A decision rule based on the mean square error for correcting relative fishing power differences in trawl survey data

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Abstract.–Some combinations of trawler, trawl, and crew catch fish better than others. Systematic error enters catch per unit of effort (CPUE) data from trawl surveys through such relative differences in efficiency among sampling instruments. Correcting relative fishing power differences can remove bias due to systematic error but may also increase the variance of the mean CPUE estimate. As a result, the overall error of the estimate may actually become worse, even when the fishing power difference is statistically significant. A decision rule specified by the mean square error (MSE) of the mean CPUE estimate avoids this mistake: namely a correction that reduces the error in the mean CPUE estimate would be applied, a correction that increases the error would not be applied. I describe and demonstrate an algorithm, based on minimizing the MSE, for deciding to correct a fishing power difference. The strategy requires that a probability density function exist that models the CPUE data reasonably well.

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Trawl surveys are often used to collect data on catch observations standardized by fishing effort (the catch per unit of effort [CPUE]), and the mean CPUE is often interpreted as an index of abundance. Ideally, fishing power, or fish catching efficiency, must be held constant in trawl surveys lest altered catch rates be confounded with changes in abundance of fish or invertebrates. Unfortunately, the sampling instrument is a complex system that includes the vessel, vessel operators, and fishing gear, all of which may vary from survey to survey, introducing changes in fishing power (Gulland, 1956). Correcting fishing power differences seems necessary for proper interpretation of mean CPUE. However, methods have not been established for determining if an improved estimate of mean CPUE actually results from such correction.

Relative differences in fishing power make standardization in trawl surveys difficult. Technological changes in fishing gear, as well as replacement of older research vessels, may affect fishing power (Azarowitz, 1981; Byrne et al., 1991). Fishing power differences are an inherent part of multiple vessel surveys. Examples of this type of survey are annual and triennial surveys in several regions of the north Pacific Ocean and Bering Sea conducted by the Alaska Fisheries Science Center (AFSC) of the National Marine Fisheries Service (NMFS) (Harrison, 1992; Weinberg et al., 1994; Munro and Hoff, 1995; Goddard and Zimmermann[1]) and the International Young Fish Survey in the North Sea (Anonymous[2]). Koeller and Smith (1983) reported change in a single vessel's ability to measure speed over a 3-year period and hypothesized that this may have altered its fishing power from year to year. Operator effects have also been shown to account for fishing power differences among vessels (Munro and Hoff, 1995) and thus may be inferred for change in operators of a single vessel. (In what

[1] Goddard, P., and M. Zimmermann. 1993. Distribution, abundance, and biological characteristics of groundfish in the eastern Bering Sea based on results of the U.S. bottom trawl survey during June–September 1991. U.S. Dep. Commer., NOAA, Natl. Mar. Fish. Serv., Alaska Fish. Sci. Cent., 7600 Sand Point Way NE, Seattle, WA 98115-0070, Proc. Rep. 93-15, 324 p.

[2] Anonymous. 1986. Manual for the International Young Fish Surveys in the North Sea, Skagerrak, and Kattegat. International Council for the Exploration of the Sea, Palaegade 2-4, DK-1261, Copenhagen K, Denmark. ICES Council Meeting 1986/H:2.

follows, "vessel" refers to the entire system that comprises the sampling instrument, from the bow of the fishing vessel to the codend.)

A fishing power difference forces a choice between two estimators of mean CPUE, one that incorporates a fishing power correction and one that does not. Correcting a fishing power difference amounts to changing an observation to an estimate. The following model is used to estimate what a standard vessel would have caught had it executed exactly the same tow as was done by a nonstandard vessel:

$$\hat{x}_i = y_i \hat{FPC},$$

where $\hat{x}_i$ = estimated CPUE at station i by the standard vessel;
y_i = observed CPUE at station i by the nonstandard vessel; and
$\hat{FPC}$ = estimated fishing power correction factor.

