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Acoustic surveys in the full monte: simulating uncertainty

George Rose*, Stéphane Gauthier, Gareth Lawson

Fisheries and Marine Institute of Memorial University of Newfoundland, St. John's, NF, Canada A1C 5R3

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Abstract − A method is presented to estimate and diagnose the sources of uncertainty in acoustic survey measures of fish density. The method involves simultaneous Monte Carlo simulation of density and uncertainty resulting from imprecision in all terms in acoustic analyses. Known bias can also be considered. Results are presented from theoretical simulations based on assumed distributions of fish density and acoustic parameters at sample sizes from 10–1 000, and on survey data for Atlantic cod and redfish. Uncertainty can be reduced by either increasing the sample rate or by decreasing the error in input variables (system and ocean parameters, backscatter, target strength, species identification, detectability). Uncertainty in inshore cod surveys in Newfoundland waters can be attributed for the most part to heterogeneous fish distribution and detectability variance (total $R^2 = 0.64$). Uncertainty in offshore redfish surveys is attributed to heterogeneous fish distribution, and variance in target strength and species identification (total $R^2 = 0.82$). Uncertainty can be reduced by survey design, not only by the classical methods of achieving less diverse measures of backscatter, but also by increasing precision in the input parameters to the density estimate, in particular, target strength, detectability, and species identification. © 2000 Ifremer/CNRS/INRA/IRD/Cemagref/Éditions scientifiques et médicales Elsevier SAS

acoustic survey / uncertainty / Monte Carlo / target strength / detectability / cod / redfish

Résumé − Campagnes acoustiques mises à nu : simuler l'incertitude. Une méthode est présentée pour estimer et déterminer les caractéristiques des sources d'incertitude dans les mesures de densité de poissons lors des campagnes acoustiques. La méthode implique simultanément une simulation au hasard de la densité et de l'incertitude résultant de l'imprécision dans tous les termes des analyses acoustiques. Le biais connu peut aussi être considéré. Les résultats sont présentés à partir des simulations théoriques basées sur les distributions présumées de poissons et les paramètres acoustiques pour un échantillonnage entre 10 et 1 000 m, et pour des données sur la morue et le sébaste. L'incertitude peut être réduite soit en augmentant le taux d'échantillonnage ou en diminuant l'erreur des variables introduites (paramètres du système et océaniques, rétrodiffusion, indice de réflexion des cibles, identification des espèces, détectabilité). L'incertitude dans les campagnes de morue côtière dans les eaux de Terre Neuve peut être attribuée en grande partie à l'hétérogénéité de la répartition des poissons et à la variance de la détectabilité (R^2 total = 0,64). L'incertitude dans les campagnes au large concernant le sébaste est attribué à l'hétérogénéité de la répartition des poissons, et à la variance de l'indice de réflexion et à l'identification de l'espèce (R^2 total = 0,82). L'incertitude peut être réduite par le programme de campagne, non seulement par des méthodes classiques d'obtention de mesures moins hétérogènes de rétrodiffusion, mais aussi en augmentant la précision des paramètres introduits, ceux de l'estimation de la densité en particulier, l'indice de réflexion, la détectabilité et l'identification des espèces. © 2000 Ifremer/CNRS/INRA/IRD/Cemagref/Éditions scientifiques et médicales Elsevier SAS

campagnes acoustiques / incertitude / Monte Carlo / indice de réflexion / détectabilité / morue / sébastes

1. INTRODUCTION

A criterion for fisheries surveys and models is their usefulness. To be useful, surveys should be reported with an estimate of the uncertainty of the results. Acoustic survey summaries are often presented as either relative or absolute estimates of density, abundance, or biomass with no estimate of the uncertainty of these measures (Rose and Leggett, 1988; Anderson et al., 1998). Where measures of uncertainty have been

**Correspondence and reprints.*
E-mail address: grose@caribou.mi.mun.ca (G. Rose).

Table I. Terms, notations, and measures required to estimate their distributions.

