returns or spawning escapement, are also input to the model. The calibration process itself involves iteratively estimating stock and brood year survival scalars to achieve the best fit with the historic and forecast catch and terminal run/escapement data. After the CTC has reached agreement on a model calibration, the model is run to generate chinook abundance estimates for AABM fisheries. These abundance estimates are then translated into allowable catches as outlined in the PSC agreement and input to the model as quota catches. As the management season progresses, the model is used to generate effort scalars for the northern fisheries for use in Chinook FRAM, and for evaluation of ISBM and other indices. More details about the PFMC management process is provided in the Chinook FRAM documentation.

Primary Use:

The Chinook Fishery Regulation Assessment Model (Chinook FRAM) is currently employed by the PFMC to evaluate impacts of ocean and Puget Sound fisheries from California to central British Columbia on chinook stocks originating from southern British Columbia, Puget Sound, and the Columbia River.

Brief History of Development:

In the late 1970s, the Washington Department of Fisheries and U.S. National Bureau of Standards developed a model to provide a means of evaluating alternative fishery regulatory packages. The WDF/NBS Model could be configured for either chinook or coho by using different data files. This model was coded in FORTRAN and ran on a CDC mainframe computer at the University of Washington. Model runs were usually processed over night; results were painstakingly extracted from large volumes of printed output reports. The WDF/NBS model was not extensively employed by the PFMC because it proved costly to operate and results were difficult to obtain in a timely manner.

In the mid 1980s a spreadsheet model was developed to evaluate impacts of PFMC management on Columbia River Chinook.

In the mid 1990s, an early version of Chinook FRAM was developed in QUICK BASIC, primarily to assess the impacts of PFMC regulations on Puget Sound stocks and fisheries. As needs grew, Chinook FRAM was expanded to include more stocks, fisheries, and time periods. In 1998, FRAM was converted to VISUAL BASIC to take advantage of improved user interfaces available through the MS WINDOWS operating system. The computer code for Chinook FRAM is currently maintained by Jim Packer of the Washington Department of Fish & Wildlife. A multi-agency Model Evaluation Subgroup periodically reviews model performance and parameter estimation methods and coordinates revisions to model capabilities.

Stratification:

Stocks:

There are 32 stocks represented in the Chinook FRAM. In some cases, stocks have been combined for purposes of ocean fishery assessments (e.g., Nooksack/Samish; Cowlitz/Kalama/Lewis).

Puget Sound	Columbia River/Oregon	Canada
1. Nooksack/Samish Fall 2. N.F. Nooksack Spring 3. S.F. Nooksack Spring 4. Skagit Summer/Fall Fingerling 5. Skagit Summer/Fall Yearling 6. Skagit Spring Yearling 7. Snohomish Fall Fingerling 8. Snohomish Fall Yearling 9. Stillaguamish Fall Fingerling 10. Tulalip Fall Fingerling 11. Mid Puget Sound Fall Fingerling 12. U.W. Accelerated 13. South Puget Sound Fall Fingerling 14. South Puget Sound Fall Yearling 15. White River Spring Fingerling 16. Hood Canal Fall Fingerling 17. Hood Canal Fall Yearling 18. Juan de Fuca Tribs Fall	19. Oregon Hatchery Tule 20. Washington Hatchery Tule 21. Lower Columbia River Wild 22. Bonneville Pool Hatchery 23. Columbia River upriver Summer 24. Columbia River Upriver Bright 25. Cowlitz/Kalama/Lewis Spring 26. Willamette Spring 27. Snake River Fall 28. Oregon Coastal North migrating Fall	29. West Coast Vancouver Island Fall 30. Fraser Late Fall 31. Fraser Early Fall 32. Lower Georgia Strait Fall

Fisheries:

There are 73 fisheries represented in Chinook FRAM. Fisheries can be considered preterminal or terminal, for each stock.

Troll	Sport	Net
Southeast Alaska	Southeast Alaska	Southeast Alaska
North/Central BC	BC Outside	North/Central BC
WCVI	WCVI	WCVI
Strait of Georgia	North Strait of Georgia	Strait of Georgia
Treaty Juan de Fuca	South Strait of Georgia	BC Juan de Fuca
Non-treaty Wash Areas 3,4,4B	BC Juan de Fuca	N. Wash Coastal
Treaty Wash Areas 3,4,4B	Wash Areas 3,4	Non-treaty Greys Harbor
Non-treaty Wash Area 2	Wash Area 2	Treaty Greys Harbor
Treaty Wash Area 2	Wash Area 1	Willapa Bay
Wash Area 1	CR Bouy 10	Columbia River
Central Oregon	Central Oregon	Non-treaty Wash Area 6A,7,7A
Klamath Management Zone	Klamath Mgmt Zone	Treaty Wash Area 6A,7,7A
Southern California	Southern California	Non-treaty Wash Area 7B-7D
	Wash Areas 5,6	Treaty Wash Area 7B-7D
	Wash Area 7	Non-treaty Juan de Fuca
	Wash Area 8-1	Treaty Juan de Fuca
	Wash Area 8D	Non-treaty Skagit
	Wash Area 9	Treaty Skagit
	Wash Area 10	Non-treaty Stilly/Snohomish
	Wash Area 10A	Treaty Stilly/Snohomish
	Wash Area 10E	Non-treaty Tulalip Bay
	Wash Area 11	Treaty Tulalip Bay
	Wash Area 12	Non-treaty Wash Area 6B,9
	Wash Area 13	Treaty Wash Area 6B,9
	Freshwater	Non-treaty Wash Area 10,11
		Treaty Wash Area 10,11
		Treaty Wash Area 10A
		Treaty Wash Area 10E
		Non-treaty Hood Canal
		Treaty Hood Canal
		Non-treaty South Puget

		Sound Treaty South Puget Sound Non-treaty Area 13A Treaty Area 13A Freshwater

Time Periods:

Chinook FRAM uses four time steps over an 18 month period. The time steps are:
October 1 (previous year) – April 30 (current year)
May 1 – June 30
July 1 – September 30
October 1 (current year) – April 30 (next year)

Base Period:

Chinook FRAM is calibrated using escapement, catch, recovery data from the 1979-1981 base. The CWT recovery data from this period reflect exploitation patterns over an extensive geographic area during an extended period of time. This is important to permit evaluation of fishery impacts under a wide variety of season structures. Base period exploitation rates for preterminal fisheries, harvest rates for terminal fisheries, and maturation rates are estimated for by stock through cohort analysis procedures.

Not all stocks represented in Chinook FRAM have CWT data directly available from the 1979 –1981 base. (e.g. Snake River Fall Chinook). These stocks are known as 'Out of Base' stocks. For these stocks, time series of available CWT derived exploitation rates (harvest rates in terminal fisheries) by fishery are used to estimate what the base period recoveries would have been had the stock been CWTed. These generated recoveries are then used in cohort analysis procedures to estimate base period exploitation rates for the stock.

Capacity to Evaluate Fishery Regulations:

Chinook FRAM has the capacity to simulate three general types of measures to constrain fishery impacts: (1) effort controls; (2) catch ceilings; and (3) catch quotas.

- **Effort controls** are specified by the user by fishery as scalar values reflecting expected effort levels relative to those observed during the 1979-1981 base period. In addition, the user can specify stock specific scalars to apply to base period exploitation rates to evaluate management measures that are expected to differentially impact individual stocks. Effort scalars are computed externally to the model.

- **Catch ceilings** represent the maximum allowable retained catch specified by the user for a given time-area-fishery stratum. Catch ceilings are simulated by computing scalars that reflect the ratio between expected catches and the target ceiling levels given estimates of cohort abundance and base period exploitation rates (harvest rates in the case of terminal fisheries). Model catches are computed through an iterative process that estimates the ceiling ratio [cohort abundance * proportion vulnerable * effort scalars * base period exploitation/harvest rates * ceiling ratio] until the model catches approximate target levels within specified precision. With catch ceilings, the scalar value is not allowed to exceed 1.0, that is, catch cannot exceed the level expected under base period exploitation rates applied to current year abundances. PFMC catch 'guidelines' are modeled as catch ceilings in Chinook FRAM.

- **Catch quotas** represent the allowable level of retained catch specified by the user for a given time-area-fishery stratum. Catch quotas are computed identically to catch ceilings, except that the exploitation rate scalar is not constrained in any way. In a quota fishery, the exploitation rate scalar may exceed 1.0; it is adjusted as needed to to force the fishery to take the entire allowable catch.

Model Structure:

Chinook FRAM is a deterministic model that essentially performs book-keeping functions to track the progress of individual stock/age groups as they are exploited by various fisheries over time.

Individual stock/age groups are exploited as a single pool; that is, in each time step, all pre-terminal fisheries operate on the entire cohort and all terminal fisheries operate on the mature run. Each fishery is modeled independently. This structure poses a potential problem in that it is possible for all fisheries combined to catch more fish than exist in the entire cohort or mature run. If this occurs, Chinook FRAM issues a warning message to alert the user, but continues with its calculations.

Chinook FRAM does not contain an explicit migration mechanism, other than the movement of fish from preterminal fishing areas to terminal fishing areas upon maturation. Migration is otherwise implied by base period exploitation rates that vary by time, age, and fishery strata.

Sequence of Computations:

For each timestep and fishery strata, Chinook FRAM simulates fishery regulations using the sequence of computations depicted in figure 1:

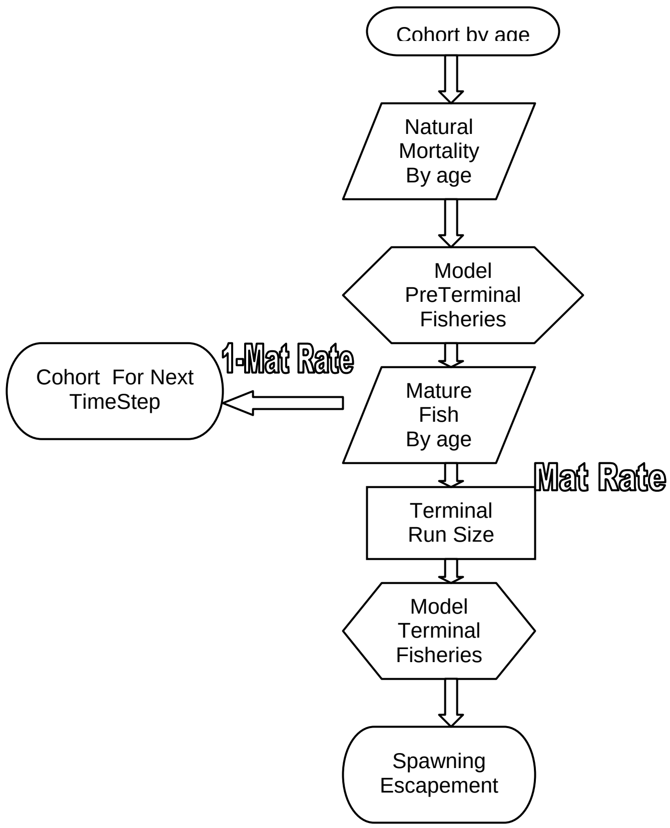


Figure 1. Sequence of Computations for Chinook FRAM

Algorithms:

Chinook FRAM models fisheries through the use of simple linear equations. If all fish can be retained above a given size, the following general form is used:

$$C_{s,a,f} = BPER_{s,a,f} * N_{s,a} * PV_{s,a,f} * S_f$$

Where:

$C_{s,a,f}$	Catch for stock ***s*** of age **a** in fishery ***f***
$BPER_{s,a,f}$	Base Period Exploitation Rate (Harvest Rate for Terminal Fisheries) for stock ***s*** of age **a** in fishery ***f***. The BPER is derived from cohort analysis using CWT release and recovery data for 1979-1981.
$N_{s,a}$	Number of fish in cohort (for Preterminal Fisheries; Terminal Run Size for Terminal Fisheries) for stock ***s*** of age **a**
$PV_{s,a,f}$	Proportion of Cohort of age **a** vulnerable to the gear employed in fishery ***f***.
S_f	Impact scalar for fishery ***f*** relative to the base period

The parameter ***S*** lies at the crux of the model's fishery simulation algorithms. Chinook FRAM can evaluate two general types of fisheries: (1) effort-based; or (2) catch-based. For effort-based fisheries, the parameter ***S*** is specified by the modeler to reflect expected effort relative to the effort observed during the model's base period. For catch-based fisheries, ***S*** is computed automatically so as to attain a specified catch level. If the catch level is to be modeled as a quota, then ***S*** is computed as:

$$S_f = \frac{QuotaLevel_f}{\sum_s C_{s,f}}$$

If the catch level is to be modeled as a ceiling or guideline, then ***S*** is computed in the same manner, but has a maximum value of 1.0.

Shaker mortalities are computed only for stocks with landed catch in a fishery.

The following steps are used to compute shaker mortalities:

5. For the stocks with landed catch in a fishery, compute the encounter rate as the ratio of the combined total of the sublegal populations to combined legal populations.

6. Compute the total sublegals encountered by multiplying the landed catch by the encounter rate.

7. Compute the incidental mortality by multiplying encounters by the sum of the release mortality rate and the drop off mortality rate.

8. Allocate the total incidental mortality to each stock and age in proportion to fraction of the total sublegal populations which is comprised of that stock and age.

An additional ‘dropoff’ mortality is also included as a percentage of the landed catch.

ESA Assessments:

Chinook FRAM outputs are used in ESA assessments for a number of Puget Sound and Columbia River basin chinook stocks. For Snake River Fall Chinook, an age 3/4 adult equivalent exploitation rate, indexed to the 1988-1993 average, is computed for PFMC fisheries from the U.S./Canada border to Cape Falcon, Cape Falcon to Pigeon point, and inside Puget Sound. These indices are combined with analogous indices from the PSC Chinook model for northern fisheries to create the Snake River Fall Index.

For other listed Columbia basin and Puget Sound stocks, calendar year total exploitation rates and/or escapements are estimated and used in the assessments.

Annual Management Process:

Chinook FRAM is used extensively during the annual management process that leads to the development of recommendations for regulation of ocean salmon fisheries in the PFMC area. The elements of this process are described below and are graphically depicted in figure 2.

- The annual management process is initiated in mid-February when abundance forecasts for the individual stock groups represented in Chinook FRAM become available. These forecasts are provided by state and tribal managers and are reviewed by the Salmon Technical Team. The forecasts may be of ocean abundance, ocean escapement, or spawning escapement. They are age specific for some, but not all, model stocks.

- Chinook FRAM is configured each year by scaling stock abundance to correspond to forecast levels. Forecasts of abundance are provided by the Salmon Technical Team in Preseason Report I.

- Planning processes involving state and tribal managers and their fishery constituencies are convened for North of Cape Falcon, South of Cape Falcon and the Klamath Management Area. Meetings occur prior to the March and April meetings of the PFMC to discuss the range of alternatives to be considered by the PFMC.

- The PFMC adopts a set of options in March and publishes its Preseason Report II. This report serves two purposes: (1) facilitates discussion of resource status and fishery impacts for public hearings and written comments; and (2) provides information for continuation of planning processes using Chinook FRAM. It is between the March and April meetings of the Council regional meetings are convened to identify a preferred regulatory package.

- In April, the PFMC identifies a set of tentative options which is evaluated using Chinook FRAM along with other tools and models. The PFMC concludes the meeting with adoption of a regulatory package to submit for consideration by the Secretary of Commerce. The STT and PFMC staff submit the recommended regulations in the Preseason Report III along with a biological opinion for ESA-listed species and an Environmental Assessment to the Secretary.

- If the Secretary disapproves the package, then the PFMC is reconvened to modify its recommendations. If the package is approved, regulations are published in the Federal Register and implemented.

- The adoption of the ocean fishery regulatory package is accompanied by tentative agreements and understandings between State and Tribal managers regarding the conduct of inside fisheries impacting critical stocks. These agreements are generally formalized following the PFMC's April meeting, generally by June.

- As inseason management proceeds, sometimes Chinook FRAM is used to adjust allowable catch levels so as to maintain impacts on limiting stocks at levels anticipated during the preseason process.

- At the conclusion of the season, fishery performance and escapements are compiled and reported in the PFMC's annual Post-Season Review.

In essence, Chinook FRAM is employed in an iterative planning process involving multiple model runs to help shape fisheries so as to distribute allowable stock-specific impacts in a socially acceptable manner (Figure 3). It is not unusual for managers and fishery constituents to generate dozens of scenarios during the course of their deliberations in preseason planning processes.

Documentation of Regulatory Packages Using Chinook FRAM:

Each model run is identified by a unique 4 character name to facilitate sharing of model results. Input data for Chinook FRAM are documented and maintained through the use of "command files" (*.CMD). CMD files contain all the information required to model a specific package of regulations and includes the basic data required to configure the model (e.g., fisheries, stock groups, abundance forecasts, exploitation rate scalers, etc). Base period data are contained in a separate file. Details regarding inside Puget Sound fishery regimes are similarly recorded and maintained in Terminal Area Management Module spreadsheets. Outputs from Chinook FRAM are generated either from a set of standard reports specified by “driver files” (*.DRV) or from a custom report designed by the user.

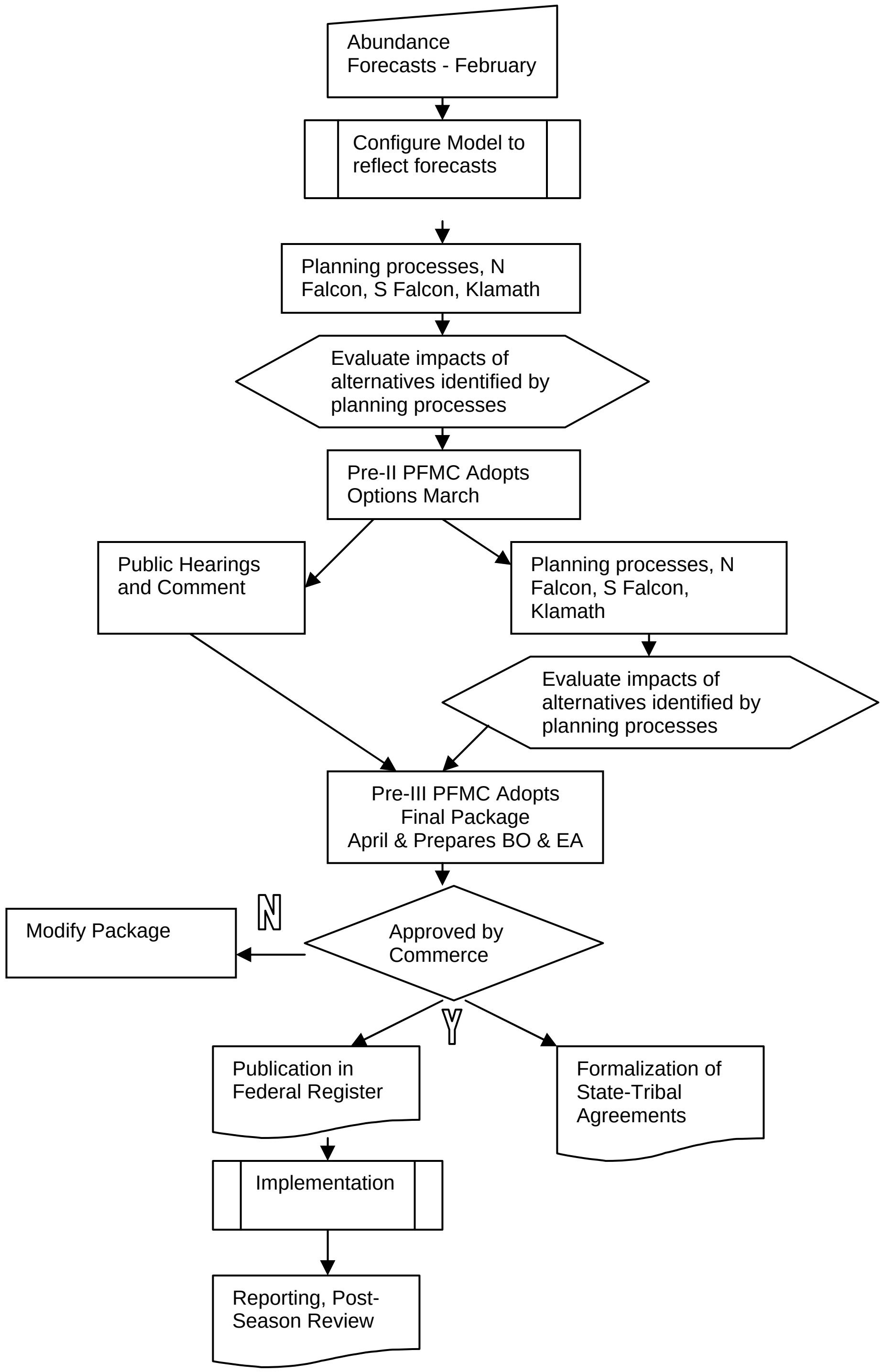


Figure 2. Annual PFMC Planning Process

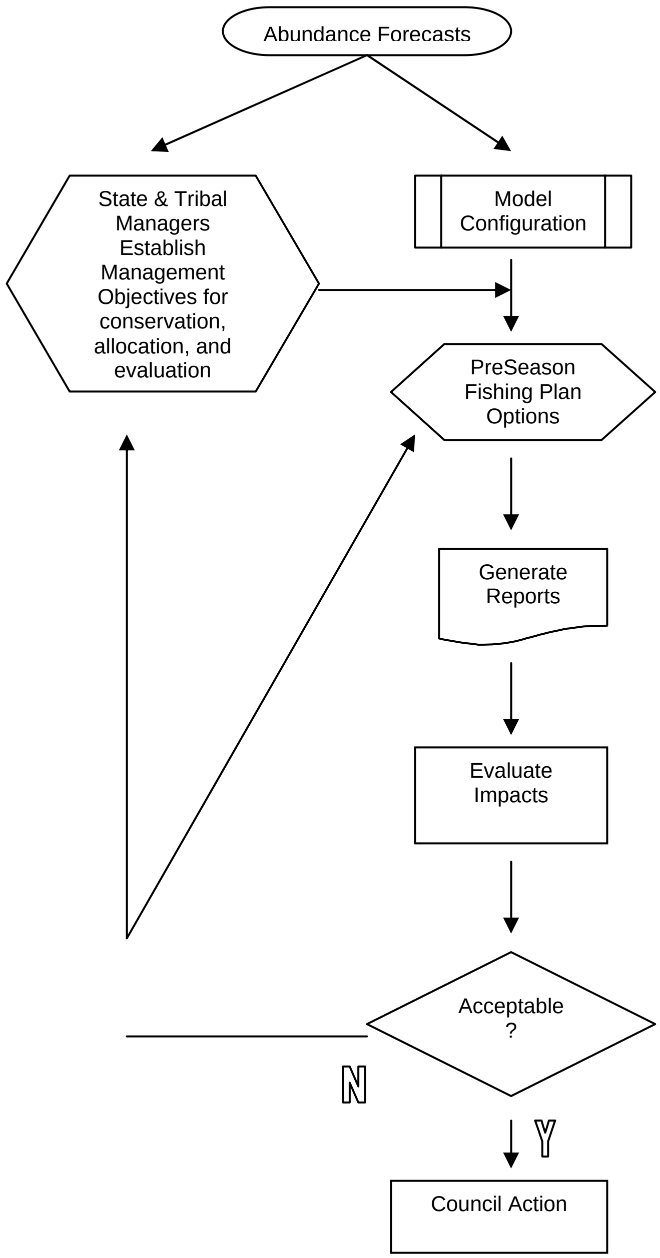


Figure 3. Iterative use of Chinook FRAM in PFMC Preseason Planning Process

2.1.2 Comparison Between Fishery Specific Stock composition Estimates Derived From The PSC Chinook Model And From Genetic Stock Identification

John Carlile
Alaska Department of Fish and Game

The Pacific Salmon Commission's (PSC) Chinook Model was originally developed as a tool to evaluate the effect of fishery management actions on the rebuilding of depressed Chinook stocks. The number of stocks and fisheries in the model has grown from 4 stocks and 9 fisheries at the time the Pacific Salmon Treaty was signed in 1985 to 30 stocks and 25 fisheries currently. The main purpose of the model in the early years was to determine the effects of proposed management actions on the terminal runs or escapements of the stocks in the model. However, over the years the PSC Chinook Model was adapted for other uses. Currently the main use of the model is in determining an index of the overall abundance of Chinook in the Aggregate Abundance Based Management (AABM) fisheries. There are currently three AABM fisheries, the Southeast Alaska All-gear fishery (Troll, Net and Sport), North BC Troll and Sport, and the WCVI Troll and Outside Sport. Over the years of its existence, the PSC Chinook Model has also been used for another task to which it is not ideally suited. The model has been used to generate yearly estimates of the stock composition for fisheries represented in the model. Utilizing the PSC Chinook Model for this purpose has several drawbacks. These drawbacks include:

1. Not all stock groups present in the fisheries are represented in the model.
2. The catches that are modeled are catches of "treaty" Chinook which are sometimes less than the actual total catch in the fishery.
3. The yearly stock and fishery specific catch estimates provided by the PSC Chinook Model are the partially the result of various model based assumptions. For example, assumptions underlie the use of CWT indicator stocks and the methods used to scale the base period exploitation rates.

Notwithstanding these limitations, and with a few additional adjustments, comparisons can be made between the fishery specific stock composition estimates derived from the PSC Chinook Model and from Genetic Stock Identification (GSI).

Although the Southeast Alaska AABM fishery consists of troll, net and sport gears, only the Southeast Alaska troll fishery was chosen for comparison purposes in this paper due to a longer and more complete time series of GSI data for the troll fishery as compared to the other gears. PSC Chinook Model stock composition estimates are available from 1979 to the present and GSI stock composition estimates for the Southeast Alaska troll fishery are available for the years 2001 through 2005. Although stock composition estimates can be obtained from both sources, some manipulation of the stock composition estimates from the PSC Chinook Model is required to make them more directly comparable to the estimates derived from GSI. This manipulation is needed due to the fact the allowable catch of "treaty" Chinook or treaty catch that is actually less than the total catch of Chinook in the Southeast Alaska troll fishery. Since the GSI stock composition estimates reflect the composition of the total catch and the PSC Chinook Model stock composition estimates reflect the composition of the treaty catch, adjustments to the PSC Chinook Model estimates must be made so that they reflect the composition of the total catch.

The discrepancy between the treaty catch and the total catch comes from two sources. One source is from the exclusion of the catch of wild Chinook from the transboundary river systems of the Taku and Stikine in areas adjacent to these wild systems. The second source is from something entitled the Alaska Hatchery Addon. The Alaska Hatchery Addon is an increase or "add-on" to the treaty catch to account for increased Chinook production from Alaska hatcheries above the level present in 1985 when the original Pacific Salmon Treaty was signed. The Addon is calculated as a lower 90% one sided confidence limit of the estimated contribution of Alaska hatchery Chinook based on coded-wire-tags minus the pre-1985 contribution level of approximately 5,000 Alaska hatchery Chinook. Therefore, adding the wild transboundary excluded catch and the Alaska Hatchery Addon to the catch composition estimates from the PSC Chinook Model will provide estimates more directly comparable with the GSI estimates.

The PSC Chinook Model operates on a yearly time step. However, GSI stock composition estimates for the Southeast Alaska troll fishery were collected from several distinct time periods during the year. The Southeast Alaska troll fishery operates on an accounting year that stretches from October 1 of the prior calendar year to September 30 of the current calendar year. The Early Winter period runs from October to December, the Late Winter period runs from January to April, the Spring period occurs in May and June and the Summer periods (the are usually 2 or more) occur from July through September. In order to make the GSI stock composition estimates from these individual time periods comparable to the model estimates, the period specific estimates were multiplied by the associated total troll catch from each period and summed across the year. This effectively weighted the stock composition estimates by the catch level in each of the time periods.

In order to facilitate comparisons between the PSC Chinook Model stock composition estimates and the GSI based estimates some aggregation of stocks in both the PSC Chinook Model and the GSI estimates was necessary due to the lack of one-to-one correspondence between the stocks from the two methods. This aggregation also had the advantage of producing less cluttered charts and tables for comparison purposes.

Table 1. PSC Chinook Model Stocks and Stock Group Aggregations for Comparison Purposes.