Each original observation, y_i, has no error beyond measurement error. Every $\hat{x}_i$ has error due to the variance of the estimate of FPC. Consequently the mean CPUE estimated from the $\hat{x}_i$ has at least two components of variation, one stemming from the usual sampling variance in the observations (y_i), the other due to uncertainty in the estimate of FPC. This added component of estimation error has been recognized as the cost of correcting systematic error in the observations, but only in passing, (Sissenwine and Bowman, 1978; Byrne et al., 1981; Koeller and Smith, 1983; Fanning, 1984).

Estimators are often chosen on the basis of their relative error, yet most researchers have ignored this in deciding whether or not to correct a fishing power difference. Investigations have been focused on estimating the difference but have not evaluated it in terms of estimating mean CPUE. Very few decision rules have been explicitly stated, most having been implied by testing the statistical significance of the fishing power difference itself. Early CPUE calibrations (Gulland, 1956; Robson, 1966) were based on multiplicative models of different sources of variability in CPUE data, including vessel effects. Log transformation of the data produced linear models with coefficients that could be estimated with regressions and for which classical hypotheses could be formulated and tested. Sissenwine and Bowman (1978), Kimura (1981), and Gavaris (1980) have followed this strategy in their decisions to apply FPCs. Gavaris (1980) estimated the FPC using the method of Bradu and Mundlak (1970) and reported approximate confidence intervals, without explicitly stating a decision rule. Fanning (1984) proposed an explicit decision rule using a beta-distributed index for the fishing power difference in paired observations. If the confidence interval included the value that represented identical fishing power, he recommended that the estimated FPC not be applied. Byrne and Fogarty (1985) tested the significance of fishing power differences using Hotelling's t-squared test when several species were considered simultaneously, or the nonparametric Friedman's test for a single species. They offered no interpretation of a significant fishing power difference, in particular, whether or not it should be corrected. The t-test was used by Byrne et al. (1991) to determine the significance of a fishing power difference. In response to a significant difference, they estimated an FPC using the method of Bradu and Mundlak (1970). They then produced confidence intervals for that estimate using a bootstrap approximation. However, they did not state an explicit decision rule based on those intervals.

Correcting a fishing power difference would be worthwhile only when it reduces the error in the estimate of mean CPUE. Statistical significance of a fishing power difference is not a compelling justification because the cost of the added uncertainty may out weigh the benefit of removing bias that entered through systematic error in CPUE data. If the estimate of a correction factor has a lot of uncertainty, then the error of the estimate of mean CPUE could actually become worse by correcting data, even for a statistically significant fishing power difference. A decision rule for correcting a fishing power difference must avoid this mistake by accounting for the cost of correcting as well as the benefit. Such a rule would permit choosing the estimate of mean CPUE that yields the lower total error.

Methods

The notion of the mean square error (MSE) lends a useful structure for defining such a decision rule. The MSE is a widely recognized measure of error between an estimator and its parameter (Mood et al., 1974). The MSE is defined as

$$MSE\,[\hat{C}] = E\left[(\hat{C} - C)^2\right],$$

which is the expectation of the squared difference between the estimator of mean CPUE, $\hat{C}$, and the parameter being estimated, true CPUE or, C. The MSE can be rewritten as

$$MSE\,[\hat{C}] = \mathrm{Var}\,[\hat{C}] + b^2\,[\hat{C}],$$

or the sum of the variance and the squared bias of the estimator. By defining the following estimators,

$\hat{C}(\underline{w})$ = estimator as a function of uncorrected data

$\hat{C}(\underline{\hat{w}}_{\hat{FPC}})$ = estimator as a function of data corrected with an estimated *FPC*,

where $\underline{w} = (x_1, x_2, \ldots, x_{n_x}, y_1, y_2, \ldots y_n)$

= a mixed vector of CPUE observations from two vessels

and

$\underline{w}_{\hat{FPC}} = (x_1, x_2, \ldots, x_{n_x}, y_1 \hat{FPC}, y_2 \hat{FPC}, \ldots y_{n_y} \hat{FPC})$

= a mixed vector of CPUE observations and estimates,

a model for the decision rule can be stated as: Apply the FPC if

$$MSE\left[\hat{C}(\underline{w})\right] > MSE\left[\hat{C}(\underline{\hat{w}}_{\hat{FPC}})\right]$$

and do not apply the FPC if

$$MSE\left[\hat{C}(\underline{w})\right] \leq MSE\left[\hat{C}(\underline{\hat{w}}_{\hat{FPC}})\right].$$

(Note, this explication of the MSE of mean CPUE has been framed in terms of a single survey with two vessels. But the notion of MSE lends itself equally well to any situation in which data must be "corrected," including the common case of a single, nonstandard vessel conducting a standard survey.)

