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IMPROVING POPULATION ESTIMATES OBTAINED FROM HIGHLY VARIABLE TRAWL DATA

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Improving Population Estimates Obtained from Highly Variable Trawl Data

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Abstract

The spatial distributions of marine biota are frequently patchy. Samples taken from these populations are characterized by values which are mostly small, relative to the population mean, and a few that are very large. It is therefore difficult to estimate stock size using conventional methods. We performed Monte Carlo simulations based on trawl data for Dungeness crab and compared the behavior of three estimators of central tendency: sample mean, geometric mean, and a lognormal estimate. Results indicate that though the sample mean is unbiased, single estimates of the population mean (and thus population estimates obtained using area-swept) may be overly sensitive to extreme values; confidence intervals capture the true value at a level well below that prescribed. Estimates of the geometric mean exhibit more stable behavior about its parameter, with the lognormal estimate falling in between. We conclude that abundance of aggregated stocks should be indexed with an estimator that has more desirable statistical properties, such as the geometric mean. Until robustness is better understood, we suggest a conservative approach based on comparison of trends found in the "comparative triad" of the three estimators. This may reduce error associated with conventional fisheries stock assessment practices and thus provide for more effective management of overdispersed stocks.

Introduction

Effective scientific management of fishery resources requires reliable measures of abundance. Research trawl surveys are routinely used in concert with fishery catch statistics to provide estimates of commercially important population parameters. Random survey data are commonly stratified according to depth, and catches are standardized according to the area of bottom sampled (Alverson and Pereyra 1969; Smith and Somerton 1981; Azarovitz 1981; Otto 1986). Average catch-per-unit-effort (CPUE) is generally considered proportional to the size of the population. Analytical procedures often rely on an assumption that statistical methods based on normal probability theory are appropriate and, as such, that the individuals in the population are not aggregated in space (see Elliott 1977).

Marine biota, however, are commonly overdispersed, and generally the logarithms of abundance follow the normal (see comment by Gaddum, 1945) or Gaussian distribution. The pattern is well-represented across a broad spectrum of life in the sea, ranging from primary producers (Hermann et al. 1989) and zooplankton (Winsor and Clarke 1940; Reilly 1983) to a diverse assemblage of marine fish and invertebrate taxa (Smith and Walters 1982). Most, if not all, commercially important groundfish (Rivard 1981) and many shellfish stocks are characteristically overdispersed (bivalve: Jamieson 1986, Robert and Jamieson 1986; shrimp: Garcia and LeReste 1981, Parsons and Sandeman 1981; lobster: Barnes and Bagenal 1951, Bahamonde et al. 1986; crab: Miller 1975, Gotshall 1978, Sinoda and Kobayashi 1982, Hayes 1983, Armstrong et al. 1985, Bertuche et al. 1985, Brown 1986, McCabe et al. 1986, Armetta and Stevens 1987, this study). As such, it is unlikely that overdispersion is an artifact of sampling.

Samples taken from these populations are characterized by mostly small values relative to the population mean, and a few very large ones. Densities within aggregations can be orders of magnitude greater than the average value (Omori and Hamner 1982; this study). Single estimates of the population mean from the arithmetic mean (sample average) may be too low because the very large values are often underrepresented at the levels of sampling effort

common to research trawl surveys. When large catches are present in a sample, they are problematic, since variance estimates become excessively high. Indeed, a high degree of uncertainty is often associated with estimates of stock abundance obtained from research trawl surveys (Doubleday and Rivard 1981; Smith and Hewitt 1985; Elner and Bailey 1986; Jamieson 1986, Otto 1986). A variety of alternatives have been considered (Sissenwine 1978; Smith 1988a; Zweifel and Smith 1981; Pennington 1983; Conan 1985; Kimura and Balsiger 1985; Gavaris and Smith 1987); none has found broad application. Moreover, management often ignores this uncertainty when formulating management strategies (Rivard 1981).

We investigated two alternative measures of central tendency and compared their statistical behavior to that of the sample mean. A new approach based on a "comparative triad" of the three estimators is proposed. This approach should reduce error associated with the conventional index of abundance while reducing the likelihood of false conclusions concerning trends in stock abundance.

The Lognormal Distribution and Parameter Estimation

The spatial dispersion of a population determines the relationship between its mean abundance and variance (Elliott 1977). Preliminary comparisons between the sample means and variances of CPUE data, as well as graphical analyses of log-transformed data, suggested use of the lognormal distribution. Further analyses (see Methods) indicated that our CPUE data did not deviate substantially from a lognormal distribution. Therefore, a brief review of the underlying theory for the lognormal distribution is presented here.

A random variable X is considered to be lognormally distributed when the natural logarithm of X, $Y = \ln(X)$, has a normal distribution. Specifically, if Y is normally distributed with mean μ_{LN} and standard deviation σ_{LN}, then $X = \exp(Y)$ is lognormally distributed with density function (Lindgren 1968):

$$(1) \qquad f(x) = \frac{1}{\sqrt{2\pi}\sigma_{LN}x}\exp\left\{\frac{-(\ln x-\mu_{LN})^2}{2\sigma_{LN}^2}\right\} .$$

The kth moment about zero, $E(X^k)$ is expressed as:

$$(2) \qquad E(X^k) = E(e^{kY}) = \exp\left(k\mu_{LN}+\frac{\sigma_{LN}^2k^2}{2}\right) .$$

In particular,

$$(3) \qquad \text{Population Mean} = \mu = \exp\left(\mu_{LN}+\frac{\sigma_{LN}^2}{2}\right)$$

$$(4) \qquad \text{Variance } (X) = \sigma^2 = \{\exp(\sigma_{LN}^2)-1\}\{\exp(2\mu_{LN}+\sigma_{LN}^2)\}$$

$$(5) \qquad \text{Geometric Mean} = \text{Median } (X) = \exp(\mu_{LN}) .$$

The relevant notation to distinguish between untransformed and transformed scales, and population parameters and their estimates, may be found in Table 1. Note that both μ and σ^2 for the lognormal distribution are functions of two parameters, μ_{LN} and σ_{LN}^2, making them difficult to estimate. In particular, any estimate of μ involves location and dispersion parameters.

The Arithmetic Mean

The ordinary sample mean

$$(6) \qquad \overline{X} = \frac{\sum X_i}{n} , \quad n = \text{number of data points in the sample}$$

is an unbiased estimator of μ regardless of the underlying frequency distribution. When the underlying frequency distribution is normal, the sample mean is also the minimum variance unbiased estimator (MVU, the one with the smallest variance of all unbiased estimators) of μ. Unfortunately, the sample mean does not have this MVU property when the underlying distribution is lognormal (Gilbert 1987). Also, it is sensitive to the presence of one or more large data values. (Note that these extreme data values are not outliers; they simply reflect the right-skewed nature of the lognormal distribution.) Finney (1941) points out the inefficiency of the sample mean when the standard error of the population is greater than 100%; Koch and Link (1980) suggest using the sample mean when the coefficient of variation is believed to be less than 1.2. For highly skewed distributions, larger sample sizes are required in order to invoke the Central Limit Theorem, which justifies use of the sample mean for inferences about means of populations which are not normally distributed (Jahn 1987). Sample sizes in excess of $n = 100 - 200$ may be required under certain circumstances (Sissenwine 1978).

The Finney-Sichel Estimator

Among alternative estimators of μ that have been investigated is a MVU estimator of μ (Finney 1941, Sichel 1952), which also has been described as equivalent to a maximum likelihood estimator by Aitchison and Brown (1969). The Finney-Sichel method adjusts the geometric mean upwards and is commonly used in gold and trace mineral assay work, where ore concentrations are typically lognormally distributed (Sichel 1952). If we let $\overline{Y}$ and s_y^2 represent the ordinary sample mean and variance of the log-transformed values $(Y = \ln(X))$, the Finney-Sichel estimate for μ is:

$$FM = \{\exp(\overline{Y})\}\psi_n\left(\frac{s_y^2}{2}\right) \tag{7}$$

where $\psi_n(t)$ is the infinite series

$$(8) \qquad 1+\frac{(n-1)t}{n}+\frac{(n-1)^3t^2}{2!\,n^2(n+1)}+\frac{(n-1)^5t^3}{3!\,n^2(n+1)(n+3)}+\frac{(n-1)^7t^4}{4!\,n^4(n+1)(n+3)(n+5)}+\cdots$$

Tables of the above function are available (Sichel 1952; Aitchison and Brown 1969, Table A2; Bradu and Mundlak 1970; Koch and Link 1980, Table A7) and may also be programmed on a computer (see Link et al. 1971). Although both Finney (1941) and Sichel (1952) derived the MVU estimator of the variance of the lognormal distribution, neither made specific comments on derivation of confidence intervals.

Confidence limits for the lognormal mean are not symmetric because of the skewed nature of the underlying distribution. Hence, it becomes necessary to compute separate upper and lower confidence limits. Land (1971, 1975) obtained upper one-sided $100(1-\alpha)\%$ and lower one-sided $100\alpha\%$ confidence limits for the lognormal mean:

$$(9) \qquad UL_{1-\alpha} = \exp\left(\bar{Y}+\frac{s_y^2}{2}+\frac{s_y H_{1-\alpha}}{\sqrt{n-1}}\right)$$

$$(10) \qquad LL_{\alpha} = \exp\left(\bar{Y}+\frac{s_y^2}{2}+\frac{s_y H_{\alpha}}{\sqrt{n-1}}\right)$$

The quantities $H_{1-\alpha}$ and H_{α} (functions of α, $(n-1)$ and s_y) are obtained from tables in Land (1975) for sample sizes of $n \geq 3$.

Lognormal theory cannot be applied directly to any sample which contains a zero value, since the logarithm of zero is undefined. However, one can pursue a variety of alternatives. One alternative is to add a constant c to the data before using the log transformation (the transformation $\ln(x+1)$ is commonly used). Another is to use the Δ-distribution, which may be characterized as a lognormal distribution plus a proportion Δ of zeroes; see Pennington (1983, 1985, 1986) and Smith (1988a,b). Relying solely on the Δ-distribution for catch

estimates may depend too heavily upon the assumption of underlying lognormality of the nonzero catches (Rivard 1981). Also, our data exhibit only the occasional zero catch. Other authors have had to contend with 40%-50% zeros for fish catch data; examples are given in Doubleday and Rivard (1981).

The Geometric Mean

The geometric mean, $\exp(\overline{Y})$, will clearly be a biased estimate of μ (Equation 3), but because it only involves a single parameter, may do better in terms of precision. When exponentiated, the population mean of the transformed data, (μ_{LN}), is the geometric mean (GM) catch and, equivalently, the median catch. It remains unaffected by skewness, a function of $(\exp(\sigma^2_{LN})-1)$. It is less affected by large values of X (owing to the nature of a logarithmic transformation); hence, its sampling distribution is less skewed than that for $\overline{X}$. Aitchison and Brown (1969, p. 111) note that "since the arithmetic mean involves both the location and dispersion parameters, it is not a pure measure of the [catches] under the lognormal hypothesis: for this the geometric mean is to be preferred."

Bias Correction Methods for Deriving the Mean of a Lognormal Distribution

Despite the one-to-one correspondence between data points on the transformed and untransformed scales, adjustment is required for deriving the mean and variance of one frequency distribution from the other (see Johnson 1949). Since the derived mean obtained by exponentiating the mean of the log-transformed values underestimates μ, the population mean in the untransformed scale, many authors have proposed upward adjustments to the derived mean to obtain more reliable estimates of μ. Note that many of these efforts followed the description of unbiased estimators for the lognormal (Finney 1941; Sichel 1952) and Δ-distribution (Aitchison and Brown 1969), yet are of questionable use. For this reason and because of the frequency with which some of these publications are cited today (particularly Ricker 1975 and Elliot 1977), we include a brief summary here.

Davies (1925) presented an algebraic method for estimating μ using a formula for a parabola. Bagenal (1955) noted that for hypothesis testing, it was better to perform all comparisons on the transformed values rather than risk confusion between the geometric and arithmetic means. Clark (1981) used formulas for backtransforming means on the logarithmic scale to means in the original scale by substituting estimates $\overline{Y}$ and s_y^2 for μ_{LN} and σ_{LN}^2 in Equation (3). Sichel (1952) had noted that this estimate was positively biased for smaller sample sizes whereas the Finney-Sichel maximum likelihood estimator is more accurate for any finite number of samples.

Constant correction factor. Some authors have recommended using a constant correction factor in estimating the population mean μ. Often there is little accompanying evidence as to how this constant correction factor was obtained. Barnes (1952) and Elliott (1977) recommended that 1.15 times the variance should be added to the transformed mean (base 10 logarithms) before exponentiating back. Jones (1956) made a similar recommendation with respect to survival rate estimation for natural logarithms. Ricker (1975) also used 1.15 times the variance, along with a correction for sample sizes.

Finney solution. Aitchison and Brown (1969) noted that the Finney method is equivalent to maximum likelihood "and therefore cannot be bettered"; the ψ_n function would of course be laborious to compute if tables or computing access were not available. In their book, Aitchison and Brown included tables for the "correction function" for the Finney estimate. More extensive tables are provided in Link et al. (1971); these authors claim that linear interpolation between tabled values gives close approximation for estimates of μ. They also included a FORTRAN program for the ψ_n function, which we used in computing FM, the Finney-Sichel estimate of the population mean.

Methods

Probability Distributions

Dungeness crab trawl data collected for three consecutive years from two locations in coastal Washington State were used to obtain representative values of CPUE (number/hectare) for subsequent simulations comparing the accuracy and precision of three measures of central tendency. A strong relationship between the means and standard deviations of these data (Figures 1a and 1b) suggested a logarithmic transformation (Barnes and Bagenal 1951; Thoni 1967; Elliott 1977). The Kolmogorov test for normality (Zar 1984) was applied to the CPUE data for each cruise before and after a logarithmic transformation. If catches of zero were present in the data set, the constant 1 was added to all CPUEs from a particular cruise prior to logarithmic transformation (Gaddum 1945; Barnes 1952; Zar 1984). These preliminary analyses suggested that the data were lognormally distributed (Table 2).

A single mean and standard deviation were calculated for each location using CPUE by cruise (Figures 2a, 2b and 2c) and two representative lognormal distributions were identified. These are defined as lognormal (4,2) for the coastal area and lognormal (6,1) for the adjacent estuarine area. These distributions have means of 4.0 and 6.0 and standard deviations of 2.0 and 1.0 respectively for the log-transformed variable and will, hereafter, be referred to as LOGN (4,2) and LOGN (6,1) (see Figure 3).

Monte Carlo Simulations

Monte Carlo simulations consist of calculations made on data sets whose elements are randomly selected from specified distributions. This approach permits an evaluation of various point estimation procedures on the basis of expected outcomes. For this investigation, we created 1,000 sets of simulated CPUE data for each of 13 sample sizes (2,4,6,8,10,15,20,25,30,35,40,45,50) for each of the two lognormal distributions using a

pseudo-random number generator (Minitab, Inc., University Park, PA). Sample sizes were selected to encompass the range of values associated with ongoing research trawl surveys. Tables 3 and 4 presents descriptive statistics for each of these data sets.

A "Comparative Triad" of Estimators

We investigated three methods -- referred to as a "comparative triad" -- of estimating central tendency. The "conventional" (CONV) method consists of computing ordinary sample means according to Equation (6) and traditional confidence intervals (e.g., at 90% confidence) based on the Student's t-distribution:

$$\overline{X} \pm t_{n-1} \frac{s_x}{\sqrt{n}} \tag{11}$$

where s_x = sample standard deviation of the untransformed data

t_{n-1} = tabled value from a t-distribution with $n-1$ degrees of freedom

n = number of data points in the sample.

The "lognormal" (LN) method uses the Finney-Sichel estimate for the mean of a lognormal distribution as presented in Equations (7) and (8). For confidence limits, the method by Land (1975) as presented in Equations (9) and (10) is used.

The "geometric" (GEOM) method uses $\exp(\overline{Y})$ as an estimate of $\exp(\mu_{LN})$, the geometric mean (or median) in the untransformed scale. A 90% confidence interval is derived as follows:

$$\exp\left(\overline{Y} - t_{n-1} \frac{s_y}{\sqrt{n}}\right), \quad \exp\left(\overline{Y} + t_{n-1} \frac{s_y}{\sqrt{n}}\right) . \tag{12}$$

This method estimates a different parameter (the median rather than the population mean) than the first two methods. However, because the median is only a function of a single parameter, μ_{LN}, the GEOM method tends to give more stable estimates for its parameter, and it is interesting to compare its performance (as yet another index of central tendency) to that of the first two methods.