PSC Model Stock	Stock Group
Alaska TBR[1]	AK/BC Transboundary
Fraser Early	Fraser
Fraser Late	Fraser
Fall Cowlitz Hat	Lower Columbia
Lewis R Wild	Lower Columbia
Lwr Bonneville Hat	Lower Columbia
Spr Cowlitz Hat	Lower Columbia
Spring Creek Hat	Lower Columbia
Willamette R	Lower Columbia
Col R Summer	Mid/Upper Columbia
Lyons Ferry	Mid/Upper Columbia
Mid Col R Brights	Mid/Upper Columbia
UpRiver Brights	Mid/Upper Columbia
North/Centr	North/Central BC
Oregon Coast	Oregon Coast
Nooksack Fall	Puget Sound
Nooksack Spring	Puget Sound
Pgt Sd Fing	Puget Sound
Pgt Sd NatF	Puget Sound
Pgt Sd Year	Puget Sound
Skagit Wild	Puget Sound
Snohomish Wild	Puget Sound
Stillaguamish Wild	Puget Sound
Alaska South SE	Southeast Alaska
Alaska Hatchery[1]	Southeast Alaska (H)
Georgia St. Lwr Ha	Strait of Georgia
Georgia St. Lwr Na	Strait of Georgia
Georgia St. Upper	Strait of Georgia
Unknown	Unknown
WA Coastal Hat	Washington Coast
WA Coastal Wild	Washington Coast
WCVI Hatchery	WCVI
WCVI Natural	WCVI

[1] Not an actual PSC Chinook Model stock.

Table 2. GSI Stocks from 2001-2003 Allozyme-Based Estimates and Stock Group Aggregations for Comparison Purposes.

Stock	Stock Group
AK/BC Transboundary	AK/BC Transboundary
California, S. Oregon Coastal	California
Central Valley (Sp, F, W)	California
Klamath (Sp and F)	California
Lower Fraser	Fraser
Mid and Upper Fraser	Fraser
Thompson River	Fraser
Lower Columbia Spring and Fall	Lower Columbia
Willamette	Lower Columbia
Mid and Upper Columbia, Snake Sp	Mid/Upper Columbia
Upper Columbia (Su, F), Snake F	Mid/Upper Columbia
Central BC Coastal	North/Central BC
Nass	North/Central BC
Skeena	North/Central BC
Mid and North Oregon Coastal	Oregon Coast
AK Peninsula	Other Alaska
Gulf of Alaska	Other Alaska
Kodiak	Other Alaska
Susitna	Other Alaska
Western AK	Other Alaska
Puget Sound	Puget Sound
Chilkat	Southeast Alaska
King Salmon River	Southeast Alaska
Southern SE AK	Southeast Alaska
Strait of Georgia	Strait of Georgia
Unknown	Unknown
Upper Canadian Yukon	Upper Canadian Yukon
Washington Coastal	Washington Coast
WCVI	WCVI

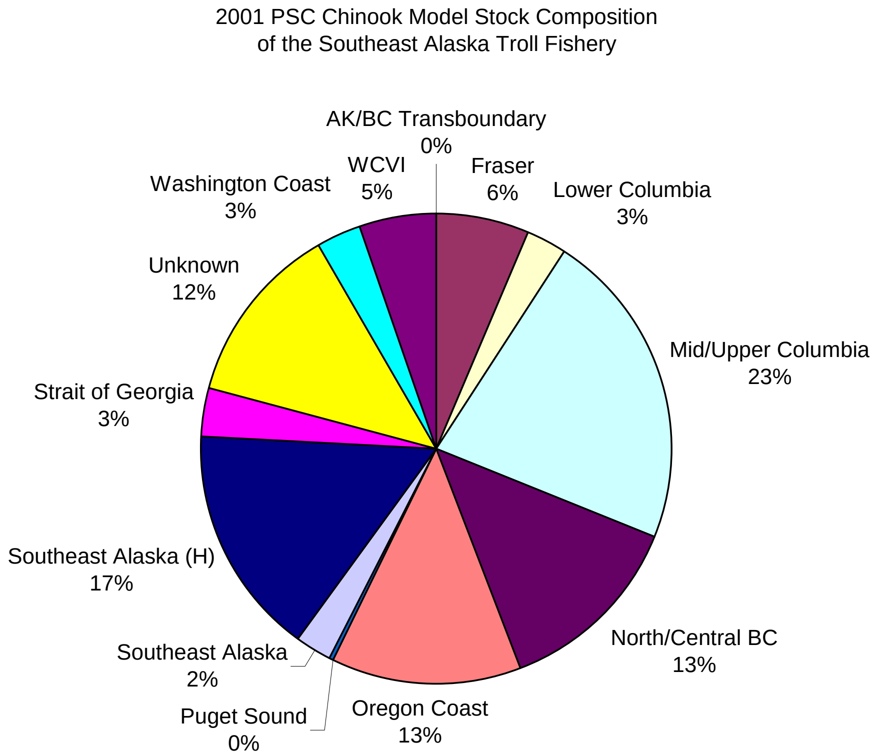
Table 3. GSI Stocks from 2004-2005 Microsatellite-Based Estimates and Stock Group Aggregations for Comparison Purposes.

Stock	Stock Group
Taku River	AK/BC Transboundary
Upper Stikine R	AK/BC Transboundary
California Coast	California
Central Valley Fa	California
Central Valley Sp	California
Central Valley Wi	California
Kalamath R Basin	California
Lower Fraser	Fraser
Lower Thompson	Fraser
Mid Fraser	Fraser
North Thompson R	Fraser
South Thompson	Fraser
Upper Fraser	Fraser
Lower Columbia Fa	Lower Columbia
Lower Columbia Sp	Lower Columbia
Willamette River	Lower Columbia
Deschutes R fa	Mid/Upper Columbia
Mid and Upp Columbia	Mid/Upper Columbia
Mid Columbia tule	Mid/Upper Columbia
Snake R fa	Mid/Upper Columbia
Snake River Sp Su	Mid/Upper Columbia
Upp Columbia Su Fa	Mid/Upper Columbia
Central BC Coast	North/Central BC
Lower Skeena	North/Central BC
Nass River	North/Central BC
Upper Skeena	North/Central BC
Mid Oregon Coast	Oregon Coast
North CA, South OR coast	Oregon Coast
North OR Coast	Oregon Coast
Rogue River	Oregon Coast
Hood Canal	Puget Sound
Juan de Fuca	Puget Sound
North Puget Sound	Puget Sound
South Puget Sound	Puget Sound
Alsek R	Southeast Alaska
Andrew Creek	Southeast Alaska
Chilkat R	Southeast Alaska
King Salmon	Southeast Alaska
S. Southeast AK	Southeast Alaska
Situk R	Southeast Alaska
East Vancouver	Strait of Georgia
South BC Mainland	Strait of Georgia
Unknown	Unknown
Washington Coast	Washington Coast
West Vancouver	WCVI

Figures 1-5 present comparisons of the PSC Chinook Model calibration #0705 and GSI stock composition estimates for the years 2001 through 2005 respectively. The PSC Chinook Model estimates were modified to include the Southeast Alaska (H) group that represents the Alaska Hatchery Addon, the AK/BC Transboundary group that represents the transboundary excluded catch and an Unknown group that represents the difference between the PSC Chinook Model's estimated catch and the treaty catch. This was done so that the catch composition estimates would represent the total catch in the fishery and would therefore be more directly comparable with the GSI catch composition estimates. The GSI Model estimates were modified to include some terminal Alaska hatchery catch that is not sampled for GSI as part of the Southeast Alaska stock. This hatchery terminal catch only accounts for a few thousand fish per year. The 2001 through 2003 GSI estimates are based on allozyme data and the 2004 to 2005 data are based on microsatellite data using the GAPS 2.0 baseline.

Table 4 contains the numerical estimates of the Southeast Alaska troll catch by stock as estimated by the PSC Chinook Model for 2001 to 2005. Tables 5-9 contain the numerical estimates of the Southeast Alaska troll catch by stock as estimated by GSI for the years 2001 to 2005.

Figure 1. 2001 PSC Model and GSI Stock Composition Estimates for the SEAK Troll Fishery.



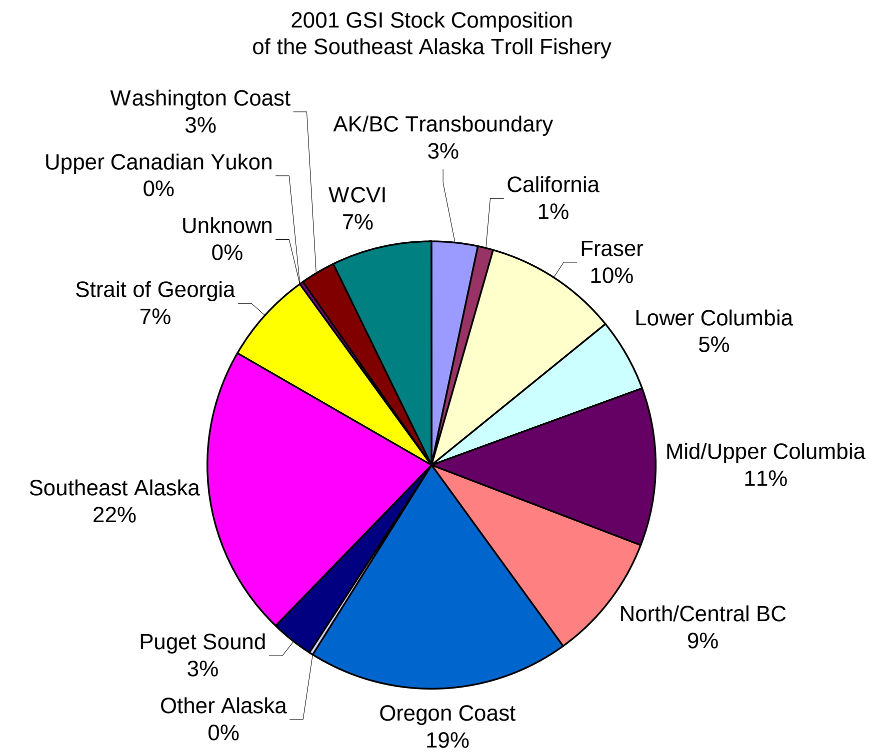
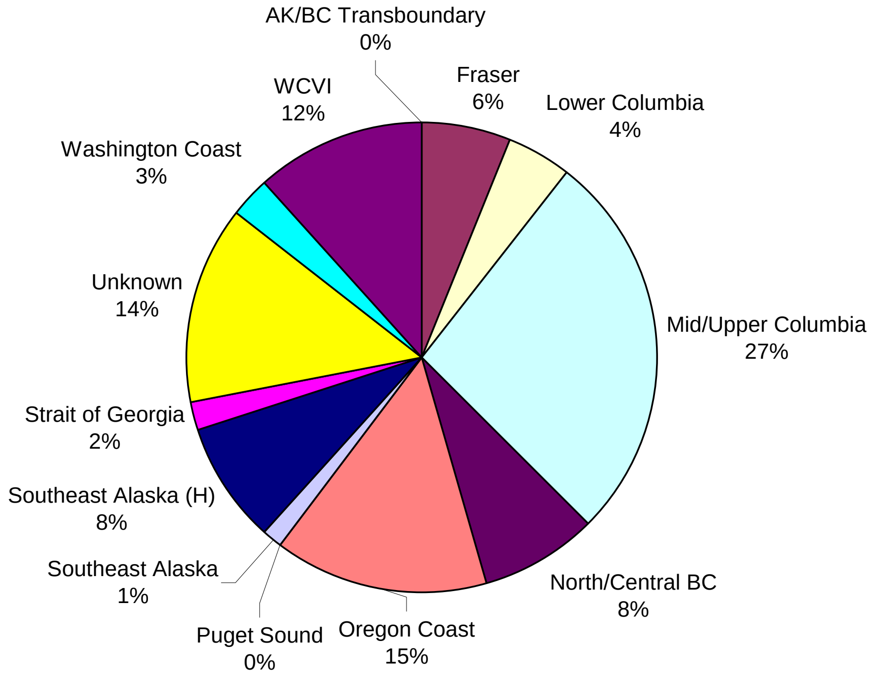


Figure 2. 2002 PSC Model and GSI Stock Composition Estimates for the SEAK Troll Fishery.

2002 PSC Chinook Model Stock Composition
of the Southeast Alaska Troll Fishery



2002 GSI Stock Composition
of the Southeast Alaska Troll Fishery

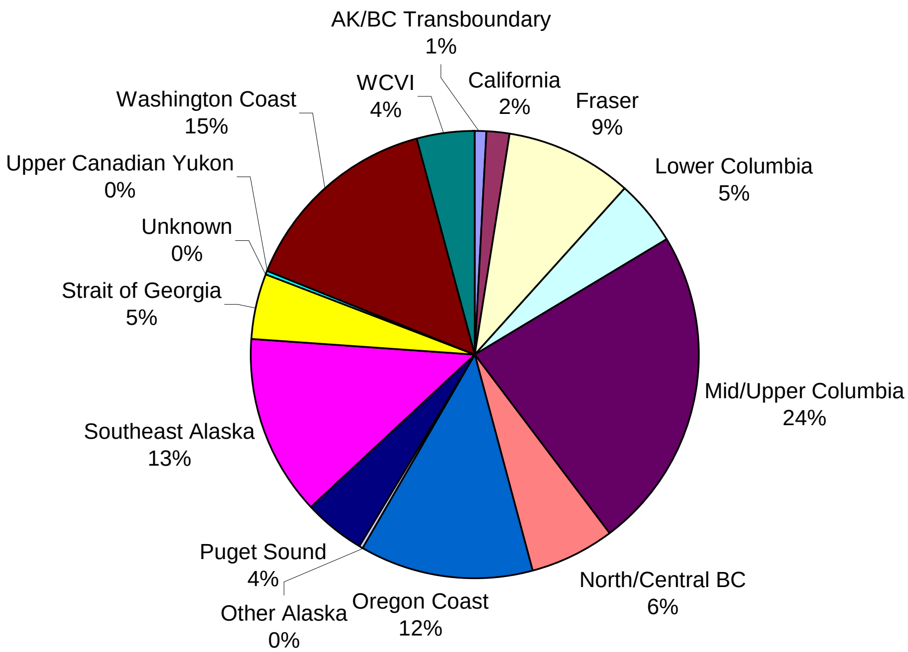
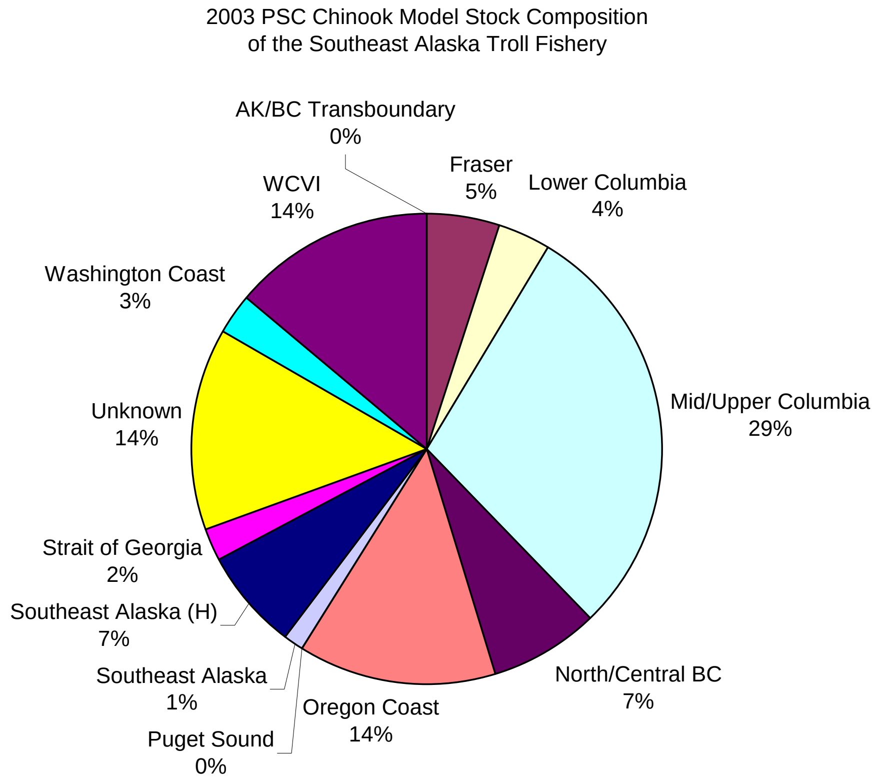


Figure 3. 2003 PSC Model and GSI Stock Composition Estimates for the SEAK Troll Fishery.



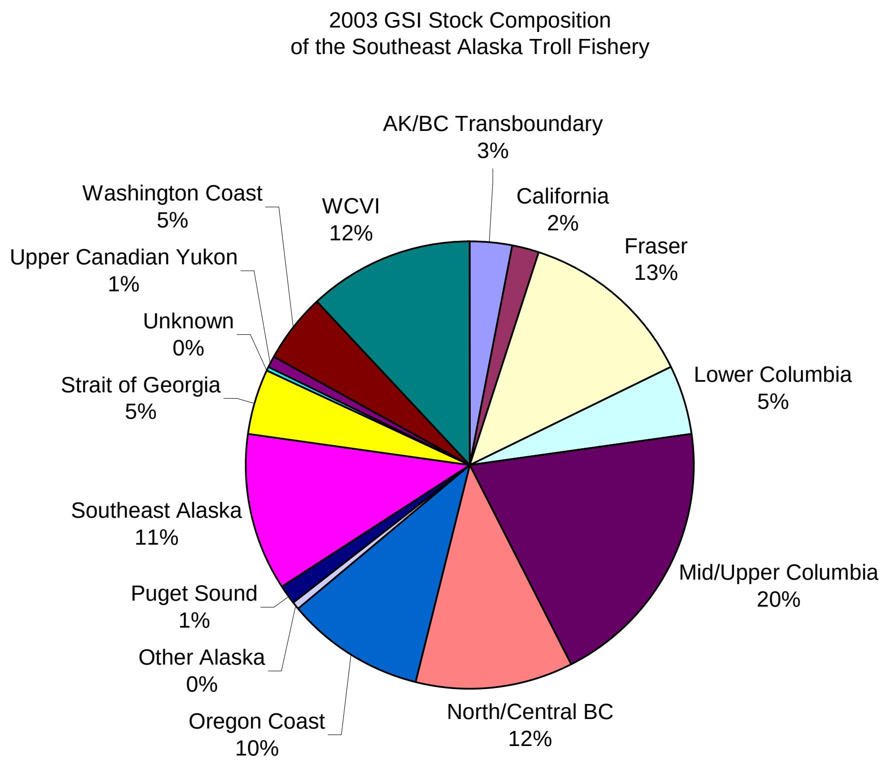
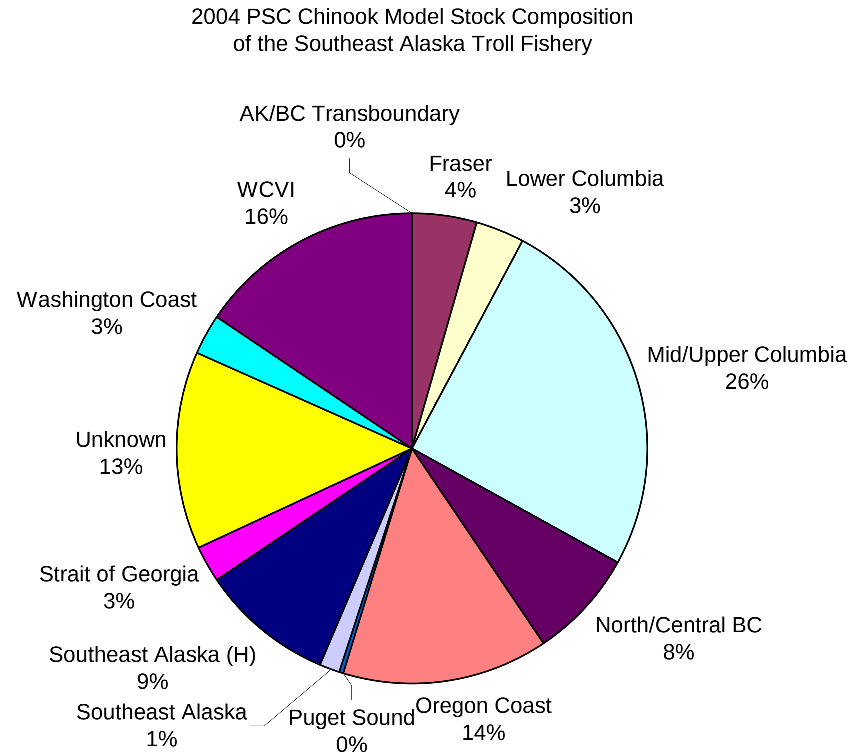


Figure 4. 2004 PSC Model and GSI Stock Composition Estimates for the SEAK Troll Fishery.



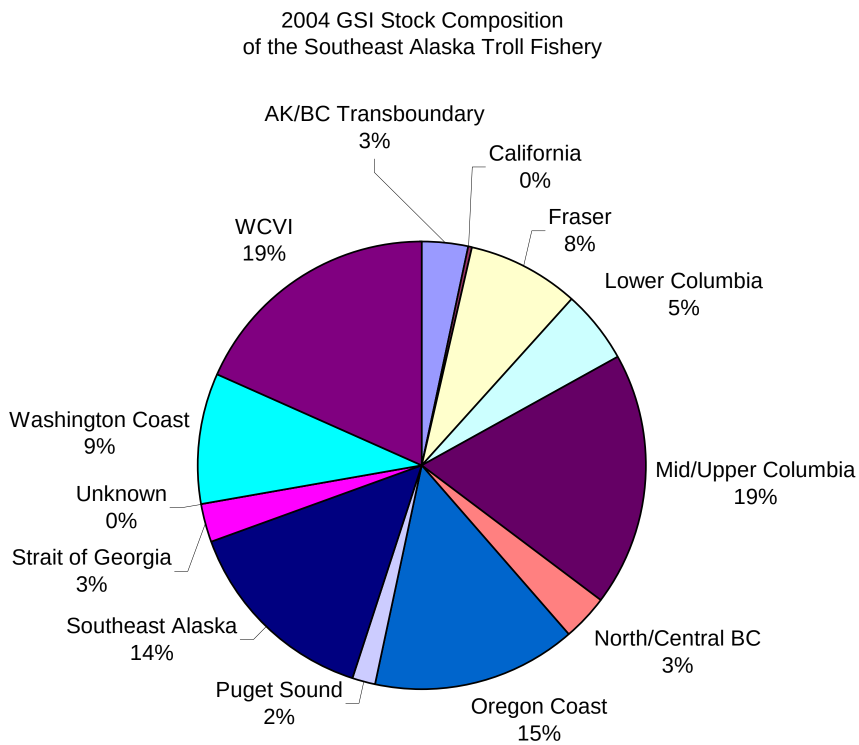
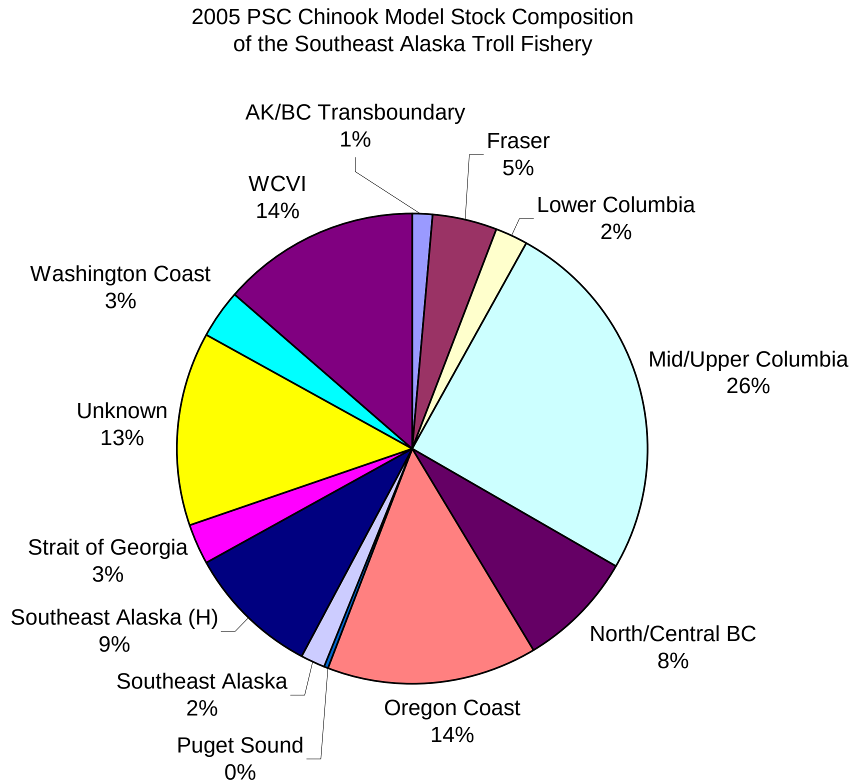


Figure 5. 2005 PSC Model and GSI Stock Composition Estimates for the SEAK Troll Fishery.



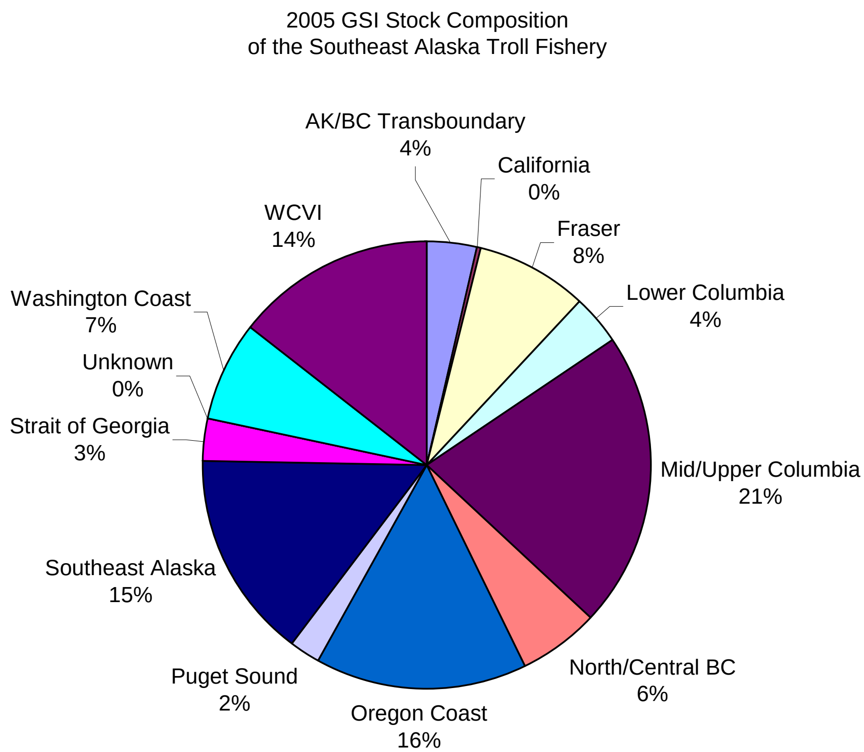


Table 4. PSC Chinook Model Estimates of the Stock Composition of the Southeast Alaska Troll Fishery Catch for 2001-2005 from Calibration #0705.

