# INFERENCES ABOUT THE VARIABILITY OF MEANS FROM CENSORED DATA 

## by

A.H. El-Shaarawi*, P.B. Kauss ${ }^{+}$, M.K. Kirby ${ }^{+}$, and M. Walsh ${ }^{+}$

*Rivers Research Branch<br>National Water Research Institute Canada Centre for Inland Waters Burlington, Ontario, L7R 4A6

+Ontario Ministry of the Environment Water Resources Branch Toronto, Ontario M4V IK6

In recent years, intensive biological monitoring studies have been carried out on the Niagara River by the Ontario Ministry of the Environment. The basic objective was to determine the relative bioavailability of trace contaminants at various locations in the river, and to identify sources. A recurring difficulty encountered with the generated data is that substantial portions of sample concentrations of many toxic pollutants are below the limits of detection established by analytical laboratories. Under the assumption that the distribution of the data is log normal, the likelihood ratio test for testing the equality of several means for type I censored data is derived and its use for evaluating the spatial variability of trace contaminants in the river is illustrated.

## rÉSUME

Au cours des dernières années, le ministère de l'Environnement de l'Ontario a fait d'importantes études de surveillance biologique dans 1 a rivièrer Niagara avec comme principal objectif l'étude de la biodisponibilité relative des contaminants à l'état de traces à divers endroits dans la rivière, et lidentification des sources. Une difficulté qui revient fréquemment avec les données produites est qu'une grande partie des concentrations des échantillons de nombreux polluants toxiques sont en-deçà des limites de détection établies par les laboratoires analytiques. En supposant que la distribution des données est lognormale, le test du rapport des vraisemblances dans le but de tester l'égalité de plusieurs moyennes de données censurées de type I est dérivé, et son utilisation en vue de l'évaluation de la variabilité spatiale des contaminants à l'état de traces dans la rivière est illustrée.

## MANAGEMENT PERSPECTIVE

In the presence of censored water quality data, a test statistic has been developed for testing the spatial and temporal heterogeneity of the concentration data for trace contaminants. The test does not require extensive computation and is fairly robust to distributional assumptions. The basic objective for developing the test was to determine the relative bioavailability of trace contaminants at various locations in a river and to identify sources. The application of the test is illustrated using an example from the Niagara River biomonitoring data.

En présence de données censurées sur la qualité de l'eau, un test statistique a été mis au point pour tester l'hétérogénéité spatio-temporelle des donneés sur la concentration des contaminants à l'état de traces. Le test ne nécessite pas d'importants calculs et se prête assez bien aux hypothèses de distribution. Le principal objectif de la mise au point de ce test était d'établir la biodisponibilité relative des contaminants à l'état de traces à divers endroits dans la rivière et d'en identifier les sources. L'application du test est illustrée à l'aide d'un exemple faisant appel aux données de biosurveillance de la rivière Niagara.

Both ambient water sampling and effiuent monitoring are important tools in the identification and quantification of point and non-point contaminant inputs and their consequent effects on water quality. However, the importance of biological monitoring, either with natural or introduced species, should not be neglected in such monitoring studies, since it offers several distinct advantages. This stems from the continuous contact of the aquatic organisms with their environment and the tendency of persistent contaminants to accumulate in their tissues or lipids to concentrations which are more readily detectable than in ambient water samples. Therefore, contaminant levels in biota can provide information on the presence of nearby sources of contaminants. Furthermore, biota will tend to reflect inputs of contaminants which may be too sporadic to be detected by routine water quality monitoring programs.

In recent years, extensive biological monitoring programs have been conducted in the Niagara River by the Ontario Ministry of the Environment's (MOE) Water Resources Branch. These studies, using both natural and introduced species from various trophic levels, were included in the report of the Niagara River Toxics Committee (NRTC) released in 1984. In its report, the NRTC recommended a minimum "Long Term Monitoring Program" for a number of "Chemicals of Concern" identified in the river. This list of chemicals included those group I contaminants requiring: "immediate attention to determine
their origin and spatial and temporal trends", as well as those requiring additional data to make an adequate assessment of their significance.