Comparison Measures to Evaluate Performance of Estimators

We used the following measures of comparison to evaluate the performance of the estimators: root mean squared error (RMSE), deviation of estimate from true parameter (DEV), average length of 90% confidence interval (AVL), standard deviation of 90% confidence interval length (SDCI), and percent containment of parameter by the confidence interval estimate (PERCON). These were estimated as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{1000} (\text{estimated parameter from ith data set} - \text{true value})^2}{1000}} .$$

Root mean squared error is a measure of the average variation in the estimated mean relative to the true mean CPUE and, as such, is a measure of accuracy. For any unbiased estimate (where the expected value of the estimator is the parameter itself), the RMSE is the same as the variance of the estimator, in terms of expected value. Estimators with low RMSE can be expected to provide estimates of mean CPUE that combine low bias with low variance and, as such, would be more accurate and more precise.

$$DEV = \frac{\sum_{i=1}^{1000} (\text{estimated parameter from ith data set} - \text{true value})}{1000}$$

$$= (\text{average value of estimated parameter} - \text{true parameter}).$$

The deviation of the estimate from the parameter essentially measures bias (the average amount by which the estimate tends to "miss" its respective parameter).

$$AVL = \frac{\sum_{i=1}^{1000} (UL-LL)_i}{1000} = \frac{\sum_{i=1}^{1000} \text{length}_i}{1000}$$

where $(UL-LL)_i$ = length of a single 90% confidence interval for the ith data set. The average length is a measure of precision.

$$SDCI = \sqrt{\frac{\sum_{i=1}^{1000} (\text{length}_i - \text{AVL})^2}{(1000-1)}}$$

is a measure of the spread of the confidence interval lengths around the average length. An estimate that exhibited confidence intervals with relatively low variability in length might be said to be the most reproducible estimate of the precision of the estimated mean.

The frequency with which a confidence interval includes the true value of the parameter defines the containment rate. If the assumptions of sampling and the appropriateness of statistical model are met, 90% confidence intervals should contain the CPUE parameter being estimated around 90% of the time.

The three estimators of central tendency and their confidence intervals outlined previously (AM, FM, GM) were calculated for CPUE data obtained during regular trawl surveys of *C. magister* populations in coastal areas of Washington state. Survey methodology is discussed in Armstrong and Gunderson (1985) and Gunderson et al. (1990). Two large systems are considered and are hereafter referred to as Coast [LOGN (4,2)] and Estuary [LOGN (6,1)].

Results

Monte Carlo Simulations

Root mean square error

The RMSE was consistently lower for estimates of the GM than for the other measures of central tendency (Figures 4a, 4b). The LN method provid d point estimates of μ that were consistently more accurate (except at very small sample sizes) than the CONV method, particularly as skewness increased (c.f. Figure 1). The RMSE of estimates of the GM, and of μ obtained with the LN method, declined steadily as sample size increased whereas the CONV response, although generally declining, was somewhat less regular and much more erratic (see Figure 4a, n=40). Closer inspection of the LOGN (4,2) data set revealed a single extreme value out of 40,000 data points (Figure 4c) that caused a considerable increase in the RMSE associated with the AM estimate. It is noteworthy that the magnitude of this simulated CPUE-value is in keeping with extreme values observed in the field. Accuracy of GM estimation improved dramatically as skewness increased, in contrast to the FM and AM responses wherein accuracy increased as skewness decreased.

Deviation of the estimator from the parameter

Overall, the most extreme deviations were associated with the smallest sample sizes and this disparity decreased as sample sizes increased (Figures 5a, 5b). Estimates of the GM deviated less, stabilized at smaller sample sizes and, despite a persistent positive bias, converged much more predictably to the parametric value than was the case for the two estimators of μ. In general, estimates of μ oscillate about the parametric value and converge as sample size increases. The absolute values of the deviations from μ are smaller for the LN method than for the CONV method in 19 of the 26 cases examined, without an obvious trend related to the skewness of the data.

Average length of the interval estimate

The average length of the 1,000 90% confidence intervals (CIs) calculated for each sample size was consistently shorter for the GM (which only estimates one parameter) than for the two intervals calculated for μ (Figures 6a, 6b). The degree of difference between them decreased overall as sample size increased and as skewness decreased. Average lengths were inordinately large at the smallest sample sizes (and somewhat larger sample sizes for the LN method) and decreased rapidly thereafter. The average CI length for the GM decreased as skewness increased, in contrast with CI lengths for μ, which increased because of increased skewness of the data.

Standard deviation of the confidence interval length

The standard deviation of the 1,000 CIs calculated for each sample size was consistently lower for the GM than for the two intervals calculated for μ (Figures 7a, 7b). At smaller sample sizes, the standard deviations for the CONV method were lower than those for the LN method. However, this pattern was reversed at larger sample sizes such that the LN method provided the more precise interval estimate (note the crossovers at n=35 and n=25 in Figures 7a and 7b, respectively). Overall, the precision of the interval estimates declined as sample size decreased and as skewness increased; the effect was most pronounced for the LN method. Once again, however, the GM response was unique; precision increased as skewness increased. Of particular note is the dramatic loss of precision of the CONV interval estimate apparent in Figure 7a (n=40) which may be attributed to a single extreme value (Figure 4c), as before.

Parameter containment within interval estimate

The GM parameter occurred within its interval estimates, as did μ within the intervals obtained by the LN method, at the prescribed confidence level (90%; Figures 8a, 8b). The rate of GM containment oscillated within 1%-2% of this level under all circumstances. CIs generated with the LN method contained μ at the rates of 89.1%-93.6% [LOGN (6,1) data] and

89.1%-92.3% [LOGN (4,2) data]; the highest percentages were associated with the smallest sample size, perhaps due to their relatively greater lengths (Figures 6a, 6b). In contrast, interval estimates using the CONV (i.e., t-based) method contained μ at rates of only 47.7%-65.8% [LOGN (4,2) data; Figure 8a] and 76.9%-85.3% [LOGN (6,1) data; Figure 8b], well below the prescribed level of confidence.

Evaluation of Trends in Catch Data

This section concerns the application of the comparative triad of estimators to CPUE data for *C. magister* to assess the gain in information over using any single estimator alone. Trends in abundance, as measured by the three estimators of central tendency, routinely paralleled one another, differing only by their relative magnitude (Estuary; Figure 9a). Characteristically, estimates of μ obtained with the LN method exceeded those calculated in conventional fashion from survey data which, in turn, exceeded estimates of the GM parameter. From Table 2, we see that this parallel behavior of the estimates corresponds to the changing values of $\bar{Y}$ (mean of transformed data) along with little change in s_y^2 (variance of transformed data).

In some cases, trends in the estimates were diametrically opposed (Coast; Figure 9b). Note that the conventional estimates of μ suggest a precipitous drop in abundance during the interval between cruises 3 (with two extreme values) and 4 whereas both the LN and GEOM procedures indicate an increasing trend during the same period. From the nature of the three estimators, we conclude that between cruises 2 and 4, μ_{LN} may be increasing slightly, but σ_{LN}^2 (and thus the skewness of the distribution) probably increases and then decreases, affecting the LN and CONV estimates (the latter more strongly) but not the GM estimate. This is verified by checking the $\bar{y}$ and s_y^2 values in Table 2. Changes in skewness relate to the size of the larger catches when they are encountered (the greater the skewness, the larger the big catches); such information is of value to the fishery manager. Plotting the results of the comparative triad has allowed us to extract more information, easily and graphically, about the fishery than using only one estimator from the triad.

Discussion

Research trawl surveys must consider carefully the biology of the species when sampling. Furthermore, it is imperative that subsequent analyses address the influence of the biology on the data properties if reliable abundance estimates are to be obtained. Failure to do so may introduce further error into the estimation process and contribute to false conclusions concerning trends in abundance. This could jeopardize the renewable nature of fishery resources.

Conventional population estimates are generated using untransformed catch data and arithmetic mean calculations (BIOMASS: Gunderson et al. 1978; STRAP: Smith and Somerton 1981; Forest and Minet 1981). Standard formulas are used to calculate stratified means and variances (see Cochran 1977); confidence intervals are calculated with the t-distribution (Equation 11). These procedures are entirely appropriate for normally distributed means, but the sampling distributions for the sample means may be more right skewed than expected under the usual "invocation" of the Central Limit Theorem.

The Phenomenon of Overdispersion

As has been previously discussed, the spatial distributions of marine biota are frequently patchy. It is unlikely that overdispersion is an artifact of sampling; aggregated distributions may be attributed to the proportional, rather than linear, nature of biological responses (Bartlett 1947; Crisp 1974). Overdispersion of adults may reflect processes acting throughout the life history that tend to maintain aggregations in response to selective forces. Aggregations that originate during the release of eggs (Silliman 1946; Picquelle and Stauffer 1985; Smith and Hewitt 1985) or larvae (Scarratt 1964; Zweifel and Smith 1981; Reilly 1983; Fogarty and Idoine 1986; Harding et al. 1987) are often maintained, or regenerated, during the subsequent postlarval and juvenile stages (Miller 1975; Armstrong et al. 1985; Booth et al. 1985; Staples and Vance 1985; Incze et al. 1986; MacDonald 1986). This may be attributed to features of the circulation (Harding et al. 1982; Cobb et al. 1983; Hatfield 1983; Reilly 1983; Hamner and Schneider 1986; Epifanio 1987;

Jamieson et al. 1989) or common behavioral responses to exogenous stimuli (Powell and Nickerson 1965; Crisp 1974; Strathmann 1974; Rice and Kristensen 1982; Zeldis and Jillett 1982; Epifanio et al. 1984; Sulkin 1984). Significant adaptive value may be associated with this spatial pattern, particularly among sessile organisms, which rely on external fertilization, and those species which school to minimize predation.

Properties of Skewed Catch Data

If individuals comprising the population are overdispersed, the frequency distribution of catches (and mean catches) from random (trawl) samples will be markedly skewed. Data sets will be characterized by catches which are mostly small, relative to the population mean, and a few that are very large; densities within aggregations can be orders of magnitude greater than the average value (Omori and Hamner 1982; this study). Following a logarithmic transformation, catch data from research trawl surveys will often conform with normal probability theory (Silliman 1946; Forest and Minet 1981; Pitt et al. 1981; Smith and Walters 1982; Booth et al. 1985; Peterman and Bradford 1987; Table 2, this study; and others).

Recall that the population mean of lognormal data incorporates both the location and dispersion parameters (Equation 3). Under these circumstances, sample averages may not provide good estimates of true mean values for the population in question and variances about point estimates may be excessively large (results from Figures 4a, 5a, 6a, 7a, 8a, 8b). However, when calculations are performed on the transformed data, full use may be made of the properties of the underlying normal distribution, and the manner that μ_{LN} and σ^2_{LN} for the transformed data relate to μ for the original data (Equation 3).

Conventional Analysis of Catch Data

Conventional analysis of catch data may be inappropriate if the underlying probability distribution is highly skewed. Furthermore, sample sizes are often too small to justify procedures based on the Central Limit Theorem (see Sissenwine 1978). Conclusions reached

using these methods may be invalid. A variety of procedures have been considered as alternatives (Sissenwine 1978; Smith 1988b; Zweifel and Smith 1981; Pennington 1983; Conan 1985; Kimura and Balsiger 1985), although none has emerged as a widely accepted standard for the fisheries discipline.

Several ad hoc methods exist for reducing the variance associated with estimates of mean abundance despite recognizable limitations. Catch data are commonly stratified after sampling is completed (Picquelle and Stauffer 1985; Otto 1986). But post-stratification that is based upon seeing the data first to determine strata is not a valid way to proceed and is not recommended. Other methods are expedient yet may be based on the specious assumption that extreme values are "outliers" and are therefore not integral to the data set. Included is the practice of eliminating extreme values or the use of trimmed (or Winsorized) means (Halliday and Koeller 1981; Bates 1987; Harding et al. 1987; Smith 1988b). Ignoring instances where human error is involved, these procedures may introduce substantial negative bias to estimates of the true population mean (e.g., Table 3) thereby contributing to misleading conclusions about trends in the data.

Uncertainty about population parameters is commonly ignored (Rivard 1981; Jamieson 1986), despite potentially serious repercussions (Ludwig and Walters 1981). Although rarely used on a stand-alone basis, these estimates are a key component of production models and may thus confound management efforts. For example, it has been demonstrated that catch projections are particularly sensitive to systematic biases/error for stock size (Rivard 1981).

Redefining the Sampling Frame

Gavaris and Smith (1987) have demonstrated that modifying the sampling frame for the eastern Scotian Shelf groundfish survey enables substantial reductions in variance. They report that the precision of abundance estimates obtained with stratified random sampling is inferior to that from a simple random design, owing to suboptimal allocation of stations to strata. They go on to suggest a decrease in the number of strata as a solution, so as to provide for more flexible

allocation of total sampling effort. However, many of the problems attendant with specifying stratum boundaries will persist (i.e., interannual variability in distribution and abundance of stocks related to environmental factors and the typical multi-species scope of research trawl surveys).

The Comparative Triad

Unbiased and efficient estimators of the population average are needed to adequately assess the abundance of overdispersed fishery resources and manage them effectively. Improved estimates of mean abundance are obtained when a logarithmic transformation normalizes catch data (Finney 1941; Sichel 1952; this study; Thoni [1967] reviews analogous bias corrections for other probability distributions). However, data transformation is a "double-edged sword" and should not be applied indiscriminately (Koch and Link 1970; Link et al. 1971). For these reasons, coupled with the rather ubiquitous nature of overdispersion in the marine environment, we propose an approach based on a triad of comparative estimators, namely the (conventional) arithmetic mean, the geometric mean, and the Finney-Sichel estimator of μ. By taking this comparative approach, one may be reasonably certain of apparent trends in the data when the pattern is consistent for the three estimators (e.g., Figure 9a). However, should there be significant disagreement among the three estimators (e.g., Figure 9b), the data set should be carefully evaluated as to its underlying probability distribution and the most appropriate index selected. Such comparisons are not unprecedented in the fisheries literature: Pitt et al. (1981) made direct comparisons between the conventional method and the GEOM approach, which revealed an opposing trend in abundance during one of the years investigated (c.f. our Figure 9b). They also concluded that mortalities at age for redfish stocks, which had been calculated from sample means, may be excessively high.

It is commonly recognized that stock size estimates are rarely better than indices of abundance since catchability coefficients are not routinely considered (Anonymous 1981; Caddy 1986). Harvest levels for the fishery are set by applying a target exploitation rate (often a fixed percentage; Otto 1986) to this stock size index. In instances where the lognormal distribution is

reasonable, it is interesting to speculate whether an analogous rate could be determined for a population estimate derived from the geometric mean, given its greater accuracy (Figures 4a, 4b, 5a, 5b) and higher precision (Figures 6a, 6b, 7a, 7b) relative to estimates of μ. The geometric mean is relatively insensitive to extreme values (Figures 4a and 4c) and, at times, may well be the preferred estimator (Aitchison and Brown 1969, p. 111). Given the assumptions that samples are randomly taken from the population (Sissenwine 1978) and that sample size adequately reflects the dispersion of the population (Leaman 1981), calculating other dynamic population parameters, such as mortality rates, using a GM-based CPUE index of abundance may also be reasonable.

Summary

Estimates of stock abundance based on research trawl surveys must be reliable if management of a fishery resource is to be effective. However, these estimates are frequently inadequate, reflecting, at least in part, the overdispersed nature of the population. Analytical methods currently in use may be inconsistent with certain aspects of the biology of the species (particularly spatial characteristics) and, thus, fundamental attributes of the data. In view of the pervasive pattern of overdispersion among marine biota and the statistical ramifications demonstrated herein, we suggest that the sole use of the conventional estimator of relative abundance (the AM) may not be prudent. We recommend that the abundance of overdispersed stocks be apprised using the geometric mean and the "comparative triad" approach described herein. This approach may provide a sounder basis for discerning potentially false indicators of abundance while contributing important information for the management of commercially important stocks. The data sets used for the Monte Carlo simulations are archived on magnetic tapes and copies may be obtained from the authors. We encourage communication concerning this issue and further analysis of statistical properties of the lognormal estimators, such as robustness.

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References

AITCHISON, J., AND J.A.C. BROWN. 1969. The lognormal distribution, with special reference to its uses in economics. University Press, Cambridge 176 p.

ALVERSON, D.L., AND W.T. PEREYRA. 1969. Demersal fish explorations in the northeastern Pacific Ocean - an evaluation of exploratory fishing methods and analytical approaches to stock size and yield forecasts. J. Fish. Res. Bd. Canada 26: 1985-2001.

ANONYMOUS. 1981. Workshop report, p. 7-19. *In* W. G. Doubleday and D. Rivard [ed.] Bottom trawl surveys. Can. Spec. Publ. Fish. Aquat. Sci. 58: 7-19.

ARMETTA, T.M., AND B.G. STEVENS. 1987. Aspects of the biology of the hair crab, *Erimacrus isenbeckii*, in the eastern Bering Sea. Fish. Bull., U.S. 85: 523-545.

ARMSTRONG, D.A., AND D.R. GUNDERSON. 1985. The role of estuaries in Dungeness crab early life history: a case study in Grays Harbor, Washington, p. 145-170. *In* B.R. Melteff [symp. coord.] Proceedings of the symposium on Dungeness crab biology and management. Alaska Sea Grant Prog. Rept. No. 85-3, Univ. of Alaska, Anchorage.