This decision rule is unattainable because it requires that the true value of the fishing power difference and CPUE sampling distributions be known. However, simulations can be used to estimate the mean square error. One such simulation strategy takes the following form: Assume a probability distribution for CPUE. Generate realizations of this distribution to represent a survey in which a fishing power difference is suspected. Impose an assumed fishing power difference on the simulated survey. Estimate the fishing power difference and apply the estimate to correct the assumed fishing power difference. (Estimating the fishing power difference may require further distributional assumptions and simulations, depending on the estimator and the kind of data it requires, especially if fishing power difference is to be estimated from experiments conducted independently of the survey.) The MSEs of the estimated mean CPUE are then calculated from the realizations with and with out the fishing power corrections. This procedure is repeated for a range of selected fishing power differences. Whether the observed fishing power difference (estimated from real data) falls within the range of the fishing power difference for which correcting reduces the MSE of the estimated mean CPUE can then be determined.

This general strategy is illustrated by constructing an algorithm to apply it to a real problem. Any algorithm for implementing this decision rule will depend on specific circumstances. In this case the particulars are defined by a fishing power problem in an annual survey of the eastern Bering Sea, conducted by the AFSC (Wakabayashi et al., 1985; Goddard and Zimmermann[1]). Two vessels systematically sample all strata, following interleaved station patterns that produce approximately equal numbers of CPUE observations. From these two sets of unpaired data a fishing power difference between two vessels is estimated for each of a number of species. The question is "Should this estimated FPC be used to correct CPUEs of one vessel to the fishing efficiency of the other?" This general MSE decision rule takes the following form (the specifics of the Bering Sea survey being addressed within this framework):

1 Simulate surveys from an appropriate sampling distribution for data collected by a "standard" vessel.
2 Impose a known fishing power difference on the CPUE data in each simulated survey. (In these examples half the data were altered to emulate a two-vessel survey.)
3 For each simulated survey, estimate an FPC to correct the fishing power difference that was imposed in the previous step. (FPCs may be estimated from simulation from independent experimental data or, as in these examples, estimated from the simulated survey itself. The important aspect is that the error structure of the FPC estimator be incorporated in the simulation process.)
4 Estimate the mean CPUE for each simulated survey with and without correcting for the fishing power difference.
5 Repeat steps 2 through 4 for a range of fishing power differences.
6 Compute MSEs for estimated mean CPUE for each level of fishing power difference.
7 Plot the estimated MSEs against the fishing power differences imposed in Step 2 (Fig. 1).
8 Determine the range of fishing power difference where the MSE for corrected data is lower than the MSE for uncorrected data (Fig. 1).

The region of increased error is centered around the value 1.0, which represents equal fishing powers, and is sandwiched between regions of reduced error (Fig. 1). The smaller the true fishing power difference the more likely that correcting it will lead to increased error in mean CPUE, and the greater the fishing power difference the more likely that correcting it will improve error in mean CPUE. For the range of the relative fishing power difference for which correction increases (becomes worse), the MSE will be called the "noncorrection region." The two ranges of the relative fishing power difference for which correcting reduces (improves) the MSE will be referred to collectively as the "correction region."