Stock Group	PSC Chinook Model Stock	YEAR				
		2001	2002	2003	2004	2005
Southeast Alaska (H)	Alaska Hatchery[2]	24,588	27,176	23,312	32,724	31,074
Southeast Alaska	Alaska South SE	3,781	3,825	3,838	4,795	6,249
AK/BC Transboundary	Alaska TBR[3]	0	0	0	0	4,288
Mid/Upper Columbia	Col R Summer	6,734	14,426	11,833	11,668	12,361
Lower Columbia	Fall Cowlitz Hat	495	2,083	4,073	1,967	2,466
Fraser	Fraser Early	9,474	19,411	15,622	15,276	15,187
Fraser	Fraser Late	148	344	666	392	248
Strait of Georgia	Georgia St. Lwr Ha	367	386	400	345	454
Strait of Georgia	Georgia St. Lwr Na	84	121	102	107	96
Strait of Georgia	Georgia St. Upper	4,499	6,352	7,329	8,706	8,917
Lower Columbia	Lewis R Wild	899	2,135	2,789	3,272	1,519
Lower Columbia	Lwr Bonneville Hat	0	0	0	0	0
Mid/Upper Columbia	Lyons Ferry	216	489	371	470	531
Mid/Upper Columbia	Mid Col R Brights	7,240	24,900	27,810	22,176	18,173
Puget Sound	Nooksack Fall	34	33	28	20	19
Puget Sound	Nooksack Spring	0	0	0	0	0
North/Central BC	North/Centr	20,178	25,893	23,953	26,792	27,281
Oregon Coast	Oregon Coast	19,727	47,794	45,251	50,238	48,626
Puget Sound	Pgt Sd Fing	146	210	169	189	227
Puget Sound	Pgt Sd NatF	43	59	43	54	38
Puget Sound	Pgt Sd Year	7	9	11	13	17
Puget Sound	Skagit Wild	133	153	211	296	280
Puget Sound	Snohomish Wild	47	38	63	98	69
Lower Columbia	Spr Cowlitz Hat	38	152	248	242	188
Lower Columbia	Spring Creek Hat	0	0	0	0	0
Puget Sound	Stillaguamish Wild	49	35	46	62	50
Unknown	Unknown[4]	19,100	44,247	45,620	47,781	44,981
Mid/Upper Columbia	UpRiver Brights	19,506	48,269	57,079	55,409	54,871
Washington Coast	WA Coastal Hat	1,971	3,879	3,512	4,187	4,571
Washington Coast	WA Coastal Wild	2,778	5,488	5,114	6,129	6,247
WCVI	WCVI Hatchery	7,098	33,413	42,149	51,206	42,751
WCVI	WCVI Natural	978	4,089	4,217	3,946	3,476
Lower Columbia	Willamette R	2,923	9,898	4,834	6,106	3,182

[2] Not present in the PSC Chinook Model. This represents Alaska Hatchery Addon fish.
[3] Not present in the PSC Chinook Model. This represents transboundary river excluded fish.
[4] Not present in the PSC Chinook Model. This is the difference between the number of treaty fish and the fish that can be accounted for in the model.

Table 5. GSI Stock Composition Estimate of Southeast Alaska Troll Fishery Catch for 2001.

Region	Stock Group	Early Winter	Late Winter	Spring	Summer1	Summer2	Terminal[5]	Total
	Harvest	11,198	11,388	28,250	64,854	30,509	7,081	153,280
Central Valley (Sp, F, W)	California	0	0	0	363	46		409
California, S. Oregon Coastal	California	0	35	0	0	802		838
Klamath (Sp and F)	California	0	0	0	590	3		593
Mid and North Oregon Coastal	Oregon Coast	228	0	144	15,046	13,561		28,980
Lower Columbia Spring and Fall	Lower Columbia	956	288	93	5,545	366		7,249
Willamette	Lower Columbia	22	0	0	655	159		836
Mid and Upper Columbia, Snake Sp	Mid/Upper Columbia	0	52	0	830	52		934
Upper Columbia (Su, F), Snake F	Mid/Upper Columbia	3,163	1,103	418	8,022	3,832		16,539
Washington Coastal	Washington Coast	0	79	192	0	3,621		3,892
Puget Sound	Puget Sound	475	814	814	305	2,096		4,503
Lower Fraser	Fraser	0	0	0	0	0		0
Thompson River	Fraser	50	358	946	10,422	464		12,240
Mid and Upper Fraser	Fraser	0	73	737	1,783	296		2,890
Strait of Georgia	Strait of Georgia	1,327	1,877	1,701	4,955	580		10,439
WCVI	WCVI	847	134	184	8,061	1,724		10,950
Central BC Coastal	North/Central BC	862	855	1,503	0	1,336		4,557
Skeena	North/Central BC	1,359	2,188	692	2,082	0		6,321
Nass	North/Central BC	0	162	302	2,426	0		2,890
AK/BC Transboundary	AK/BC Transboundary	0	174	3,037	1,725	0		4,936
Southern SE AK	Southeast Alaska	1,632	2,956	16,518	1,342	1,400	7,081	30,929
King Salmon River	Southeast Alaska	58	0	0	337	3		399
Chilkat	Southeast Alaska	71	0	802	0	168		1,041
Gulf of Alaska	Other Alaska	0	130	0	39	0		169
Susitna	Other Alaska	148	0	141	0	0		289
Kodiak	Other Alaska	0	0	0	0	0		0
AK Peninsula	Other Alaska	0	110	28	0	0		139
Western AK	Other Alaska	0	0	0	0	0		0
Upper Canadian Yukon	Upper Canadian Yukon	0	0	0	337	0		337
Unknown	Unknown	-1	-1	-3	-13	0		-18

[5] Terminal catch of Alaska hatchery Chinook. No GSI sampling but assumed to be 100% Alaska hatchery fish.

Table 6. GSI Stock Composition Estimate of Southeast Alaska Troll Fishery Catch for 2002.

Region	Stock Group	Early Winter	Late Winter	Spring	Summer1	Summer2	Terminal[6]	Total
	Harvest	17,152	12,237	37,610	187,003	65,266	6,040	325,308
Central Valley (Sp, F, W)	California	0	34	0	991	0		1,025
California, S. Oregon Coastal	California	1,235	116	263	1,346	633		3,594
Klamath (Sp and F)	California	334	37	0	0	0		371
Mid and North Oregon Coastal	Oregon Coast	518	124	282	21,711	17,994		40,629
Lower Columbia Spring and Fall	Lower Columbia	580	1	0	12,024	1,096		13,702
Willamette	Lower Columbia	244	274	0	842	398		1,757
Mid and Upper Columbia, Snake Sp	Mid/Upper Columbia	328	318	260	9,144	2,350		12,399
Upper Columbia (Su, F), Snake F	Mid/Upper Columbia	5,240	2,024	1,395	34,970	19,227		62,856
Washington Coastal	Washington Coast	0	306	327	36,858	10,351		47,843
Puget Sound	Puget Sound	3,135	568	801	5,030	5,091		14,625
Lower Fraser	Fraser	0	297	0	0	0		297
Thompson River	Fraser	377	1,296	3,359	21,767	176		26,975
Mid and Upper Fraser	Fraser	0	135	60	2,356	646		3,197
Strait of Georgia	Strait of Georgia	2,583	1,308	1,689	4,750	4,895		15,225
WCVI	WCVI	0	1,712	2,802	9,406	0		13,920
Central BC Coastal	North/Central BC	1,221	1,273	2,129	4,395	0		9,017
Skeena	North/Central BC	398	126	940	8,770	463		10,698
Nass	North/Central BC	0	379	87	0	209		675
AK/BC Transboundary	AK/BC Transboundary	0	549	1,493	0	796		2,839
Southern SE AK	Southeast Alaska	849	1,245	21,378	11,632	764	6,040	41,906
King Salmon River	Southeast Alaska	0	0	0	0	0		0
Chilkat	Southeast Alaska	0	55	11	524	0		590
Gulf of Alaska	Other Alaska	0	28	0	0	0		28
Susitna	Other Alaska	0	0	0	0	0		0
Kodiak	Other Alaska	0	0	0	0	0		0
AK Peninsula	Other Alaska	0	0	229	505	0		734
Western AK	Other Alaska	0	0	113	0	0		113
Upper Canadian Yukon	Upper Canadian Yukon	41	33	0	0	0		74
Unknown	Unknown	69	-1	-8	-19	176		217

[6] See footnote 4.

Table 7. GSI Stock Composition Estimate of Southeast Alaska Troll Fishery Catch for 2003.

Region	Stock Group	Early Winter	Late Winter	Spring	Summer1	Summer2	Terminal[7]	Total
	Harvest	18,672	32,182	35,435	240,577	0	3,826	330,692
Central Valley (Sp, F, W)	California	665	0	0	0	0		665
California, S. Oregon Coastal	California	1,122	1,242	188	2,646	0		5,199
Klamath (Sp and F)	California	0	0	967	0	0		967
Mid and North Oregon Coastal	Oregon Coast	0	592	996	31,612	0		33,200
Lower Columbia Spring and Fall	Lower Columbia	1,539	3,241	549	8,949	0		14,278
Willamette	Lower Columbia	1,453	1,619	0	0	0		3,071
Mid and Upper Columbia, Snake Sp	Mid/Upper Columbia	288	257	273	1,877	0		2,694
Upper Columbia (Su, F), Snake F	Mid/Upper Columbia	3,320	8,091	1,403	49,030	0		61,843
Washington Coastal	Washington Coast	0	245	677	15,758	0		16,679
Puget Sound	Puget Sound	1,223	1,429	532	1,419	0		4,603
Lower Fraser	Fraser	0	978	0	3,055	0		4,034
Thompson River	Fraser	1,042	2,230	2,746	30,818	0		36,836
Mid and Upper Fraser	Fraser	0	544	0	0	0		544
Strait of Georgia	Strait of Georgia	2,476	1,924	220	11,067	0		15,687
WCVI	WCVI	164	2,945	2,523	34,114	0		39,746
Central BC Coastal	North/Central BC	0	2,771	3,753	15,204	0		21,728
Skeena	North/Central BC	508	2,176	0	7,723	0		10,406
Nass	North/Central BC	0	0	0	5,942	0		5,942
AK/BC Transboundary	AK/BC Transboundary	0	0	3,051	7,097	0		10,148
Southern SE AK	Southeast Alaska	4,188	1,262	16,807	10,922	0	3,826	37,005
King Salmon River	Southeast Alaska	0	0	0	0	0		0
Chilkat	Southeast Alaska	0	0	0	409	0		409
Gulf of Alaska	Other Alaska	284	357	0	0	0		641
Susitna	Other Alaska	405	0	0	0	0		405
Kodiak	Other Alaska	0	0	0	0	0		0
AK Peninsula	Other Alaska	0	167	50	217	0		433
Western AK	Other Alaska	0	0	106	0	0		106
Upper Canadian Yukon	Upper Canadian Yukon	0	0	595	1,492	0		2,087
Unknown	Unknown	-4	113	0	1,227	0		1,336

[7] See footnote 4.

Table 8. GSI Stock Composition Estimate of Southeast Alaska Troll Fishery Catch for 2004.

Region	Stock Group	Early Winter	Late Winter	Spring	Summer1	Summer2	Terminal[8]	Total
	Harvest	12,686	40,200	55,193	194,045	50,937	1,603	354,664
Central Valley Fa	California	0	0	0	524	0		524
Central Valley Sp	California	0	0	0	349	0		349
Central Valley Wi	California	0	0	0	0	0		0
California Coast	California	0	0	0	0	0		0
Kalamath R Basin	California	0	0	0	0	0		0
North CA, South OR coast	Oregon Coast	0	0	79	407	0		486
Rogue River	Oregon Coast	0	0	0	155	0		155
Mid Oregon Coast	Oregon Coast	157	655	476	14,534	7,365		23,188
North OR Coast	Oregon Coast	0	181	823	20,297	7,432		28,733
Lower Columbia Sp	Lower Columbia	270	84	0	0	372		726
Lower Columbia Fa	Lower Columbia	464	860	430	7,839	1,885		11,479
Willamette River	Lower Columbia	594	2,299	0	2,445	1,228		6,566
Mid Columbia tule	Mid/Upper Columbia	207	0	0	310	0		517
Mid and Upp Columbia	Mid/Upper Columbia	0	0	0	0	0		0
Deschutes R fa	Mid/Upper Columbia	0	113	111	2,988	0		3,212
Upp Columbia Su Fa	Mid/Upper Columbia	4,311	3,863	2,779	36,985	10,014		57,952
Snake R fa	Mid/Upper Columbia	105	245	381	1,455	662		2,849
Snake River Sp Su	Mid/Upper Columbia	98	0	0	0	138		235
Washington Coast	Washington Coast	122	334	1,100	22,393	9,271		33,219
Hood Canal	Puget Sound	0	0	288	0	0		288
South Puget Sound	Puget Sound	0	0	0	0	0		0
North Puget Sound	Puget Sound	1,081	764	314	1,611	509		4,278
Juan de Fuca	Puget Sound	108	551	0	427	0		1,085
Lower Fraser	Fraser	0	0	60	0	148		208
Lower Thompson	Fraser	0	0	0	0	0		0
South Thompson	Fraser	207	3,015	2,783	16,668	2,644		25,317
North Thompson R	Fraser	0	117	0	485	138		739
Mid Fraser	Fraser	0	0	168	1,591	10		1,769
Upper Fraser	Fraser	98	0	65	175	0		337

[8] See footnote 4.

Table 8. Continued.

Region	Stock Group	Early Winter	Late Winter	Spring	Summer1	Summer2	Terminal[9]	Total
	Harvest	12,686	40,200	55,193	194,045	50,937	1,603	354,664
East Vancouver	Strait of Georgia	742	1,013	1,500	3,997	565		7,817
West Vancouver	WCVI	1,271	15,545	6,808	36,907	4,350		64,882
South BC Mainland	Strait of Georgia	0	354	421	1,688	0		2,463
Central BC Coast	North/Central BC	1,237	2,090	456	1,591	586		5,960
Lower Skeena	North/Central BC	655	900	63	970	132		2,720
Upper Skeena	North/Central BC	58	539	298	582	372		1,849
Nass River	North/Central BC	43	539	585	0	458		1,626
Upper Stikine R	AK/BC Transboundary	96	571	2,631	1,417	204		4,919
Taku River	AK/BC Transboundary	0	1,435	5,185	407	0		7,027
S. Southeast AK	Southeast Alaska	507	2,661	7,758	6,772	1,711	1,603	21,013
Andrew Creek	Southeast Alaska	256	1,471	19,224	8,053	677		29,682
King Salmon	Southeast Alaska	0	0	0	0	0		0
Chilkat R	Southeast Alaska	0	0	408	0	0		408
Alsek R	Southeast Alaska	0	0	0	0	76		76
Situk R	Southeast Alaska	0	0	0	0	0		0
Unknown	Unknown	-1	0	0	19	-10		8

[9] See footnote 4.

Table 9. GSI Stock Composition Estimate of Southeast Alaska Troll Fishery Catch for 2005.

Region	Stock Group	Early Winter	Late Winter	Spring	Summer1	Summer2	TBR	Terminal[10]	Total
	Harvest	12,982	37,479	53,986	151,555	75,725	4,446	2,264	338,437
Central Valley Fa	California	0	0	0	0	0	0		0
Central Valley Sp	California	0	0	0	0	159	0		159
Central Valley Wi	California	0	0	0	0	0	0		0
California Coast	California	0	0	0	333	0	0		333
Kalamath R Basin	California	0	0	0	0	0	0		0
North CA, South OR coast	Oregon Coast	0	0	0	0	0	0		0
Rogue River	Oregon Coast	0	0	0	0	0	0		0
Mid Oregon Coast	Oregon Coast	178	322	180	13,716	5,339	0		19,735
North OR Coast	Oregon Coast	197	90	228	20,975	11,253	0		32,743
Lower Columbia Sp	Lower Columbia	205	0	77	0	0	0		282
Lower Columbia Fa	Lower Columbia	73	424	0	5,047	2,143	30		7,716
Willamette River	Lower Columbia	251	1,612	189	1,682	333	33		4,100
Mid Columbia tule	Mid/Upper Columbia	40	0	0	0	0	0		40
Mid and Upp Columbia	Mid/Upper Columbia	0	49	69	0	8	0		126
Deschutes R fa	Mid/Upper Columbia	86	124	74	3,986	1,863	0		6,132
Upp Columbia Su Fa	Mid/Upper Columbia	3,296	3,152	1,483	29,189	23,876	252		61,248
Snake R fa	Mid/Upper Columbia	34	0	220	2,122	1,780	51		4,206
Snake River Sp Su	Mid/Upper Columbia	30	0	74	121	0	0		225
Washington Coast	Washington Coast	121	881	320	14,686	8,792	0		24,799
Hood Canal	Puget Sound	0	0	80	409	0	0		489
South Puget Sound	Puget Sound	122	266	0	0	45	33		467
North Puget Sound	Puget Sound	698	420	220	3,562	394	8		5,301
Juan de Fuca	Puget Sound	134	127	155	0	0	0		416
Lower Fraser	Fraser	217	124	0	394	833	0		1,567
Lower Thompson	Fraser	0	0	4	0	0	0		4
South Thompson	Fraser	90	855	1,768	16,792	6,217	0		25,721
North Thompson R	Fraser	32	0	104	0	0	0		136
Mid Fraser	Fraser	151	0	0	0	212	0		363
Upper Fraser	Fraser	60	0	0	0	0	0		60

[10] See footnote 4.

Table 9. Continued.

Region	Stock Group	Early Winter	Late Winter	Spring	Summer1	Summer2	TBR	Terminal[11]	Total
	Harvest	12,982	37,479	53,986	151,555	75,725	4,446	2,264	338,437
East Vancouver	Strait of Georgia	853	1,533	1,369	3,849	1,355	66		9,026
West Vancouver	WCVI	1,458	16,330	12,218	11,154	7,360	367		48,887
South BC Mainland	Strait of Georgia	96	131	346	0	424	0		997
Central BC Coast	North/Central BC	1,907	4,936	2,845	1,137	931	95		11,851
Lower Skeena	North/Central BC	0	768	1,260	2,895	0	231		5,154
Upper Skeena	North/Central BC	123	0	255	576	0	0		954
Nass River	North/Central BC	164	0	336	606	318	93		1,517
Upper Stikine R	AK/BC Transboundary	216	0	3,305	152	386	1,140		5,198
Taku River	AK/BC Transboundary	92	1,529	4,115	591	220	749		7,296
S. Southeast AK	Southeast Alaska	1,415	2,878	9,821	13,443	977	879	2,264	31,678
Andrew Creek	Southeast Alaska	641	929	12,525	4,137	492	420		19,145
King Salmon	Southeast Alaska	0	0	0	0	0	0		0
Chilkat R	Southeast Alaska	0	0	216	0	0	0		216
Alsek R	Southeast Alaska	0	0	74	0	0	0		74
Situk R	Southeast Alaska	0	0	51	0	0	0		51
Unknown	Unknown	4	0	6	0	15	0		24

[11] See footnote 4.

Table 10. Side by Side comparison of Yearly PSC Chinook Model and GSI Catch Composition Estimates for the Southeast Alaska Troll Fishery from 2001 to 2005.

	PSC Chinook Model Catch Composition Estimates.					GSI Catch Composition Estimates.				
Stock Group	2001	2002	2003	2004	2005	2001	2002	2003	2004	2005
AK/BC Transboundary	0	0	0	0	4,288	4,936	2,839	10,148	11,946	12,495
California						1,840	4,991	6,831	873	492
Fraser	9,622	19,755	16,288	15,668	15,435	15,130	30,470	41,414	28,371	27,851
Lower Columbia	4,355	14,268	11,944	11,587	7,355	8,085	15,459	17,349	18,771	12,098
Mid/Upper Columbia	33,697	88,085	97,093	89,723	85,936	17,474	75,255	64,538	64,765	71,977
North/Central BC	20,178	25,893	23,953	26,792	27,281	13,767	20,390	38,076	12,155	19,476
Oregon Coast	19,727	47,794	45,251	50,238	48,626	28,980	40,629	33,200	52,562	52,478
Other Alaska						597	875	1,586		
Puget Sound	458	537	571	731	701	4,503	14,625	4,603	5,652	6,673
Southeast Alaska	3,781	3,825	3,838	4,795	6,249	32,369	42,496	37,414	51,179	51,163
Southeast Alaska (H)	24,588	27,176	23,312	32,724	31,074					
Strait of Georgia	4,950	6,859	7,831	9,157	9,467	10,439	15,225	15,687	10,280	10,023
Unknown[12]	19,100	44,247	45,620	47,781	44,981	-18	217	1,336	8	24
Upper Canadian Yukon						337	74	2,087		
Washington Coast	4,748	9,367	8,627	10,316	10,817	3,892	47,843	16,679	33,219	24,799
WCVI	8,076	37,502	46,366	55,152	46,227	10,950	13,920	39,746	64,882	48,887
Grand Total	153,280	325,308	330,692	354,664	338,437	153,280	325,308	330,692	354,664	338,437

[12] The Unknown component from the PSC Chinook Model is due to factors such as unrepresented stock groups or poor choices for CWT indicator stocks. However, the Unknown category for GSI estimates is due to the inability to assign all fish in a sample to a stock group.

Table 11. Absolute and Relative Deviations of the Yearly PSC Chinook Model from the GSI Catch Composition Estimates for the Southeast Alaska Troll Fishery from 2001 to 2005.

	Deviation of PSC Model from GSI.					Relative Deviation of PSC Model from GSI.				
Stock Group	2001	2002	2003	2004	2005	2001	2002	2003	2004	2005
AK/BC Transboundary	-4,936	-2,839	-10,148	-11,946	-8,206	-100%	-100%	-100%	-100%	-66%
California	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Fraser	-5,508	-10,715	-25,126	-12,703	-12,417	-36%	-35%	-61%	-45%	-45%
Lower Columbia	-3,729	-1,191	-5,406	-7,185	-4,743	-46%	-8%	-31%	-38%	-39%
Mid/Upper Columbia	16,223	12,829	32,555	24,959	13,959	93%	17%	50%	39%	19%
North/Central BC	6,411	5,503	-14,123	14,637	7,805	47%	27%	-37%	120%	40%
Oregon Coast	-9,253	7,166	12,051	-2,325	-3,852	-32%	18%	36%	-4%	-7%
Other Alaska	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Puget Sound	-4,045	-14,088	-4,032	-4,920	-5,972	-90%	-96%	-88%	-87%	-89%
Southeast Alaska[13]	-4,000	-11,495	-10,263	-13,659	-13,840	-12%	-27%	-27%	-27%	-27%
Strait of Georgia	-5,489	-8,365	-7,856	-1,124	-556	-53%	-55%	-50%	-11%	-6%
Unknown[14]										
Upper Canadian Yukon	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Washington Coast	856	-38,476	-8,053	-22,903	-13,982	22%	-80%	-48%	-69%	-56%
WCVI	-2,874	23,581	6,620	-9,730	-2,661	-26%	169%	17%	-15%	-5%

Summary:

The PSC Chinook Model was not originally intended to produce total catch composition estimates for the fisheries present in the model. However, with the addition of auxiliary information on the magnitude of the Alaska Hatchery Addon and the magnitude of Transboundary river exclusion catches comparisons can be made between the catch compositions from the PSC Chinook Model and GSI estimates in the Southeast Alaska troll fishery. Due to an incomplete representation of stocks in the model, the use of potentially inappropriate CWT indicator stocks and other factors the stock composition estimates from the PSC Chinook Model has a fairly large unknown component. Given the shortcomings of the model the comparisons between the model estimates and the GSI estimates were surprisingly similar, although there were some consistent biases for several stock groups. The Fraser, Lower Columbia and Puget Sound stock groups were consistently underestimated and the Mid/Upper Columbia stock group was consistently over-estimated by the PSC Chinook Model.

[13] The deviations for the Southeast Alaska stock were computed using the combination of the Southeast Alaska and Southeast Alaska (H) stocks.
[14] Comparisons for the Unknowns from the PSC Chinook Model and from GSI were not made due to the disparate nature of the Unknowns from these two methods.

2.2 The CTC model assumes that exploitation rates estimated from CWT data for hatchery stocks adequately represent the exploitation rates on wild stocks. How can GSI data be used to evaluate or avoid this assumption?

No analysis undertaken.

2.3 Incidental Mortality

Robert Kope

Management of mixed-stock ocean salmon fisheries for Chinook and coho salmon is based on total mortality. This includes both landed catch and incidental mortality. Incidental mortality in salmon fisheries is mortality resulting from fishing activity, but not landed as catch. This includes fish brought to the boat (encounters), but released or discarded because of their size, species, or mark status (discards), as well as fish that die as the result of encountering fishing gear without being brought to the boat because they escape from the gear, or are removed by predators (dropoffs/dropouts).

Dropoff/Dropout

Dropoff and dropout mortality is currently assumed to have the same stock composition as that of encountered fish in the same fishery, and is calculated as a fraction of total encounters. This fraction depends on gear and location and is based on observations were these data are available. Where no observational data specific to a fishery are available, default, agreed upon, gear–specific rates are used. Because fish escape from gear unobserved, and most fish removed from gear by predators are also unobserved, there is a good deal of uncertainty about the magnitude of dropoff/dropout mortality. However, there is no reason to suspect that the stock composition of this mortality should differ from that of encountered fish. Further, because these fish escape the gear before they are brought to the boat, there is no opportunity to collect tissue samples, and thus no way for GSI to provide additional information about stock composition. The same cannot be said of discards.

Discards

Fish may be discarded because they are undersized (shakers), regulations do not permit retention of the species, or they are unmarked fish in a mark-selective fishery. Regardless of the type of discards, similar problems are encountered in estimating the incidental mortality associated with discards. In order to account for discard mortality, estimates are needed for the total amount of discard, the discard mortality rate, and the stock/age composition of the mortalities.

Currently, a variety of methods are used to estimate the total amount of discard. All methods for estimating shaker mortality depend on a discard rate applied to landed catch. The rate may be based on direct estimates from observer programs, reported discards from logbooks, rates in similar fisheries, or historic average rates which may, or may not, be scaled to account for current abundance. Discard mortality is then estimated by multiplying total discards by the release mortality rate. Release mortality rates are gear specific and are based on studies that have been done over several decades. The estimates of discard mortality must then be allocated to the stocks. The current model structure requires that it also be attributed to cohorts within the stocks.

Historically, there has been no means to routinely estimate stock composition of discards. With CWT programs, information is only provided for marked stocks, and recovery of that information requires lethal sampling. Alternatively, it would be possible to apply tags to released fish and use terminal area recoveries to estimate the stock composition of releases. This type of marking program was carried out in high seas fisheries under the International North Pacific Fisheries Commission, but it is a very expensive methodology because of the cost of tagging at sea, and low tag recovery rates. The cost precludes its use for routine stock composition estimates.

Currently, estimates of stock composition of discards are derived from harvest models, and depend on numerous assumptions (CTC 2004). For shakers, the PSC Chinook model allocates sub-legal mortality based on the relative abundance of sub-legal fish in all stocks that contribute to the landed catch in a fishery. This scheme for allocation of sub-legal impacts implicitly assumes that sub-legal fish from each stock that has a non-zero catch in the fishery are equally vulnerable to the fishery regardless of the stock-specific exploitation rates of legal-sized fish in that fishery. Encounter rate studies in Southeast Alaska troll fisheries using GSI have demonstrated problems with this allocation scheme.

Several methods are currently used to estimate the amount of discard in non-retention fisheries. The choice of method usually depends on the data available. Methods used include: direct input of discards estimated by observer programs, the ratio of effort in non-retention periods to that in periods of legal retention, the ratio of days open to non-retention to that of legal retention, observed encounter rates of legal sized fish during periods of non-retention, and the use of a calculated catchability coefficient when there is no legal retention. Regardless of the method for estimating discards, they are assumed to have the same stock composition as that of landed catch.

Application of GSI

The PSC Chinook model currently does not have the capability of assessing impacts of mark-selective fisheries. Model-based methods to allocate incidental mortality to stock are not likely to perform well because the underlying premise of mark-selective fisheries is that the fish released have a different stock composition than those retained. With CWTs, information is only available for landed catch.

GSI offers a method for obtaining direct estimates of the stock composition of discards that do not rely on the assumptions of the current methods. However, this would either require fishermen to collect tissue samples or on-board observers to collect tissue samples from released fish. Observer programs would offer the additional benefit of allowing direct estimates of discard rates to provide better estimates of total discards, but would be expensive to conduct. Alternatively, tissues could be collected by fishermen, and logbooks could be used to estimate discard rates. This would be less expensive, but the data may be less reliable.

Either way, GSI alone can only provide estimates of the stock composition of the discard component of incidental mortality. It cannot provide information on the age composition, or improve estimates of release mortality rates.

Literature cited

Chinook Technical Committee. 2004. Estimation and application of incidental fishing mortality in Chinook salmon management under the 1999 agreement to the Pacific Salmon Treaty. Report TCCHINOOK (04)-1. Pacific Salmon Commission, Vancouver.

2.4 How can GSI Data Be Used to Improve Estimates of the Underlying Stock Distribution Over Space and Time?

Peter Lawson

The CTC model assumes that the underlying distribution of stocks is consistent over time. A baseline distribution estimated from CWT recoveries (and a variety of other factors) is used as the starting point for estimating fishery impacts. In order to collect enough CWT recoveries to estimate the distributions of all stocks of interest, data from a number of years is combined. Spatial resolution is by area of catch (10 – 200 km) and temporal resolution in the Chinook model is 3 months. Collection of the data is fishery-dependent, and assumes constant distributions over years.

