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Improving area swept estimates from bottom trawl surveys☆

Stan Kotwicki*,[1], Michael H. Martin[1], Edward A. Laman

Alaska Fisheries Science Center, National Marine Fisheries Service, 7600 Sand Point Way NE, Seattle, WA 98115-0070, USA

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ABSTRACT

Estimation of area swept is a key component for standardizing catch per unit effort (CPUE) data from fishery independent bottom trawl surveys and survey trawl gear experiments. Given technological advances and the proliferation of data streams from net mensuration equipment and global positioning system (GPS), techniques for estimating survey effort can be improved. Here we investigate new analytical techniques for improving the accuracy and precision of survey effort estimation. Sources of error and bias associated with two of the components used to compute area swept as a measure of fishing effort, distance fished by the trawl and net spread, are systematically examined and their influence quantified using both simulated and survey data. New analytical methods, a cubic spline smoothing algorithm to smooth GPS and net spread data, a haversine great circle algorithm to calculate distance between smoothed GPS track points, and a sequential outlier rejection algorithm to diminish the influence of noise on mean net spread estimates are shown to reduce or even eliminate the influence of biased observations on area swept estimators.

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1. Introduction

Fishery-independent trawl surveys provide vital information for fish stock assessment and management in many countries throughout the world. Abundance estimates based on results from these surveys are considered to be more reliable than those derived strictly from commercial fisheries data because survey effort and trawl catchability can be controlled through standardization (e.g., Stauffer, 2004) to minimize variability of these two parameters in time and space. The problem of both spatial or temporal changes in catchability that result in bias leading to errors in stock assessment and management and its ramifications have been well studied (e.g., Beverton and Holt, 1957; Byrne et al., 1981; Collie and Sissenwine, 1983; Pennington, 1986; Swain et al., 1994; Pennington and Godø, 1995). However, the analogous problem of spatial or temporal variability in the error associated with fishing effort estimation has surprisingly received little attention (e.g., Gould et al., 1997), although this bias is often combined or confounded with changes in catchability.

Technological advances have allowed for greater precision in the estimation of effort in trawl surveys over time. For instance, fishing time (e.g., catch/hour) is often used as a standard unit of effort, but even relatively small differences in mean vessel speed over the sampling period can produce large changes in the sampled area or catch rates (Alderstein and Ehrich, 2002). The advent of more accurate and precise positioning methods (i.e., GPS) allows better estimates of the distance traveled by the net during the sampling period (distance fished) and many surveys currently use distance as the standard unit of effort. The development of acoustic net mensuration systems now allows continuous monitoring and recording of net spread throughout the tow (ICES, 2009), which in tandem with distance fished can be used to calculate area swept (distance fished × net spread) allowing a much more accurate, precise, and unbiased estimator of standard fishing effort. This study focuses on the development of methods to more accurately and precisely estimate components of survey effort that may reduce some of the variability of bottom trawl survey area swept estimates. This is done by systematically evaluating the methods currently being used at the U.S. National Marine Fisheries Service (NMFS), Alaska Fisheries Science Center (AFSC), to screen data coming from survey instrumentation, in addition to examining the analytical procedures used to compute area swept as latent sources of bias. Although we use only data from the AFSC surveys, the methods presented here should be applicable to other bottom trawl surveys around the world that use area swept estimates of effort derived from GPS and acoustic net mensuration equipment.

A known source of error in the estimation of distance fished is the noise inherent in the GPS system. GPS noise results from atmospheric conditions, measurement noise, ephemeris errors (the difference between actual and expected orbital position of a GPS satellite), clock drift, or multipath errors (error resulting from a

Abbreviations: GPS, global positioning system; CPUE, catch per unit effort; AFSC, Alaska Fisheries Science Center; NMFS, National Marine Fishery Service; SOR, sequential outlier rejection; MSE, mean squared error.

☆ The findings and conclusions in the paper are those of the authors and do not necessarily represent the views of the National Marine Fisheries Service.

* Corresponding author. Tel.: +1 206 526 6614; fax: +1 206 526 6723.
E-mail address: stan.kotwicki@noaa.gov (S. Kotwicki).
[1] Equal authorship.

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signal that rebounds from a local obstruction before being received by the GPS unit; Hofmann-Wellenhof et al., 1997), hence each position along a tow path is subject to estimation error. Additional systematic sources of error can also result from GPS antenna motion caused by the pitch and roll of the vessel. A popular approach to reducing the effect of these types of error has been to reduce the polling frequency of positional information (Palmer, 2008). As polling frequency decreases, the error in distance fished as a fraction of the total distance fished decreases. Some surveys decrease polling frequency to the lowest rate possible and calculate the distance fished as a straight line between the start and end positions of the tow (e.g., Stauffer, 2004). However, low polling frequency can result in large underestimation of distance fished when tow paths are sinuous (Palmer, 2008). Another approach has been to smooth GPS data before the application of a distance algorithm in an attempt to describe the true tow path after noise removal. Several different smoothing algorithms have been applied to GPS data from trawl surveys, including simple exponential smoothing and moving average type smoothers (Stauffer, 2004).

Bias can also result from the algorithm used to estimate the distance fished along a smoothed tow path. Most surveys have employed a variant of either a great circle (Vincenty, 1975) or a Euclidean (Stauffer, 2004) distance estimator. Some implementations of the great circle estimator are inaccurate when estimating very small distances due to rounding errors introduced through the underlying trigonometric functions (Snyder, 1987). The Euclidean method of estimating distance underestimates the path length over long distances on the Earth's surface, since it assumes a planar system and yields the length of the chord bounding the segment whose arc (the distance traveled) connects the chord's endpoints. This estimation error is likely quite small over the short distance covered by a typical survey tow (ca. 1–3 km). Euclidean estimators can also be inaccurate over short distances if the assumed ellipsoidal model of the earth's surface is incorrect.

