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DETECTION OF TRENDS IN STREAM QUALITY: MONITORING NETWORK DESIGN AND DATA ANALYSIS

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PREFACE

This report is the result of a study funded by the Washington State Department of Ecology (DOE) to review DOE's existing ambient stream quality monitoring program and to analyze certain records from the existing network for possible trends. Since the two activities were essentially independent, this report has been divided into two sections. In addition to the activities mentioned above, a computer program was developed to assist in the data analysis required in Part II; this program is described and documented in Appendix B.

While some of the work reported herein is specific to problems faced by DOE, and the data analysis is, of course, specific to Washington State streams, most of the material presented in Part I is general in applicability. This work arose from an earlier, theoretical investigation conducted by the author (Lettenmaier, 1975); some of the results of the earlier study indicated that the existing ambient water quality monitoring program conducted by DOE, which has as its primary objective the detection of trends in water quality, includes too many stations with insufficient sampling frequencies at each station. The original analysis, however, was conducted for data collection activities where the sampling frequency is constant; application of this work was complicated by the fact that the existing DOE strategy utilizes a variable or stratified sampling strategy in which each station is sampled fairly intensely (two samples per month) at each active station, while the active station pool rotates so that each station is active only one year in three. This strategy was adopted because it results in regional economies which allow more total samples to be taken than could be were each station uniformly sampled. Since the existing program utilizes "grab samples," each sample or set of samples requires movement of a sample crew; by regionalizing the active sample station's travel time and expense is greatly reduced. While the travel time problem might be eliminated by implementing automatic monitoring equipment, past DOE experiences with poor reliability and high capital cost of automatic sampling equipment, coupled with the inability of existing equipment to automatically sample some parameters, has resulted in continuation of the grab sampling approach. The DOE experience has been reported elsewhere (Ward, 1973; Beck, et. al., 1976).

The first part of this report investigates the trade-off between reduction in statistical power (trend detectability) of tests on data collected under the stratified (one year in three) and continuous sampling strategies. In Part II of the report, techniques for assessing autocorrelated time series for trend are reviewed, and an number of the practical problems in data analysis are discussed. The emphasis is on graphical screening techniques, followed by appropriate use of two nonparametric tests, Spearman's rho and Mann Whitney's. These two tests were utilized in the earlier (Lettenmaier, 1975) report; a limited Monte Carlo sampling program was conducted here to allow estimation of rejection levels for a certain kind of sample dependence described by the lag one Markov process. Finally, analyses of a number of records collected from DOE's existing ambient monitoring network are conducted. The results of the analyses are reported along with a review of possible causes for the apparent trends observed.

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CHAPTER I.1 INTRODUCTION

With the increase of expenditures in a nationwide effort to upgrade water quality has come increased emphasis on the monitoring of waterways to identify trends. Several large scale studies of nationwide water quality, however, (Wolman (1971); Steele, et al. (1974) and EPA (1974)) have cited the inadequacy of existing data for trend assessment. Deficiencies of data include sporadic sampling, lack of samples of indicators of biological growth such as nutrients, and changes in laboratory analysis methods which invalidate comparisons using historic data. These deficiencies may generally be traced to the lack of design guidelines for establishing trend monitoring programs. In this paper a methodology for designing trend monitoring networks is developed.

Several problems are faced by agencies establishing trend monitoring programs. The first of these is to determine the basic strategy for collecting samples in time. Samples may be taken either uniformly, i.e., at equal intervals in time, or a stratified, or unequal time increment strategy may be followed. Two recent studies have addressed the problem of sampling strategy (Beck, et al. (1976); Lettenmaier (1975)); both these studies have suggested a uniform sampling strategy. However, in establishing trend monitoring programs in jurisdictions of moderate to large size, such as the western states, geographical locations of stations are a very important consideration, since the time which must be allocated for traveling of sample crews may be substantial. This consideration favors stratified sampling. The State of Washington Department of Ecology, for example, has adopted a sampling strategy in which the state is divided into three regions; stations in each region are sampled uniformly on a rotating basis one year in three. The stratified samping strategy allows more total samples to be taken at a given station because of the regional travel economies achieved, however, the sampling pattern at any given station consists of a year of data followed by two years of no data.

In addition to establishing the basic strategy, the desired sampling frequency at each station must be selected. A tradeoff must also be established between the sampling frequency at any given station and the number of stations to be established.

In this paper the statistical power of uniform and stratified sampling strategies are compared on the basis of modified t- and F-tests for any trend which may be described at least approximately as a polynomial in time. The relative power of the two tests aid in choice of the basic sampling strategy to be followed. General guidelines and tables which may be used to aid in selecting sampling frequencies are developed, and some guidelines for determining sample station locations are given. In addition, the use of a relatively new approach to detection of trends in dependent time series, intervention analysis (Box and Tiac (1975)) and its implications for sampling strategy are discussed. While in each section of the paper a sufficient statistical basis is provided to support the required derivations, the mathematical framework is not essential to an understanding of the results. The reader who is willing to accept the derivations may proceed directly to the end of each section, in which the results and implications of the results for trend monitoring design are given.

CHAPTER I.2 STATISTICAL FRAMEWORK FOR TREND ASSESSMENT

The problem of asserting the existence or nonexistence of trend in a recorded time series may be treated in the classical hypothesis testing framework. Two hypotheses are considered. H_o, the null hypothesis is the "no change" (no trend) alternative, while H_1, the alternative hypothesis is that a trend exists. The choice between H_o and H_1 is made on the basis of an as yet unspecified test statistic, T, computed from the data. The computed test statistic T is compared to a critical value, T_c, and the null hypothesis, H_o is either accepted or rejected. Many such test statistics exist; tables of "critical values" are available for the most common tests. Four combinations of states of nature (truth) and test indications are possible:

Test Indication

		H_o true	H_1 true
States of Nature	H_o true	$P = 1 - \alpha$	$P = \alpha$ (type 1 error)
	H_1 true	$P = \beta$ (type β error)	$P = 1 - \beta$

The confidence level α is normally specified apriori, the critical value of the test statistic is a function of α and the sample size, n. At a fixed value of α, the power of a test gives the probability of choosing the alternative hypothesis given that it is true; in the present case this is the probability of detecting a trend when one exists. The power and confidence of a test are inversely related; increasing the confidence level of a test will lower its power.

Two of the most straightforward types or trends are step and linear. A step trend is an instantaneous jump in process mean level at some point in the record, i.e.,

$$X_t = \mu_1 + [\mu_2 - \mu_1]_T + \varepsilon_t \qquad \text{I.2.1}$$

where μ_1 and μ_2 are the true means of the first and second half of the record, the notation $[L]_T$ denotes a function with value zero for $t \leq T$ and L for $t > T$, and ε_t is a stochastic noise term. A linear trend is simply a uniform increase in process mean level;

$$X_t = \mu + t/T\Delta\mu + \varepsilon_t \qquad \text{I.2.2}$$

For large sample sizes or when the variance of ε_t is known, the power of the classical two-tailed t-tests (Breiman (1973)) against the trend in eqs. I.2.1 and I.2.2, where the noise terms ε_t are statistically independent and normally distributed with mean zero and variance σ_ε^2, is

$$1 - \beta = F_g(N_T - W_{1 - \alpha/2}) \qquad \text{I.2.3}$$

where F_g is the cumulative distribution function of a standard normal probability distribution, $W_{1-\alpha/2}$ is the standard normal quantile at probability level $1 - \alpha/2$, and

$$N_T = \frac{T_r \sqrt{n}}{2\,\sigma_\varepsilon} \quad \text{(step trend)}$$

$$N_T = \frac{T_r \sqrt{n(n+1)(n-1)}}{n\sqrt{12}\,\sigma_\varepsilon} \approx \frac{T_r \sqrt{n}}{\sqrt{12}\,\sigma_\varepsilon} \quad \text{(linear trend).}$$

Where T_r is the trend magnitude (total change in mean level over the record length) and is equal to $|\mu_1 - \mu_2|$ for the step trend and $\Delta\mu$ for the linear trend.

I.2.1 General Polynomial Trends

While the linear and step trend models described above often give a sufficient approximation to time series containing trends, a more general model to the deterministic (trend) component is sometimes desired. Beck, et. al. (1976) and others have suggested use of a general polynomial in time to describe trend effects:

$$X_k = \sum_{1=0}^{m} a_i k^i + \varepsilon_k \qquad \text{I.2.4}$$

where k denotes discrete time steps with $t = k\Delta t$, the noise term ε_k is assumed to be normally distributed with variance σ_ε^2 and mean zero. It will be shown that the power of the t-test against such trends has a form very similar to eq. I.2.3.

The deterministic part of eq. I.2.4 (noise term set to zero) may be described by the (linear) vector differential equation

$$\frac{d}{dt}\begin{vmatrix} X_1 \\ X_2 \\ X_3 \\ \vdots \\ X_m \\ X_{m+1} \end{vmatrix} = \begin{vmatrix} X_2 \\ X_3 \\ \vdots \\ X_m \\ X_{m+1} \\ 0 \end{vmatrix} \quad \text{where } X_{m+1} = m!a_m, \qquad \text{I.2.5}$$

allowing use of the Kalman filter algorithm (Jazwinski (1970), Lettenmaier and Burges (1976)) to compute the variance of the estimate of the coefficient of the highest order term, a_m. The state covariance matrix is defined as $P = E(\underline{X}-\overline{\underline{X}})(\underline{X}-\overline{\underline{X}})^T$ where $\overline{\underline{X}}$ is the true value of the state vector and $\underline{X}$ is the Kalman filter estimate. The Kalman filter algorithm computes P_k, the state covariance matrix after the k'th measurement, as

$$P_k' = \Phi(\Delta t)P\Phi^T(\Delta t) \qquad \text{I.2.6a}$$

$$K = P_k'M^T(MP_k'M^T + R)^{-1} \qquad \text{I.2.6b}$$

$$P_k = (I_{m+1} - KM)P_k' \qquad \text{I.2.6c}$$

where M is a $1 \times m+1$ matrix with elements $M_i = \begin{vmatrix} 1, & i = 1 \\ 0, & \text{otherwise,} \end{vmatrix}$

R is the measurement error variance and is equal to σ_ε^2, the variance of

ε_k in eq. I.2.4, I_{m+1} is the m+1 x m+1 identity matrix, and $\phi(\Delta t)$ is the solution to $\frac{d\Phi}{dt} = F\Phi$, where $\frac{dX}{dt} = F\underline{X}$, hence from eq. I.2.5

$$F = \begin{vmatrix} 0 & 1 & 0 \ldots & 0 \\ 0 & 0 & 1 \ldots & 0 \\ \vdots & & & \\ 0 & 0 & 0 \ldots & 1 \\ 0 & 0 & 0 \ldots & 0 \end{vmatrix} \qquad \text{I.2.7}$$

and

$$\Phi = \begin{vmatrix} 1 & \Delta t & \frac{\Delta t^2}{2} & \ldots & \frac{\Delta t^m}{m!} \\ 0 & 1 & \Delta t & \ldots & \frac{\Delta t^{m-1}}{(m-1)!} \\ \vdots & & & & \\ 0 & 0 & 0 & \ldots. & 1 \end{vmatrix}$$

If the set of equations I.2.6 is initialized with $P_{ij} = \begin{cases} \infty & i = j \\ 0 & i \neq j \end{cases}$

the Kalman filter is equivalent to a sequential updating method for the classical regression solution for the variance of the coefficient of the highest order term in the polynomial. Estimation of only the variance of the highest order term is not a severe constraint, however, since statistical significance of the highest order term is a necessary and sufficient condition to justify fitting of a polynomial of that order to the data. The special case for m = 1 (linear trend) is given in Lettenmaier (1975); additional simulations for m = 2, 3, and 4 were performed in this work. Although a closed form solution for the variance of the estimate $\hat{a}_m$ of a_m is intractable for m > 1, the variance may be calculated numerically. For the measurement error variance $R = \sigma_\varepsilon^2$ taken as 1 (with no loss in generality), the variance of $\hat{a}_m$ was computed as a function of Δt and n. Δt was taken as $1/2^j$, j = 0, 1, 2, ... 6, for a number of time steps $n_{max} = 10x2^j$, hence the total time covered in the simulations was the same in each case, only the sample frequency varied. The dependence of $\sigma^2_{\hat{a}_m}$ on n may be shown by plotting $\sigma^2_{\hat{a}_m}$ against $n\Delta t$; the results are shown for m = 2 (2nd order or parabolic process) in Figure I.1, from which it is clear that $\sigma^2_{\hat{a}_2} \cong Kn^{-5}$. The constant K may be estimated from the computed variance directly. Since there is a transient numerical effect resulting from the use of a finite value for the initial diagonal element of P (10^9 was used here), it is best to estimate K from the last calculated value of $\sigma^2_{\hat{a}_m}$ at time $t = N\Delta t$. In addition, a convergence in the estimate of K was usually apparent as Δt increases, apparently corresponding to the faster loss of initialization effects in the cases where a greater number of smaller time steps were used. The estimates of K given below are the values to which K appeared to be converging. The value of K for m = 1 is known to be 12, as derived in Lettenmaier (1975) the numerical estimate was identical to this value to within three decimal places.

In general, then, the test for significance of the highest order coefficient of a polynomial fit to a time series will depend on the normalized test statistic

$$T = \frac{\hat{a}_m n^{\frac{2m+1}{2}}}{\sqrt{K_m}\,\sigma_\varepsilon} \qquad \text{I.2.8}$$

and the noncentrality parameter of the test for significance for normally distributed data will be given by

$$N_T = \frac{a_m n^{\frac{2m+1}{2}}}{\sqrt{K_m}\ \sigma_\varepsilon} \qquad \text{I.2.9}$$

with power given by $P_w = F_g(N_T - W_{1-\alpha/2})$ for a two-tailed test and where for small n $W_{1-\alpha/2}$ is replaced by $t_{1-\alpha/2,\nu}$ where ν is the degrees of freedom of the test. In this form, a_m is a function of the sampling interval, however if eq. I.2.3 is rewritten

$$X_k = \sum_{i=0}^{m} a_i \left(k \frac{n_o}{n}\right)^i + \varepsilon_k \qquad \text{I.2.10}$$

then letting

$$a_i^* = a_i (n_o)^i \qquad \text{I.2.11}$$

the resulting normalized form is

$$X_k = \sum_{i=0}^{m} a_i^* n^{-i} k^i + \varepsilon_k \qquad \text{I.2.12}$$

This formulation has the advantage that

$$N_T = \frac{a_m^* n^{\frac{2m+1-m}{2}}}{\sqrt{K_m}\ \sigma_\varepsilon} = \frac{a_m^* \sqrt{n}}{\sqrt{K_m}\ \sigma_\varepsilon} \qquad \text{I.2.13}$$

which has the same form for all m regardless of the sampling interval. As a result of this analysis, the power curves originally derived by Lettenmaier (1976) for step and linear trends are valid for any general polynomial with only a change in the constant K_m; the noncentrality parameters N_T are computed in exactly the same manner as for step and linear trends. While a polynomial form may not be conceptually reasonable, especially considering the algebraic unboundedness of eq. I.2.10 as $k \to \infty$, in practice a general polynomial will often yield a very good fit to a nonlinear trend over a limited range. For this reason, knowledge of the form of the power curves for a general polynomial may be useful in trend network design. Consequently, the monitoring recommendations made in the following sections based on the analysis of this section hold for a quite general class of trends.

Table I.1: Estimated Values of K_m

m	K_m
0	4*
1	12*
2	180
3	2.80×10^3
4	4.411×10^4

*exact analytical result

I.2.2 Stratified Sampling

For a uniform sampling strategy and independence of the error terms ε, it has been shown in the previous section that for moderate to large sample size, the power of the classical t-tests may be expressed as

$$P_w = F_g\left(\frac{T_r\sqrt{n}}{\sqrt{K_m}\,\sigma_\varepsilon} - W_{1-\alpha/2}\right) \qquad \text{I.2.14}$$

with K_m a function of the order of the polynomial m and T_r the trend magnitude expressed as the total change over the record length. For the case of dependence of the observations, the power becomes $P_w = F_g\ (T_r \sqrt{n_b^*}/K_m \sigma_\varepsilon - W_{1 - \alpha/2})$ where n_b^* is the effective independent sample size given by Bayley and Hammersley. A common form of time series dependence is the lag one Markov process,

$$\varepsilon_t = \rho\varepsilon_{t-1} + \eta_t \qquad \text{I.2.15}$$

where ρ is the lag one correlation coefficient and η_t is a normal independent process with mean zero and variance $\sigma_\eta^2 = (1 - \rho^2)\sigma_\varepsilon^2$. Lettenmaier (1975) investigated several records of daily water quality observations which suggested that the lag one Markov model may be generally applicable to water quality time series.

When a stratified sampling strategy is used, the t-tests used in detecting trend in continuous records are no longer appropriate. Rather, the F-test, used for detecting differences in mean levels in several records, should be used. The F-test for independent error terms makes use of the test statistic

$$T = \frac{n}{N_t - 1} \sum_{i=1}^{N_t} \frac{(\hat{\mu}_i - \hat{\mu})^2}{S} \qquad \text{I.2.16}$$

where there are N_t groups (years) with n measurements in each group, $\hat{\mu}_i$ is the sample mean of the i'th group, $\hat{\mu}$ is the grand sample mean,

$\hat{\mu} = 1/N_t \sum_{i=1}^{N_t} \hat{\mu}_i$, and S^2 is the sample variance. When there is no trend, $\mu_i = \mu$, and T has an F distribution with $N_t - 1$ and $n(N_t - 1)$ degrees of freedom (Breiman (1973)). For $N_t n > 20$, $S^2 \simeq \sigma^2$, and T is distributed approximately as $\chi^2 N_{t-1}/N_t - 1$. This approximation is equivalent to the normal approximation to a t-test for moderate to large sample sizes.

It may be shown that when the groups are described by a lag one Markov process,

$$X_{t_i} - \mu_i = \rho(X_{(t-1)_i} - \mu_i) + \eta_{t_i} \quad i = 1.2, \ldots N_t \qquad \text{I.2.17}$$

the classical test may be modified by using the effective independent sample size,

$$T = \frac{n_b^*}{N_t - 1} \sum_{i=1}^{N_t} \frac{(\hat{\mu}_i - \hat{\mu})^2}{S^2} \qquad \text{I.2.18}$$

We note that for $S^2 \simeq \sigma^2$, and for normally distributed error terms the numerator remains the square of a normal random variate, and hence has the χ^2 distribution. Further, the expectation of the test statistic becomes

$$E(T) = \frac{n_b^*}{(N_t - 1)\sigma^2} = E\left\{\sum_{i=1}^{N_t} (\hat{\mu}_i - \hat{\mu})^2\right\} \qquad \text{I.2.19}$$

However, from the definition of the effective independent sample size, $E(\hat{\mu}_i - \hat{\mu})^2 = \sigma^2/n_b^*$, hence $E(T) = 1$, and the test statistic is distributed as $\chi^2_{N_{t-1}}/N_t - 1$ when $\mu_i = \mu$.

The power of the test is calculated by noting that when $\mu_i \neq u$, T is the sum of the squares of N_t non-zero mean normal variates, which has a non-central χ^2 distribution (Lehman (1959). If we let $\mu_i = \mu + \Delta_i$, the expectation of the test statistic becomes

$$E(T) = 1 + \sum_{i=1}^{N_t} \frac{\Delta_i^2 n_b^*}{\sigma^2 (N_t - 1)}$$

where the quantity $\Sigma\Delta_i^2 n_b^*/\sigma^2(N_t-1)$ is the noncentrality parameter.

Further, the variance of T is $\frac{n}{N_t-1} E(\sum_{i=1}^{N_t} \frac{\hat{\mu}_i - \hat{\mu}}{\sigma} - \frac{\Delta_i}{\sigma})^2 = 1$, hence $(N_t - 1)T$ has the standard noncentral χ^2 distribution with $N_t - 1$ degrees of freedom and noncentrality parameter $\lambda = \sum_{i=1}^{N_t} \frac{\Delta_i^2 n_b^*}{\sigma^2}$.

The expected value of the test statistic may also be written as

$$E(T) = 1+K_m' n_b^* (\frac{T_r}{\sigma})^2$$

where T_r is the total change in process mean level over the record length as for the t-tests. For a step trend, K_m has a value of 0.25 when N_t is odd and a value of $0.25 \frac{N_t}{N_t-1}$ when N_t is even. For linear trends, the values of K'_m are given below:

N_t	K'_m
2	0.5
3	0.25
4	0.185
5	0.156
6	0.140
7	0.130
8	0.122
9	0.117
10	0.113

The effective independent sample size n_b^* may be computed using eq. I.2.20 For sample sizes n of 24 and 48 samples per year, the ratio n_b^*/n is plotted as a function of ρ, the one day lag one correlation coefficient for a lag one Markov model in Figure I.2. It should be noted that the actual correlation coefficient for the lag one Markov model is $\rho' = \rho^{\frac{365}{n}}$ for instance, for n = 48 and $\rho = 0.9$, $\rho' = 0.45$.

The power of the modified F-test* for dependent samples was calculated as

$$P_w = 1 - F'_{\chi^2}(\chi^2_{1-\alpha}, \nu) \qquad \text{I.2.19a}$$

where $\nu = N_t - 1$ and F'_{χ^2} is the cumulative distribution function of the noncentral χ^2 distribution with noncentrality parameter $\lambda = (E(T)-1)(N_t-1)$

*The test discussed is referred to as the "modified F-test" even though the large sample assumption has been made resulting in the test statistic T having a noncentral χ^2, other than F distribution.

and degrees of freedom $\nu = N_t - 1$. The cumulative distribution function of the noncentral χ^2 distribution was computed numerically using the second approximation given by Abdel-Aty (1954). The power curves defined by Eq. I.2.19a are plotted in Figure 3 for convenience, since the noncentral χ^2 distribution is not commonly available in tabular form.

Given the power of the modified F-test, the number of samples required to obtain the same power from a uniform sampling strategy may be calculated in a straightforward manner by using eqs. I.2.3 and I.2.9 and solving for n_b^*. Noting that for a lag one Markov process,

$$\frac{1}{n_b^*} = \frac{1}{n} + \frac{2}{n^2} \frac{(n-1)\rho^t - n\rho^{2t} + \rho^{(n+1)t}}{(\rho^t - 1)^2} \approx \frac{1}{n}\left[1 + \frac{2(\rho^t - \rho^{2t})}{(\rho^t - 1)^2}\right] \qquad \text{I.2.20}$$

where t is the sampling interval in days, the ratio n/n_b^* may easily be computed, and the required number of samples n for the same power from a uniform strategy calculated. Figures I.4-I.6 give the ratio of the number of samples required in a uniform strategy to the number required in a stratified strategy at the same power level, N_u/N_s, for linear and step trends and for trend to standard deviation ratios of 0.5 and 1.0. These values of trend to standard deviation ratio were chosen because they result in power levels in the approximate range 0.2-0.9 over the range of sample sizes and lag one correlation coefficients thought to be typical of most monitoring programs. The N_u/N_s ratios are given as a function of the lag one correlation coefficient of a lag one Markov model. The confidence level has been taken as 95 percent for both tests; sampling in the stratified strategy was assumed to be done either twice or four times monthly one year in three.

The flat region for $\rho \lesssim .65$ in Figures I.4 thru I.6 corresponds to effective independence of samples in both strategies. The reduction of effective independent sample size is felt first in the stratified samples since $\rho' = \rho^{365/n}$, where n is the number of samples taken yearly and ρ is the daily lag one correlation coefficient of the data. The lag one correlation coefficient of the uniform samples is $\rho'' = \rho^{365x3/n} = \rho^{.3}$. In all cases the stratified strategy becomes considerably less effective as ρ increases until a final increase occurs for $\rho \gtrsim .95$, however daily correlations of this magnitude are unrealistically high, and for practical purposes, the effectiveness may be considered to decrease as ρ increases.

When samples are effectively independent, the ratio N_u/N_s, where N_u and N_s are the number of samples required for the same power from uniform and stratified sampling strategies, respectively, is on the order of 0.6 for step trends and decreases from a value of about 0.9 to about 0.6 as N_t increases from three to seven. At higher values of ρ, this ratio drops to a value as low as about 0.2. Clearly, the stratified strategy is, in general, much less efficient than the uniform sampling strategy. Unless regional travel economies allow on the order of two to three times as many samples to be taken as with the uniform strategy, the uniform strategy is preferred.

I.2.3 Intervention Analysis

Recently, Box and Tiao (1975) have given a generalization of the autoregressive integrated moving average (ARIMA) model (Box and Jenkins (1970) to include the effect of one or more interventions, where an intervention is any event which might effect the mean level of a time series. The technique is particularly well adapted to detecting the effect of event-related trends, but may also be used in assessing the effect of gradual changes (such as a linear trend) where no definite intervention is identifiable; in these cases the "intervention" is simply taken as occurring at the beginning of the time series. The Intervention Analysis model for N_I interventions is

$$Y_t = \sum_{k=1}^{N_I} \frac{\omega^{(k)}(B)}{\delta^{(k)}(B)} \xi_t^{(k)} + U_t \qquad \text{I.2.21}$$

where Y_t is an appropriate transformation of the data to yield approximately normally distributed residuals,

$$\omega^{(k)}(B) = \omega_o^{(k)} - \omega_1^{(k)}B - \omega_2^{(k)}B^2 - \ldots$$

$$\delta^{(k)}(B) = 1 - \delta_1^{(k)}B - \delta_2^{(k)}B^2 - \ldots$$

$$B^j Z_t = Z_{t-j}$$

$$\xi_t^{(k)} = \begin{cases} 1, & t = T_k \\ 0, & \text{otherwise} \end{cases}$$

and U_t is an autoregressive integrated moving average process. T_k is the time at which the k'th intervention occurs. The general form given by Eq.I.2.21 may be used to model the simple step and linear trends illustrated above, however it is also possible to model the effects of interventions which may be characterized by decaying transients, delayed responses, slow movement toward a new mean level, etc. In general, the class of intervention effects which may be modeled is far more extensive than the general modified t-test which is restricted to polynomial trends. In addition, intervention analysis (IA) has the advantage that it may be used in a predictive mode if several constraints on parameters are observed; this is not possible with a general polynomial which must ultimately grow without bound. Generalizations of eq. I.2.21 given by Box and Tiao (1975) and Hipel, et al. (1975) allow modeling of seasonal time series as well as the effect of covarying time series, for instance, the effect of streamflow on sediment load levels may be estimated along with intervention effects. This feature is extremely useful in removing effects of covarying time series which might suggest spurious trends; the t-tests make no provisions for such effects.

While IA is a very new technique, it shows great promise and will very likely become the accepted method of assessing trends in autocorrelated time series in the future. However, one requirement of the method is that the data be spaced equally in time; there does not appear to be any straightforward method of adapting the approach to stratified data, particularly since the data collected near the intervention times T_k are weighted quite heavily in the estimates of the parameters $\omega_j^{(k)}$ and $\delta_j^{(k)}$ (Box and Tiao (1975)). Consequently, in addition to the results of the previous section derived in terms of modified t- and F-tests, the availability of a new more powerful tool in IA also strongly suggests that a uniform sampling strategy is to be preferred.

I.2.4 Sample Statistics

The derivations of the power of trend tests for time series show that the design of trend monitoring systems require knowledge of the trend to standard deviation ratios and lag one correlation coefficients of the trend time series being collected. In general, the lag one correlation coefficient and standard deviation are not known *a priori*, but must be estimated. In many cases, previous records will not exist at proposed station locations and data collected at other stations must be used to estimate the desired parameters. While extensive computations have been made of hydrologic time series summary statistics, relatively little work has been done on water quality time series, and it appears useful to provide sufficient summary statistics to allow a rough idea of the magnitude of lag one correlation coefficients and standard deviations (coefficients of variation) present in time series of water quality parameters.

Earlier work by Lettenmaier (1976) has found daily lag one correlation coefficients for water quality data to be in the range 0.75-0.9; however, the data analyzed included only temperature, dissolved oxygen, suspended solids, and specific conductivity; no microbial or nutrient data were included and only seven records were analyzed. In an attempt to give a better background for estimating daily lag one correlation coefficients and variances which might be expected for different water quality indicators, ten Washington stations with up to six parameters at each station were analyzed.

The geographic locations, parameters and record lengths of the time series analyzed are given in Table I.2 Specific conductance and total coliform records were initially transformed by a natural logarithmic transformation. Each record was residualized by computing monthly mean values and subtracting the monthly mean from each value. Nonstationority was removed by computing, for each observation, the moving average of the ten adjacent terms of the deseasonalized time series, then computing the residual of the observation from this moving average. Subsequent computations were performed on this stationary (with respect to mean level) time series.

Table I.3 gives the results. The lag one correlation coefficient was computed as

$$\hat{\rho} = \frac{\frac{1}{p} \sum_{j=1}^{N-1} I(j)I(j+1)(X_j - \overline{X})(X_{j+1} - \overline{X})}{\frac{1}{q} \sum_{j=1}^{N} I(j)(X_j - \overline{X})^2}$$

where I is the indicator function with $I(j) = 0$ if X_j is missing and $I(j) = 1$ otherwise, and $p = \sum_{j=1}^{N-1} I(j)I(j + t)$, $q = \sum_{j=1}^{N} I(j)$ (Jones (1971)). In all cases the nominal sampling period was monthly. The average correlation coefficients were computed as weighted averages using the p's as the weighting factor, while the average standard deviations and coefficients of variation were computed by weighting with the q's.

The standard error of the correlation coefficient for a lag one Markov model is given by $Var(\rho) = \frac{1 - \rho^2}{n}$ (Box and Jenkins (1970)). Accordingly, the approximate 95 percent confidence intervals for the average correlation coefficients were computed and compared with the estimated values to determine the significance of the differences from zero. At the 99 percent confidence level, only the values for NO_3 and OPO_4 are significantly different from zero, while at the 90 percent confidence level, NO_3, OPO_4, and SPC are significantly different from zero. Unfortunately, however, the correlation structure of a lag one Markov model is given by $\rho_k = \rho_1^k$, so even if the daily lag one correlation coefficient ρ_1 were as large as 0.9, the monthly value would be only 0.04 which will require many more samples than were available to be statistically distinguishable from zero.

To establish conclusively the characteristics of the correlation structure of water quality parameters, records with a more frequent sampling base, preferably daily, must be analyzed. In general, since daily records are normally not available, summary statistics from the few stations with such frequent sampling periods must be utilized. Fortunately, the seven records analyzed by Lettenmaier (1976) show a relatively narrow band of estimated daily lag one correlation coefficients, and the average of these estimates might be used as a starting point for design purposes. While the estimated correlation coefficients of Table I.3 are primarily useful to illustrate the difficulty of estimating the daily value required for design purposes, the estimated standard deviations may be used in estimating trend detection thresholds from given trend to standard deviation ratios, such as those given in Figures I.4-I.6.

CHAPTER I.3 NETWORK DESIGN

I.3.1 Sampling Frequency

A key question to be answered is the frequency at which samples should be taken. Increasing the sample frequency increases the effective independent sample size and hence the power of a trend test, however, for a lag one Markov model, a finite upper limit on the effective independent sample size which may be collected in a given time period (e.g., one year) exists. When the effective independent sample size corresponding to a given sampling frequency exceeds about 80-90 percent of the maximum value, a point of diminishing returns exists where the effective independent sample size increases only very slowly as sampling frequency increases. Table I.4 below gives, for several values of the lag one correlation coefficient (daily value) of a lag one Markov model, the number of samples which must be taken to reach 50, 70, and 90 percent of the maximum effective independent sample size.

Table I.4: Number of Yearly Samples Required to Reach Given Proportion of Yearly Maximum Effective Independent Sample Size

	% of n_{max}		
ρ	50	70	90
0.65	41	73	124
0.70	33	52	119
0.75	28	46	91
0.80	21	37	73
0.85	16	26	52
0.90	10	17	33
0.95	5	8	17

In an earlier study, Lettenmaier (1975) found that in determining the number of sample stations which should be established in a given river basin, it is best to "saturate" each station to roughly 70 percent of the maximum effective independent sample size before establishing an additional station. Hence, Table I.3 may be used to estimate maximum desirable sample frequencies in conjunction with the estimated lag one correlation coefficients given by Lettenmaier (1975).

Determination of the actual sample frequency requires consideration of the trend detectability (power) desired, given (for a uniform sampling strategy) by eq. I.2.14. The cumulative Gaussian distribution function is available in standard tables, e.g., Hald (1952). The trend magnitude must be specified apriori as a threshold level; the standard deviation and lag one correlation coefficient may be estimated from historic data. Table I.5 shows required sampling frequencies for given power and trend to standard deviation ratios at the 95 percent confidence level for a step trend. It should be noted that the table is not strictly correct when the total sample size given is less than about 20, since at these sample sizes, the large sample approximation to the t-test power given by eq. I.2.3 is not valid. The effect of the large sample assumption is that slightly higher sample frequencies than those given by table I.5 are required for $n \lesssim 20$.

Table I.5 may be used as follows. An acceptable power level is chosen. For a primary station, this power level would be relatively high, say 0.90, since fairly reliable trend information is required. At a secondary station, a somewhat lower power might be accepted. The best available estimate of the daily lag one correlation coefficient is used; in practice, sufficient records for estimation of the daily correlation coefficient rarely exist, and as shown by the results of Table I.2, use of less frequently collected (e.g. monthly) data to estimate the daily value will usually be unsuccessful. Until the results of more extensive analyses become available, use of the average daily correlation coefficient given by Lettenmaier (1976) of about 0.85 is suggested. The sample standard deviation, S may, however, be estimated from historic data such as those given in Table I.3. With this information, a range of trend to standard deviation ratios and accompanying sample frequencies are surveyed. Actual trend magnitudes are calculated by multiplying the trend to standard deviation ratio by the sample standard deviation. Results of such an analysis for the Nooksack River near Ferndale, Washington, are given in Table I.6 for a power of 0.90 and daily lag one correlation coefficient of 0.85, and record lengths of 5 and 10 years.

It is clear from Table I.6 that the trend detection threshold for a biweekly sampling program is nearly as small as for a weekly program. The greatest difference in detectable trend level appears to be between bimonthly and monthly sampling. These results suggest that the best sampling frequency will be at least monthly, but not more frequently than biweekly. The actual detectable trend levels should be compared with established criteria to determine if they are sufficiently small. If they are not, the only alternative is to establish a larger record length for trend assessment. More frequent sampling is clearly not the answer.

It should be emphasized that Tables I.5 and I.6 are based on a step trend, so the trend magnitude is independent of the record length. For a linear trend or any higher order polynomial, the trend magnitude will increase with increased record length, which will greatly enhance trend detectability (lower threshold trend detection levels at a given power). However, in general, such unbounded trends are not physically reasonable, as most biochemical processes ultimately seek some equilibrium level, and it seems more reasonable to design monitoring systems on the basis of a fixed trend magnitude.

I.3.2 Station Location

A number of techniques have been proposed for locating sample stations, for instance Sharp (1970; 1971), Moore (1971), and Lettenmaier (1975) have proposed analytical methods for locating sample stations. Lettenmaier (1975) found, however, using a statistical criterion that the location of sample stations was much less important than the number of stations established when maximization of basin-wide trend detectability was taken as the objective and a constraint was met on the number of samples which could be taken basin-wide. Consequently, it appears that the inclusion of a number of criterion in a less formal, matrix style approach such as that discussed by Sargent (1972) may be preferable to an analytical technique in establishing station locations. Factors which should be considered in such an approach include at least the following:

1. Consideration should be given to making use of existing stations or stations at which earlier data from discontinued stations can be corrected for inclusion in trend analysis of data collected at the new station.

2. Stations should be situated so as to monitor a substantial proportion of the total runoff from a river basin. In general, this consideration favors location of stations as far downstream as is possible, consistent with other factors.

3. Stations should be located so that trend analysis of data collected at the given station taken together with data collected at adjacent stations can isolate effects of suspected trend causes (interventions). Trend causes may include the effects of large urban centers, growing suburban areas expected to result in increased nonpoint pollutant loads, impoundments, etc.

4. Sample stations should be located such that the best available estimate of cross sectional stream quality is given by a single grab sample; for instance, samples taken from bridges often allow more representative sampling than do shore samples.

5. Care should be taken to locate samples such that local effects do not indicate spurious trends; for instance, stations should not be located in areas where major highways construction, stream channelization, etc. are planned or appear likely unless it is desired to assess the impact of these projects on stream quality.

6. At each established station, it is desirable to establish a correction curve to compensate for diurnal effects. This may be accomplished by use of an automatic monitor to collect high frequency data over several days, possibly seasonally. Samples should then be

corrected to a common sampling time; for instance, 12:00 noon. For some parameters, diurnal variations may be negligible; however, for biologically influenced variables (e.g., dissolved oxygen, HCO_3, etc.), slight variations in the time at which samples are collected can induce extra variability or even spurious trends in the data.

7. When compatible with considerations 1-6, stations should be located in such a manner as to minimize sample transport time and sample crew travel requirements.