GSI has the potential to improve our estimates of stock distributions, and test some of the assumptions of CWT-based estimates. The principal advantage of GSI is that it enables stock proportions to be estimated from smaller samples than required for CWTs because information can be obtained from each fish sampled. A sample of a few hundred fish (exact sample sizes for specific applications to be determined) should be sufficient to determine stock composition, and can be collected from a closely defined area over a short period of time.

GSI does not provide age data. Ages can be read from scales, but there is some question whether scales can be read accurately enough for use in cohort analysis. It may be that scales from ocean fisheries are useful, but scales from terminal runs taken after the resorption process has begun cannot be used reliably. At the very least, age compositions derived from CWT data could be applied to the GSI stock proportions to arrive at a stock-specific age distribution.

The GSI data collected in this way are no different from CWT data in their fishery-dependence. However, there is the potential for survey fisheries to collect fishery-independent data in a way that is not feasible with CWTs. Again, this stems from the ability to obtain stock information from every fish sampled, rather than from the roughly 5% of fish marked with CWTs.

Sampling at a much finer spatio-temporal scale, utilizing GPS locations to map the fishing effort and location of each fish caught, is being conducted by the CROOS project in Oregon. Data at this scale are not necessary for fishery management as implemented by the PSC, but could be useful for local efforts to respond rapidly to the movement of sensitive stocks.

Although GSI does not solve all the problems of estimating stock distribution, it gives us the ability to measure stock composition of fish at smaller time and space scales than is feasible with CWTs. We could then test the assumption that stock composition is constant from year to year, and potentially map migration patterns at monthly or finer time scales and 10-50 km spatial scales. This can be done with fishery-dependent sampling as in the current CWT program, or with a combination of fishery-dependent and fishery-independent sampling. Age compositions can potentially be derived from CWT data. Some error may be introduced into the stock identifications relative to the CWT ids which are (more or less) absolute. Some stocks will be harder to id with GSI than with CWTs. By and large, a considerable improvement in the resolution of stock composition and distribution data should be achievable using GSI in combination with scale analysis and CWT recoveries.

The CROOS pilot project in 2006 provides some insight into the potential for determining fine-scale changes in stock distributions using GSI. It also highlights some of the limitations and problems with this approach. This was treated in considerable detail in the Genetics section of the 2006 annual report.

2.5.1 Use of Improved Stock Distribution Information From GSI Data for InSeason Fishery Management.

Brain Riddell

<See Power Point from Brian Ridell, Sept. 12, 2007>

2.5.2 Alternative Management Strategies

Gary Morishima

Current management of chinook and coho salmon is based primarily on stock-age-fishery specific estimates of exploitation rates derived from cohort analysis of CWT data. An alternative management approach that would constrain fishery mortalities on specific groups of fish may warrant investigation.

Harvest managers covet flexibility as they strive to increase social benefits from fishing while constraining impacts on stocks of concern to acceptable levels. Interest has been high in gathering GSI data to establish an information base to help "shape" fisheries. For example, GSI data have been used to manage the West Coast Vancouver Island (WCVI) troll fishery to limit impacts on depressed WCVI, Fraser River, and Lower Strait of Georgia stocks to a pre-determined level. The CROOS project is intended to provide data to help shape Northern California and Central Oregon ocean fisheries to minimize impacts on Klamath fall chinook.

Information presented at the GSI workshop indicated that assignment error can be reduced through the use of reporting groups. Basically, aggregation takes advantage of the fact that stock assignment error is likely largest with stocks with similar genetic profiles. Aggregation would reduce uncertainty of contributions for larger stock groups, but would leave the manager without information regarding impacts on individual stocks that might be of particular concern, most likely a problem for stocks which comprise a small proportion of the catch.

The increased reliability of aggregated reporting groups for GSI-based data could be integrated into a management strategy that incorporates variable resolution into its structure. For instance, it may be feasible to employ a high degree of aggregation in instances where the proportion of the sampled population accounted for by individual stocks is small due to distribution and then disaggregate where the proportion increases or where greater resolution might be possible through the use of a more detailed local GSI baseline. Such an approach would accommodate greater uncertainty where stock-specific impacts would be expected to be of least concern.

An approach that might be employed to constrain impacts on stocks of concern using planning models, CWT experiments, and GSI data is outlined below for consideration.

- Use planning models (e.g., CTC Model, Chinook FRAM) to forecast stock compositions in major fisheries.

- Aggregate contributions of stocks which would comprise a small proportion of the catch.

- Estimate mortalities of stock (groups) allowable under agreed coastwide fishing regimes.

- Convert these mortalities into landed catch (or encounters for non-retention, size limit, or mark selective fishing) constraints

- Allow harvest managers the flexibility to shape fisheries in the manner of their choosing so long as the morality constraints are not exceeded.

- In-season monitoring and fishery regulation would be based on data collected from an in-season GSI sampling program designed to estimate contributions of the selected stock (groups) with acceptable accuracy and precision.

- Evaluate cumulative effects across fisheries through CWT-based cohort analysis on appropriate indicator stocks.

A simulation study, incorporating errors from important sources (e.g., sampling, stock-age misassignment and unassigned fish, uncertainty in catch or escapements, etc.) could provide insight into likely performance of this alternative management strategy.

2.6.1 Stock Assignment Error

Gary Morishima

A strength of CWT data is that individual recoveries of CWT'd fish can be assigned to a specific release group with very little chance of error. With GSI microsatellite methods, the ability to determine the origin of fish depends on a variety of factors, including genetic homogeneity within a population of interest, genetic heterogeneity between populations of interest in the GSI baseline, and the methods employed (e.g., loci, analysis algorithms). It is useful to examine uncertainty associated with GSI microsat results in terms of two general concepts described by Ken Warheit (WDFW) at the GSI Workshop: ***Confidence*** and ***Power***.

> ***Confidence*** is the probability that a fish from a specific population will be correctly assigned to that population.
>
> ***Power*** is the probability that a fish assigned to a specific population is actually from that population.

Mathematically, if the notation P(J|I) represents the probability that a fish from stock I is assigned to stock J, then ***Confidence*** = P(I|I). The assignment probability for a fish from a given stock can be characterized as an assignment vector. For a given stock, with no assignment error ***Confidence*** = 1 and P(J|I) =0 for J≠ I.

Power depends on both the assignment probability vectors for the stocks that are in the sample and the relative sizes of those stocks.

$$Pwr(I) = \frac{sp(I) * P(I \mid I)}{\sum_j sp(J) * P(I|J)} \qquad (1)$$

where sp(I) = the proportion of the sample comprised of stock I.

When the sample is comprised only of fish from the baseline stocks and when the ***Confidence*** for all stocks =1, then the ***Power*** =1 for all stocks. In this case, stock assignment error = 0. Otherwise, for at least one stock, ***Power*** < 1 and stock assignment error results.

With GSI microsatellite methods, the usual objective of the analysis is to estimate stock proportions in a given fishery sample. Ken Warheit's presentation at the GSI Workshop indicated that the probabilities for stock assignment error can be expected to vary for the stocks in the current GAPs GSI Baseline. In the presence of assignment error, the estimated proportion of the sample comprised of a given stock *EstP(I)* is:

$$EstP(I) = \sum_J sp(J) * P(I \mid J) \qquad (2)$$

This is simply the denominator for the calculation of Power in equation (1).

For stock(I), *EstP(I)* incorporates two types of errors: (A) the probability that a fish from Stock(I) is incorrectly assigned to another stock; and (B) the probability that a fish from another stock is incorrectly assigned to Stock(I), which may partially offset one another. Both types of errors can have serious consequences for management because they can lead to over/under estimation of fishery impacts. For instance, if a stock that comprises a large proportion of the sample has even a small probability of misassignment to a small stock of conservation concern, such as one listed under the Endangered Species Act, action may be taken to constrain the fishery inappropriately even if the real impact on the ESA stock is much smaller.

The true error in the estimate of the contribution for *stock I* is:

$$TrueError(I) = P(I|I) - 1 = Conf(I) - 1$$

Effects of assignment error on apparent sample compositions

The following example illustrates the concepts described above using a 5-stock baseline.

- The top portion depicts the Assignment matrix (the probability of a fish from one stock being assigned to other stocks in the baseline); the italicized values along the decreasing diagonal represent the *Conf(I)*.
- The leftmost column in the middle portion of the example indicated the true proportion of the sample comprised of each of the stocks.
- The matrix in the middle portion of the example shows the resulting proportions assigned to each stock.
- "GSI" represents the GSI-estimate of sample composition.
- "Power" represents the probability that a fish assigned to a given stock is really from that stock.
- "AppRelativeError" is the *(GSI- True stock proportion)/True stock proportion*.
- "TrueRelativeError" is the *(Proportion of the sample composition which is assigned to the correct stock – True stock proportion)/True stock proportion = Conf(I)-1*.

Example 1(A)

TrueProp	STOCK FROM\TO	A	B	C	D	E
		ASSIGNMENT MATRIX				
	A	***0.90***	0.05	0.03	0.00	0.02
	B	0.05	***0.80***	0.05	0.05	0.05
	C	0.00	0.20	***0.70***	0.00	0.10
	D	0.50	0.00	0.00	***0.50***	0.00
	E	0.10	0.10	0.10	0.10	***0.60***
0.2400	**A**	0.2160	0.0120	0.0072	0.0000	0.0048
0.1000	**B**	0.0050	0.0800	0.0050	0.0050	0.0050
0.5000	**C**	0.0000	0.1000	0.3500	0.0000	0.0500
0.1500	**D**	0.0750	0.0000	0.0000	0.0750	0.0000
0.0100	**E**	0.0010	0.0010	0.0010	0.0010	0.0060
1.0000	**GSI**	0.2970	0.1930	0.3632	0.0810	0.0658
	Power	0.7273	0.4145	0.9637	0.9259	0.0912
	AppRelative Error	23.8%	93.0%	**-27.4%**	**-46.0%**	558.0%
	TrueRelativeError	**-10.0%**	**-20.0%**	**-30.0%**	**-50.0%**	**-40.0%**

In this example, the AppRelativeError is substantial, ranging from -46% to +558%, even with a 90% *confidence* for the largest stock. Thus, serious bias can be introduced into estimates of the contribution of small stocks. The magnitude and direction of the apparent relative error depends on the true composition of the sampled population. In example 1(B) the proportions of the sample comprised of stocks B and C are switched. Note that in this case, the direction of the apparent relative errors for stocks B and C are reversed.

Example 1(B).

TrueProp	FROM\TO	A	B	C	D	E
		ASSIGNMENT MATRIX				
	A	***0.90***	0.05	0.03	0.00	0.02
	B	0.05	***0.80***	0.05	0.05	0.05
	C	0.00	0.20	***0.70***	0.00	0.10
	D	0.50	0.00	0.00	***0.50***	0.00
	E	0.10	0.10	0.10	0.10	***0.60***
0.2400	**A**	0.2160	0.0120	0.0072	0.0000	0.0048
0.5000	**B**	0.0250	0.4000	0.0250	0.0250	0.0250
0.1000	**C**	0.0000	0.0200	0.0700	0.0000	0.0100
0.1500	**D**	0.0750	0.0000	0.0000	0.0750	0.0000
0.0100	**E**	0.0010	0.0010	0.0010	0.0010	0.0060
1.0000	**GSI**	0.3170	0.4330	0.1032	0.1010	0.0458
	Power	0.6814	0.9238	0.6783	0.7426	0.1310
	AppRelative Error	32.1%	**- 13.4%**	3.2%	**- 32.7%**	358.0%
	TrueRelativeError	**- 10.0%**	**- 20.0%**	**- 30.0%**	**- 50.0%**	**-40.0%**

This example is not to be interpreted as a real-life situation, but rather is intended illustrates the challenges confronting the use of GSI to provide data for estimation of stock composition or cohort analysis in the presence of stock assignment error.

The difficulty, of course, is that the magnitude and direction of stock assignment error cannot be determined without information on the {sp(J)}, the true stock proportions present in the sample.

The challenge is to find methods to either adjust for stock assignment error or establish criteria that can reliably determine when estimates of stock composition are unreliable.

A Method to Estimate Sample Compositions From Apparent Sample Compositions in the Presence of Assignment Error?

With the GAPs baseline, Ken demonstrated that the ability to assign fish to its correct population cannot reasonably be assumed to be perfect. The example presented above indicates that the failure to correct for misassignment can result in substantial errors. A means to overcome the effects of stock and age assignment errors is necessary to estimate true contributions to a fishery stratum.

A simple optimization procedure can be used to estimate the stock proportions in a sample from the assignment matrix and GSI estimates of compositions which include assignment error, provided that the fish in the sample reflect the same variability within and between stock groups represented by the fish in the baseline.

The assignment matrix consists of stock-specific vectors of probabilities of assignment to stocks included in a GSI baseline. The GSI estimates of compositions reflect the results of the assignment matrix and the true proportions of the populations.

The optimization Model: find the stock proportions {*sp(J)*} such that:

$$\min \sum_{I} \left[GSI(I) - \sum_{J} sp(J) * P(I \mid J) \right]^2$$

where *GSI(I)* is the estimated proportion of the sample comprised of stock I resulting from assignment error.

If the fish in the sample reflect the same variability within and between the stock groups represented in the baseline, a GSI baseline that includes all stocks encountered in the sample, and ***Confidence*** levels which are acceptable for all stocks, this model would be expected to generate estimates of sample composition which are close to the correct values.

The Problem of Unassigned Fish

At the GSI Workshop, Ken also described the relationship between "Posterior Probability Cutoffs (criteria for acceptance that an assignment is correct) and Unassigned Fish." Rarely would no assignment error be expected for a given stock. Some GSI analyses report stock-composition results that reflect the highest probability stock assignments regardless of the actual magnitude; other analyses report only the stock-compositions of fish that can be assigned with a selected level of certainty (e.g., 90%); still others report the proportion of the sample that cannot be reliably assigned to any stock in the GSI Baseline.

Ken's presentation indicated that:

- Stock assignment error rates differ by stocks and the baseline used
- Increasing stringency (higher cutoff criteria) will decrease stock assignment error, but will increase the proportion of individual fish that cannot be assigned to a particular stock.
- The relationship between stringency and unassignment differs by stock.

In addition, unassignment and assignment error and can result when the baseline employed for the GSI analysis does not include populations that occur in the sample.

There are two major consequences of stringency criteria and unassignment: (a) larger sample sizes would be required to obtain estimates of desired reliability; and (b) greater uncertainty with respect to estimates of stock composition. Four basic alternatives have been proposed to address the unassigned fish problem: (1) Report results only for fish that satisfy stringency criteria; (2) Report results for fish that satisfy stringency criteria plus the proportion of the sample that could not be assigned; (3) Report confidence intervals about estimates of stock contributions and leave interpretation up to policy decision-makers; and (4) Assume that the stock proportions of unassigned fish are not equal to stock proportions of assigned fish. Ken's presentation demonstrated that the last alternative would be ill-advised.

The Problem of Aggregation

Ken's presentation at the GSI workshop also indicated that assignment error can be reduced through the use of reporting groups. Basically, this approach would take advantage of the fact that stock assignment error is likely largest with stocks with similar genetic profiles. Aggregation would reduce uncertainty of contributions for larger stock groups, but would leave the manager without information regarding impacts on individual stocks that might be of particular concern,

The problem of aggregation needs to be investigated. Aggregation is most likely to be a problem for stocks which comprise a small proportion of the sample and for stocks with similar genetic characteristics.

Stock assignment error needs to be investigated. The challenge is that the implications of stock assignment error and attendant consequences are situational, that is, they will depend on the stocks involved, their relative proportions in the exploited population, the baseline and methods employed for analysis, and the size/representativeness of the samples used to estimate stock proportions. Because of these factors, it will be extremely difficult to develop standardized formulas or methods for adjusting GSI-based estimates of fishery impacts which are sufficiently robust to be usefully applied in a wide variety of circumstances.

It may be possible, however, to devise a simulation study or model that could be employed to evaluate the implications of stock assignment error, the application of various algorithms to allocate unassigned fish, and issues relating to stock-specific variability that may result from aggregation.

2.6.2 Effects of Aging Error on Cohort Analysis

Gary Morishima

Fish from a given stock of Chinook salmon *(Oncorhynchus tshawytscha)* may be harvested at various ages and stages of maturity over an extensive geographic range. The ability to accurately age fish is vitally important for management of this species. Age data are required for a variety of brood-year based analyses, including cohort reconstruction, evaluation of exploitation relative to productive capacity, variability in marine survival, abundance forecasting, and assessment of fishery impacts.

The usual method of aging Pacific salmon is by scale analysis based on the interpretation of circuli, although other methods involving dissection of bony structures (otoliths, fins) have also been employed. Several difficulties have been identified with aging fish by scale reading, such as the ability to distinguish estuarine from ocean age checks, and resorbtion when fish enter rivers to spawn. Resorbtion results in the loss of circuli and annuli on the periphery of scales which contributes to error in age determination; aging error is likely to increase for older-aged spawners. Both these types of problems suggest that aging error is likely to be fishery and stock-dependent. Aging error in highly mixed stock fisheries will result from variability in patterns of growth and migration during early life history of the exploited stocks. In terminal areas, less variability in scale patterns for early life history would be expected because the number of stocks would be more limited but resorbtion becomes a key consideration.

<u>Method to evaluate effects of aging error in cohort reconstruction</u>

Case study: Klamath fall chinook

Several years of data on the accuracy of scale-aging and estimates of ocean exploitation rates derived from cohort analysis are available for Klamath fall chinook. The following procedure is proposed to use these data to evaluate the effects of aging error on cohort analysis:

1. Generate brood-year escapements for Klamath fall chinook by allocating annual estimates of terminal run sizes or natural escapements to age based on scale reading results.

2. Use CWT-based estimates of in-river harvest rates and ocean exploitation rates by age to generate estimates of fishery catches for these broods.

3. Perform a cohort analysis using the data from steps 1 & 2.

4. Compare estimates of in-river harvest rates, ocean exploitation rates, and maturation rates obtained from Step 3 with the corresponding values derived from CWT-based cohort analysis of the same broods.

2.6.3 Using GSI when Ageing Data is Not Available in Harvest – Small Area Estimation

Carl Schwarz

The current CWT system provides data on the number of fish harvested in a fishery and the number of spawners that is used to compute a run-reconstruction (assuming knowledge of yearly survival rates).

For example, the following two matrices are a representation of the data available from the CWT for a index stock subject to a year fishery with a some returns to the spawning grounds at age 2, 3 or 4. There are 5 brood years, and each brood year is not subject to harvest until age 2. For example, from brood year 1, 1000 fish were marked with CWT and released. There were 10 fish were harvested in calendar year 2 (at age 2), 19.44 fish were harvested in calendar year 3 (age 3), and 7.62 fish were harvested in calendar year 4 (age 4). There were 9.00, 13.61, and 17.78 spawners at ages 2, 3, 4 (after the harvest) respectively.

Number of CWT released

Brood Year				
1	2	3	4	5
1000	2000	1000	2000	1000

Harvest Fish (expanded from CTW counts and sampling fraction)

Calendar	Brood Year					
Year	1	2	3	4	5	GSI
0	0.00	0.00	0.00	0.00	0.00	
1	0.00	0.00	0.00	0.00	0.00	
2	10.00	0.00	0.00	0.00	0.00	10.00
3	19.44	20.00	0.00	0.00	0.00	39.44
4	7.62	38.88	10.00	0.00	0.00	56.50
5	0.00	15.24	19.44	20.00	0.00	54.68
6	0.00	0.00	7.62	38.88	10.00	56.50
7	0.00	0.00	0.00	15.24	19.44	…
8	0.00	0.00	0.00	0.00	7.62	…

Spawners (known from spawning surveys)

Calendar	Brood Year				
Year	1	2	3	4	5
0	0.00	0.00	0.00	0.00	0.00
1	0.00	0.00	0.00	0.00	0.00
2	9.00	0.00	0.00	0.00	0.00
3	13.61	18.00	0.00	0.00	0.00
4	17.78	27.22	9.00	0.00	0.00
5	0.00	35.56	13.61	18.00	0.00
6	0.00	0.00	17.78	27.22	9.00

7	0.00	0.00	0.00	35.56	13.61
8	0.00	0.00	0.00	0.00	17.78

The run reconstruction assumes knowledge of the yearly survival rates (in this case assumed to be 0.80 $year^{-1}$, and works backwards from the oldest fish:

Example of run reconstruction for cohort 1

Spawners at age 4	17.78
Harvest at age 4	7.62
Alive at age 4 prior to harvest or maturation	25.4
Survival Age 3 -> 4	0.8
Alive at age 3 after harvest	31.75
Spawners at age 3	13.61
Harvest at age 3	19.44
Alive at age 3 prior to harvest or maturation	64.80
Survival Age 3 -> 4	0.8
Alive at age 2 after harvest	81
Spawners at age 2	9.00
Harvest at age 2	10.00
Alive at age 2 prior to harvest or maturation	100.00
Initial Release	1000
Survival to age 2	0.1

These match the parameters used to generate the initial table (assuming that yearly survival rate is known and correct).

If GSI methods are used to estimate the harvest of fish from this stock, the age of the harvest fish are unknown. For example, GSI methods can determine the proportion composition of the catch and given the total catch of all fish of all ages, the total number of fish harvest from each stock (over all ages) will be known. This corresponds to the ROW SUMs of the harvested table. [Ignore for now that GSI will give the total harvest from this stock and not just the CWT fish from this stock – the principles are the same.]

If a separate run reconstruction is required for each cohort, it does not appear to be possible to do this given the GSI summary information. Each year's harvest provides 1 data point but represents the sum of 3 new values and so would require additional constraints to be imposed to remove the non-identifiability.

A simple example of Small Area Estimation

The current CWT system treats every release cohort and index stream independently of each other in determining estimates of exploitation and run reconstructions. The index systems were chosen to be representative of broad geographical areas. By concentrating marking effort on these index system, (mostly) sufficient recoveries of CWT are obtained that provide estimates with reasonable precision. These types of estimators are called **direct** estimators because they only reply upon recoveries from each individual index stream and cohort to provide estimates applicable to that index stream and cohort.

The proposed GSI system will enable identification of fish to much smaller scales, i.e. to individual rivers and streams. However, total sampling effort in the harvest and spawning enumeration is unlikely to be increased over current levels which implies that the number of fish identified to these small management units will be very small giving estimates at small geographical areas that will be very imprecise.

This type of problem is generically called **small area estimation** (e.g. Rao, 2003). Direct estimates based solely upon the observed data for a particular small area will have very poor precision because they are based on very small amounts of data. The principle behind small area estimation is that **synthetic estimators** are constructed that rely upon spatial and temporal correlations with neighboring areas. In essence, localized pooling is used to improve estimators at the small area. These estimators can also be improved though use of covariates to build a prediction model, but I do not think that covariates will be useful in the GSI/CWT context.

Information from the small areas can be aggregated to larger (regional) levels. At the same time, these regional estimates are often calibrated from other information. For example, CWT methods may give estimates of total exploitation at the regional level which can be compared to the aggregate estimates from the small area estimates. If these differ considerably, a calibration step is often performed. I haven't considered the calibration problem here as it is not clear what data would be used for calibration.

This following example is just to illustrate how small area estimation would work and is not intended to be a definitive treatment of the information in the CWT system.

Refer to Figure 1. An exploitation rate was generated for 100 index streams based on the smooth sinusoidal curve. Streams with similar "index-numbers" are considered geographically close, i.e. stream 1 is close to stream 2, but far from stream 50. Then based on the value of the exploitation rate on the curve, a number of fish harvested was generated using independent binomial distributions (with a common index of 25). The raw estimates are shown in the thin black line. There is considerable uncertainty in the estimates with huge swings seen in neighbouring streams.

A very simple conditional first order autoregressive moving average model (CAR(1)) (Besag and Kooperberg, 1995; Rao, 2003, Section 5.4.4). is often used for "uni-dimensional" series. In this model:

$$Y_i \sim Binomial(25, p_i)$$

where localized smoothing is done on the (logit) of the p's by looking at the preceding and following "disturbances" from the overall mean:

$$\text{logit}(p_i) = \mu + \varepsilon_i$$

$$\varepsilon_{\mathrm{i}}|\varepsilon_{\text{-i}} \sim \begin{cases} Normal(\varepsilon_{i+1}, \sigma^2) & i = 1 \\ Normal(\dfrac{\varepsilon_{i-1} + \varepsilon_{i+1}}{2}, \dfrac{\sigma^2}{2}) & i = 2, \ldots, N \\ Normal(\varepsilon_{i-1}, \sigma^2) & i = N \end{cases}$$

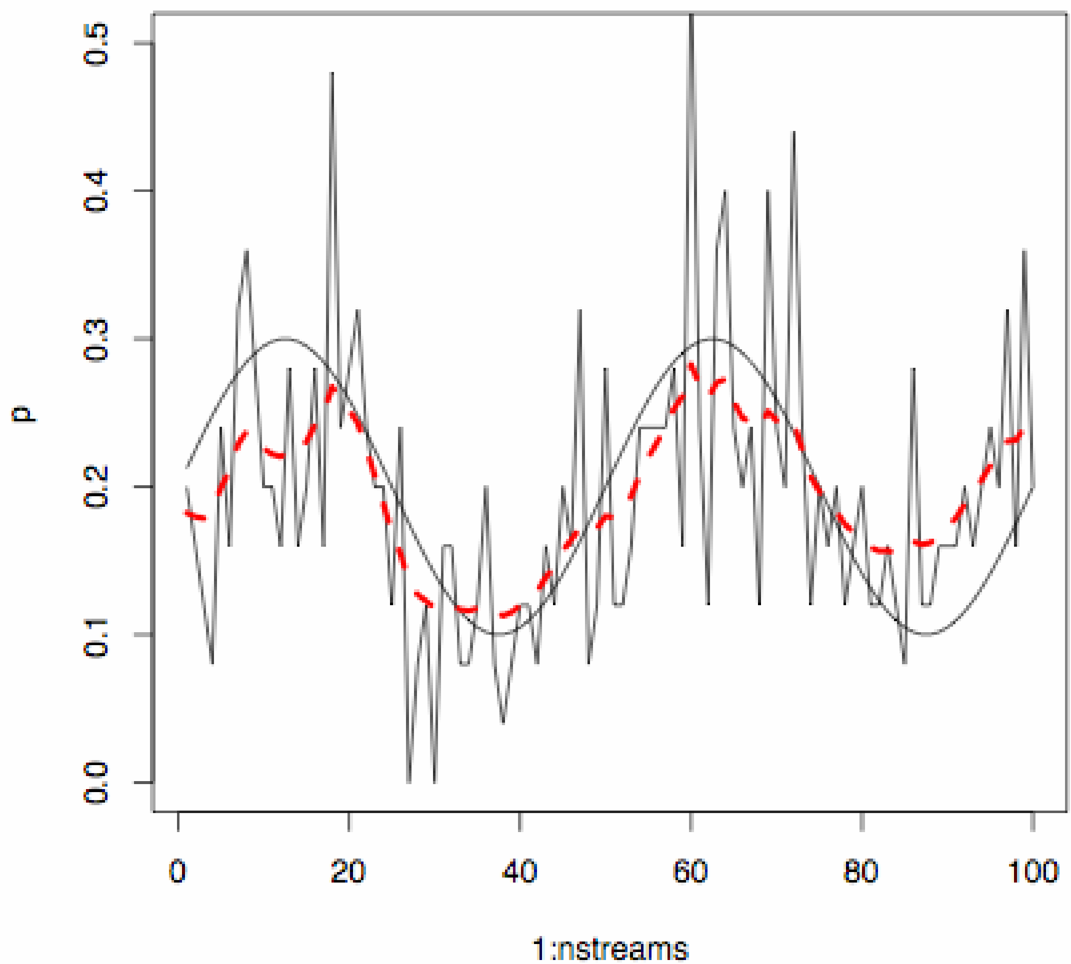
The notation ε_{-i} refers to all other streams except index *i*.

This model was fit using WINBUGS with the resulting smoothed estimates shown in the thick red-dashed line in Figure 1. As seen, there is considerable localized smoothing. The shape of the underlying curve was NOT used in the smoothing process – only returns from neighboring streams were used. The smoothing distance can be extended to more streams "below" and "above" the current stream, with higher weights given to streams that are "closer" to the stream of interest. Weights can also be functions of distance.