ARMSTRONG, D.A., J.L. ARMSTRONG, R. PALACIOS, G. WILLIAMS, G.C. JENSEN AND W. PEARSON. 1985. Early life history of juvenile blue king crab, *Paralithodes platypus*, around the Pribilof Islands, p. 211-229. *In* B.R. Melteff [symp. coord.] Proceedings of the international king crab symposium. Univ. of Alaska Sea Grant Prog. Rep. No. 85-12, Univ. of Alaska, Anchorage.

AZAROVITZ, T.R. 1981. A brief historical review of the Woods Hole Laboratory trawl survey time series, p. 62-67. *In* W.G. Doubleday and D. Rivard [ed.] Bottom trawl surveys. Can. Spec. Publ. Fish. Aquat. Sci. 58.

BAGENAL, M. 1955. A note on the relations of certain parameters following a logarithmic transformation. J. Mar. Biol. Ass. U.K. 34: 289-296.

BAHAMONDE, N., G. HENRIQUEZ, A. ZULETA, H. BUSTOS AND R. BAHAMONDE. 1986. Population dynamics and fisheries of squat lobsters, family Galatheidae, in Chile, p. 254-268. *In* G.S. Jamieson and N. Bourne [ed.] North Pacific workshop on stock assessment and management of invertebrates. Can. Spec. Publ. Fish. Aquat. Sci. 92.

BARNES, H. 1952. The use of transformations in marine biological statistics. J. Cons. Explor. Mer 18: 61-71.

BARNES, H., AND T.B. BAGENAL. 1951. A statistical study of variability in catch obtained by short repeated trawls taken over an inshore ground. J. Mar. Biol. Assoc. U.K. 29: 649-660.

BARTLETT, M.S. 1947. The use of transformations. Biometrics 3: 39-52.

BATES, R.D. 1987. Estimation of egg production, spawner biomass and egg mortality for walleye pollock, *Theragra chalcogramma*, in Shelikof Strait from ichthyoplankton surveys during 1981. NWAFC Proc. Rept. 87-20, Nat. Mar. Fish. Serv., Seattle. 192 p.

BERTUCHE, D.A., J.G. WYNGAARD AND E.E. BOSCHI. 1985. The fishery biology of Beagle Channel king crab (*Lithodes antarcticus*), p. 293-318. *In* B.R. Melteff [symp. coord.] Proceedings of the international king crab symposium. Univ. of Alaska Sea Grant Prog. Rep. No. 85-12, Univ. of Alaska, Anchorage.

BOOTH, J., A. PHILLIPS AND G.S. JAMIESON. 1985. Fine scale spatial distribution of *Cancer magister* megalopae and its relevance to sampling methodology, p. 273-286. *In* B.R. Melteff [symp. coord.] Proceedings of the symposium on Dungeness crab biology and management. Alaska Sea Grant Prog. Rep. No. 85-3, Univ. of Alaska, Anchorage.

BRADU, D., AND Y. MUNDLAK. 1970. Estimation in lognormal linear models. J. Amer. Statist. Soc. 65: 198-211.

BROWN, I.W. 1986. South Queensland spanner crabs: a growing fishery. Australian Fish. 45: 3-7.

CADDY, J.F. 1986. Stock assessment in data limited situations: the experience in tropical fisheries and its possible relevance to evaluation of invertebrate resources, p. 379-392. *In* G.S. Jamieson and N. Bourne [ed.] North Pacific workshop on stock assessment and management of invertebrates. Can. Spec. Publ. Fish. Aquat. Sci. 92.

CLARK, S.H. 1981. Use of trawl data in assessments, p. 82-92. *In* W.G. Doubleday and D. Rivard [ed.] Bottom trawl surveys. Can. Spec. Publ. Fish. Aquat. Sci. 58.

COBB, J.S., T. GULBRANSEN, B.F. PHILLIPS, D. WANG AND M. SYSLO. 1983. Behavior and distribution of larval and early juvenile *Homarus americanus*. Can. J. Fish. Aquat. Sci. 40: 2184-2188.

COCHRAN, W.G. 1977. Sampling techniques. John Wiley and Sons, Inc., N.Y. 428 p.

CONAN, G.Y. 1985. Assessment of shellfish stocks by geostatistical techniques. Intern. Coun. Explor. Sea Publ. No. ICES C.M./K. 30: 24 p.

CRISP, D.J. 1974. Factors influencing the settlement of marine invertebrate larvae, p. 177-265. *In* P.T. Grant and A.M. Mackie [ed.] Chemoreception in marine organisms. Academic Press, N.Y.

DAVIES, G.R. 1925. The logarithmic curve of distribution. J. Amer. Statist. Soc. 152: 467-480.

DOUBLEDAY, W.G., AND D. RIVARD [ed.] 1981. Bottom trawl surveys. Can. Spec. Publ. Fish. Aquat. Sci. 58. 273 p.

ELLIOTT, J.M. 1977. Statistical analysis of samples of benthic invertebrates. Freshwater Biol. Assoc. Sci. Publ. No. 25. 157 pp.

ELNER, R.W., AND R.F.J. BAILEY. 1986. Differential susceptibility of Atlantic snow crab, *Chionoecetes opilio*, stocks to management, p. 335-346. *In* G.S. Jamieson and N. Bourne [ed.] North Pacific workshop on stock assessment and management of invertebrates. Can. Spec. Publ. Fish. Aquat. Sci. 92.

EPIFANIO, C.E. 1987. The role of tidal fronts in maintaining patches of brachyuran zoeae in estuarine waters. J. Crustacean Biol. 7(3): 513-517.

EPIFANIO, C.E., C.C. VALENTI AND A.E. PEMBROKE. 1984. Dispersal and recruitment of blue crab larvae in Delaware Bay, U.S.A. Estuarine Coastal Shelf Sci. 18: 1-12.

FINNEY, D.J. 1941. On the distribution of a variate whose logarithm is normally distributed. J. Roy. Stat. Soc. Suppl. 7: 155-161.

FOGARTY, M.J., AND J.S. IDOINE. 1986. Recruitment dynamics in an American lobster (*Homarus americanus*) population. Can. J. Fish. Aquat. Sci. 43: 2368-2376.

FOREST, A., AND J.P. MINET. 1981. Abundance estimates of the trawlable resources around the islands of Saint-Pierre and Miquelon (NAFO subdiv. 3Ps): methods used during the French research surveys and discussion of some results, p. 68-81. *In* W.G. Doubleday and D. Rivard [ed.] Bottom trawl surveys. Can. Spec. Publ. Fish. Aquat. Sci. 58

GADDUM, J.H. 1945. Lognormal distributions. Nature 156: 463-466.

GARCIA, S., AND L. LERESTE. 1981. Life cycles, dynamics, exploitation and management of coastal penaeid shrimp stocks. FAO Fish. Tech. Paper 203. 223 p.

GAVARIS, S., AND S.J. SMITH. 1987. Effect of allocation and statification strategies on precision of survey abundance estimates for Atlantic cod (*Gadus morhua*) on the eastern Scotian Shelf. J. Northw. Atl. Fish. Sci. 7: 137-144.

GILBERT, R.O. 1987. Statistical methods for environmental pollution monitoring. Van Nostrand Reinhold Co., N.Y. 320 p.

GOTSHALL, D.W. 1978. Relative abundance studies of Dungeness crabs, *Cancer magister*, in northern California. Calif. Fish Game 64: 24-37.

GUNDERSON, D., D. WORLUND AND B. GIBBS. 1978. Users guide to BMS09: estimation of biomass and population size by the area-swept method. NWAFC internal doc., Nat. Mar. Fish. Serv., Seattle. 23 p.

GUNDERSON, D.G., D.A. ARMSTRONG, Y. SHI AND R.A. MCCONNAUGHEY. 1990. Patterns of estuarine use by juvenile English sole (*Parophrys vetulus*) and Dungeness crab (*Cancer magister*). Estuaries 13 (in press).

HALLIDAY, R.G., AND P.A. KOELLER. 1981. A history of Canadian groundfish trawling surveys and data usage in ICNAF divisions 4TVWX, p. 27-41. *In* W.G. Doubleday and D. Rivard [ed.] Bottom trawl surveys. Can. Spec. Publ. Fish. Aquat. Sci. 58.

HAMNER, W.H., AND D. SCHNEIDER. 1986. Regularly spaced rows of medusae in the Bering Sea: role of Langmuir circulation. Limnol. Oceanogr. 31: 171-177.

HARDING, G.C., J.D. PRINGLE, W.P. VASS, S. PEARRE, JR., and S.J. SMITH. 1987. Vertical distribution and daily movements of larval lobsters *Homarus americanus* over Browns Bank, Nova Scotia. Mar. Ecol. Prog. Ser. 41: 29-41.

HARDING, G.C., W.P. VASS AND K.F. DRINKWATER. 1982. Aspects of larval American lobster (*Homarus americanus*) ecology in St. Georges Bay, Nova Scotia. Can. J. Fish. Aquat. Sci. 39: 1117-1129.

HATFIELD, S.E. 1983. Intermolt staging and distribution of Dungeness crab, *Cancer magister*, megalopae, p. 85-96. *In* P.W. Wild and R.N. Tasto [ed.] Life history, environment, and mariculture studies of the Dungeness crab, *Cancer magister*, with emphasis on the central California fishery resource. Calif. Dep. Fish Game Fish Bull. 172.

HAYES, M.L. 1983. Variation in the abundance of crab and shrimp with some hypotheses on its relationship to environmental causes, p. 86-101. *In* W. Wooster [ed.] From year to year: interannual variability of the environment and fisheries of the Gulf of Alaska and the eastern Bering Sea. Washington Sea Grant Prog. Publ. No. WSG-WO-83-3. Univ. of Wash., Seattle.

HERMANN, A.J., B.M. HICKEY, M.R. LANDRY AND D.F. WINTER. 1989. Coastal upwelling dynamics, p. 211-253. *In* B.M. Hickey and M.R. Landry [ed.] Coastal oceanography of the Pacific Northwest. Elsevier, New York.

INCZE, L.S., R.S. OTTO AND M.K. MCDOWELL. 1986. Recruitment variability of juvenile red king crab, *Paralithodes camtschatika*, in the southeastern Bering Sea, p. 370-378. *In* G.S. Jamieson and N. Bourne [ed.] North Pacific workshop on stock assessment and management of invertebrates. Can. Spec. Publ. Fish. Aquat. Sci. 92.

JAHN, A.E. 1987. Precision of estimates of abundance of coastal fish larvae. Amer. Fish. Soc. Symp. 2: 30-38.

JAMIESON, G.S. 1986. A perspective on invertebrate fisheries management - the British Columbia experience, p. 57-74. *In* G.S. Jamieson and N. Bourne [ed.] North Pacific workshop on stock assessment and management of invertebrates. Can. Spec. Publ. Fish. Aquat. Sci. 92.

JAMIESON, G.S., A.C. PHILLIPS, AND W.S. Huggett. 1989. Effects of ocean variability on the abundance of Dungeness crab (*Cancer magister*) megalopae. *In* R.J. Beamish and G.A. McFarlane [ed.] Effects of ocean variability on recruitment and evaluation of parameters used in stock assessment models. Can. Spec. Publ. Fish. Aquat. Sci. 108.

JOHNSON, N.L. 1949. Systems of frequency curves generated by methods of translation. Biometrika 36: 149-176.

JONES, R. 1956. The analysis of trawl haul statistics with particular reference to the estimation of survival rates. Cons. Perm. Intern. Explor. Mer, Rapp. P.-v. Reun. 140: 30-39.

KIMURA, D.K. AND J.W. BALSIGER. 1985. Bootstrap methods for evaluating sablefish pot index surveys. N. Am. J. Fish. Manage. 5: 47-56.

KOCH, G.S., Jr., AND R.F. LINK. 1980. Statistical analysis of geological data. John Wiley and Sons, Inc, N.Y.

LAND, C.E. 1971. Confidence intervals for linear functions of the normal mean and variance. Ann. Math. Statist. 42: 1187-1205.

LAND, C.E. 1975. Tables of confidence limits for linear functions of the normal mean and variance. Sel. Tables Math. Statist. 3: 385-419.

LEAMAN, B.M. 1981. A brief review of survey methodology with regard to groundfish stock assessment, p. 113-123. *In* W.G. Doubleday and D. Rivard [ed.] Bottom trawl surveys. Can. Spec. Publ. Fish. Aquat. Sci. 58.

LINDGREN, B.W. 1968. Statistical theory. MacMillan Co., New York. 521 p.

LINK, R.F., G.S. KOCH, JR., AND J.H. SCHUENEMEYER. 1971. Statistical analysis of gold assay and other trace-element data. U.S. Bur. Mines Rept. Investig. 7495. 127 p.

LUDWIG, D., AND C.J. WALTERS. 1981. Measurement errors and uncertainty in parameter estimates for stock and recruitment. Can. J. Fish. Aquat. Sci. 38: 711-720.

MACDONALD, C. 1986. Recruitment of the puerulus of the spiny lobster, *Panulirus marginatus*, in Hawaii. Can. J. Fish. Aquat. Sci. 43: 2118-2125.

MCCABE, G.T., JR., R.L. EMMETT, T.C. COLEY AND R.J. MCCONNELL. 1986. Distribution, abundance and size-class structure of Dungeness crabs in the Columbia River estuary. Final Rep. to U.S. Army Corps of Engineers. Nat. Mar. Fish. Serv., Northw. Alaska Fish. Ctr., Seattle. 57 p.

MILLER, R.J. 1975. Density of the commercial spider crab, *Chionoecetes opilio*, and calibration of effective area fished using bottom photography. J. Fish. Res. Bd. Canada 32: 761-768.

OMORI, M., AND W.H. HAMNER. 1982. Patchy distributions of zooplankton: population assessment and sampling problems. Mar. Biol. (Berl.) 72: 193-200.

OTTO, R.S. 1986. Management and assessment of eastern Bering Sea king crab stocks, p. 83-106. *In* G.S. Jamieson and N. Bourne [ed.] North Pacific workshop on stock assessment and management of invertebrates. Can. Spec. Publ. Fish. Aquat. Sci. 92.

PARSONS, D.G., AND E.J. SANDEMAN. 1981. Groundfish survey techniques as applied to abundance surveys for shrimp, p. 124-146. *In* W.G. Doubleday and D. Rivard [ed.] Bottom trawl surveys. Can. Spec. Publ. Fish. Aquat. Sci. 58.

PENNINGTON, M. 1983. Efficient estimators of abundance for fish and plankton surveys. Biometrics 39: 281-286.

PENNINGTON, M. 1985. Estimating the relative abundance of fish from a series of trawl surveys. Biometrics 41: 197-202.

PENNINGTON, M. 1986. Some statistical techniques for estimating abundance indices from trawl surveys. Fish. Bull. (U.S.) 84: 519-525.

PETERMAN, R.M., AND M.J. BRADFORD. 1987. Statistical power of trends in fish abundance. Can. J. Fish. Aquat. Sci. 44: 1879-1889.

PICQUELLE, S. AND G. STAUFFER. 1985. Parameter estimation for an egg production method of northern anchovy biomass estimation, p. 7-15. *In* R. Lasker [ed.] An egg production method for estimating spawning biomass of pelagic fish: application to the northern anchovy, *Engraulis mordax*. NOAA Tech. Rep. NMFS 36.

PITT, T.K., R. WELLS AND W.D. MCKONE. 1981. A critique of research vessel otter trawl surveys by the St. John's Research and Resource Service, p. 42-61. *In* W.G. Doubleday and D. Rivard [ed.] Bottom trawl surveys. Can. Spec. Publ. Fish. Aquat. Sci. 58.

POWELL, G. AND R. NICKERSON. 1965. Aggregations among juvenile king crabs, *Paralithodes camtschatika*, Kodiak, Alaska. Animal Behav. 13: 374-380.

REILLY, P.N. 1983. Dynamics of Dungeness crab, *Cancer magister*, larvae off central and northern California, p. 57-84. *In* P.W. Wild and R.N. Tasto [ed.] Life history, environment and mariculture studies of the Dungeness crab, *Cancer magister*, with emphasis on the central California fishery resource. Calif. Dep. Fish Game Fish. Bull. 172.

RICE, A.L., AND I. KRISTENSEN. 1982. Surface swarms of swimming crab megalopae at Curacao (Decapoda, Brachyura). Crustaceana 42: 233-240.

RICKER, W.E. 1975. Computation and interpretation of biological statistics of fish populations. Fish. Res. Bd. Can. Bull. 191. 382 p.

RIVARD, D. 1981. Catch projections and their relation to sampling error of research surveys, p. 93-109. *In* W.G. Doubleday and D. Rivard [ed.] Bottom trawl surveys. Can. Spec. Publ. Fish. Aquat. Sci. 58.

ROBERT, G., AND JAMIESON, G.S. 1986. Commercial fishery data isopleths and their use in offshore sea scallop (*Placopecten magellanicus*) stock evaluation, p. 76-82. *In* G.S. Jamieson and N. Bourne [ed.] North Pacific workshop on stock assessment and management of invertebrates. Can. Spec. Publ. Fish. Aquat. Sci. 92.