The accuracy of net spread observations from net mensuration systems are affected by several factors. Sound sources other than the two transducers that produce sound at or near the specified transmission frequencies can result in incorrect readings. Although the beam angles of these systems are typically quite large, misalignment of the transducers can lead to indirect path signals resulting in overestimation of the distance between the transducers. Any movement of the sensors independent of the movement of the net or doors can also result in measurement error. The most common net mensuration systems estimate the distance between transducers by converting the time between sending and receiving a signal into distance, assuming a constant sound speed of 1500 m s^{-1}. However, sound speed is not constant and varies with water temperature, pressure, and salinity. Therefore errors also can occur in the calculation of mean spread estimates when surveys sample over variable environmental conditions. Mean net spread estimates for a tow are often calculated by first eliminating spurious observations, typically rejecting values outside an acceptable range, and calculating a mean from the remaining spread values (ICES, 2009). We will refer to this method as gating (or using fixed gates) in the remainder of this manuscript. If accurate spread measurements are excluded or inaccurate spread measurements are included, biased estimates will result.

2. Material and methods

2.1. Distance fished

We considered two components of estimation of over ground distance fished: the data smoother and the algorithm to estimate distance from the smoothed points. Four smoothing algorithms were evaluated: a moving average smoother; simple exponential smoothing (Brown and Meyer, 1961); Friedman's super smoother (Friedman, 1984); and the cubic spline (Hastie and Tibshirani, 1990). A series of simulations were undertaken to evaluate the relative performance of each smoother. Each simulation consisted of first constructing a tow path with a total distance traveled of 2.778 km (1.5 nm) simulating GPS data collected at 2 s intervals for 30 min at a speed of three knots. The course along the tow path was changed at each observation by randomly choosing a course change from a range of allowed values at the given sinuosity level. As the sinuosity level increased, the range of course change allowed between consecutive observations increased, thereby increasing the sinuosity of the tow path. The result was then considered the 'known' tow path. Random noise was added to the known tow path by randomly choosing a distance from a normal distribution with a standard deviation equal to the pre-selected noise level and then randomly choosing a direction from the known observation. The 'observed' position was then calculated using the distance and direction from the known position. Each smoother was then applied to the simulated GPS data and a distance was calculated for the smoothed tow path. Since each smoother investigated has some sort of smoothing parameter mechanism to control overall smoothness, each smoother was investigated at several smoothness levels which we hereafter refer to as span. Five hundred simulations were conducted at each of six noise levels (1, 5, 10, 15, 25, 50), six sinuosity levels (0.05, 1, 2.5, 5, 7.5, 10), and seven span levels (4, 6, 8, 10, 15, 30, and 60; Fig. 1).

The running mean smoother used mimicked the smoother currently used to smooth GPS data from AFSC surveys. The latitude and longitude of each smoothed position was estimated as the mean of the latitudes and longitudes of the current point and span level $\times 2^{-1}$ points both before and after the current point. For simple exponential smoothing, the smoothing parameter α was set at $2 \times (\text{span}+1)^{-1}$. We used the 'supsmu' function in R to implement the super smoother, using a span of span $\times$ (total number of GPS observations)$^{-1}$. We used the 'smooth spline' function in R (version 2.11.1, R Development Core Team (2010)) to implement the cubic spline algorithm, setting the number of knots argument (*n*knots) to (total number of GPS observations)$\cdot$span^{-1}. Although the spans are not completely analogous among the smoothers due to their different methodologies, we hoped that the inclusion of this parameter would give us some insight into the tradeoffs between the ability to accurately measure distance while the vessel is changing course and eliciting the true vessel path in the presence of large amounts of noise. The mean and variance of the differences between estimated and known tow path lengths were examined to evaluate each smoother's robustness to random noise and changes in course (i.e., sinuosity).

The distance algorithm used was an implementation of the haversine great-circle algorithm (Sinnott, 1984) correcting for the oblate spheroid of the earth. This algorithm was chosen because of its ability to accurately estimate distance even for points in very close proximity (i.e., <1 m apart). Some great circle algorithms commonly used to calculate distance do not perform well at small distances due to rounding errors incurred in the underlying inverse cosine function. The haversine algorithm avoids the inverse cosine function and therefore allows much more accurate estimation of small distances.

2.2. Net spread

Two aspects of net spread estimation were considered. First, simulated net spread data were used to develop a robust method of estimating mean spread using iterative sequential outlier rejection (SOR) and smoothing. Second, survey observations of temperature and depth were used to estimate sound speed on a tow-by-tow