While the smoothed curve seems to underfit for the first 20 and last 20 streams, notice that the actual data were all, by chance, below or above the actual generating curve. The pointwise 95% credible intervals do contain the generating curve except for a few streams.

Typical estimates of precision based on about 5 CTW returned will have se of $\sqrt{5}$ (using the poisson approximation) for a relative se of about 45%. The average relative se of the smoothed estimates was about 16%. To achieve the same level of precision without smoothing would require about a $(45/16)^2$=8 times increase in effort to get additional CTW back from each stream!

Figure 1: Illustration of small area estimation – CAR model



As well temporal averaging could also be done when a sufficient time series is established.

This type of smoothing could be used for any of the exploitation rates where many small sources are measured, each with very small numbers of fish (or CWT) are measured. It could also be used for the year 0 to year 2 initial survival rate that is currently estimated from the run reconstruction values.

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2.7 Using Stock Synthesis Modelling Approaches for Chinook Management

Rishi Sharma

Introduction

The Pacific Salmon Commission (PSC) was established in 1985. The primary objective was to manage for the conservation of different species of Pacific salmon in Alaska, Canada, Oregon and Washington. One of the most valuable stocks both commercially and recreationally managed by the PSC is Chinook (*Oncorhynchus Tschawaycha*). An appendix to this Treaty signed in 1999, describes the principles behind the management of these stocks (PSC 1999). Under the PST's Aggregate Abundance Based Management (AABM) approach for Chinook, the annual allowable harvest level in specific ocean fisheries increases or decreases based upon corresponding changes in the abundance of the stock aggregates that contribute to that fishery. This management approach also makes provisions to make additional adjustments for declines in specific weak stock groups. Under this management system, the more abundant stocks have a greater influence on the abundance index and the resulting harvest level. Changes in the productivity (survival) of the more abundant stocks have a proportionally greater impact on a fishery. Stocks that contribute heavily to any fishery are commonly called "driver" stocks. Columbia Upriver Bright fall Chinook salmon stocks, which spawn in Hanford Reach, tend to be far north migrating and contribute heavily to ocean fisheries in Southeast Alaska (SEAK) and Northern British Columbia (NBC), making them driver stocks for those fisheries.

Currently, the PST uses a cohort analysis algorithm that scales current abundance to a historic base period (1979-1982) abundance, and projects terminal runsize or escapements for thirty different stocks by estimating environmental variability parameters that scale a Ricker stock-production relationship for a particular stock to the observed terminal run size or escapement for that stock. The algorithm as such does not fit abundance to match fishery specific catches but adjusts the cohort size on a stock complex to adjust the quota on certain fisheries.

Over the last few decades, numerous age-structured models have been developed to manage long lived species such as cod and halibut (Clark 2003, Sullivan et. al. 1999). These models simultaneously estimate numerous parameters to give the best fit to the observed data (Patterson et. al. 2001, Fournier and Archibald 1982, Deriso and Parma 1987). Algorithms such as the generic age structured algorithm developed by Fournier and Archibold (1982) are adapted in numerous ways to model the species being managed. Coleraine (Hilborn et. al. 2003),and Sock Synthesis (Methot et. al. 2001) are two modeling tools being used to forecast and manage commercial fisheries in New Zealand and the west coast of the United States which adapt these algorithms. For Pacific salmon however, only recently have such models been developed (Severide and Quinn 2004), and are still waiting to be developed with complex fishery and stock structure.

We present an alternative approach, a catch at age model using the life history of Chinook salmon and a time series of Coded Wire Tag (CWT) data (Johnson 1990, Lapi et al. 1990) and terminal run data to fit to ocean catches, terminal catches and terminal escapement. Potentials of using this model with different types of data collected from different techniques and its implications on Chinook salmon management could also be evaluated under this approach as we can evaluate uncertainty and precision in the estimates using this approach.

Methods

Fournier and Archibald (1992) describe a statistical catch at age model. A slight modification of their approach could be used to model Chinook salmon. In essence, different components of ocean catch, and terminal catch data by stock and age in conjunction with escapement data, can be used to estimate parameters such as recruitment to age 2, fishing mortality by fisheries, stock and age, maturation and vulnerability schedules by age for fisheries. This method can be extremely useful in cases where our escapement data may not be up to data standards (e.g. some of the Puget Sound, and North Central British Columbia escapement data).

Forward Projection Model

The method uses a forward projection algorithm (Figure 1.7, Chapter 4) that is based on estimation of certain key parameters, namely recruitment to age 2 ocean fish, maturation of age 2, 3 and 4, catchability by ocean and terminal fishery and vulnerability by gear type in each fishery. The model uses an optimization function to find the parameters that minimize the difference between model projections and observed ocean catches of the stock by age and fishery of concern (Deriso et al 1985) by maximizing the likelihood functions between observed and predicted catches in fisheries and escapements (Figure 1).

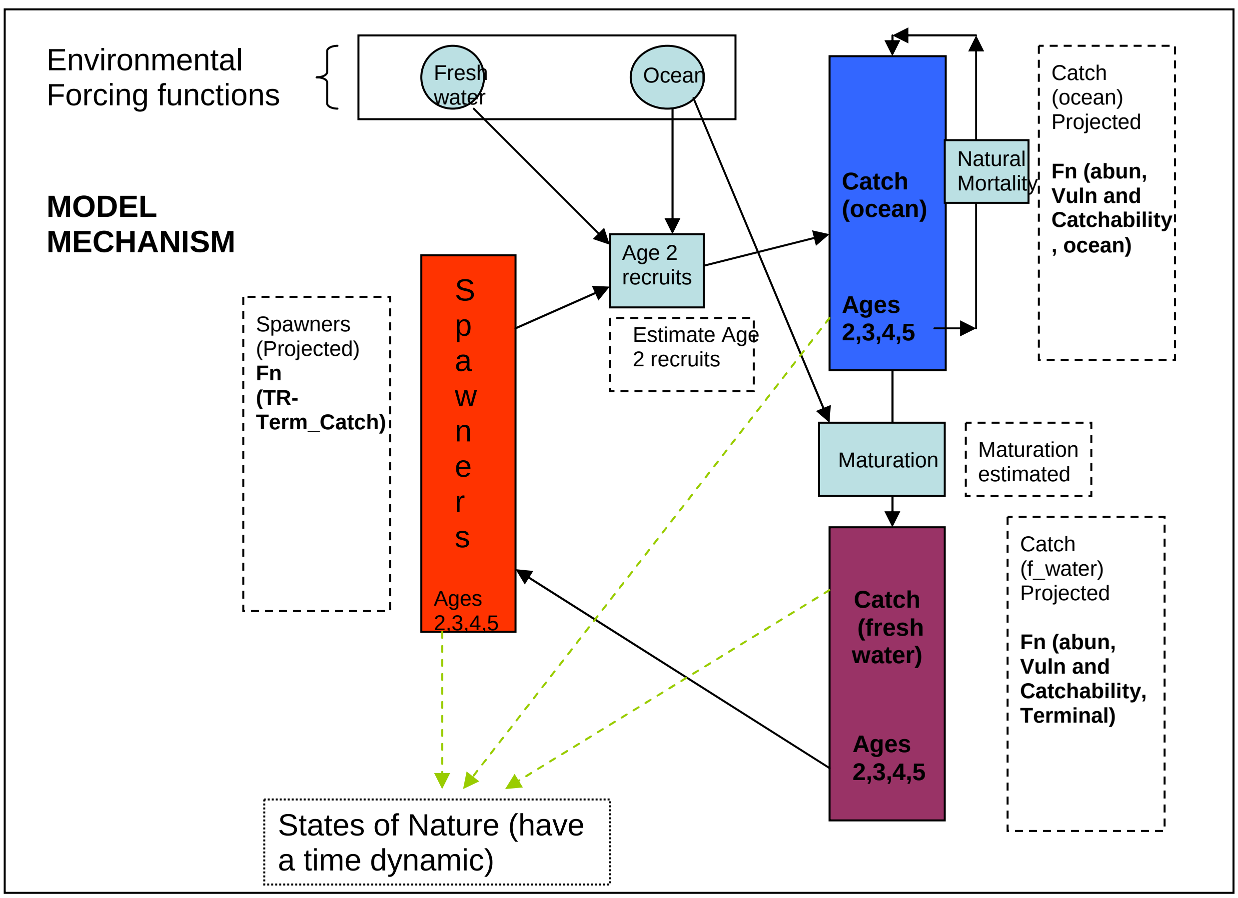

Figure 1 Schematic used to estimate Age 2 recruitment, catchability, vulnerability and maturation using statistical catch at age techniques for a simple 2 area model (ocean and terminal).

Ocean Fisheries:

$$N_{2,t} = Recruitment \text{ estimated} \tag{1}$$

Recruitment to age 2 and time t is estimated as a function of the model projected catches and escapement.

$$N_{a+1,t+1} = N_{a,t} e^{-(F_{a,t}+M_a)} - N_{a,t} \times MR_{a,t} \tag{2}$$

Essentially population size at time t, is a function of population size at time t-1, and is a function of both fishing mortality at that age and time, and natural mortality at that age (equation 2) as well as the fraction of the population that matured at the previous age (MR) and entered the terminal area.

In order to project catch, we need to estimate a catchability coefficient (q_0) as a function of effort (equation 3).

$$Ffull_t = q_O \times E_t \tag{3}$$

Fishing mortality at age is then estimated as a function of age specific vulnerability and F (full) (eq.4)

$$F_{a,t} = V_{a,t} \times Ffull_t \tag{4}$$

Catch at age and time is then projected as a function of ocean cohort at a particular age, and fishing mortality and natural mortality at that age (eq. 5).

$$C_{a,t} = N_{a,t} \times (1 - e^{-(F_{a,t}+M_a)}) \times \frac{F_{a,t}}{F_{a,t} + M_a} \tag{5}$$

Terminal Fisheries

For terminal fisheries, we have another set of equation. They are similar to the ones used above but have the added component of estimating maturation from the ocean cohort to the terminal area.

$$N_{a,t_T} = \left(N_{a,t} - C_{a,t}\right) \times MR_{a,t} \tag{6}$$

where $N_{a,t\,(T)}$ is the age a abundance at time t in terminal area (T), and MR is the maturation rate at age a (time t). This is a function of the ocean cohort at time, t.

Equation similar the ones above (eq. 3,4 and 5) are used to project terminal catch (eq. 7, 8 and 9).

$$Ffull_{tT} = q_T \times E_{tT} \tag{7}$$

where the subscript T indicates terminal effort (E) and catchability (q).

$$F_{a,tT} = V_{a,t_T} Ffull_{tT} \tag{8}$$

where F(a,t, T) is fishery specific mortality by age and is a function of vulnerability by age.

$$C_{a,tT} = N_{a,tT} \times (1 - e^{-(F_{a,tT})}) \tag{9}$$

where C(a,t T) is the projected catch in the terminal area (we assume loss due to Natural Mortality is zero).

Escapement at age is then calculated using equation10.

$$Esc_{a,t} = N_{a,t_T} - C_{a,t_T} \tag{10}$$

The Likelihood Equation used in fitting these different data with a Normal error structure sources is:

$$L(C_{a,t,f} \mid \theta) = \prod_{f=1}^{n} \frac{1}{\sqrt{2\pi\sigma_f^{\;2}}} \exp\left[-\frac{\left(C_{a,t,f}) - (\hat{C}_{a,t,f})\right)^2}{2\sigma_f^{\;2}} \right] \tag{11}$$

In Log space using a log-normal error, this can be re written (ignoring the constants) as

$$-\ln L(C_{a,t,f} \mid \theta) = \sum_{f=1}^{n} \ln\left(\sigma_f\right) + \frac{\ln\left(\left(C_{a,t,f}\right) - \ln\left(\hat{C}_{a,t,f}\right)\right)^2}{2\sigma_f^2} \tag{!2}$$

As is evident from the above equation, the likelihood could be weighed by the data estimates in each of the fisheries. Thus, we could possibly use some information from GSI methods by using the assignment error and weighing that with coded-wire tag information that has no assignment error. In addition, we could possibly use this structure by using both historical CWT data and GSI data simultaneously. Such approaches could be tested and simulated across fisheries to test the robustness of the estimation algorithms presented here. This is thus the engine of the stock assessment model that would be analogous to some of the new techniques developed for ground fish such as stock synthesis (Methot 2001) and Coleraine (Hilborn et. al. 2003).

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Appendix: Using the current assessment structure to evaluate uncertainty

Reverse Mode (assuming all fish in Amax mature)

$$T_{t,a} = E_{t,a} + \sum_{g\in\text{terminal}} C_{g,t}\, p_{g,t,a}$$

$$m_{t,a} = \frac{1}{\dfrac{N_{t+1,a+1}}{T_{t,a}} + 1} \qquad \text{a < amax}$$

$$N_{t,a} = \frac{T_{t,a}}{\exp\left[-M_a\right] m_{t,a}} + \frac{\sum_{g\in\text{ocean}} C_{g,t}\, p_{g,t,a}}{\exp\left[-\delta M_a\right]}$$

$$p_{g,t,a} = \frac{C_{g,t,a}}{\sum_a C_{g,t,a}}$$

Likelihoods

$$-\ln L\left(C^{obs} \mid \theta\right) = \sum_{g,t} \ln\left[\sigma_g\right] + \frac{\left(\ln\left[C_{g,t}^{obs}\right] - \ln\left[C_{g,t}\right]\right)^2}{2\sigma_g^2}$$

$$-\ln L\left(E^{obs} \mid \theta\right) = \sum_{t,a} \ln\left[\sigma_E\right] + \frac{\left(\ln\left[\phi E_{t,a}^{obs}\right] - \ln\left[E_{t,a}\right]\right)^2}{2\sigma_E^2}$$

In this structure, the parameters catch and escapement are assumed as unknowns rather than known. This is true as we have a pesky little thing known as sampling error, and incorporating that into our assessment will provide us a benchmark for uncertainty.

Parameters to estimate
$E_{t,a}$, $C_{g,t}$, σ_R,
Fixed parameters
δ, M_a, σ_g, ϕ, σ_E

2.8.1 Methods to Determine Sample Size Requirements Using GSI Methods

Gary Morishima

This draft working paper was prepared to help initiate investigations into the feasibility of developing a tool to facilitate the estimation of sample size requirements using GSI methods. The draft reflects my preliminary thoughts as to methods and thus represents a ***work in progress***. Undoubtedly, others will have ideas of their own. Investigations into this topic would certainly benefit from thoughtful review or volunteers who are willing to take charge to revise, extend and refine methods. Ultimately, the hope is that a tool that will provide useful guidance to decision-makers responsible for budget allocation will become available.

Several major issues affecting sample size requirements have not yet been explored in the current draft:

(1) effects of mis-assignment (stock and age);

(2) effects of the level of confidence and disposition of samples that cannot be classified with a desired degree of accuracy;

(3) effects of aggregation;

(4) the development of methods to quantify the level of uncertainty that can be expected for a fixed sample size – it should be readily possible to extend the methods already contained in this draft to provide information on the expected confidence intervals for a given stock, depending on the proportion of the sampled population it comprises. This would enable more direct understanding of the relationship between confidence & budgets available for sampling; and

(5) cost considerations regarding expenses incurred for sample collection, processing, analysis, archiving, and reporting

GSI Sample Sizes

A fundamental problem for sampling design is to determine how the sample size required when the stock composition of the exploited population is not known in advance.

Before addressing that problem, it is useful to step back and examine the statistical relationship between sample sizes, the proportion of the exploited population comprised of a stock of interest, and uncertainty. When determining sample sizes for GSI experiments, it is important to clearly specify the statistical requirements for the estimated contribution of the stock of interest (proportion of the total exploited population comprised of the stock, or equivalently, the probability that an individual fish from the stock will be caught[15]). The sample size will depend on the number of fish in the population to be fished, the proportion comprised of the stock of interest, and the desired degree of precision around the estimated contribution. The degree of precision is normally expressed in terms of either standard error or relative standard error. The difference between the two is critical to understand.

[15] (CWT Release)*(Survival)*(Fishery Exploitation Rate)

The standard error (*SE*) is the square root of the variance about the estimated contribution. For a fished population >20000, the binomial approximation can be used, so *SE* is approximately:

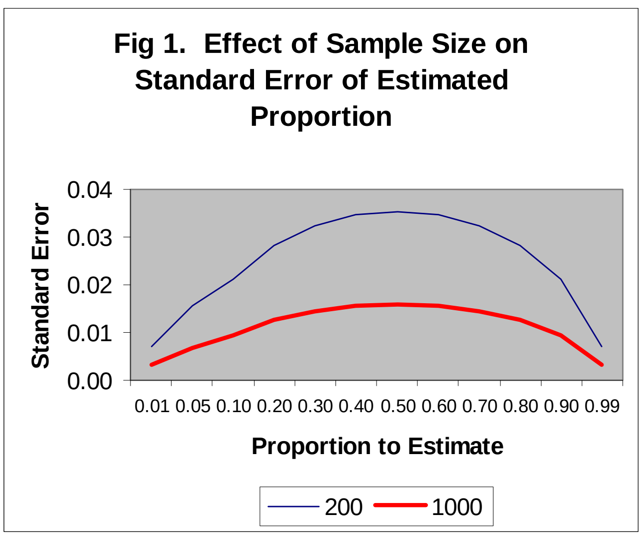
$$SE = \sqrt{\frac{p(1-p)}{n}} \qquad (1)$$

Where *n* is the sample size and *p* is the proportion comprised of the stock of interest.

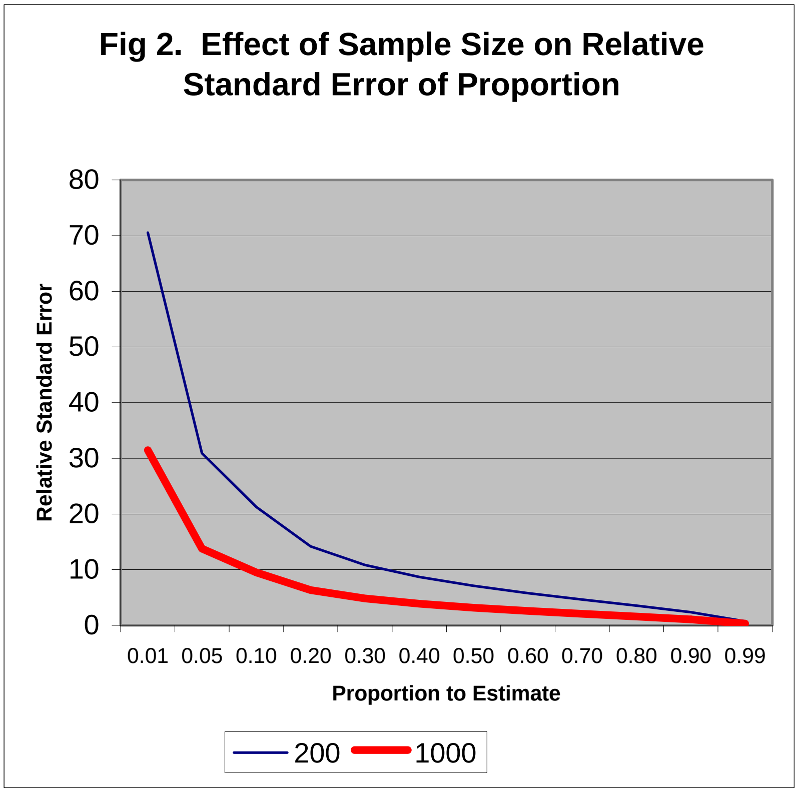
The relative standard error (*RSE*) is the standard error divided by the proportion comprised of the stock of interest.

$$RSE = \frac{\sqrt{\frac{p(1-p)}{n}}}{p} \qquad (2)$$

These two measures of precision interact with sample size n and the proportion *p* in different ways. The *SE* becomes largest when *p*=.50 and its magnitude decreases as the sample size increases (fig 1).



In contrast, *RSE* decreases asymptotically as *p* increases and its magnitude decreases with increasing sample sizes (fig 2).



When the stock of interest comprises a small proportion of the fished population, a small *SE* represents a large *RSE*. For a proportion of the sampled population comprised of a stock of interest, the RSE can be related to the sample size through the use of power functions.

$$RSE = a * n^b$$
$$\ln(RSE) = \ln(a) + b * \ln(n)$$

Parameters for the power function are provided in the following table for proportions ranging from 1% to 10%

Proportion	ln(a)	B
1%	2.97114	-0.5001
5%	1.36170	-0.5001
10%	0.66855	-0.5001

Determining required sample sizes

In determining required sample sizes, the desired degree of confidence for the results are defined by the concepts of risk and error tolerance, i.e., there is an α% chance that the true value lies within the estimated proportion by E amount.

For proportions, risk is characterized through the use of a standard normal distribution (mean=0, variance =1). The familiar bell-shaped curve of the normal distribution indicates that the probability of observing a value decreases the further the value is from zero. The probability that an observation will deviate from zero by at least E amount is expressed through the use of a *z* statistic – the larger the value of z, the smaller the probability. Risk is the probability that the true proportion of the population lies outside the desired confidence interval. Commonly confidence intervals, associated risk, and z values are depicted in Table 1.

Table 1. Two-Sided Confidence intervals, levels of risk, and z-values.

Confidence Interval	80%	90%	95%	99%
Risk	20%	10%	5%	1%
z value	1.282	1.645	1.960	2.236

When *SE* is used to characterize the error tolerance, the required sample size can be approximated using equation (1) as[16]:

$$n = \frac{z^2 p(1-p)}{E^2} \qquad (3)$$

For example, if a 95% confidence interval is specified with an acceptable *SE* of 5% is specified for a stock comprising 1% of the exploited population, then the required sample size would be:

---

[16] This approximation is known the Wald interval (Wald, A. 1943. *Tests of Statistical Hypotheses Concerning Several Parameters When the Number of Observations is Large*, Transactions of the American Mathematical Society, **54**, (1943), 426-482). The Wald approximation does not work well if N is small or p is close to 0 or 1. Clopper & Pearson (1934. *The use of confidence or fiducial limits illustrated in the case of the binomial.* Biometrika 26:404-413) proposed an "exact" method of computing the confidence interval, but the method tends to over-estimate the width of the confidence interval. Agresti & Couli (1998, *Approximation is better than "exact" for interval estimation of binomial proportion*, Am Statist.52(2):119-126.) developed the 95% modified Wald interval as:

$$p' = \frac{S+2}{N+4}$$

$$p' \pm 1.96\sqrt{\frac{p'(1-p')}{N+4}}$$

The numbers 2 and 4 are actually the z and z^2 critical values from the Gaussian distribution. Since 95% of all values of a normal distribution lie within 1.96 of the mean, z=1.96 (rounded to 2) for 95% confidence intervals.

$$
\begin{aligned}
n &= \frac{z^2 p(1-p)}{E^2} \\
&= \frac{1.96^2(.01)(1-.01)}{.05^2} \\
&= 15
\end{aligned}
$$

While the sample size is small, the resulting estimate of the proportion of the population comprised of the stock of interest may not be of much interest. The confidence interval includes the range from 0 to 6%, not very informative for a stock that comprises only 1% of the fished population. For conservation purposes, *RSE* is likely to be of greater relevance than *SE*; it will be more important to estimate contributions with a high degree of relative precision, e.g., to estimate the proportion of the catch comprised of a stock of interest within x% of the true value.

Consequently, *RSE* is likely to be the more relevant statistic for harvest management. When *RSE* is used to characterize the error tolerance, the required sample size can be computed by the formula:

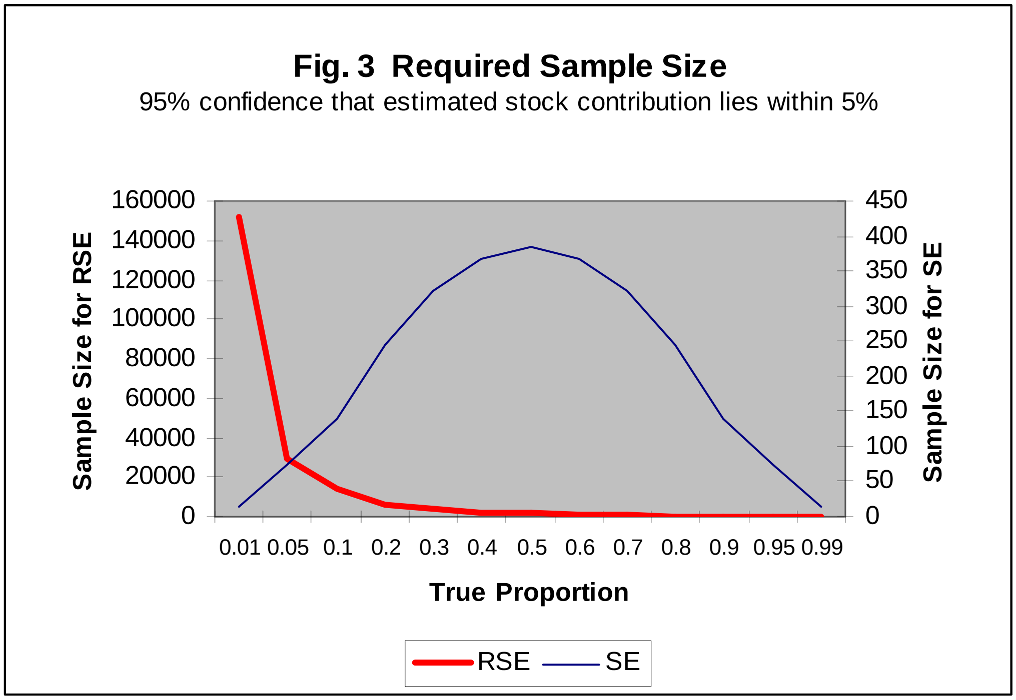
$$
n = \frac{z^2(1-p)}{E^2 p} \qquad (4)
$$

Note that equation (4) is simply equation (3) divided by the square of the proportion of the population comprised of the stock of interest. This indicates that the difference in required sample sizes resulting from the use of *SE* or *RSE* is dramatically affected by the contribution of the stock of interest. To illustrate, if a *RSE* of 5% is specified in the previous example, then the required sample size is:

$$
\begin{aligned}
n &= \frac{z^2(1-p)}{E^2 p} \\
&= \frac{1.96^2(1-.01)}{.05^2 * (.01)} \\
&= 152{,}127
\end{aligned}
$$

Sample size requirements would apply for each strata of interest. A sample size large enough to provide a *RSE* of 5% for a stock that comprises 1% of the exploited population would not only be costly to process, but could also require harvesting the population at a rate that may exceed the allowable level for a stock of conservation concern.

The relationship between required sample sizes and the true proportion of the population comprised of the stock of concern is depicted in figure 3, assuming a 95% confidence level that the estimated proportion lies within 5% (for any *SE*; of the true value for *RSE*).



Error Resulting From A Selected Sample Size

The number of GSI samples that can be taken and processed will be limited by available budget. Another way to view the issue of sample size is to examine the confidence that can be placed on estimates of proportions resulting from a given sample size.

The *SE* surrounding an estimated proportion for a given sample size, stock proportion, and specified level of risk is:

$$\pm z * \sqrt{\frac{p(1-p)}{n}} \qquad (5)$$

The *RSE* surrounding an estimated proportion for a given sample size, stock proportion, and specified level of risk is:

$$\pm \frac{z}{p} * \sqrt{\frac{p(1-p)}{n}} \qquad (6)$$

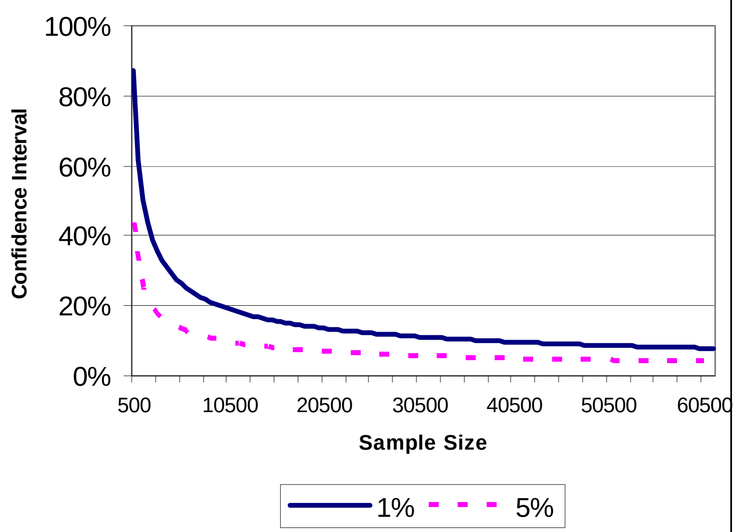
Confidence intervals for absolute and relative error for sample sizes of 200 fish and 10,000 fish are compared in Table 2 (courtesy of Bob Conrad, NWIFC. Note that in Bob's formulation, *n* is replaced by *n-1* per Cochran's correction).