SCARRATT, D.J. 1964. Abundance and distribution of lobster larvae (*Homarus americanus*) in Northumberland Strait. J. Fish. Res. Bd. Canada 21: 661-680.

SICHEL, H.S. 1952. New methods in the statistical evaluation of mine sampling data. Trans. Inst. Mining Metal. (London) 61: 261-288.

SILLIMAN, R.P. 1946. A study of variability in plankton townet catches of Pacific pilchard, *Sardinops caerulea* eggs. J. Mar. Res. 6: 74-83.

SINODA, M. AND T. KOBAYASHI. 1982. Some effects of long-term exploitation of *Chionoectetes opilio* stocks in the southwest Japan Sea, p. 421-441. *In* B.R. Melteff [symp. coord.] Proceedings of the international symposium on the genus *Chionoecetes*. Alaska Sea Grant Prog. Rep. No. 82-10, Univ. of Alaska, Anchorage.

SISSENWINE, M.P. 1978. Using the USA research vessel spring bottom trawl survey as an index of Atlantic mackeral abundance. Intern. Comm. Northw. Atl. Fish. Sel. Pap. 3: 49-55.

SMITH, G.B. AND G.E. WALTERS. 1982. Relationships between crab and groundfish in the eastern Bering Sea, p. 581-614. *In* B.R. Melteff [symp. coord.] Proceedings of the international symposium on the genus *Chionoecetes*. Alaska Sea Grant Prog. Rep. No. 82-10, Univ. of Alaska, Anchorage.

SMITH, P.E., AND R.P. HEWITT. 1985. Sea survey design and analysis for an egg production method of anchovy biomass assessment, p. 17-26. *In* R. Lasker [ed.] An egg production method for estimating spawning biomass of pelagic fish: application to the northern anchovy, *Engraulis mordax*. NOAA Tech. Rep. NMFS 36.

SMITH, S.J. 1988a. Abundance indices from research survey data, p. 16-43. *In* D. Rivard [ed.] Collected papers on stock assessment methods. Can. Atl. Fish. Sci. Advis. Comm. Res. Doc. 88/61.

SMITH, S. J. 1988b. Evaluating the efficiency of the Δ-distribution mean estimator. Biometrics 44: 485-493.

SMITH, S.J., AND G.D. SOMERTON. 1981. STRAP: a user-oriented computer analysis system for groundfish research trawl survey data. Can. Tech. Rep. Fish. Aquat. Sci. No. 1030. 66 p.

STAPLES, D.L., AND D.J. VANCE. 1985. Short-term and long-term influences on the immigration of postlarval banana prawns *Penaeus merguiensis*, into a mangrove estuary of the Gulf of Carpentaria, Australia. Mar. Ecol. Prog. Ser. 23: 15-29.

STRATHMANN, R. 1974. The spread of sibling larvae of sedentary marine invertebrates. Amer. Nat. 108: 29-44.

SULKIN, S.D. 1984. Behavioral basis of depth regulation in the larvae of brachyuran crabs. Mar. Ecol. Prog. Ser. 15: 181-205.

THONI, H. 1967. Transformations of variables used in the analysis of experimental and observational data: a review. Tech. Rept. No. 7, Stat. Lab., Iowa State Univ., Ames. 61 p.

WINSOR, C.P., AND G.L. CLARKE. 1940. A statistical study of variation in the catch of plankton nets. J. Mar. Res. 3: 1-34.

ZAR, J.H. 1984. Biostatistical analysis. Prentice-Hall, Inc., Englewood Cliffs. 718 p.

ZELDIS, J.R., AND J.B. JILLETT. 1982. Aggregation of pelagic *Munida gregaria* (Fabricus) (Decapoda, Anomura) by coastal fronts and internal waves. J. Plankton Res. 4: 839-857.

ZWEIFEL, J.R., AND P.E. SMITH. 1981. Estimates of abundance and mortality of larval anchovies (1951-75): application of a new method. Rapp. P.-v. Reun. Cons. int. Explor. Mer 178: 248-259.

Table 1. Notation

	Untransformed	Log Transformed
ith Observation	X_i	Y_i
Average Value		
Sample	$\bar{X} = AM$	$\bar{Y}$
Population	μ	μ_{LN}
Variance		
Sample	s_X^2	s_Y^2
Population	σ^2	σ_{LN}^2

Table 2.

Results of Kolmogorov Test for Normality

	Goodness-of-Fit Probability									
	Coast					Estuary				
Cruise	n	CPUE*	LOG**	Mean (LOG)	Variance (LOG)	n	CPUE	LOG	Mean (LOG)	Variance (LOG)
1	35	.006	1.000	4.20	5.54	20	.156	1.000	6.33	1.43
2	41	.000	1.000	4.65	6.25	20	.110	1.000	6.21	1.24
3	42	.000	1.000	4.96	8.03	20	1.000	1.000	6.27	.43
4	38	.000	1.000	6.63	4.69	20	.169	.394	5.96	.61
5	42	.000	1.000	5.31	5.09	20	.205	.999	5.73	.31
6	44	.025	.328	3.32	3.84	16	.373	.411	4.90	2.94
7	40	.113	.242	3.09	2.98	20	.004	.418	6.04	1.47
8	43	.004	1.000	3.59	2.45	20	.088	1.000	5.64	1.48
9	44	.000	.164	2.91	4.34	20	.013	.999	5.66	1.89
10	43	.016	.528	3.90	3.16	20	.140	1.000	5.44	.93
11	44	.017	.102	3.16	4.39	20	.172	1.000	4.62	1.39
12	44	.002	1.000	3.62	3.75	20	.129	1.000	5.81	1.03
13	44	.000	1.000	4.57	4.66	20	.435	1.000	6.61	1.08
14	44	.000	.522	3.87	6.15	20	.311	1.000	5.92	1.13
15	44	.000	.306	5.05	4.85	20	.336	1.000	6.41	1.22

* P-value for CPUEs of untransformed data.

** P-value for CPUEs of log-transformed data.

Table 3a.

Descriptive Statistics for 1,000 Simulated Trawl Data Sets

[Lognormal (4 2)]

	Arithmetic Mean		Trimmed Mean		Standard Deviation			
n	CPUE*	LOG**	CPUE	LOG	CPUE	LOG	Minimum	Maximum
2	431	4.104	192	4.106	1,949	2.026	0	48,860
4	382	4.003	163	4.004	1,714	1.999	0	64,248
6	398	3.987	162	3.988	1,946	2.007	0	62,131
8	370	3.985	157	3.984	1,818	1.982	0	71,789
10	386	4.001	161	4.002	1,964	1.996	0	110,761
15	378	4.002	163	4.007	1,723	2.002	0	82,492
20	391	4.004	162	4.003	1,920	1.997	0	122,967
25	394	3.999	159	4.002	2,313	1.991	0	160,546
30	407	4.002	161	4.004	2,603	2.000	0	236,341
35	422	4.016	162	4.015	3,301	1.992	0	380,743
40	419	3.999	161	3.999	7,609	1.997	0	1,479,353
45	397	3.989	162	3.989	2,167	2.010	0	226,970
50	411	4.003	163	4.003	2.525	2.008	0	323,734

Results are given in integer values for untransformed data.

True value of μ is 403.43.

* CPUE for untransformed data.

** CPUE for log-transformed data.

Table 3b.

Descriptive Statistics for 1,000 Simulated Trawl Data Sets

[Lognormal (6 1)]

	Arithmetic Mean		Trimmed Mean		Standard Deviation			
n	CPUE*	LOG**	CPUE	LOG	CPUE	LOG	Minimum	Maximum
2	633	5.968	528	5.971	739	.994	10	5,703
4	676	6.007	552	6.007	860	1.012	10	10,525
6	682	6.026	557	6.024	924	.993	11	24,259
8	690	6.010	553	6.006	955	1.016	12	20,499
10	659	5.993	541	5.995	835	1.004	6	13,333
15	650	5.986	537	5.986	816	.993	12	18,877
20	655	5.992	538	5.993	825	.998	8	13,756
25	667	6.000	544	5.999	868	1.003	4	19,785
30	664	5.995	543	5.995	857	1.004	5	21,060
35	664	5.999	541	5.998	901	.995	7	30,309
40	657	5.996	540	5.995	844	.993	9	20,555
45	666	6.004	547	6.004	869	.997	6	30,655
50	664	6.001	544	6.002	856	.998	7	18,725

Results are given in integer values for untransformed data.

True value of μ is 665.14.

* CPUE for untransformed data.

** CPUE for log-transformed data.

Figure Legends

Figure 1. Simple linear regression between mean and standard deviation of untransformed catch data from (a) coastal area and (b) the estuarine area.

Figure 2. Histogram of log transformed catch data from coastal and estuarine areas for year 1 (a), year 2 (b) and year 3 (c) with superimposed best-fit normal curve. ($\ln(x+1)$ transformation used for data sets containing zero.)

Figure 3. Probability density functions for the representative lognormal distributions.

Figure 4. Comparison of root mean square error values associated with the three estimators of central tendency according to sample size. (a) LOGN (4,2) data representative of coastal population used for Monte Carlo simulations. See text for outlier explanation. (b) LOGN (6,1) data representative of estuarine population used for Monte Carlo simulations. (c) Histogram of 1,000 sets of LOGN (4,2) data with sample size of 40 used for Monte Carlo simulations.

Figure 5. Comparison of the degree of deviation from the parameter (scaled to 0) for the three estimators of central tendency according to sample size. (a) LOGN (4,2) data representative of coastal population used for Monte Carlo simulations. (b) LOGN (6,1) data representative of estuarine population used for Monte Carlo simulations.

Figure 6. Comparison of the average length of 90% confidence interval for the three estimators of central tendency according to sample size. Dashed lines indicate off-scale values. (a) LOGN (4,2) data representative of coastal population used for Monte Carlo simulations. (b) LOGN (6,1) data representative of coastal population used for Monte Carlo simulations.

Figure 7. Comparison of the standard deviation of the length of 90% confidence interval for the three estimators of central tendency according to sample size.

Dashed lines indicate off-scale values. (a) LOGN (4,2) data representative of coastal population used for Monte Carlo simulations. (b) LOGN (6,1) data representative of estuarine population used for Monte Carlo simulations.

Figure 8. Comparison of the percent occurrence of the parameter in the 90% confidence interval for the three estimators of central tendency according to sample size. (a) LOGN (4,2) data representative of coastal population used for Monte Carlo simulations. (b) LOGN (6,1) data representative of estuarine population used for Monte Carlo simulations.

Figure 9. Comparison of values for the three measures of central tendency calculated using actual trawl data for 1 year from (a) the estuarine area and (b) the coastal area.

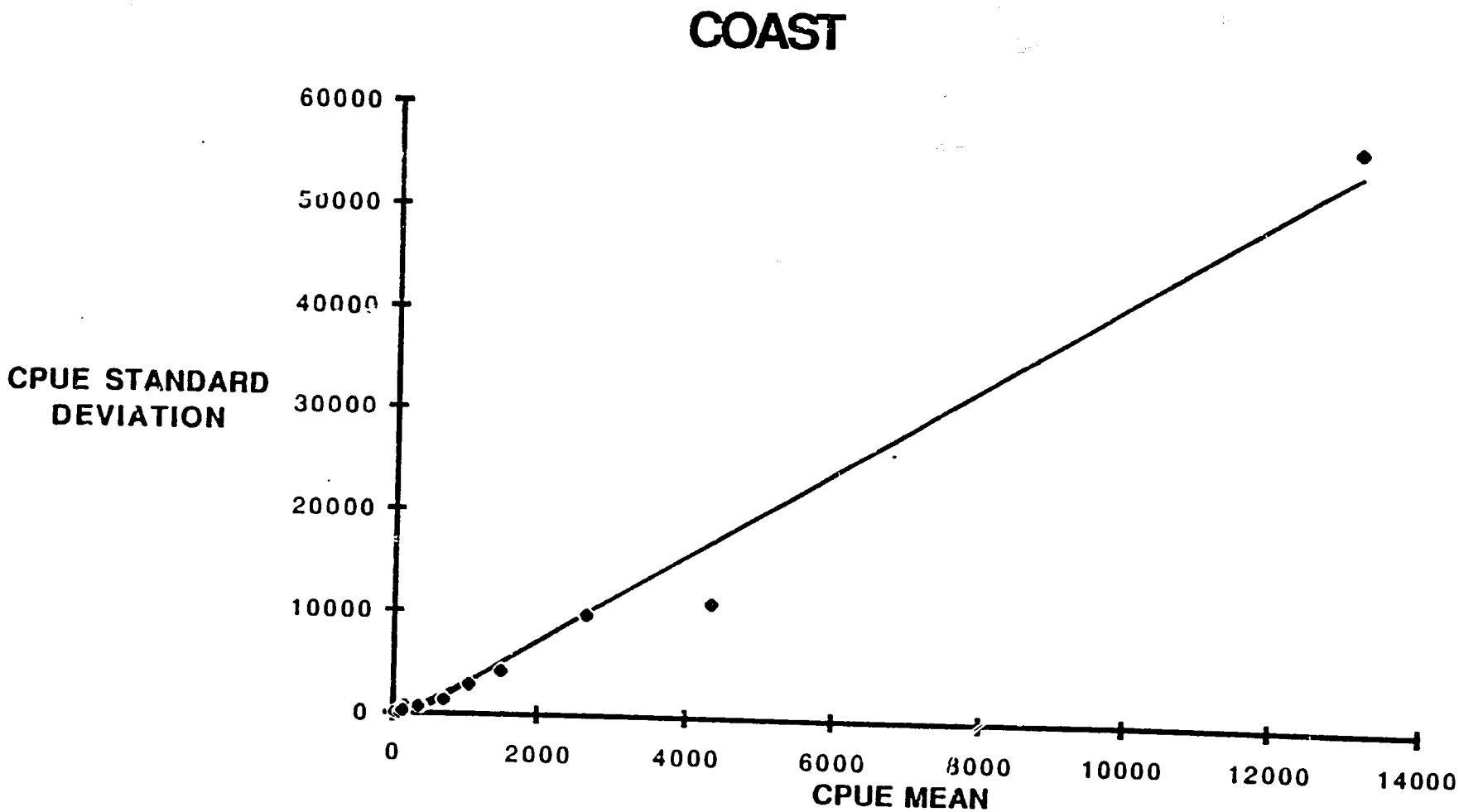
COAST
CPUE STANDARD DEVIATION
60000
50000
40000
30000
20000
10000
0
0
2000
4000
6000
8000
10000
12000
14000
CPUE MEAN

Fig. 1a

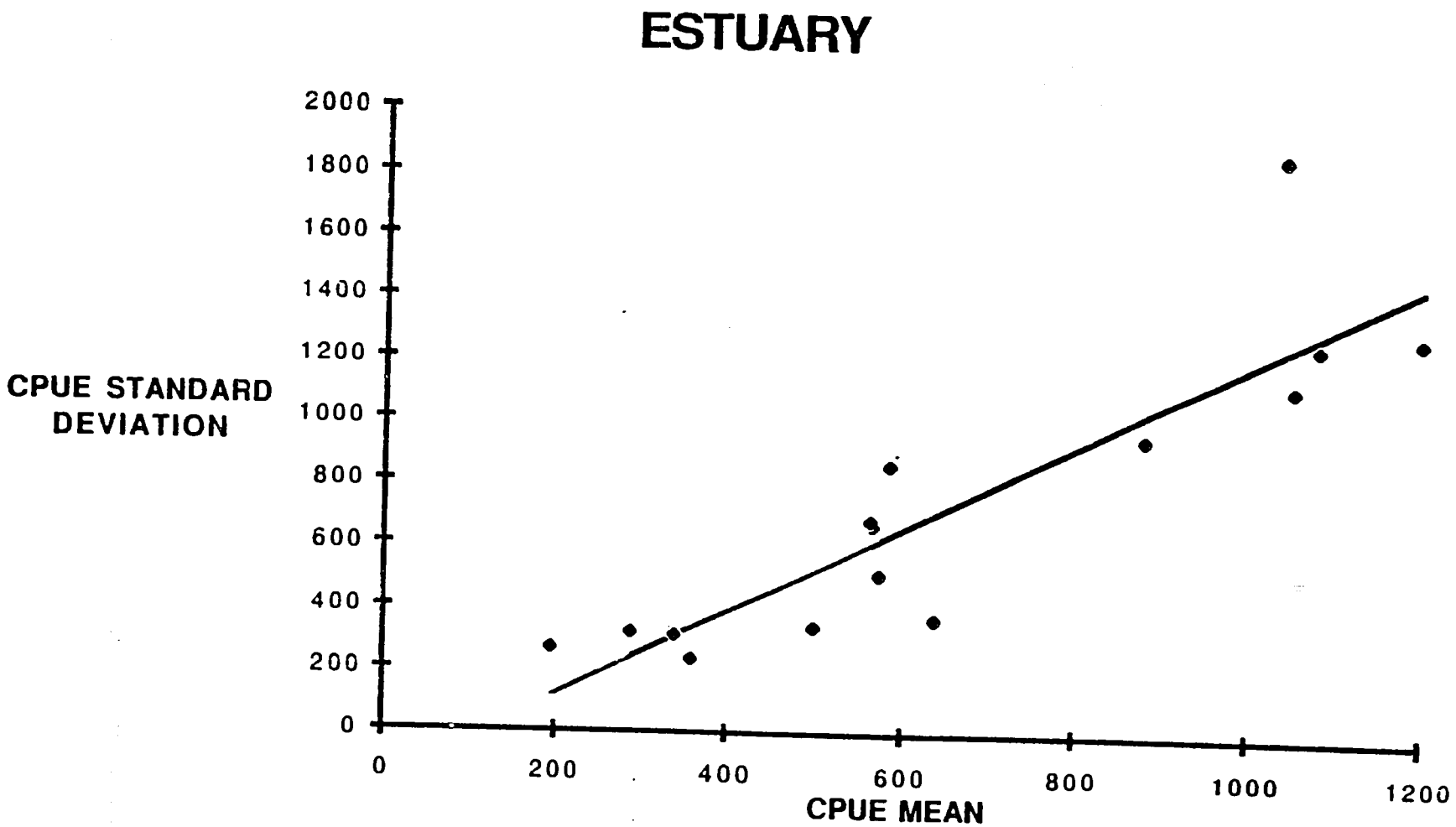
ESTUARY
CPUE STANDARD DEVIATION
2000
1800
1600
1400
1200
1000
800
600
400
200
0
0
200
400
600
800
1000
1200
CPUE MEAN