Term	Notation	Distribution	Mean	sd	Max.	Min.	*P*
Source level (dB)	*SL*	Normal	X	X			
Receive sensitivity (dB)	*R*	Normal	X	X			
Pulse duration (ms)	τ	Normal	X	X			
Sound speed (m·s^{-1})	*S*	Normal	X	X			
Target strength (dB)	*TS*	Normal	X	X			
Detectability (%)	*D*	Flat			X	X	
Species identification	*ID*	Binomial					X
Density distribution (dB)	*AC*	Poisson or	X				
		Normal					
			X	X			

given, they are typically based solely on sampling error calculated from mean transect densities or spatial analyses (e.g., Jolly and Hampton, 1990; MacLennan and Simmonds, 1992; Murray, 1996). Trawl and other net-based surveys often take a similar perspective. Such approaches do not assess the full range of uncertainty associated with the survey method, and do not allow investigators to diagnose and quantify the chief sources of uncertainty in their survey methods and results.

Uncertainty in a survey result may be attributable to both bias and imprecision. Bias refers to systematic deviation from the true value. Bias often cannot be quantified. Surveys with constant bias are often useful for relative indices, especially if undertaken over long time periods. Imprecision assesses the repeatability of the estimate, without regard for its absolute value. Imprecision is typically expressed as the standard error, coefficient of variation, or confidence interval. Imprecision has different ramifications for survey usefulness than does bias. An imprecise survey may estimate the true value without bias, but be relatively useless for fisheries monitoring because of the large uncertainty about the result. For acoustic surveys, it is important to differentiate between these two statistical concepts, in particular because bias may be introduced by several factors that also affect imprecision (e.g., target strength: *TS*, detectability: *D*). If an acoustic system is improperly calibrated, for example recording signal amplitudes 2 dB less than if properly calibrated, that error would introduce a bias in the output (fish density), but would not affect precision about the average density value recorded. However, within-survey dynamics in the distribution of fish lengths, condition, or tilt angle may influence the precision of the *TS*, but the *TS*-length model may also be biased (e.g., indicate a –34 dB mean where it should be –36 dB).

In this paper, we describe a simulation method for simultaneously estimating uncertainty resulting from imprecision in all sources that apply to acoustic surveys. In this method, all terms in the acoustic equation and in scaling of backscatter to abundance over a survey area are treated not as absolute measures but as random variables that can be described with a statistical distribution. In estimating uncertainty, each statistical distribution is sampled at random in Monte Carlo simulations of an acoustic density calculation. We present theoretical examples to describe the method under simulated fish distributions and survey conditions, and two examples using real survey data from Atlantic cod (*Gadus morhua*) and Atlantic redfish (*Sebastes* sp.) from Newfoundland waters.

2. METHODS

The terms of the acoustic equation and survey estimation are given in *table I* (some approaches use pooled terms, for example for source level and receiver sensitivity, or a single gain). The sonar calibration-parameter estimates and distributions should be determined using a standard target (Foote et al., 1987). Variations in pulse duration (τ) and beam pattern (*B*) are likely to be very small and can be estimated by the manufacturer (in the event that they are unknown they can be ignored in most cases). Sound-speed variation should be determined empirically. Variation in target strength (*TS*), detectability (*D*), and species identification (*ID*) require experimentation at the survey site. Variation in backscatter (*S*) can be calculated from the survey data.

All simulations were performed using SPSS scripts. The script assigns a distribution to each variable that is to be randomly sampled in each calculation. Theoretical examples used reasonable parameter-level distributions and values for 38-kHz scientific echosounders with sample size $N = 1\,000$, 500, 100, and 10. We show cases where the distribution can be described as a Poisson process (coefficient of variation $cv = 1$), but any distribution could be used. Ten runs were made with high and low uncertainty in input variables (*table II*). Factors that accounted for the uncertainty in the mean estimate of abundance were identified through a stepwise regression model in SPSS. Values not already in the logarithmic domain were logged prior to entry in the model in an attempt to equalize variance.

The real cod survey data was derived from research in inshore Newfoundland conducted in 1997 with a Biosonics DT4000 single-beam 38-kHz echosounder

Table II. Values of parameters and distributions used in the simulations*.