Ultimately, the techniques of the evolving field of multiple-objective planning (Cohon and Marks (1975)) may be brought to bear on the station location problem. The problem does not, however, lend itself easily to the formulation of a mathematical objective function, and for the present a less formal approach appears sufficient.

CHAPTER I.4 CONCLUSIONS

An analytical comparison of the power in trend detectability of two alternate strategies, uniform data collection in time and a more travel-economical time-stratified strategy has shown that the uniform strategy is generally preferred. This conclusion holds even if the travel economies in the stratified strategy allow as many as 2-3 times as many samples to be taken, and holds for any trend which may be described at least approximately as a polynomial in time. In addition, the emergence of a new statistical technique, Intervention Analysis, tailored to the detection of trend in autocorrelated time series, favors the implementation of uniform data collection strategies for trend detection. When total data collection capabilities are constrained, it is important that a relatively complete record be collected at each station even if the resulting network is quite sparse geographically. The optimal data collection frequency at each station appears to be in the range from biweekly to monthly; at any given station and for any given parameter, this judgment will depend on the actual correlation structure present.

An attempt to estimate the correlation structure for a number of parameters on ten Washington rivers was largely unsuccessful because the available sampling intervals are too large. In contrast to the desirable data collection frequencies for trend detection, frequently sampled data (preferably daily) is necessary in order to adequately estimate persistence structure. Since relatively few such records exist, it will probably be necessary to employ a regionalized approach to estimating correlation structure for water quality parameters. At present, the best available procedure is to use the average daily correlation coefficients from several very complete water quality records analyzed in past studies.

In determining the geographic location of sample stations, the best procedure appears to be utilization of a matrix-style approach in which a number of factors are weighed subjectively. Suggested factors for inclusion in such an approach have been given.

The importance of incorporating an analysis of the statistical power of a proposed trend network cannot be overemphasized. Because of mathematical limits on the power, or trend detectability of a station over a base time period of fixed length, failure to evaluate the power of a proposed network can result in either unobtainable sample network objectives, collection of a large number of samples which add little or nothing to trend detectability of the network, or both. The approach presented herein should aid the designer in avoiding both of those pitfalls.

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Table I.2: Time Series Analyzed

Station a/ Number	Location	Period of Record	Parameter
01A070	Nooksack River near Ferndale	1961-66	DO, pH, NO_3, OPO_4, TCX
62A150	Pend Oreille River at Newport	1959-66	SPC, DO, pH, NO_3, OPO_4, TXC
45A070	Wenatchee River at Wenatchee	1960-76	SPC, DO, pH, NO_3, TCX
08B070	Sammamish River near Bothel	1959-70	SPC, DO, pH, NO_3, TCX
23A070	Chehalis River at Porter	1959-70	SPC, DO, pH, NO_3
10A050	Puyallup River at Puyallup	1959-70	SPC, DO, pH, NO_3, OPO_4
32A070	Walla Walla River near Touchet	1959-66	SPC, pH, NO_3, OPO_4
37A090	Yakima River at Kiona	1959-66	SPC, pH, NO_3
54A070	Spokane River at Long Lake	1959-70	SPC, DO, pH, NO_3
07A090	Snohomish River at Snohomish	1959-70	SPC, DO, pH, NO_3, OPO_4

SPC = Specific Conductivity

DO = Dissolved Oxygen

NO_3 = Dissolved Inorganic Nitrate

OPO_4 = Dissolved Inorganic Phosphate (Orthophosphate)

TCX = Total Coliform

a/ Station numbers are STORET station identification numbers.

Table I.3: Summary Statistics

Parameter	Station	p	q	$\hat{\rho}$	$S(C_v)$
SPC	62A150	73	78	-0.07	0.03
	45A070	50	74	-0.19	0.14
	03B070	80	92	0.18	0.07
	23A070	114	121	-0.18	0.11
	10A050	55	75	-0.05	0.14
	32A070	75	76	0.24	0.27
	37A090	60	61	0.47	0.18
	54A070	95	99	0.23	0.14
	07A090	115	118	0.07	0.18
	Average	717	794	0.07	0.14
DO	01A070	51	53	-0.01	0.69
	62A150	73	76	0.18	0.72
	45A070	42	64	0.04	0.79
	08B070	77	96	0.05	0.63
	23A070	98	99	0.13	0.58
	10A050	40	56	-0.40	0.45
	54A070	56	63	0.21	1.46
	07A090	85	87	-0.10	0.58
	Average	522	594	0.03	0.72
pH	01A070	51	54	-0.16	0.15
	62A150	73	78	0.10	0.19
	45A070	50	74	0.07	0.25
	08B070	80	97	-0.08	0.17
	23A070	114	121	-0.11	0.16
	10A050	55	74	-0.13	0.17
	32A070	75	76	0.00	0.22
	37A090	60	61	0.36	0.20
	54A070	95	98	-0.07	0.20
	07A090	115	116	-0.14	0.18
	Average	768	849	-0.03	0.19
NO_3	01A070	51	54	0.02	0.06 (0.34)
	62A150	65	72	-0.08	0.03 (0.59)
	45A070	50	74	-0.51	0.07 (0.47)
	08B070	80	97	0.19	0.44 (0.41)
	23A070	114	120	0.24	0.27 (0.53)
	10A050	54	73	0.05	0.22 (0.60)
	32A070	68	76	0.10	0.38 (0.39)
	37A090	26	34	0.14	0.73 (0.27)
	54A070	89	99	0.39	0.51 (0.41)
	07A090	114	115	0.04	0.36 (0.72)
	Average	711	814	0.09	0.30 (0.46)

Table I.3: Summary Statistics (Continued)

Parameter	Station	p	q	$\hat{\rho}$	$S(C_v)$
OPO_4	01A070	39	43	-0.01	0.01 (0.36)
	62A150	50	63	-0.24	0.05 (1.62)
	10A050	26	42	0.36	0.02 (0.40)
	32A070	67	70	-0.08	0.09 (0.24)
	07A090	64	67	-0.42	0.02 (0.82)
	Average	246	285	-0.14	0.04 (0.69)
TCX	01A070	51	54	-0.01	1.07
	62A150	28	47	-0.30	1.15
	45A070	34	55	-0.01	1.06
	08B070	44	65	-0.10	0.93
	Average	157	221	-0.09	1.04

Table I.4: Required Total Sample Sizes for Given Power Against A Step Trend at 95% Confidence Level a/

P_w \ T_r/σ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0	1.5	2.0
	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (287)	- (100)	39 (33)	18 (18)
0.99	- (-)	- (-)	- (-)	- (-)	- (1813)	- (214)	- (157)	154 (116)	101 (91)	77 (74)	33 (33)	18 (18)
	- (-)	- (-)	- (-)	- (793)	- (316)	276 (207)	162 (150)	118 (115)	91 (909)	74 (74)	33 (33)	18 (18)
	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (172)	- (79)	- (55)	76 (43)	19 (19)	10 (10)
0.90	- (-)	- (-)	- (-)	- (446)	- (181)	159 (118)	93 (86)	67 (66)	52 (52)	42 (42)	19 (19)	10 (10)
	- (-)	- (-)	- (843)	326 (274)	191 (169)	120 (118)	86 (86)	66 (66)	52 (52)	42 (42)	19 (19)	10 (10)
	- (-)	- (-)	- (-)	- (-)	- (-)	- (190)	- (76)	- (52)	57 (39)	36 (31)	14 (14)	8 (8)
0.80	- (-)	- (-)	- (-)	- (227)	195 (128)	95 (87)	65 (64)	49 (49)	39 (39)	31 (31)	14 (14)	8 (8)
	- (-)	- (-)	- (404)	251 (198)	130 (126)	87 (87)	64 (64)	49 (49)	39 (39)	31 (31)	14 (14)	8 (8)
	- (-)	- (-)	- (-)	- (-)	- (71)	82 (44)	36 (31)	25 (24)	19 (19)	15 (15)	7 (7)	4 (4)
0.50	- (-)	- -	- (185)	110 (96)	63 (61)	43 (43)	31 (31)	24 (24)	19 (19)	15 (15)	7 (7)	4 (4)
	- (-)	- (482)	196 (171)	97 (96)	61 (61)	43 (43)	31 (31)	24 (24)	19 (19)	15 (15)	7 (7)	4 (4)

a/ At each trend to standard deviation ratio and power, the left and right (parentheses) columns correspond to record lengths of 5 and 10 years respectively and the three rows correspond to daily lag one correlation coefficients of 0.95, 0.85, and 0.75. Blanks denote unobtainable power.

Table I.5a: Required Sample Interval in Days for Given Power Against a Step Trend at 99% Confidence Level a/

P_w \ T_r/σ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0	1.5	2.0
0.99	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	22 (83)	72 (152)
	- (-)	- (-)	- (-)	- (-)	- (-)	- (7)	- (16)	- (23)	11 (30)	17 (38)	43 (85)	76 (152)
	- (-)	- (-)	- (-)	- (-)	- (8)	- (13)	(18)	11 (24)	15 (31)	19 (38)	43 (85)	76 (152)
0.90	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (7)	- (37)	- (54)	64 (138)	122 (245)
	- (-)	- (-)	- (-)	- (-)	- (11)	- (21)	10 (30)	17 (39)	24 (50)	30 (61)	69 (138)	123 (245)
	- (-)	- (-)	- (-)	- (8)	4 (15)	10 (22)	15 (30)	19 (39)	25 (50)	31 (61)	69 (138)	123 (245)
0.80	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (37)	- (57)	7 (75)	86 (176)	156 (312)
	- (-)	- (-)	- (-)	- (3)	- (17)	8 (27)	17 (38)	24 (50)	31 (63)	39 (78)	88 (176)	156 (312)
	- (-)	- (-)	- (1)	- (12)	8 (19)	14 (28)	19 (38)	25 (50)	32 (63)	39 (78)	88 (176)	156 (312)
0.50	- (-)	- (-)	- (-)	- (-)	- (-)	- (36)	- (62)	25 (86)	47 (111)	64 (137)	155 (309)	275 (550)
	- (-)	- (-)	- (2)	- (20)	14 (34)	24 (50)	33 (67)	44 (88)	56 (111)	69 (138)	155 (309)	275 (550)
	- (-)	- (-)	- (12)	10 (22)	17 (34)	25 (50)	34 (67)	44 (88)	56 (111)	69 (138)	155 (309)	275 (550)

a/ At each trend to standard deviation ratio and power, the left and right (parentheses) columns correspond to record lengths of 5 and 10 years respectively and the three rows correspond to daily lag one correlation coefficients of 0.95, 0.85, and 0.75. Blanks denote unobtainable power.

Table I.5b: Required Sample Interval in Days for Given Power Against a Step Trend at 95% Confidence Level a/

P_w \ T_r/σ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0	1.5	2.0
	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (13)	- (36)	47 (111)	98 (198)
0.99	- (-)	- (-)	- (-)	- (-)	- (2)	- (15)	- (23)	12 (31)	18 (40)	24 (50)	56 (112)	99 (198)
	- (-)	- (-)	- (-)	- (5)	- (12)	7 (18)	11 (24)	15 (32)	20 (40)	25 (50)	56 (112)	99 (198)
	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (21)	- (46)	- (66)	24 (85)	96 (196)	174 (350)
0.90	- (-)	- (-)	- (-)	- (8)	- (20)	11 (31)	20 (43)	27 (56)	35 (70)	43 (87)	98 (196)	174 (350)
	- (-)	- (-)	- (4)	1 (13)	10 (22)	15 (31)	21 (43)	28 (56)	35 (70)	43 (87)	98 (196)	174 (350)
	- (-)	- (-)	- (-)	- (-)	- (-)	- (19)	- (48)	- (71)	32 (93)	56 (116)	131 (262)	233 (466)
0.80	- (-)	- (-)	- (-)	- (16)	9 (29)	19 (42)	28 (57)	37 (74)	47 (94)	58 (116)	131 (262)	233 (466)
	- (-)	- (-)	- (9)	7 (18)	14 (29)	21 (42)	28 (57)	37 (74)	47 (94)	58 (116)	131 (262)	233 (466)
	- (-)	- (-)	- (-)	- (-)	- (52)	22 (83)	50 (116)	73 (152)	95 (192)	118 (238)	267 (534)	475 (950)
0.50	- (-)	- (-)	- (20)	17 (38)	29 (59)	43 (86)	58 (116)	76 (152)	96 (192)	119 (238)	267 (534)	475 (950)
	- (-)	- (8)	9 (21)	19 (38)	30 (59)	43 (86)	58 (116)	76 (152)	96 (192)	119 (238)	267 (534)	475 (950)

a/ At each trend to standard deviation ratio and power, the left and right (parentheses) columns correspond to record lengths of 5 and 10 years respectively and the three rows correspond to daily lag one correlation coefficients of 0.95, 0.85, and 0.75. Blanks denote unobtainable power.

Table 1.5c: Required Sample Interval in Days for Given Power Against a Step Trend at 90% Confidence Level a/

P_w \ T_r/σ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0	1.5	2.0
	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (31)	- (50)	59 (130)	115 (231)
0.99	- (-)	- (-)	- (-)	- (-)	- (9)	- (19)	9 (28)	16 (37)	22 (47)	28 (58)	65 (130)	116 (231)
	- (-)	- (-)	- (-)	- (7)	2 (14)	9 (21)	14 (28)	18 (37)	24 (47)	29 (58)	65 (130)	116 (231)
	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (41)	- (63)	23 (84)	43 (106)	119 (240)	213 (426)
0.90	- (-)	- (-)	- (-)	- (14)	6 (26)	17 (38)	25 (52)	34 (68)	43 (86)	53 (107)	120 (240)	213 (426)
	- (-)	- (-)	- (8)	6 (17)	13 (27)	19 (38)	26 (52)	34 (68)	43 (86)	53 (107)	120 (240)	213 (426)
	- (-)	- (-)	- (-)	- (-)	- (-)	- (42)	- (68)	32 (93)	52 (119)	70 (147)	166 (332)	295 (590)
0.80	- (-)	- (-)	- (6)	- (22)	16 (37)	26 (53)	36 (72)	47 (94)	60 (120)	74 (148)	166 (332)	295 (590)
	- (-)	- (-)	- (13)	11 (24)	18 (37)	27 (53)	36 (72)	47 (94)	60 (120)	74 (148)	166 (332)	295 (590)
	- (-)	- (-)	- (-)	- (44)	21 (82)	54 (121)	80 (165)	107 (216)	136 (273)	169 (337)	379 (759)	674 (1350)
0.50	- (-)	- (7)	11 (30)	26 (54)	42 (84)	61 (121)	83 (165)	108 (216)	137 (273)	169 (337)	379 (759)	674 (1350)
	- (-)	- (13)	15 (30)	27 (54)	42 (84)	61 (121)	83 (165)	108 (216)	137 (273)	169 (337)	379 (759)	674 (1350)

a/ At each trend to standard deviation ratio and power, the left and right (parentheses) columns correspond to record lengths of 5 and 10 years respectively and the three rows correspond to daily lag one correlation coefficients of 0.95, 0.85, and 0.75. Blanks denote unobtainable power.

Table 1.5d: Required Sample Interval in Days for Given Power Against a Step Trend at 80% Confidence Level a/

P_w \ T_r/σ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0	1.5	2.0
	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	- (27)	- (48)	- (65)	76 (158)	140 (280)
0.99	- (-)	- (-)	- (-)	- (-)	- (14)	4 (24)	14 (34)	21 (45)	28 (57)	35 (70)	79 (158)	140 (280)
	- (-)	- (-)	- (-)	- (10)	6 (17)	12 (25)	17 (34)	22 (45)	28 (57)	35 (70)	79 (158)	140 (280)
	- (-)	- (-)	- (-)	- (-)	- (-)	- (37)	- (63)	26 (87)	47 (112)	65 (139)	156 (312)	278 (555)
0.90	- (-)	- (-)	- (3)	- (21)	14 (34)	24 (50)	34 (68)	44 (89)	56 (112)	69 (139)	156 (312)	278 (555)
	- (-)	- (-)	- (12)	10 (22)	17 (35)	25 (50)	34 (68)	44 (89)	56 (112)	69 (139)	156 (312)	278 (555)
	- (-)	- (-)	- (-)	- (-)	- (38)	- (69)	37 (98)	59 (129)	74 (164)	100 (202)	228 (455)	405 (809)
0.80	- (-)	- (-)	- (16)	12 (32)	24 (50)	36 (73)	50 (99)	65 (129)	82 (164)	101 (202)	228 (455)	405 (809)
	- (-)	- (5)	7 (18)	16 (32)	25 (51)	36 (73)	50 (99)	65 (129)	82 (164)	101 (202)	228 (455)	405 (809)
	- (-)	- (-)	- (37)	26 (87)	65 (139)	99 (200)	136 (272)	178 (355)	225 (450)	278 (555)	625(1249)	1110(2200)
0.50	- (-)	- (21)	24 (50)	44 (89)	69 (139)	100 (200)	136 (272)	178 (355)	225 (450)	278 (555)	625(1249)	1110(2200)
	- (-)	10 (22)	25 (50)	44 (89)	69 (139)	100 (200)	136 (272)	178 (355)	225 (450)	278 (555)	625(1249)	1110(2200)

a/ At each trend to standard deviation ratio and power, the left and right (parentheses) columns correspond to record lengths of 5 and 10 years respectively and the three rows correspond to daily lag one correlation coefficients of 0.95, 0.85, and 0.75. Blanks denote unobtainable power.

Table I.6:Trend Detectabilities at 95% Confidence for 90% Power (Nooksack River near Ferndale, Washington) a/

Sampling Frequency	T_r/σ	DO b/	pH c/	NO_3 b/	OPO_4 b/	TCX d/
Weekly	0.58 (0.39)	0.40 (0.27)	0.09 0.06	0.03 (0.02	0.006 (0.004)	0.62 (0.42)
Biweekly	0.63 (0.45)	0.43 (0.31)	0.09 (0.07)	0.04 (0.03)	0.006 (0.005)	0.67 (0.48)
Monthly	0.84 (0.60)	0.58 (0.41)	0.13 (0.09)	0.05 (0.04)	0.008 (0.006)	0.90 (0.64)
Bimonthly	1.15 (0.83)	0.79 (0.57)	0.17 (0.12)	0.07 (0.05)	0.012 (0.008)	1.23 (0.89)
Quarterly	1.43 (1.01)	0.99 (0.70)	0.21 (0.15)	0.09 (0.06)	0.014 (0.010)	1.53 (1.08)
Semiannual	>2 (1.43)	>1.38 (0.99)	>0.30 (0.21)	>0.12 (0.09)	>0.020 (0.014)	>2.14 (1.53)

a/ Values listed are for daily lag one correlation coefficients of 0.85 and record length of 5 years, values in parentheses are for 10 year record length.

b/ mg/1

c/ Standard units

d/ MPN, natural logarithmic units

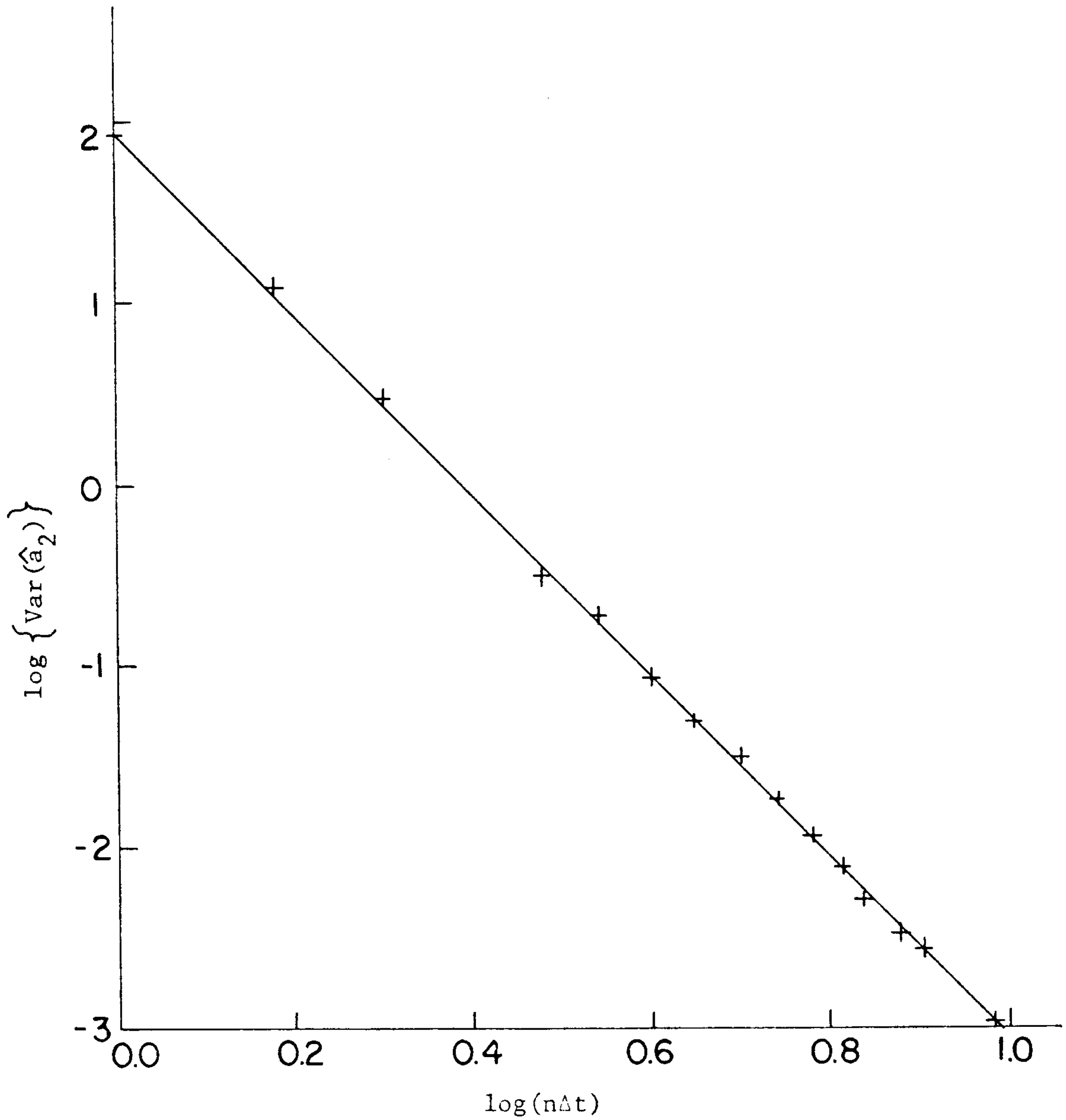

Figure I.1: Log-log Plot of Variance of the Estimate of the Highest Order Term versus Normalized Number of Samples for a Parabolic (m=2) Process

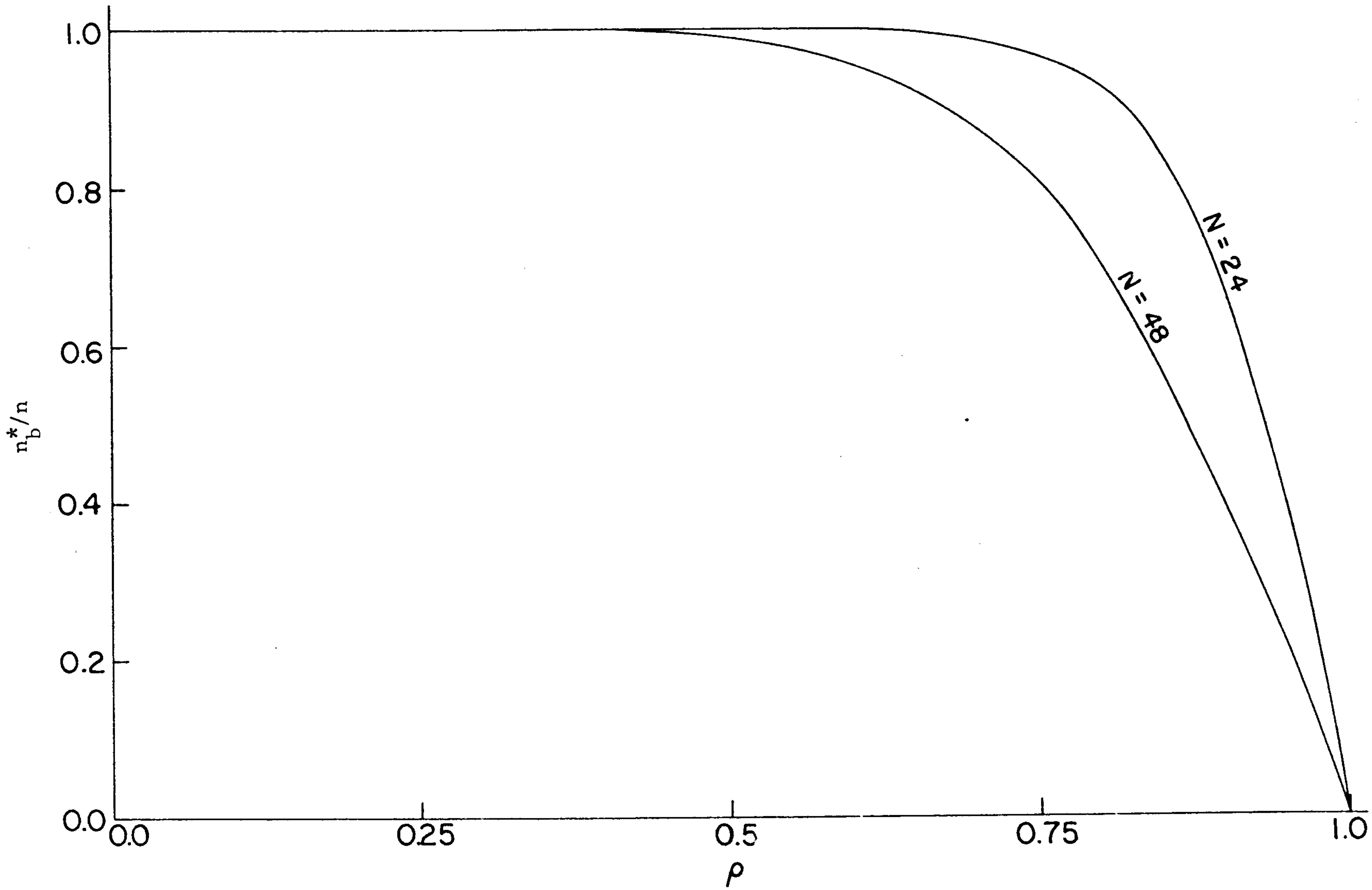

Figure I.2: Effective Independent Sample Size to Actual Sample Size Ratio for 24 and 48 Samples per Year

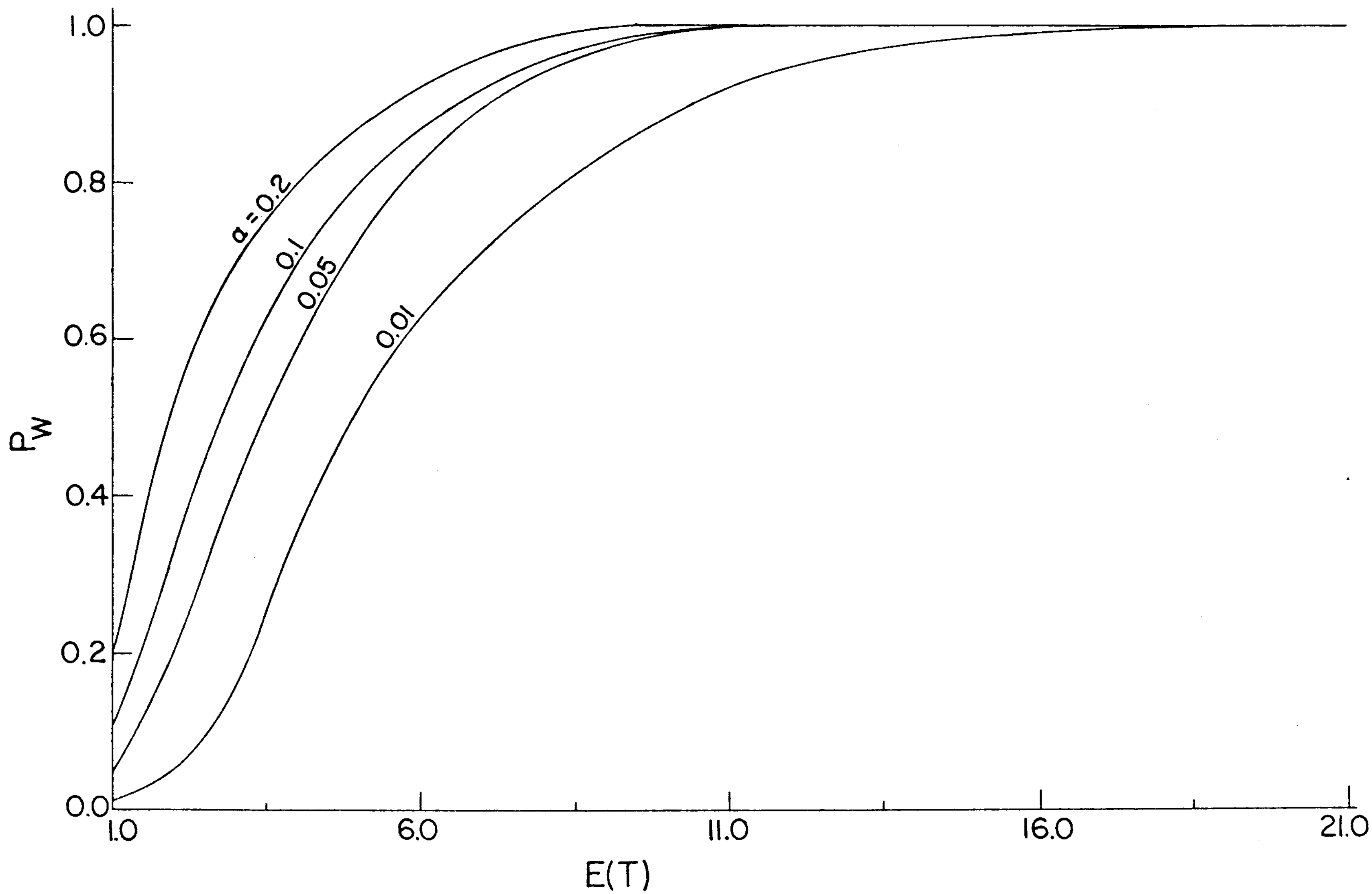

Figure I.3a: Noncentral χ^2 Power Function for N_t = 3

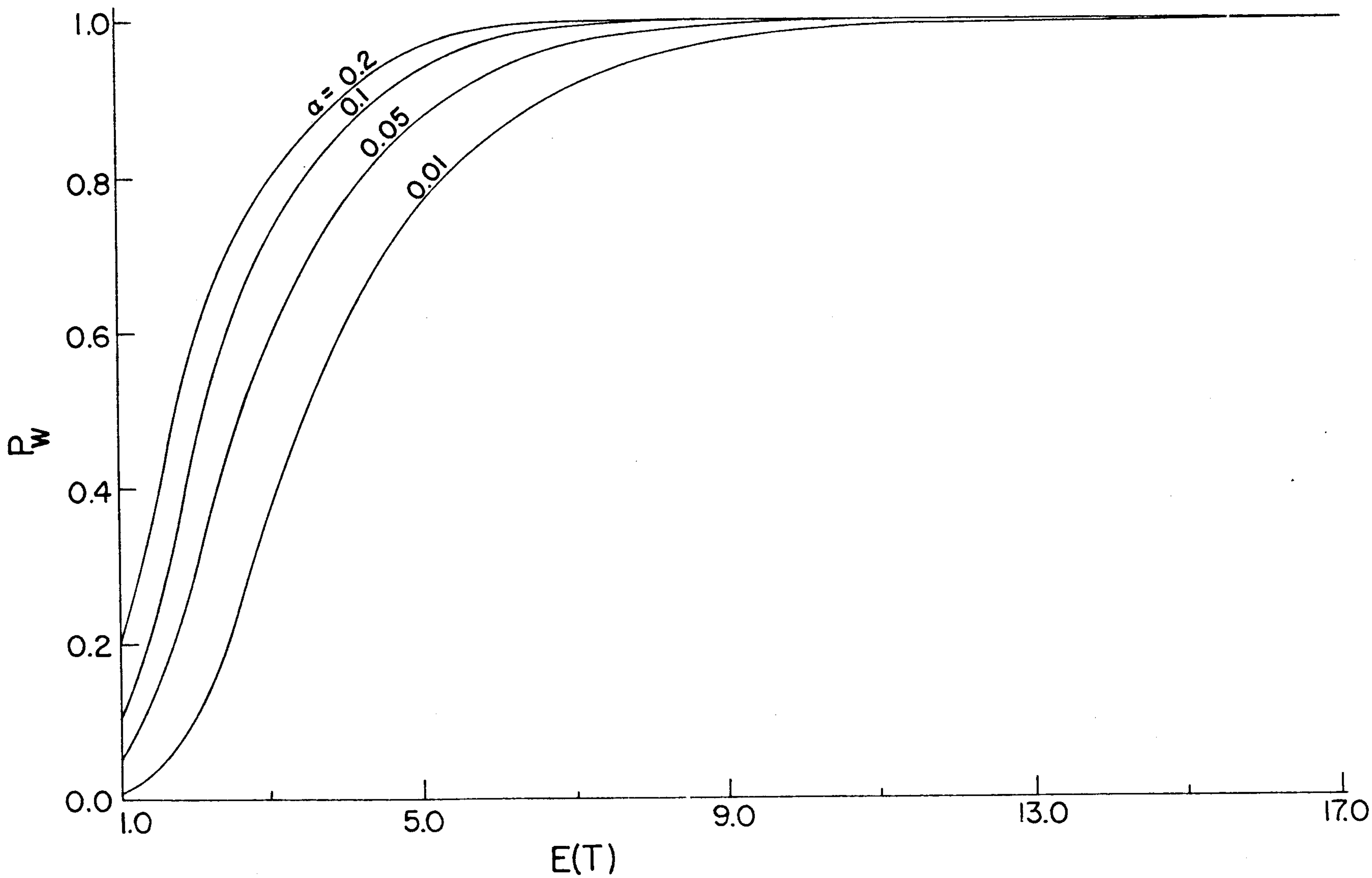

Figure I.3b: Noncentral χ^2 Power Function for $N_t = 5$

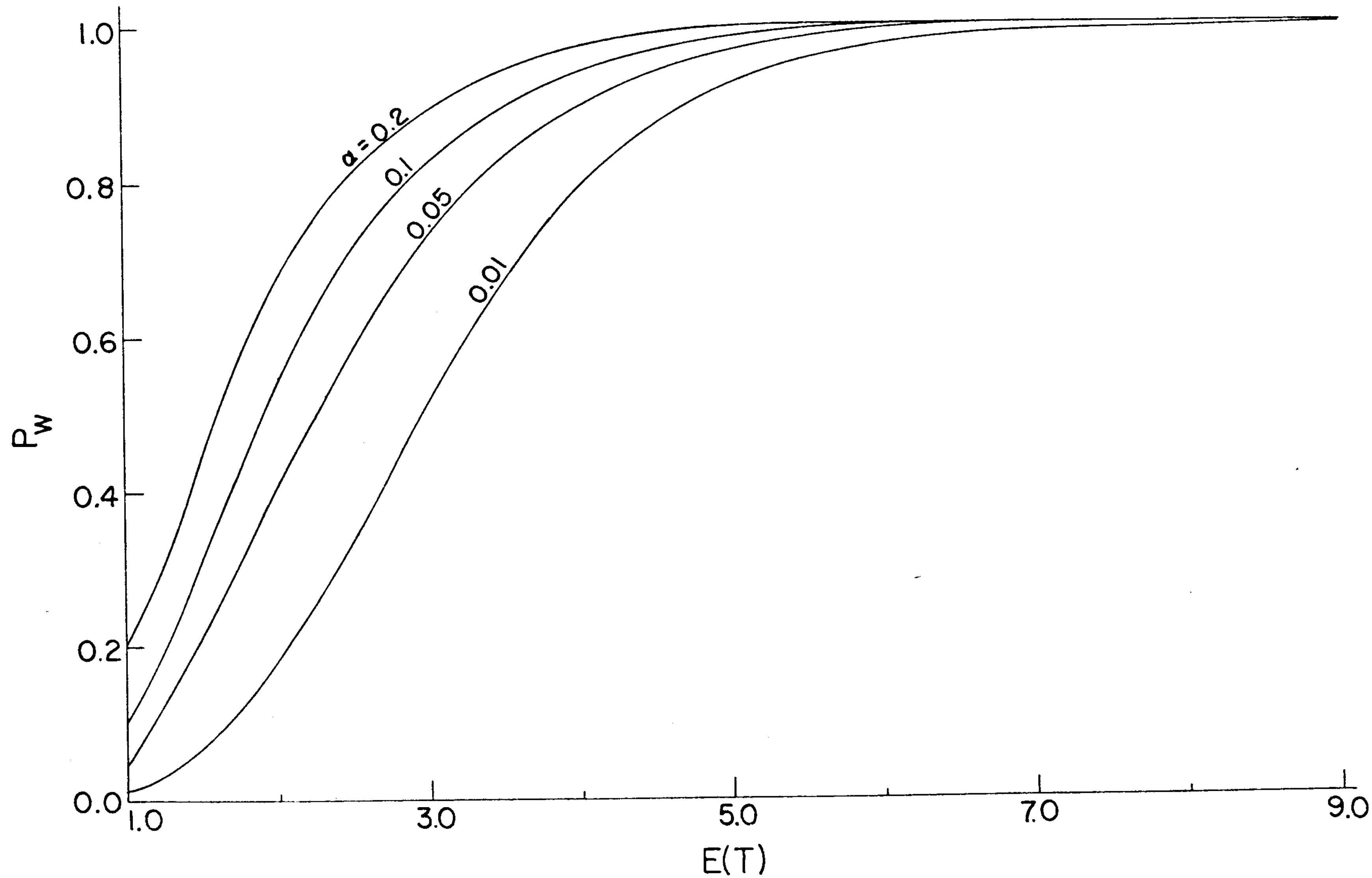

Figure I.3c: Noncentral χ^2 Power Function for N_t = 7

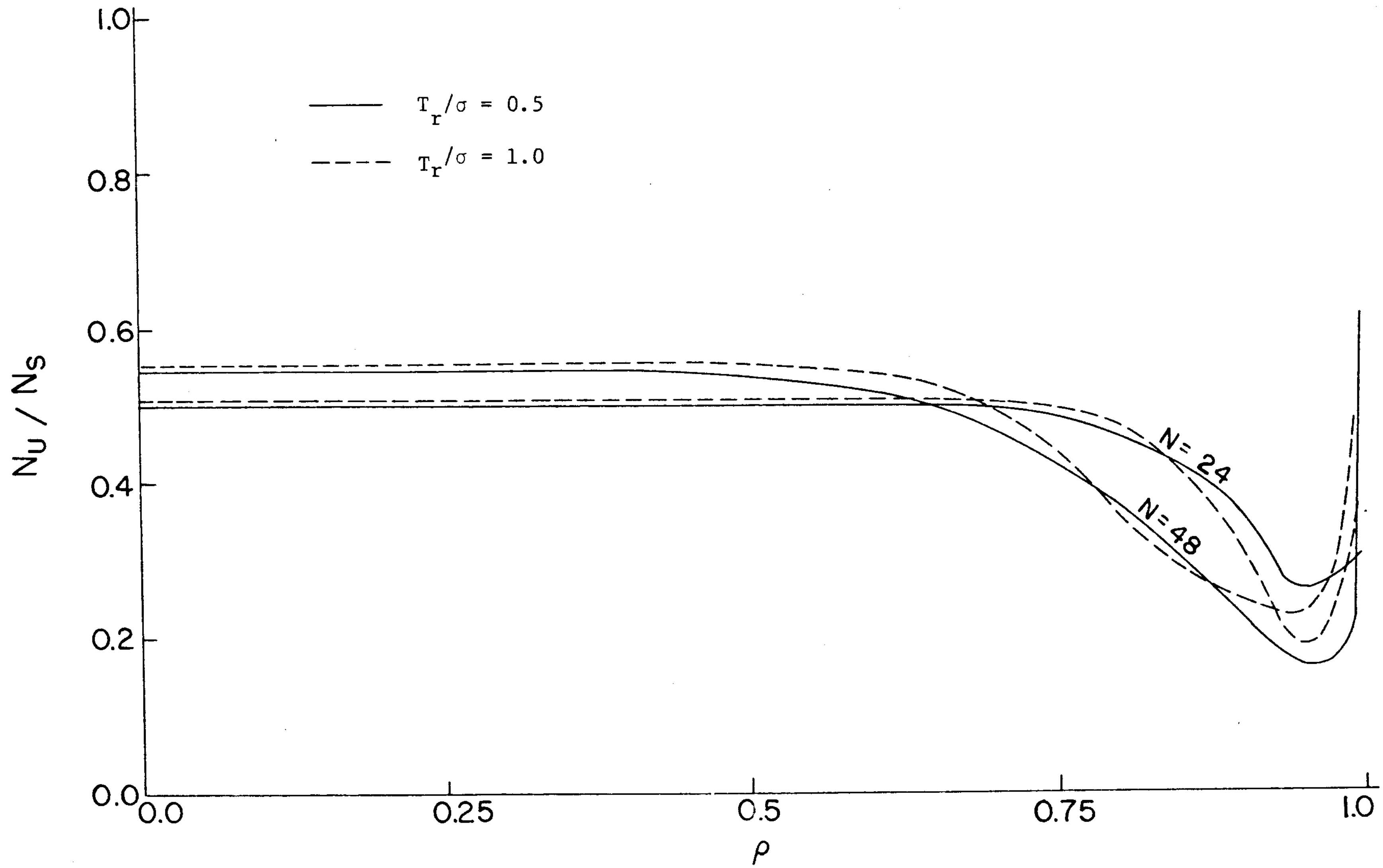

Figure I.4a: Relative Sample Size, Required for Uniform and Stratified Strategy for Step Trend, N_t = 3