Table 2. Comparison between *SE* and *RSE* values for sample sizes of 200 and 10,000, at various levels of stock contribution.

	SAMPLE SIZE:	200				10,000			
		Expected % Contribution (p)				Expected % Contribution (p)			
Alpha Level	z value	0.01	0.02	0.05	0.10	0.01	0.02	0.05	0.10
		SE (± % absolute)							
0.99	2.58	1.82%	2.56%	3.98%	5.48%	0.26%	0.36%	0.56%	0.77%
0.95	1.96	1.38%	1.95%	3.03%	4.17%	0.20%	0.27%	0.43%	0.59%
0.90	1.65	1.16%	1.64%	2.55%	3.51%	0.16%	0.23%	0.36%	0.50%
0.85	1.44	1.02%	1.43%	2.22%	3.06%	0.14%	0.20%	0.31%	0.43%
0.80	1.28	0.90%	1.27%	1.98%	2.73%	0.13%	0.18%	0.28%	0.38%
		RSE (± % of expected contribution)							
0.99	2.58	181.68%	127.82%	79.59%	54.78%	25.63%	18.03%	11.23%	7.73%
0.95	1.96	138.24%	97.26%	60.56%	41.68%	19.50%	13.72%	8.54%	5.88%
0.90	1.65	116.38%	81.88%	50.98%	35.09%	16.42%	11.55%	7.19%	4.95%
0.85	1.44	101.57%	71.46%	44.50%	30.62%	14.33%	10.08%	6.28%	4.32%
0.80	1.28	90.39%	63.60%	39.60%	27.26%	12.75%	8.97%	5.59%	3.84%

RSE confidence intervals become smaller at a decreasing rate as sample sizes increase (fig.4).

Figure 4. Effect of Sample Size on The 95% Confidence Interval (Relative Error) For a Stock Comprising 1% or 5% of the Population

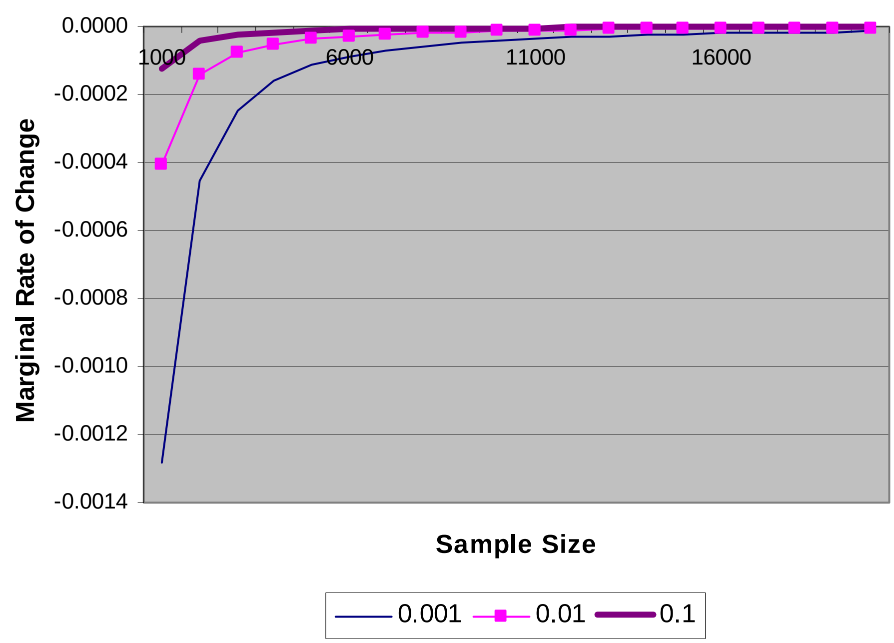


For a given *z value*, the shape of the *RSE* relationship to sample size is consistent for all values of *p*, but the magnitude differs. It is likely that many stocks of conservation concern would comprise a relatively small proportion of the catch in a highly mixed-stock fishery; large sample sizes would be required to estimate the catch of such stocks with a high degree of precision. Because the number of samples that can be taken and processed will be limited by budgetary considerations, some other metric may be needed as a means to determine optimal sample sizes. In this regard, it is useful to examine the marginal rate of relative reductions in *RSE* confidence intervals in relation to sample size. The marginal rate of reduction at any given sample size *n* is mathematically the value of the derivative of the *RSE* at that point.

$$\frac{-z * p * (1-p)}{2 * p * n^2 * \sqrt{\frac{p * (1-p)}{n}}}$$

The marginal rate of reduction in *RSE* confidence intervals rapidly approaches zero as sample sizes approach 10,000; large increases in sample sizes beyond that point result in little improvement (fig 5). This relationship can provide managers with a means to evaluate trade-offs between the precision of the estimate of stock contribution and costs of sampling.

Figure 5. Marginal Rate of Change in RSE in Relation to Sample Size For Stock Proportions Ranging from 0.001 to 0.100



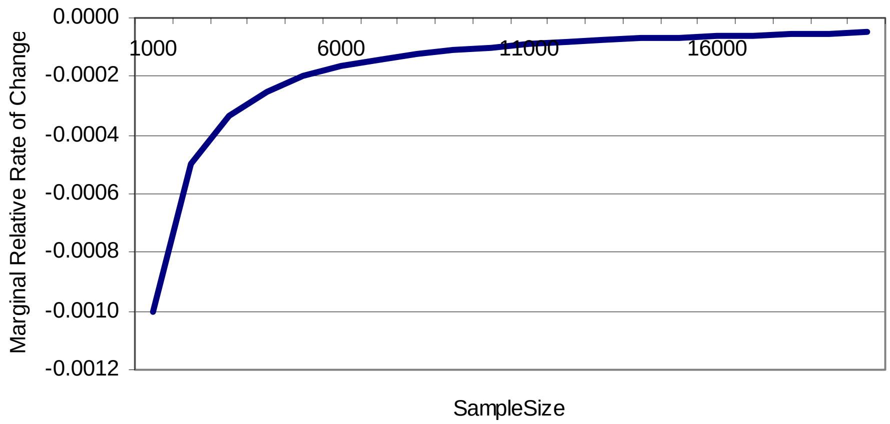
The difficulty with the above methods of determining sample size, of course, is that some means to determine, *a priori*, the proportion of the exploited population comprised of the stock of interest must be available.

Interestingly, the relative marginal rate of reduction in *RSE* is independent of the proportion p and the *z-value*, i.e., the same reduction in the relative marginal rate of reduction in RSE is attained for a given sample size.

$$\frac{-z*p*(1-p)}{2*p*n^2*\sqrt{\frac{p*(1-p)}{n}}}*\frac{p}{z*\sqrt{\frac{p*(1-p)}{n}}}=\frac{-1}{2*n}$$

Because this relationship (fig. 6) asymptotically approaches zero with increasing sample size, the potential to employ a different fishery sampling strategy for estimating stock compositions using GSI than is presently used for recovering CWTs appears. With CWTs, the generally accepted standard is to sample a minimum of 20% of the catch in a given strata of interest so the number of fish sampled varies with the size of the catch. With GSI, however, it may be sufficient to employ a representative fixed sample size strategy since improvements in the relative marginal precision of the contribution rate estimate becomes less and less apparent with stratum sample sizes larger than about 10,000.

Figure 6. Marginal Relative Rate of Change in RSE In Relation to Sample Size



Alternative Approach To Determining Sample Size Requirements

There are alternative ways to estimate require sample sizes besides using *SE* or *RSE*. One way would be to determine the sample size required to provide a specified confidence that at least k fish from the stock of interest would be observed. In this instance, using a binomial probability model, the probability is:

$$\Pr(k \le s \le n) \ge 1-\sum_{i=0}^{k-1}\binom{n}{i}p^i*(1-p)^{n-i}$$

where:

k Minimum number of fish from the stock of interest to be observed

s The number of fish from the stock of interest in the sample
n Sample size
p Proportion of the population comprised of the stock of interes

For a large k and n, the cumulative density function can be a bit of a chore to compute so an approximation would be helpful. The binomial probability function built into Excel can be used to find the minimum sample size *n* required to have a specified probability *PR* of obtaining at least *k* fish from the stock of interest.

$$(1 - Binomdist(k-1, n, p, 1)) \geq PR$$

For example, Table 3 provides estimates of 95% and 90% sample size requirements for observing at least 10 fish from a stock of interest which comprises from 0.005 to 0.50 of the sampled population.

Table 3. Sample sizes which provide 95% and 90% confidence to obtain at least 10 fish from a group of interest which comprises from 0.005 to 0.50 of the total population.

p	N=10; 95%	n=10; 90%	p	N=10; 95%	n=10; 90%	P	N=10; 95%	n=10; 90%
0.0005	31408	28410	0.0205	763	691	0.05	310	282
0.0010	15702	14204	0.0210	745	674	0.06	259	235
0.0015	10467	9469	0.0215	728	659	0.07	221	201
0.0020	7850	7101	0.0220	711	644	0.08	193	175
0.0025	6279	5680	0.0225	695	629	0.09	172	156
0.0030	5232	4733	0.0230	680	616	0.10	154	140
0.0035	4484	4057	0.0235	665	602	0.11	140	127
0.0040	3923	3549	0.0240	652	590	0.12	128	116
0.0045	3487	3155	0.0245	638	578	0.13	118	107
0.0050	3138	2839	0.0250	625	566	0.14	109	99
0.0055	2853	2581	0.0255	613	555	0.15	102	93
0.0060	2615	2366	0.0260	601	544	0.16	95	87
0.0065	2413	2183	0.0265	590	534	0.17	89	82
0.0070	2241	2027	0.0270	579	524	0.18	84	77
0.0075	2091	1892	0.0275	568	514	0.19	80	73
0.0080	1960	1774	0.0280	558	505	0.20	76	69
0.0085	1845	1669	0.0285	548	496	0.21	72	65
0.0090	1742	1576	0.0290	539	488	0.22	68	62
0.0095	1650	1493	0.0295	530	479	0.23	65	60
0.0100	1568	1418	0.0300	521	471	0.24	62	57
0.0105	1493	1351	0.0305	512	464	0.25	60	55
0.0110	1425	1289	0.0310	504	456	0.26	57	52
0.0115	1363	1233	0.0315	496	449	0.27	55	50
0.0120	1306	1182	0.0320	488	442	0.28	53	48
0.0125	1254	1134	0.0325	480	435	0.29	51	47
0.0130	1205	1091	0.0330	473	428	0.30	49	45
0.0135	1160	1050	0.0335	466	422	0.35	42	38
0.0140	1119	1013	0.0340	459	416	0.40	36	33

0.0145	1080	978	0.0345	452	410	0.45	32	29
0.0150	1044	945	0.0350	446	404	0.50	28	26
0.0155	1010	914	0.0355	440	398			
0.0160	979	886	0.0360	433	392			
0.0165	949	859	0.0365	427	387			
0.0170	921	834	0.0370	422	382			
0.0175	895	810	0.0375	416	377			
0.0180	870	787	0.0380	410	372			
0.0185	846	766	0.0385	405	367			
0.0190	824	746	0.0390	400	362			
0.0195	803	726	0.0395	395	358			
0.0200	782	708	0.0400	390	353			

The relationship between required sample sizes and the proportion of the sampled population comprised of a stock group is depicted in figure 7.

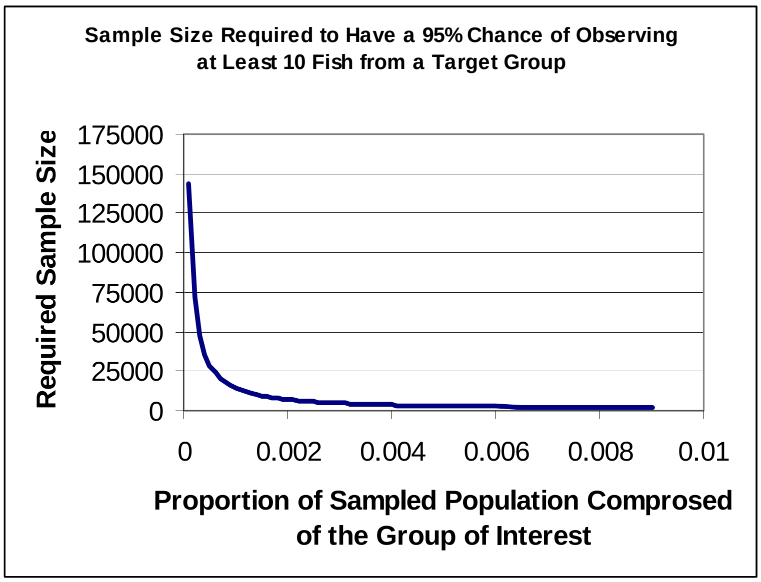


Fig. 7. Sample Size required to observe at least 10 fish

This is obviously a form of power function, indicating that a simple formula can be developed to estimate the sample sizes required, based on the proportion of the sampled population which is comprised of the group of interest.

$$n = a * p^b$$
$$\ln(n) = \ln(a) + b * \ln(p)$$

Parameters for power functions to estimate sample sizes required to observe at least 10 fish with 80%, 90%, and 95% confidence are presented below.

Confidence	ln(a)	B

80%	2.502833	-1.00438
90%	2.617341	-1.00656
95%	2.762440	-0.98825

There are alternative ways to determine the sample size, such as using the entropy function or the normal approximation to the binomial.

If we define α*n*=*k-1*, (α would represent the fraction of the sample comprised of the population of interest), the entropy function can be used.

$$H(\alpha) \cong \alpha \log_2\left(\frac{1}{\alpha}\right) + (1-\alpha)\log_2\left(\frac{1}{1-\alpha}\right)$$

This would allow the following approximation to be used (provided that α < p):

$$\sum_{i=0}^{k-1}\binom{n}{i} p^i * (1-p)^{n-i} \le \frac{1-\alpha}{1-\frac{\alpha}{p}} * \frac{2^{nH(\alpha)}}{\sqrt{2\pi\alpha(1-\alpha)n}} * p^{an} * (1-p)^{(1-\alpha)n}$$

Required minimum sample sizes can also be estimated using the normal approximation to the binomial. Let:

$$a = p^2$$
$$b = z^2 * (p^2 - p) - 2 * m * p$$
$$c = m^2$$

The minimum sample size can then be estimated using the quadratic equation as:

$$n = \frac{-b + \sqrt{b^2 - 4 * a * c}}{2 * a}$$

where:

- m Minimum number of fish from the group to be observed
- n Minimum sample size
- p Proportion of the sampled population comprised of the group of interest (can also be considered as the probability that a fish from the group will be caught)
- z one-sided z-value associated with the desired confidence level

Annette Hoffman used this approach in estimating the sample sizes presented in table 9 in the USCTCSG response to assignment 7.

Confidence Intervals for Estimates of Total Contributions For a Given Stock Across Heterogeneous Sample Strata

Because ocean fisheries harvest a complex and dynamic mixture of stocks, both the catch and the proportion of the catch comprised of a given stock of interest can be expected to vary substantially by time and area. This poses an interesting challenge for estimating confidence intervals for the total catch of a given stock across heterogeneous strata.

This topic seems to have received surprisingly little attention in the literature. A method to determine confidence intervals for heterogeneous sampling strata follows. The approach is a modification of results of a simulation study by Nanthakumar and Selvavel.[17] As with all methods based on Wald-type normal approximation of the binomial density function, the confidence interval may not achieve the desired coverage probability when *p* is near 0 or 1. This may be of particular concern to managers who are concerned about fishery impacts on stocks that comprise a small proportion of the catch; the procedure presented below will likely underestimate the size of confidence intervals for stocks that comprise a small portion of the catch.

Notation:

N_h	Catch estimate for stratum h
n_h	Sample size for stratum h
k	Number of strata
$N = \sum_k N_h$	Estimate of total catch for all strata combined
p	Proportion of the stock of interest in the stratified population
p_h	Proportion of the stock of interest in stratum h
x_h	Number of fish from the stock of interest in n_h
$\hat{p}_h = \frac{x_h}{n_h}$	Estimate of the proportion of sample n_h which is comprised of the stock of interest
$f_h = \frac{n_h}{N_h}$	Sample fraction for stratum h
$\sigma_h = \sqrt{\frac{\hat{p}_h * (1 - \hat{p}_h)}{n_h}}$	Wald normal approximation for the standard deviation of the proportion of the stock of interest in stratum h

The stratified estimate for *n* is simply the average of the $\hat{p}_h$ weighted by the proportions of the total catch represented by the strata.

$$\hat{p} = \sum_h \frac{N_h}{N} * \hat{p}_h$$

[17] Nanthakumar, A, and K. Selvavel. 2004. Estimation of Proportion of Success From a Stratified Population: A Comparative Study. Communications in Statistics. Theory and Methods 33:99): 2245-2257.

The variance of $\hat{p}$ is:

$$\mathrm{var}(\hat{p}) = \sum_h \left[\frac{N_h}{N}\right]^2 * \sigma_h^2$$

The (1-x%) Wilson-type confidence interval for $\hat{p}$ is:

$$\hat{p} \pm t_{\frac{\alpha}{2},df} * \mathrm{var}(\hat{p})$$

The degrees of freedom can be estimated as:

$$df \approx \frac{\left[\sum_h \left\{\frac{N_h}{N}\right\}^2 * \sigma_h^2\right]^2}{\sum_h \left\{\frac{N_h}{N}\right\}^4 * \sigma_h^4 * \frac{1}{(n_h - 1)}}$$

Example. Five strata

Stratum	$\hat{p}_h$	$(1-\hat{p}_h)$	n_h	N_h	Wald Normal σ_h	σ_h^2	Components Proportion	Components Variance	Components DF(denom)
1	0.10	0.90	200	5000	0.021	0.000450	0.006173	1.71468E-06	1.47745E-14
2	0.01	0.99	10000	50000	0.001	0.000001	0.006173	3.77229E-07	1.42316E-17
3	0.05	0.95	1000	10000	0.007	0.000048	0.006173	7.23975E-07	5.24664E-16
4	0.10	0.90	2500	15000	0.006	0.000036	0.018519	1.23457E-06	6.09907E-16
5	0.02	0.98	100	1000	0.014	0.000196	0.000247	2.98735E-08	9.01440E-18
			N	81000		p	0.03728395	4.08032E-06	1.59323E-14
								df	1044.9872

The total catch = 81,000, the estimated proportion comprised of the stock of interest is 0.0373, and the variance about that estimate is 4.08E-06 (standard deviation 0.00202).

The degrees of freedom are estimated as:

$$df \approx \frac{(4.08E-06)^2}{1.593E-14} = 1045$$

For a 95% confidence interval, the *t* value for df this large would approximate the *z-value* from the normal distribution (1.96), so the estimated confidence interval for *p* would be:

$$.0373 \pm 1.96 * 0.00202 = [0.03332, 0.04124]$$

The confidence interval for the estimate for the total catch for the stock of interest is:

$$3020 \pm 321$$

With estimates of catches, stock sizes, and variances in hand, it should be possible to estimate confidence intervals surrounding estimates of exploitation rates using bootstrapping or Bayesian methods.

2.8.2 Sample Size Considerations for GSI Studies

Michael Mohr

As Morishima (Section 2.8.1) mentions, this is hardly the first time the question of sample size relative to estimation of p using GSI has come up. In my view, a suite of metrics should be considered simultaneously in determining the appropriate sampling level:

1. Q: probability of detecting ≥ 1 individual from stock
2. CV: coefficient of variation of $\hat{p}$
3. w: confidence interval width for p
4. d: minimum detectable difference between two contribution rates

Morishima (Section 2.8.1) discusses #1–#3: his version of #1 is more general ($\geq k$); re. #2 he uses the equivalent term RSE rather than CV; re. #3 he reports on the half-interval width, $w/2$. Formulas relating the quantities in #1–#4 to p and n are provided in the following section ("Sample size formulas"), and a graphical display of the implied relationships is provided in Figure 1, under the following assumptions:

1. <u>All</u> collected tissues are GSI processed and classified as to stock-of-origin.
2. <u>All</u> GSI stock-of-origin classifications are 100% accurate.
3. Type I and Type II error rates are applicable to p_i for an individual stock i of interest, rather than to a set of $\{p_i\}$ as a whole.
4. Simple random sampling within each stratum.
5. Sampling fraction is negligible.
6. The normal distribution is a satisfactory approximation to the binomial distribution, particularly for small contribution rates.

If these assumptions are not met, particularly #1–#4, the derived sample sizes will be insufficient to meet the objectives, and should be increased accordingly.

Sample Size Formulas

Notation

$n =$ sample size

$Y =$ number of individuals in sample from stock of interest

$p =$ stock contribution rate

$CV =$ coefficient of variation of $\hat{p}$

$Q =$ probability of detecting ≥ 1 individuals from stock

$w =$ confidence interval width for p

$d =$ minimum detectable difference between two contribution rates, p_1 and p_2

$Z =$ standard normal cumulative density function

Probability of detecting ≥ 1 individuals from stock

The binomial model, $P(Y = y) = \binom{n}{y} p^y (1-p)^{n-y}$, implies

$$Q = P(Y \geq 1) = 1 - P(Y = 0) = 1 - (1-p)^n, \tag{1}$$

$$n = \log(1-Q)/\log(1-p). \tag{2}$$

Coefficient of variation of $\hat{p}$

For the binomial model, $V(\hat{p}) = p(1-p)/n$, which implies that

$$CV = \sqrt{V(\hat{p})}/p = \sqrt{(1-p)/(np)}, \tag{3}$$

$$n = (1-p)/(p \cdot CV^2). \tag{4}$$

Confidence interval width for p

With the binomial model and normal approximation for the distribution of $\hat{p}$,

$$w = 2 \cdot Z_{1-\alpha/2} \cdot \sqrt{p(1-p)/n}, \tag{5}$$

$$n = 4 \cdot Z^2_{1-\alpha/2} \cdot p(1-p)/w^2. \tag{6}$$

Detectable difference between two contribution rates

With the binomial model and normal approximation for the distribution of $\hat{p}_1$ and $\hat{p}_2$,

$$n' = \left[Z_{1-\alpha}\sqrt{2\bar{p}(1-\bar{p})} + Z_{\text{power}}\sqrt{p_1(1-p_1) + p_2(1-p_2)} \right]^2 / d^2, \tag{7}$$

$$n = (n'/4)\left[1 + \sqrt{1 + (4/(n'd))}\right]^2. \tag{8}$$

where $p_1 > p_2, p = p_1, d = p_1 - p_2, \bar{p} = (p_1 + p_2)/2$. Equation (7) for n' is from Zar (1996, Eq. 23.71), and Equation (8) for n is from Zar (1996, Eq. 23.74).

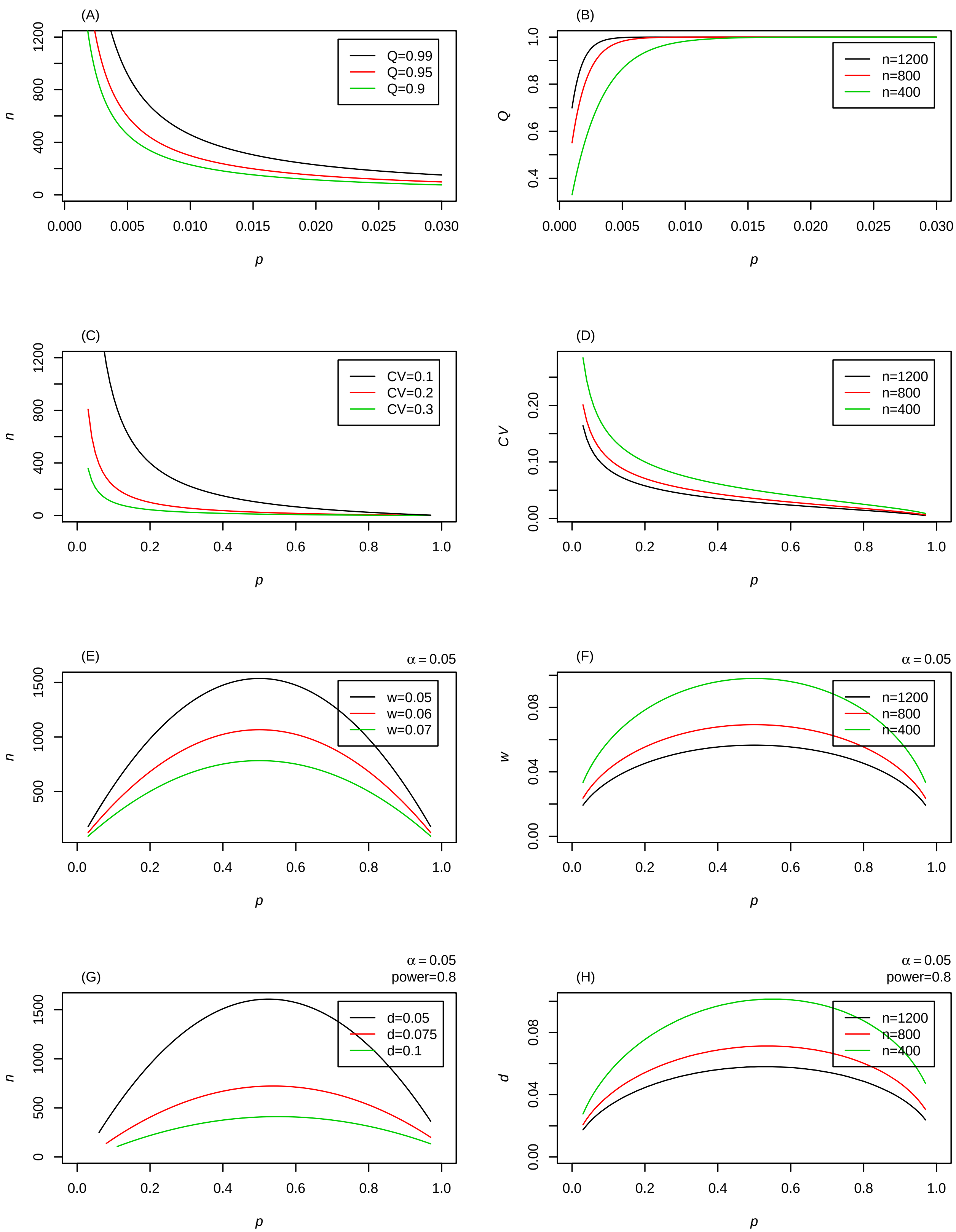


Figure 1. Sample size relationships.

Example Application

The sample size required depends on the study goals, as well as the statistical objectives. Three such example applications are outlined below. In each example, the time-area-fishery specific n is determined that *simultaneously meets all of the associated statistical objectives*.

Application I

- Goals
  - $\hat{p}$ for all stocks by time, area, fishery
- Statistical Objectives
  - $Q \geq 0.999$ for $p \geq 0.01$
  - $CV \leq 0.20$ for $p \geq 0.03$
- Minimum n per stratum
  - ≈ 800

Application II

- Goals
  - $\hat{p}$ for all stocks by time, area, fishery
- Statistical Objectives
  - $Q \geq 0.999$ for $p \geq 0.01$
  - $CV \leq 0.20$ for $p \geq 0.03$
  - $w \leq 0.06$ for $p \geq 0.01$ with $\alpha = 0.05$
- Minimum n per stratum
  - $\approx 1{,}070$

Application III

- Goals
  - $\hat{p}$ for all stocks by time, area, fishery
  - Compare p inshore versus offshore
- Statistical Objectives
  - $Q \geq 0.999$ for $p \geq 0.01$

- $CV \leq 0.20$ for $p \geq 0.03$
- $w \leq 0.06$ for $p \geq 0.01$ with $\alpha = 0.05$
- power ≥ 0.80 to detect $d = p_{off} - p_{in}$ with $\alpha = 0.05$
  - assume $p_{off} \geq 0.03$, and $p_{in} \leq p_{off}/2$

- Minimum n_{in}, n_{off} per stratum
  - $\approx 1{,}350$

The statistical objectives specified above are, of course, arbitrary. Application I presumes that an n that would provide: (a) a 99.9% chance of detecting a stock given its contribution rate was at least 1%, and (b) a CV less than 20% for $p \geq 3\%$, is an appropriate compromise, but its certainly arguable. The n required to achieve a CV of less than 20% for $p \leq 0.03$ rises rapidly to untenable levels as p approaches zero, so that "good" estimates of p for weakly contributing stocks (e.g. $p <$ 2%) are probably not achievable given practical cost constraints.