Term	Notation	Distribution	Low	High	Cod	Redfish
Source level (dB)	*SL*	Normal	225.3 (0.25)	225.3 (0.25)	*SL* + *R*	Gain
Receive sensitivity (dB)	*R*	Normal	–156.8 (0.25)	–156.8 (0.25)	67 (0.25)	–26.5 (0.25)
Pulse duration (ms)	τ	Normal	0.8	0.8	0.8	1
2-way beam pattern (dB)	*B*	Normal	–19.1 (0.25)	–19.1 (0.25)	–19.1 (0.25)	–20.5 (0.25)
Sound speed ($m \cdot s^{-1}$)	*S*	Normal	1450 (20)	1450 (20)	1450 (20)	1480 (30)
Target strength (dB)	*TS*	Normal	–30 (1.0)	–30 (3.0)	–34 (1.0)	–42 (2.2)
Detectability (%)	*D*	Flat	0.9,1	0.1,1	0.1,1	0.7,1
Species identification	*ID*	Binomial	0.95	0.6	0.95	0.95
Density distribution (dB)	*AC*	Poisson	1	1	0.08	0.23

* Numbers are: means (sd) for normally distributed variables, minimum and maximum values for flat distribution, probability level for binomial distribution, and mean for Poisson distribution.

(Lawson and Rose, 1999). Estimates of the acoustic parameters were determined by calibration with a tungsten-carbide standard sphere. *SL* and *R* were pooled (*table II*). *TS* estimates were made using a Simrad EK500 38-kHz splitbeam echosounder in situ and the model of Rose and Porter (1996) applied to mean fish lengths observed during concurrent research fishing. *ID* was estimated by combining the fishing results with acoustic identification algorithms in FASIT (Fisheries Assessment and Species Identification Toolkit) (LeFeuvre et al., 2000). *D* estimates were based on experiments using a submersible and surface and sub-mounted transducers (Lawson and Rose, 1999). *S* values for both the DT4000 and EK500 were integrated each 100 m using FASIT. We initially applied no particular survey design but used all *S* data from all transects to capture the full variability in cod distribution. To achieve a field of independent density estimates, these full data were re-sampled along each transect at a decreasing rate until no significant serial correlation remained. We then sampled the full data at that rate a 100 times. The derived data was used to determine the distribution properties of the density.

Redfish data were obtained from offshore Newfoundland waters in 1997 using a Simrad EK500 38-kHz splitbeam echosounder (Gauthier and Rose, 1998). Acoustic system parameters were determined by calibration. The acoustic gain was used as the basis for variations in system performance (Simrad, 1996) (*table II*). Distributions for *S*, *ID*, and *TS* were made using similar methods as described for cod. The TS model was from Gauthier and Rose (1998). A new species-identification algorithm for redfish was used in FASIT. Detectability was estimated from experiments conducted during several 24-h periods on single aggregations, combined with bottom and mid-water trawling. The analytical strategy for redfish was the same as for cod.

After the assessment of the factors that were influencing the uncertainty in the density estimates of cod and redfish were completed, an attempt was made to counter the chief sources of bias evident from the initial analyses. We applied a survey design that took into account the differences in distribution and *D* between day and night and transects, then re-ran the simulations with the revised estimates of *S* and *D*.

3. RESULTS

The theoretical simulations showed that if there is low uncertainty in the input values to the acoustic calculation (*table II*), a small $N = 10$ will yield a mean density estimate with 95% *CI* of approximately 25% on either side of the mean. $N = 100$ reduces uncertainty to approximately 10% (*figure 1a*). There is little gain in precision with $N > 100$. Alternatively, if there is high uncertainty in input values, then *N* must be much larger to yield the same precision ($N = 100$ yields 95% *CI*'s of approximately 25%), and uncertainty approaching 10% is not reached until $N > 500$ (*figure 1b*).

In general, under conditions of low uncertainty in input parameters with poisson distributed backscatter and a moderate sampling rate ($N = 100$), S dominated the uncertainty about density (*table III*). However, under conditions of high uncertainty in input parameters, factors other than *S* became increasingly important (*table III*). Trials run with *S* distributed normally showed variation strongly dominated by *TS*, *ID*, and *D*, and *cv*'s << 1 (not reported).

In our Atlantic cod survey data, *S* was Poisson distributed (*figure 2a*). *D* was highly variable over the diel cycle, being on average higher in daytime than at night by an order of magnitude (*table II*). Hence, *D* was treated as both a source of uncertainty and as a bias by multiplying calculated density by mean *D*. Target strength variability based on fish length was relatively small ($sd = 1$ dB). The mean density was 0.11 $fish \cdot m^{-2}$ ($se = 0.018$; 95% *CI* 0.08–0.15; $cv = 1.7$). The largest sources of uncertainty in cod density estimates were from *S* and *D* (*table IV*). These accounted for approximately 60–65% of the variance in the estimated density in several trial runs (*table IV*). *ID* and *TS* accounted for another few percent of the variance. Other measures were not significant in any trial ($P > 0.05$). For this cod example, application of a sampling design that used transect means as the