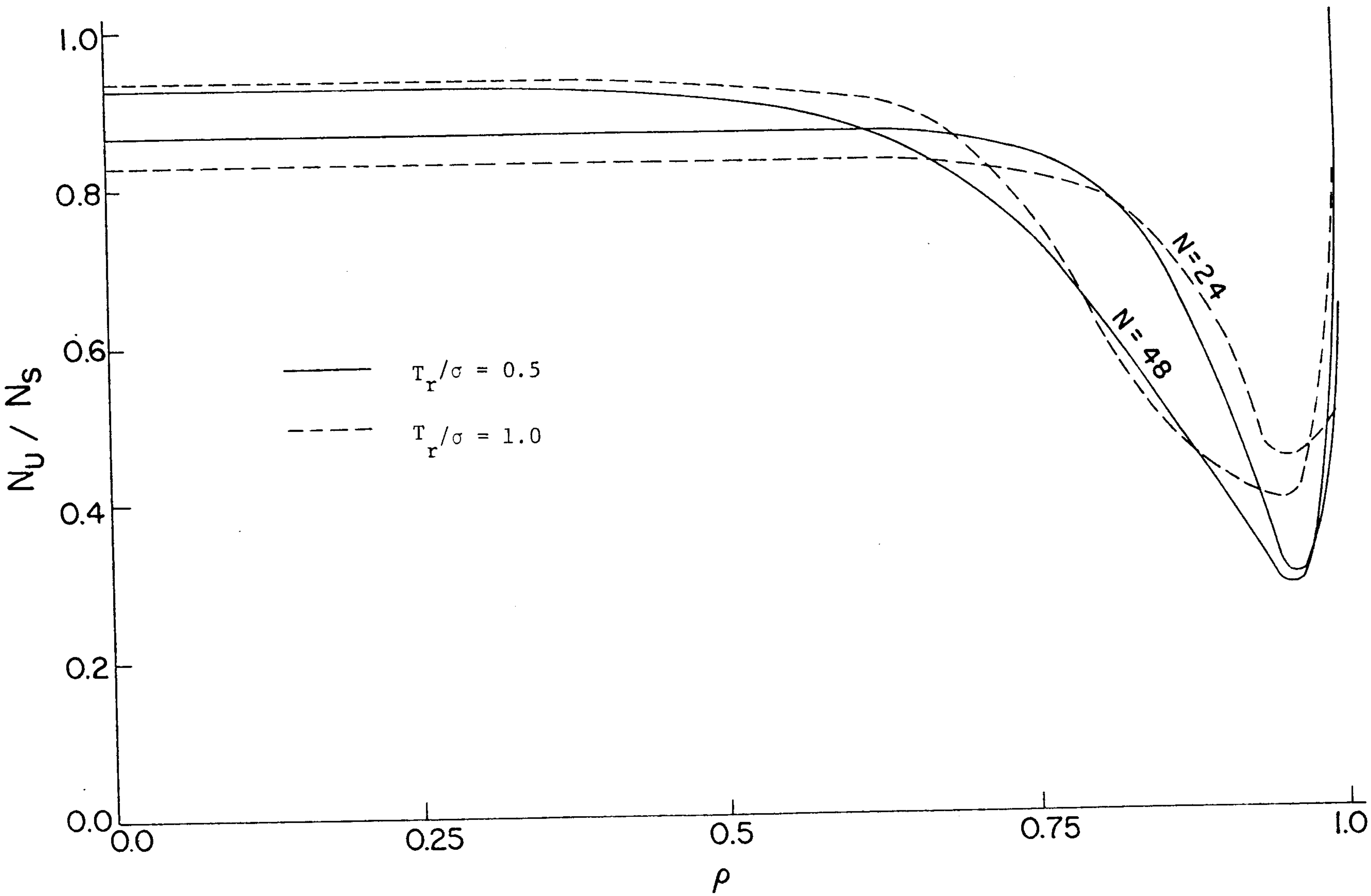

Figure I.4b: Relative Sample Size, Required for Uniform and Stratified Strategy for Linear Trend, $N_t = 3$

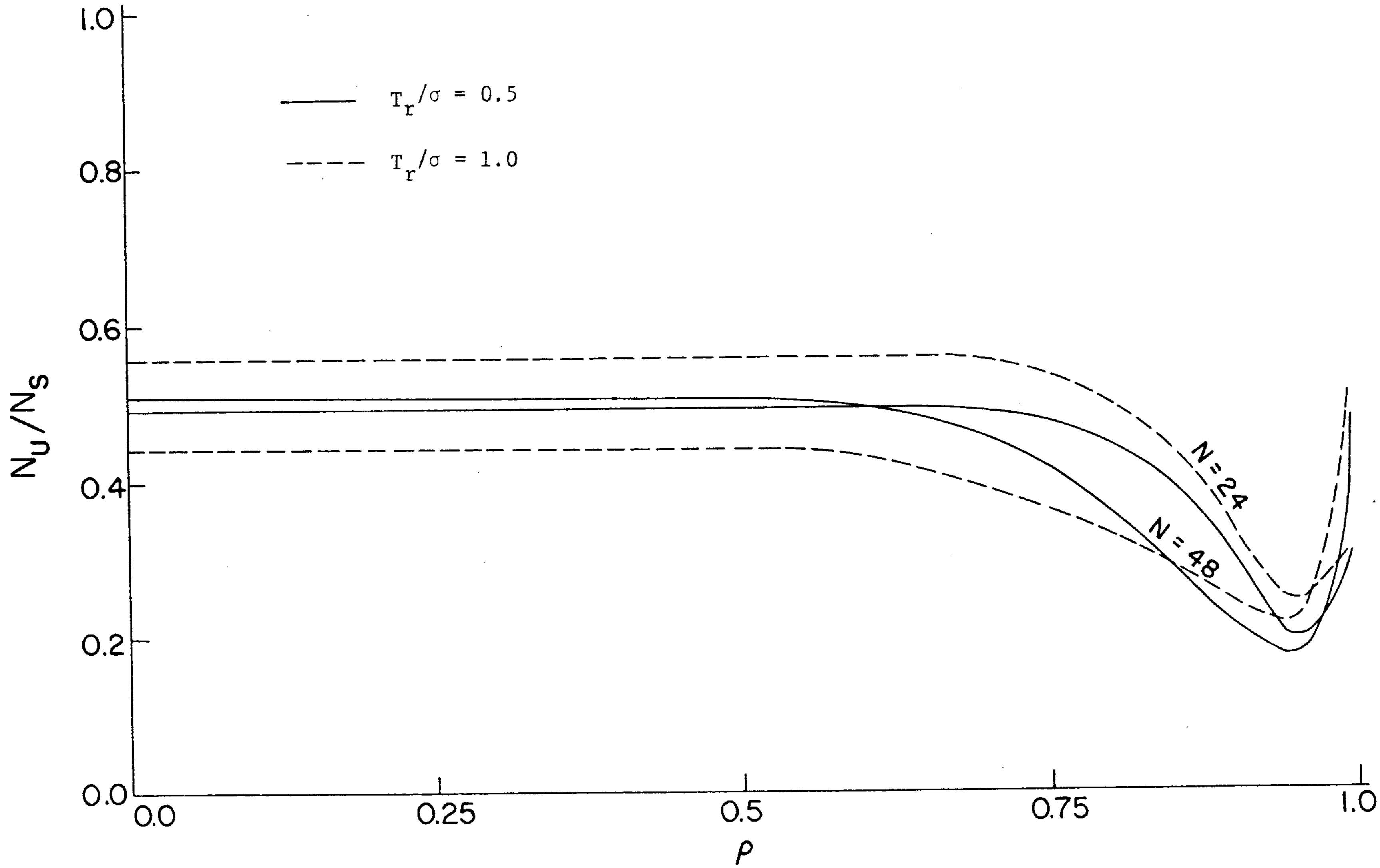

Figure I.5a: Relative Sample Size, Required for Uniform and Stratified Strategy for Step Trend, N_t = 5

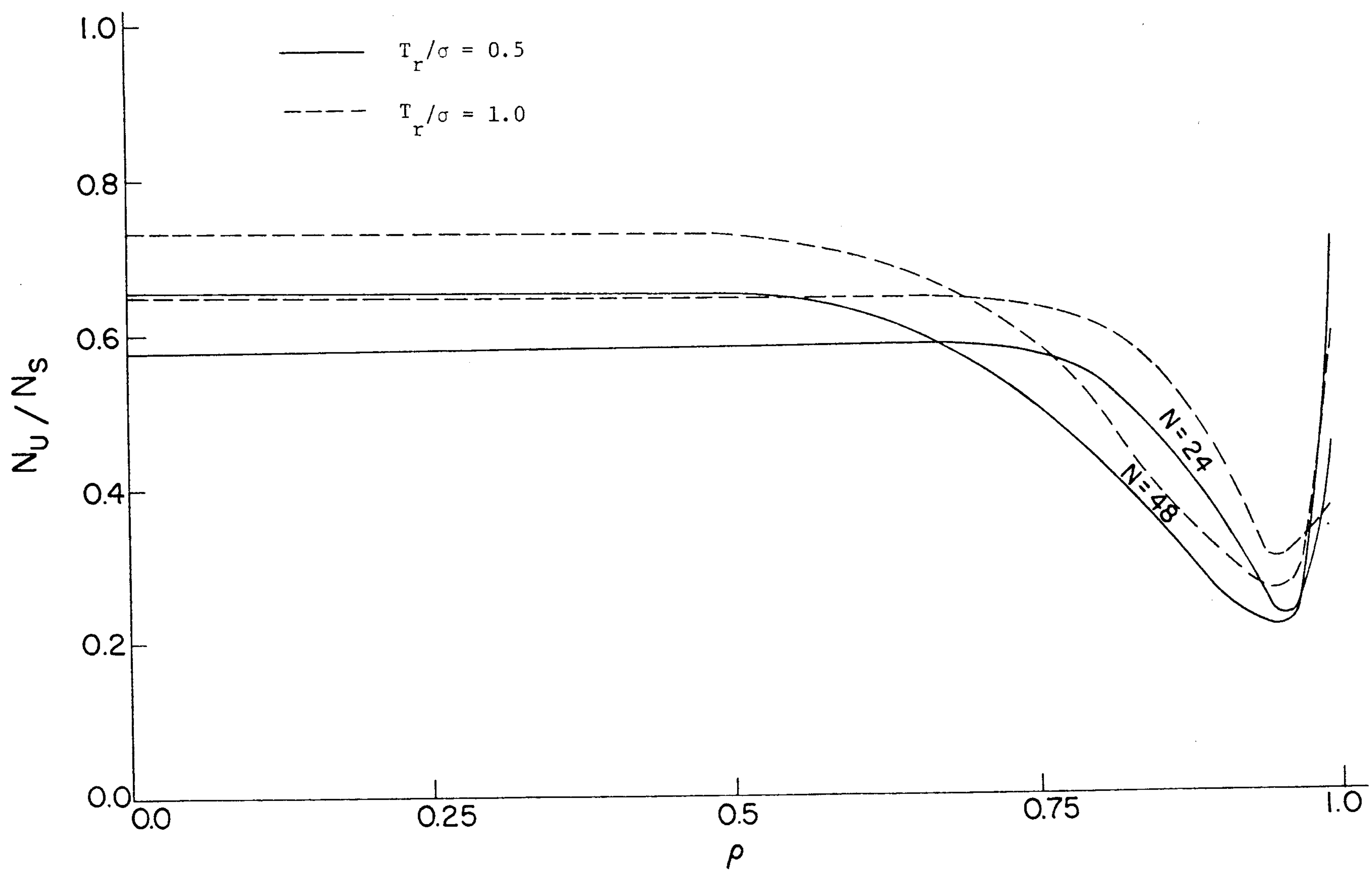

Figure I.5b: Relative Sample Size, Required for Uniform and Stratified Strategy for Linear Trend, $N_t = 5$

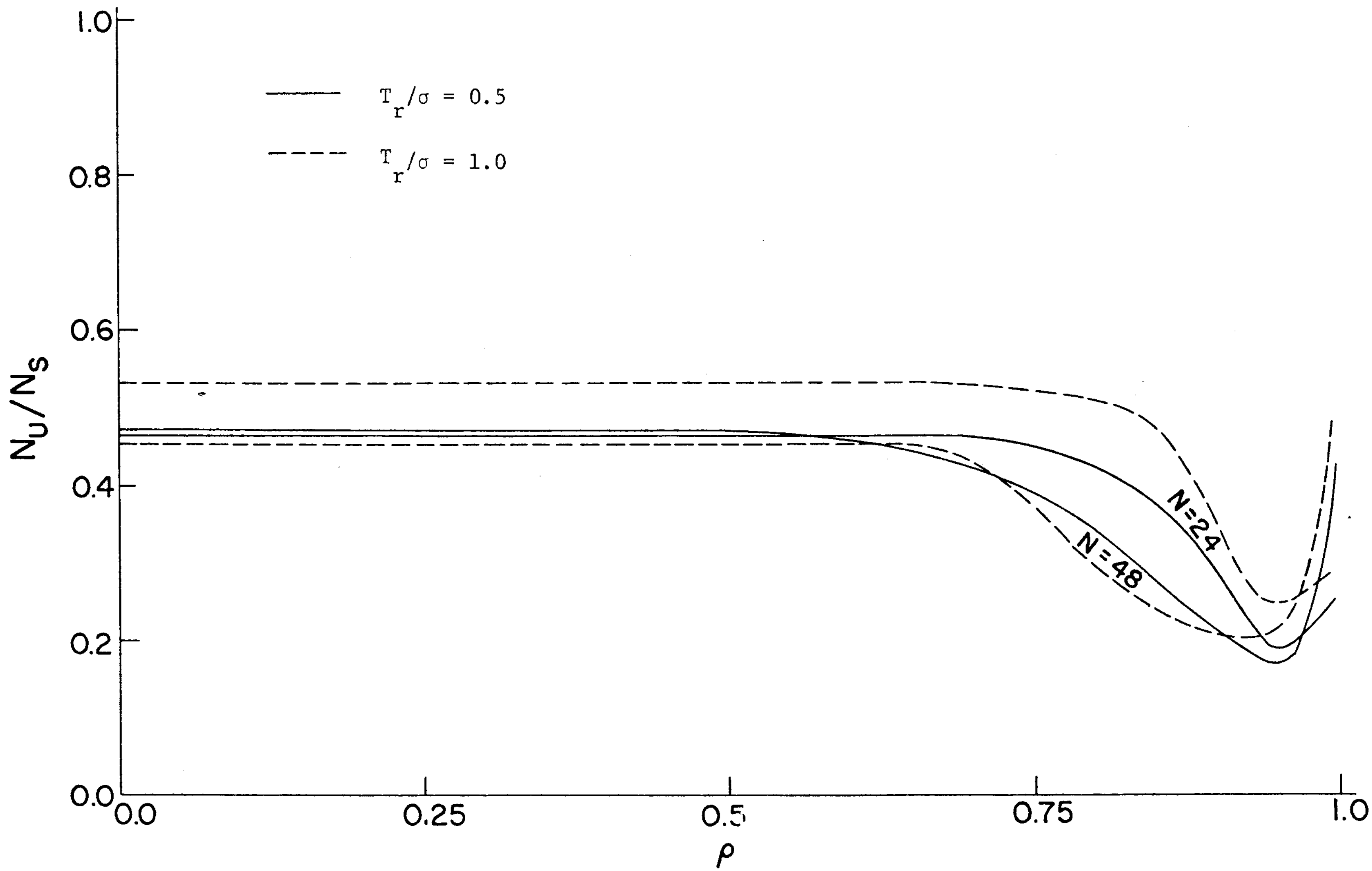

Figure I.6a: Relative Sample Size, Required for Uniform and Stratified Strategy for Step Trend, $N_t = 7$

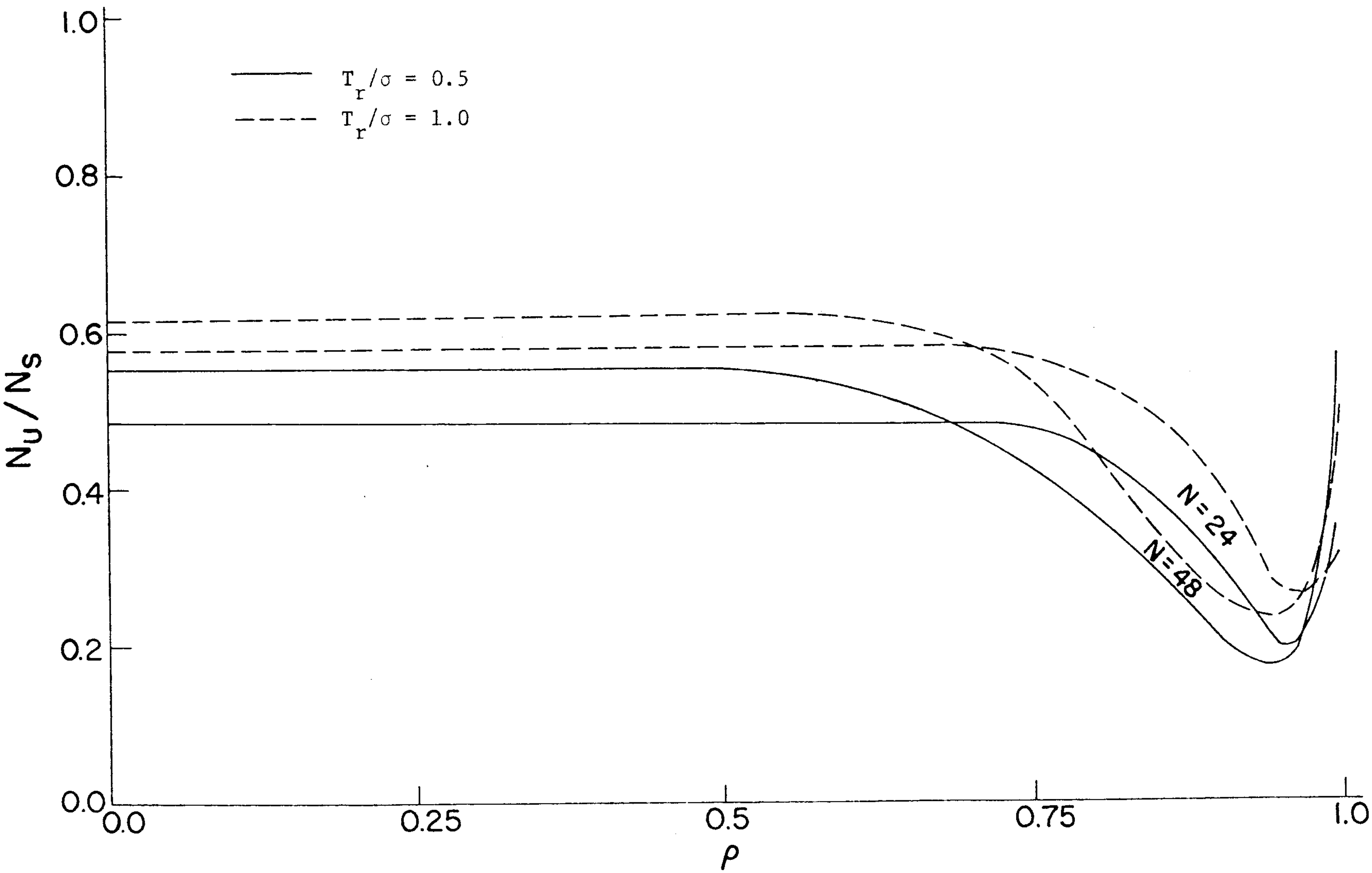

Figure I.6b: Relative Sample Size, Required for Uniform and Stratified Strategy for Linear Trend, N_t = 7

PART II. DATA ANALYSIS

PART II. DATA ANALYSIS

Chapter II.1 Analytical Methods

Part I of this report has described suggested data collection procedures. Implementation of these procedures will ensure the future availability of historic water quality time series suitable for such parametric time series analysis techniques as Intervention Analysis, discussed in Part I. However, existing time series of water quality data are often not well suited to parametric techniques which require equal data spacing in time with no "gaps" in the record. Nevertheless, utilization of existing data is essential to identify current trends in water quality regionally. Consequently, an approach to analysis of existing time series, which may not meet the rigorous requirements of parametric time series analysis is given. Application is illustrated for 13 DOE stations with two to six parameters at each station. The analytic techniques described are not limited to use with incomplete data records; in fact, the screening techniques discussed are recommended for general use. However, in analysis of complete records which "pass" the screening tests, use of the more powerful tools of time series analysis, and in particular, Intervention Analysis (Box and Tiao, 1975) which includes predictive capability, may be preferred.

II.1.1 Recommended Approach: Data Editing

Figure II.1 shows schematically the recommended approach to analysis of time series for possible trends. The final step is to compute test statistics for one of two nonparametric tests, Spearman's rho (SR) or Mann Whitney's (MW). The preliminary steps are designed to edit the data in such a manner that the assumptions required for the tests are met, and to screen out records for which a visual inspection suggests that no trend exists.

The principal assumption of the tests is that the data possess a symmetric probability density function (PDF), i.e., at each time, the mean, the median, and the mode (assuming a unimodal distribution) coincide, and that the data are independent in time. The latter requirement may be relaxed, and will be discussed in detail below. Most water quality data have a lower bound of zero, but no absolute upper bound, hence the data are often positively skewed. In some cases, the data rarely lie near the lower bound or have no lower bound and the raw data are approximately symmetrically distributed; examples are temperature, dissolved oxygen, and nutrients. When the raw data are skewed, the data may be transformed so that the transformed data are nearly symmetrically distributed. The logarithmic transformation, $Y_t = \ln(X_t)$ is often adequate and in some cases has a physical interpretation. When, for example, a process is generated as the product of a number of random variables the logarithmic transformation will yield a transformed time series with PDF similar to that of the random variables composing the product. For instance, coliform bacteria counts are the products of the counts of each of a

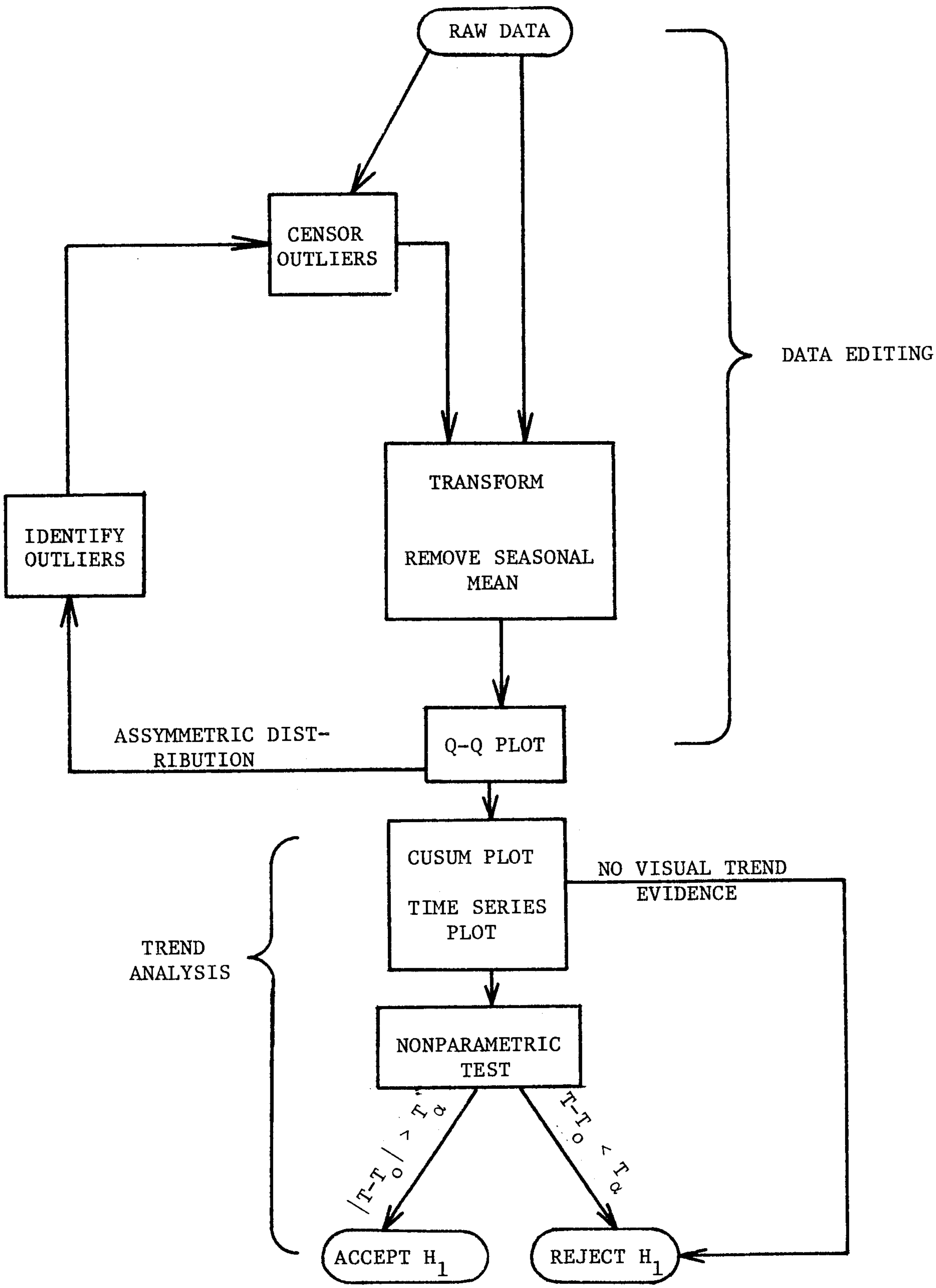

Figure II.1. Suggested Procedure for Data Analysis series of bacteria generations, which themselves are randomly distributed owing to a variety of external factors, hence the logarithms of the measured coliform counts should approximately follow the same PDF (and exactly if the PDF of the individual generations is normal) as the individual generations. Consequently, the logarithmic transformation is a natural one for coliform counts.

In any event, a tool is available for checking whether the data meet the symmetric PDF requirement. This tool is the Q-Q plot, in which the sample percentiles of the data are computed (usually as $P_j = j/(n+1)$ where the n data have been ordered) and the corresponding observation is plotted against the theoretical quantile at percentile P_j, X_{P_j}. The technique, described in detail by Wilk and Gnadesikan (1968) amplifies departures from the theoretical distribution in the "tails" of the distribution; if the data follow the theoretical distribution, the Q-Q plot is a straight line, otherwise "bending" is observed at the extreme quantiles. If the theoretical distribution is symmetric (the program given in Appendix B uses the normal distribution as the theoretical distribution) and the observed deviations at the upper and lower quantiles are symmetric, the actual PDF may be assumed symmetric, even though different from the theoretical PDF used. For example, Figures II.2a and b are Q-Q plots for two independent data sets generated from the t (with 2 degrees of freedom) and the lognormal PDF's where the theoretical distribution is normal. The deviations at extreme quantiles for the t distribution are symmetric, while those for the lognormal are not. In the latter case some transformation of the data is indicated.

In practice, time series data are usually correlated, and water quality data are no exception. However, it is possible to make use of an effective independent sample size if a certain correlated structure is assumed for the residuals of the data from the trend in process level, if any. The form of the correlation structure assumed here is that of the lag one Markov process, discussed in Part I of this report. The principal requirement of this assumption is that the residuals be stationary to second order, i.e., that the residual process mean (assumed zero), variance, and autocorrelation function be independent of time. In order to meet this requirement, seasonal effects must be removed from the data. A number of approaches may be used; one of the most straightforward is to divide the year into seasons (months, quarters, etc.), estimate the grand mean over the record for each season, and form a new time series as the difference between the raw time series and the appropriate seasonal mean. A subroutine is given in the program documented in Appendix B which removes seasonal fluctuations in the data in this manner. The recommended season length is two months when monthly data are available, and one quarter when the data are collected quarterly.

The recommended approach to transformation and removal of seasonal means is as follows. First, the raw data should be deseasonalized, then a Q-Q plot made. If the deseasonalized data appear to be symmetrically distributed, the deseasonalized time series is used as the input to the second loop in Fig.II.1. However, if data transformation is required, the raw data are transformed <u>first</u>, then seasonal means are removed. This order is taken because in some cases in which the variance, as well as the process mean, varies seasonally; transformation will tend to level out the seasonal fluctuations in the variance. This is a secondary advantage of some transformations (particularly the logarithmic); however, even if the residual variance contains seasonal fluctuations, the validity of the trend tests for changes in mean level are not greatly affected; removal of seasonal nonstationarity in mean level is much more critical.

One final check should be made in the data editing stage. In some cases, the Q-Q plot will indicate a very few (usually one or two) values which deviate very greatly from the remaining data. Frequently, these values, known as outliers, are attributable to mistakes in data coding or laboratory analyses, or, sometimes the recordings are legitimate, but represent an extreme event which cannot be considered to belong to the same statistical population which has generated the remaining data (the primary population). In such cases the outliers may be edited, i.e., treated as missing data. In general, this step should be taken only if there is reason to believe that they could not have come from the primary population. Care should be taken not to edit data merely because they deviate greatly from the apparent process mean. Since the tests used (SR and MW) are nonparametric, the results will not normally be highly sensitive to data editing; one great advantage of nonparametric tests. However, the nonparametric tests will estimate only the direction of trends, and not their magnitude. If estimates of trend magnitude are made, they will be quite sensitive to outliers, and the editing issue is more critical.

II.1.2 Recommended Approach: Trend Analysis

With the editing stage complete, a time series is available which is presumed to consist of (possibly) a trend in mean value with additive noise modeled as a lag one Markov process. The objective is to determine whether a statistically significant trend in mean value exists (alternative hypothesis), or whether the mean value is constant with time (null hypothesis). Again, the basic form of the hypothesis test discussed in Part I of this report should be emphasized; the tests are conservative with respect to type I errors.

In applying the MW and SR tests, it is necessary to specify the subsequences to be tested. Care must be exercised here. The temptation is to screen the data visually, and test the most extreme subsequences for significance of differences in estimated process mean. However, the confidence limits for the most extreme case are substantially different than for any two subsequences picked at random. For example, if an independent sequence of length n = 200 is split into ten subsequences of length 20 and a test performed for the significance of differences between the local and grand mean, at the 90 percent confidence level on the average the test should show one sequence to have mean level significantly different than the mean when the mean level is constant (no trend exists). Hence, the most extreme subsequence will only have a probability on the order of 50 percent, rather than 90 percent, of exceeding the test statistic. The true rejection levels for the extreme subsequence are much higher than for a single (randomly selected) subsequence. This problem is not of great significance so long as the subsequences taken together comprise most of the record length, for instance, the first and second halves of the record. However, testing of much shorter subsequences, for instance, years one and two of a ten-year sequence, should be avoided.

With this note of caution in mind, the visual screening tests are introduced. The first, and simplest test is to plot the data against the time of collection (time series plot). In this manner, long range trends may sometimes be identified. A slightly more sophisticated technique, the cumulative sum plot, where the cumulative sum is defined as $CUSUM_j = \sum_{i=1}^{j} X_i - j/m \sum_{i=1}^{m} X_i$, may also be used. The cumulative sum is simply a fraction of the area under the mean of the first m observations and the area under the local mean up to point j. Clearly, if the mean is constant, the CUSUM local mean up to point j. Clearly, if the mean is constant, the CUSUM is zero; if a change in mean level occurs at time step m, the CUSUM plot is linear for t>m, if a linear change begins at t = m, the CUSUM is quadratic for t> m, etc. No confidence limits are placed on the CUSUM plot; it is only a visual test, hence no conclusions as to trend existence should be based solely on the CUSUM. However, in many cases it will be apparent from examination of the CUSUM and time series plots that no apparent trends exist, and the alternative hypothesis may be rejected without further analysis.