Stock Assessment

The proportion of some specific stock in the landings, p, is not necessarily the quantity of interest for assessment purposes, although the quantity of interest is likely to be a function of p. Morishima (Section 2.8.1) provides one such example ("Confidence intervals for estimates of total contributions for a given stock across heterogeneous sample strata"). This fact seems to be generally under-appreciated, and it should be recognized that sample size recommendations based on the uncertainty associated with $\hat{p}$ may not be adequate for other derived metrics of interest.

The quantity p is a function of the ocean stock abundances of all contributing stocks to that fishery, their distribution, their catchability, and their probability of being legal size (exceeding the minimum size limit). To first order, for stock i in stratum j:

$$p_{ij} = \frac{C_{ij}}{\sum_k C_{kj}} = \frac{N_i \alpha_{ij} q_{ij} \ell_{ij} f_j}{\sum_k N_k \alpha_{kj} q_{kj} \ell_{kj} f_j} = \frac{N_i \alpha_{ij} q_{ij} \ell_{ij}}{\sum_k N_k \alpha_{kj} q_{kj} \ell_{kj}}. \tag{9}$$

where, C is the catch, N is oceanwide abundance, α is distributional coefficient (fraction of N in stratum), q is catchability, ℓ is the proportion legal size, and f is fishing effort. Thus, assuming equal catchabilities, a historical time-series of p may be of direct interest for forecasting the impacts of a planned quota fishery, assuming estimates of the component historical stock abundances and proportions legal size are available to adjust those p for the current mix of expected abundances and legal size proportions (depends on size limit). Here p, expressed as a percentage, is directly interpretable: number of the stock expected to be caught per 100 fish in the quota fishery. In other contexts however (e.g., for cohort analysis and seasonal management), one may need to estimate the total number of the stock *contacted* in the stratum ($[Cp/\ell]$), or per day of fishing ($[Cp/\ell]/d$), or per unit of effort ($[Cp/\ell]/f$). Here, C, ℓ, and f will themselves need to be estimated, so that the uncertainty of the quantity of interest depends on the uncertainty of C, ℓ, and possibly f, as well as p.

It also appears to be generally under-appreciated that observed differences in p across strata for the stock of interest i may be entirely due to variation in $\{\alpha_{kj}\}$ across these strata for some dominant stock k, rather than due to variation in $\{\alpha_{ij}\}$ (variation in the denominator of equation (9) rather than the numerator). From the numerator of equation (9), and noting that $\sum_h \alpha_{ih} = 1$ for a particular time period and fishery-type (commercial or recreational), to first order

$$\alpha_{ij} = \frac{C_{ij}/(N_i q_{ij} \ell_{ij} f_j)}{\sum_h C_{ih}/(N_i q_{ih} \ell_{ih} f_h)} = \frac{C_{ij}/(q_{ij} \ell_{ij} f_j)}{\sum_h C_{ih}/(q_{ih} \ell_{ih} f_h)}, \tag{10}$$

so that assuming constant catchability across strata for stock i, inference re. its ocean distribution should be based on variation in $\{C_{ij}/(\ell_{ij} f_j)\} = \{(C_j p_{ij})/(\ell_{ij} f_j)\}$ across j during a particular period of time and fishery-type; not on variation in $\{p_{ij}\}$.

Other Considerations

- *Age-specific p.* If the sampling goals include achieving the statistical objectives with respect to each age class (e.g., for Chinook), the approach and formulas outlined above can be used if the mixture is redefined to be a collection of the various stock-age combinations, rather than the collection of stocks. Of course, the age-stratified p components will be less than for the stock as a whole and as a result, considering that stock alone, the required n will increase (or if the n is not increased, the precision will be less than desired). For age-specific p, the sample size formulas further assume no age assignment errors for the sampled fish, and stock classification will presumably be done by individual assignment analysis (IAA) rather than mixed stock analysis (MSA) because the age-determination is fish-specific (and there is no reason to believe that the stocks in the mixture will all have the same age structure in that stratum). Currently, the assumption that "GSI classification uncertainty is negligible" appears to be far less supportable for IAA than for MSA.

- *Adequacy of binomial distribution, normal approximation.* While simple, the sampling models and approximations used here are probably adequate for *general planning purposes* if the objective of estimation is p. Whether they are adequate for very low levels of p should be further investigated. Of course the actual $V(\hat{p})$ depends on the actual survey design employed within a stratum, and may be quite complicated. For *estimation purposes*, estimators of p and $V(\hat{p})$ that are appropriate for the specific sampling design employed should be used on the actual data. The binomial-based $V(\hat{p})$ will likely be conservative wrt the actual $V(\hat{p})$ if the sampling fraction is non-negligible. For example, if the stratum overall catch is 1000, and 500 fish are sampled from it, the actual $V(\hat{p})$ will be substantially less than for a sample of 500 from a catch of 20000. The simplest sampling model to account for such a non-negligble sampling fraction is the hypergeometric distribution, however use of that model for planning purposes would require specification of the anticipated overall catch in addition to p.

- *Ocean population or fishery landings estimator?* The previous item raises another question: is the goal of estimation the population, or the catch? For example, is the goal estimation of the stock composition of the mixture of stocks in the ocean in some particular stratum, or is it the stock composition of the mixture of stocks in the catch in that stratum? With the former, even if the entire catch were sampled ($n = C$), $V(\hat{p})$ would not be 0 as the catch is only a sample of the ocean mixture. With the latter, if the entire catch were sampled, $V(\hat{p})$ would be 0 (assuming no non-sampling errors).

- *Inverse sampling for low p.* Another approach, also discussed by Morishima (Section 2.8.1), is to continue to sample a stratum until at least m fish are detected from the stock of interest, where m is set at a level which will insure an acceptable CV for stocks with a low contribution rate. Cochran (1977, Section 4.5) indicates that for C large, p small, and $m \geq 10$, $CV \leq \sqrt{m}/(m-1)$ so that, for example, $CV \leq 0.2$ if $m = 27$, independent of p. While this would insure a good estimate of a small p of the stock of interest in each stratum, it would not alter the expected level of n required for that value of p. E.g., for $p = 0.03$, $E[n] \approx 27/0.03 = 900$ (close to the 800 previously identified for $p = 0.03$ and $CV = 0.2$); for $p = 0.01$, $E[n] \approx 27/0.01 = 2700$. While this inverse sampling approach would not seem to be practical for dockside sampling (realtime GSI transport, processing, feedback required; may encourage "front-loading" of stratum sampling effort to insure meeting the $m = 27$ requirement resulting in uneven sample coverage of strata), perhaps a hybrid scheme with large n taken dockside and an m-type stopping rule applied at the GSI processing phase might save money and/or maintain quality of the estimates for small p. However, unless there is only one or a few stocks of interest, where would the line be drawn on which stocks in which strata should be represented by at least m individuals in the sample? And what if there aren't m individuals of each of those stocks in the stratum catch—would the entire catch end up being sampled?

- *Specified sampling fraction or specified sample size?* For the CWT coastwide sampling program, the objective is to sample a constant fraction (20%) of the catch in every stratum. This constant sampling fraction approach (known as "proportional allocation" in the sample survey literature on stratified sampling, Cochran 1977) is an optimal allocation of sampling effort if the statistical objective is to simultaneously minimize the sampling variances of the estimated *coastwide catchs* of the stocks of interest. However, if the statistical objectives involve minimum acceptable levels of precision within each stratum (as presumed here), this overides the notion of a constant sampling fraction, and the optimal allocation of sampling effort in this case is the minimum n necessary to meet the stratum-specific statistical objectives.

- *Stratified sampling for p.* With respect to stratified sampling for estimation of a proportion, Morishima (Section 2.8.1) states that "This topic seems to have received surprisingly little attention in the literature", however quite a bit of work has been done on this topic under the umbrella of sample survey design, see e.g. Cochran (1977) Sections 5.10, 5.11, and 5.12 for $\hat{p}$ with stratified sampling, and Section 5.4 for associated CI's and degrees of freedom. However, I would formulate this problem slightly differently than Morishima (Section 2.8.1) if the objective of estimation is C_i, the coastwide catch of stock i. Rather than estimate the coastwide p_i as a weighted combination of the stratum-specific $\hat{p}_{ij}$ and then expand $\hat{p}_i$ by the all-stocks coastwide C to estimate $\hat{C}_i$, I would instead estimate the C_{ij} for each stratum and then sum those for $\hat{C}_i$ as follows:

$$\hat{C}_i = \sum_j \hat{C}_{ij} = \sum_j C_j \hat{p}_{ij}, \tag{11}$$

with associated sampling variance

$$V(\hat{C}_i) = \sum_j V(\hat{C}_{ij}) = \sum_j C_j^2 V(\hat{p}_{ij}). \tag{12}$$

The advantage of this formulation is that it provides the stratum-specific catch estimates for the stock of interest, and their variance, and is easier to generalize to more complicated situations. For example, the above equations assume that the stratum catch C_j is known rather than estimated. With estimated $\{\hat{C}_j\}$:

$$\hat{C}_i = \sum_j \hat{C}_{ij} = \sum_j \hat{C}_j \hat{p}_{ij}, \tag{13}$$

with associated sampling variance

$$V(\hat{C}_i) = \sum_j V(\hat{C}_{ij}). = \sum_j V(\hat{C}_j \hat{p}_{ij}). \tag{14}$$

The variance of $\hat{C}_{ij}$ is now more complicated (the variance of a product of random variables), but the $\{V(\hat{C}_{ij})\}$ are still additive across strata due to the independence of sampling across strata.

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2.8.3 Comments on Morishima's Sample Size Analysis (Section 2.8.1)

Jerome Pella

The draft (Section 2.8.2 by G. Morishima) covers well the use of the binomial sampling model when unique stock identifiers, or marks, such as CWTs are available and 100% of the population is marked. The difference between genetic marks (e.g., microsatellites or SNPs) and CWTs in terms of their specificity is not discussed, and it seems to me the distinction would benefit the discussion. The CWTs' great appeal is that the source of a marked individual is known with certainty, but the major shortcoming for coast-wide chinook management is that few of the sources are marked. The genetic marks' great appeal is that all individuals of all sources are marked, but the major shortcoming is that in practical terms the source of marked individuals can only be delimited to subsets or groups of stocks that are genetically similar. Although in theory the source composition and identity of every mixture individual can be evaluated from genetic marks to the level of individual stocks, the evaluation is based on probabilities, and the source probabilities of individuals decrease (or source uncertainty increases) as greater source detail is attempted. The totality of possible source stocks is usually partitioned into reporting stock groups, and this reporting partition is a compromise between the desire for detail and the concern for uncertainty. The choice of the reporting partition and definition of reporting stock groups is typically guided by statistical measures of genetic similarity among stocks as well as experimentation in estimating composition of simulated stock mixtures. Criteria to use in selection of the reporting partition are not standard and routine. Quite conceivably, as the number of genetic characters is increased in the future, their combination could become nearly as certain as a CWT in identifying stock sources, and the reporting partition would become irrelevant.

With the current microsatellite baseline and practical-sized samples, the source composition of a chinook salmon mixture can apparently be reliably estimated to the level of 41 reporting groups (12 GAPS authors. 2005. Interlaboratory standardization of coast-wide chinook salmon genetic data for international harvest management. Final Report). The reporting group identities of mixture individuals can be probabilistically evaluated and used to assign them to source group with good success as well. Evidently the GAPS team felt comfortable with their reporting partition, but at some finer level of stock detail, uncertainty in composition estimation or in individual assignments became problematic. Limitation on detail is characteristic of stock mixture analysis, whenever natural features, e.g., patterns or chemical signatures on hard parts and scales, morphological measurements, or genetic traits, are used to distinguish sources, This stock confusion problem can occur whether few or many stocks compose the mixture. The sorting or separation of mixture individuals to their sources becomes increasingly difficult in progressing from larger similarity stock groups toward the individual comprising stocks. Stock confusion becomes especially problematic when presence of a rare (< a few % of the mixture) stock has to be estimated or detected in the catch. However, the corresponding reporting group, of which the rare stock is a member, could serve as an indicator of its possible presence.

Stock confusion can be reduced by either increasing the number of characters measured on individuals, or by introducing additional prior (external to the catch sample) information about stock composition of the catch mixture. Commonly, an uninformative prior for stock composition is used in Bayesian stock mixture analysis, but the option of using an informative prior is available. The informative prior could be fixed and external to the chinook model and depend on historical observations of timing and relative magnitudes for the various stocks' presence in fisheries. Or possibly better, the informative prior might be integrated into the chinook model with the latter parameterized so that the stock mixture compositions of catches could be computed from its parameters and variables. The chinook model parameters and variables could be updated by the genetic samples from the catches. The estimation could then loop back to update the informative prior for the stock mixture compositions in the catches. The possibility of using such a Markov chain Monte Carlo estimation process could be examined. The development of informative priors for stock mixtures of catches is an open area, and it has potential to reduce the stock confusion problem.

Specific comments:

1. Under "GSI Sample Sizes", 2nd paragraph. The population to be sampled could be the "number of fish in the population to be fished", or else the catch itself. Usually, the catch is the "population" from which the GSI samples are drawn and to which inferences apply. The final section title "Confidence Intervals …Across Heterogeneous Sample Strata" indicates that catch is the population of interest. If the catch is randomly drawn from the mixed stocks in a fishing stratum, its composition can be used to infer that of the mixed stocks. The distinction—population fished vs. catch—could be important for small catches when the proportion sampled becomes relatively large (>5%) so that the binomial would be less accurate than the hypergeometric distribution.
2. Under "Alternative Approach To Determining Sample Size Requirements", I wonder if simple detection of an endangered stock might be useful? Detection would be the finding of one or more individuals in the catch. Entomologists use this approach in sampling for pests during quarantine inspections (see Venette, R., R. Moon, and W. Hutchison. 2002. Strategies and statistics of sampling for rare individuals. Annual Review of Entomology, 47: 143-174.) Figure 1 (below) is repeated from Venette et al. 2002. Given a mixture sample size of 200, a 100%-marked stock (the mark is not confused with that of other stocks) with contribution or relative frequency of only 0.004 (0.4%) results in the probability of detection exceeding 0.5, a relative frequency of 0.010 (1.0%) results in the probability of detection equal to 0.87, and a relative frequency of 0.020 (2.0%) results in the probability of detection exceeding 0.98. If detection is the goal, and all individuals of the rare stock were perfectly identifiable from its mark, the necessary sample sizes to achieve high probability of detection could be practical.
3. Another detection result from Venette et al. 2002 concerns the fact that sampling for marks cannot prove an endangered stock is absent from a catch or mixture, and the best that can be done is to demonstrate its contribution is below some level. Restated, what is the maximum proportion of the 100%-marked and endangered stock, say $p_{\max}$, in a catch if none of its individuals are found after sampling n fish? To compute $p_{\max}$, only the sample size n and the desired probability of detection, Prob ($x > 0$), are needed, and then $p_{\max} = 1 - [1 - \text{Prob}\ (x > 0)]^{1/n}$. The true and unknown proportion of the endangered stock lies between 0 and $p_{\max}$ with confidence equal to Prob ($x > 0$) $\cdot$100%. Using $n = 200$ and Prob ($x > 0$) = 0.98, $p_{\max} = 0.0194$, which is in agreement within rounding of the statement of comment 2 above regarding a sample size of $n = 200$: "a relative frequency

of 0.020 (2.0%) results in the probability of detection exceeding 0.98". The latter statement would be more precisely stated as "a relative frequency of 0.01995 (1.995%) results in the probability of detection exceeding 0.98224."

4. The equation in comment 3 above can be rearranged to calculate the sampling effort to detect a specified endangered stock proportion with specified detection probability, namely $n = \ln\left[1 - \text{Prob}(x > 0)\right] / \ln(1 - p)$. For example, to detect with 95% confidence a 100% marked endangered stock in a mixture when its proportion is p = 0.01 requires a sample of $n = \ln(1 - 0.95)/\ln(1 - 0.01) = 298$.

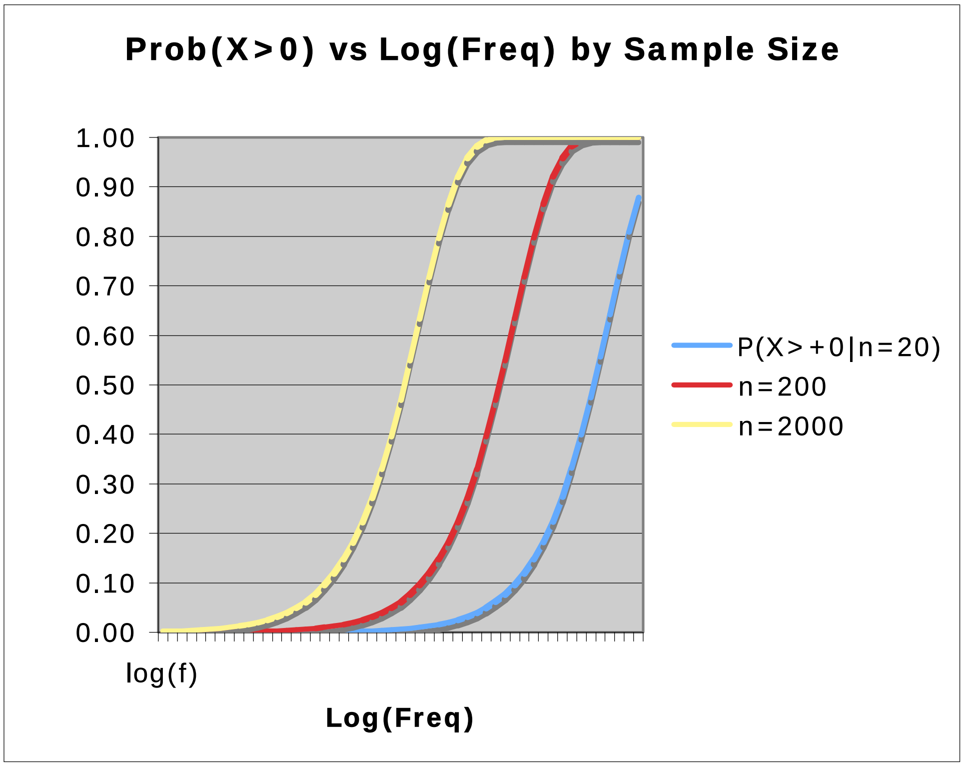

Figure 1. Detection probability for rare individuals as related to their frequency, or proportion, in a binomial population (the linear scale for common logarithm, Log (Freq), ranges from 10^{-6} = 0.000001on the left to 10^{-1} = 0.1 on the right.) The three curves correspond to random samples of sizes n = 20 (blue), n = 200 (red), and n = 2000 (yellow). (From Venette et al. 2002).

2.8.4 Catch Sampling to Determine Stock Composition with GSI: Sample Sizes and procedures

David R. Bernard

I've found over the years that successful catch sampling is a matter of knowing what you want and how the fishery works. Knowing the information you want and why you want it helps to determine sample-size targets needed to gain desired precision in statistics. However, sample-size targets are determined under the presumption of random sampling, a presumption that is invariably wrong. Sampling according to how the fishery works, therefore, improves accuracy in statistics. For these reasons I've divided my contribution to our discussion into two parts: sample sizes and procedures. I'll begin with the more traditional 'determination of sample sizes.'

Sample Sizes: Planning catch sampling programs to estimate stock composition with GSI has the following 10 issues:

1) the objective(s) of sampling,
2) standards for meeting the objective,
3) definition of the sampling frame,
4) simultaneous or single estimation of parameters,
5) use of relative or absolute precision to describe uncertainty in estimates,
6) finite sampling,
7) stratification,
8) misclassification,
9) subsampling, and
10) additional measurement error.

Most of the procedures to determine sample-size targets have been long established. However, objectives of sampling are obviously specific to the matter at hand, so I'll start with them.

Objectives: Ostensibly the objective for sampling is given in Dave's KEYISSUES document dated 19 June as 'to estimate specified stock proportions … (with) special problems of small populations.' I presume Dave's referring to estimating proportions in landed catches (and perhaps non-retained catches as well). Other objectives might be to detect the presence of a stock, or to test some hypothesis based on comparing two or more proportions representing the same or different stocks. Detecting presence usually involves a lower sample-size target than does estimating proportions, and estimating proportions lower than testing hypotheses. For now, I'll follow Dave's directive and presume we're estimating proportions.

Standards for Meeting the Objective. Criteria for successfully meeting an objective are usually couched in terms of confidence intervals based on estimates, such that, a large percentage (usually 95%) would cover the true proportion. How large these intervals (and hence sample-size targets) should be depends on how estimates will be analyzed (stock-recruit analysis, exploitation rate analysis, forecasting, etc.). Given the precision required of estimated proportions for analysis, a person responsible for a catch sampling program would use established statistical procedures in the form of a table, graph, or equation to link the desired outcome to the appropriate sample-size target (presuming that sampling will be random).

Dave begins Section III.A. with 'Sample size requirements to estimate …'. The word 'requirements' implies that a standard like those in USCTC (1997) will be used to determine a sample-size target. That's more than putting together a table (or graph) linking sample sizes to precision; that's specifying which line on the table to use. Are we determining those standards for estimating catch by stock with GSI? If we are, we need to consider how the resulting statistic will be used. One important issue for us to address about standards is how small a proportion must be to render it inestimable with reasonable confidence. One percent? Five percent? A half percent?

Definition of the Sampling Frame. The sampling frame for a stratified catch sampling program is obvious with the fish being the basic sampling unit and a stratum being all fish caught during a specified time and/or in a location. If a stratum is further subdivided, say into offshore or onshore, some post stratification is involved, but sample-size targets would be unaffected. For the sake of generalized planning, however, I suggest we determine a sample-size target for a sampling frame from which a 'simple' random sample will be drawn without replacement. Such a sample-size target will be germane to one stratum at a time, or to many collectively, depending upon the desired scope of the estimated proportion.

Simultaneous vs. Single Estimation. I imagine that we would be interested in estimating proportions for several stocks at once. That would up sample-size targets to some degree over estimating a single parameter. The reference I have used with success in the past is Thompson (1992, p. 31-40). Given a standard for meeting the objective using absolute precision, the worst-case scenarios are given in the Thompson's Table 5.1 for a simple random sample:

TABLE 5.1. Sample Size n_0 for Simultaneously Estimating Several Proportions within Distance d of the True Values at Confidence Level $1-\alpha$

α	$d^2 n_0$	n_0 with $d = .05$	m
.50	.44129	177	4
.40	.50729	203	4
.30	.60123	241	3
.20	.74739	299	3
.10	1.00635	403	3
.05	1.27359	510	3
.025	1.55963	624	2
.02	1.65872	664	2
.01	1.96986	788	2
.005	2.28514	915	2
.001	3.02892	1212	2
.0005	3.33530	1342	2
.0001	4.11209	1645	2

Source: S.K. Thompson, "Sample size for estimating multinomial proportions," 1987, *The American Statistician* **41** 42–46. With permission from the American Statistical Association.

The table above is based on *absolute* precision under the worst-case scenario which occurs when *m* stocks in the catch represent equal proportions and the remaining stocks zero. For example, sample-size target for a confidence level of 95% and a width of 0.05 is 510 ($m = 3$ here). A sample-size target for $\alpha = 0.05$ and a $d = 0.01$ is 12,736 ($= 1.2735/d^2$). These sample sizes will give at worst the specified absolute precision on all proportions and probably much better. In contrast sample-size targets from methods in Cochran (1977) eq. 4.2 for the worst-case scenario involving a single stock are 384 (d = 0.05) and 9,604 (d = 0.01). Sample-size targets based on *relative* precision can be obtained from the table above by scaling d to an estimated proportion. For instance, if p = 0.08 is the smallest proportion of interest to you, and you want relative precision of 25%, d = 0.02 for use in the table. For the worst case distribution of parameters, relative precision would be met for all $p \geq 0.08$ and not met for all $p < 0.08$.

Relative or Absolute Precision. I'm a fan of absolute precision myself, primarily because I have built quite a few brood tables in my day. Such tables are usually built for relatively large stocks or stock groups, and size and larger proportions make for better precision. However, if you want to scare a biologist, show them the sample size required to obtain 'good' relative precision for a stock represented by a small proportion of the catch in a single stratum. However, there is little need to show with confidence that a catch of stock A in a stratum is 1% as opposed to 2%. Small is small, and with few exceptions, small stocks should not influence the management of a fishery on an aggregate of stocks. Outside of management plans and treaties, the major exception is that the small stock is in jeopardy of extinction. However, protecting such stocks from extinction does not require highly precise estimates of the proportions caught.

Finite Sampling. Sampling from a finite population means that uncertainty is reduced as the sampling fraction approaches one, reduced to certainty if all units are sampled and there is no misclassification. There is no reason to set a sample-size target that is beyond the catch in a stratum. For the workshop we (I) don't have the information on catches needed to rationally reduce sample-size targets, but we can and should explain the *fpc* (finite population correction) and how it's used to adjust sample-size targets downward. For the table above, the *fpc* can be found in Thompson (1992, P. 40):

$$n = \frac{1}{1/n_o + 1/C}$$

where n_o is the unadjusted sample-size target from the table above, n is the target adjusted for sampling from a finite population, and C is the expected catch (the expected size of the finite population) in a stratum.

Stratification. If the sampling frame for the estimated proportion is larger than a single stratum, the sample-size targets from the table need to be spread across strata. Proportional allocation of sampling is:

$$n_{oj} \cong n_o \frac{C_j}{\sum_{j'} C_{j'}}$$

where n_o comes from the table above, n_{oj} is the new sample-size target from stratum j, C_j is the anticipated catch from stratum j, and j′ denotes a stratum for purposes of summation. If the desired statistics are proportions from 10 strata collectively, and each stratum represented the same catch, $n_o/10$ would be the sample-size target for each stratum. In the examples above, these new targets n_{oj} sans an *fpc* would be 51 for d = 0.05 and 1274 for d = 0.01. The anticipated *fpc* would be applied to the n_{oj}. For instance, if C_j = 10,000, the new sample-size target for a stratum would remain at 51 when d = 0.05, but would drop to 1,130 [= $(1/1{,}274 + 1/10{,}000)^{-1}$] when d = 0.01. The new targets would actually improve precision (lower the realized α below the desired level) to the extent that the C_j differ across all strata (see Cochran 1970, Section 5.10). This is an opportunity to lower *n* (the overall sample-size target), however, to do so requires some a priori knowledge of the proportions to be estimated. Ironically, possession of such knowledge would permit optimal allocation of sampling for a further improvement in precision or lowering of *n*. Considering that such a priori knowledge is unavailable to this workgroup at this time, my recommendation for setting planning rules would be to assume that proportions will follow the worst-case scenarios in every stratum. I suggest that part of our recommendations include descriptions of the general procedures for determining sample-size targets in a stratified program. Individual planners can use these procedures to reduce sample-size targets for sampling in their strata accordingly based on more detailed knowledge. An alternative recommendation would be to consider subsampling (see below).

Misclassification. Errors in assigning salmon to the wrong stock will add uncertainty to estimated proportions which can be countered to some degree by increasing sample-size targets over those in the table above. Ignoring the *fpc* for the time being, and assuming that misclassification is random and independent of sampling, the variance of $\hat{p}$ can be approximated with:

$$V(\hat{p}) \cong \frac{\pi(1-\pi)}{n} + \frac{p(1-p)}{n}$$

where π is the expected fraction of fish correctly classified in the sample. Dividing $V(\hat{p})$ by variance due to sampling error [$(p(1 - p)/n$] and subtracting one from the result produces the fraction that the sample-size needs to be increased to meet expected precision. Given the worst-case scenario that $p = 0.5$, the inset table provides expansions. Given a standard of 90% correct classification for GSI, sample-size targets for our 10-stratum example with 10,000 fish per stratum would be 69 when $d = 0.05$ and 1733 when $d = 0.01$. Obviously this approach is not very robust and perhaps a bit amusing in a naïve sort of way. A rigorous solution needs a lot more work … or needs someone in the know (Jerry?). In the long distant past the Department ran simulations to establish sample sizes for scale patterns analysis, a technique to estimate stock composition from a mixture that was fraught with misclassification. Simulations could prove useful here as well, but I would hope Jerry is correct when he said that most of these techniques have been worked out.