Fig. 1b

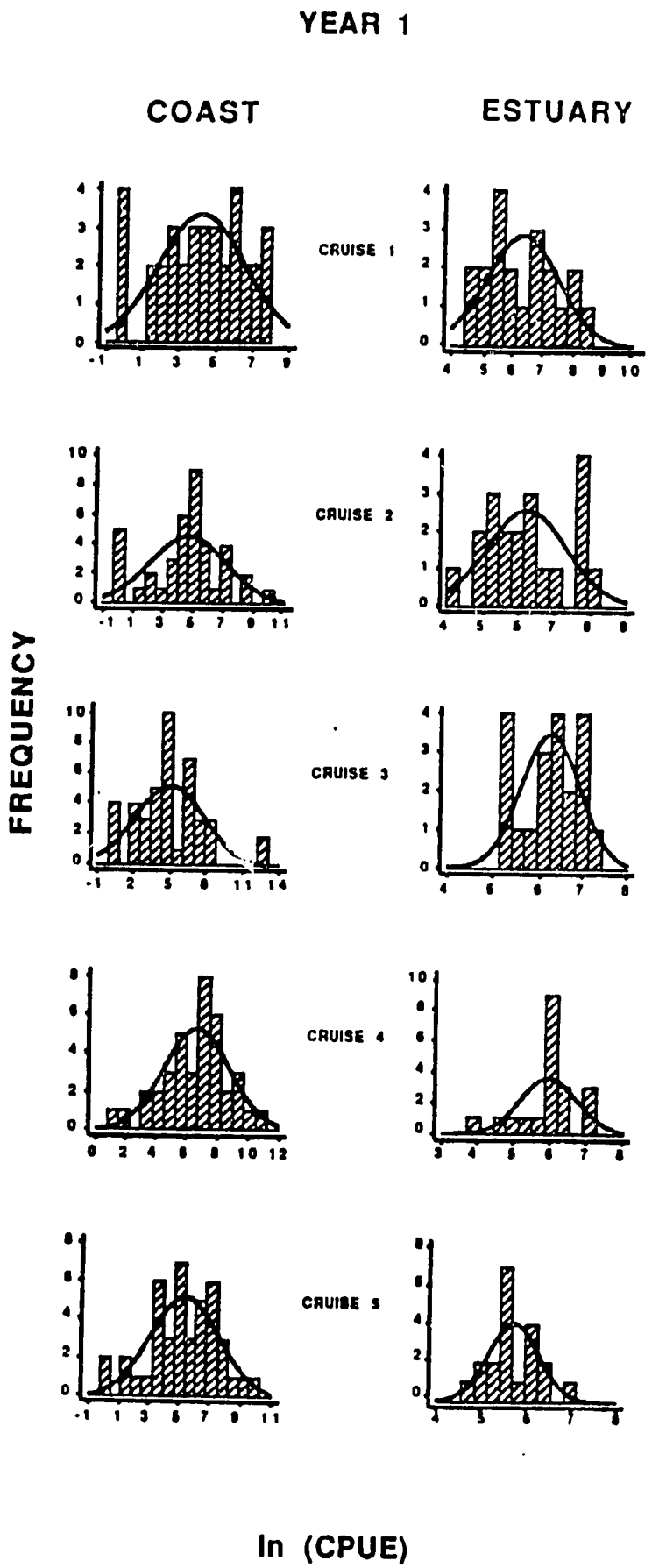
YEAR 1
COAST
ESTUARY
CRUISE 1
CRUISE 2
CRUISE 3
CRUISE 4
CRUISE 5
FREQUENCY
ln (CPUE)

Fig 2a

YEAR 2

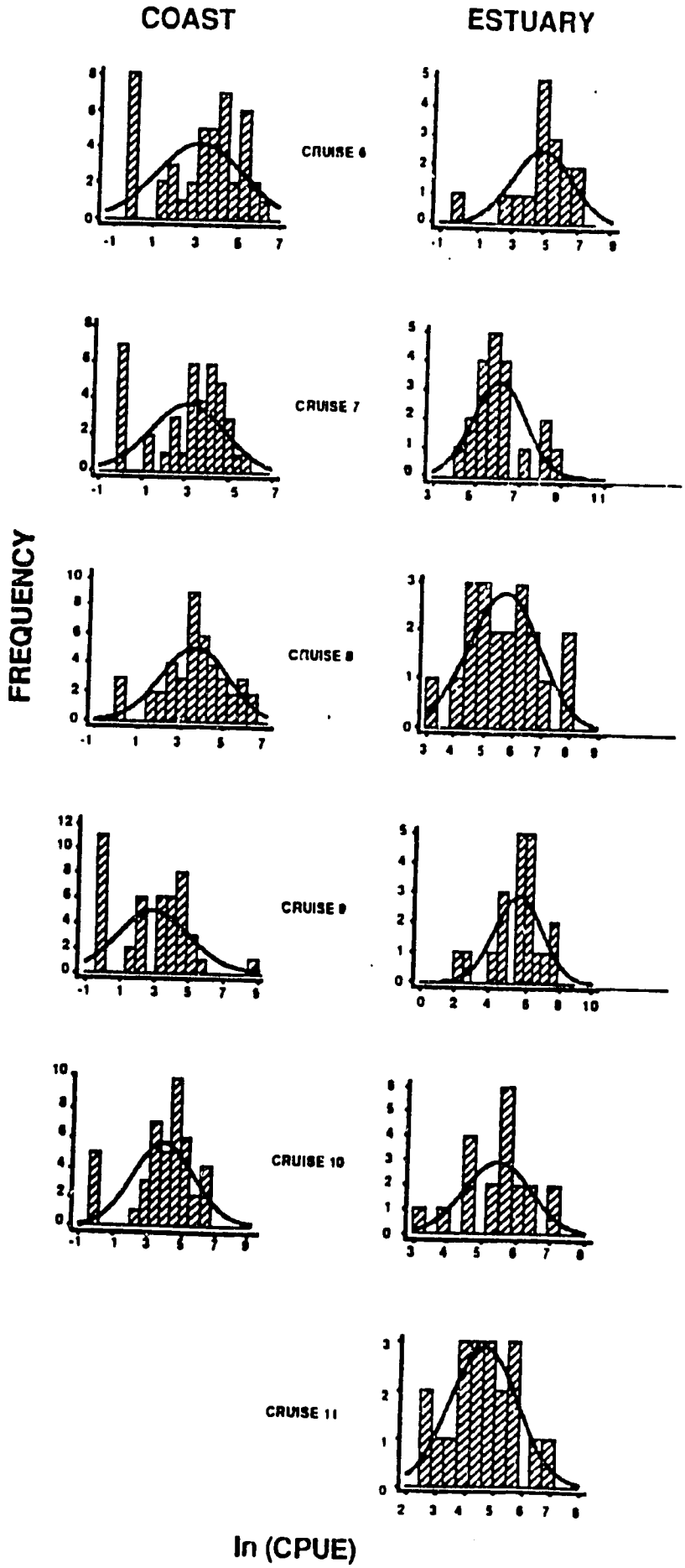

Fig 2b

44

YEAR 3

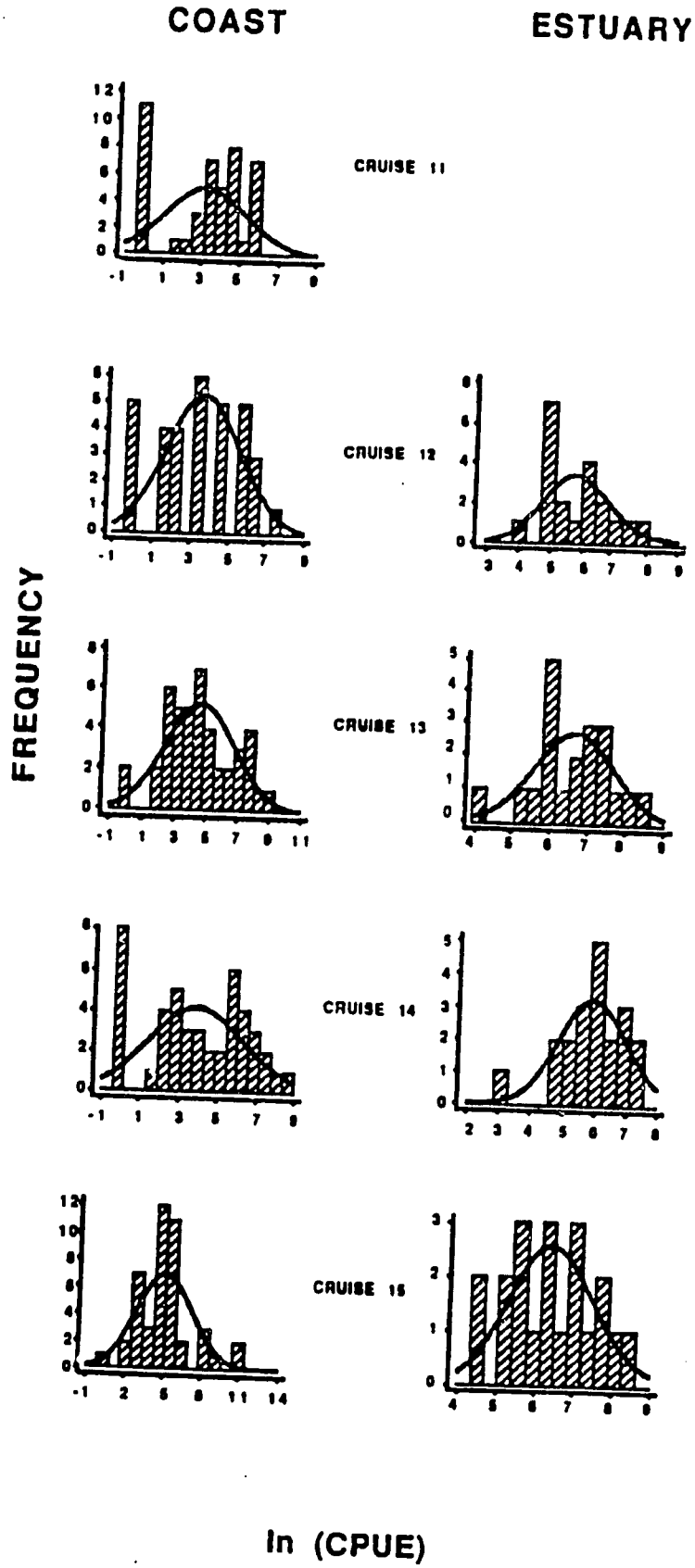
COAST
ESTUARY
CRUISE 11
CRUISE 12
CRUISE 13
CRUISE 14
CRUISE 15
FREQUENCY
ln (CPUE)

Fig 2c

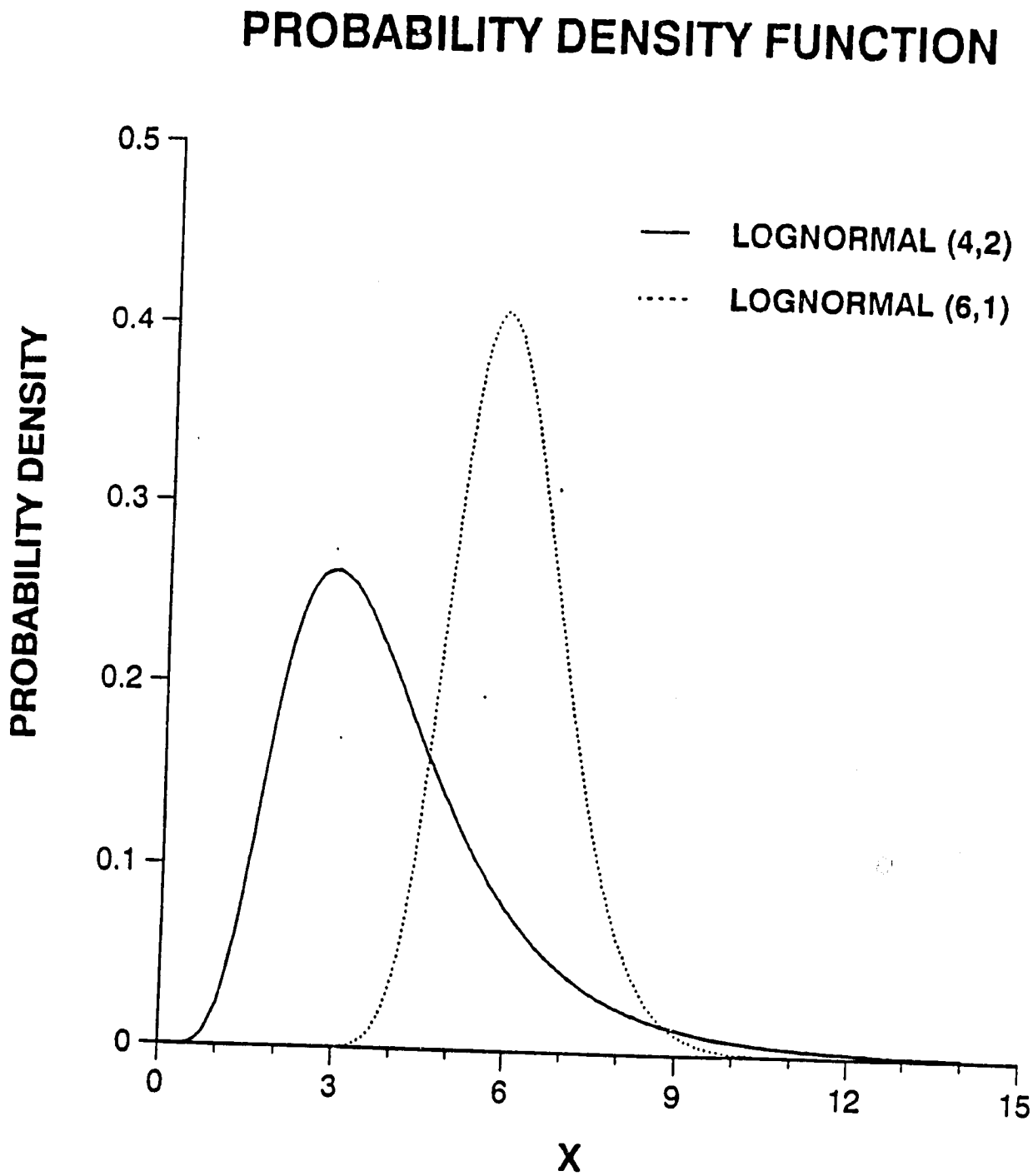
PROBABILITY DENSITY FUNCTION
LOGNORMAL (4,2)
LOGNORMAL (6,1)
PROBABILITY DENSITY
0.5
0.4
0.3
0.2
0.1
0
0
3
6
9
12
15
X