Records which "pass" the screening tests are subject to either the MW or SR test at this point. The mechanics of the tests are described in Appendix A, but briefly the MW test statistic is derived by summing the pooled ranks of the first partition of the data, while the SR test statistic is derived from the sum of the squares of the differences between the pooled ranks and the original data order. The MW test is generally most powerful against abrupt (e.g., step) changes in mean level while the SR test is most powerful against gradual (e.g., linear) changes. This consideration will dictate the most appropriate test in any given situation.

When the data are independent, the computation of the appropriate test statistic and comparison with tabulated critical levels completes the trend analysis. With dependent data, however, one further step remains. When the data are dependent, the critical levels for independent data (e.g., Tables 8 and 9 of Conover (1971)) must be modified. The modification required depends on the form of the data dependence. A Monte Carlo sampling program was performed to identify the correction required when the data dependence is of the lag one Markov type discussed earlier. Details of the experiments performed and results are given in Appendix A.

The corrections given in Tables A.1 and A.2 are factors applied to the difference between the table critical levels (for independent data) and the upper or lower bound of the test statistic distribution. The new, modified critical level is calculated as the upper or lower limit plus the scaled difference:

$$T'_{C_\ell} = L_\ell + f(n, \alpha, \rho)(T_{C_\ell} - L_\ell) \qquad \text{(II.1.1)}$$

$$T'_{C_u} = L_u + f(n, \alpha, \rho)(T_{C_u} - L_u) \qquad \text{(II.1.2)}$$

where T'_{C_ℓ}, T'_{C_u} are the modified lower and upper critical values, $f(n, \alpha, \rho)$ is the correction from Table A.1 or A.2, T_{C_ℓ} and T_{C_u} are the upper and lower critical levels of the test statistic, for independent random variates, and L_ℓ and L_u are the distribution upper and lower bounds. For example, to derive corrected critical levels for Spearman's rho test with $n = 30$, $\rho = .2$, $\alpha = .05$, the procedure is as follows: From Conover (1971, Table 9) for a two-sided test, the critical levels (corresponding to $p = \alpha/2 = .025$ and $p = 1-\alpha/2 = .975$) are 2032 and 6958, respectively. From Table A.2, the appropriate correction factor is .854, hence $T'_{C_\ell} = 0 + .854\times2032 = 1735$, and $T'_{C_u} = 8990 - .854\times2032 = 7255$. Note that for the SR test, the lower limit is zero and the upper limit is $1/3n(n^2-1)$, and that the test statistic is symmetrically distributed. For the MW test, the lower bound of the test statistic is zero and the upper limit is n_1n_2, where n_1 and n_2 are the number of data in the first and second data partitions, respectively. It should also be noted that if the Conover (1971) tables are used, the approximate formula for the critical levels of the test statistic for the MW test for n_1, $n_2 > 20$ is incorrect, and should read

$$W_p = \frac{n_1n_2}{2} + X_p\sqrt{\frac{n_1n_2(n_1+n_2+1)}{12}}$$

II.1.3 Example Analysis

To illustrate the approach to trend analysis recommended here, details of the analysis of the specific conductance record for the Chehalis River near Porter, Washington are given. Initially, means for two-month "seasons" (e.g., January-February) were estimated and subtracted from the raw data. No transformation was made initially based on earlier experience that transformation of specific conductance data is not usually required. The Q-Q plot for the deseasonalized data is given in Fig. II.3 and is clearly nonlinear. However, most of the distortion is in the upper end of the scale (large data values), and is apparently attributable to a single data point. The time series plot of the data is given as Fig. II.4, and shows an outlier at t = 161 which is so much larger than the remainder of the data that it is extremely unlikely to have come from the same statistical population as the rest of the data. When this outlier is censored, the Q-Q plot of Fig. II.5 results, and suggests that a normal assumption is reasonable. Examination of Fig. II.4 suggests that there may be a gradually increasing trend in the data. A further check is provided by the CUSUM plot shown in Fig. II.6, where m, the "break point" has been arbitrarily taken at t = 101, approximately halfway through the record. The cusum plot verifies that an apparently increasing trend exists, and a rigorous statistical analysis is indicated. Further examination of the time series plot and the CUSUM plot suggests either a possible gradual increase from about t = 50 on or perhaps an abrupt change at about t = 70. The first possibility was checked using Spearman's rho test and the second using Mann Whitney's test. The test statistics calculated were

MW $T = 1742,\ n_1 = 68,\ n_2 = 99$

SR $T = 156670,\ n = 119$

The sample sizes are less than the time spans because some of the data are missing, and so are ignored in calculating the test statistic.

Critical test levels at the 99 percent confidence level for a two-sided test are

	T'_{C_u}	T'_{C_ℓ}
MW	4157	2575
SR	366715	194964

where $\ell = .2$ has been selected apriori. This value is quite conservative, since the data were collected at monthly intervals and $\rho = .2$ would imply $\rho_o = .2^{1/30} = .948$ which is higher than would normally be expected. Nevertheless, both computed test statistics are well below the lower critical level at 99 percent confidence level, hence an increasing trend is indicated. Note that, for both the SR and MW tests, small test statistics indicate increasing trends, and large test statistics indicate decreasing trends. Similar analyses were conducted for 15 Washington State ambient stream quality monitoring stations with up to six parameters at each station. The results of these analyses are discussed in the following chapter.

Table II.1 Group 1 Stations and Parameters

Station	Description	Dates	Parameters
41A070	Crab Creek near Beverly	1959-76	T, DO, SPC, TN
23A070	Chehalis River at Porter	1959-75	T, DO, SPC, TN
37A190	Yakima River near Parker	1970-76	T, DO, SPC, TN, TC
07A090	Snohomish River at Snohomish	1959-76	T, DO, SPC, TN
03A060	Skagit River at Mount Vernon	1959-70	T, DO, SPC, TN
04A100	Skagit River at Marblemount	1959-70	T, DO, SPC, TN
37A090	Yakima River at Kiona	1952-62	SPC, TN
37A090	Yakima River at Kiona	1968-75	T, DO, SPC, TN, TC

where T = temperature
DO = dissolved oxygen
SPC = specific conductivity
TN = total inorganic nitrate
TC = total coliform
OP = orthophosphate

Table II.2 Group 2 Stations and Parameters

Station	Description	Dates	Parameters
34A070	Palouse River at Hooper	1959-66	SPC, TN, OP
34A070	Palouse River at Hooper	1970-76	T, DO, SPC, TC, TN, OP
13A050	Deschutes River at Tumwater	1962-69	T, DO, SPC, TN
13A080	Deschutes River near Olympia	1970-77	T, DO, SPC, TC, TN, OP
12A070	Chambers Creek nr.Steilacoom	1962-66	T, DO, SPC, TN, OP
12A070	Chambers Creek nr.Steilacoom	1971-76	T, DO, SPC, TC, TN, OP
03B050	Samish River nr.Burlington	1959-74	T, DO, SPC, TC, TN, OP
10A050	Puyallup River at Puyallup	1959-76	T, DO, SPC, TC, TN

Table II.3a Hypothesized Changes for Group 1 Stations Based on Preliminary Screening

Station Number	Possible Trend
41A070	T decrease DO increase SPC increase 1959-67, Decrease 1969-72 TN increase
23A070	T decrease SPC increase TN increase 1959-69, decrease 1969-72
37A190	SPC decrease 1973-76 TN decrease TC decrease
07A090	TN increase
03A060	T decrease 1959-64, increase 1964-70 SPC increase 1959-65, decrease 1965-70 TN increase
04A100	SPC increase TN increase
37A090 (1952-62)	No changes
37A090 (1968-75)	TN decrease

Table II.3b Hypothesized Changes for Group 2 Stations Based on Preliminary Screening

Station Number	Possible Trend
34A070	SPC increase 1959-63
	SPC decrease 1964-66
	TN increase 1959-62
	TN decrease 1963-66
	OP increase 1959-62
	OP decrease 1963-66
	DO decrease 1973-76
13A050	TN increase 1962-69
13A080	none
12A070	SPC increase 1962-66
03B050	DO increase 1959-74
	SPC increase 1959-74
	TN increase 1959-65
	TN decrease 1966-74
	OP decrease 1959-66
	OP increase 1967-74
10A050	DO increase 1959-76

Table II.4a Summary of Test Results for Group 1 Stations

Station	Parameter	Test	Time	Trend	Significance (%)
Crab Creek near Beverly	T	MW	1-100, 101-205	Decrease	95
	DO	MW	1-100, 101-205	Decrease	95
	SPC	MW	1-100, 101-205	None	
	SPC	SR	84-205	Decrease	99
	TN	MW	1-100, 101-205	Increase	80
	TN	SR	1-125	Increase	99
Chehalis River at Porter	T	MW	1-96, 97-195	Decrease	80
	T	SR	1-195	Decrease	95
	SPC	MW	1-70, 71-195	Increase	99
	SPC	SR	50-195	Increase	99
	TN	MW	1-60, 61-195	Increase	99
	TN	SR	24-130	Increase	99
	TN	SR	130-195	None	
Yakima River near Parker	SPC	MW	1-24, 25-69	Increase	90
	SPC	SR	24-72	Decrease	95
	TN	SR	1-69	Decrease	95
	TC	MW	1-36, 37-69	Decrease	90
	TC	SR	1-69	Decrease	90
Snohomish River at Snohomish	TN	MW	1-75, 76-183	Increase	99
Skagit River at Mount Vernon	T	MW	24-60, 61-134	None	
	T	SR	60-134	None	
	SPC	MW	1-80, 81-134	None	
	SPC	SR	1-80	Increase	80
	SPC	MW	50-80, 81-134	Increase	80
	TN	MW	1-70, 71-134	None	
	TN	SR	1-70	Increase	99
	TN	SR	50-134	None	
Skagit River at Marblemount	SPC	MW	1-20, 21-40	None	
	TN	MW	1-20, 21-41	None	
Yakima River at Kiona (1968-75)	TN	MW	1-30, 31-83	Decrease	99

Table II.4b Summary of Test Results for Group 2 Stations

Station	Parameter	Test	Time	Trend	Significance (%)
Palouse River at Hooper (1959-66)	SPC	SR	1-52	up	95
	SPC	MW	25-52,53-81	down	99
	TN	SR	1-40	up	95
	TN	SR	41-81	down	80
	OP	SR	1-40	up	99
	OP	SR	41-81	down	99
Palouse River at Hooper (1970-76)	DO	SR	40-72	down	99
Deschutes River at Tumwater	TN	SR	1-29	down	99
Chambers Creek near Steilacoom	SPC	SR	1-44	up	99
Samish River near Burlington	DO	SR	1-183	up	95
	SPC	SR	1-183	up	99
	TN	MW	1-80,81-130	up	99
	TN	MW	81-130,131-183	down	99
	OP	SR	1-120	down	99
	OP	MW	70-130,131-183	up	99
Puyallup River at Puyallup	DO	SR	1-210	up	99
	TN	SR	1-140	down	90
	TN	MW	60-140,141-210	up	99

CHAPTER II.2 RESULTS

The recommended analysis outlined in Figure II.1 was applied to historic data from two groups of Department of Ecology stream quality monitoring stations. The first group given in Table II.1 are the same stations for which statistical analyses were conducted in Part I. Parameters available at these stations include one or more of temperature, dissolved oxygen, and specific conductance and total inorganic nitrate. The Yakima River at Kiona record has been split into two separate records because of the lack of data collected during the period 1962-68. The additional stations included in Group 2 (Table II.2) were selected because of the availability of orthophosphate measurements. Orthophosphate is an important nutrient which often limits nuisance algal growth. The records for the Palouse River at Hooper and Chambers Creek near Steilacoom were split because of the existence of large data gaps. The Deschutes River records were split because of movement of the sample station in 1970. Upon detailed investigation it was found that the number of orthophosphate measurements for the Puyallup River at Puyallup (station 10A050) and the early Deschutes River (1962-69) records were insufficient to justify a detailed analysis, so this parameter was dropped from these two records.

The analyses proceeded exactly as for the example in the preceding chapter. The first step was visual editing and screening to establish those records for which trends appeared to exist. The results of this screening are given in Tables II.3a and II.3b for Group 1 and 2 stations, respectively.

Analyses were then conducted for those records which appeared to contain underlying trends. In all cases, an assumed lag one correlation of $\rho = 0.1$ was used. This value is high for the monthly data available so the results should be conservative (actual significance level higher than computed).

The results of the analyses are given in Tables II.4a and II.4b for Group 1 and 2 stations, respectively. Figures II.7-II.17 are the deseasonalized time series plots for these records. For the Group 1 stations (Figs. II.7-II.13) time series plots are shown for all the records summarized in Table II.1, while for the Group 2 stations plots are given only for the records containing statistically significant trends. For the Group 2 stations, the best fit (least squares) step and linear trend lines are shown where Mann-Whitney's and Spearman's rho tests, respectively, have been used. These trend lines are used as a graphical aid only; no confidence limits have been placed about these trend lines.

A detailed investigation of factors leading to possible trends for each of the stations analyzed has not been conducted. It is only possible, then, to attempt to identify general characteristics of stations and parameters for which trends appear to be present, eg., by geographic location or by parameter. Table II.5 shows the results of the analyses by parameter. In determining the total number of records analyzed for each parameter, those stations having split records (Tables II.1 and II.2) are treated as two records. The totals of the number of records showing increases, decreases, and no change may exceed the total number of records analyzed since some records show both significant increases and decreases.

Table II.5 Results of Statistical Tests by Parameter

	T	DO	SPC	TN	OP	TC
Records Analyzed	14	12	16	16	5	2
Increasing Trends	0	2	6	7	2	0
Decreasing Trends	2	2	3	6	2	1
No Change	17	9	8	4	2	1

Table II.5 suggests that temperature or dissolved oxygen changes are not widespread. Of the two stations showing temperature changes, one is located in the eastern part of the state and the other in the west. Of the stations with apparent dissolved oxygen changes, both of the stations with decreases are Eastern Washington stations, while both of the stations with increases are located in the western part of the state.

The Crab Creek stations, which showed a dissolved oxygen decrease, also had a declining trend in the temperature record. Decreasing temperatures would tend to result in higher DO, so the apparent DO trend may be stronger than the initial analysis would indicate. Specific conductance tended to increase in most of the cases in which trends were apparent. Two of the three decreases in SPC were for stations which showed an initial increase, so in the early part of the records the overall chemical quality of the stations analyzed appeared to reflect some degradation. There was, however, no clear geographical pattern in these results. The results of the dissolved inorganic nitrate analyses were less clear-cut. Perhaps significantly, most of the stations analyzed showed some apparent trend in this parameter. However, the results are somewhat clouded by a possible change in the method of chemical analysis of this parameter in the early 1960's (Cunningham, 1977) so the potential usefulness of the TN results may be limited. Only a few records had sufficient orthophosphate records for analysis; the results showed two stations each with apparent increases and decreases. Adequate coliform records were even more sparse; of the two records available one showed a decrease and the other no change.

On a station by station basis, only a few stations showed fairly consistent results. For the Palouse River at Hooper, TN, OP and SPC all showed initial increases with subsequent decreases; the DO record showed a decrease over the entire record. This station is located downstream of a major agricultural area, so the chemical quality may well reflect the effects of agricultural activity in the area. The results for Crab Creek show a dissolved oxygen decrease and TN decrease, which might suggest increased biological activity as the result of increased nutrient washoff from surrounding agricultural areas. An OP record was not available for this stations. However, SPC showed a decrease for this station. It is, of course, possible for SPC to drop while nutrient levels increase; however if increased nutrient levels are attributable to agricultural washoff an accompanying increase in TDS would appear more likely. The records for the two Yakima River stations showed a general improvement in overall quality, with the exception of an early increase in conductivity at the Parker station. TN and TC decreased at the Parker station, as did TN at the Kiona station.

The only Western Washington stream showing fairly consistent trends were the Chehalis River (SPC and TN increases, no OP record) and the Skagit River at Mount Vernon (SPC increase, TN increase near the end of the record). At a further upstream station (Marblemount) no apparent trends were found. The lack of consistent changes in the other records may be attributable more to the lack of an adequate data base than to the absence of trends. Certainly, following the discussion in Chapter I.1 the lack of a statistically significant trend should not be taken as evidence that no trend exists.

In general, the results appear to be inconclusive. The exceptions are two Eastern Washington stations in areas of great agricultural activity where some early degradation of stream quality appeared to take place, followed by a later recovery. For the two Western Washington stations which appeared to show consistent results, the trend appeared to be toward degradation near the end of the record length. However, the records are so sketchy and the coverage so sparse that any conclusion regarding trends in stream quality statewide would be premature.

CHAPTER II.3 SUMMARY

A proposed approach to trend assessment of water quality records has been illustrated in this chapter. The method incorporates a screening phase, in which visual tests are used to eliminate records with no apparent underlying trends. The principle visual screen tools are the quantile-quantile plot, used to check for symmetry of the marginal probability distribution, and the time series and CUSUM plots used to identify trends. If more detailed analysis is indicated, use of either Mann-Whitney's test for step trends or Spearman's rho test for linear or other gradual trends is recommended. In all cases, seasonal effects are accommodated by forming a new time series of residuals of the raw data or transformed data from the seasonal means. All screening and detailed analyses, if necessary, are conducted on this deseasonalized time series.

The methodology has been applied to thirteen Washington streams with records generally covering part or all of the period from 1959 to 1976. Most records include substantial gaps in the data record; in some cases the records were split into two shorter, more continuous records. The results of the analyses were generally inconclusive, with the exception of two Eastern Washington streams which showed fairly consistent changes in chemical quality possibly attributable to agricultural practices. Some of the apparent changes in other stations for which changes were not consistent for most or all of the parameters assessed may have been attributable to changes in laboratory analysis techniques.

While no clear pattern of statewide water quality changes emerged from the analyses, the results are useful in demonstrating the potential of the recommended approach to trend assessment. In addition, the results serve to underscore the importance of the recommended monitoring network design practices introduced in Part I of this report.

APPENDIX A

Nonparametric Tests

A.1 Test Descriptions

Brief descriptions of the two nonparametric tests used in this paper are given below. For more complete descriptions and tables of rejection levels for both tests, Conover (1971) may be consulted.

A.1.1 Mann-Whitney's Test

Given a data vector $\underline{X} = (X_1, X_2, \ldots X_n)$, partition $\underline{X}$ such that

$$\underline{Y} = (X_1, X_2, \ldots X_m)$$

$$\underline{Z} = (X_{m+1}, X_{m+2}, \ldots X_n).$$

The two-tailed Mann-Whitney's test tests the hypothesis H_o that $P(y<z) = 1/2$ against the alternative hypothesis H_1 that $P(y<z) \neq 1/2$, where y and z are arbitrary elements of the data vectors $\underline{Y}$ and $\underline{Z}$, respectively. The test statistic is

$$T = \sum_{i=1}^{n} R(Y_i) - \frac{m(m+1)}{2}$$

where $R(Y_i)$ is the rank of Y_i in the pooled data vector $\underline{X}$.

The assumptions of the test are that the X_i are independent with symmetric (not necessarily identical) probability distributions and that the X_i are continuous random variables (although a limited number of ties may be handled as described in Conover (1971). Mann-Whitney's test is most appropriate for testing against differences in central tendency in two partitions of a data vector, such as a step trend.

A.1.2 Spearman's Rho Test

Given a data vector $\underline{X} = (X_1, X_2, \ldots)$, the two-tailed Spearman's Rho test against trend tests the null hypothesis H_o that all the X_i are identically distributed against the alternative hypothesis that the X_i tend to increase or decrease with i. The test statistic is

$$T = \sum_{i=1}^{n} (R(X_i) - i)^2$$

where $R(X_i)$ is the rank of the i'th observation X_i in the sample of size n.

The assumptions of this test are that the X_i are mutually independent and that the random variables X_i are continuous. As in Mann-Whitney's test, a limited number of ties are permissible. Spearman's rho test is most appropriate for testing against continuous (e.g., linear) trends.

A.2 Correction Factors for Rejection Levels of Spearman's Rho and Mann Tests with Lag One Markov Noise

Critical levels of test statistics for Mann Whitney's (MW) and Spearman's Rho (SR) tests described in Appendix A.1 are commonly available in statistical tables such as those given by Conover (1971). These tabulated values are applicable to data of the form

$$Y_t = N_t + g(t)$$

where N_t is independently (not necessarily identically) distributed random variates with mean zero, and g(t) describes the mean level as a function of time. When the N_t are dependent, $E(N_t N_{t+k}) \neq 0$, and the tabulated critical values are not applicable. An analytical derivation of the distribution of the test statistics, T in such cases would be quite difficult, however, if certain assumptions regarding N_t are made, numerical experiments (Monte Carlo sampling) on the computer will yield estimates of the correct rejection levels.

The assumption made here is that N_t is lag one Markov,

$$N_t = \rho N_{t-1} + \varepsilon_t$$

where ε_t is assumed to be independently normally distributed with mean zero and variance $1-\rho^2$, hence N_t has mean zero and variance one, and $E(N_t N_{t+k}) = \rho^k$. Choice of the zero mean unit variance process leads to no loss in generality, since the nonparametric tests make use of ranks, rather than magnitudes, and the ranks are preserved under scaling and translation of the noise.

A.2.1 Monte Carlo Tests

In order to estimate the test rejection levels, 500 traces each of length $n = 30, 50, 70, 100, 150$, and 200 and $\rho = .1, .2, .3$ were generated from a psuedo-random number generator. For the MW test, the ratio n_1/n was taken as .1(.1).5. For each set of parameters ρ, n, α, and n_1/n, the 500 test statistics were calculated and ordered. Estimated critical levels were calculated by interpolating at the $p = \alpha/2$ probability levels from the unbiased estimate of the sample percentiles, $\hat{X}_p = X_{\hat{p}}$, where $\hat{p} = j/(n+1)$ and the X_j have been ranked. Use was made of the symmetry of the test statistic distributions by taking

$$\hat{\hat{X}}_p = \frac{1}{2} [\hat{X}_p + L_u - \hat{X}_{1-p}]$$

where L_u is the upper bound of the test statistic. Ratios of the estimated test statistics for the lower tails, $\hat{\hat{X}}_p$ to the tabulated (independent) test statistics were computed as $f(n, \alpha, \rho) = \hat{\hat{X}}_p/X_p$ where X_p^* is the test statistic for independent data. For the MW test, estimated critical level ratios were computed at several values of n_1/n, however, the computed values $f(n, \alpha, \rho)$ appeared to be independent of n_1/n except at $n = 30$, where for $n_1/n = .1$, the ratio $f(n, \alpha, \rho)$ becomes greater than one. However, this case corresponds to $n_1 = 3$, which is probably too small for a meaningful test. Consequently, for the NW test the computed levels of $f(n, \alpha, \rho)$ are the average of the values for $n_1/n = .1(.1).5$, except that for n = 30, they are the median value.

The results are given as Tables A.1 and A.2. General trends are apparent, for instance, the corrections are more substantial as α decreases (owing to the increased effect of deviations of the tails from the assymptotic normal distribution of the test statistics at small tail probabilities) and (generally) as n decreases. Some anomolies appear, but are probably attributable to the small (500 traces) number of runs made. The correction factors given may be considered accurate to two decimal places.

A.2.2 Use of Tables A.1 and A.2

To compute estimated rejection levels for given values of n, α, and ρ, the appropriate value of $f(n, \alpha, \rho)$ is found in the tables or by interpolation, if necessary. Upper and lower critical levels, T_{C_ℓ} and T_{C_u} for independent statistics, corresponding to n, α, (and n_1 for the MW test) are taken from the appropriate tables (e.g., Conover, 1971). Corrected critical levels T'_{C_ℓ} and T'_{C_u} are computed as

$$T'_{C_\ell} = L_\ell + f(n, \alpha, \rho)(T_{C_\ell} - L_\ell)$$

$$T'_{C_u} = L_u + f(n, \alpha, \rho)(T_{C_u} - L_u)$$

The α levels given are for a two-sided test, if a one-sided test is desired at significance level α, the tables should be entered with $\alpha' = 2\alpha$.

Table A.1 Estimated Mann Whitney's Test Rejection Level Ratios for Lag One Markov Noise 1/

$\rho = .10$

n	$\alpha = .01$	$\alpha = .05$	$\alpha = .1$	$\alpha = .2$
30	.903	.938	.980	.975
50	.895	.910	.928	.944
70	.912	.942	.945	.964
100	.885	.945	.963	.974
150	.968	.968	.963	.974
200	.942	.971	.973	.977

$\rho = .20$

n	$\alpha = .01$	$\alpha = .05$	$\alpha = .1$	$\alpha = .2$
30	.715	.876	.882	.903
50	.781	.854	.587	.916
70	.839	.889	.906	.924
100	.851	.897	.923	.942
150	.856	.938	.953	.968
200	.898	.928	.944	.959

$\rho = .30$

n	$\alpha = .01$	$\alpha = .05$	$\alpha = .10$	$\alpha = .20$
30	.688	.769	.790	.847
50	.714	.787	.828	.874
70	.724	.828	.876	.898
100	.815	.863	.878	.907
150	.846	.883	.918	.941
200	.871	.899	.913	.933

1/ Values given are $f(n, \alpha, \rho)$ and are averages of five estimates for $n_1/n = .1(.1).5$, except for n = 30 where given is median estimate.

Table A.2 Estimated Spearman's Rho Rejection Level Ratios for Lag One Markov Noise

$\rho = .10$

n	$\alpha = .01$	$\alpha = .05$	$\alpha = .10$	$\alpha = .20$
30	.923	.930	.939	.926
50	.925	.929	.939	.953
70	.972	.994	.989	.976
100	.944	.954	.970	.976
150	.930	.976	.979	.988
200	.956	.977	.982	.987

$\rho = .20$

n	$\alpha = .01$	$\alpha = .05$	$\alpha = .10$	$\alpha = .20$
30	.786	.854	.875	.906
50	.869	.895	.911	.926
70	.887	.914	.926	.947
100	.954	.941	.942	.961
150	.928	.945	.962	.979
200	.928	.961	.967	.972

$\rho = .30$

n	$\alpha = .01$	$\alpha = .05$	$\alpha = .10$	$\alpha = .20$
30	.785	.806	.830	.870
50	.777	.786	.857	.901
70	.876	.898	.912	.937
100	.874	.905	.923	.935
150	.884	.912	.934	.951
200	.898	.937	.952	.960

APPENDIX B

TREND Program Documentation and Listing

B.1 Program Documentation

B.1.1 Overview

TREND is a Fortran IV program capable of performing a number of analyses on time series aimed at testing against the existence of underlying trends. Twelve program options are available, including time series plots, cumulative sum and quantile-quantile plots, and Mann-Whitney's and Spearman's rho test statistic computation discussed in the main text of the report. With the exception of the plotting routines, which utilize softwear available only at the University of Washington CDC 6400 installation, the program is transportable.

A program flow chart is given in Figure B-1 below. The basic structural elements of the program are data channels and channel options. Six data channels are available, with twelve channel options. Initially, the raw data supplied to the program is read into channel 1. The program then proceeds to the first channel option, where any necessary data is read in. The input channel for the first channel option must always be channel 1, the output channel is specified by the user. After the desired data manipulation has been performed, the program proceeds to the second channel option, which has input and output channels specified by the user. This procedure continues until all the channel options for the first parameter have been performed, the analysis is then performed for the second parameter, which has its own set of channels and channel options read in. This format is particularly convenient because it allows storage of data on which various manipulations have been performed for future analysis; the

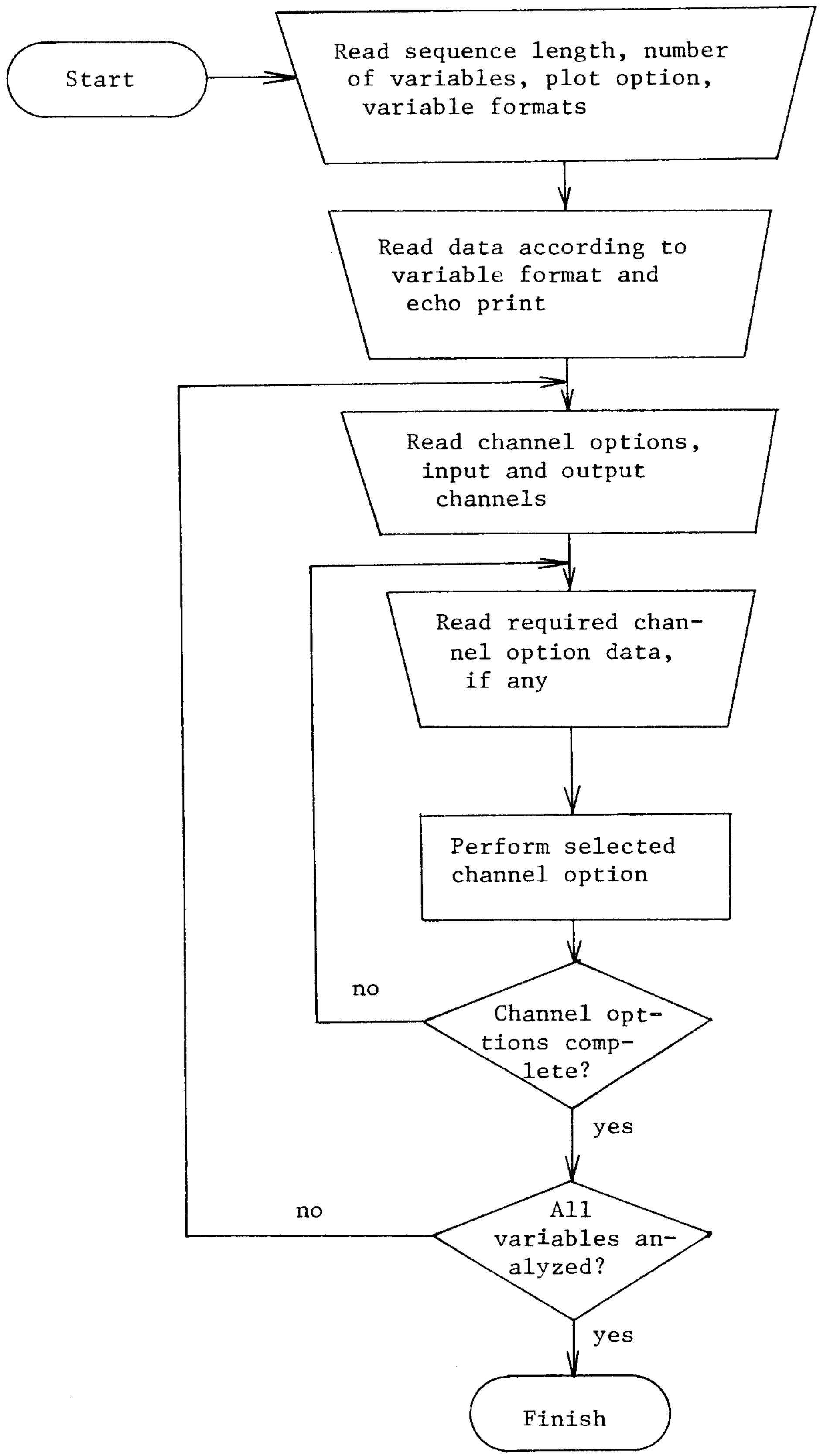

Figure B.1 TREND Program Flowchart

the output data are not destroyed by subsequent operations unless the user desires to store data in a previously used channel, in which case the original data are lost. The program keeps track of the number of data in each channel, for instance some operations such as differencing and computation of residuals from a moving average result in loss of one or more data at the beginning or end of the record.

B.1.2 Program Input Requirements

In addition to the program itself, the user must submit a control card record at the beginning of the deck and an input data record at the end of the deck. The control card record simply contains the job control language necessary to tell the computer where to look for the program, store plot information, etc. The control card records given here are those required by the CDC 6400 computer, other installations will have different control card requirements.

Control card records sufficient to compile and store the program on CDC permanent file are given, this option avoids the necessity of having to read in the program itself each time multiple runs are performed. Note that CDC control cards are always punched beginning in column 1, for input data the required formats are given below for each card.

Control Card Setups

Option 1: To compile and store program on permanent file:

Card No.		Notes
1	Job Card[1]	Use CM 50000
2	Account Card[1]	
3	REQUEST(TAPE,*PF)	
4	FORTRAN.	Period is essential
5	EDITLIB.	
6	CATALOG(TAPE,TREND,ID=lfn,RP=14)	lfn may be any desired 3-letter identification code, file is retained 14 days beyond last use
7	789	multiple punch column 1
8-N+8	program deck	first card should be PROGRAM MAIN(...), last card should be END
N+9	789	multiple punch colmn 1
N+10	LIBRARY(TAPE,NEW)	
N+11	ADD(*,LGO,AL=1)	
N+12	FINISH.	period essential
N+13	ENDRUN.	"
N+14	6789	multiple punch colmn 1

Option 2a: To run program stored on permanent file TREND--No Calcomp plots requested.

Card No.		Notes
1	Job Card[1]	use CM 50000
2	Account Card[1]	
3	ATTACH(TREND,ID=lfn)	
4	LDSET(LIB=TREND)	
5	MAIN.	period essential
6	789	multiple punch colmn 1
7 - M+7	data deck	see below
M+8	6789	multiple punch colmn 1

Option 2b: To run program stored on permanent file TREND--Calcomp Plots requested

Card no.		Notes
1	Job Card[1]	Use CM 75000
2	Account Card[1]	
3	ATTACH(TREND,ID=lfn)	
4	PUBLIC(GRAFIX)	
5	DISPOSE(TAPE99,*CC)	
6	LDSET(LIB=TREND/GRAFIX)	
7	MAIN.	period essential
8	789	multiple punch colmn 1
9 - M+9	data deck	see below
M+10	6789	multiple punch colmn 1

Option 3a: To run program from source deck--No Calcomp plots requested.

Card No.		Notes
1	Job Card[1]	Use CM 50000
2	Account Card[1]	
3	FORTRAN.	period essential
4	LGO.	"
5	789	multiple punch column 1
6 - 6+N		Program source deck- first card PROGRAM MAIN(...) last card END
N+7	789	multiple punch column 1
N+8 - N+M+8	data deck	see below
N+M+9	6789	multiple punch column 1

Option 3b: To run program from source deck--Calcomp plots requested.

Card No.		Notes
1	Job Card[1]	Use CM 75000
2	Account Card[1]	
3	PUBLIC(GRAFIX)	
4	DISPOSE(TAPE99,*CC)	
5	FORTRAN.	period essential
6	LDSET(LIB=GRAFIX)	
7	LGO.	period essential
8	789	multiple punch column 1
9 - 9+N	program source deck	First card PROGRAM MAIN (...), last card END
10+N - 10+N+M	data deck (see below)	
11+N+M	6789	multiple punch column 1

1/ See University of Washington CDC 6400 User's guide.

Data Deck Setup

The first 6+N cards are always required, subsequent cards depend on the channel options desired and the sequence in which they are called. These optional cards are described below with the channel option descriptions.

Card No.	Variables Read	Format	Description
1	NCHAN,N	16I5	Number of parameters, length of data record
2	(NAME(J,K),K=1,8), J=1,NCHAN)	8A10	Identifier for each parameter (1 card per parameter, all 80 columns may be used)

Card No.	Variables Read	Format	Description
3	(FMT1(J),J=1,4)	4A10	Variable read format for data, use first 40 columns of card only, must include parentheses
4	(FMT2(J),J=1,4)	4A10	Variable read format for missing data code (XMD) use first 40 columns only, must include parentheses
5	(FMT3(J),J=1,4)	4A10	Variable write format for echo print of input data--use first 40 columns only, must include parentheses
6	XMDAT	FMT2	Missing data code[2]
7 - 7+N	data	FMT1	Data read in according to given variable format, only requirement is that all NPAR values at given time be located on one card
N+8	(IAR1(J), IAR2(J), J√1,16)	16(2I2,1X)	Channel option input and output channels, if less than 16 options used leave remainder blank
N+9	(ICOMP(J), J=1,16)	16I5	Channel options--if less than 16 options leave remainder blank

Data Channel Option Descriptions

Option 1: Data transformation--This option performs either a natural logarithmic or a power transformation on the data, e.g., $X_j' = \ln(X_j)$ or $X_j' = (X_j)^{POW}$.

Data Read: ITRANS, POW (transformation option, 1 = natural log, 2 - power, and power POW if ITRANS = 2, leave blank otherwise).

Format: I10, F10.0

Option 2: Seasonal mean removal--This option subtracts from the data the corresponding seasonal mean, for instance if monthly seasons are used, each January datum is computed as the difference between the original value and the mean of all January data available.

Data read: NGP, NYR (number of data grouped for each season, number of data per year). For instance, if monthly data are given and the seasons are months, NGP = 1, NYR = 12.

Format: 16I5

Option 3: Data Differencing--This option computes a new data set as the differences of the input data, e.g., $X'_j = X_j - X_{j-NDIF}$.

Data Read: NDIF (number of data points lagged in differencing).

Format: 16I5

Option 4: Quantile-Quantile plot--Data are ordered without respect to time, sample quantiles computed and plotted against theoretical quantiles of the normal distribution. Plot is lineprinter plot, no CalComp plot available. Output data channel is same as input channel, no manipulation on data is performed, hence specified output channel is ignored.

Data Read: None.