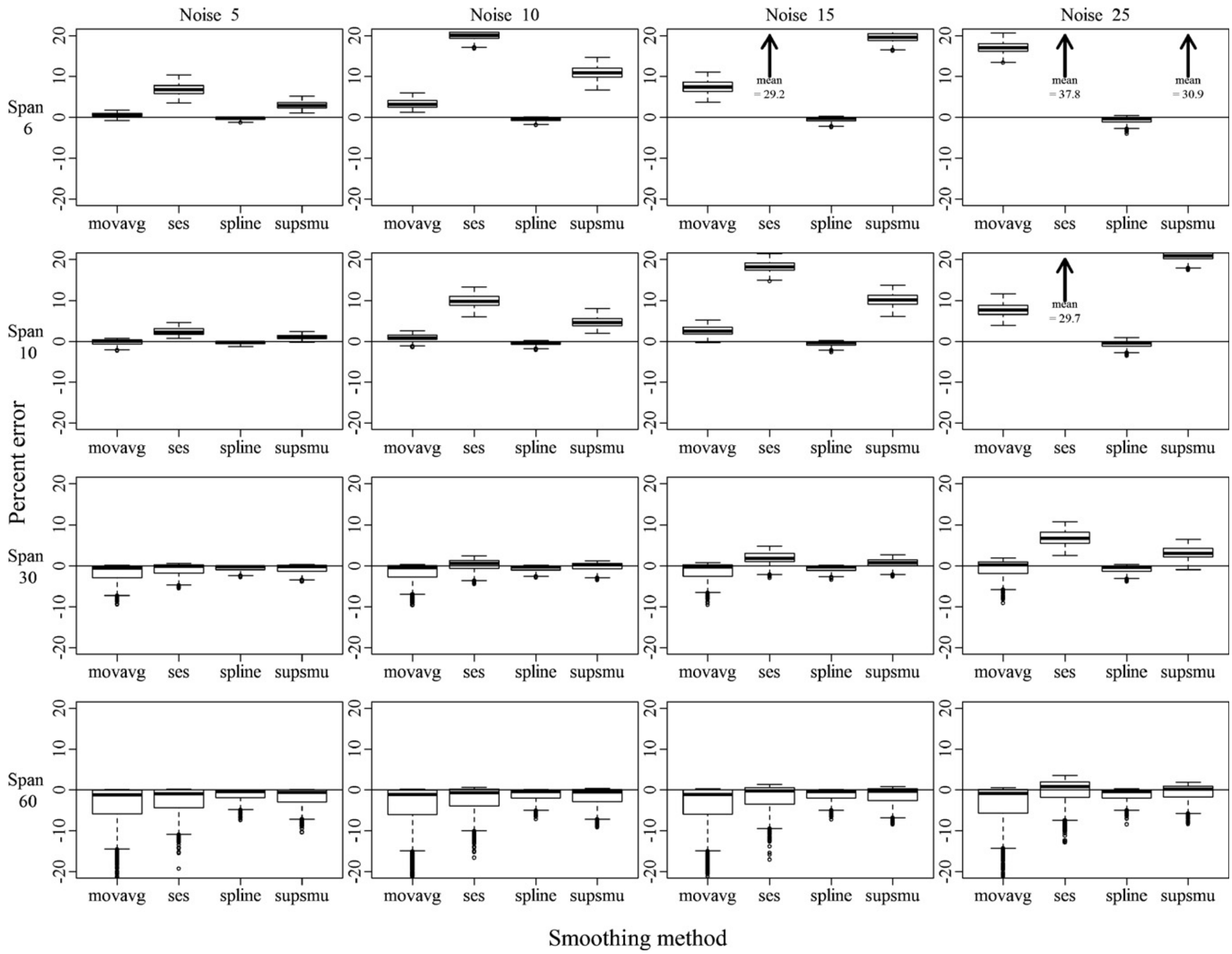

Fig. 1. Results of smoother comparison simulations. Each plot depicts a comparison of the performance for smoothers used in simulations at different span and noise levels across all sinuosity levels. Each boxplot represents the range, median, and upper and low quartiles of a simulation with 500 replicates.

basis to increase the accuracy of acoustically-derived estimates of spread.

A flexible and robust procedure was developed in R to estimate mean net spread, even under conditions of noisy and biased raw data, which is often a case with actual survey data. Net spread data simulating a 30 min tow were created by choosing a starting net spread value, then allowing the net spread to vary randomly within given limitations at two second intervals, creating a series of 'known' net spread values. Random noise was created for each known value by randomly selecting a value from a normal distribution with a mean of zero and a given standard deviation (noise level), and adding this value to the known net spread value. Non-random error (bias) was then added in a similar way by selecting from a beta distribution with a given bias level specified by the α and β parameters. Using this method, we were able to examine in detail the effects of both random (noise) and non-random (bias) error on mean net spread estimates. Appropriate ranges of noise and bias were determined from extensive observations of previously collected survey net spread data. Simulations were conducted at 11 noise levels with standard deviation between 0.5 and 5 m and six bias levels from −2 to +2 m. Five hundred iterations at each combination of standard deviation and bias level were performed.

A sequential outlier rejection and smoothing procedure was iteratively applied to the simulated data to identify and reject outliers from the raw data stream. The SOR procedure was initiated by fitting a cubic spline smoother to the simulated net spread data and removing points greater than a given rejection distance from the smoothed line. We began with a rejection distance of 20 m. Then the cubic spline was fitted to the data again and outlier rejection distance decreased by 0.1 m. This procedure was iteratively repeated in increments of 0.1 m until all values > 0.1 m from the smoothed line were rejected. The squared error (SE_i) and bias (B_i) were then calculated for each SOR iteration by comparison to the known values. The mean squared error (MSE_i) for each iteration was calculated according to the formula: $\mathrm{MSE}_i = \mathrm{SE}_i + B_i^2$

Results from the iterative SOR simulation (Fig. 2) were analyzed to identify the minimum MSE_i (MMSE). The MMSE was then used to estimate a SOR stopping rule most appropriate for each combination of noise and bias levels. The mean stopping distance and 95% confidence bounds for each combination were then calculated (Fig. 3). The noise level determined the stopping rule almost exclusively, while bias levels had little or no effect (except for the highest noise levels). As a result, a function that related stopping distance to noise level was calculated and this function was used to determine the stopping rule in the generalized SOR procedure (Fig. 4). This function would be used to estimate the most appropriate stopping rule for the SOR procedure when analyzing actual survey data. Results from SOR procedure were then compared to the outcome of the fixed gate outlier rejection that is currently used in AFSC. This method rejects all the values that are outside an acceptable range,

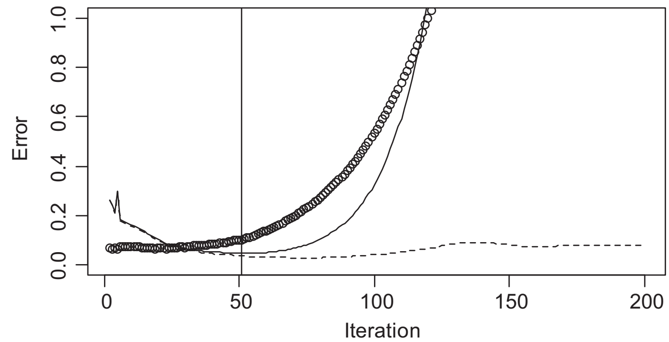

Fig. 2. Example of the stopping rule estimation in the sequential outlier rejection (SOR) simulation analysis. The stopping rule was estimated from the total error (solid line) which was the sum of the squared error (open circles) and the squared bias (dashed line). The vertical line indicates the minimum mean square error (MMSE).