Since then, annual biomonitoring using filamentous algae and young forage fish has been conducted at many of the sites recommended by the NRTC report. In addition, an extensive study using introduced (caged) mussels was conducted in the river by the MOE during 1983. One of the main objectives of the latter study was to determine the relative bioavailability of organochlorine contaminants in different areas of the Niagara River and to identify sources.

A recurring difficulty encountered during the course of the study was that, in a substantial portion of the samples, concentrations of many toxic pollutants were below the limits of detection established by analytical laboratories. The problem of estimating the mean and standard deviation from censored water quality data has been addressed by Gilliom and Helsel (1986), Helsel (1986), El-Shaarawi (1989), and El-Shaarawi and Dolan (1989).

In this paper we extend the work of El-Shaarawi and Dolan (1989) from making inferences about the $\log$ normal mean to that of testing the differences between several means. Specifically, the likelihood ratio test (LRT) for testing the equality of several means for type I censored data is derived. The application of the LRT test is illustrated using an example from the Niagara River biomonitoring data.

FIELD STUDY

The 1983 Niagara River biomonitoring study was conducted at 27 nearshore stations (Figure 1) and consisted of six surveys. At each station, clean mussels were exposed for 15 weeks (August 3 to November 16) in galvanized wire cages (Survey 6) and then recovered and processed as described by Kauss and Hamdy (1985). Mussels were also exposed for five consecutive 3 week periods (Surveys 1 to 5) during the above period at 20 of the stations to determine the temporal variability in contaminants input/bioavailability. These "intensive" stations were concentrated near suspected contaminant sources along the New York mainland shore (Figure 1). For each station and survey, the complete soft tissues of three replicates were each analyzed for 25 organochiorine contaminants including pesticides and industrial organics.

STATISTICAL METHODS

## 1. One Hay Analysis of Variance for Censored Data

Let $X_{i j}$ be the concentration of the contaminant in the $j$ th sample at the ith sampling location where $j=1,2, \ldots, n_{i}$; $1=1,2, \ldots, k$ and let $X_{0}$ be the limit of detection established by the analytical laboratory. Suppose that $d_{i}$ out of $n_{i}$ samples have concentrations below $X_{0}$ and the remaining $m_{i}=n_{i}-d_{i}$ samples have the measured concentrations $X_{i 1}, X_{12}, \ldots, X_{i m}$. Assuming
the $X_{i j}$ is an observation from the log normal distribution with mean $\eta_{i}=\operatorname{Exp}\left\{\mu_{i}+\sigma^{2 / 2\}}\right.$ and variance $\beta_{i}=\eta_{i}{ }^{2}\left\{\operatorname{Exp}\left(\sigma^{2}\right)-1\right\}$, then $y_{i j}=\ln X_{i j}$ is normal with mean $\mu_{i}$ and variance $\sigma^{2}$. The aim is to test the equality of the means at the different stations, i.e., the null hypothesis is

$$
H_{0}: \quad \eta_{i}=\eta \quad \text { for all } i=1,2, \ldots k .
$$

This is equivalent to testing the equality of $\mu_{1}, \ldots, \mu_{k}$.
The likelihood function for $\mu_{1}, \mu_{2}, \ldots, \mu_{k}$ and $\sigma^{2}$ is given by

$$
\begin{equation*}
L_{1} a \prod_{i=1}^{k} \Phi\left(\xi_{i}\right) o^{-m_{i}} \operatorname{Exp}\left\{-\frac{m_{i}\left(s_{i}^{2}+\left(\bar{y}_{i}-\mu_{i}\right)^{2}\right)}{2 \sigma^{2}}\right\}, \tag{1}
\end{equation*}
$$

where

$$
\begin{aligned}
& s_{i}^{2}=\frac{1}{m_{i}} \sum_{j=1}^{m}\left(y_{i j}-\bar{y}_{i}\right)^{2}, \bar{y}_{i}=\frac{1}{m_{i}} \sum_{j=1}^{m_{i}} y_{i j}, \\
& \xi_{i}=\left(y_{0}-\mu_{i}\right) / \sigma, \Phi\left(\xi_{i}\right)=\int_{-\infty}^{\xi_{i}} \phi\left(\xi_{i}\right) d \xi_{i},
\end{aligned}
$$

and

$$
\phi\left(\xi_{i}\right)=\frac{1}{\sqrt{2 \Pi}} \operatorname{Exp}\left(-\xi_{i}^{2} / 2\right)
$$