Option 5: Time eries plot of data--Data in given input channel are plotted versus time. CalComp and lineprinter plots are available (must use control card deck 2b or 3b) if CalComp desired, preferable (but not necessarily 2a or 3a if no CalComp. Output channel is ignored. No data are read if lineprinter plots chosen.

Data Read:

Card No.	Variable(s)	Format	Comment
1	NBP	16I5	Bypass option--NBP = 0 with CalComp option, reads cards 2-7 (must set NBP = 0 on first parameter run if CalComp plots desired). NBP = 1 eliminates need for cards 2-5, uses previously suppled values. If NBP = 0, do not supply cards 2-7.
2	NPER, NYR, IPER, IYR	16I5	Number of data collected per year, number of years data (round up), initial period for first data point, initial year number.
3	XMIN, XMAX, YMIN, YMAX	8F10.0	Location in inches of X-axis, end of X-axis, Y-axis, end of Y-axis from arbitrarily defined plotter origin. Suggested values are 1.0, 9.0, 1.5, 7.0.
4	XLSZ1, XLSZ2, XLSZ3	8F10.0	Lettering size for axis increments, axis plots and labels, plot title. Suggested values are .098, .114, .140.
5	(TEXTB(J), J=1,8)	8A10	X-axis label, any alphameric information up to 80 characters.
6	(TEXTL(J), J=1,8)	8A10	Y-axis label, any alphameric information up to 80 characters.
7.	(XTIT(J), J=1,8)	8A10	Plot label, any alphameric information up to 80 characters.

Option 6: Data transfer--Transfers data from input to output channel.

Data Read: None.

Option 7: Time series model identification--Computes summary statistics, correlation and partial autocorrelation functions and plots (lineprinter only). Suggested procedure is to use output from data option 10 as input to remove nonstationarity.

Data Read: NLAG, JCHAN (maximum number of lags for which autocorrelation computed), channel from which mean estimated for calculating summary statistics (need not be same as input channel).

Format: 16I5

Option 8: CUSUM plot--Plots cumulative sum of data (see main text for description). Plot is lineprinter only.

Data Read: NDP, final point from which pre-intervention mean computed. Must be certain that some data occur prior to t = NDP.

Format: 16I5

Option 9: Data censoring--Censors given data, treating as if given point(s) were missing. Maximum of 16 points per pass.

Data Read: (N1(J), J=1,16) (sequence numbers of data censored, if less than 16, leave remainder blank). Input and output channels are same--if original data is to be saved, must first store in alternate channels using option 6.

Format: 16I5

Option 10: Residuals from moving average--Computes new time series as residuals of input channels data from moving average of data in specified channel. At each time, average of NAV points surrounding J (J is central point if NAV odd; if NAV is even, NAV/2 of points to be averaged precede J) is computed. Output time series is computed as difference between raw data and moving average at each time. This option is particularly useful for removing trends prior to estimating correlation and autocorrelation functions via Option 7.

Data Read: NAV, KCHAN (number of data points averaged, channel from which moving average is computed--need not be same as input channel).

Option 11: Nonparametric tests--Given necessary beginning and ending data indices, Mann-Whitney's or Spearman's rho test statistic is computed from data. Number of data points in first (and, for Mann-Whitney's test, second) partition of data are computed and written, ignoring missing data, for use in computing critical levels.

Data Read: NTEST, IS1, IF1, IS2, IF2 (test option, 1 for Mann-Whitney's, 2 for Spearman's rho, initial and final points of first and second data partition--leave IS2, IF2 bland for Spearman's rho).

Format: 16I5

Option 12: Computes step or linear changes in estimated mean level via least squares and estimated standard deviation of change. Also plots estimated step and linear trends if desired. Variance is computed on basis of effective independent sample size for lag one Markov process.

Data Read: KSL, KPL, IS1, IF1, IS2, IF2, ILOOP, RO, KGAP. KSL is trend type, 1 for step, 2 for linear; KPL is plot option--0 gives no plot, 1 gives lineprinter, 2 gives CalComp. IS1, IF1, IS2, IF2 are same as for Option 11. ILOOP is multiple loop parameter when it is desired to plot more than one estimated trend on same time series plot--use 1 for start of multiple loop, 0 for single iteration only, -1 for continuation of multiple loop, -2 for end of multiple loop. If KPL = 2, plot data must be read in exactly as for Option 5, but plot data are read in only when ILOOP = 0 or 1. RO is daily lag one correlation coefficient, KGAP is sampling interval in days (eg. for monthly data KGAP = 30). Suggested value for RO is 0.85 in absence of data-based estimate.

Format: 7I5, F5.0, I5

APPENDIX B.2 PROGRAM LISTING

```
      PROGRAM MAIN(INPUT,OUTPUT,TAPE5=INPUT,TAPE6=OUTPUT)
      COMMON/COM1/Y(6,250)
      COMMON/COM5/T(250)
      COMMON/COM3/XHOLD(250),XT(250)
      DIMENSION T1(250), XJ1(250)
      DIMENSION LCHAN(6)   , IAR2(16), FMT2(4), NAME(6,8)
      DIMENSION FMT1(4), IAR1(16), X(6,250), ICOMP(16)     , FMT3(4)
      DIMENSION XAR(2), YAR(2)  ,N1(16)    , YR(15)   , YYR(5), YR1(5)
      DIMENSION GY(3), XYR(20), TEXTB(8), TEXTL(8), XTIT(8)
      READ(5,1) NCHAN, N , IPLOT
      IF(IPLOT .EQ. 3) CALL PRNTON
      IF(IPLOT .EQ. 2) CALL STCCON(48H
     $                                              )
      READ(5,2) ((NAME(J,K), K= 1,8), J= 1, NCHAN)
      DO 106 J = 1, 6
106   LCHAN(J) = N
      READ(5,2) (FMT1(J), J= 1,4)
      READ(5,2) (FMT2(J), J= 1,4)
      READ(5,2) (FMT3(J), J= 1,4)
      READ(5,FMT2) XMDAT
1     FORMAT(16I5)
2     FORMAT(8A10)
      READ(5,FMT1) ((X(J,I), J= 1, NCHAN), I= 1,N)
      WRITE(6,100)
100   FORMAT(1H1, 40X, *ECHO PRINT OF INPUT DATA*,//)
      WRITE(6,FMT3) ((X(J,I), J= 1, NCHAN), I= 1,N)
C -- ICOMP(J) HOLDS DATA COMPUTATION OPTIONS
C -- IAR1 HOLDS THE INPUT ARRAY, IAR2 HOLDS THE OUTPUT ARRAY
C -- DATA COMPUTATION OPTIONS ARE
C --     1 -- TRANSFORMS  DATA (MUST READ IN TRANSFORMATION OPTION,
C --     1 = NATURAL LOG, 2 = POWER (READ IN POWER ON SAME CARD)
C --     2 -- REMOVE SEASONAL MEAN (MUST READ IN NUMBER OF DATA POINTS
C --     IN EACH SEASON, NUMBER OF DATA POINTS PER YEAR)
C --     3 -- DIFFERENCES DATA (READ IN NUMBER OF LAGS)
C --     4 -- DRAWS Q-Q PLOT
C --     5 -- PLOTS DATA (READ IN PLOT OPTION, 1 = LINEPRINTER, 2 =
C --     CALCOMP. IF CALCOMP, ADDITIONAL INPUT PARAMETERS REQ,D (SEE
C --     DOCUMENTATION))
```

```
C -- NPER IS NUMBER OF SEASONS/YR
C -- NYR IS NUMBER OF YEARS OF RECORD (NOT USED)
C -- IPER IS INDEX OF INITIAL SEASON
C -- IYR IS INITIAL YEAR
C --     6 -- PLACES DATA IN INPUT CHANNEL INTO OUTPUT CHANNEL
C --     7 -- COMPUTES CORRELATION, PARTIAL AUTOCORRELATION AND PLOTS
C --     (MUST READ IN MAXIMUM NUMBER OF LAGS)
C --     8 -- PLOTS CUSUM OF GIVEN CHANNEL (MUST READ IN NUMBER OF
C --     DATA POINTS FROM WHICH MEAN IS CALCULATED
C --     9 -- IGNORES GIVEN DATA POINTS (READ IN SEQUENCE NUMBERS OF
C --     POINTS, UP TO 16)
C --     10 -- TAKES RESIDUALS FROM MOVING AVERAGE (MUST READ IN NUMBER
C --     OF DATA POINTS TO BE AVERAGED, CHANNEL FROM WHICH DATA IS AV-
C --     ERAGED
C --     11 -- CALCULATES MANN-WHITNEY≠S OR SPEARMAN≠S RHO TEST STAT-
C --     ISTIC ON DATA. READ IN TEST OPTION (1=MW, 2=SR). INITIAL AND
C --     FINAL DATA POINT OF FIRST DATA SEGMENT (COMPLETE RECORD FOR SR)
C --     AND INITIAL AND FINAL POINTS FOR SECOND DATA SEGMENT
C --     12 -- CALCULATES STEP HEIGHT OR LINEAR SLOPE HEIGHT VIA LEAST
C --     SQUARES. READ IN STEP OR LINEAR OPTION, PLOT OPTION (NONE, LINE
C --     PRINTER, OR CALCOMP. FOR CALCOMP, MUST READ IN NORMAL CAL-
C --     COMP PLOT PARAMETERS (SEE DOCUMENTATION). BASE LAG ONE CORRELA-
C --     TION COEFFICIENT, SAMPLING INTERVAL IN DAYS ALSO REQUIRED
C --     ILOOP = 1, START MULTIPLE LOOP, 0, SINGLE ITERATION ONLY,
C --     -1, CONTINUE MULTIPLE LOOP, -2, END MULTIPLE LOOP
C -- XMDAT IS THE MISSING DATA CODE
         DO 1000 KJ = 1, NCHAN
         DO 21 J= 1,6
         DO 21 K= 1,200
21       Y(J,K) = 0.
        READ(5,4) (IAR1(J), IAR2(J), J= 1,16)
           READ(5,1) (ICOMP(J), J= 1,16)
4         FORMAT(16(2I2,1X))
        DO 11 J= 1,16
11        IF(ICOMP(J) .EQ. 0) GO TO 12
12        JMAX = J-1
         WRITE(6,35)  (NAME(KJ,J), J= 1,8)
35       FORMAT(/////,    10X, 8A10)
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          WRITE(6,36) (ICOMP(J), J= 1,JMAX)
36        FORMAT(//, 10X, *ARRAY OPTIONS ARE*, 3X, 16I5)
           WRITE(6,37) (IAR1(J), IAR2(J), J= 1,JMAX)
37        FORMAT(//, 10X, *CHANNEL OPTIONS ARE*, 1X, 16(2I2, 1X))
          DO 45 J = 1,N
          Y(1,J) = X(KJ,J)
45       IF(Y(1,J) .EQ. XMDAT) Y(1,J) = 0.
            KSL = ILOOP = 0
          DO 50 JJ = 1, JMAX
          IC = ICOMP(JJ)
          JAR1 = IAR1(JJ) $ JAR2 = IAR2(JJ)
          GO TO (51,52,53,54,55,56,57,58,59,60,61,62), IC
51       READ(5,110) ITRANS, POW
          LL = LCHAN(JAR1)
110        FORMAT(I10, F10.0)
          GO TO (210,211), ITRANS
210       DO 212 J = 1,LL
          Y(JAR2,J) = Y(JAR1,J)
212       IF(Y(JAR1,J) .NE. 0.) Y(JAR2,J) = ALOG(Y(JAR1,J))
           GO TO 50
211       DO 213 J = 1,N
213       IF(Y(1,J) .NE. 0.) Y(2,J) = Y(1,J)**POW
          GO TO 50
52        READ(5,1) NGP, NYR
          LL = LCHAN(JAR1)
C -- NGP IS THE NUMBER OF DATA POINTS GROUPED FOR SEASONAL MEANS,
C -- NYR IS THE NUMBER OF DATA POINTS PER YEAR
          NN = NYR/NGP  $ NNN =LL/NYR + 1
          NDATT = 0
           DO 120 J= 1, NN
          NSTART = (J-1)*NGP
          SUM = 0. $ NDAT = 0
          DO 121 K = 1, NNN
          DO 121 L = 1, NGP
          KK = NSTART + (K-1)*NYR + L
          IF(KK .GT.LL) GO TO 122
          XXX = ABS(Y(JAR1,KK))/(ABS(Y(JAR1,KK)) + 1.E-06)  + 1.E-04
            IND = XXX
```

```
          SUM = SUM + Y(JAR1,KK)*IND
121       NDAT = NDAT + IND
122       XBAR = SUM/NDAT
          XHOLD(J) = 'XBAR
            XT(J) = NDAT
          NDATT = NDATT + NDAT
          DO 123 K = 1, NNN
          DO 123 L= 1,NGP
         KK = NSTART + (K-1)*NYR + L
          IF(KK .GT.LL) GO TO 120
          Y(JAR2,KK) = Y(JAR1,KK)
         IF(Y(JAR1,KK) .NE. 0.)
     $    Y(JAR2,KK) = Y(JAR1,KK) - XBAR
123       CONTINUE
120       CONTINUE
           XBAR = 0.
          DO 1200 J = 1, NN
1200       XBAR = XBAR + XT(J)/NDATT*XHOLD(J)
          DO 1201 J= 1, LL
1201       IF(Y(JAR2,J) .NE. 0.) Y(JAR2,J) = Y(JAR2,J) + XBAR
           GO TO 50
53        READ(5,1) NDIF
          LL = LCHAN(JAR1)
        NM = LL- NDIF
          DO 130 J = 1, NM
          Y(JAR2,J) = 0.
          IF(Y(JAR1,J+NDIF) .NE. 0. .AND. Y(JAR1,J) .NE. 0.)
     $    Y(JAR2,J) = Y(JAR1,J+NDIF) - Y(JAR1,J)
130       CONTINUE
          LCHAN(JAR2) = LCHAN(JAR1)- NDIF
         GO TO 50
54        LL = LCHAN(JAR1)
          CALL QQPLOT(LL, JAR1)
          GO TO 50
55        LL = LCHAN(JAR1)
          IF(IPLOT .EQ. 1) GO TO 555
         IF(ILOOP .LT. 0) GO TO 179
          READ(5,1) NBP
```

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555       IF(ILOOP .LT. 0) GO TO 271
          DO 140 J= 1, LL
          T(J) = J
140        XHOLD(J) = Y(JAR1,J)
           CALL QKRSRT(LL)
          XAR(1) = LL $ XAR(2) = 0 $ YAR(1) = XHOLD(LL) $ YAR(2) = XHOLD(
     $1)
          DO 142 J= 1, LL
142       XHOLD(J) = Y(JAR1,J)
          IF(IPLOT .EQ. 1) GO TO 143
           IF(NBP .NE. 0) GO TO 147
          READ(5,1) NPER, NYR, IPER , IYR
          READ(5,201) XMIN,XMAX,YMIN,YMAX
          READ(5,201) XLSZ1, XLSZ2, XLSZ3
201       FORMAT(8F10.0)
          READ(5,2) (TEXTB(J), J=1,8)
147       READ(5,2) (TEXTL(J), J=1,8)
            READ(5,2) (XTIT(J), J= 1,8)
           CALL STS20B(XMIN,XMAX,YMIN,YMAX)
          GY(1) = YAR(1) $ GY(2) = YAR(2) $ GY(3) = 10
          MAX = (LL-1)/NPER + 1
           XPLT = MAX*NPER
           CALL STNDIV(MAX,1)
           CALL STSUBJ(0.,XPLT,0.,GY(1))
          CALL FABLIY(GY)
           CALL AXLILI $ CALL STCHSZ(XLSZ1)
            CALL STNDEC(0) $ CALL NODLIB $ CALL STNDEC(2) $ CALL NODLIL
        XINT = NPER*(XMAX-XMIN)/XPLT
         XI = (NPER/2+1 - IPER)*XINT/NPER - XINT/NPER/2.
           IP = 0
          IF(XI .GT. 0.) GO TO 243
          IP = 1
          XI = XI + XINT $ IYR = IYR + 1
243     DO 144 J= 1,15
144       YR(J) = IYR+ J - 1
          NMAX = 10*MAX
          IF(NMAX .LT. 150) GO TO 240
          MMAX = NMAX-150
```

```
         MMAX1 = MMAX/10
          NMAX = 150
          DO 241 J= 1, MMAX1
241       YR1(J) = YR(15) + J
        ENCODE(50,145,YYR) YR1
          DO 242 J= 1, MMAX1
242       XYR(J+15) = YYR(J)
240      ENCODE(150,145,XYR) YR
145       FORMAT(20(3H     , F4.0, 3H      ))
            XSTART = XMIN + XI - 4.*XLSZ2
           IYR = IYR - IP
           CALL STCHSZ(XLSZ2)
           YSTART = YMIN - 4.*XLSZ1
          MMAX = MAX-1
           CALL STNCHR(10)
           DO 146 J= 1, MMAX
          CALL OBLNST(XSTART, YSTART)
          TEXT = XYR(J)
          CALL TITLEG(TEXT)
146        XSTART = XSTART + XINT
           CALL STNCHR(80)
          CALL TITLEL(TEXTL)
            XSTART = XMIN + (XMAX-XMIN)/2. - 30.*XLSZ3
          YSTART = YMIN - 4.*XLSZ1 - 4.*XLSZ2
          CALL OBLNST(XSTART,YSTART)
          CALL TITLEG(TEXTB)
          YSTART = YMAX
          CALL OBLNST(XSTART,YSTART)
          CALL STCHSZ(XLSZ3)
            CALL TITLEG(XTIT)
          CALL STNPTS(LL)
         CALL STTXTR(1)
           CALL SLLILI(T, XHOLD)
179       IF(KSL .EQ. 0) GO TO 554
          CALL STTXTR(2)
          CALL STNPTS(JPOINTS)
          CALL SLLILI(T1, XJ1)
          IF(IABS(ILOOP) .EQ. 1) GO TO 62
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```
554      CALL ADVANC(999.,999.)
        GO TO 50
143      IF(ILOOP .LT. 0) GO TO 271
        WRITE(6,141) JAR1
141      FORMAT(1H1, 40X, *PLOT OF DATA IN CHANNEL*, I5, //)
        CALL PLOTA(XAR,2,YAR,2)
        CALL PLOTB(D,D,D,D)
        CALL PLOT3(1H*, T, XHOLD,LL)
        IF(KSL .EQ. 0) GO TO 273
271      CALL PLOT3(1H+, T1, XJ1, JPOINTS)
        IF(IABS(ILOOP) .EQ. 1) GO TO 62
273     CALL PLOT4(0,0)
        GO TO 50
56      LL = LCHAN(JAR1)
        DO 150 J= 1,LL
150     Y(JAR2,J) = Y(JAR1,J)
        LCHAN(JAR2) = LCHAN(JAR1)
         GO TO 50
57      LL = LCHAN(JAR1)
        READ(5,1) NLAG , JCHAN
         DO 160 J= 1,LL
160      XHOLD(J) = Y(JAR1,J)
         SUM = 0. $ JSUM = 0
        L = JCHAN
        IF(L .EQ. 0) L = 1
         DO 161 J = 1, N
        IF(Y(L,J) .EQ. 0.) GO TO 161
         SUM = SUM + Y(L,J)
         JSUM = JSUM + 1
161       CONTINUE
         XBAR = SUM/JSUM
        CALL PCOR(NLAG, LL, 1, XBAR)
       GO TO 50
58      LL = LCHAN(JAR1)
        READ(5,1) NDP
         SUM = 0. $ JSUM =    0
        DO 170 J = 1, NDP
         IF(Y(JAR1,J) .EQ. 0) GO TO 170
```

```
        JSUM = JSUM + 1
         SUM = SUM + Y(JAR1,J)
170     CONTINUE
        XBAR = SUM/JSUM
        SUM = 0. $ JSUM = 0
         DO 171 J = 1,LL
        XHOLD(J) = 0.
        IF(Y(JAR1,J) .EQ. 0.) GO TO 171
        SUM = SUM + Y(JAR1,J)
         JSUM = JSUM + 1
         XHOLD(J) = SUM-XBAR*JSUM
171     CONTINUE
        XAR(1) = LL $ XAR(2) = 1
         DO 172 J = 1,LL
172      T(J) = XHOLD(J)
        CALL QKRSRT(LL)
        YAR(1) = XHOLD(LL)
         YAR(2) = XHOLD(1)
       DO 173 J = 1,LL
        XHOLD(J) = T(J)
173      T(J) = J
        NNDP = NDP + 1
        WRITE(6,174) JAR1, NNDP
174     FORMAT(1H1, 20X, *CUSUM PLOT OF DATA IN CHANNEL*, I3, * WITH IN
    $TERVENTION AVERAGE AT DATA POINT NUMBER*, I3, //)
       CALL PLOTA(XAR,2,YAR,2)
        CALL PLOTB(D,D,D,D)
        CALL PLOT3(1H*, T, XHOLD, LL)
         CALL PLOT4(0,0)
        GO TO 50
59      READ(5,1) (N1(J), J= 1,16)
        DO 180 J= 1,16
        LL = N1(J)
         IF(LL .EQ. 0) GO TO 50
180      Y(JAR1,LL) = 0.
         GO TO 50
60      READ(5,1) NAV, KCHAN
        IF(KCHAN .EQ. 0) KCHAN = 1
```

```
      LL = LCHAN(KCHAN) $ LLL = LL - NAV
       DO 191 J = 1, LLL
      JJJ = J + NAV/2
      XHOLD(JJJ) = 0. $ JSUM = 0
      DO 192 K = 1, NAV
      IF(Y(KCHAN, J+K-1) .EQ. 0.) GO TO 192
     XHOLD(JJJ) = XHOLD(JJJ) + Y(KCHAN, J+K-1)
      JSUM = JSUM + 1
192   CONTINUE
      IF(XHOLD(JJJ) .NE. 0.) XHOLD(JJJ) = XHOLD(JJJ)/JSUM
191    IF(XHOLD(JJJ) .EQ. 0.) XHOLD(JJJ) = XHOLD(JJJ-1)
      JJ1 = NAV/2
     DO 193 J = 1, JJ1
193   XHOLD(J) = XHOLD(JJ1 + 1)
      JJ2 = LLL + NAV/2 + 1
      DO 194 J = JJ2, LL
194  XHOLD(J) = XHOLD(JJ2-1)
      LL = LCHAN(JAR1)
      DO 195 J= 1,LL
     Y(JAR2,J) = 0.
195   IF(Y(JAR1,J) .NE. 0.) Y(JAR2,J) = Y(JAR1,J) - XHOLD(J)
      GO TO 50
61    READ(5,1) NTEST, IS1, IF1, IS2, IF2
     GO TO (220,221), NTEST
220  M1 = IF1 - IS1 + 1
     DO 222 J = 1, M1
222   Y(JAR2,J) = Y(JAR1, IS1+J-1)
      N2 = IF2 - IS2 + 1
    N1P1 = M1 + 1 $ NNN = M1 + N2
      DO 223 J = N1P1, NNN
223   Y(JAR2,J) = Y(JAR1, J-N1P1 + IS2)
      ICC = 0
    DO 224 J= 1, M1
      IF(Y(JAR2,J) .EQ. 0.) GO TO 224
      ICC = ICC + 1 $ XHOLD(ICC)= Y(JAR2,J)
224   CONTINUE
     M1 = ICC
      DO 225 J = N1P1, NNN
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         IF(Y(JAR2,J) .EQ. 0.) GO TO 225
        ICC = ICC + 1 $ XHOLD(ICC)= Y(JAR2,J)
225      CONTINUE
         NNN = ICC
       CALL MNWHIT(NNN,M1,TSTAT)
       WRITE(6,226) NNN, M1, TSTAT, IS1, IF1, IS2, IF2
226      FORMAT(//, 20X, *MANN-WHITNEY≠S TEST STATISTIC FOR DATA WITH N
     $= *, I4, *, N1 = *, I4, *, IS*, F7.0, /, 20X, *INITIAL AND FINAL P
     $OINTS IN FIRST AND SECOND DATA SEGMENTS ARE*, I4, *,*, I4, *,*, I4
     $,*,*, I4, *,*, * RESPECTIVELY*,//)
         GO TO 50
221     M1 = IF1-IS1+1
        DO 230 J= 1, M1
230      Y(JAR2,J) = Y(JAR1,IS1+J-1)
         ICC = 0
         DO 231 J= 1, M1
         IF(Y(JAR2,J) .EQ. 0.) GO TO 231
         ICC = ICC + 1 $ XHOLD(ICC)= Y(JAR2,J)
231     CONTINUE
         NNN = ICC
          CALL SPEARRO(NNN, TSTAT)
         WRITE(6,232) NNN, TSTAT, IS1, IF1
232      FORMAT(//, 20X, *SPEARMAN≠S RHO TEST STATISTIC FOR DATA WITH N
     $= *, I5, * IS*, F7.0,/, 20X, *INITIAL AND FINAL DATA POINTS ARE*,
     $I4, *,*, I4, *, RESPECTIVELY*,//)
          GO TO 50
62       READ(5,250) KSL, KPL, IS1, IF1, IS2, IF2, ILOOP, RO, KGAP
250      FORMAT(7I5, F5.0, 8I5)
         XRAT = (1. + RO**KGAP)/(1.-RO**KGAP)
         GO TO (251, 252), KSL
251      SUM1 = SUM2 = 0.
        SUMV1 = SUMV2 = 0.
         LC1 = LC2 = 0
       DO 257 J = IS1, IF1
         LC = ABS(Y(JAR1,J))/(ABS(Y(JAR1,J))+ 1.E-06) + 1.E-04
         SUMV1 = SUMV1 + Y(JAR1,J)*Y(JAR1,J)
        SUM1 = SUM1 + Y(JAR1,J)
257     LC1 = LC1 + LC
```

```
          XBAR1 = SUM1/LC1
         DO 253 J= IS2, IF2
         LC = ABS(Y(JAR1,J))/(ABS(Y(JAR1,J))+ 1.E-06) + 1.E-04
         SUM2 = SUM2 + Y(JAR1,J)
        SUMV2 = SUMV2 + Y(JAR1,J)*Y(JAR1,J)
253       LC2 = LC2  + LC
          XBAR2 = SUM2/LC2
         XJUMP = XBAR2 - XBAR1
         SSC1 = SUMV1/LC1 - XBAR1*XBAR1
          SSQ2 = SUMV2/LC2 - XBAR2*XBAR2
         XVAR = (SSC1/LC1 + SSQ2/LC2)*XRAT
         XSD = SQRT(XVAR)
          WRITE(6,254) IS1, IF1, IS2, IF2, LC1, LC2, XJUMP, XSD
254      FORMAT(//, 20X, *ESTIMATED STEP TREND MAGNITUDE FOR START AND E
     $ND POINTS*, I5, *,*, I5, *,*, I5, *,*,* AND*, I5, *,*,* WITH NUMBE
     $R OF DATA*, /, 20X, I5,* AND*, I5, *, IS*, F10.2, * WITH STANDARD
     $DEVIATION*, F10.2, //)
         IPLOT = KPL
          IF(IPLOT .EQ. 0) GO TO 50
        DO 255 J= IS1, IF1
          T1(J-IS1 + 1) = J
255      XJ1(J-IS1 + 1) = XBAR1
        JSTAG = IF1-IS1 + 1
        DO 256 J= IS2, IF2
          T1(J-IS2 + 1 + JSTAG) = J
256      XJ1(J-IS2+ 1 + JSTAG) = XBAR2
         JPOINTS = IF1-IS1 + 1 + IF2-IS2 + 1
         GO TO 55
252      SUM1 = SUM2 = SUM3 = SUM4 = 0.
         LC1 = 0
        DO 260 J= IS1, IF1
         LC =ABS(Y(JAR1,J))/(ABS(Y(JAR1,J))+ 1.E-06) + 1.E-04
        LC1 = LC1 + LC
         SUM1 = SUM1 + Y(JAR1,J)
         SUM2 = SUM2 + LC*J
         SUM3 = SUM3 + Y(JAR1,J)*J
260        SUM4 = SUM4 + LC*J*J
         BETA = (SUM1*SUM2 - LC1*SUM3)/(SUM2*SUM2 - LC1*SUM4)
```

```
      ALPHA = 1./LC1*(SUM1-BETA*SUM2)
      XTR = BETA*(IF1-IS1)
      SUMV = 0.
      SUMX1 = SUMX2 = 0.
       DO 261 J= IS1, IF1
      LC = ABS(Y(JAR1,J))/(ABS(Y(JAR1,J)) + 1.E-06) + 1.E-04
     SUMX1 = SUMX1 + J
      SUMX2 = SUMX2 + J*J
      UX = (ALPHA + BETA*J - Y(JAR1,J))*LC
261   SUMV = SUMV + UX*UX
       SQ = SUMV/(LC1-2)
      VARB = SQ/(SUMX2-SUMX1*SUMX1/(IF1-IS1+1)/(IF1-IS1+1))
        SDB = SQRT(VARB)*(IF1-IS1)
       XJUMP = BETA*(IF1-IS1)
       WRITE(6,265) IS1, IF1, LC1, XJUMP, SDB
265   FORMAT(//, 20X, *ESTIMATED LINEAR TREND MAGNITUDE FOR START AND
    $ END POINTS*, I5, *,*, I5, * WITH NUMBER OF DATA*, I5,  /, 20X,
    $*IS*, F10.2, * WITH STANDARD DEVIATION*, F10.3, //)
      IPLOT = KPL
      IF(IPLOT .EQ. 0) GO TO 50
        DO 262 J= IS1, IF1
         T1(J-IS1+1) = J
262    XJ1(J-IS1+1) = ALPHA + BETA*J
      JPOINTS = IF1-IS1 + 1
     GO TO 55
50     KSL = ILOOP = 0
1000   CONTINUE
      IF(IPLOT .GE. 2) CALL EXITPL
     END
```

```
      SUBROUTINE AUTCOR(L,RM,V,N)
      COMMON/COM4/R(401), RP(401), SC(401,2)
        COMMON/COM3/X(500)
      DO 1 J= 1,L
        IC1 = 0
      KK = N-J
      DUM = 0.
      DO 2 I= 1,KK
       IND1 = X(I)/(X(I) + 1.E-06) + 1.E-04
        IND2 = X(I+J)/(X(I+J)+1.E-06) + 1.E-04
          IC1 = IC1 + IND1*IND2
2      DUM = DUM + (X(I)-RM)*(X(I+J)-RM)  *IND1*IND2
        R(J) = 0.
        IF(IC1 .EQ. 0)GO TO 1
         R(J) = DUM/IC1/V
1       CONTINUE
      RETURN
     END
```

```
      SUBROUTINE CPLOT(L)
      COMMON/COM4/R(401), RR(401), X(401)
      XL = L
      CALL STS2OB(.5,6.5,.5,3.5)
      CALL STSUBJ(0.,XL,-1.,1.)
      DO 1 J = 1,L
      X(J) = J-1
      JJ = L-J + 1
      R(JJ + 1) = R(JJ)
1     RR(JJ+1) =RR(JJ)
      R(1) = RR(1) = 1.
      LL = L-1 + 2
      X(LL) = LL-1
      CALL STNDEC(2)
      CALL STNPTS(LL)
      DO 10 J = 1,2
      CALL STNDIV(1,2)
      CALL GDLILI
      CALL STNDIV(10,10)
      CALL AXLILI
      CALL NODLIB $ CALL NODLIL
      IF(J .EQ. 2) GO TO 11
      CALL SLLILI(X,R)
      CALL ADVANC(999.,999.)
      GO TO 10
11    CALL SLLILI(X,RR)
10    CONTINUE
      CALL EXITPL
      RETURN
      END
```

```
      SUBROUTINE PCOR(L,N,INDIC, XXBAR)
     COMMON/COM4/R(401), RF(401), SC(4C1,2)
       COMMON/COM3/X(250)   , DUM(250)
      DIMENSION IMAGE(700), RJ(100)
      IF(NPLOT .EQ. 1) CALL STCCON(48H
     $                                )
      SUM1 = SUM2 = 0.
        IC = 0
     DO 1 J= 1,N
     IND = X(J)/(X(J) + 1.E-06) + 1.E-04
       IC = IC + IND
     SUM1 = SUM1 + X(J)*IND
1    SUM2 = SUM2 + X(J)*X(J)   *IND
      XBAR = SUM1/IC
     VAR = SUM2/IC   -XBAR*XBAR
      CALL AUTCOR(L,XBAR,VAR,N)
     RR(1) = SC(1) = R(1)
     DO 12 K= 2,L
     KK = K-1
     SUM1 = SUM2 = 0.
     DO 8 J= 1,KK
     SUM1 = SUM1 + SC(J)*R(K-J)
8    SUM2 = SUM2 + SC(J)*R(J)
     RR(K) = (R(K)-SUM1)/(1.-SUM2)
     DO 9 J= 1,KK
9    SC(J,2) = SC(J)-RR(K)*SC(K-J)
     DO 1C J= 1,KK
10    SC(J) = SC(J,2)
12    SC(K) = RR(K)
      RL = L
     IF(INDIC .NE. 1) RETURN
     WRITE(6,20)
20    FORMAT(1H1, 40X, *PLOT OF AUTOCORRELATION FUNCTION OF INPUT DATA
     $*)
     DO 2 J= 1,L
2     FJ(J) = J
      CALL PLOT2(IMAGE,RL,C.,1.,-1.)
      CALL PLOT3(1H*, RJ,R,L)
```

```
      RX = 0. $ RY = 1.
      CALL PLOT3(1H*, RX,RY,1)
     CALL PLOT4(0,0)
      WRITE(6,3)
3    FORMAT(1H1, *CORRELATIONS ARE*, //, 25X, *LAG*, 7X, *COR*,///
    $/)
     WRITE(6,4) (J, R (J), J = 1,L)
4     FORMAT(18X, I10, F10.3)
       SDD = SQRT(VAR)
        CVV = SDD/XXBAR
       WRITE(6,706)XXBAR, SOD    , CVV
706    FORMAT(///, 40X, *SUMMARY STATISTICS ARE          *, //,
    $ 46X, *MEAN*, 13X, *STD DEV*, 18X, *CV*, //, 30X, 2E20.3, F20.3)
       WRITE(6,21)
21    FORMAT(1H1, 40X, *PLCT OF PARTIAL AUTOCORRELATION FUNCTION OF IN
    $PUT DATA*)
     CALL PLOT2(IMAGE,RL,0.,1.,-1.)
     CALL PLOT3(1H*, RJ,RR,L)
     CALL PLOT3(1H*, RX,RY,1)
     CALL PLOT4(0,0)
      WRITE(6,5)
5     FORMAT(1H1, *PARTIAL CORRELATIONS ARE*,//, 25X, *LAG*, 5X,
    $*P COR*, ////)
      WRITE(6,4) (J, RR(J), J= 1,L)
       IF(NPLOT .EQ. 1) CALL CPLOT(L)
     PETURN
    END
```

```
      SUBROUTINE QQPLOT(LL,JAR1)
      COMMON/COM3/XHOLD(250)   ,XXP(250)
      COMMON/COM5/XP(250)
      COMMON/COM1/Y(6,250)
      COMMON/COM2/IMAGE(600)
      DIMENSION T(250)      , XAR(2) , YAR(2)
      JJ = 0
      DO 1 J= 1,LL
      IF(Y(JAR1,J) .EQ. 0.) GO TO 1
      JJ = JJ + 1
      XHOLD(JJ) = Y(JAR1,J)
1      CONTINUE
      DO 81 I= 1,JJ
      PP = (I-.5)/JJ
     IF = PP/.5 + 1
      IFF = (IF-1)*2 - 1
      GO TO (82,83), IF
82    TT = SQRT(ALOG(1./PP/PP))
      GO TO 84
83     TT = SQRT(ALOG(1./(1.-PP)/(1.-PP)))
84   XP(I) =            IFF*(TT-(2.30753 + .27061*TT)/(1. + .99229*TT +
    $ .04481*TT*TT))
81     T(I) = I
       CALL QKRSRT(JJ)
     XAR(1) = 3. $ XAR(2) = -3.
       YAR(1) = XHOLD(JJ) $ YAR(2) = XHOLD(1)
      CALL PLOTA(XAR,2,YAR,2)
      CALL PLOTB(D,D,D,D)
       WRITE(6,2) JAR1
2       FORMAT(1H1, 40X, *C-Q PLOT OF DATA IN CHANNEL*, I3, * AGAINST
    $A NORMAL DISTRIBUTION*,/)
        CALL PLOT3(1H*, XP, XHOLD,JJ)
      CALL PLOT4(0,0)
      RETURN
     END
```