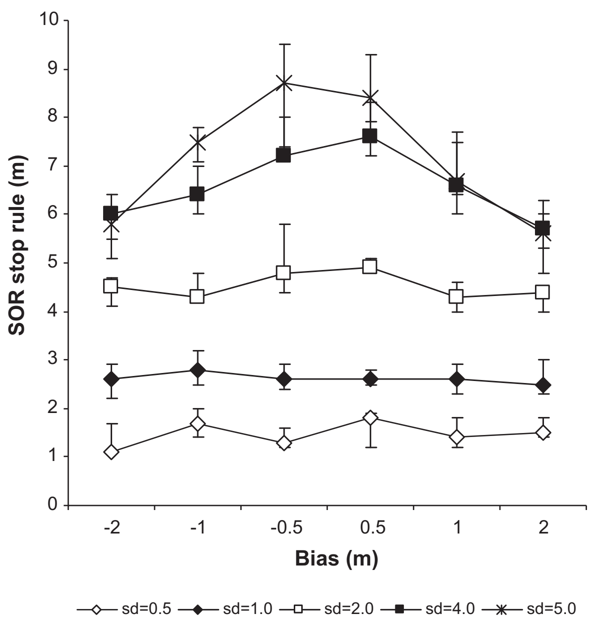

Fig. 3. The effect of bias and noise (sd) on the appropriate stopping rule for the sequential outlier rejection (SOR) procedure derived from simulation. Note that noise has the most deterministic effect on the stopping rule while bias has considerably smaller effect or no effect at all for smaller noise levels.

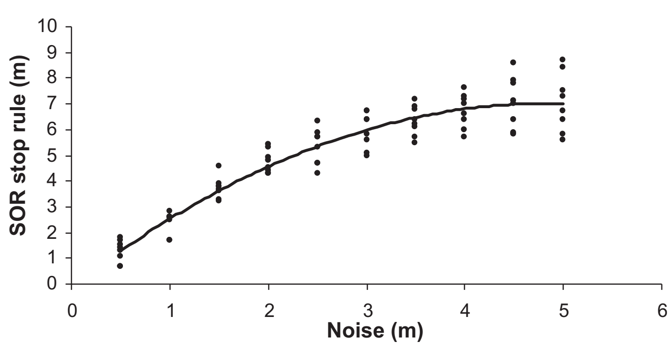

Fig. 4. Generalized relation between the sequential outlier rejection (SOR) stopping distance and noise level ($y = -0.3034x^2 + 2.9428x - 0.1112$).

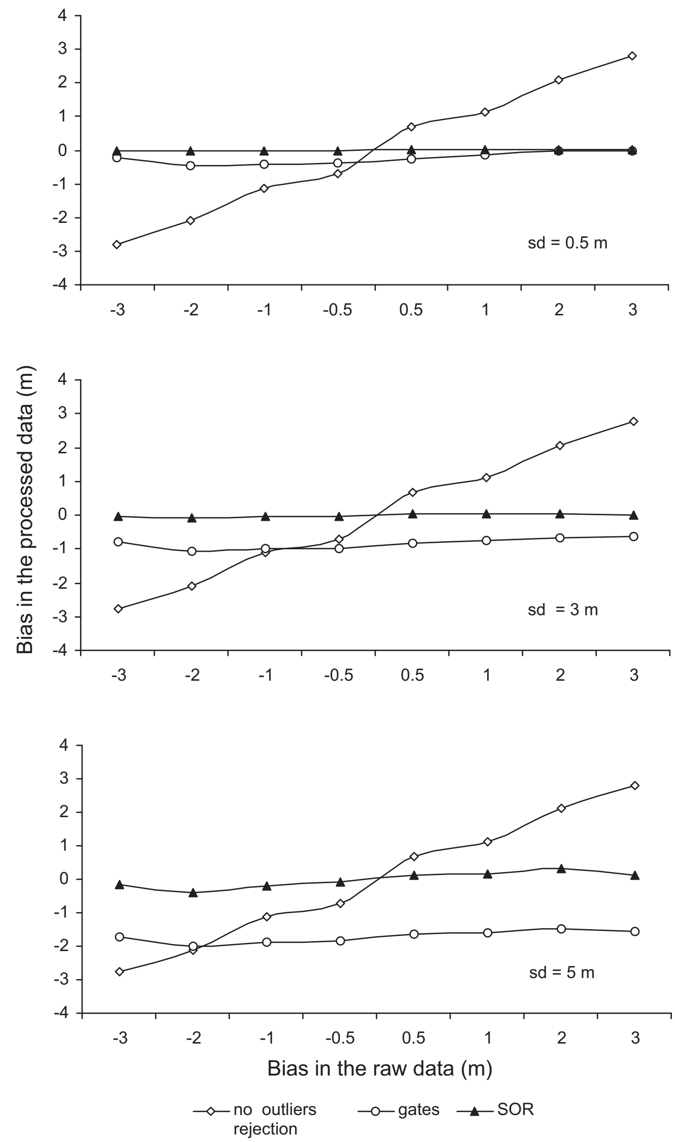

Fig. 5. Bias that remains in the net spread estimates after processing raw net spread data, using no outlier rejection, fixed gates to reject outliers, and sequential outlier rejection (SOR).

which is 10–22 m for all Alaskan bottom trawl surveys conducted by the AFSC.