The maximum likelihood estimates (MLE) $\hat{\mu}_{\mathfrak{i}}$ and $\hat{\sigma}^{2}$ satisfy the equations

$$
\begin{align*}
\hat{\sigma}^{2} & =\sum_{i=1}^{k} m_{i}\left\{s_{i}^{2}+\left(\bar{y}_{i}-\hat{\mu}_{i}\right)\left(\bar{y}_{i}-y_{0}\right)\right\} / M,  \tag{2}\\
\text { and } \hat{\mu}_{i} & =\bar{y}_{i}-\frac{d_{i} \hat{\sigma}}{m_{i}} g\left(\hat{\xi}_{i}\right)(i=1,2, \ldots, k), \tag{3}
\end{align*}
$$

where

$$
\begin{aligned}
& M=\sum_{i=1}^{k} m_{i}, \quad g\left(\xi_{i}\right)=\phi\left(\xi_{i}\right) / \Phi\left(\xi_{i}\right), \\
& \hat{\xi}_{i}=\left(y_{0}-\hat{\mu}_{i}\right) / \hat{\sigma}, \text { and } y_{0}=\ln x_{0} .
\end{aligned}
$$

The solution of the above system of equations for $\hat{\sigma}$ and $\hat{\mu}_{i}$ is not very simple due to the non-linearity of $g\left(\hat{\boldsymbol{\xi}}_{\mathfrak{j}}\right)$. Tiku's (1967) approximation for $g\left(\hat{\boldsymbol{\xi}}_{\mathcal{i}}\right)$ results in obtaining explicit estimates for $\hat{\mu}_{i}$ and $\hat{\boldsymbol{o}}^{\mathbf{2}}$ which have the same asymptotic efficiencies as those estimates obtained by the method of maximum likelihood. The approximate expression for $g\left(\hat{\xi}_{j}\right)$ is $a_{i}+b_{i} \hat{\xi}_{i}$, where

$$
\begin{aligned}
& b_{i}=\left\{g\left(\hat{\xi}_{i u}\right)-g\left(\hat{\xi}_{i j}\right)\right\} /\left(\hat{\xi}_{i u}-\hat{\xi}_{i 1}\right), \\
& a_{i}=g\left(\hat{\xi}_{i 1}\right)-\hat{\xi}_{i 1} b_{i}, \\
& \hat{\xi}_{i u}=\mathbb{I}^{-1}\left(P_{i}+\sqrt{P_{i}\left(1-P_{i}\right)} n_{i}\right) \\
& \hat{\xi}_{i 1}=-1\left(P_{i}-\sqrt{P_{i}\left(1-P_{i}\right)} \underset{n_{i}}{)}\right.
\end{aligned}
$$

and $P_{i}=d_{i} / n_{i}$.

Using this approximation results in estimating $\mu_{i}$ by

$$
\begin{equation*}
\hat{\mu}_{i}=\left(\bar{y}_{i}-h_{i} b_{i} y_{0}-h_{i} a_{i} \hat{\sigma}\right) /\left(1-h_{i} b_{i}\right) \tag{4}
\end{equation*}
$$

where $h_{j}=d_{j} / m_{j}$. Substituting (4) into (2) results in a quadratic equation for $\hat{\sigma}$. The positive root of the equation gives the estimate for 0 which is

$$
\begin{equation*}
\hat{\sigma}=-\frac{1}{2} B+\frac{1}{2} \sqrt{ } B^{2}+4 C \tag{5}
\end{equation*}
$$

where $B=\sum\left\{m_{i}\left(y_{0}-\bar{y}_{i}\right) h_{i} a_{i} / M\left(1-h_{i} b_{i}\right)\right\}$,
and $\quad c=\sum \frac{m_{i}}{M}\left\{s_{i}^{2}-\frac{h_{i} b_{i}\left(y_{0}-\bar{y}_{i}\right)^{2}}{1-h_{i} b_{i}}\right\}$