```
      SUBROUTINE QKRSRT(JJ)
        COMMON/COM3/NA(250), IA(250)
      DIMENSION NUT(20), NLT(20)
     LOGICAL LE2,GE2
      REAL NA, NT, NX
     J=JJ
      DO 99 I= 1,J
99     IA(I) = I
     I=1
     M=1
  10 I1=I+1
     IF(J.LE.I1) GO TO 90
     NP=(J+I)/2
     NT=NA(NP)
      IT = IA(NP)
     NA(NP)=NA(I)
       IA(NP) = IA(I)
     NQ = J
     K=I
  15 K=K+1
     IF(K.GT.NQ) GO TO 50
     IF(NA(K).LE.NT) GO TO 15
     NQ=NQ+1
  20 NQ=NQ-1
     IF(NQ.LT.K) GO TO 30
     IF(NA(NQ).GE.NT) GO TO 20
     NX=NA(K)
     NA(K) = NA(NQ)
     NA(NQ)=NX
      IX = IA(K)
      IA(K) = IA(NQ)
      IA(NQ) = IX
     NQ=NQ-1
     GO TO 15
  30 NQ=K-1
  50 NA(I)=NA(NQ)
     NA(NQ)=NT
       IA(I) = IA(NQ)
```

```
      IA(NQ) = IT
    IF(2*NQ-I-J) 70,70,60
 60 NLT(M)=I
    NUT(M)=NQ-1
    I=NQ+1
    GO TO 80
 70 NLT(M)=NQ+1
    NUT(M)=J
    J=NQ-1
 80 M=M+1
    GO TO 10
 90 IF(I.GE.J) GO TO 100
    IF(NA(I).LE.NA(J)) GO TO 100
    NX=NA(I)
    NA(I)=NA(J)
    NA(J)=NX
     IX = IA(I)
      IA(I) = IA(J)
      IA(J) = IX
100 M=M-1
     IF(M .EQ. 0) RETURN
    I=NLT(M)
    J=NUT(M)
    GO TO 10
    END
```

```
      SUBFOUTINE SPEARRO(L,SUM)
      COMMON/COM3/Y(250), NR(250)
      LCOUNT = 0
      CALL QKRSRT(L)
     NSUM = 0
     DO 10 J= 1,L
10   NSUM = NSUM + (J-NR(J))*(J-NR(J))
     SUM = NSUM
                     SRO = 1./6.*FLOAT(L*(L*L-1)) -1.96 *1./6.*FLOAT(L
   $*(L*L-1))/SQRT(FLOAT(L-1))
     SRO1 = 1./3.*FLOAT(L*(L*L-1)) - SRO
      IF(SUM .LT. SRO  ) LCOUNT = 1
      IF(SUM .GT. SRO1) LCOUNT = -1
      RETURN
    END
```