π	Increase In Target
0.90	36.0%
0.91	32.8%
0.92	29.4%
0.93	26.0%
0.94	22.6%
0.95	19.0%
0.96	15.4%
0.97	11.6%
0.98	7.8%
0.99	4.0%
1.00	0.0%

Subsampling. Not all samples taken need be analyzed. Considering the cost of genotyping a single sample relative to taking that sample, tossing some of the samples in the trash might be a smart thing to do. During fishing a relatively large sample would be taken from each stratum, say a set fraction of the catch (a fraction that could be recommended by this work group). Samples would then be numbered and stored. After the fishing season (or after fishing in a stratum has ceased for a time), a small subsample would be randomly drawn from storage. Information on stock proportions from genotyping the subsample and on catches would be used to produce well-informed sample-size targets that would optimize precision of estimated stock proportions. If needed, more samples in storage would be randomly selected for genotyping to meet the well-informed targets. Samples still on the shelf would then be tossed or kept as per the wishes of the lab. This stratagem trades some cheap bookkeeping and cheap sampling for expensive analysis and produces near optimal precision in estimates.

Additional Measurement Error. Michael's thoughts on estimated catch (his equations 5 and 6) touch on another aspect of planning that we should consider because it involves a very important rule. For some strata catch is known with near certainty (such as for some commercial fisheries) and in others notably for most sport fisheries), catch is estimated with some uncertainty. If catch by stock is the wanted statistic, and catch is estimated, catch by stock *i* in stratum *j* and its variance are calculated:

$$\hat{C}_{ij} = \hat{C}_j \hat{p}_{ij} \qquad v(\hat{C}_{ij}) = v(\hat{C}_j \hat{p}_{ij}) \qquad v(\hat{C}_{ij}) = v(\hat{C}_j)\hat{p}_{ij}^2 + v(\hat{p}_{ij})\hat{C}_j^2 - v(\hat{C}_j)v(\hat{p}_{ij})$$

again using Michael's notation (note that I substituted a lower case *v* for *V* to signify an estimated variance). The variance of a product of two, independent random variates is as per Goodman (1960) (estimates for *C* and *p* are assumed to have come from different sampling programs). Goodman (1960) also shows that for planning purposes (variances are 'known'):

$$CV^2(\hat{C}_{ij}) = CV^2(\hat{C}_j) + CV^2(\hat{p}_{ij}) + CV^2(\hat{C}_j)CV^2(\hat{p}_{ij})$$

which means that catch sampling as one of a set of programs to estimate C_{ij} will at best reduce precision to that of the estimated catch regardless of the number of caught fish sampled. This 'splash of cold water' needs to be included in the write-up of this assignment.

Sampling Procedures. As mentioned before, sampling catch from fisheries is not a random process. Fishermen fish an area during an opening, then deliver their catch to the nearest port, tender, or boat ramp. As commercial fisherman move across an area, those fish caught first are to be found in the bottom of the hold while those caught last tend to be on the top. Off loading on shore and on tenders has the same effect because distance of fishermen determines the order in which their catch is offloaded. Sport fishermen usually sail, fish, and return to a port or ramp nearest to their residence or to where their cruise ship is docked. In contrast, the sampler must go to the fish at a particular cannery, dock, or tender. At these sites, the sampler will not be faced with a random selection of the catch.

The only prudent response is for the sampler to follow several simple rules to get a systematic sample. Such an approach should provide accurate estimates of stock proportions in the catch, but under some circumstances provide badly inaccurate estimates of variance (see Wolter 1985, Chapter 7). If systematic samples are rigorously drawn, some alternative formulation for variance calculations can be used to reduce the bias. If not so drawn, at least the samples should be taken in a way not to significantly bias the statistics of interest.

Here are some common-sense rules:

- Within a stratum, sampling should occur in near proportion to the catch. If there are five processing plants that traditionally handle 5, 10, 15, 20, and 50% of the catch in a stratum, roughly 5, 10, 15, 20, and 50% of the samples should be taken from each processor, respectively.

- Samples from commercial fisheries should be taken proportionally through time in a stratum. Sampling should not be concentrated during the first few days in a stratum when deliveries or landings probably represent fish caught nearby. Nor should sampling be concentrated during the last few day when off loaded catches probably came from far away.

- Samples from sport fisheries should be taken proportionally through the day. Fishermen returning early probably fished nearby, those returning late in the day far away.

- When sampling from fish coming from a hold, draw the sample systematically while the hold is empties.

- Do not take all samples from a single boat or tender or a small subset of all boats or tenders.

Subsampling is of little benefit within a stratum because information on the spatial and temporal pattern of catches is not recorded or is difficult to find.

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2.9.1 Methods for Estimating Escapement Using CWTs & GSI estimates of Stock Composition

Gary Morishima

It can be difficult and costly to obtain high quality (low uncertainty) estimates of natural escapements (number of fish by age) from spawning ground survey data. A combination of GSI-based estimates of catch contribution and exploitation rates derived from cohort analysis of representative CWT experiments can be used to generate estimates of age-specific escapements using the methods described below.

Methods:

Notation (stock subscript assumed):

E	Spawning Escapement
E_a	Spawning Escapement of Age a
$EscRate_a$	Escapement rate for Age a
THR	Terminal Fishery Harvest Rate estimated from CWTs
THR_a	Terminal Fishery Harvest Rate for Age a in terminal estimated from CWTs
PSM	Post-Fishery/Pre-Spawning Mortality Rate
PSM_a	Post-Fishery/Pre-Spawning Mortality Rate for Age a
C	Catch of associated natural stock
C_a	Catch of Age a fish from associated natural stock
$C_{a,f}$	Catch of Age a fish from associated natural stock in Fishery f
IMR	Incidental Mortality Rate
IMR_a	Incidental Mortality Rate for Age a
$IMR_{a,f}$	Incidental Mortality Rate for Age a in Fishery f
$ER_{a,f}$	Exploitation Rate for Age a in Fishery f
$MR_{a,f}$	Maturation Rate for Age a in Fishery f

Assumptions:

1. GSI-based estimates of stock contributions are made without stock/aging assignment error.

2. Natural and hatchery fish have the same growth, maturation, and fishery exploitation/harvest rates.

For a given stock, escapement by age can be estimated using the simple relationship:

$$\frac{E_a}{C_{a,f}} = \frac{EscRate_a}{ER_{a,f}}$$

$$E_a = \frac{C_{a,f} * EscRate_a}{ER_{a,f}}$$

Case 1: Terminal fishery. Available data: THR, C, PSM, IMR. Natural and CWT'd population have same age structure.

$$E = \frac{C * (1 - THR - IMR - PSM)}{THR} \quad (1)$$

Case 1a: Terminal fishery. Available data: THR, C, PSM, IMR. Natural and CWT'd population DO NOT have same age structure.

$$E = \sum_a \frac{C_a * (1 - THR_a - IMR_a - PSM_a)}{THR_a} \quad (2)$$

Case 2: Preterminal Fishery. Available data: ER, THR, C, PSM, IMR. Natural and CWT'd population DO NOT have to have the same age structure.

For a given age, pick the pre-terminal fishery which has the least uncertainty about the GSI-based magnitude of the catch and the smallest relative error surrounding the estimate of the exploitation rate (Note that different fisheries could be used for each age if desired).

$$E_a = \frac{C_{a,f} * (1 - \sum_f (ER_{a,f} + IMR_{a,f})) * MR_a * (1 - THR_a - IMR_a - PSM_a)}{ER_{a,f}} \quad (3)$$

The total escapement is then simply the sum of the age-specific escapement estimates.

$$E = \sum_a E_a \quad (4)$$

<u>EVALUATION:</u>

Performance of the proposed methods in the presence of known uncertainty can be evaluated through the use of a simulation study that incorporates errors in spawning ground survey methods, GSI stock-age assignment error, and statistical uncertainty surrounding CWT-based estimates of exploitation rates.

Additionally, the proposed methods could be evaluated using information for a few selected stocks that have reliable escapement, GSI and exploitation rate data available. Two types of comparative studies could be performed: (1) Escapements could be estimated for hatchery stocks for comparison with rack recoveries where age and count data would be relatively easy to obtain; (2) Estimates of escapements generated using the methods described above could be compared to estimates derived from spawning ground surveys.

Proposed Application of GSI and Indicator Stock Data: Modification of Appendix C

A method to annually estimate the size M_{term} of terminal runs of mature Chinook salmon is described in Appendix C of the *Report of the Expert Panel on the Future of the Coded Wire Tag Recovery Program for Pacific Salmon*. Calculations for this estimator are based on landed catches from untagged stocks as estimated through genetic stock identification (GSI) and the recovery of coded wire tags (CWTs) from indicator stocks in each calendar year. A modified version of the estimator in Appendix C is presented in this essay as

$$\hat{M}_{term(W)} = \sum_a \sum_f \hat{\pi}_{a(I)} \hat{C}_{fa(W)} \tag{1}$$

where $\hat{M}_{term(W)}$ is the estimated annual run to the terminal area of wild stock W and $\hat{C}_{fa(W)}$ is the landed catch in pre-terminal fishery f of Chinook salmon age a belonging to the same wild stock as estimated through GSI. Estimated multipliers $\hat{\pi}_{a(I)}$ are functions of recovered CWTs such that

$$\hat{\pi}_{a(I)} = \frac{n_{term,a(I)}}{\sum_f n_{fa(I)}} \tag{2}$$

where $n_{fa(I)}$ is the expanded number of coded wire tags (CWTs) from indicator stock I in the landed catch in fishery f age a and $n_{term,a(I)}$ is the expanded number of CWTs from indicator stock I in the terminal run age a. No knowledge of maturation rates is required in this modification. Precision of estimates improve as more pre-terminal fisheries are included in the summation in equation (2), however, there must be a corresponding estimate of landed catch by age of the wild stock in each of the fisheries so included. Approximate variance for $\hat{M}_{term(W)}$ is

$$v(\hat{M}_{term(W)}) \cong$$

$$\sum_a \sum_f \left[v(\hat{\pi}_{a(I)})\hat{C}^2_{fa(W)} + \hat{\pi}^2_{a(I)} v(\hat{C}_{fa(W)}) - v(\hat{\pi}_{a(I)}) v(\hat{C}_{fa(W)}) + 2\sum_{b>a} \hat{\pi}_{a(I)} \hat{\pi}_{b(I)} \operatorname{cov}(\hat{C}_{fa(W)}, \hat{C}_{fb(W)}) \right] \tag{3}$$

$$\text{with } v(\hat{\pi}_{a(I)}) \cong \frac{\hat{\pi}^4_{a(I)}}{n^2_{term,a(I)}} \sum_f \frac{n_{fa(I)}}{\phi_f} + \frac{\hat{\pi}^2_{a(I)}}{\phi_{term} n_{term,a(I)}} \tag{4}$$

where b is an age other than a, and estimated variances and covariances of landed catch by age come from the GSI program.

The Modification

Landed catches of a cohort of Chinook salmon in a calendar year by fishery can be expressed as a series of general equations

$$N(1-S_{seak}) = n_{seak} \tag{5}$$
$$NS_{seak}(1-S_{nbc}) = n_{nbc} \tag{6}$$
$$NS_{seak}S_{nbc}(1-S_{wcvi}) = n_{wcvi} \tag{7}$$
$$NS_{seak}S_{nbc}S_{wcvi}(1-S_{preterm}) = n_{preterm} \tag{8}$$

where S_f is the survival rate of salmon through fishery f (=SEAK, NBC, WCVI, Pre-terminal) in a calendar year, n_f is the number of individuals in the landed catch in fishery f that year, and N is the number of salmon in that cohort available to be fished at the beginning of the season. Abundance N represents all fish that will mature that calendar year plus all those that will not, but are physically exposed to fishing. Implicit in these general equations is that there is no natural or incidental mortality, or no emigration from or immigration to the fishing grounds while the cohort is exposed to fishing or is not exposed to fishing between fisheries. Subsequent derivations will show that these assumptions are irrelevant to estimating the size of the terminal run with GSI. Note that N and n could represent either a tagged or an untagged population. The sum of landed catches across all fisheries can be expressed as

$$n_{seak} + n_{nbc} + n_{wcvi} + n_{preterm} = Nh(\mathbf{S}) \tag{9}$$

where $h(\mathbf{S}) = (1 - S_{seak}) + S_{seak}(1 - S_{nbc}) + S_{seak}S_{nbc}(1 - S_{wcvi}) + S_{seak}S_{nbc}S_{wcvi}(1 - S_{preterm})$. In contrast the number of salmon n_{term} in the terminal area (terminal fishery and escapement) in a calendar year can be expressed as

$$n_{term} = Ng(\theta, \mathbf{S}) \tag{10}$$

where $g(\theta,\mathbf{S}) = \theta S_{seak} S_{nbc} S_{wcvi} S_{preterm}$ and θ is the fraction of fishable abundance that will mature (or would have matured) that year. The ratio of the two functions g and h gives the number of salmon in the terminal area for the cohort in question as a function of the catches from all pre-terminal fishing:

$$\frac{n_{term}}{n_{seak}+n_{nbc}+n_{wcvi}+n_{preterm}}=\frac{g(\theta,\mathbf{S})}{h(\mathbf{S})}\equiv\pi \tag{11}$$

Note that the expansion π is independent of the initial size of the fishable population and for that reason is germane to any two or more cohorts with the same dynamic rates. For any such set of cohorts that meet this "gorilla assumption", an estimate of π for one cohort (call it cohort I) can be used to estimate the terminal abundance M_{term} for another cohort (call the other cohort W) given knowledge of the landed catches $\hat{C}_{f(W)}$ from the second cohort:

$$\hat{M}_{term(W)}=\hat{\pi}_{(I)}\sum_{f}\hat{C}_{f(W)} \tag{12}$$

For PSC fisheries, cohort I would be an indicator stock and cohort W a corresponding untagged wild stock. Because dynamic rates vary by age for Chinook salmon, estimating the terminal run size in a calendar year requires stratification by cohort, that is, by age:

$$\hat{M}_{term(W)}=\sum_{a}\sum_{f}\hat{\pi}_{a(I)}\hat{C}_{fa(W)} \tag{13}$$

where a signifies a cohort (indicator stock) or age (wild stock). Statistics from the same fisheries would be used to calculate $\hat{\pi}_{a(I)}$ and $\Sigma\hat{C}_{fa(W)}$ with the former based on the recovery of tags from the indicator stock and the latter on estimated landed catches of the wild stock from GSI. Statistics should be summed over as many fisheries as appropriately possible to improve precision of the result (assuming that all statistics are free of significant bias). Incidental mortality and emigration can be ignored in calculations without biasing results because these phenomena can be expressed as dynamic rates. For instance, a more complex model for an ocean fishery could be:

$$N_{a}\frac{F_{fa}}{Z_{fa}}(1-S_{fa})=n_{fa} \tag{14}$$

where Z_{fa} is instantaneous rate of mortality for age group a in fishery f and F_{fa} is the instantaneous rate of landed mortality. Note abundance N_a is still separable making the ratio $g(\ldots)/h(\ldots)$ germane to both indicator and wild cohorts so long as the "gorilla" assumption holds.

Table 1. – Expanded CWTs $n_{seak,a}$ from five cohorts recovered through sampling the SEAK fishery in 2001 that represent the NOC indicator stock along with arbitrarily apportioned landed catch by age $C_{seak,a}$ as estimated through GSI on the SEAK fishery in 2001. Statistics $n_{other,a}$ are expanded recoveries from ocean fisheries other that SEAK in 2001. Shaded cells were used to estimate π_a.

Brood Year	ages	$n_{seak,a}$	$n_{other,a}$	$n_{term,a}$	$\hat{\pi}_{a(I)}$	$\hat{C}_{seak,a(W)}$	$\hat{\pi}_{a(I)}\hat{C}_{seak,a(W)}$
1995	0.5	8	6	11	1.375	467	642
1996	0.4	52	26	267	5.135	3,033	15,571
1997	0.3	337	204	2,920	8.665	19,653	170,289
1998	0.2	43	60	989	23.000	2,508	57,677
1999	0.1	0	0	337	-	-	-
						$\hat{M}_{term(W)} \rightarrow$	244,178

The Example: the NOC Stock

From Table C1 in Appendix C, the expanded recoveries of CWTs for the NOC indicator stock in 2001 are in Table 1 above. The estimate of landed catch of the untagged (wild) NOC stocks in the SEAK troll fishery in 2001 is 25,660 Chinook salmon of all ages combined. Relative cohort composition in the SEAK troll fishery within the NOC indicator stock was used to apportion the 25,660 estimate into estimated landed catch by age in Appendix C. For demonstration in this essay, the same relative cohort composition was used in Table 1 to apportion estimated catch, even though this was probably a poor choice for a surrogate. Results reported here are exactly the same as those reported in Appendix C (244,178 Chinook salmon).

Equivalence of results reported in Appendix C and reported here is due to both approaches being mathematically equivalent. Combining equations (1-3) from Appendix C, simplifying, and summing over age shows that the estimator proffered in Appendix C is mathematically the same as equation (1) in this essay for the situation when only one pre-terminal fishery is considered:

$$\hat{M}_{term(W)} = \sum_i \left[\frac{LEGCat_y \dfrac{R_{by=y-i}}{\sum_j R_{by=y-j}} MatRte_{by=y-i}}{R_{by=y-i} MatRte_{by=y-i} \Big/ TR_{by=y-i}} \right] = \frac{LEGCat_y \sum_i TR_{by=y-i}}{\sum_j R_{by=y-j}} = \frac{n_{term(I)} \sum_a \hat{C}_{seak,a(W)}}{n_{seak(I)}} \tag{15}$$

The estimated maturity rates $MatRte_{by=y-i}$ cancel as do the recoveries by age ($R_{by=y-i}$). For this reason knowledge of maturity rates by age is not needed to accurately estimate terminal run size with GSI and CWTs. Knowledge of estimated age composition of landed catch would also be superfluous[1], but only if relative cohort composition within the indicator stock is the same as relative age composition of the untagged wild stock during fishing. This is an unlikely circumstance given that a tagged cohort begins life with an arbitrarily decided abundance.

Accurately estimating terminal run size of Chinook salmon with GSI and CWTs requires that the GSI program produce estimates of landed catch by stock and age. Direct estimates of relative age composition would be needed to fairly demonstrate the accuracy of calculations. The example above disregarded this requirement to demonstrate calculations.

The Approximated Variance

Following procedures in Goodman (1960)[2] for estimating the variance of a product, the estimated variance for $\hat{M}_{term(W)}$ is

$$v(\hat{M}_{term}) = \sum_a \sum_f \left[v(\hat{\pi}_a)\hat{C}_{fa}^2 + \hat{\pi}_a^2 v(\hat{C}_{fa}) - v(\hat{\pi}_a)v(\hat{C}_{fa}) + 2\sum_{b>a} \hat{\pi}_a \hat{\pi}_b \operatorname{cov}(\hat{C}_{fa}, \hat{C}_{fb}) \right] \qquad (16)$$

where subscripts I and W are implied and b is an age other than a. Statistics $\hat{C}_{fa}$, $v(\hat{C}_{fa})$, and $\operatorname{cov}(\hat{C}_{fa}, \hat{C}_{fb})$ would be estimated through a GSI program[3]. Statistics $\hat{\pi}_a$ and $v(\hat{\pi}_a)$ would be estimated from CWTs randomly recovered from catch sampling programs. Equation (11) describes how to calculate $\hat{\pi}_a$ in terms of the n_{fa}, however, the n_{fa} are usually the result of expanding the actual r_{fa} CWTs recovered while sampling $\phi \times 100$ % of the landed catch or terminal run such that

$$\hat{\pi}_a = \frac{n_{term,a}}{\sum_f n_{fa}} = \frac{r_{term,a} / \phi_{term}}{\sum_f r_{fa} / \phi_f} \qquad (17)$$

[1] Inspection of equation (15) shows that if cohort composition of the indicator stock is the same as age composition of the untagged wild stock, no stratification by age in the calculations is needed at all.
[2] Goddman, L. A. 1960. On the exact variance of products. Journal of the American Statistical Association 55:708-13.
[3] Because covariances for landed catches of two age groups of wild salmon in the same fishery involve age composition and multinomial distributions, they should be negative.

such that $n_{fa} = r_{fa}/\phi_f$. Although $\hat{\pi}_a$ and $\hat{\pi}_b$ from two cohorts are calculated with recoveries from the same sampling program, recoveries r_{fa} and r_{fb} from two cohorts within the same fishery have a covariance so small that it can be ignored with essentially no consequence[4].

Equation (17) forms the basis for approximating $v(\hat{\pi}_a)$. The subscript a is dropped in the following derivation with the understanding that all the statistics in the calculations for an age group correspond to age group a. From the delta method:

$$v(\hat{\pi}) \cong \sum_f \left[v(r_f)\left(\frac{\partial\hat{\pi}}{\partial r_f}\right)^2 + 2\sum_{j>f}\text{cov}(r_f, r_j)\left(\frac{\partial\hat{\pi}}{\partial r_f}\right)\left(\frac{\partial\hat{\pi}}{\partial r_j}\right)\right] + v(r_{term})\left(\frac{\partial\hat{\pi}}{\partial r_{term}}\right)^2 + 2\sum_f \text{cov}(r_f, r_{term})\left(\frac{\partial\hat{\pi}}{\partial r_f}\right)\left(\frac{\partial\hat{\pi}}{\partial r_{term}}\right) \quad (18)$$

(note that j denotes a pre-terminal fishery other than fishery f and that cov(r_f, r_j) here is for recoveries from the same cohort (implied a) across two fisheries). The N salmon in the tagged cohort extant at the beginning of the year suffer by the end of the year one of a series of fates. Some are taken in an ocean fishery and their CWTs recovered during sampling; some evade being caught and subsequently mature; some evade being caught but do not mature; some are caught but are not landed; some are caught, landed, but not sampled; etc. The numbers of tagged salmon grouped by fate follow a multinomial distribution where λ_i is the probability that a fish suffers fate i. The maximum likelihood estimate for the probability that a CWT is recovered by sampling a fishery is $\hat{\lambda}_f = r_f / N$; $\hat{\lambda}_{term} = r_{term}/N$ for recovery in the terminal area. Estimated variances for the r_f, r_{term}, and their two covariances are $N\hat{\lambda}_f(1-\hat{\lambda}_f)$, $N\hat{\lambda}_{term}(1-\hat{\lambda}_{term})$, $-N\hat{\lambda}_f\hat{\lambda}_j$, and $-N\hat{\lambda}_f\hat{\lambda}_{term}$, respectively. Partial derivatives are

$$\frac{\partial\hat{\pi}}{\partial r_f} = \frac{-\hat{\pi}^2}{\phi_f n_{term}} \text{ and } \frac{\partial\hat{\pi}}{\partial r_{term}} = \frac{\hat{\pi}}{\phi_{term} n_{term}}$$

Substituting these variances, covariances, and derivatives into equation (18) produces the approximation

[4] Bernard, D. R., and J. E. Clark. 1996. Estimating salmon harvest with coded-wire tags. Canadian Journal of Fisheries and Aquatic Sciences 53: 2323-2332.

$$v(\hat{\pi}) \cong \sum_f \left[N\hat{\lambda}_f(1-\hat{\lambda}_f)\frac{\hat{\pi}^4}{\phi_f^2 n_{term}^2} + 2\sum_{j>f} - N\hat{\lambda}_f\hat{\lambda}_j \frac{\hat{\pi}^4}{\phi_f\phi_j n_{term}^2}\right] +$$

$$\left[N\hat{\lambda}_{term}(1-\hat{\lambda}_{term})\frac{\hat{\pi}^2}{\phi_{term}^2 n_{term}^2}\right] + 2\sum_f \left[-N\hat{\lambda}_f\hat{\lambda}_{term}\frac{-\hat{\pi}^3}{\phi_f\phi_{term}n_{term}^2}\right] \quad (19)$$

Remembering that $\hat{\lambda}_f = r_f / N$ and that $r_f = n_f\phi_f$, equation (19) can be modified to become

$$v(\hat{\pi}) \cong \frac{\hat{\pi}^4}{n_{term}^2}\sum_f\left[\frac{n_f}{\phi_f} - \frac{n_f^2}{N} - 2\sum_{j>f}\frac{n_f n_j}{N}\right] + \hat{\pi}^2\left[\frac{1}{\phi_{term}n_{term}} - \frac{1}{N}\right] + 2\frac{\hat{\pi}^3}{n_{term}}\left[\sum_f \frac{n_f}{N}\right] \quad (20)$$

Substituting the relationship $\hat{\pi} = n_{term} / \Sigma n_f$ into equation (20) and collecting terms gives

$$v(\hat{\pi}) \cong \frac{\hat{\pi}^4}{n_{term}^2}\sum_f \frac{n_f}{\phi_f} + \frac{\hat{\pi}^2}{\phi_{term}n_{term}} + \frac{\hat{\pi}^2}{N}\left(1 - \frac{\sum_f n_f^2}{(\sum_f n_f)^2} - 2\frac{\sum_f\sum_{j>f} n_f n_j}{(\sum_f n_f)^2}\right) \quad (21)$$

The term in brackets in equation (21) equals zero, which means that knowledge of cohort size is unnecessary to approximating variance and that the approximation is

$$v(\hat{\pi}) \cong \frac{\hat{\pi}^4}{n_{term}^2}\sum_f \frac{n_f}{\phi_f} + \frac{\hat{\pi}^2}{\phi_{term}n_{term}} \quad (22)$$

Table 2 on the next page contains statistics for the example involving the NOC indicator stock in 2001. All ϕ_f were arbitrarily set to 0.2 and ϕ_{term} was arbitrarily set to 0.85 (20% of terminal catch sampled and 85% of escapement). Relative precision in $\hat{\pi}$:

$$cv(\hat{\pi}) \cong \sqrt{\frac{\sum_f n_f / \phi_f}{(\sum_f n_f)^2} + \frac{1}{\phi_{term}n_{term}}} \quad (23)$$

improves with more recoveries (larger numbers tagged in indicator stock, more fisheries sampled for GSI and CWTs, and higher sampling fractions in the CWT programs). Relative precision ranged in the example from 10% to 68% for age groups (see Table 2). Sampling all landed catch and escapement (all ϕ =1), relative precision would range from 2% to 30% for age groups. If relative cohort composition of the indicator stock can be shown to be the same as relative age

Table 2. - Expanded CWTs $n_{seak,a}$ and $n_{other,a}$ from five cohorts of the NOC indicator stock recovered through sampling ocean fisheries in 2001 and from the terminal area ($n_{term,a}$) in the same year. Shaded cells were used to calculated $\hat{\pi}$ and to approximate $v(\hat{\pi})$. The Totals line corresponds to the situation when relative cohort composition of the indicator stock in landed catch is the same the relative age composition of the corresponding untagged (wild) stock, a circumstance that requires no age stratification.

Brood Year	ages	$n_{seak,a}$	$n_{other,a}$	$n_{term,a}$	$\hat{\pi}_{a(I)}$	$v(\hat{\pi}_{a(I)})$	$cv(\hat{\pi}_{a(I)})$
1995	0.5	8	6	11	0.786	0.287	68%
1996	0.4	52	26	267	3.423	0.803	26%
1997	0.3	337	204	2,920	5.397	0.281	10%
1998	0.2	43	60	989	9.602	4.585	22%
1999	0.1	0	0	337	-	-	-
					$\hat{\pi}_{(I)}$	$v(\hat{\pi}_{(I)})$	$cv(\hat{\pi}_{(I)})$
Totals	0.2+	440	296	4187	5.689	0.223	8%

composition of the wild stock (unlikely, but instructive), relative precision for the estimate of the terminal run is 8% (the Totals line). Comparison of relative precision for the $\hat{\pi}_a$ and for $\hat{\pi}$ from the Totals line provides some insight into the uncertainty arising from the CWT programs in the estimates of terminal run size (at least in the context of the arbitrarily chosen values for ϕ). Completion of this example awaits knowledge of landed catch by age for the wild stock coming from a GSI program.