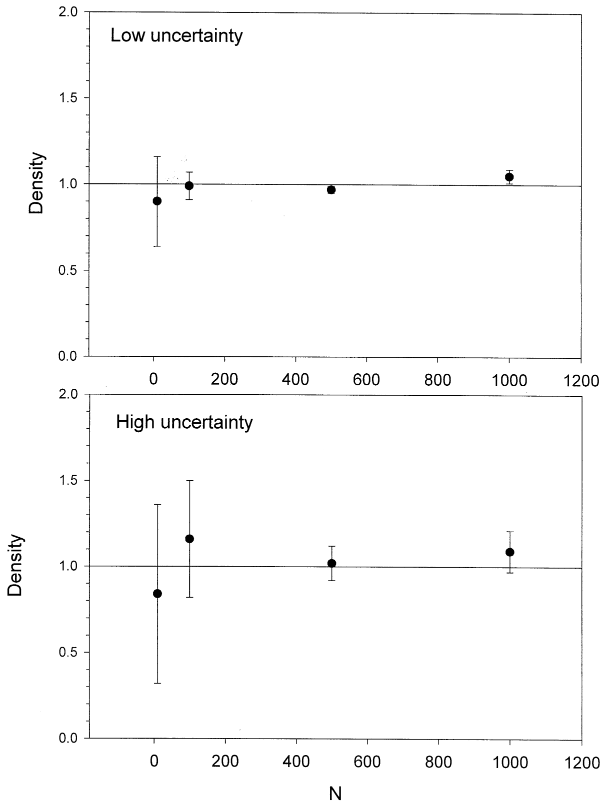

Figure 1. Uncertainty about estimates of poisson-distributed backscatter based on simulations with $N = 10$, 100, 500, and 1 000, under conditions of low uncertainty in input variables (target strength, detectability, species identification), and high uncertainty in input variables.

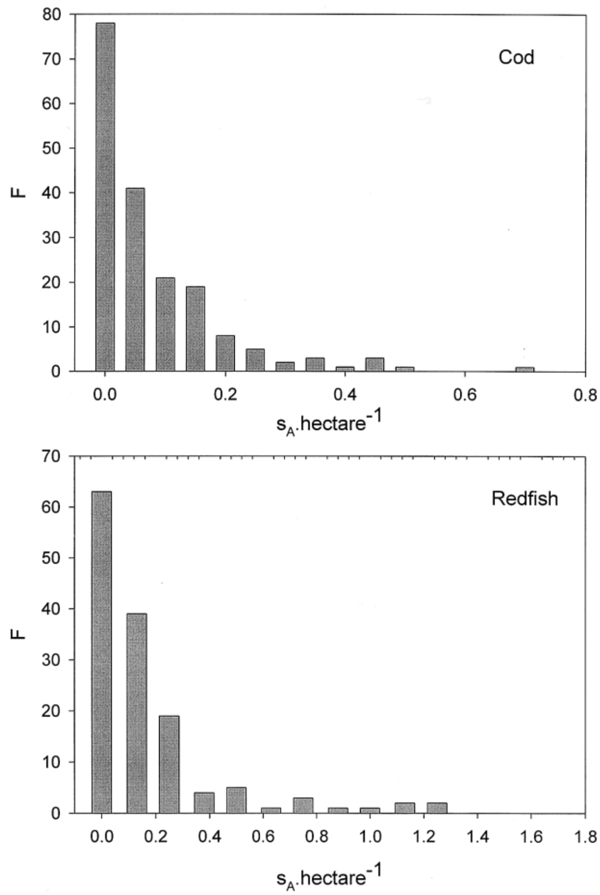

Figure 2. Distribution of S_A for cod and redfish.

Table III. Breakdown of chief contributing factors to variance in acoustic density*.