This procedure has four critical elements: simulating the CPUE data, the estimator of FPC, the estimator of mean CPUE, and the sample size in each simulation. The CPUE data (kilograms per hectare) were simulated with the Δ-distribution. The Δ-distribution has been proposed as an appropriate distribution for data that include the value 0.0 and that are heavily skewed to the right (Pennington, 1983; McConnaughey and Conquest, 1992). The probability density function for the Δ-distribution has parameters p, the probability of an observation with the value 0.0, and μ and σ, the conventional defining parameters of the lognormal distribution, which are the population mean and standard deviation of the log-transformed elements, respectively (Aitchison and Brown, 1957). The parameters for this distribution were calculated with CPUE data for flathead sole (*Hippoglossoides elassodon*) and walleye pollock (*Theragra chalcogramma*) collected in the 1992 eastern Bering Sea survey (Table 1; Fig. 2). These two species were chosen to illustrate cases of moderate and extreme skewness to the right. The mechanism for imposing a fishing power difference is also part of simulating each survey. In these examples the relative difference was applied by multiplying each CPUE from the nonstandard vessel by a ratio that represented the true mean nonstandard CPUE over the true mean standard CPUE. Two-hundred surveys were simulated at each of twenty preselected fishing power differences (Table 2). In each simulated survey, half of the data were selected to represent the standard vessel and the fishing power difference was imposed on the other half of the data, representing the nonstandard vessel. The sample sizes in two of the simulations were based on the number of observations used to calculate the parameters of the Δ-distribution: 149 per vessel for pollock and 144 per vessel for flathead sole. The third simulation was based on 50 observations per vessel for flathead sole. The smaller sample size is similar to the number of tows made in the larger strata of the annual Bering Sea survey (Goddard and Zimmermann[1]).

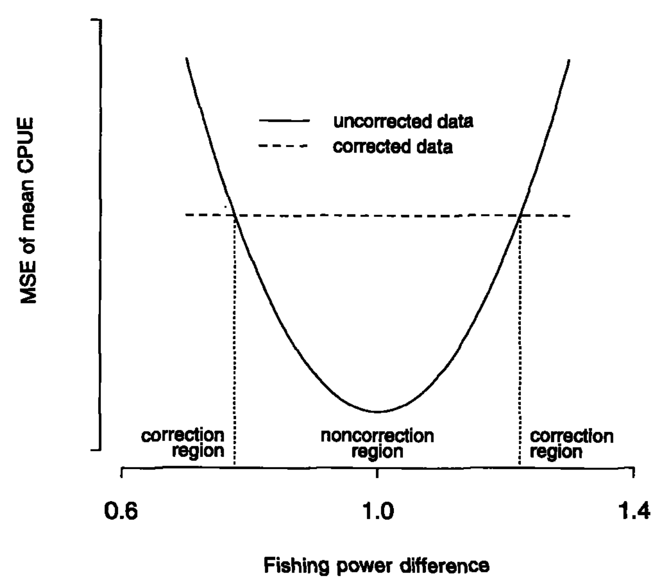

Figure 1

The noncorrection region that emerges from plotting mean square error of mean CPUE against the fishing power difference imposed on the simulated data. "Uncorrected data" refers to the scenario where mean CPUE was estimated without correcting the fishing power difference. "Corrected data" refers to the scenario where mean CPUE was estimated after correcting the fishing power difference.

Table 1

The Δ-distribution parameters and fishing power correction factors estimated from the 1992 Bering Sea survey data. Sample sizes are different because different vessels represented the "standard" vessel for each species.

	Walleye pollock (*Theragra chalcogramma*)	Flathead sole (*Hippoglossoides elassodon*)
Δ-distribution parameters		
p (fraction of zeros)	0.0336	0.1042
μ (mean of log nonzeros)	3.3590	1.5859
σ (SD of log nonzeros)	2.1194	1.4985
Number of observed CPUEs used to compute parameters	149	144
Estimated fishing power correction (FPC) factor	1.32	0.76

The Kappenman estimator of the ratio of scale parameters (Kappenman, 1992) was used to estimate the FPC in each simulated survey. Inordinately large, rare observations are typical of trawl survey CPUE data (Koeller and Smith, 1983; Weinberg et al., 1994;

Table 2

Fishing power differences imposed on the simulated data.