In order to test the effects of improving the accuracy of acoustically-derived net spread by using a more accurate estimate of sound speed, we applied Coppens formula (Coppens, 1981) as follows:

$c(D,S,t) = c(0,S,t) + (16.23 + 0.253t)D + (0.213 - 0.1t)D2 + [0.016 + 0.0002(S - 35)](S - 35)tD$

where $c(0,S,t) = 1449.05 + 45.7t - 5.21t2 + 0.23t3 + (1.333 - 0.126t + 0.009t2)(S - 35)$,where t is temperature in degrees Celsius divided by 10, S is salinity in parts per thousand, and D is depth in kilometers. Ranges of validity of this formula are: temperature 0–35 °C, salinity 0–45 parts per thousand, and depth 0–4000 m.

Mean depth and temperature were observed with a micro-bathythermograph for most of the tows between 1999 and 2007. Salinity observations were unavailable so a constant of 32 ppt was assumed. The ratio of the resulting estimated sound speed to the assumed 1500 m s^{-1} was used to infer the bias associated with the use of a fixed sound speed in net spread calculations.

2.3. Effect on CPUE estimates

The effect of implementation of these new methods was assessed using data collected during Aleutian Islands, Bering Sea,

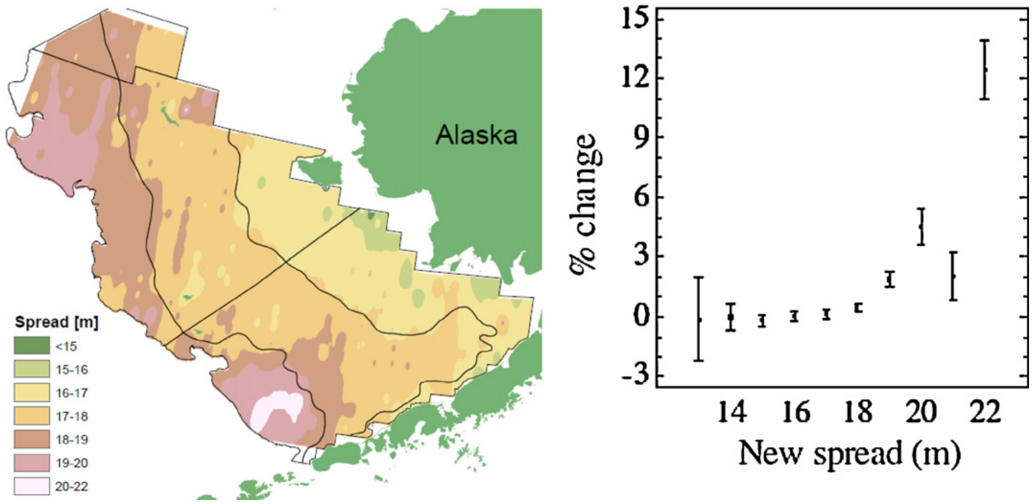

Fig. 6. Spatial variability in net spread data as observed during the 2003 Bering Sea survey (map on the left) and the effect of proposed methodological changes on effort estimated from 2003 wing spread data (with 95% least significant difference confidence bounds; graph on the right). Note that highest bias was observed for net spreads in the range of 19–22 m, which correspond to the western and deeper side of the survey area, resulting in the spatially variable bias in the area swept estimates. This bias is removed by application of SOR procedure.

and Gulf of Alaska surveys conducted between 2007 and 2010. Area swept was calculated for each tow using both current and new methods and the differences between these estimates were calculated as percent change in area swept estimates between new and old methods.

3. Results

3.1. Distance fished

The cubic spline smoother generally outperformed all other investigated smoothers in the simulations in terms of robustness to sinuosity of the tow path, random noise, and choice of span. The cubic spline produced estimates that were consistently very close to the known values and less variable than any other smoother examined (Fig. 1), although true distance fished was consistently underestimated by a small amount (typically < 0.5%). The series of simulations clearly demonstrated the importance of choosing an appropriate span for a given noise level, although the cubic spline smoother was much more robust in this regard than the other smoothers. Span levels that were smaller than indicated by the noise resulted in overestimates of distance fished, while too large a span level undersmoothed the data resulting in underestimates of distance fished. The errors associated with too small a span were often quite large, particularly in the case of the simple exponential smoother and the supersmoother (Fig. 1). All four smoothers underestimated distance fished at the highest levels of sinuosity and large spans, particularly when the noise levels were high, although again the cubic spline estimates were less variable and closer to the actual values than the other smoothers.

3.2. Net spread

The SOR procedure increased the accuracy and precision of net spread estimation in simulated data and consistently produced better estimates of net spread than methods that use fixed gates (currently used in AFSC) for removing outliers (Fig. 5). Most importantly, it greatly reduced the induced bias resulting from the asymmetrical distribution of simulated net spread observation errors. The apparent asymmetrical distribution of net spread error is commonly seen in the net mensuration data, and the SOR procedure appeared to consistently capture the spread signal from the noise and apparent bias (Fig. 6).

Estimated sound speeds during survey tows were always less than the assumed 1500 m s^{-1}, ranging from 1394 to 1497 (Fig. 7), and varied considerably in both space and time in all three surveys resulting in bias ranging from 7.1% to 0.2%. Lower temperatures and higher pressures in deeper water resulted in lower sound speeds than in shallower areas, resulting in a spatial bias in all survey areas (example of Gulf of Alaska in Fig. 8). Sound speeds were also lower in years with lower water temperatures, resulting in an important source of temporal bias (example of Bering Sea in Fig. 9).