Fig 3

146

MONTE CARLO SIMULATION

LOGNORMAL (4,2) DATA

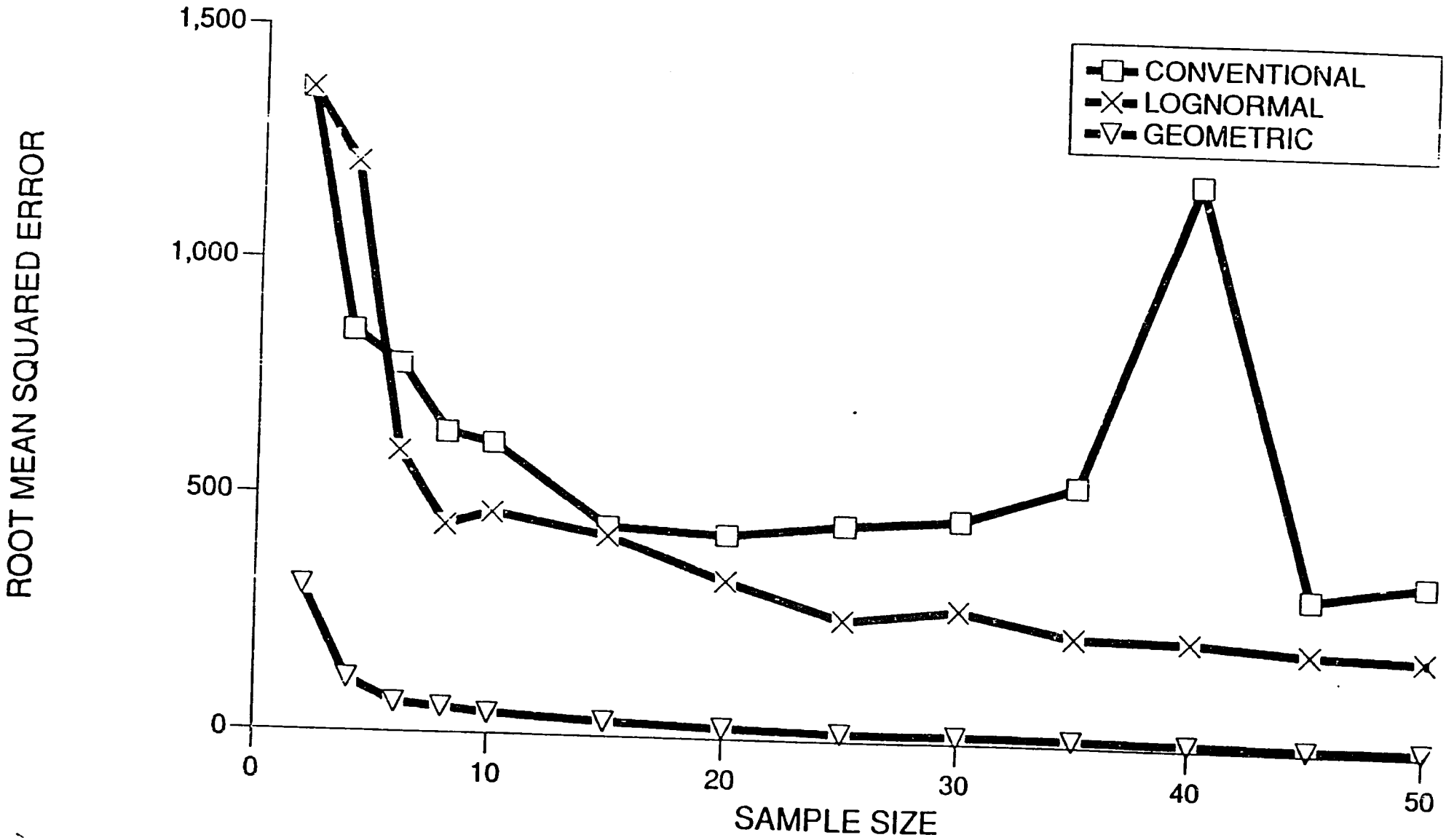

Fig 4a

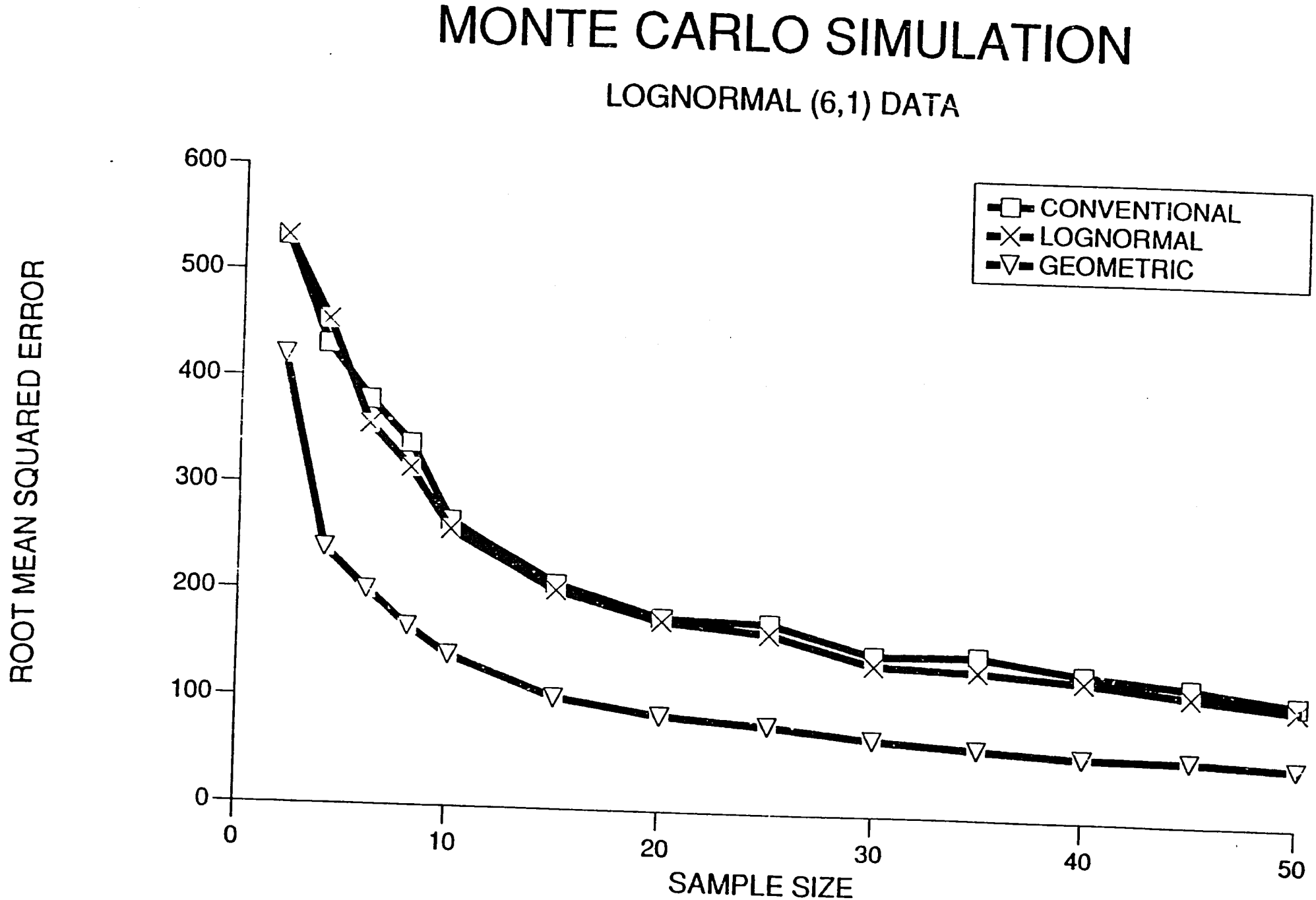
MONTE CARLO SIMULATION
LOGNORMAL (6,1) DATA
CONVENTIONAL
LOGNORMAL
GEOMETRIC
ROOT MEAN SQUARED ERROR
600
500
400
300
200
100
0
0
10
20
30
40
50
SAMPLE SIZE

Fig. 4b

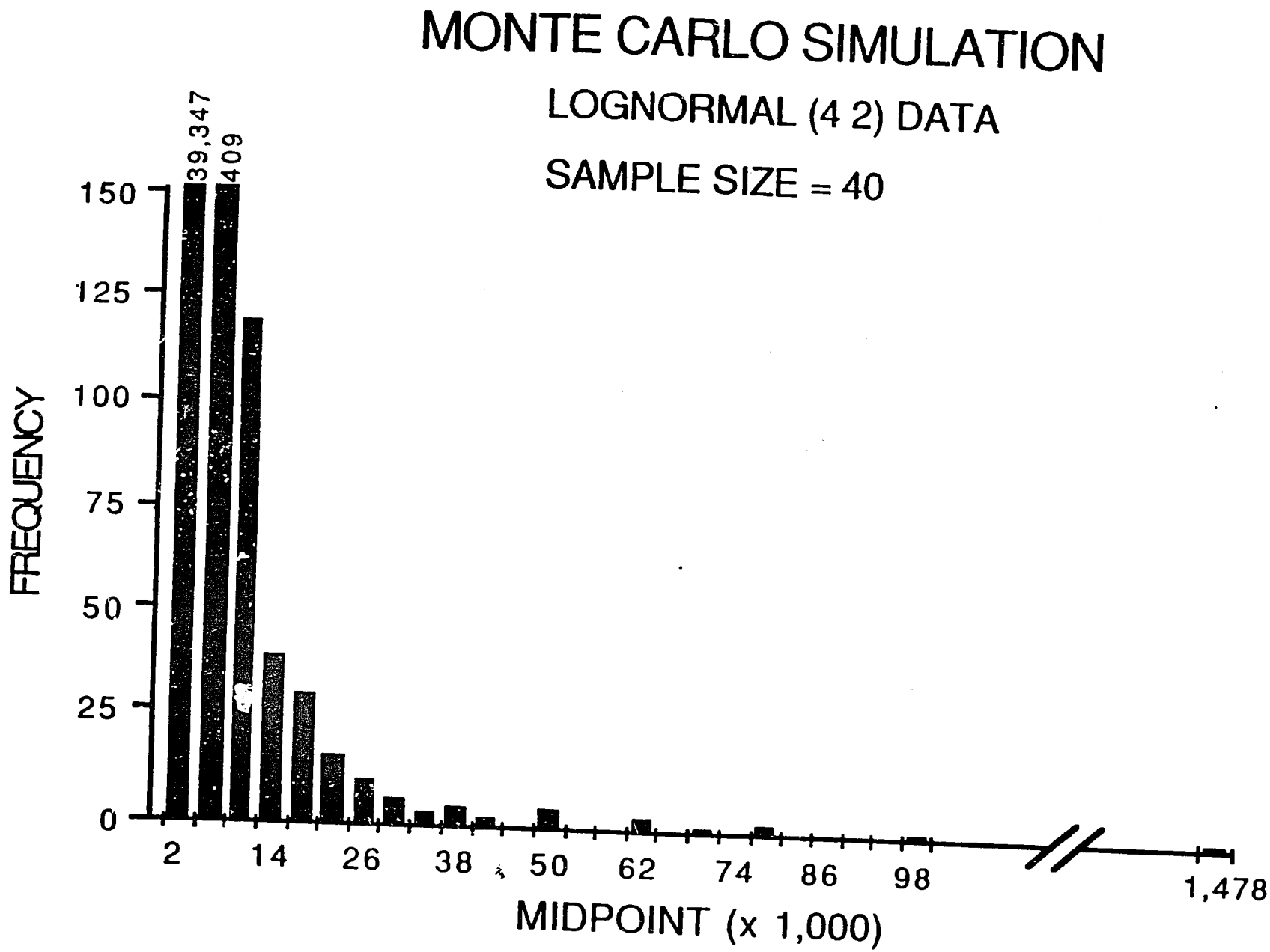
MONTE CARLO SIMULATION
LOGNORMAL (4 2) DATA
SAMPLE SIZE = 40
39,347
409
FREQUENCY
150
125
100
75
50
25
0
2
14
26
38
50
62
74
86
98
1,478
MIDPOINT (x 1,000)

Fig 4c

MONTE CARLO SIMULATION

LOGNORMAL (4,2) DATA

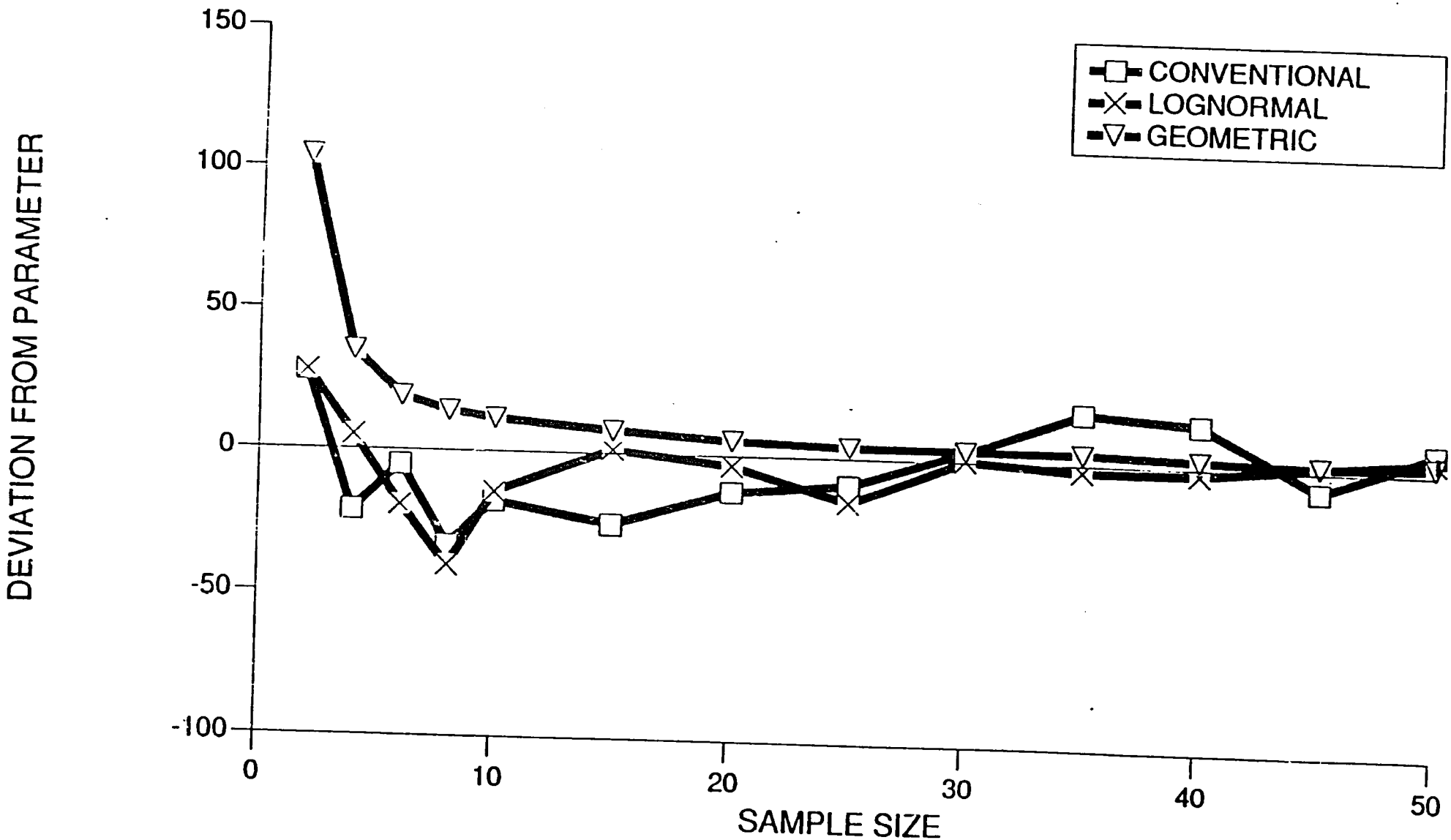

Fig. 5a

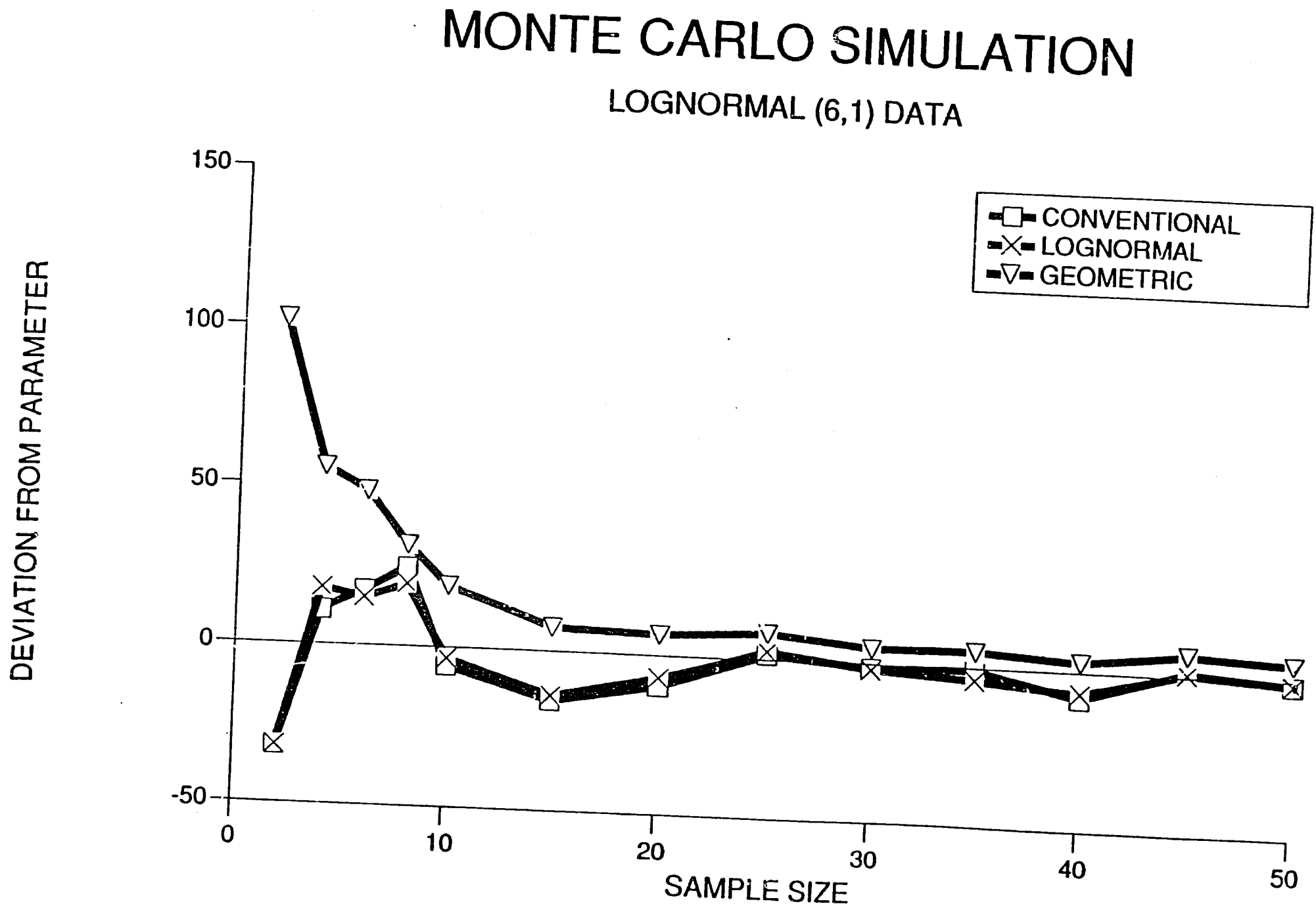
MONTE CARLO SIMULATION
LOGNORMAL (6,1) DATA
CONVENTIONAL
LOGNORMAL
GEOMETRIC
DEVIATION FROM PARAMETER
150
100
50
0
-50
0
10
20
30
40
50
SAMPLE SIZE