Catch ratio: nonstandard to standard		Catch ratio: larger to smaller
0.50	Nonstandard vessel is half as efficient	2.00
0.57		1.75
0.67		1.50
0.71		1.40
0.77		1.30
0.80		1.25
0.83		1.20
0.87		1.15
0.91		1.10
0.95		1.05
1.00	Identical fishing power	1.00
1.05		1.05
1.10		1.10
1.15		1.15
1.20		1.20
1.25		1.25
1.30		1.30
1.40		1.40
1.50		1.50
1.75		1.75
2.00	Nonstandard vessel is twice as efficient	2.00

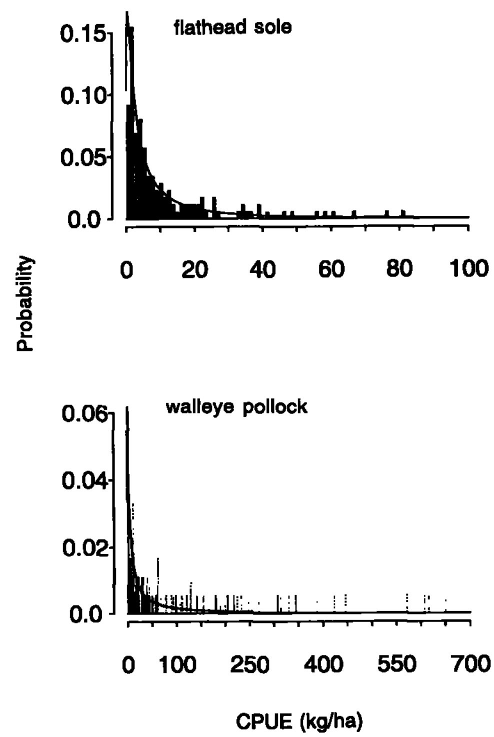

Figure 2

Histograms of catch-per-unit-of-effort (CPUE) data for flathead sole and walleye pollock overlayed by the probability density function for the Δ-distribution. The histograms are expressed as densities rather than as frequencies. The parameters specifying the Δ-distribution were estimated from the data in the histograms. The walleye pollock distribution is truncated to show reasonable detail. Not shown are the two most extreme values, 1,118.5 kg/ha and 2,906.8 kg/ha.

Goddard and Zimmermann[1]). If the rare, large observations typical of survey CPUEs are chance occurrences rather than the consequence of a fishing power difference, then a preferred estimator would be insensitive to them. The nonparametric Kappenman estimator has this property. Wilderbuer (1988) compared five FPC estimators (the ratio of means, the simple multiplicative model [Robson, 1966], the additive nested ANOVA, the multiplicative nested ANOVA, and the beta distributed index [Fanning, 1984]) and found all to have wide variability about the estimate of fishing power, indicating a sensitivity to rare large CPUEs. Wilderbuer et al. (1998) have extended this work to include the Kappenman estimator and have found it to have an estimation error equal to or lower than the others. For the Δ-distribution, s determines heaviness of the right tail of the distribution. When the Δ-distribution is more symmetric in appearance and less heavy-tailed, all of the estimators reviewed by Wilderbuer (1988) may be reasonably well-behaved. When the Δ-distribution becomes skewed to the right and the magnitude of the rare, large observations becomes quite high, the insensitivity of the Kappenman estimator results in lower estimation error.

The arithmetic mean was used as the estimator for mean CPUE because it is unbiased. Any biases observed in the means estimated in the simulations would then be due to systematic error in the data caused by fishing power differences. Also, the arithmetic mean has been argued to be the best estimator of mean CPUE (Myers and Pepin, 1990; Smith, 1990) and is commonly used (e.g., Harrison, 1992; Weinberg, et al. 1994; Goddard and Zimmermann[1]).

The issue of design-based versus model-based estimation (Smith, 1990) is raised in the choosing of the arithmetic mean to estimate mean CPUE even though the data are simulated with a probability model that has known optimal estimators. Design-based estimation is followed here because that is the strategy employed in the analysis of the Bering Sea trawl surveys. A probability model is assumed in these examples solely to provide a parameter value for estimating the MSE. In a similar vein, it would seem that the question of relative efficiency could be answered analytically rather than through a simulation, given a known probability model. Such a solution would be difficult or impossible because of the complicating factor of the estimated FPC. Even if a model-based estimation strategy were acceptable for estimating mean CPUE from uncorrected data, the appropriate probability model for the corrected data is not clear, especially if, as in these examples, the FPC estimator has an unknown distribution.