Add to model	R^2	R^2 change	*df*	*F*
Low uncertainty				
S	0.86	0.86	98	0.000
ID	0.89	0.03	97	0.000
TS	0.91	0.02	96	0.000
High uncertainty				
S	0.16	0.16	98	0.000
ID	0.31	0.15	97	0.000
D	0.40	0.09	96	0.001
TS	0.44	0.04	95	0.009

* Simulations with backscatter poisson distributed and N = 100 under assumptions of low uncertainty ($cv = 1.1$), in which detectability (*D*) is flat from 0.9 to 1, target strength (*TS*) has $sd = 1$ dB, species identification (*ID*) is binomial with $P = 0.9$; and high uncertainty ($cv = 2.6$), in which *D* is flat from 0.1 to 1, *TS* has $sd = 3$ dB, *ID* is binomial with $P = 0.6$. Other factors (system calibration and environmental parameters) were not significant ($P > 0.05$).

sampling unit and only day-time data to further reduce the bias of detectability, resulted in a more precise estimate of the mean density (0.11 fish·m^{-2}, $se = 0.01$; 95% *CI* 0.09–0.13; $cv = 0.79$). The chief sources of uncertainty under this approach were *S*, *ID*, and *TS*, and in total accounted for 89% of the variation in density (*table V*). These variables were not correlated (*P's* < 0.05).

In our Atlantic redfish example, *S* was also Poisson distributed (*figure 2b*). Initial comparisons of acoustic and trawl densities suggested that *D* was variable over the diel cycle, being near unity at night and approximately 0.7 in daytime (*table II*). *TS* variability based on fish length was substantial (> 2 dB). The overall mean density was 2.15 fish·m^{-2} ($se = 0.29$; 95% *CI* 1.57–2.73; $cv = 1.4$). The significant sources of uncertainly in this redfish density estimate were *S*, *TS*, *ID*, and *D*. Together these factors accounted for 74% of the variance in density. However, further analysis by transect and time indicated biases and complexities. One transect had consistently higher densities than the other. Only the high density transect showed significantly higher densities at night than during the day. To counter these biases, the night-time transect means

Table IV. Stepwise regression summaries for survey data for cod and redfish*.

Add to model	R^2	R^2 change	*df*	*F*
Cod				
S	0.36	0.36	98	< 0.001
D	0.59	0.24	97	< 0.001
Redfish				
S	0.52	0.52	98	< 0.001
TS	0.74	0.22	97	< 0.001
ID	0.82	0.08	96	< 0.001

* Factors entered into the model were system calibration parameters (Source level + receiver sensitivity for cod using DT4000 or gain for redfish using EK500; pulse width (ms)), environmental parameters (speed of sound), and target and survey parameters acoustic scatter (*S*), target strength (*TS*), detectability (*D*), and species identification (*ID*). All factors were in logarithmic domain (with the exception of detectability, which is binomial 0 or 1 for each case). For cod, assigned distributions were: *S* Poisson (mean S = 0.08), *D* flat (0.1,1), *TS* normal (mean = –32 dB, *sd* = 1 dB), and *ID* binomial ($P = 0.95$). For redfish, assigned distributions were: *S* Poisson (mean = 0.23), *D* flat (0.7,1), *TS* normal (mean = –41.1 dB, *sd* = 2.2 dB), and *ID* binomial ($P = 0.9$). $N = 100$. Factors not shown explained < 5% additional variance.

were used as the sampling unit and *D* was assigned from night-time experiments. This approach resulted in a more precise and higher estimate of the mean density (4.07 fish·m^{-2}, $se = 0.30$; 95% *CI* 3.43–4.59; $cv = 0.75$). Using this approach, the chief sources of uncertainty were *TS*, *ID*, *S*, and *D*, and the amount of the variation explained increased to 81% (*table V*). These variables were not correlated (*P's* < 0.05).

Table V. Stepwise regression summaries for survey data for cod and redfish including only data from periods of maximum detectability, and with acoustic scatter averaged over transects as the basic sampling unit (transects were run 2–5 times)*.

Add to model	R^2	R^2 change	*df*	*F*
Cod				
S	0.37	0.37	98	< 0.001
ID	0.74	0.37	97	< 0.001
TS	0.83	0.09	96	< 0.001
Redfish				
TS	0.60	0.60	98	< 0.001
ID	0.76	0.17	97	< 0.001

* Factors entered into the model were system calibration parameters (Source level + receiver sensitivity for cod using DT4000 or gain for redfish using EK500; pulse width (ms)), environmental parameters (speed of sound), and target and survey parameters acoustic scatter (*S*), target strength (*TS*), detectability (*D*), and species identification (*ID*). All factors were in logarithmic domain (with the exception of detectability, which is binomial 0 or 1 for each case). For cod, assigned distributions were: *S* normal (mean $S = 0.11$, $sd = 0.06$), *D* normal with mean = 1 and $sd = 0.1$, *TS* normal with mean = –32 dB and $sd = 1$ dB, and *ID* binomial ($P = 0.95$). For redfish, assigned distributions were: transect *S* normal (high and low density transects: mean = 0.61 and 0.15, $sd = 0.06$ and 0.04, respectively), *D* normal (mean = 1, $sd = 0.1$), TS normal (mean = –41.1 dB, $sd = 2.2$ dB, and *ID* binomial ($P = 0.9$). $N = 100$. Factors not shown explained less than 5% additional variance.