The same procedure can be used to estimate $\mu$ and $\sigma$ under the null hypothesis $H_{0}$. Specifically, these estimates $\tilde{\mu}$ and $\tilde{\sigma}$ are given by

$$
\begin{align*}
\tilde{\mu} & =\left(\bar{y}-h b y_{0}-h a \tilde{\sigma}\right) /(1-h b)  \tag{6}\\
\text { and } \tilde{\sigma} & =-\frac{1}{2} \tilde{B}+\frac{1}{2} \sqrt{B^{2}}+4 \tilde{C}, \tag{7}
\end{align*}
$$

where $\quad \bar{y}=\sum m_{i} y_{i} / M, \quad s^{2}=\sum m_{i} s_{i}^{2} / M$

$$
\begin{aligned}
& \tilde{B}=\left(y_{0}-\bar{y}\right) h a /(1-h b), \\
& \tilde{c}=s^{2}-\frac{h b\left(y_{0}-\bar{y}\right)^{2}}{1-h b}, \\
& h=\sum d_{i} / M, \quad b=\left(g\left(\tilde{\xi}_{u}\right)-g\left(\tilde{\xi}_{p}\right)\right) /\left(\tilde{\xi}_{u}-\tilde{\xi}_{p}\right), \\
& a=g\left(\tilde{\xi}_{j}\right)-b \tilde{\xi}_{1}, \quad \tilde{\xi}_{u}=\Phi^{-1}(P-\sqrt{P(1-P)} n), \\
& \xi_{1}=\Phi^{-1}\left(P+\sqrt{P(1-P)} \frac{n}{n}\right) \text { and } P=\sum d_{i} / n \text {. }
\end{aligned}
$$

The likelihood ratio test for testing $H_{0}$ is given by

$$
\begin{align*}
\Delta & =2\left[\sum d_{i} \ln \left\{\Phi\left(\hat{\xi}_{i}\right) / \Phi\left(\tilde{\xi}_{i}\right)\right\}+M \ln (\tilde{\sigma} / \hat{\sigma})-\sum m_{i}\left\{\frac{\left(\bar{y}_{i}-\hat{\mu}_{i}\right)\left(y_{0}-\hat{\mu}_{i}\right)}{2 \sigma^{2}}\right\}\right. \\
& \left.+M \frac{(\bar{y}-\tilde{\mu})\left(y_{0}-\tilde{\mu}\right)}{2 \tilde{\sigma}^{2}}\right] . \tag{8}
\end{align*}
$$

The distribution of $\Delta$ is approximately Chi-square $\left(x^{2}\right)$ with k-1 degrees of freedom.

## 2. Inferences About the Lognormal Parameters

The inverse of the observed Fisher's information matrix I provides a general method for deriving the variances and covariances of the estimated parameters. The variance-covariance matrix $V$ is given by

$$
\begin{align*}
V=I^{-1} & =-\left[\begin{array}{ll}
\frac{\partial^{2} \log L}{\partial \mu^{2}} & \frac{\partial^{2} \log L}{\partial \mu \partial \sigma} \\
\frac{\partial^{2} \log L}{\partial \mu \partial \sigma} & \frac{\partial^{2} \log L}{\partial \mu^{2}}
\end{array}\right]^{-1} \hat{\mu, \hat{\sigma}} \\
& =\left[\begin{array}{ll}
\operatorname{Var}(\hat{\mu}) & \operatorname{Cov}(\hat{\mu}, \hat{\sigma}) \\
\operatorname{Cov}(\hat{\mu}, \hat{\sigma}) & \operatorname{Var}(\hat{\sigma})
\end{array}\right] \tag{9}
\end{align*}
$$

where $\frac{\partial^{2} \log L}{\partial \mu^{2}}$ is the second derivative of $\log L$ with respect to $\mu$ the other elements of the matrix $I$ are defined similarly. Also $\operatorname{Var}(\hat{\mu})$, $\operatorname{Var}(\hat{\sigma})$ and $\operatorname{Cov}(\hat{\mu}, \hat{\sigma})$ represent the variances and covariances of the estimates. Hence confidence limits for $\hat{\mu}$ and $\hat{\sigma}$ either jointly or individually can be obtained in a standard way. The expressions for the elements of I are given as follows:

$$
\frac{\partial^{2} \operatorname{logL}}{\partial \mu^{2}}=-\frac{M}{\sigma^{2}}(1-h b) ; \frac{\partial^{2} \operatorname{logL}}{\partial \mu \partial \sigma}=-\frac{2 M}{\sigma^{2}}\left\{\frac{(\bar{y}-\mu)-h b\left(y_{0}-\mu\right)}{\sigma}-\frac{h a}{2}\right\}
$$

and

$$
\frac{\partial^{2} \log L}{\partial \sigma^{2}}=\frac{M}{\sigma^{2}}\left\{1-3 \frac{\left(s^{2}+(\bar{y}-\mu)^{2}\right)}{\sigma^{2}}+\frac{3 h b\left(y_{0}-\mu\right)^{2}}{\sigma^{2}}+2 h a \frac{\left(y_{0}-\mu\right)}{\sigma}\right\}
$$

Furthermore, El-Shaarawi (1989) used the above results to derive an approximate confidence limits for the lognormal mean $\eta=\operatorname{Exp}\left\{\mu+\frac{1}{2} \sigma^{2}\right\}$ which is given as
$\hat{\eta} \operatorname{Exp}\{-Q\} \leq \eta \leq \hat{\eta} \operatorname{Exp}\{Q\}$,
where $Q=Z_{1-\alpha / 2} \sqrt{\operatorname{Var}(\hat{\mu})+2 \operatorname{Cov}(\hat{\mu}, \hat{\sigma}) \hat{\sigma}+\operatorname{Var}(\hat{\sigma}) \hat{\sigma}^{2}, ~}$
$Z_{1-a / 2}$ is the endpoint of the normal distribution corresponding to the appropriate confidence coefficient and $\hat{\eta}=\operatorname{Exp}\left\{\hat{\mu}+\frac{1}{2} \hat{\sigma}^{2}\right\}$

It should be clear that in order to carry out the above analysis, at least one observation should exceed the level of detection in the sample.

## APPLICATIONS

Figure 1 shows a map of the Niagara River and the locations of the biomonitoring sampling stations. Total polychlorinated biphenyls (PCBS) concentrations are used to fllustrate the applications of the methods presented in this paper to study the spatial and temporal variability of contaminants observed in mussels. PCBs constitute a major organochiorine input to Lake Ontario from the Niagara River and several PCB Aroclors were included in the NRTC's group I Chemicals of Concern list.

Table 1 suggests that: (1) the background station has concentrations below the level of detection $\left(X_{0}=100\right)$ for all surveys; (2) the concentrations vary temporally, with variabilities for the first two surveys indicating high levels of contamination while the other surveys indicate lower levels. In fact, all the data of the 5 th survey are below the level of detection; (3) the degree of spatial variability depends on the survey, but generally the concentrations are lower at the lower and upper sections of the river and higher at the middle section; and (4) there are very high levels of variability among the replicates.

Table 2 gives the likelihood ratio test statistics for evaluating the differences between stations for each survey, with the exception of the 5 th survey where all the values were below $X_{0}$. For each survey, stations with all values below $X_{0}$ were not included in computing the test statistic. Only the first two surveys showed highly significant ( $P<0.01$ ) spatial variability among the stations included in the test.

Table $3 A$ gives the estimates of the means at each station included in the computation. Station 7 shows a consistent, high level of PCBs contamination, while stations with erratic patterns such as station 17 may be indicative of an erratic contamination source. Table 3B gives the estimates of the means under $H_{0}$ and the estimates of $\sigma$ under both $H$ and $H_{0}$. It is clear that a major proportion of variability is due to the spatial variabilities. For example, the estimate of $\sigma$ from the first survey has decreased from 0.878 to 0.456
when $H_{0}$ is correct and false respectively, which indicates that about half the variability can be attributed to spatial differences.

Finally, Table 3C gives the estimates of the lognormal means and their associated confidence limits. Testing the equality of the two lognormal means from survey 1 and 2 using El-Shaarawi's (1989) method indicates no significant difference between the two surveys. Furthermore, when the detection limit $X_{0}$ is not included within the confidence limits, then it is likely that a station with all the values below $X_{0}$ is significantly different from the stations used in generating the limits.