In this example, the two sets of simulated CPUE (standard and nonstandard prior to imposing the assumed fishing power difference) are independent and identically distributed random variables. This simulation ignored the possibility for spatial correlation among observations in a real survey. Because each station in the standard Bering Sea survey is 20 n mi from its nearest neighbor, I assumed that spatial correlation was negligible and did not attempt to build it into the simulations. This is consistent with current treatment of data collected on these surveys. A more complex procedure would be needed to simulate surveys with spatial correlation among observations.

Results

For flathead sole, with a sample size of 144 per vessel, a clear region of increased error, the noncorrection region, appeared between approximately 0.77 and 1.14 in plots of MSE against the fishing power difference (Fig. 3A). The lowest MSE occurred with uncorrected data when there was identical fishing power (the value 1.0 on the x-axis). The FPC estimated for the original data, 0.76 (Table 1), fell just outside this region.

With a sample size of 50 per vessel, a clear noncorrection region appeared between approximately 0.56 and 1.19 for flathead sole (Fig. 3B). The FPC for the original data fell within this region. The minimum MSE occurred with uncorrected data. This minimum occurred, however, when the nonstandard vessel had a CPUE of about 23% less than that of the standard vessel rather than when the vessels had identical efficiencies (fishing power difference ratios of 0.87 and 1.0, respectively). The noncorrection region was also clearly asymmetric to the left with respect to a fishing power difference ratio of 1.0.

For walleye pollock, with a sample size of 149 per vessel, the noncorrection region was not as clearly defined because the lower bound occurred at some value less than 0.50; the upper bound was approximately 1.05 (Fig. 3C). The FPC estimated for the original data, 1.32 (Table 1), fell outside this region. The minimum MSE occurred with uncorrected data at a fishing power difference ratio near 0.67, where the nonstandard vessel caught 33% less than the standard. The noncorrection region was extremely

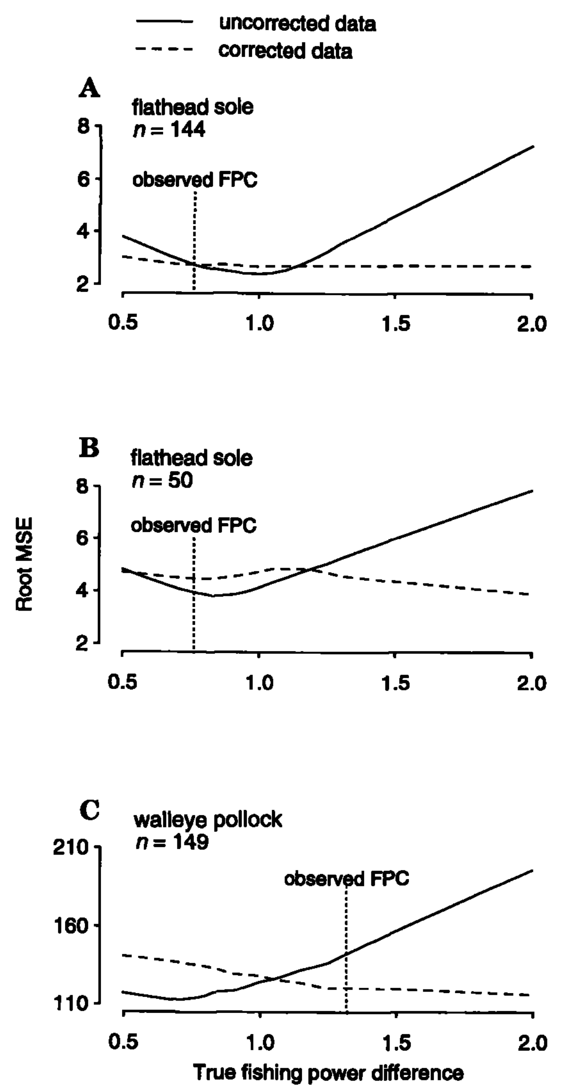

Figure 3

Simulation results: square root of the mean square error (MSE) of mean catch per unit of effort (CPUE) plotted against the true fishing power difference. The fishing power difference is expressed as the ratio of the true CPUE for the standard vessel over the true CPUE of the nonstandard vessel. "Corrected data" refers to MSEs computed from data in which the fishing power difference had been corrected. "Uncorrected data" refers to MSEs computed from data in which the fishing power difference had not been corrected. Sample size, n, refers to the number of stations realized for each vessel in each simulation. To illustrate general trends these results were smoothed with a scatterplot smoother called "lowess" in the statistical software package S-Plus (Becker et al., 1988).

asymmetric to the left with respect to a fishing power difference ratio of 1.0.