3.3. Effect on CPUE estimates

The effect of implementation of the new methods on CPUE estimates between 2007 and 2010 is presented in Fig. 10. The use of the cubic spline resulted in corrections of area swept estimates ranging from −7 to 9% with majority of the tows ranging between −3 and 2%. SOR corrections were in the range from −7 to 10%, with majority of the corrections ranging between −2 and 2%. Application of estimated sound velocities resulted in negative corrections for all tows ranging from −4 to −1% with majority between −4 and −2%. The application of all three corrections collectively changed area swept from approximately −10 to 7% with the majority of corrections in the range from −5 to 0%.

4. Discussion

We have shown an important, yet often overlooked, source of bias in abundance estimates that can result from the analytical methodology used to estimate the individual components of area swept (i.e., distance fished and net spread). Based on our results, we propose three new analytical methodologies (cubic spline smoother, haversine algorithm, and SOR) to estimate area swept that will reduce or eliminate sources of spatial or temporal bias associated with these calculations.

A necessary assumption for most fisheries stock assessments where fishery-independent survey data are available is that the index of abundance derived from a survey is directly related to the true abundance of the species of interest. Random error in the estimation of catch, effort, or catchability decreases the probability

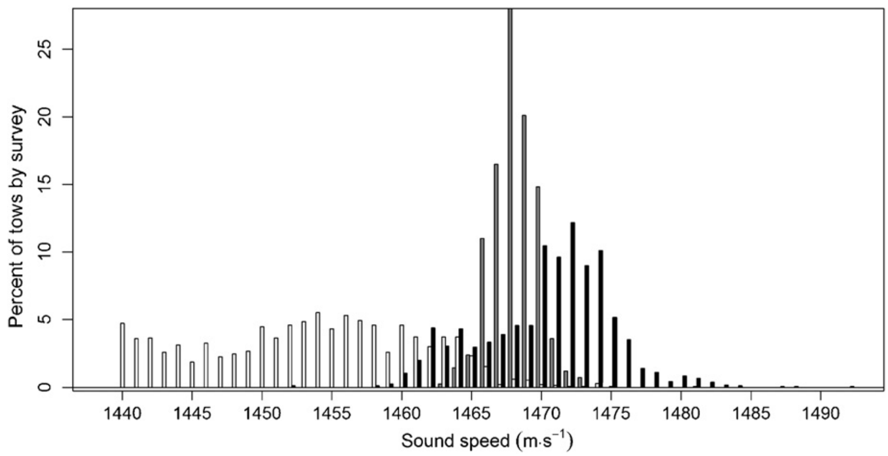

Fig. 7. Histograms of the distribution of sound speeds in near-bottom area calculated from Coppens formula (Coppens, 1981) by taking into account mean depth and temperature observed for each tow where data were available for AFSC tows between 1999 and 2007 in Bering Sea (white columns), Gulf of Alaska (black columns), and Aleutian Islands (grey columns).

of detecting changes in population density and lowers confidence in abundance estimates, but is not a source of bias. Survey estimates often exhibit much higher interannual variability than would be expected from within-survey variability (Francis et al., 2003). Several authors have demonstrated success in reducing the effects of interannual observation error from time series of survey estimates through modeling efforts (e.g., Byrne et al., 1981; Collie and Sissenwine, 1983; Pennington, 1985; Stockhausen and Fogarty, 2007). However, identifying and eliminating sources of observation error is preferable to removing their effects after the fact. Biased estimates are not problematic for most stock assessments as long as they are stationary in both space and time. However, non-stationary biases that are not properly accounted for lead to unreliable estimators of abundance.

For most trawl surveys, trawl catchability is unknown but assumed to be stationary and there is a large body of literature on the problems that can result when this assumption is not met (e.g., Godø and Engås, 1989; Hilborn and Walters, 1992; Wilberg et al., 2010). However, similar problems can arise if the unit of effort is

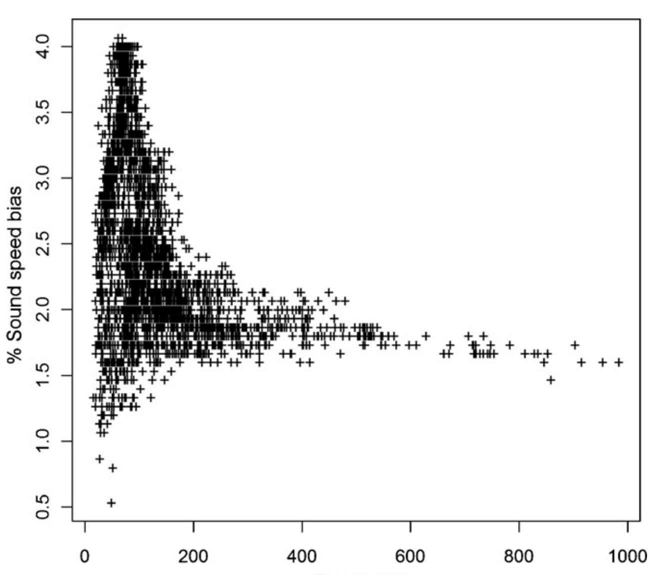

Fig. 8. Variability in bias associated with lack of correction for sound speeds vs. depth in the Gulf of Alaska surveys.

spatially or temporally non-stationary. Considerable attention has been given in recent years to the standardization of survey gear and procedures to reduce variability in survey estimates (e.g., Stauffer, 2004; ICES, 2009) since it has been demonstrated that inconsistent trawl performance (i.e., non-standard trawl geometry) can result in variable catch efficiency and increased uncertainty in CPUE estimates (e.g. Koeller, 1991; Weinberg and Kotwicki, 2008). These efforts have helped reduce problems of non-stationary effort that were caused by non-uniformity of survey gear or trawling methods used on different vessels or by different vessel personnel. Our work goes a step further by examining the algorithms used in effort estimation and proposing new methodologies that can be used to improve them.