Fig. 5b

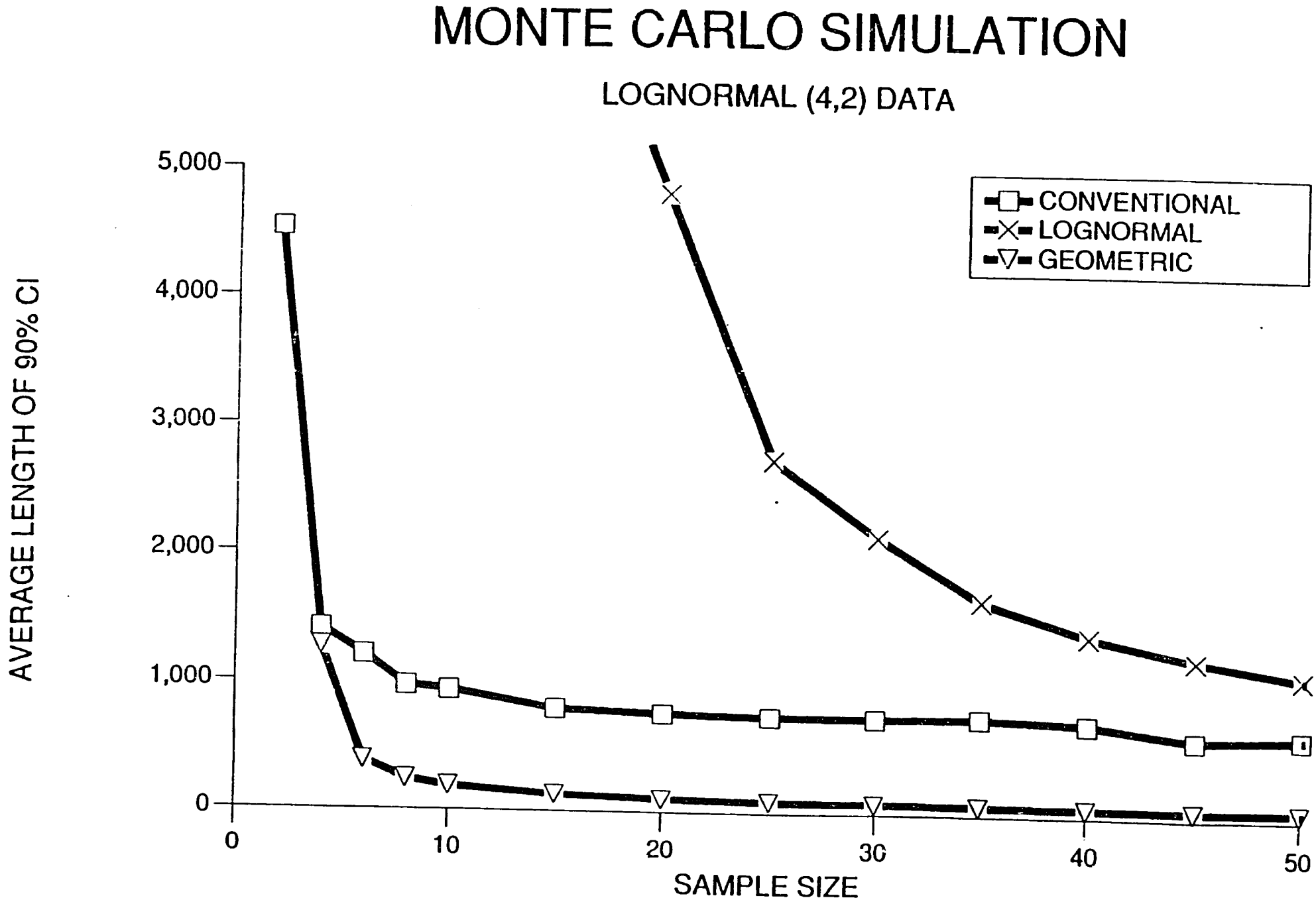
MONTE CARLO SIMULATION
LOGNORMAL (4,2) DATA
AVERAGE LENGTH OF 90% CI
5,000
4,000
3,000
2,000
1,000
0
0
10
20
30
40
50
SAMPLE SIZE
CONVENTIONAL
LOGNORMAL
GEOMETRIC

Fig. 6a

MONTE CARLO SIMULATION

LOGNORMAL (6,1) DATA

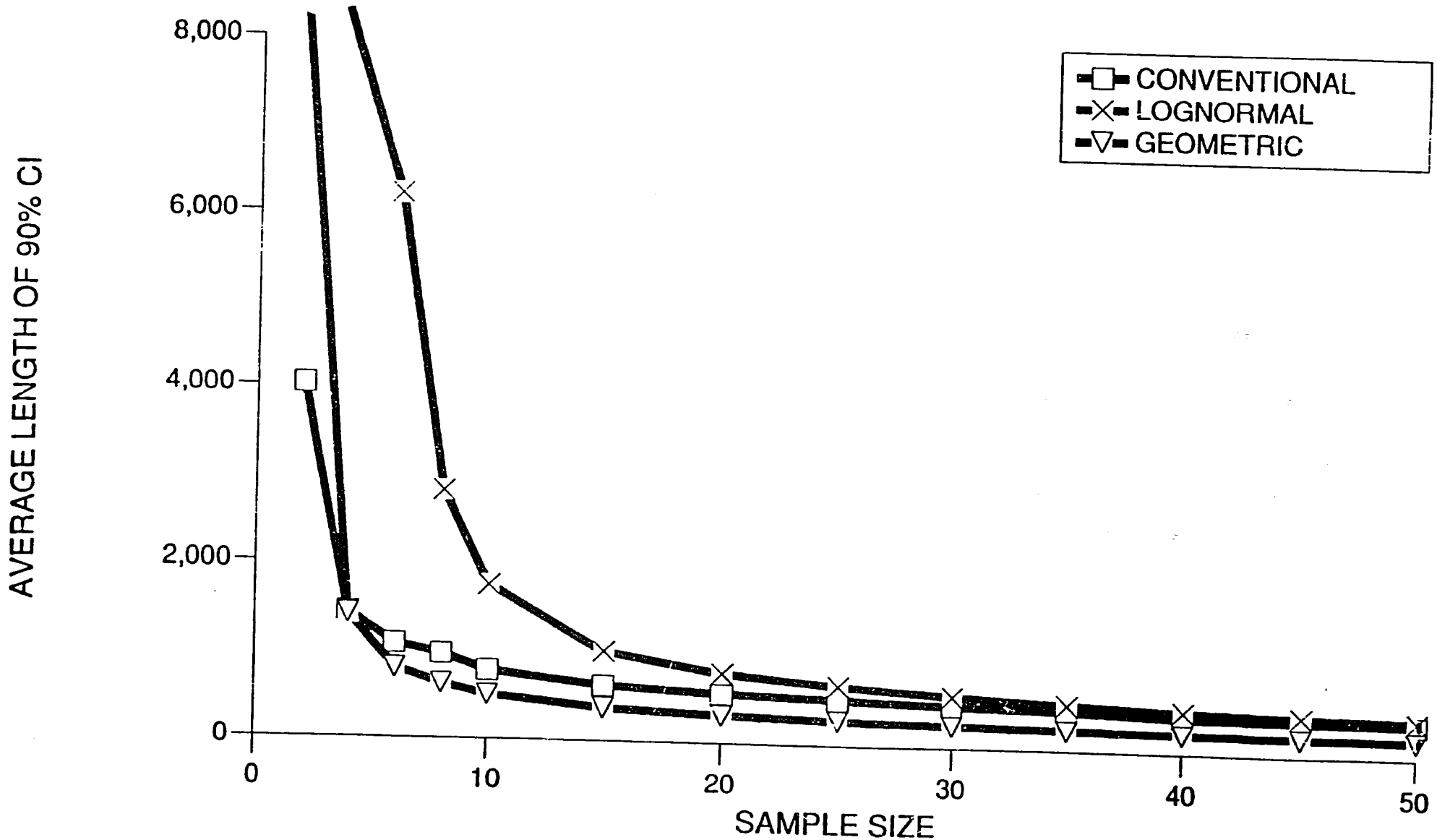

Fig. 6b

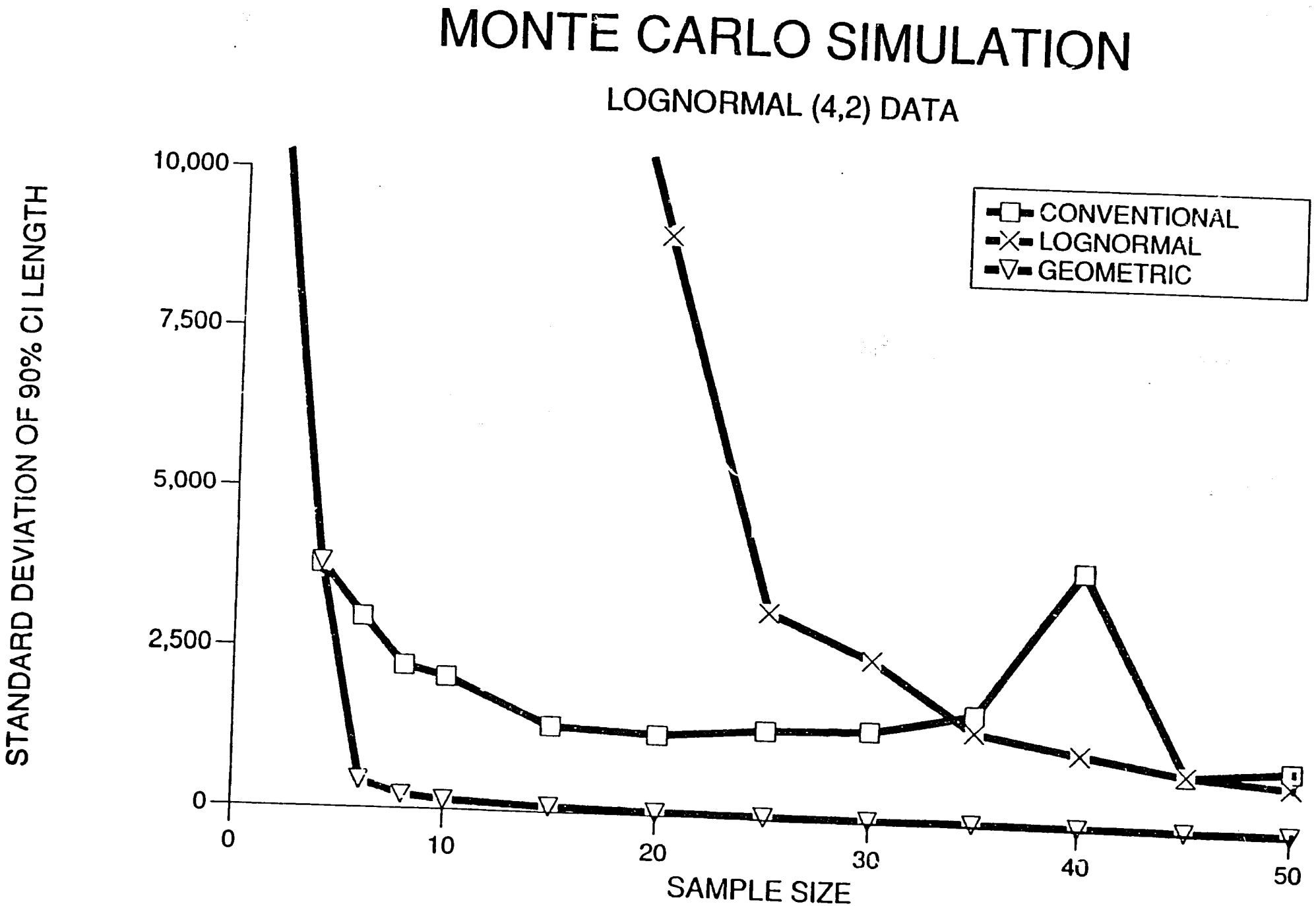
MONTE CARLO SIMULATION
LOGNORMAL (4,2) DATA
STANDARD DEVIATION OF 90% CI LENGTH
10,000
7,500
5,000
2,500
0
0
10
20
30
40
50
SAMPLE SIZE
CONVENTIONAL
LOGNORMAL
GEOMETRIC