```
      SUBROUTINE MNWHIT(N,N1, T)
       COMMON/COM3/Y(250), NR(250)
         L = N
      CALL QKRSRT(L)
     INDIC = 0
      RN = N1
      RM = N - N1
     XP =-1.96
      WP= (RN*RM)/2. + XP*SQRT(RN*RM*(RN + RM + 1.)/12.)
110   W  = N1*(N-N1)
     W = W - WP
     NSUM = 0
     DO 20 J= 1,N
     IF(NR(J) .LE. N1) NSUM = NSUM + J
20   CONTINUE
     SUM = NSUM
     T = SUM - FLOAT(N1*(N1 + 1))/2.
     RETURN
    END
```

REFERENCES PART II

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Conover, W. J., Practical Nonparametric Statistics, Wiley, New York, 1971.

Wilk, M. B., and Gnanades, Kan R., "Probability Plotting Methods for the Analysis of Data," Biometrika, Vol. 55, No. 1, pp. 1-17, 1968.

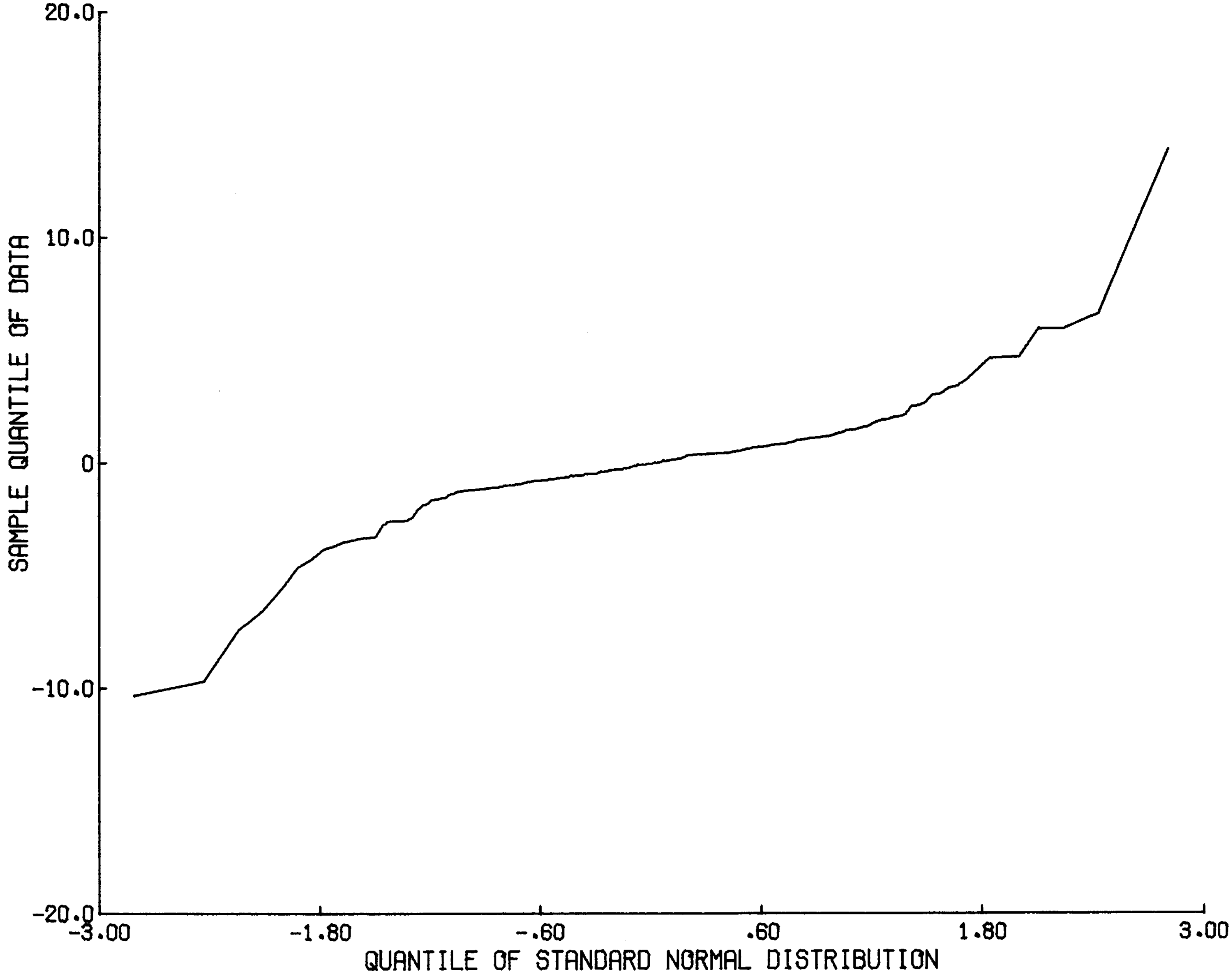

Figure II.2a Q-Q Plot for 200 Independent Student S T Variates with 2 Degrees of Freedom

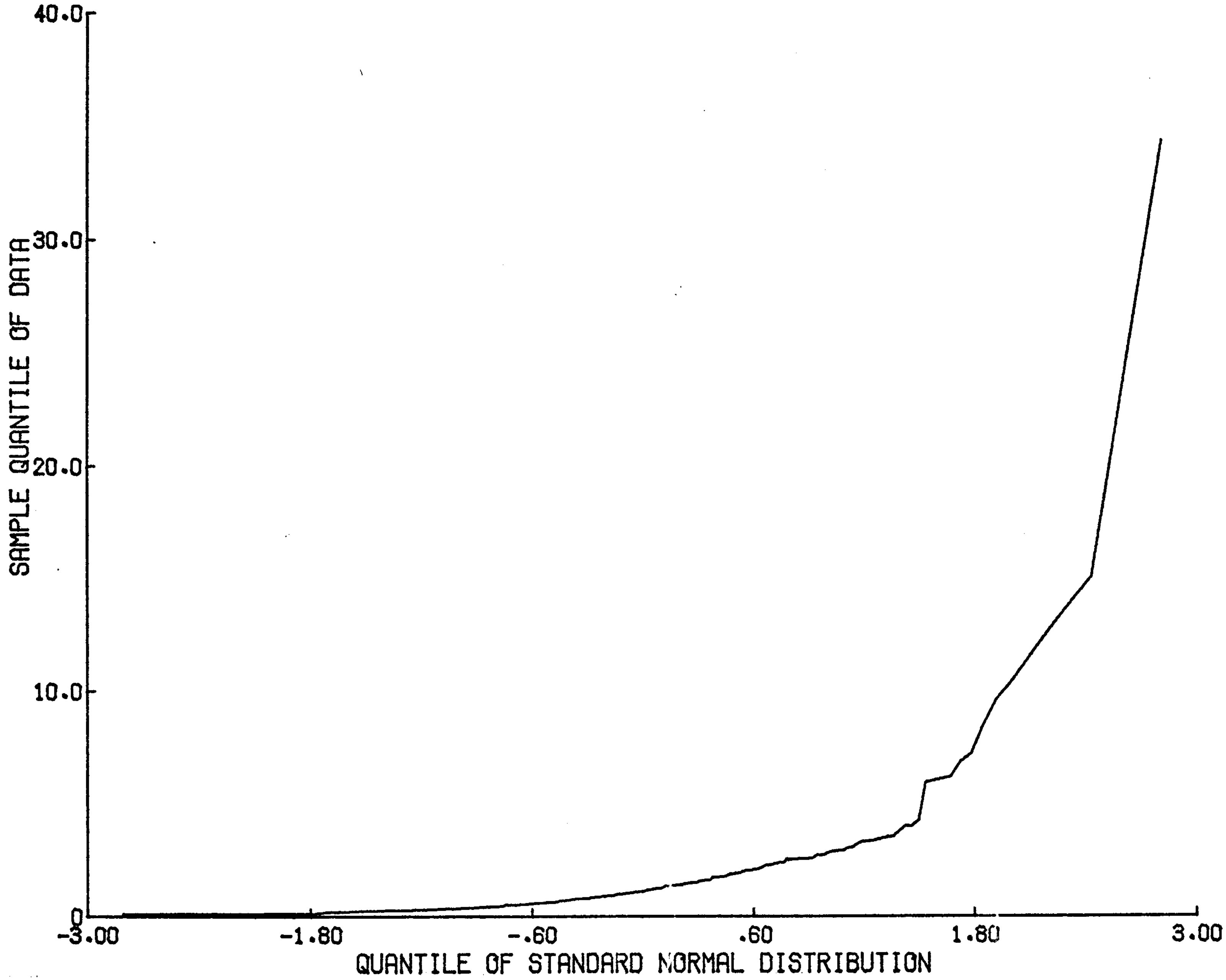

Figure II.2b Q-Q Plot for 200 Independent Log Normal Variates (Skew Coefficient = 2.88)

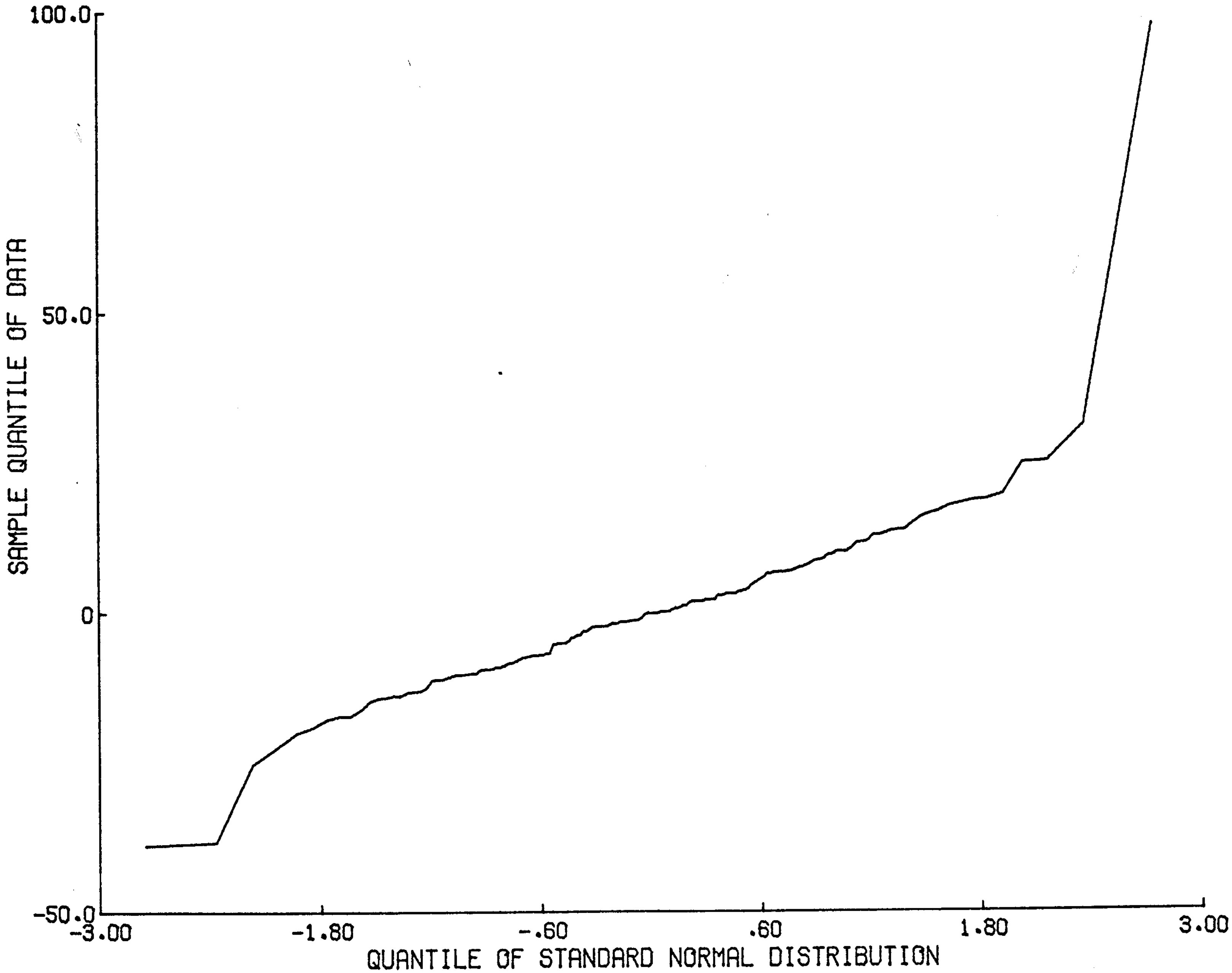

Figure II.3 Q-Q Plot for Chehalis River at Porter Specific Conductance, No Data Editing

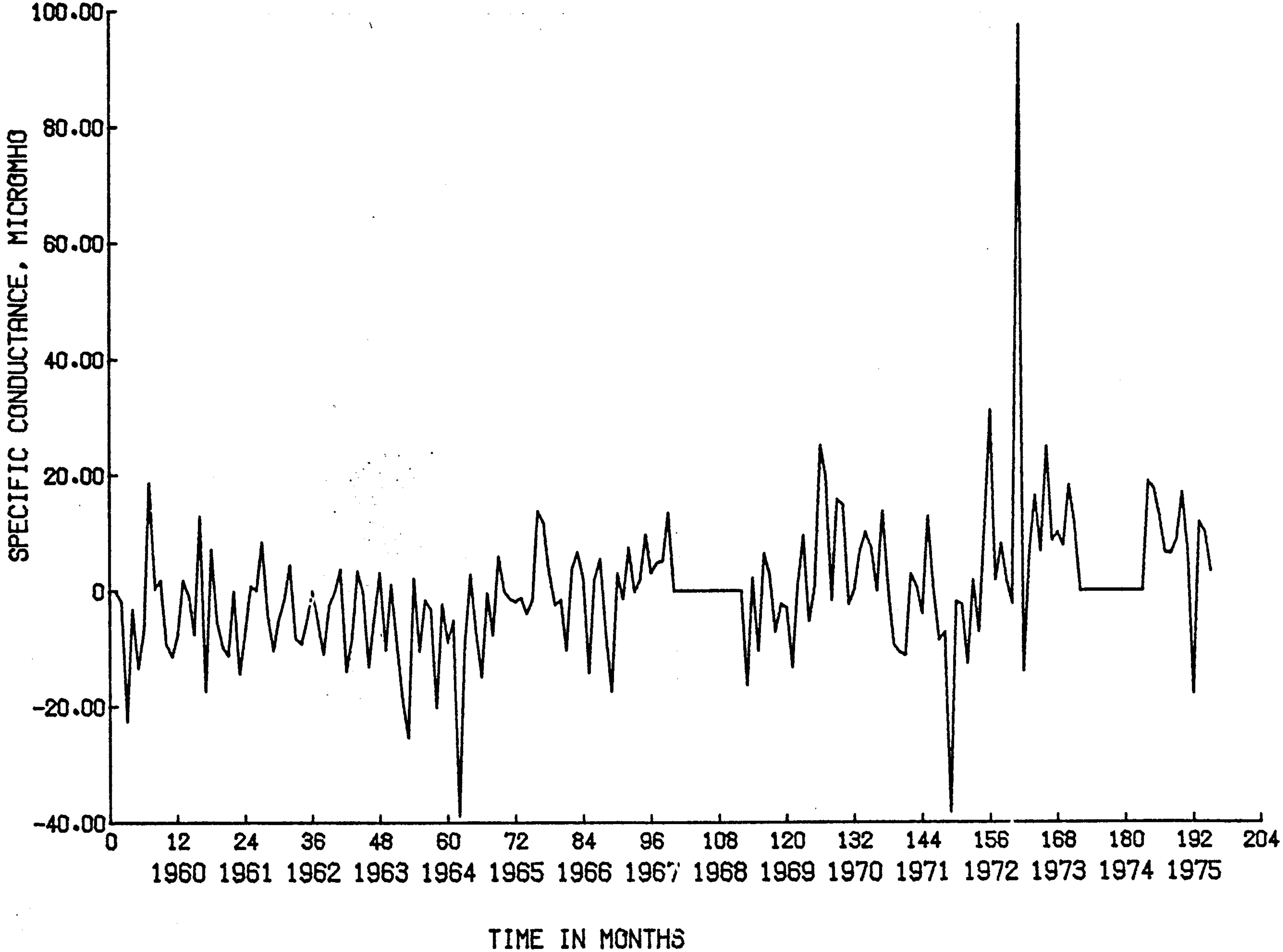

Figure II.4 Chehalis River at Porter Deseasonalized Specific Conductance

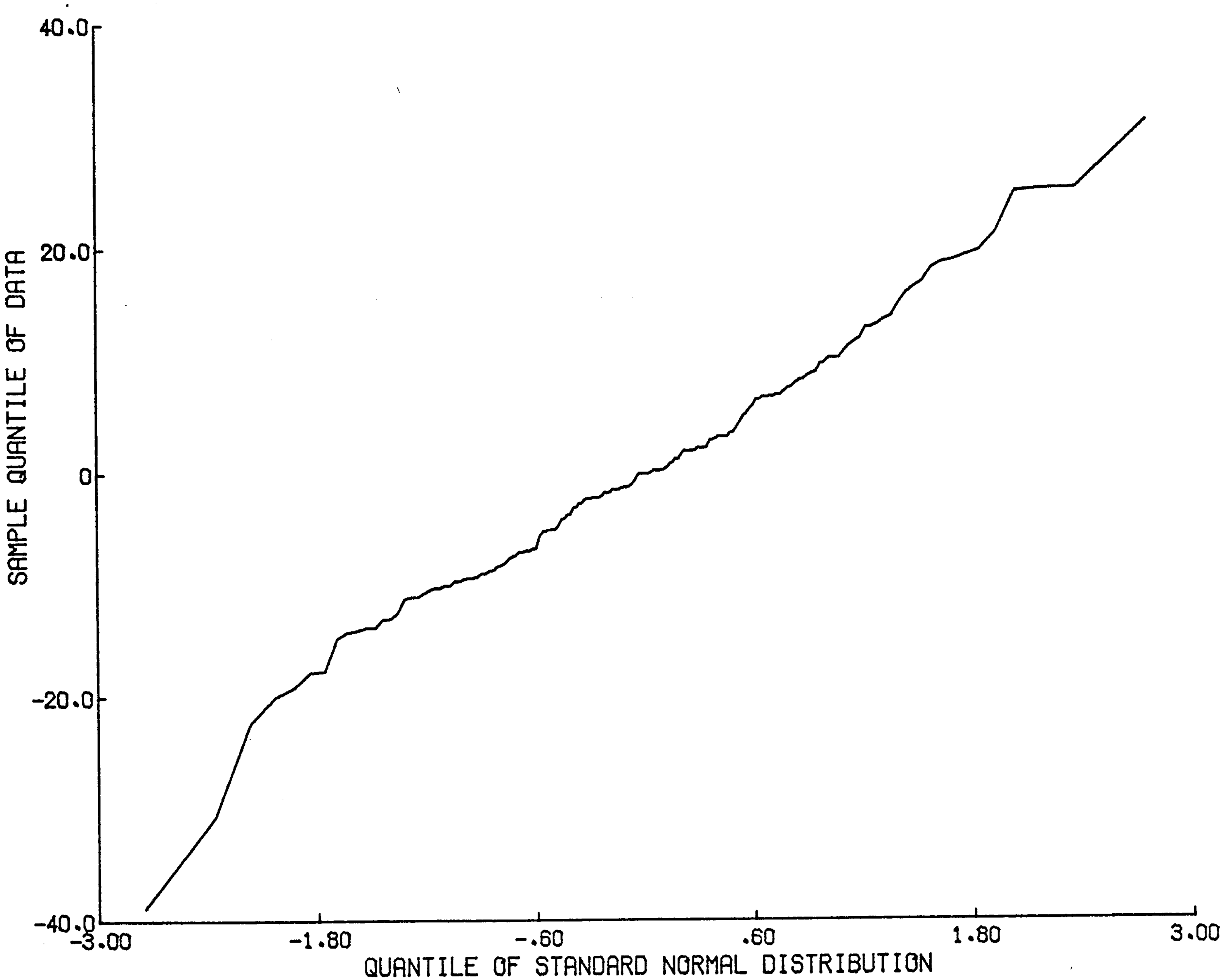

Figure II.5 Q-Q Plot for Chehalis River Specific Conductance, One Outlier Censored

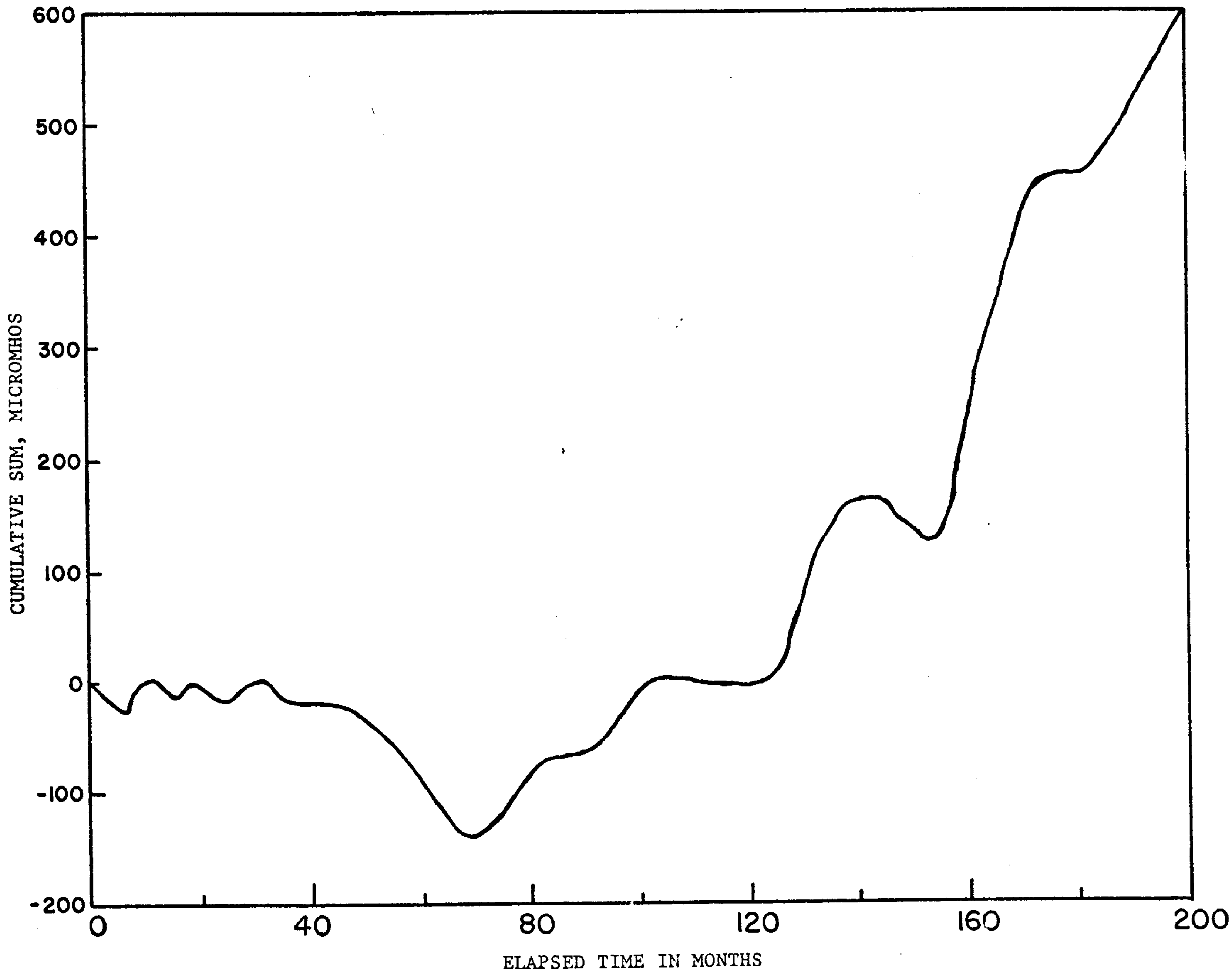

Figure II.6 Cusum Plot for Chehalis River at Porter Specific Conductance

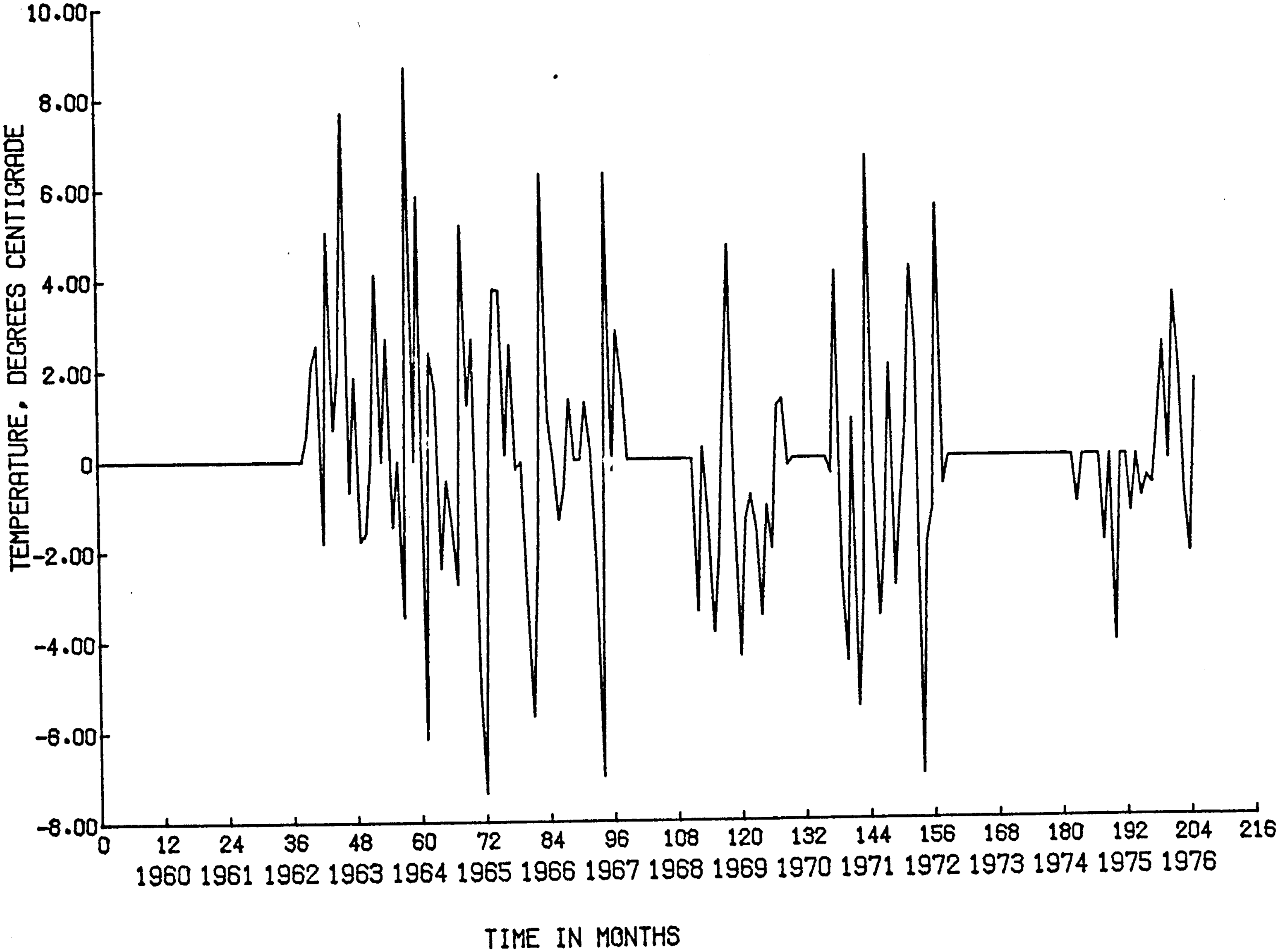

Figure II.7a Crab Creek Near Beverly Deseasonalized Temperature

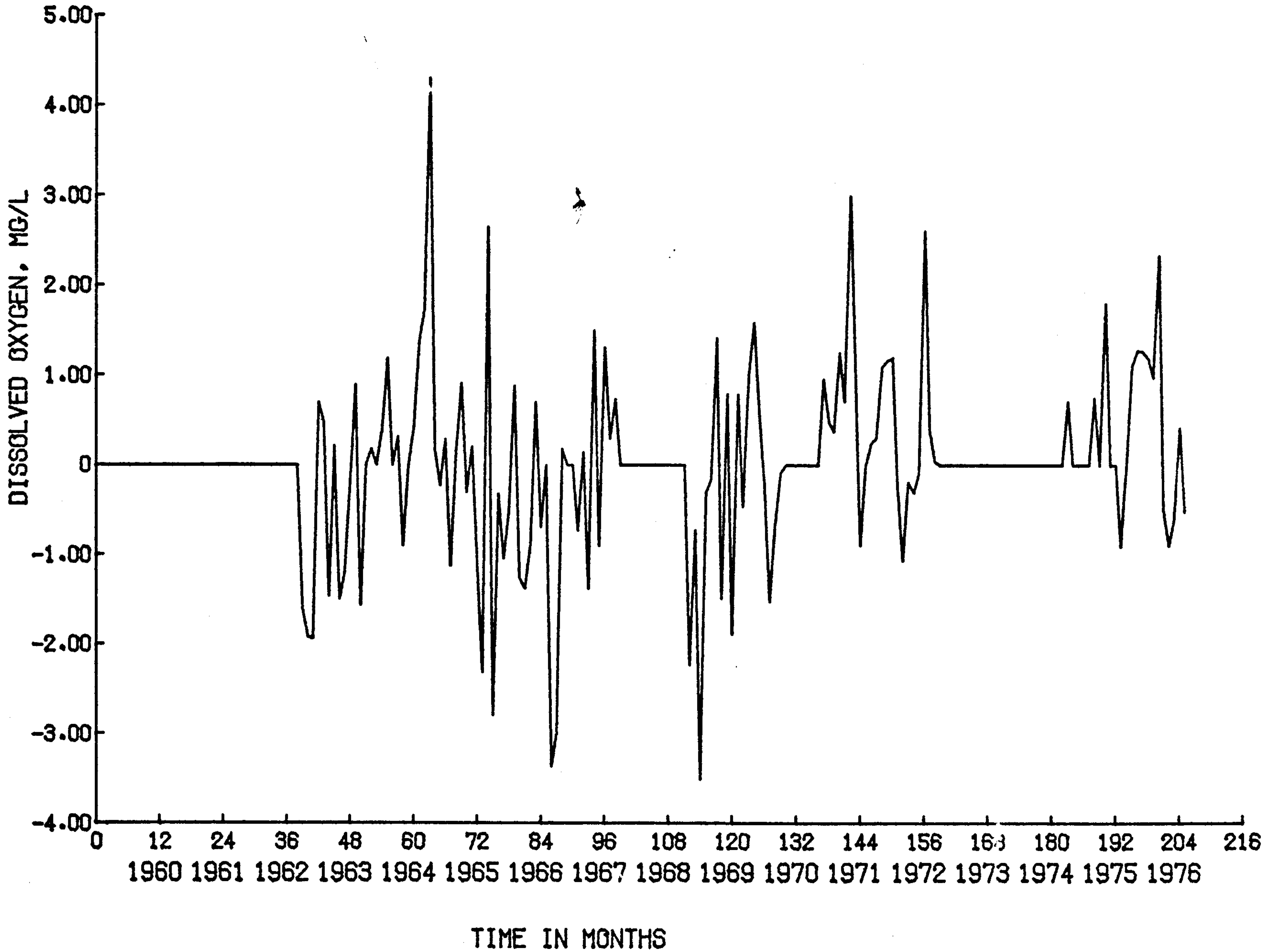

Figure II.7b Crab Creek Near Beverly Deseasonalized Dissolved Oxygen

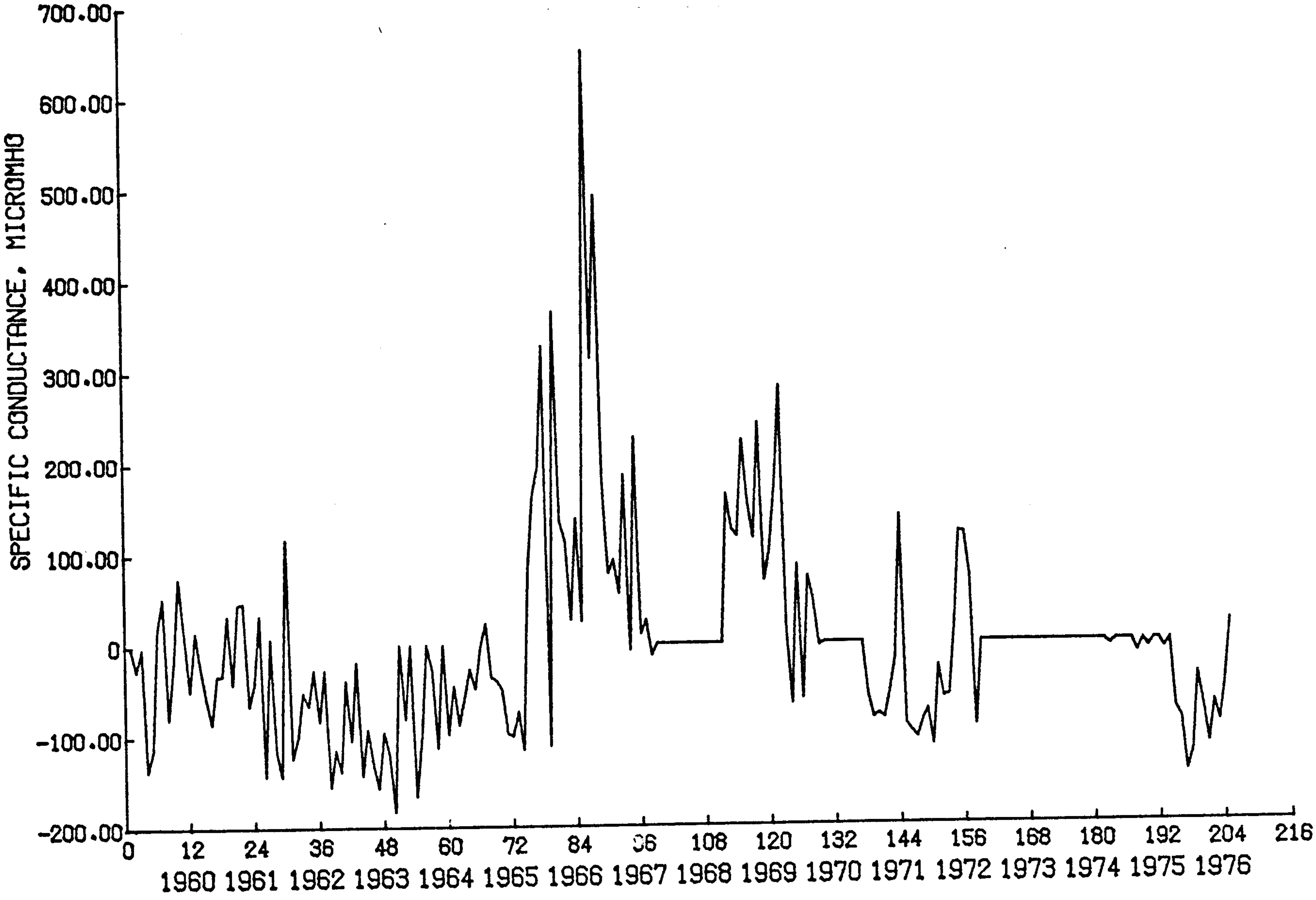

Figure II.7c Crab Creek Near Beverly Deseasonalized Specific Conductance

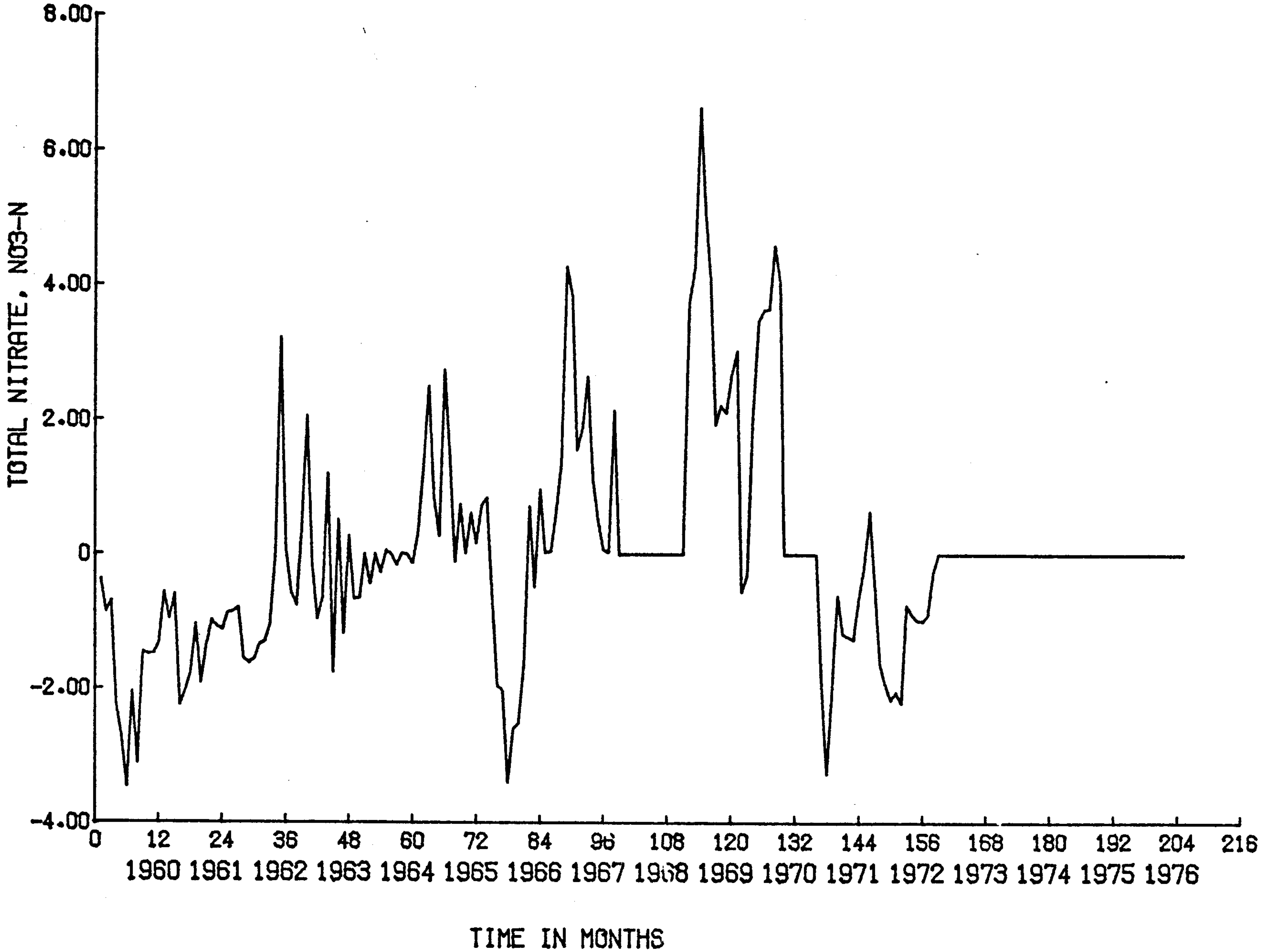

Figure II.7d Crab Creek Near Beverly Deseasonalized NO_3-N

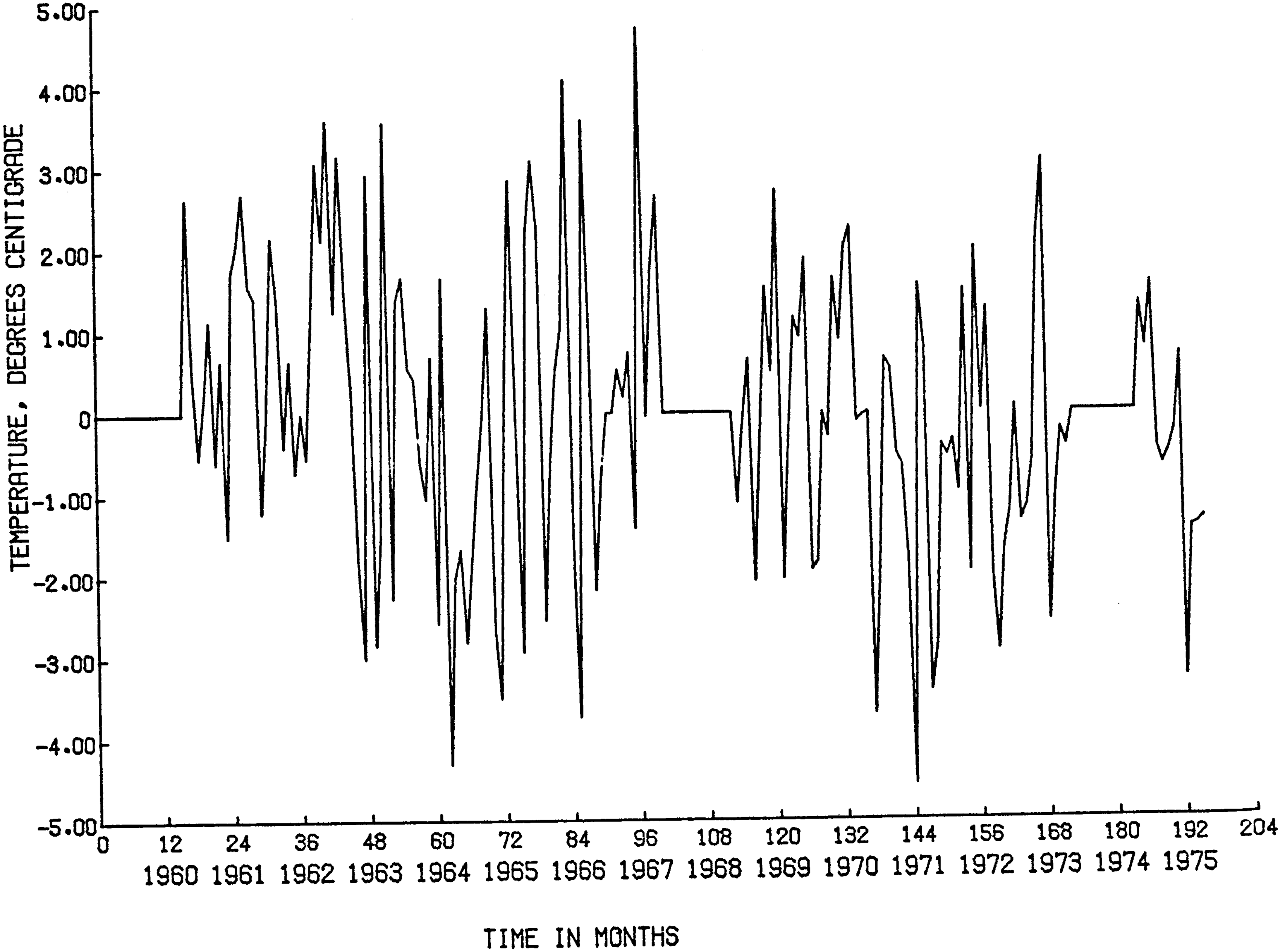