4.1. Bias associated with GPS random error

Attempts to limit the effect of GPS noise often include a smoothing algorithm to estimate the actual tow path. Several of the smoothing algorithms we tested produced biased estimates of distance fished in the presence of noisy GPS data, especially when inappropriate spans were used. When noisy GPS data are suspected, but the magnitude of the noise is unknown, it is best to err on the side of choosing too large a span rather than too small a span as the magnitude of the potential errors associated with the latter is much larger. The current AFSC method (i.e., the running mean smoother) often overestimates distance fished and this bias rapidly increases at noise levels greater than 5 m. The quality of GPS data collected routinely on the surveys we examined between 1992 and 2007 has increased over time for several reasons including higher quality receivers and the introduction of the Wide Area Augmentation System (WAAS) in North America. As a result, noise levels have decreased over time resulting in interannual differences in GPS noise bias. Many sources of GPS error are also temporally autocorrelated, which may translate into spatial differences in GPS positional accuracy as our survey vessels move through a survey area.

The elimination of spatially and temporally variable noise levels in our GPS data is important to prevent biased abundance estimates. Our simulation work shows conclusively that the bias associated with GPS noise levels can be minimized through the use of a more robust smoothing algorithm (i.e., the cubic spline), and we recommend it to replace the current running mean smoother. The cubic spline smoother also produced the least variable estimates of distance fished because it was superior at reducing the effect of random noise, thereby increasing the precision of area swept

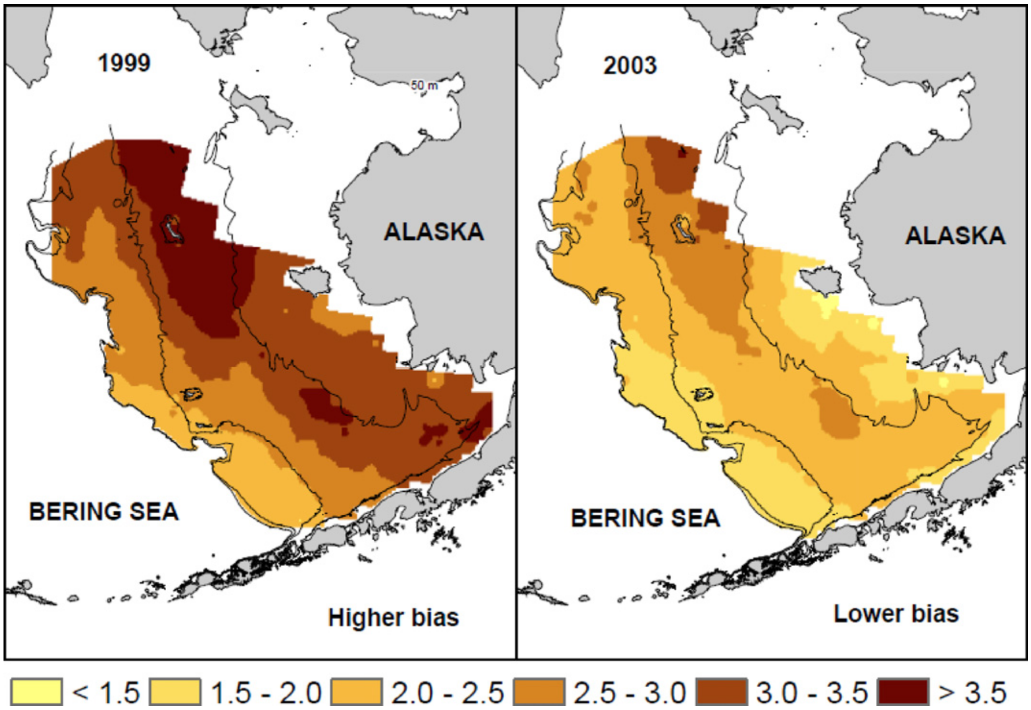

Fig. 9. Examples of spatial variability in bias (%) associated with lack of correction for sound speeds in the Bering Sea in years 1999 (colder year) and 2003 (warmer year). Note temporal aspect of variability in bias associated with between-year differences in temperature.

estimates. The only situation in which the cubic spline does not perform well with actual GPS data is in the rare case of large GPS blunders and this is true of all smoothers we examined. Therefore we recommend eliminating these obvious positional errors before the application of the distance fished procedure. Fortunately, these blunders are easily detected by plotting and examining the raw GPS data.

4.2. Bias associated with asymmetrical distribution of outliers in net spread data

Raw net spread data are often very noisy. Fixed gating methods assume that mean net spread values will vary around a known mean value and that measurement error around the mean is random. When net spread is markedly different from the assumed