Fig. 7a

MONTE CARLO SIMULATION

LOGNORMAL (6,1) DATA

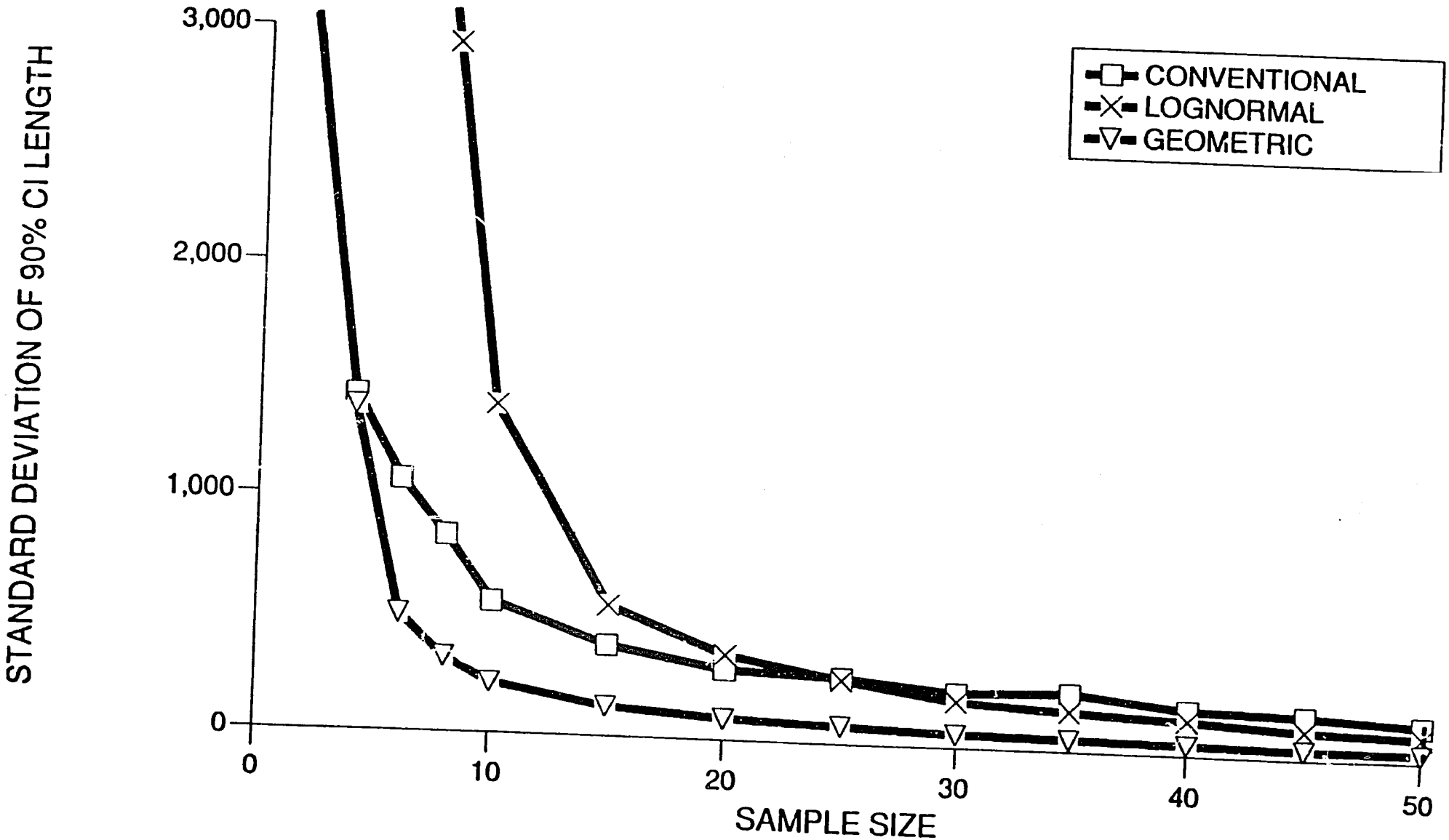

Fig 7b

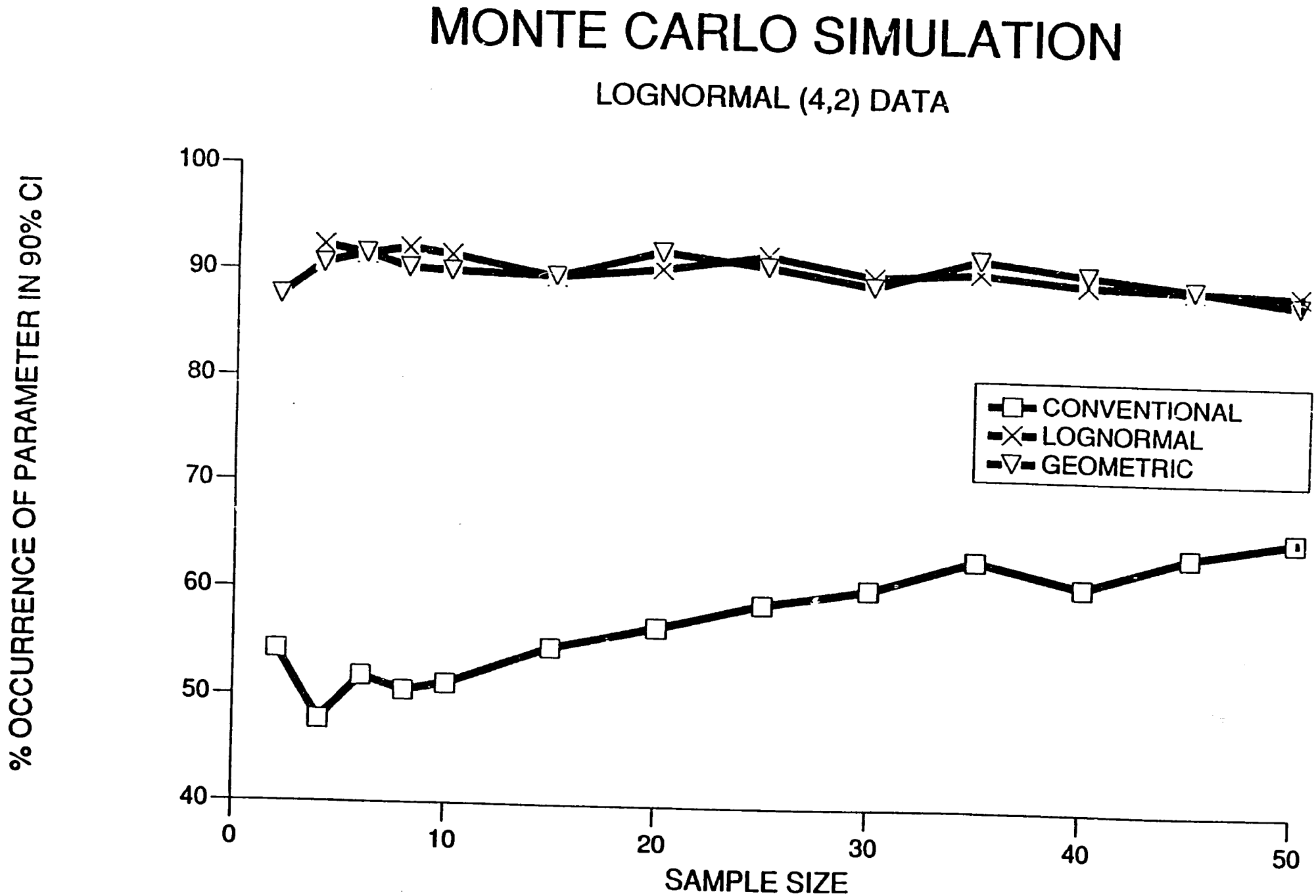
MONTE CARLO SIMULATION
LOGNORMAL (4,2) DATA
% OCCURRENCE OF PARAMETER IN 90% CI
100
90
80
70
60
50
40
0
10
20
30
40
50
SAMPLE SIZE
CONVENTIONAL
LOGNORMAL
GEOMETRIC

Fig 8a

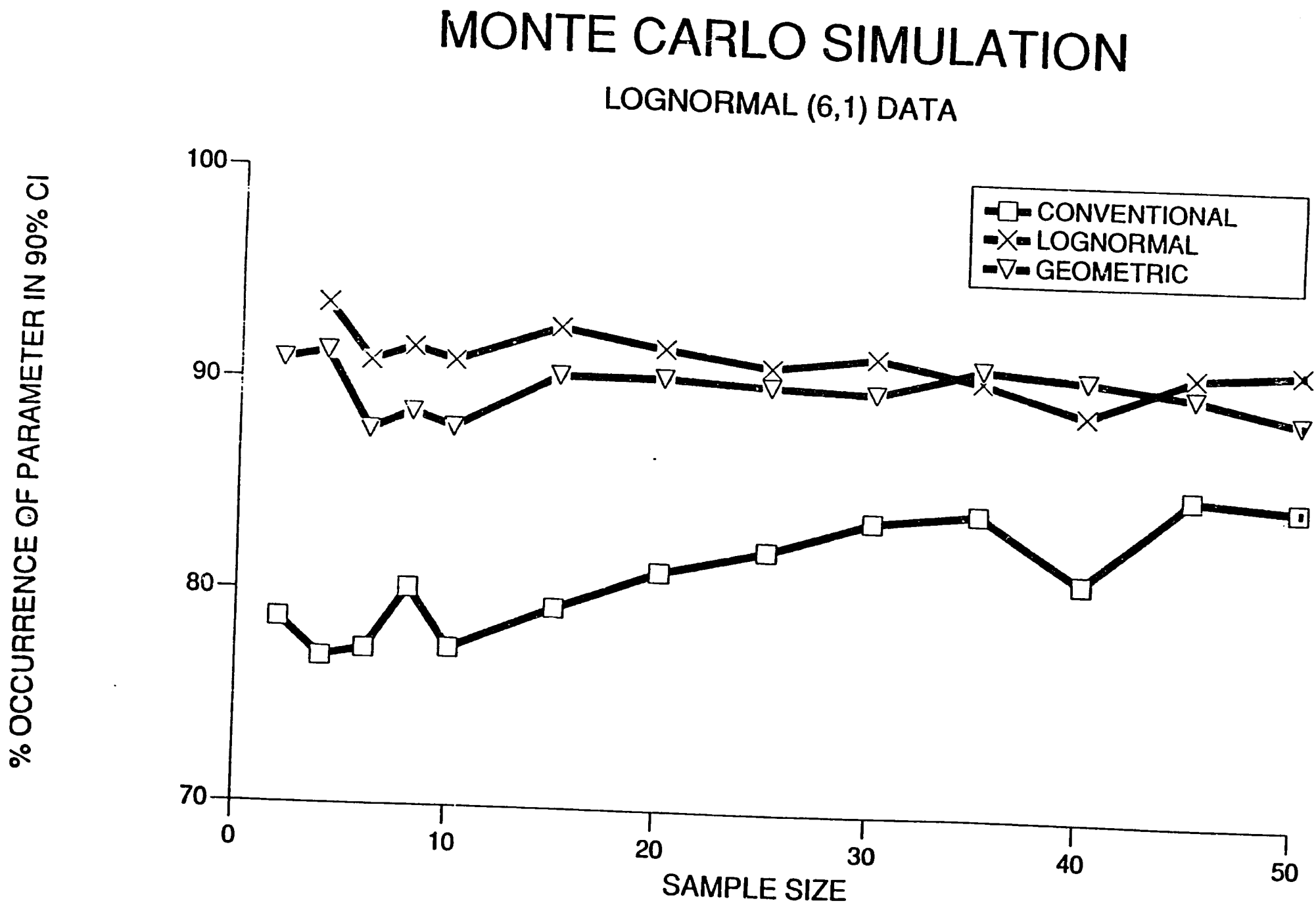
MONTE CARLO SIMULATION
LOGNORMAL (6,1) DATA
% OCCURRENCE OF PARAMETER IN 90% CI
100
90
80
70
0
10
20
30
40
50
SAMPLE SIZE
CONVENTIONAL
LOGNORMAL
GEOMETRIC

Fig. 8b

CPUE PARAMETER ESTIMATES

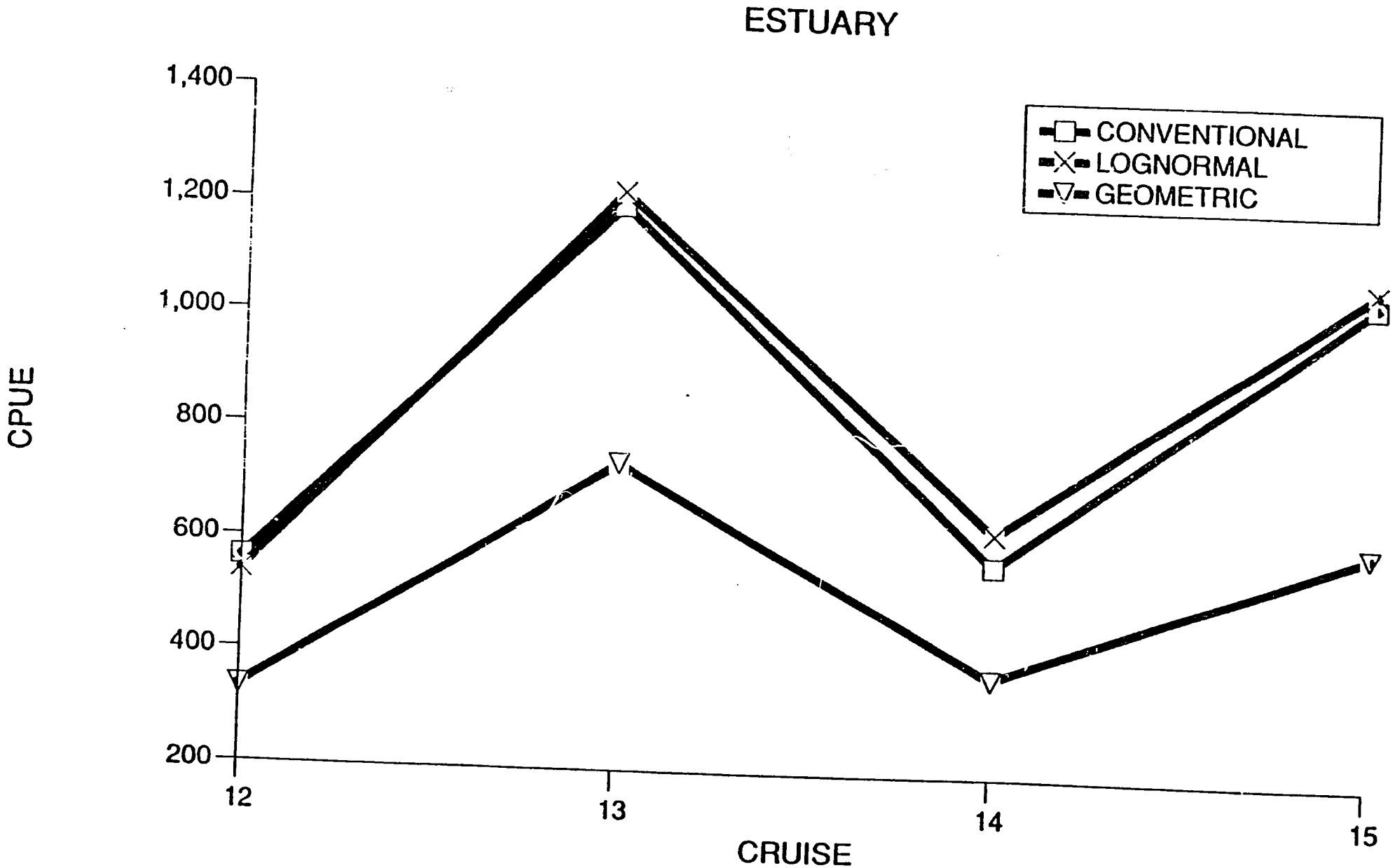

Fig. 9a

CPUE PARAMETER ESTIMATES

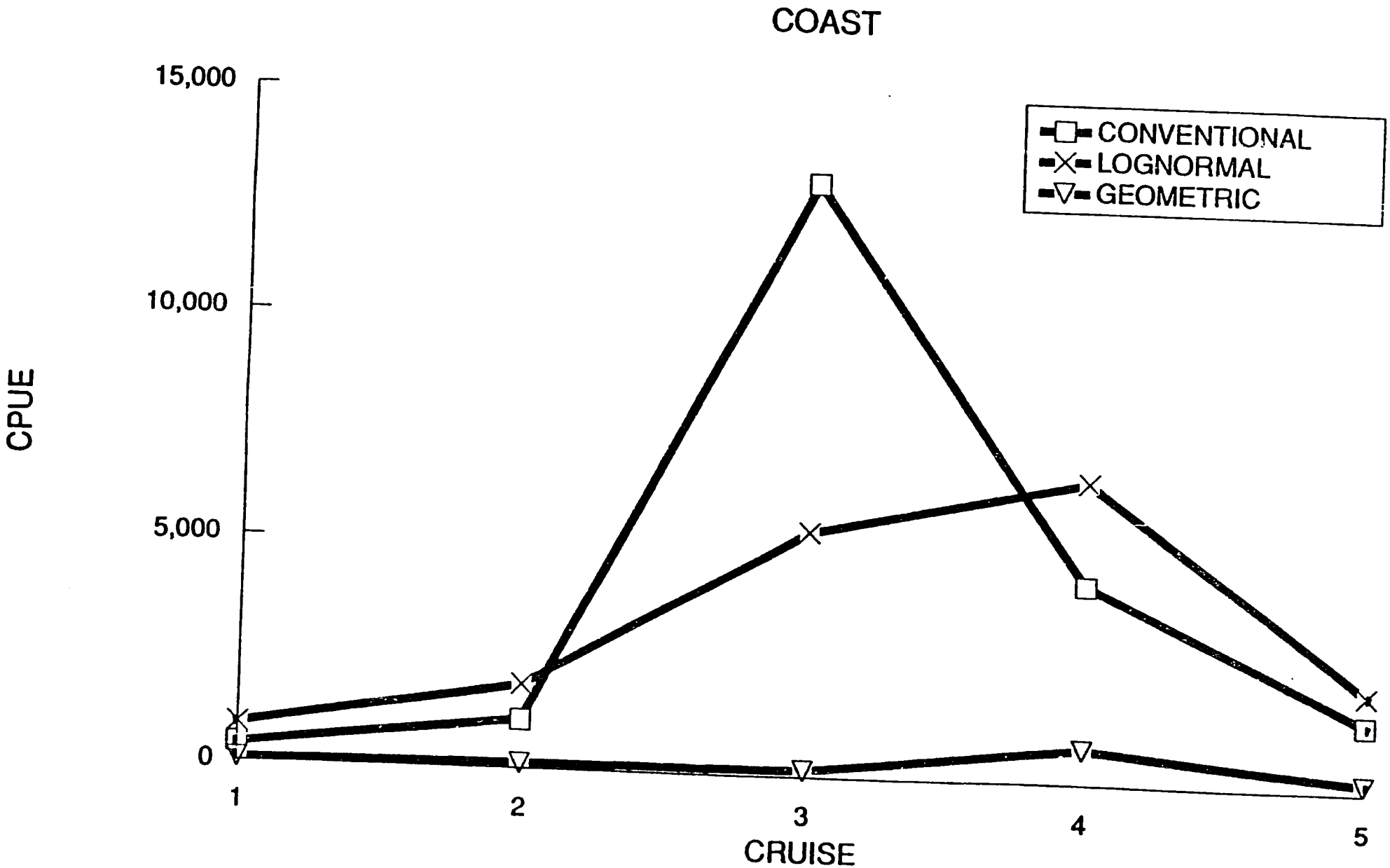

Fig. 9b