Discussion

It is a well-established ideal to choose among estimators on the basis of their relative errors. These examples demonstrate that the approach can be functional in practice as well as in the abstract when deciding whether or not to apply an FPC. It is important to distinguish between the broader notion of a decision rule based on the MSE and the specifics given here as illustrations. These examples show that regions of increased and reduced MSE can be estimated. They demonstrate common features of the regions as well as ways the regions can vary. They show that the MSE strategy is functional but also underscore problems that can arise from inappropriate choices of estimators or simulation mechanisms. In all three cases a region of increased estimation error was successfully identified and each included the value 1.0, which represents identical fishing power. However, the breadth of the noncorrection region differed depending on sample and population variance. The three noncorrection regions also differed in their symmetry about the value 1.0, which was due to an interaction between the mechanism for imposing the fishing power difference on the simulated data and the sensitivity of the arithmetic mean to rare extreme observations.

CPUE variance broadened the noncorrection region. The flathead sole simulations demonstrated the effect of the sample variance, with the smaller sample size producing the broader region (Fig. 3, plots A and B). The pollock example produced a very broad region of increased error because the population variance was quite high (Table 1; Fig. 3C). These examples confirm the truism of the MSE: the greater the variance, the less important the systematic error due to a fishing power difference. The role of variance was clearly shown in the two flathead sole simulations where the FPC observed in the original survey fell within the noncorrection region for the higher variance case, and outside the noncorrection region for the lower variance case (Fig. 3, plots A and B).

Asymmetry in the noncorrection regions was a function of the simulation mechanism. However, the problem serves to reinforce the idea that high variance tends to reduce the relative importance of bias or systematic error and reduces the benefit of correcting it. Fishing power was assumed to be a simple multiplicative effect in these simulations. The variance was altered, as well as the bias, when the fishing power difference was multiplied against Δ-distributed data, an undesirable consequence. Because the arithmetic mean is sensitive, the rare, inordinately large CPUEs exert high leverage on it. This leverage itself was altered with a multiplicative fishing power difference. For the highly skewed pollock data, the change in variance was much greater than the change in bias (Fig. 4). When the standard vessel was less efficient, the uncorrected data produced a lower MSE because the fishing power difference reduced the leverage of the rare large tows, reduc-