4. DISCUSSION

The present method quantifies the full uncertainty associated with an acoustic survey. The method can also be used as a diagnostic of the sources of uncertainty and the sampling effort required to achieve uncertainty levels within acceptable limits. It is evident that uncertainty can be reduced by either increasing sample size or employing a survey design that reduces variance in *S* and other factors, or, by increasing confidence in the input parameters, notably detectability, target strength, and species identification. Hence, if a survey is to be repeated, it may be more cost effective to increase confidence in the input parameters (e.g., *TS*, *D*, *ID*) than to increase sample size, which requires additional vessel time on each survey. Survey design should attempt to reduce uncertainty. Our method identifies its causes. In our examples with cod and redfish, the Poisson distributions of the acoustic scatter suggested that both species were aggregated in space and time. Hence, a substantial reduction in uncertainty was achieved by a simulated grouping of the initial scatter in the horizontal plane (equivalent to transect placement and analyses that give a less heterogeneous density field). Despite this improvement, uncertainty caused by *TS*, *D*, and *ID* was still relatively large. We conclude that survey design should be more than an exercise in optimising transect placement and methods to capture horizontal distribution patterns, but must also address variations in the other key factors that cause uncertainty in fish density measures.

It is noteworthy that error is not strictly additive in acoustic surveys. Our simulations show that uncertainties from the various sources do not 'add up', but at times may tend to cancel each other to some extent. Nevertheless, uncertainty based on a full assessment of the acoustic calculation is typically greater than that attributable solely to sampling or transect variability (*cv*'s increased by factors of 1.4 and 1.7 in our examples). The factors that contributed to uncertainty were not correlated in our examples.

Cod survey precision in coastal Newfoundland waters appears to be limited primarily by heterogeneous fish distribution (*S*) and variable levels of detection (*D*). Variation in *D* may be partly systematic and treated as a bias (Lawson and Rose, 1999). Reducing uncertainty in cod surveys will likely require improved survey strategies that better account for the typically aggregated distribution patterns, countering of bias in density estimates when *D* is less than unity, and not surveying when *D* is very low. In our example, uncertainty caused primarily by cod horizontal distribution variation and a diel bias in detectability was reduced considerably by application of a simulated survey design that estimated mean densities from transects run several times when detectability was high.

Redfish density measures in offshore waters were more certain than were those of cod in coastal waters. However, estimates of redfish *TS* were less certain than for cod because of bimodal distributions of fish size and acoustic size (*TS*), and incorrect species identification accounted for more of the variability than with cod. Hence, reducing uncertainty for this survey situation will require additional research on these measures in addition to increased sampling or improved survey design. As for cod, application of a simulated survey design in keeping with patterns in density predictably reduced uncertainty. However, redfish were more highly aggregated and migrated vertically to a greater degree than did cod (at least in these environments). Hence, uncertainty caused by distribution variation in the horizontal and vertical planes, and detectability, was reduced considerably by application of a survey design that employed stratified transects run several times when detectability was high.

In conclusion, fisheries surveys without comprehensive estimates of uncertainty should no longer be considered acceptable. Estimates of abundance or biomass without quantified uncertainty cannot be interpreted adequately by science or by managers, and hence are not useful. This applies to acoustic and capture-based surveys (e.g. trawl). Recent efforts to assess the risk of alternative management strategies make uncertainty estimates mandatory. There is nothing to be gained by glossing over uncertainty. For acoustic surveys, estimates of only the sampling or transect (S or S_A) variance are likely to underestimate the full uncertainty. Our method provides a relatively straightforward means of assessing the full uncertainty associated with an acoustic survey, and diagnosing its causes. Improvements in survey design should attempt to reduce uncertainty not only by the classical methods of achieving less diverse measures of backscatter, but also by increasing precision in the input parameters to the density estimate, in particular, target strength, detectability, and species identification.

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