CONCLUSIONS

This paper extends the work of El-Shaarawi (1989) and El-Shaarawi and Dolan (1989) to the case of comparing the means of several populations. For illustration, the methods presented were applied to compare the spatial differences of total PCBs in a biomonitor between sampling locations and surveys along the Niagara River. The methods can be applied when the data are assumed to be generated from the normal and lognormal models.

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[^0]Table 2. Likelihood Ratio Tests for all Surveys Except the Fifth.

| Survey Number | Degrees of Freedom | Likelihood Ratio Test Statistic |
| :---: | :---: | :---: |
| 1 | 9 | $30.76 \star *$ |
| 2 | 10 | $62.52 * *$ |
| 3 | 4 | 5.42 |
| 4 | 7 | 8.28 |
| 6 | 5 | 4.62 |

**significant at the $1 \%$ level

Table 3. Maximum Likelihood Estimates of the Parameters
Table 3A. Means under H

| Station | Survey \#1 | Survey \#2 | Survey ${ }^{\text {\# }}$ | Survey ${ }_{\text {\# }}$ | Survey \#6 |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 0 |  |  |  |  |  |
| 1 |  |  |  |  |  |
| 2 |  |  |  |  |  |
| 3 |  | 5.041 | 4.192 | 4.971 |  |
| 4 |  |  |  |  |  |
| 5 |  |  |  |  |  |
| 6 |  | 5.925 |  |  |  |
| 7 | 7.086 | 7.516 | 6.962 | 5.949 | 5.198 |
| 8 |  |  |  | 5.949 | 5.198 |
| 9 | 4.966 | 4.963 |  | 4.669 |  |
| 10 | 6.248 | 6.476 | 4.101 | 5.799 |  |
| 11 | 5.533 | 6.228 |  | 6.161 | 6.263 |
| 12 | 6.521 | 5.576 | 3.952 | 5.818 | 6.115 |
| 13 | 5.958 | 4.799 |  | 5.206 |  |
| 14 | 5.254 | 5.011 |  |  |  |
| 15 |  | 4.829 |  |  |  |
| 16 |  | 4.600 |  |  |  |
| 17 | 5.184 |  |  |  |  |
| 18 |  |  |  |  | 6.438 |
| 19 | 5.245 |  | 4.984 | 5.648 | 7.083 |
| 20 | 5.052 |  |  |  |  |
| 22 |  |  |  |  |  |
| 27 |  |  |  |  |  |

Table 3B. Standard deviations under H and $\mathrm{H}_{0}$ and the mean under $\mathrm{H}_{\mathrm{O}}$

| Parameter | Survey \#1 | Survey ${ }^{\text {W }}$ 2 | Survey \#3 | Survey \#4 | Survey ${ }^{\text {\# }} 6$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Mean ( $\mathrm{H}_{0}$ ) | 5.674 (0.164) | 5.511 (0.172) | 4.658 (0.802) | 5.22 (0.250) | 5.095 (0.440) |
| S.D. ( $\mathrm{H}_{\text {O }}$ ) | 0.878 (0.131) | 0.980 (0.129) | 2.137 (0.731) | 0.933 (0.183) | 1.589 (0.406) |
| S.D. (H) | 0.456 | 0.338 | 1.477 | 0.504 | 0.786 |

S.D. $=$ standard deviation

Values in brackets are standard errors of the estimates

Table 3c. Means and confidence limits (measurement units)

|  | Survey ${ }^{\text {F }}$ | Survey ${ }^{\text {\% }}$ | Survey ${ }^{\text {\% }}$ | Survey ${ }^{\text {F }}$ | Survey \#6 |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Mean | 428.150 | 399.924 | 1636.409 | 286.352 | 576.811 |
| ```Confidence limits (95%)``` | 294.725-621.978 | 265.733-601.88 | 81.331-32924.960 | 181.663-451.371 | 169.588-1961.886 |



Figure 1. Locations of the biomonitoring sampling stations.


[^0]:    N indicates value below detection limit
    Blank indicates no data available