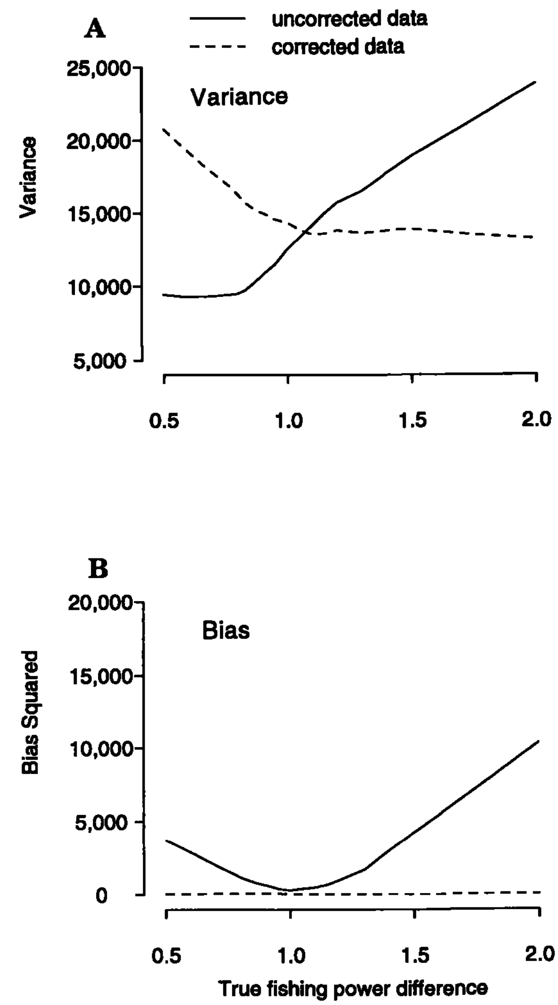

Figure 4

Components of the mean square error of the estimated mean catch per unit of effort (CPUE) of walleye pollock. "Corrected data" refers to variances and biases computed from data in which the fishing power difference had been corrected. "Uncorrected data" refers to variances and biases computed from data in which the fishing power difference had not been corrected. To illustrate general trends these results were smoothed with a scatterplot smoother called "lowess" in the statistical software package S-Plus (Becker et al., 1988).

ing the variance of the mean CPUE (Fig. 4A). The noncorrection region of data thus extended far to the left (Fig. 3C). When the nonstandard vessel was more efficient, the imposed fishing power difference had the opposite effect, increasing the variance of the mean calculated from uncorrected data (Fig. 4A). Correcting even moderate fishing power differences reduced the MSE (Fig 3C), but by reducing variance, not by correcting systematic error. This problem is purely a consequence of the fishing power mechanism in the simulations. An improved mechanism is needed to render the MSE-based decision rule a clearer tool. In this case, with highly skewed CPUE distributions, there may be a cut-off point beyond which a fishing power difference would not be imposed, because the rare, large tows are more likely to be chance occurrences than indicators of fishing power. Note that the bias did behave as expected: the uncorrected data produced a minimum when the fishing powers were identical, and corrected data produced a constant bias that was always lower than that of the uncorrected data (Fig. 4B). The pollock example illustrates how an MSE-based decision rule can be deceiving under an improperly specified model.

The noncorrection region itself is an estimate, with error around the upper and lower bounds of the range. The observed fishing power difference or correction factor will also be an estimate with its own error. Between these two sources of uncertainty, the upper and lower bounds of the noncorrection region are not as clear as they might appear in an application. Thus, a conservative approach would be to decide against using an FPC even when the observed value falls a little outside the noncorrection region. For this reason, and because improved precision generally increases certainty, it would pay to narrow the noncorrection region as much as possible through estimators with less sensitivity to the rare, large observations that characterize much CPUE data and through careful modeling of the process leading to the fishing power difference.

This decision strategy can also be used to re-evaluate old or changing fishing power problems. The concept of minimizing the MSE can accommodate changes in state-of-the-art estimation and allow the consequence of change to be examined. The decision rule remains valid regardless of improvements in simulation strategies, estimators, or understanding of processes leading to fishing power differences. The strategy can also be used to decide if experiments are warranted to calibrate the fishing power of research vessels. Such experiments tend to be very expensive yet limited in scope. Will it be possible to attain a sample size great enough to produce meaningfully narrow noncorrection regions?

A decision not to apply an FPC by these methods does not in any way imply that the fishing power difference is trivial or unimportant. For instance, if one of two vessels in a survey had a catch rate 30% lower than the other, and both vessels had equal numbers of observations, then the estimated mean CPUE could be in error by as much as 15%. An error of this magnitude could have a profound influence on a heavily exploited, closely managed stock. Yet such a fishing power difference may go uncorrected because, to correct it, would involve a risk of error of even greater magnitude. A decision against correcting is only a conclusion about the feasibility of applying an FPC, not the cost of having the systematic error in the data. Once a fishing power difference occurs in survey data, an irrevocable mistake has been made. The final estimate will have increased error, whether it is due to bias added by systematic error or due to variance added by estimating and correcting for the bias. This example illustrates the importance of maintaining standard survey techniques by illustrating the cost, in terms of precision, of correcting fishing power differences.

The decision to apply an estimated FPC is difficult. Statistical significance of a fishing power difference does not necessarily permit inference regarding the consequence of applying a correction factor when estimating mean CPUE. These three examples demonstrate the usefulness of this decision procedure. Even under difficult circumstances, high variance and an estimator sensitive to rare, large observations, the noncorrection regions are easy to defend because they are based on a clear goal—that of minimizing the error of the estimate of mean CPUE.

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