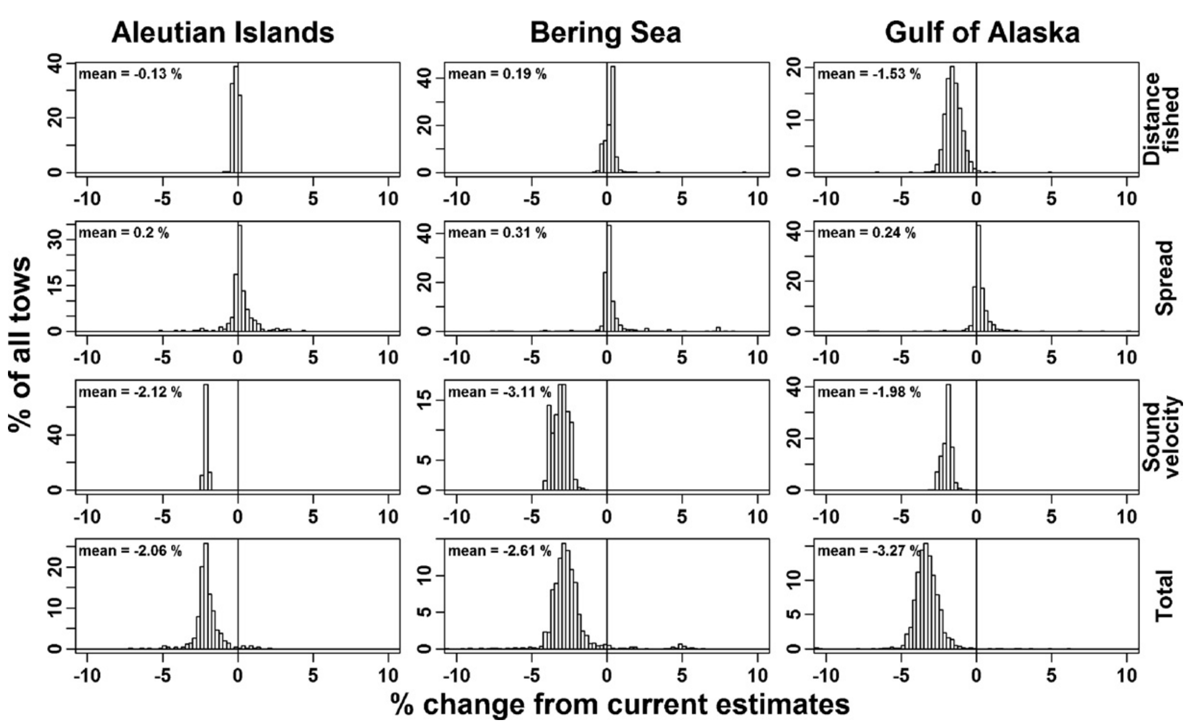

Fig. 10. Histograms of the relative differences between the old and new estimates of area swept when proposed corrections (cubic spline for distance fished, SOR and cubic spline for spread, and corrected sound velocity for spread) are applied on individual basis (three upper rows) or collectively (last row) for three bottom trawl surveys in Alaskan waters.

mean or when there is a trend in the spread data, the use of inflexible gating can create an asymmetrical distribution of error in the reduced data set, even when the observed errors are random and symmetrical, resulting in a biased estimate of mean net spread. In addition, net spread is dependent on depth which can result in spatial biases in mean net spread estimates. Regardless of the gating mechanism used, asymmetrical net spread error around the mean is often observed and brings with it similar problems even if the actual mean net spread is close to the assumed mean. Estimates can also be biased when net spread and data density vary over a single tow, since intervals with a higher density of observations are more influential in the calculation of the mean spread.

The SOR procedure resolves the gating problem by establishing flexible gates which are symmetrical around the instantaneous mean signal from the data. These gates can be established by applying the stopping rule function presented above to the net spread data from the survey. It also yields unbiased estimates when outliers are asymmetrically distributed relatively far from the mean signal. However, in some cases, asymmetrically distributed errors lying close to the mean signal were not removed by the SOR, resulting in an apparent small residual bias. Despite these minor problems, we recommend the use of the SOR procedure as a much less biased alternative to the fixed gate method. The SOR procedure presented here can be used for outlier rejection in the net spread data and is broadly applicable to other types of data. However, for each new application it would be necessary to perform analogous simulations in order to estimate an appropriate stopping rule.

4.3. Bias associated with assumption of constant sound speed in seawater

The assumption of a sound speed of 1500 m s^{-1} was not reasonable for most of the tows in Alaskan trawl surveys. High variability in near bottom temperatures among the three surveys (e.g., Lauth and Acuna, 2007) resulted not only in large intra-annual spatial differences in the magnitude of the bias but also in significant inter-annual differences related to the natural temperature fluctuations between years (Figs. 8 and 9). Additional bias can be attributed to the depth-dependence of sound speed through water. The obvious spatial and temporal aspects of this bias recommend the adoption of the tow-by-tow method of sound speed estimation using *in situ* depth, temperature and salinity observations when available. To obtain corrected net spread data (or net height) the ratio of the estimated sound speed to the assumed sound speed can be multiplied by the estimates of net spread obtained directly from instruments.

4.4. Considerations for implementing new methods to improve area swept estimates

Maintaining consistent methodology through time is one of the most important considerations for any survey whose goals include developing a time series to track changes in abundance over time. However, when new methods and technologies are developed that allow more precise and less biased estimates, the benefits of providing the best possible estimates going forward must be weighed against the potential cost of devaluing the time series by changing methodology. In our case the decision is made easier since the changes we are proposing involve analytical methodology rather than data collection and we will be able to retroactively apply these methods to years for which the requisite data are available beginning in the early 1990s. We also believe that reasonably accurate estimates for earlier years could be derived from modeling efforts leveraging data from later years.

The new area swept estimates for the years between 2007 and 2010 (Fig. 10) indicate that the expected corrections for these years will range between −5 and 0%. However we believe that corrections may be greater in years prior to 2007 due to lower quality of GPS or net spread data. These new methods of estimating area swept will undoubtedly result in changes to previously published abundance estimates of all species assessed by AFSC bottom trawl surveys and therefore some disruption in the current time series. However, considering that we will be able to project the proposed changes back about 15 years and the fact that current stock assessments will be minimally affected by potentially small biases in earlier years, we feel that the benefits of implementing the methodological changes described outweigh any problems posed by lack of information from earlier survey years and fulfill our obligation to provide population estimates using the best possible scientific methods.

5. Summary

Some methodologies that are chosen to estimate effort in fishery independent surveys are likely an additional source of uncertainty in abundance estimates from these surveys. They are also likely to change and develop over time, but shortcomings of these methodologies can be easily overlooked in the attempts to standardize surveys, and their effect on the error in CPUE estimates is often unknown. In the light of the findings of this investigation it is apparent that the sources of error in the estimates of effort in bottom trawl surveys can be significant and it is important that we consider them carefully as we seek to standardize surveys (ICES, 2004).

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