Figure II.8a Chehalis River at Porter Deseasonalized Temperature

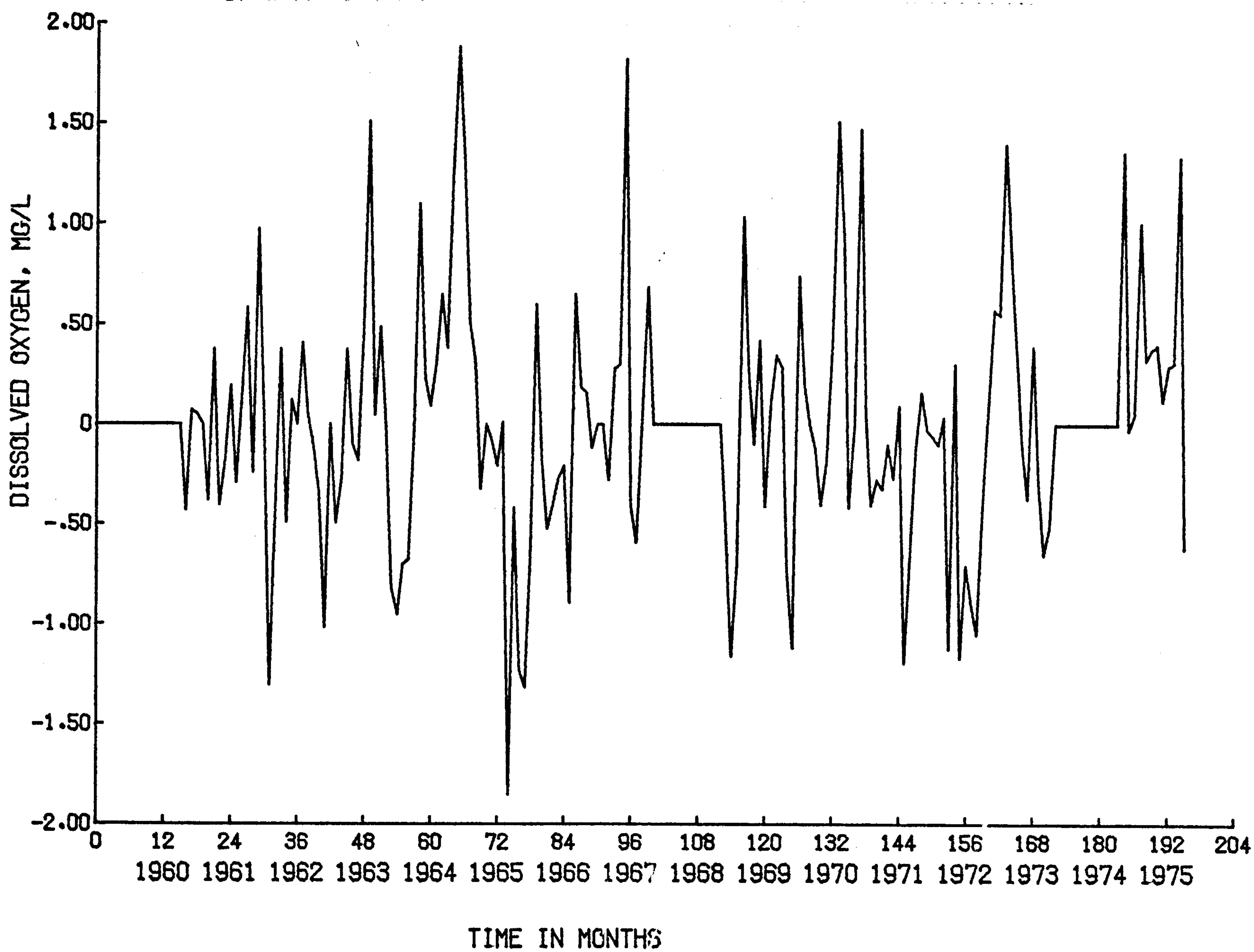

Figure II.8b Chehalis River at Porter Deseasonalized Dissolved Oxygen

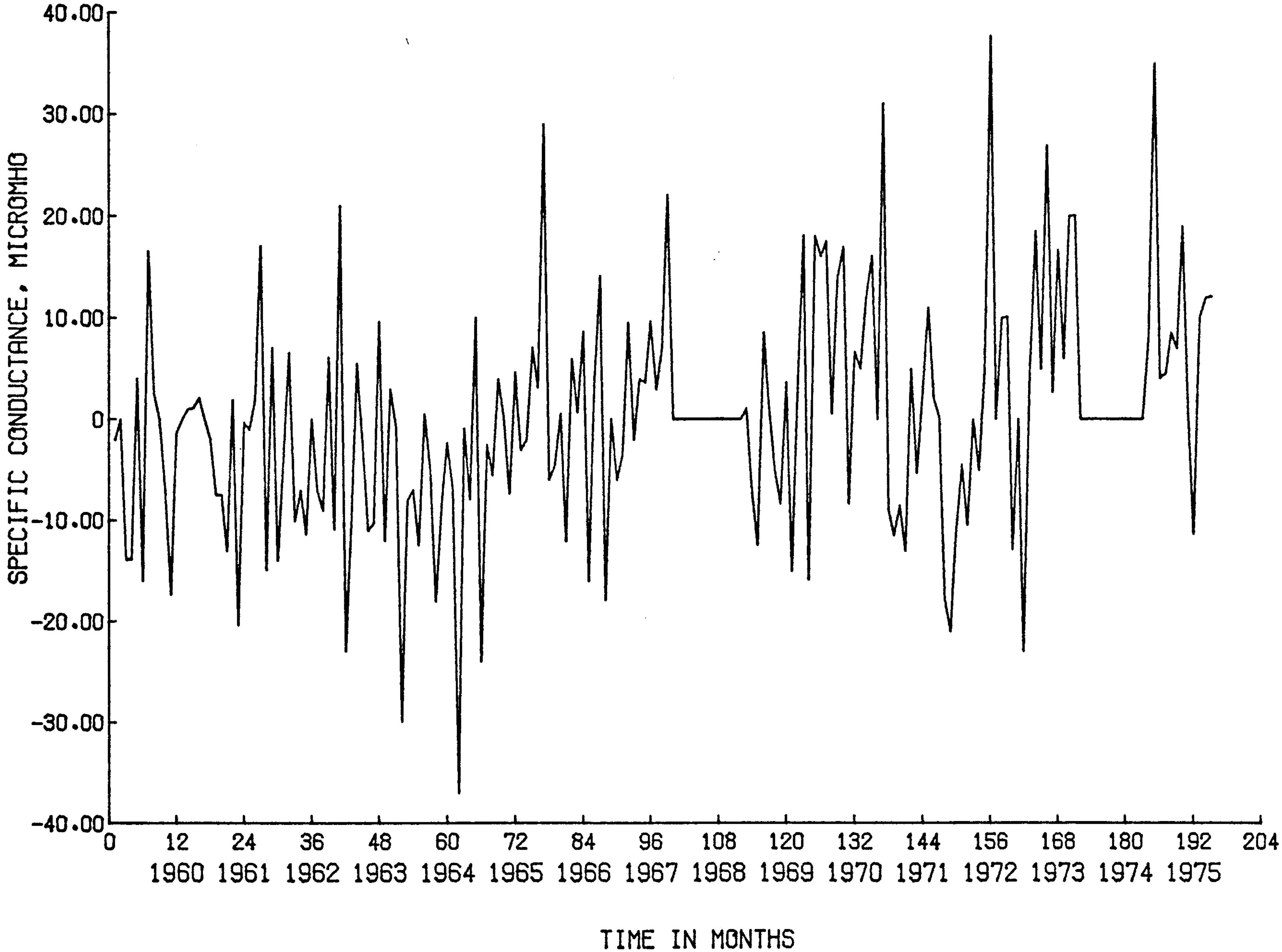

Figure II.8c Chehalis River at Porter Specific Conductance

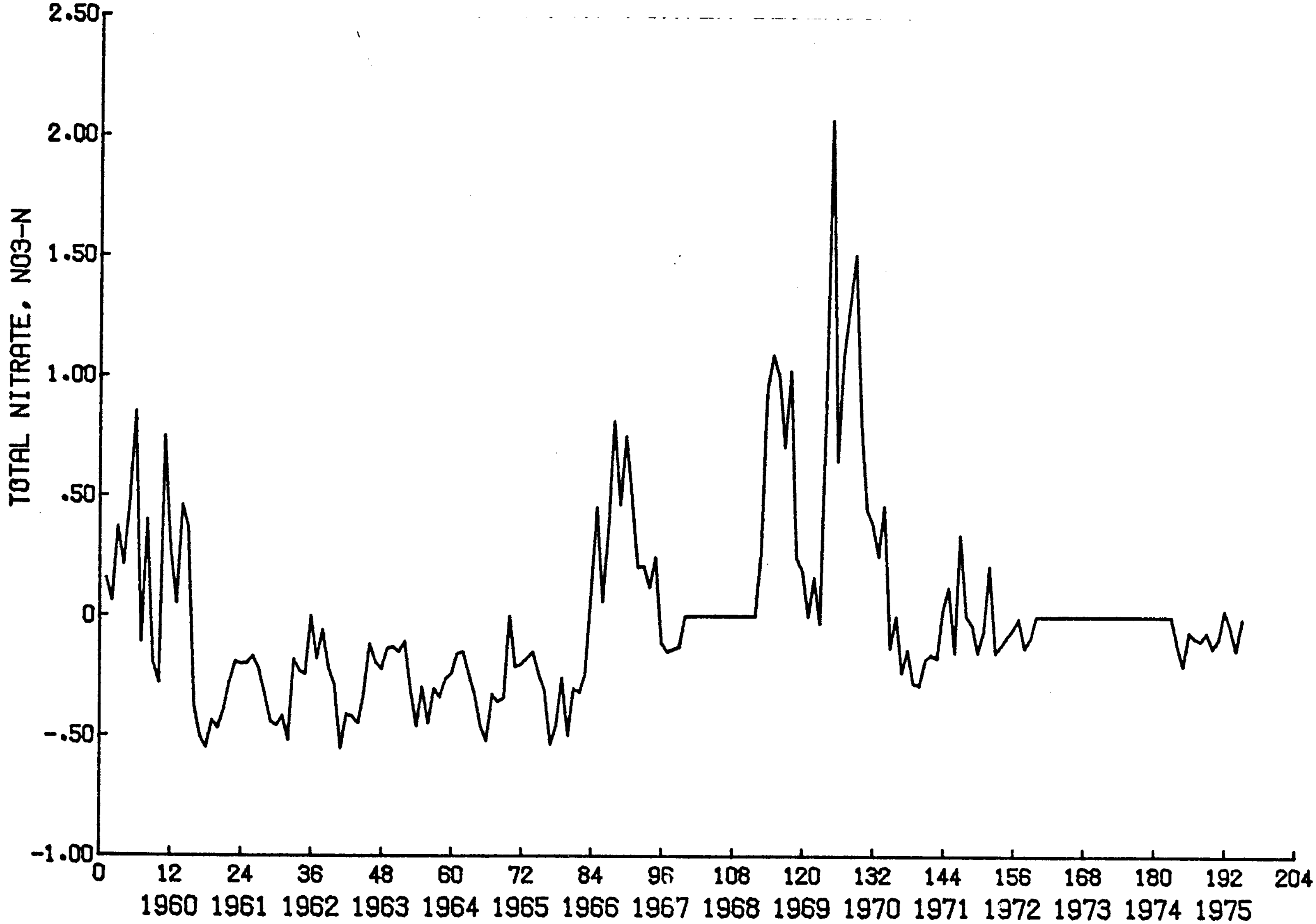

Figure II.8d Chehalis River at Porter Deseasonalized NO_3-N

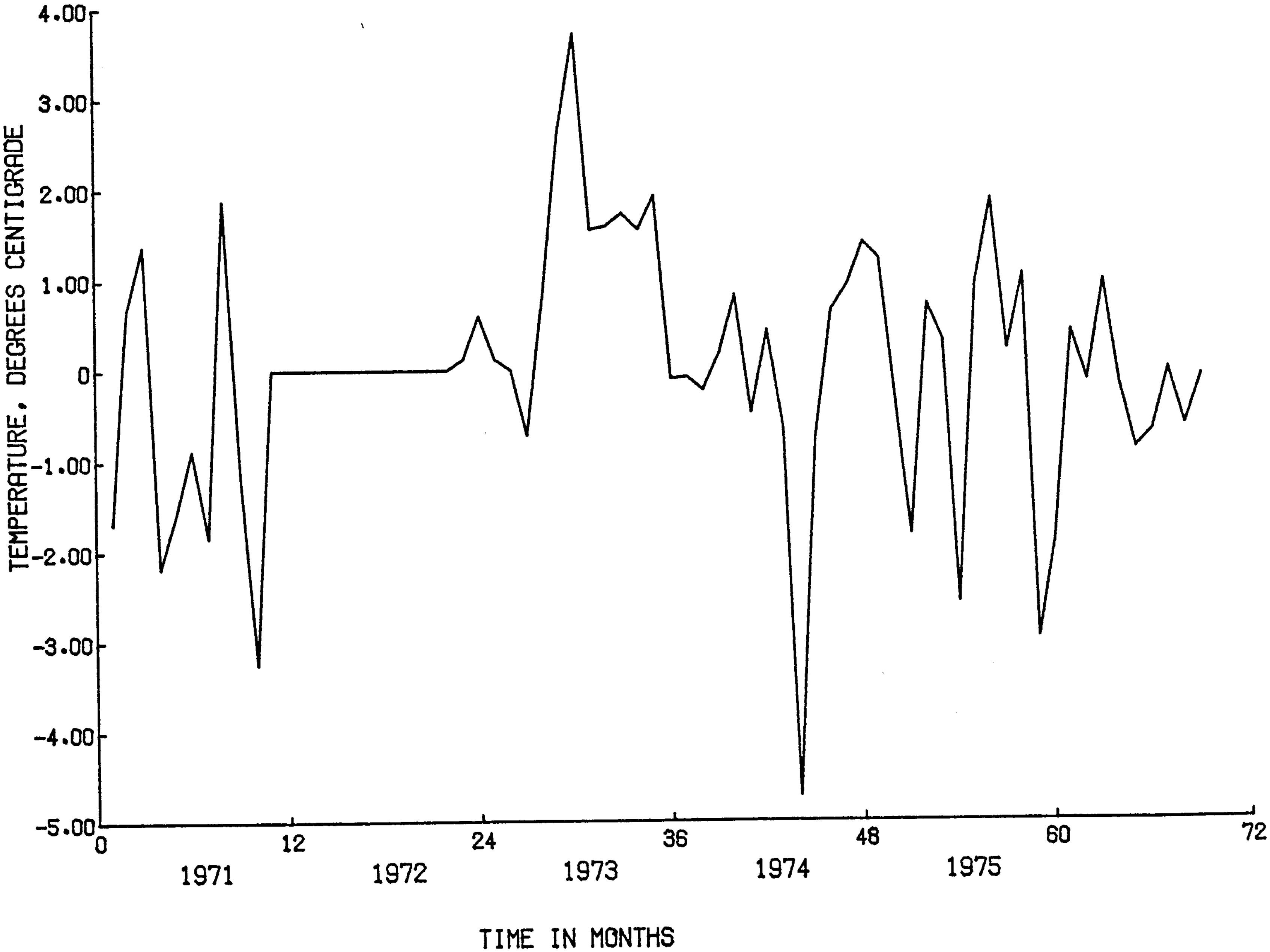

Figure II.9a Yakima River Near Parker Deseasonalized Temperature

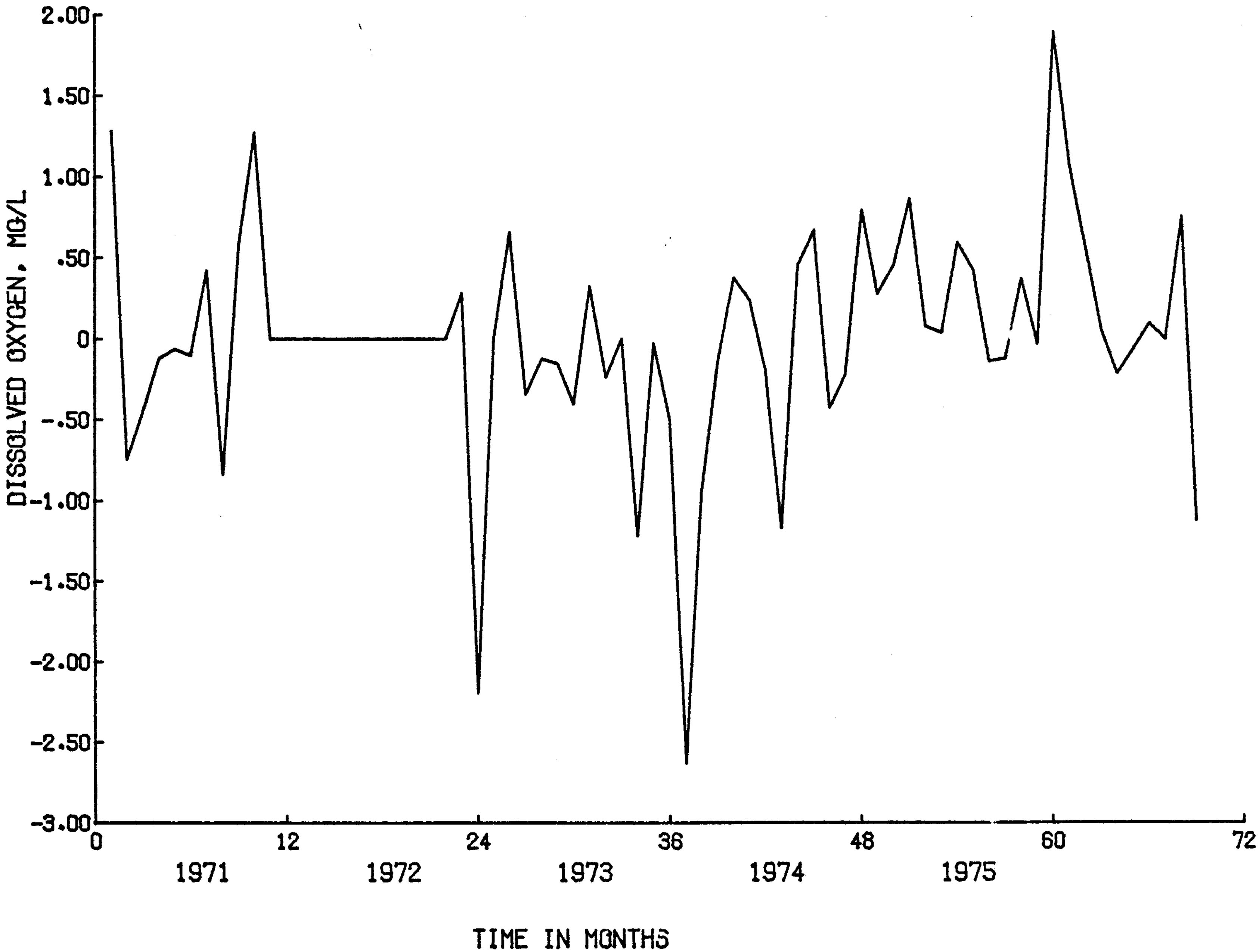

Figure II.9b Yakima River Near Parker Deseasonalized Dissolved Oxygen

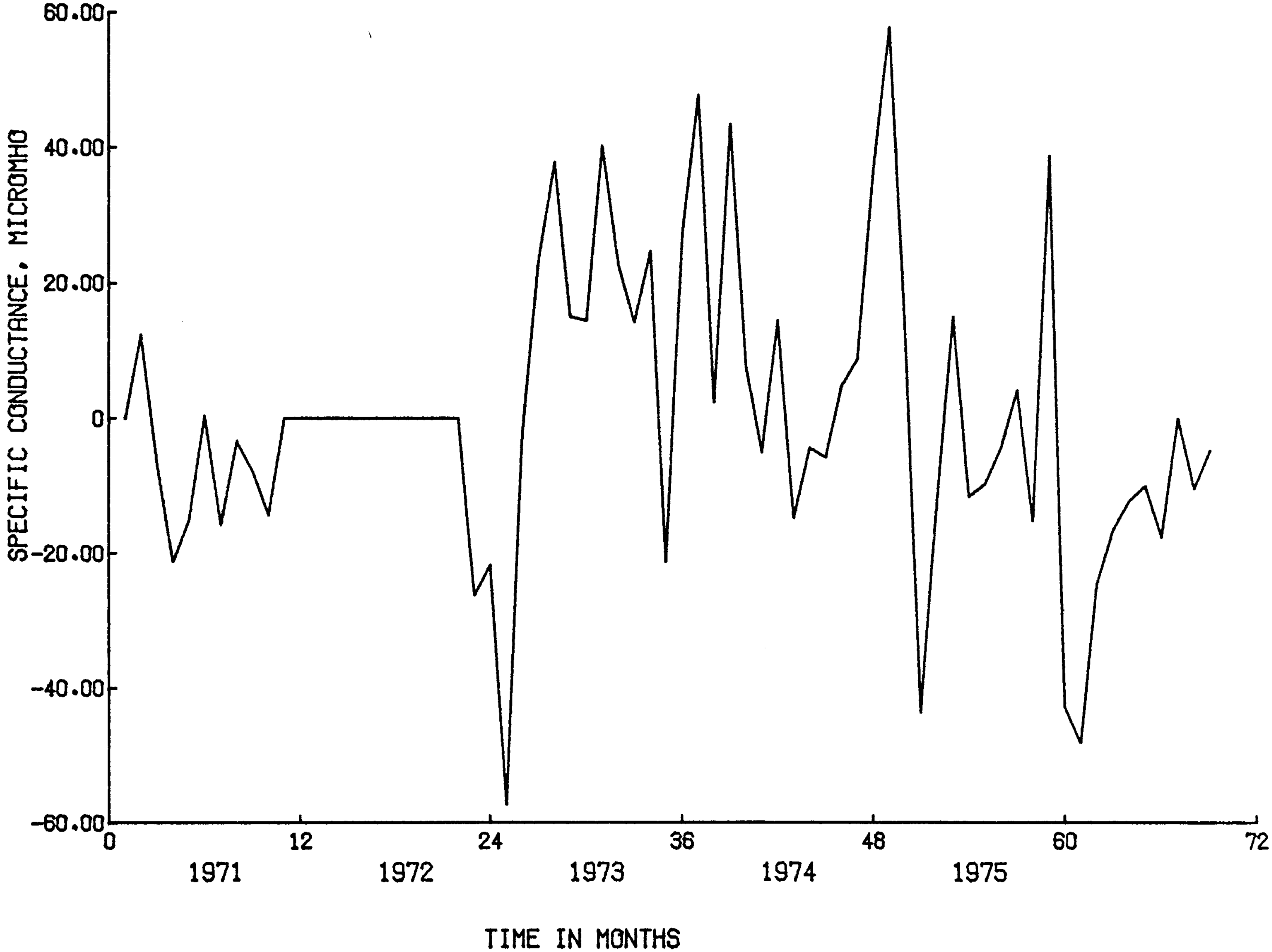

Figure II.9c Yakima River Near Parker Deseasonalized Specific Conductance

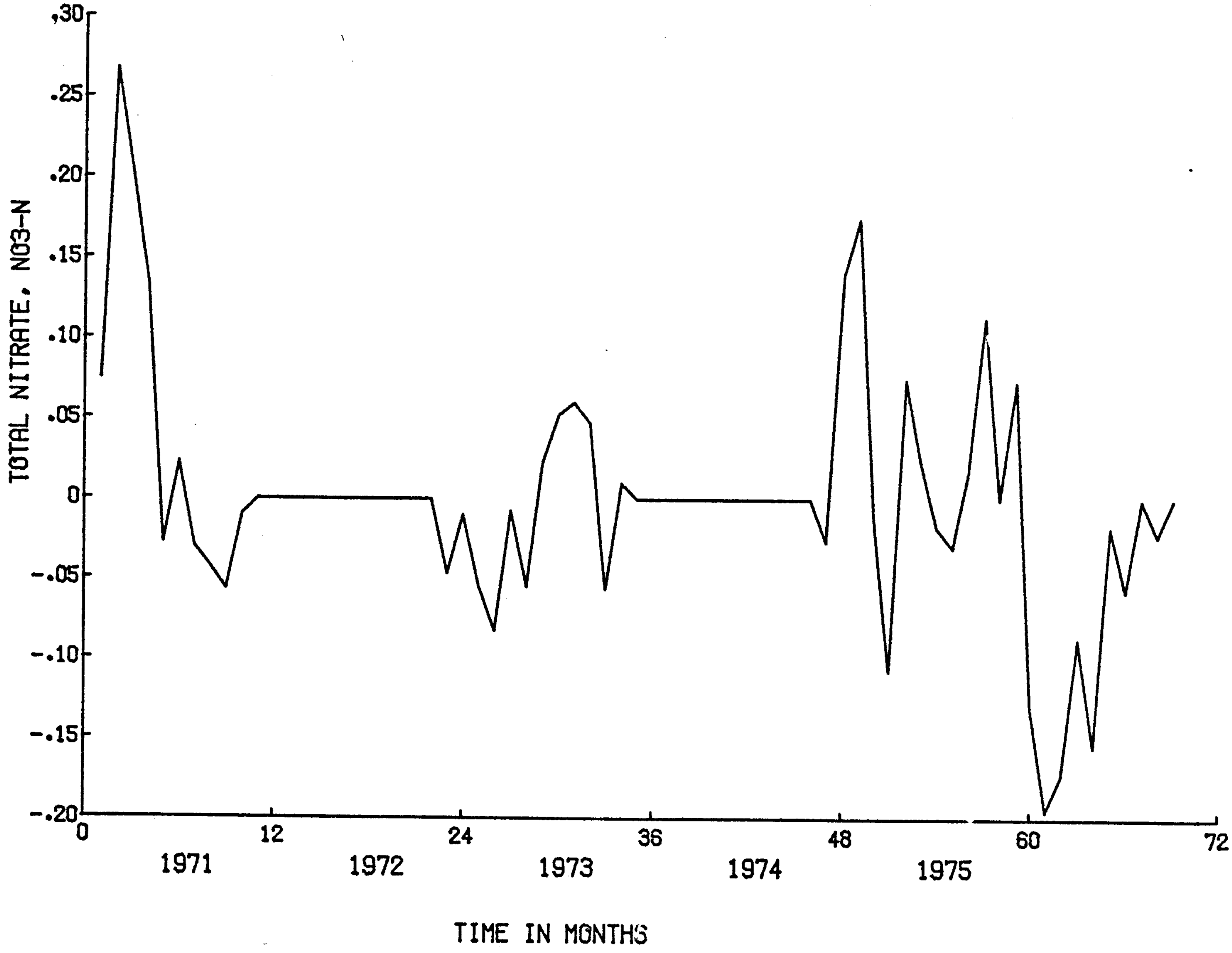

Figure II.9d Yakima River Near Parker Deseasonalized NO_3-N

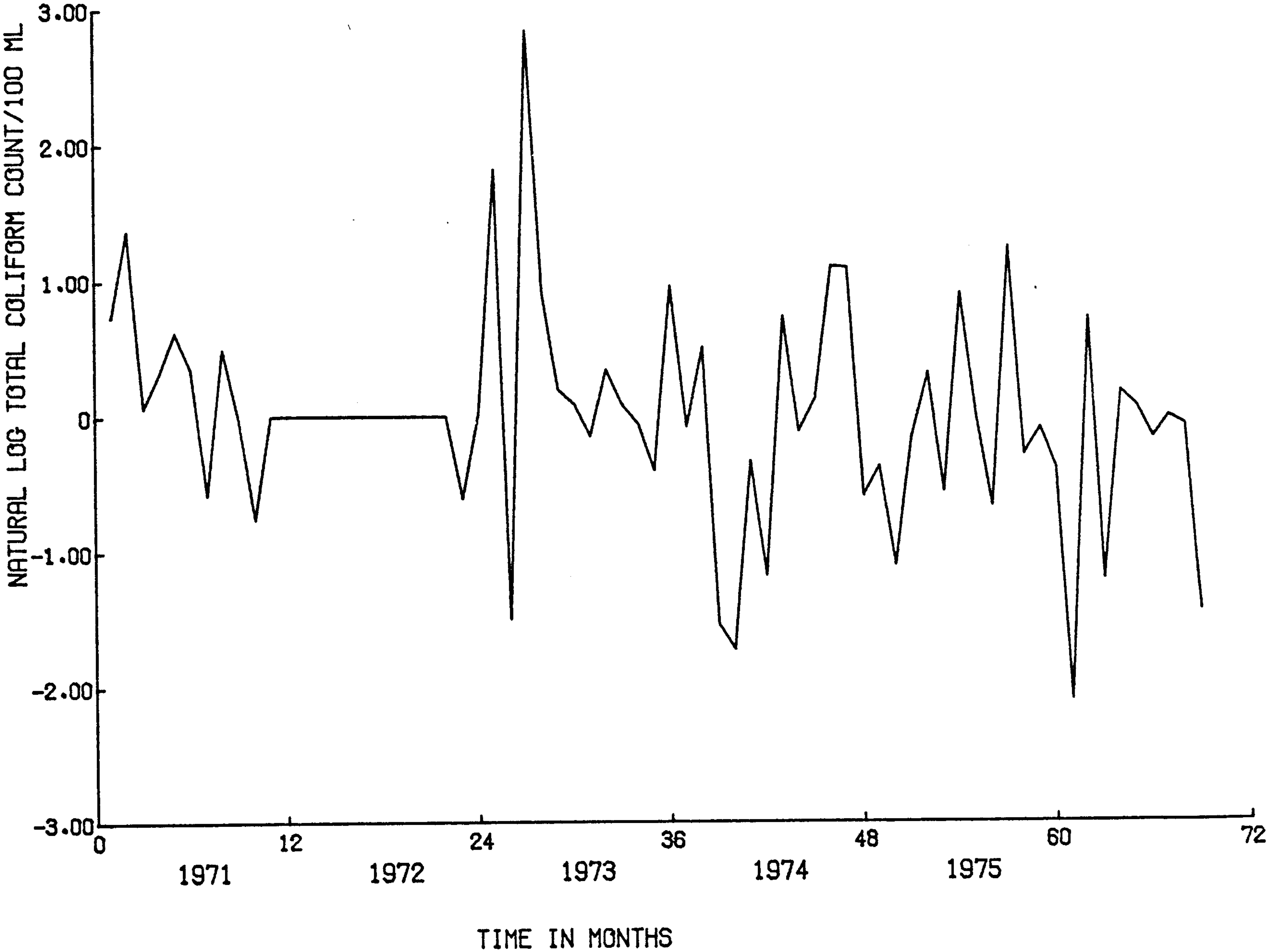

Figure II.9e Yakima River Near Parker Natural Log Coliform Count

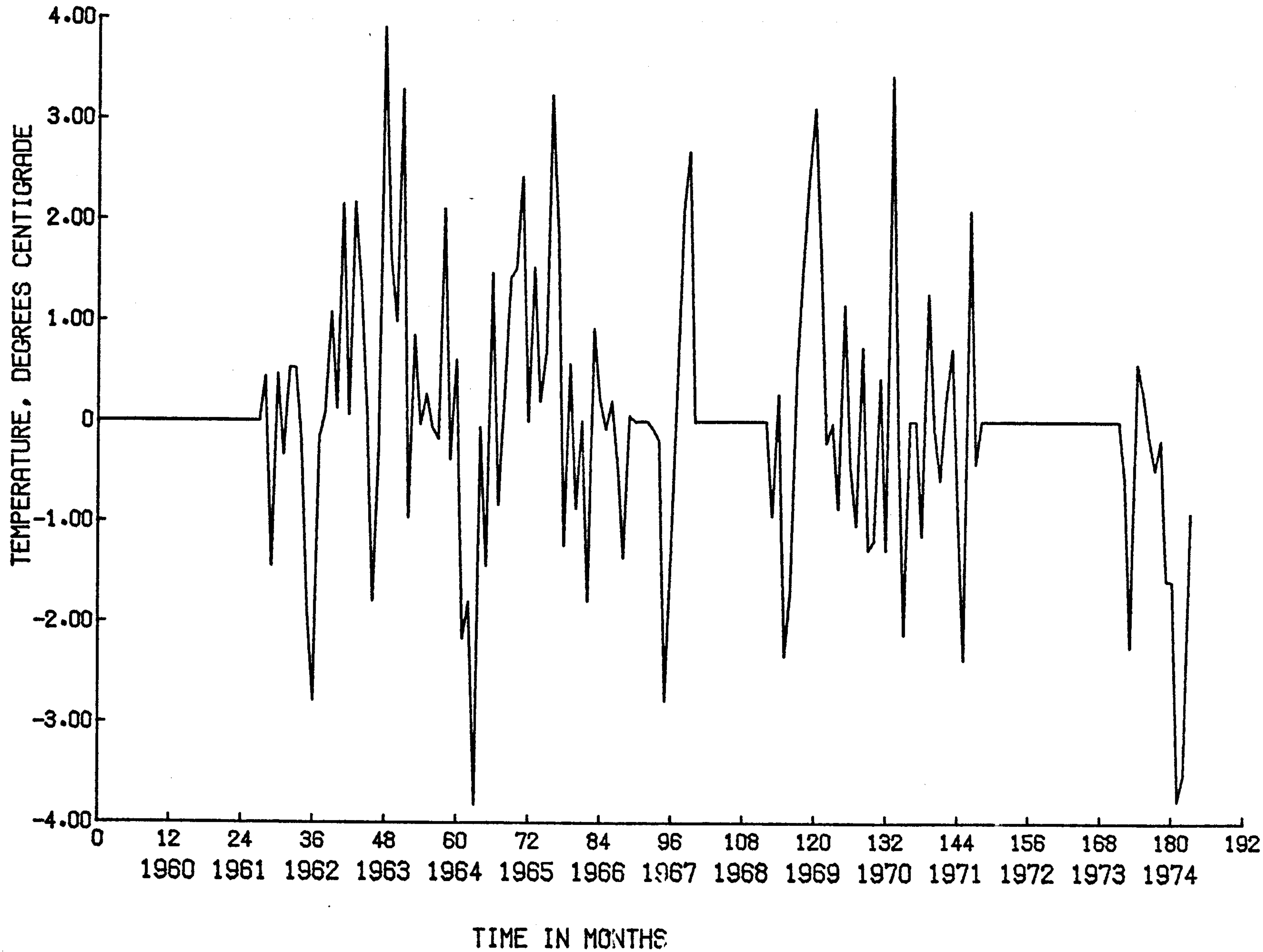

Figure II.10a Snohomish River at Snohomish Deseasonalized Temperature

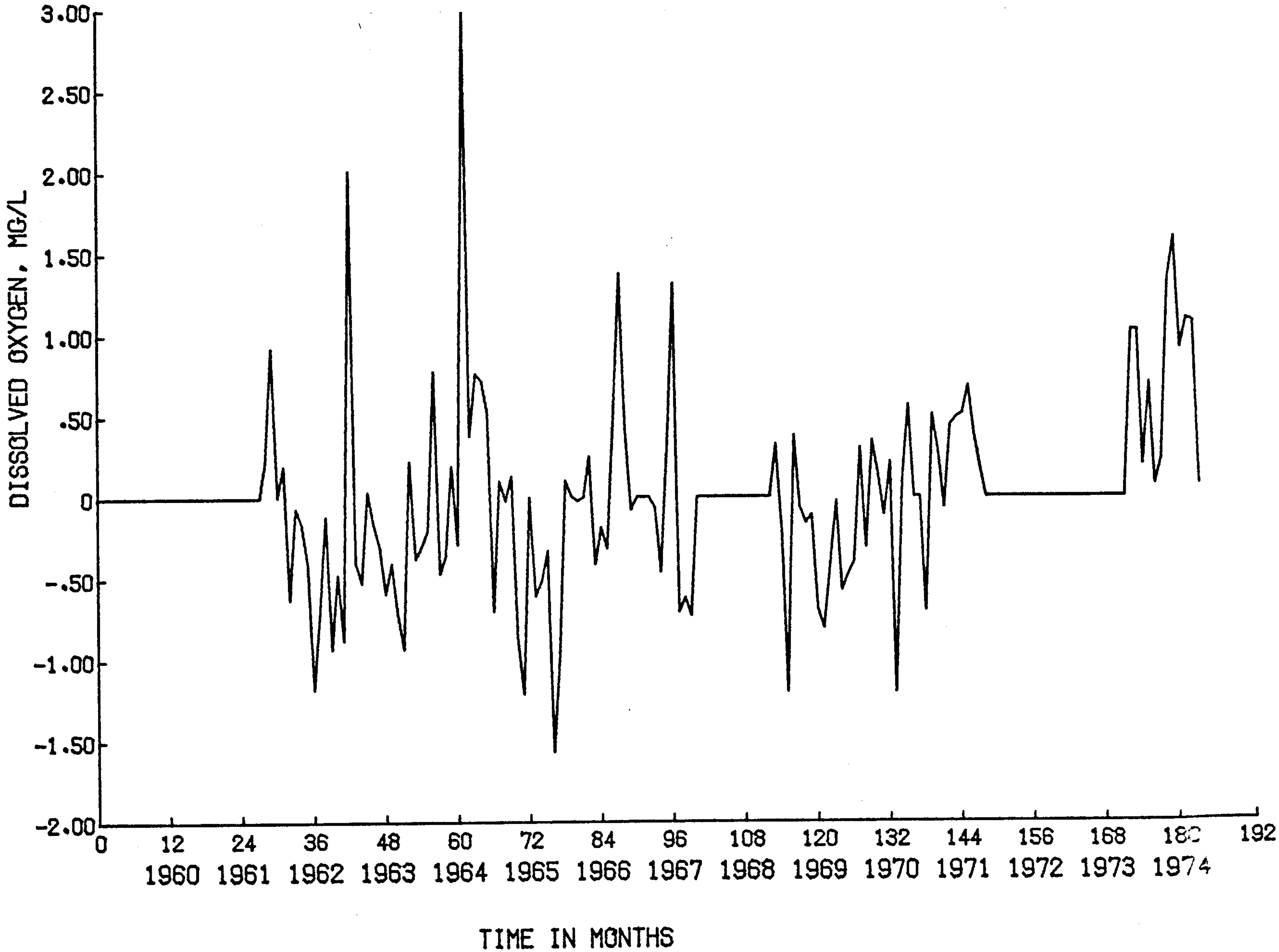

Figure II.10b Snohomish River at Snohomish Deseasonalized Dissolved Oxygen

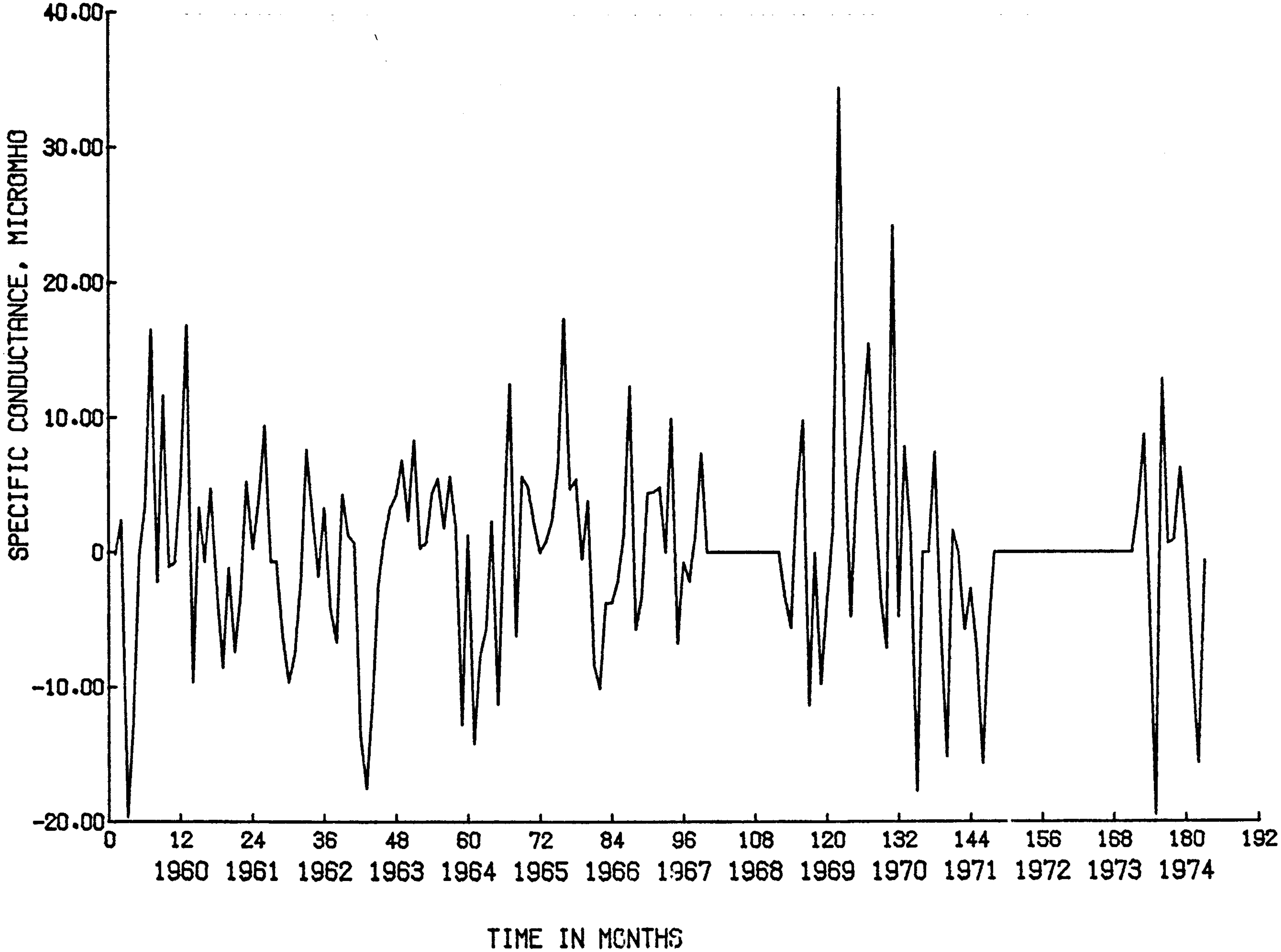

Figure II.10c Snohomish River at Snohomish Deseasonalized Specific Conductance

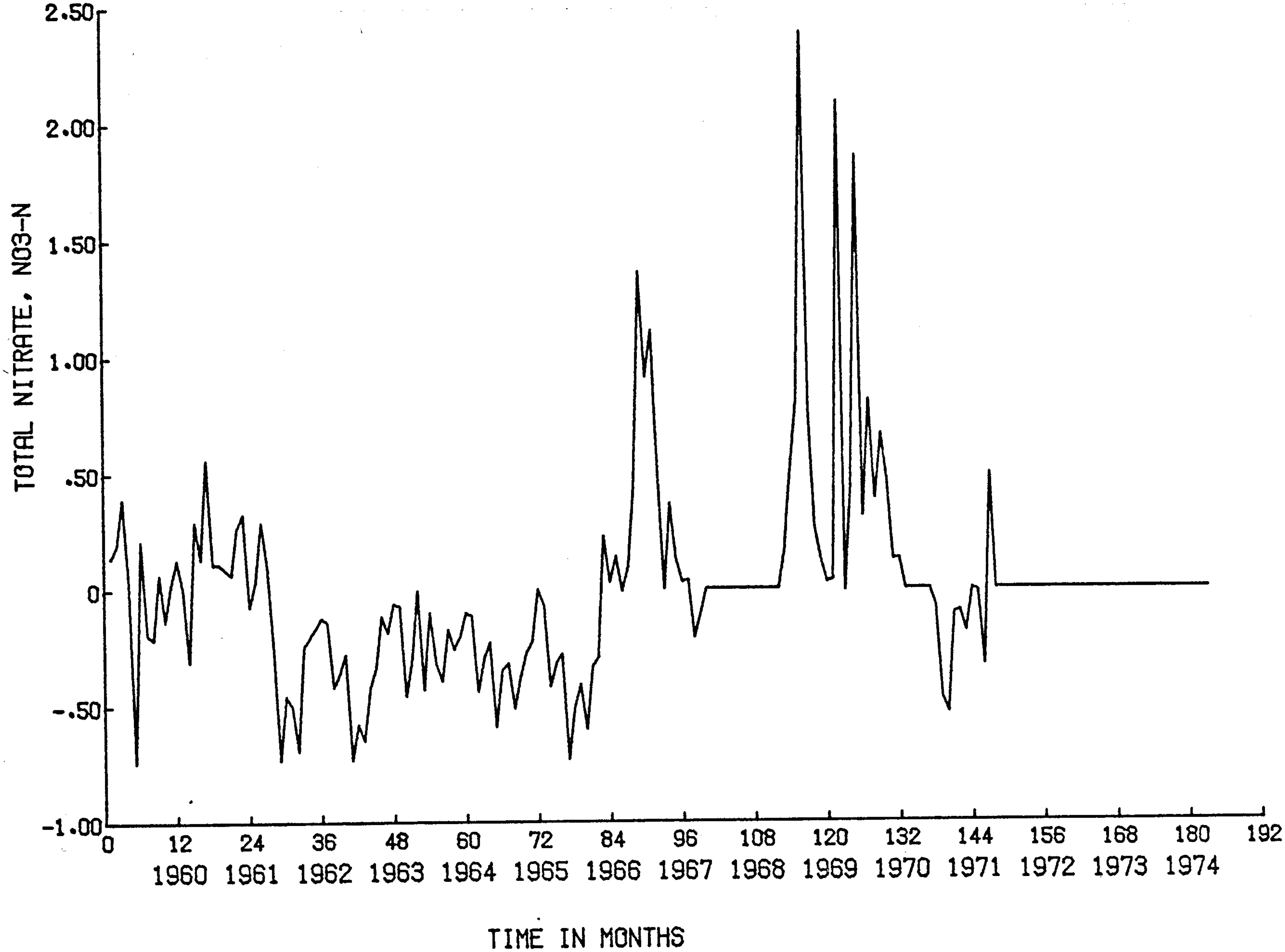

Figure II.10d Snohomish River at Snohomish Deseasonalized NO_3-N

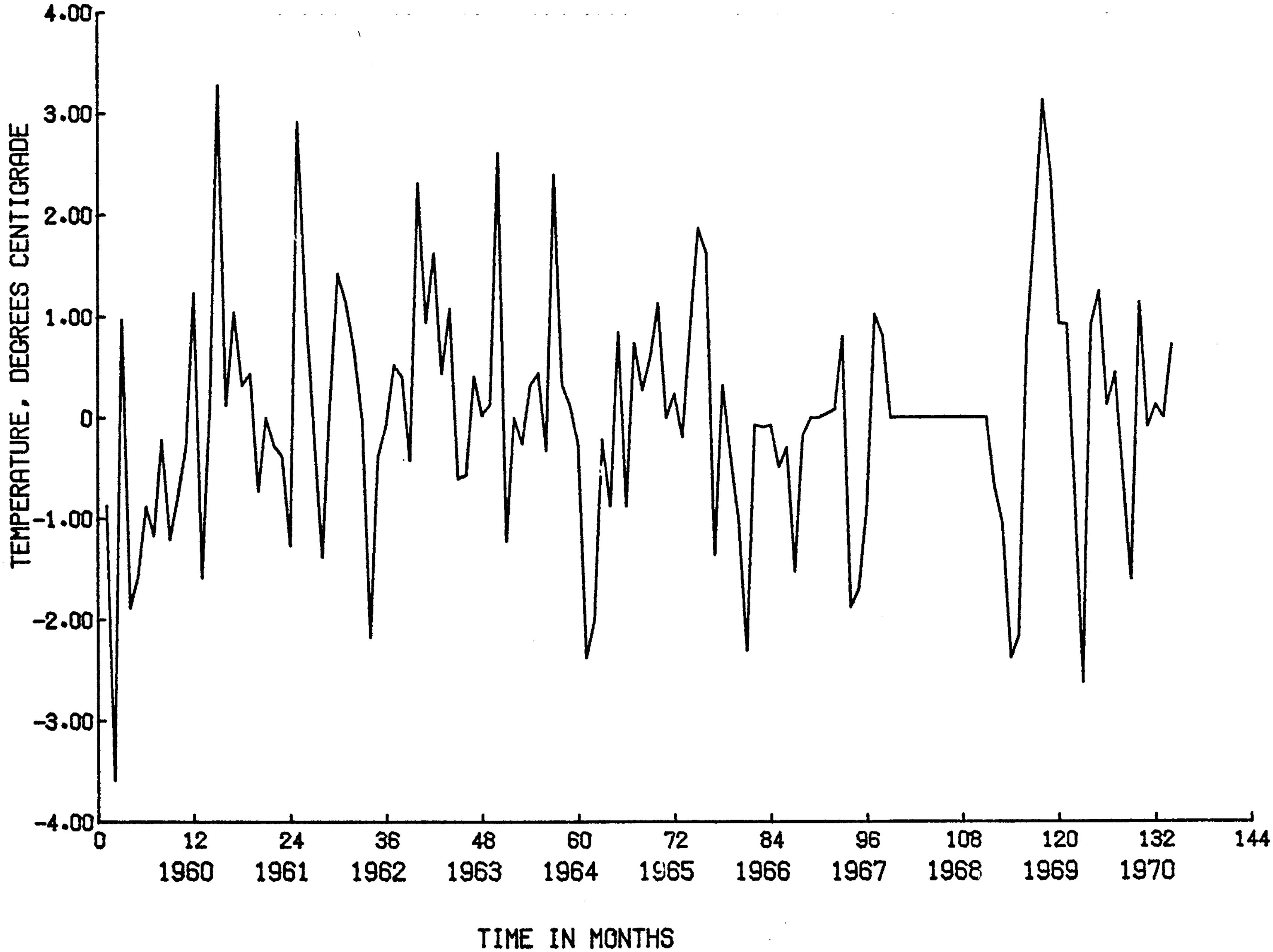

Figure II.11a Skagit River Near Mount Vernon Deseasonalized Temperature

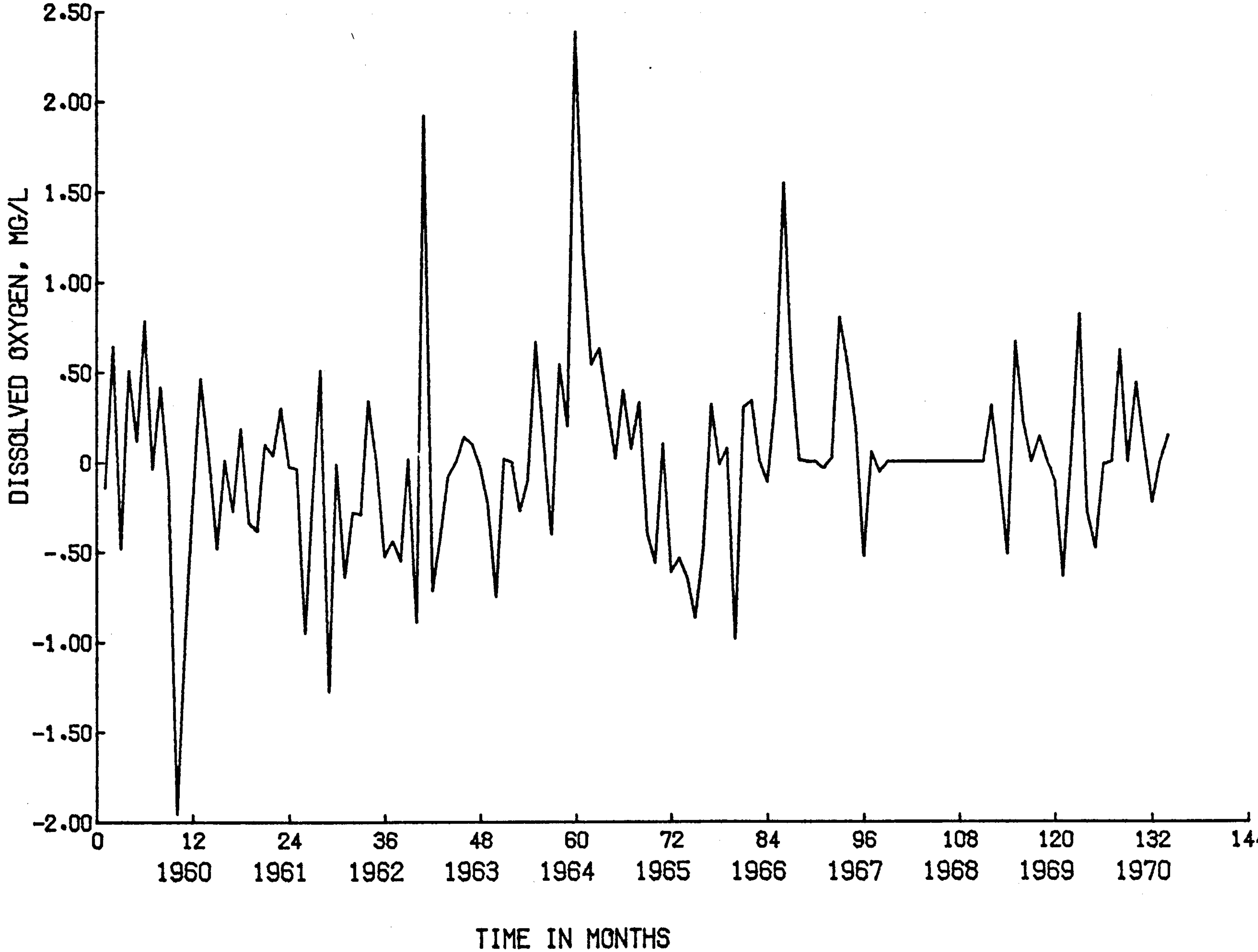

Figure II.11b Skagit River Near Mount Vernon Deseasonalized Dissolved Oxygen

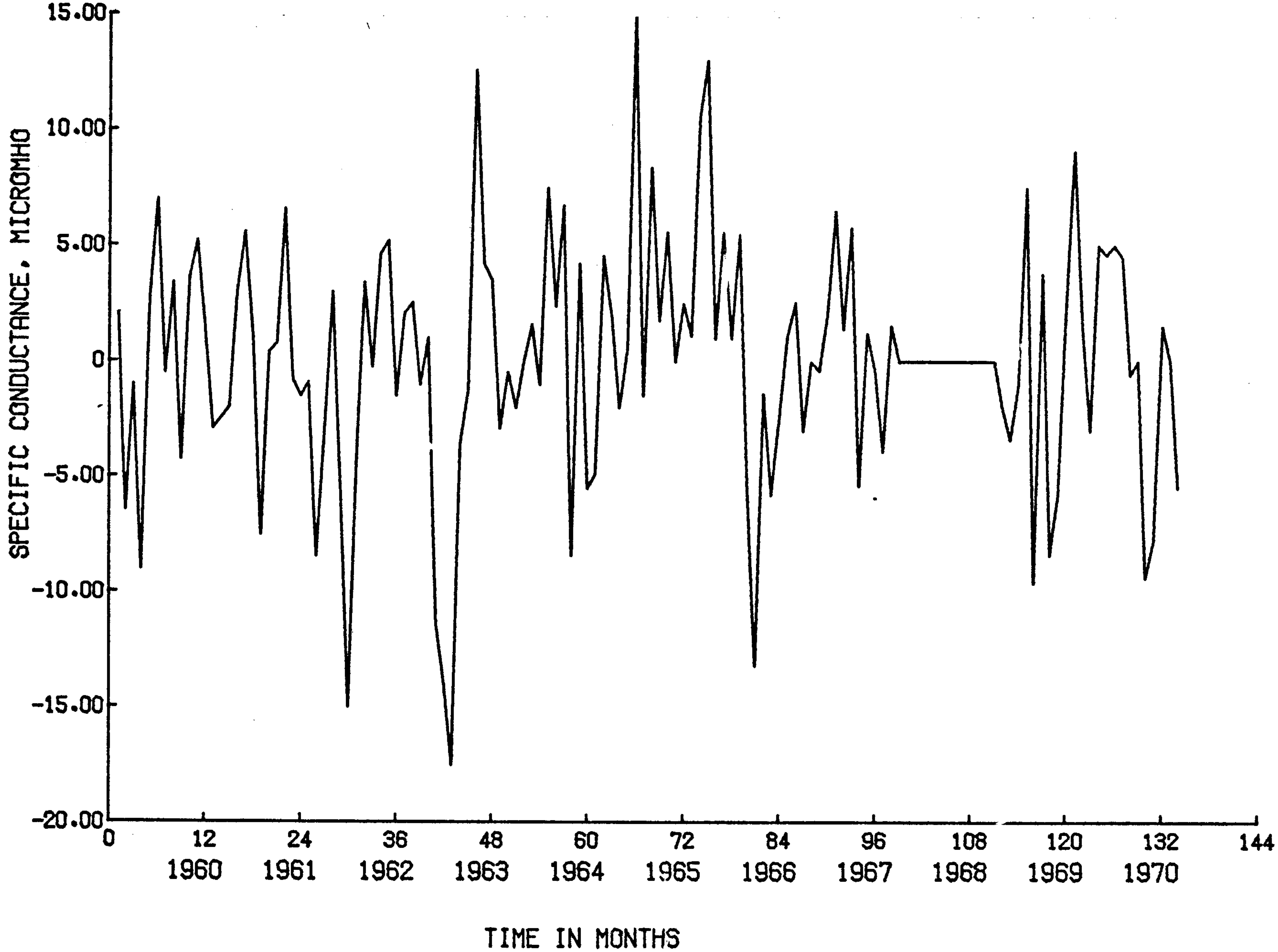

Figure II.11c Skagit River Near Mount Vernon Deseasonalized Specific Conductance

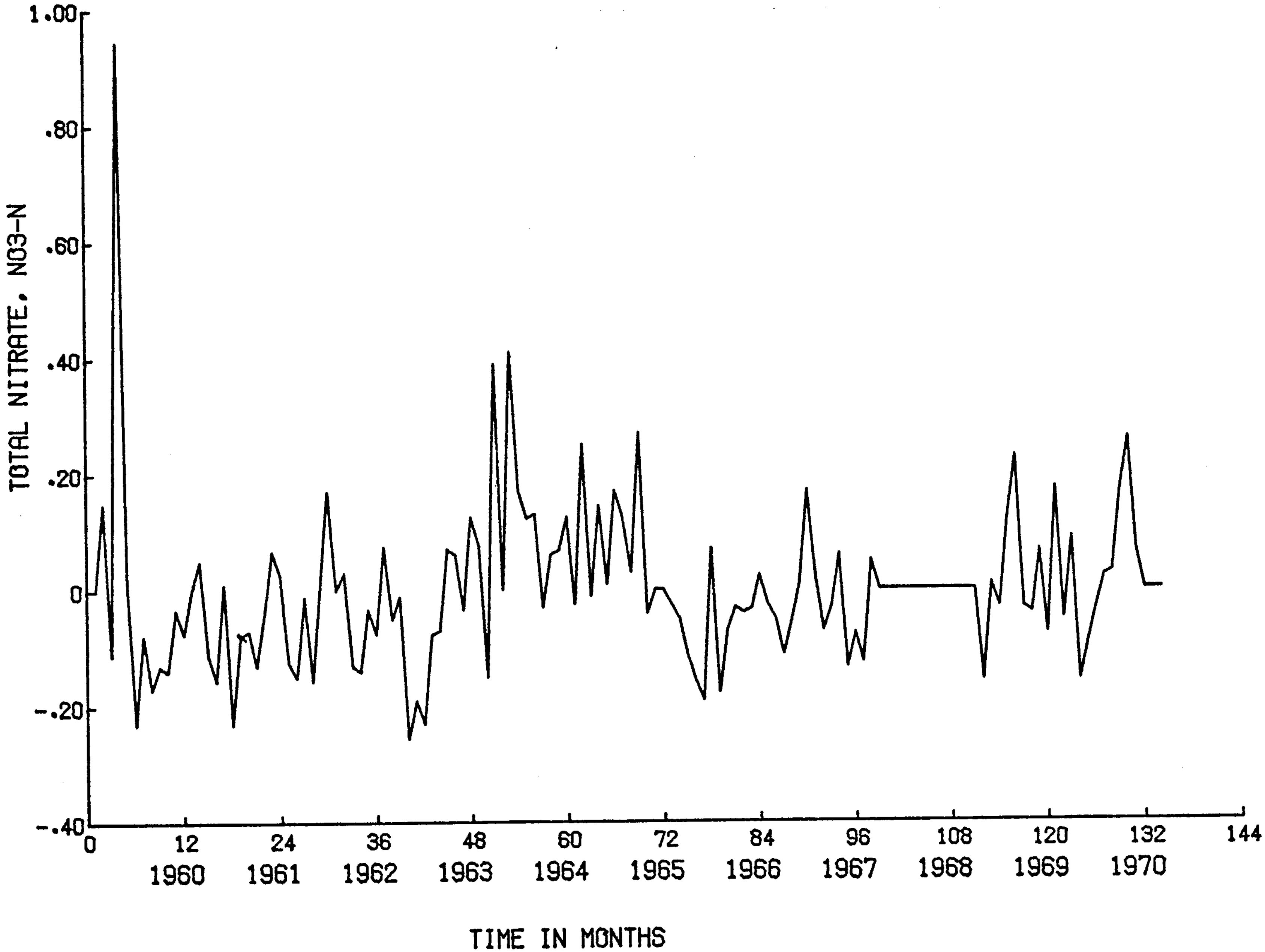

Figure II.11d Skagit River Near Mount Vernon Deseasonalized NO_3-N

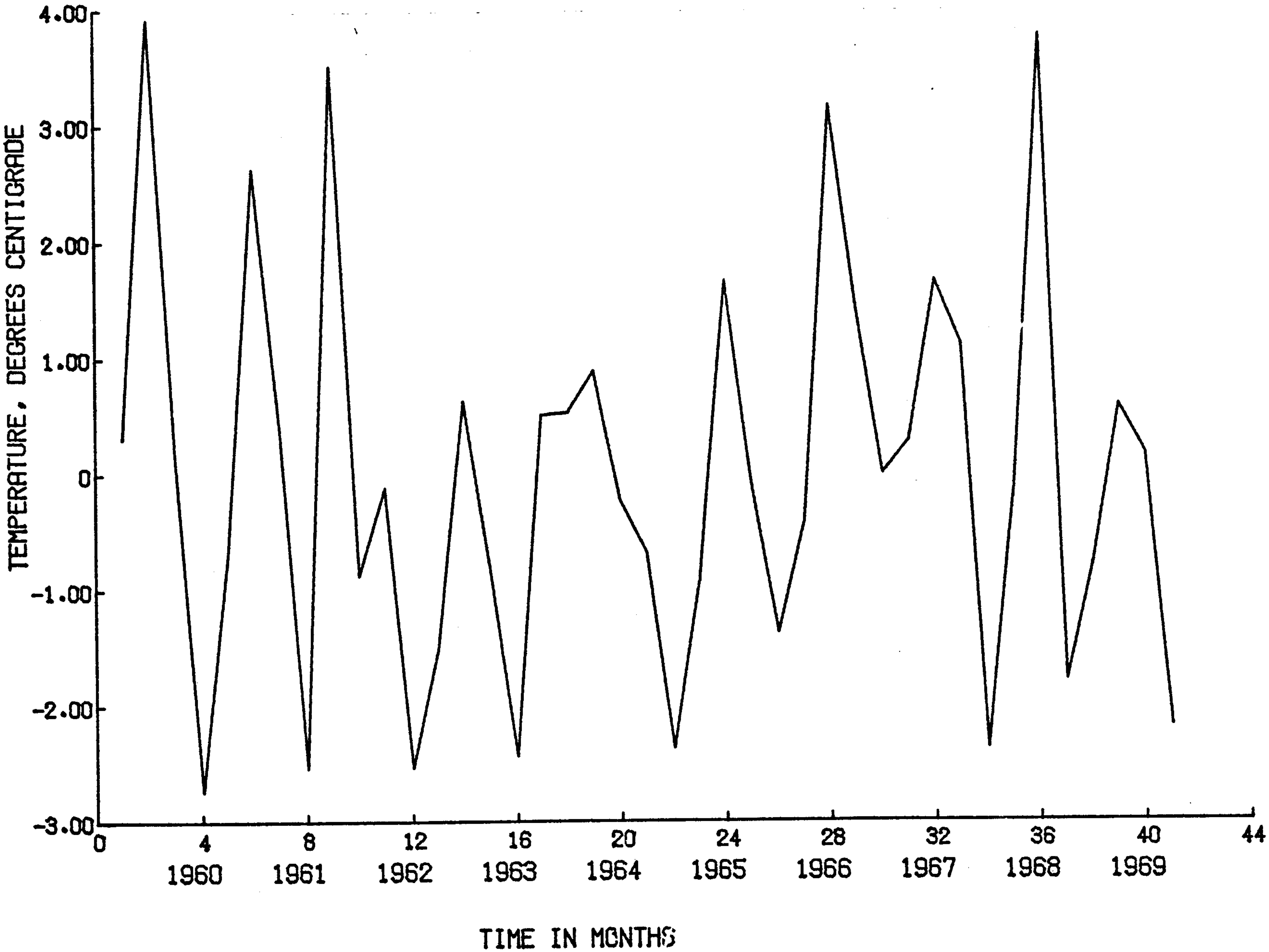

Figure II.12a Skagit River at Marblemount Deseasonalized Temperature

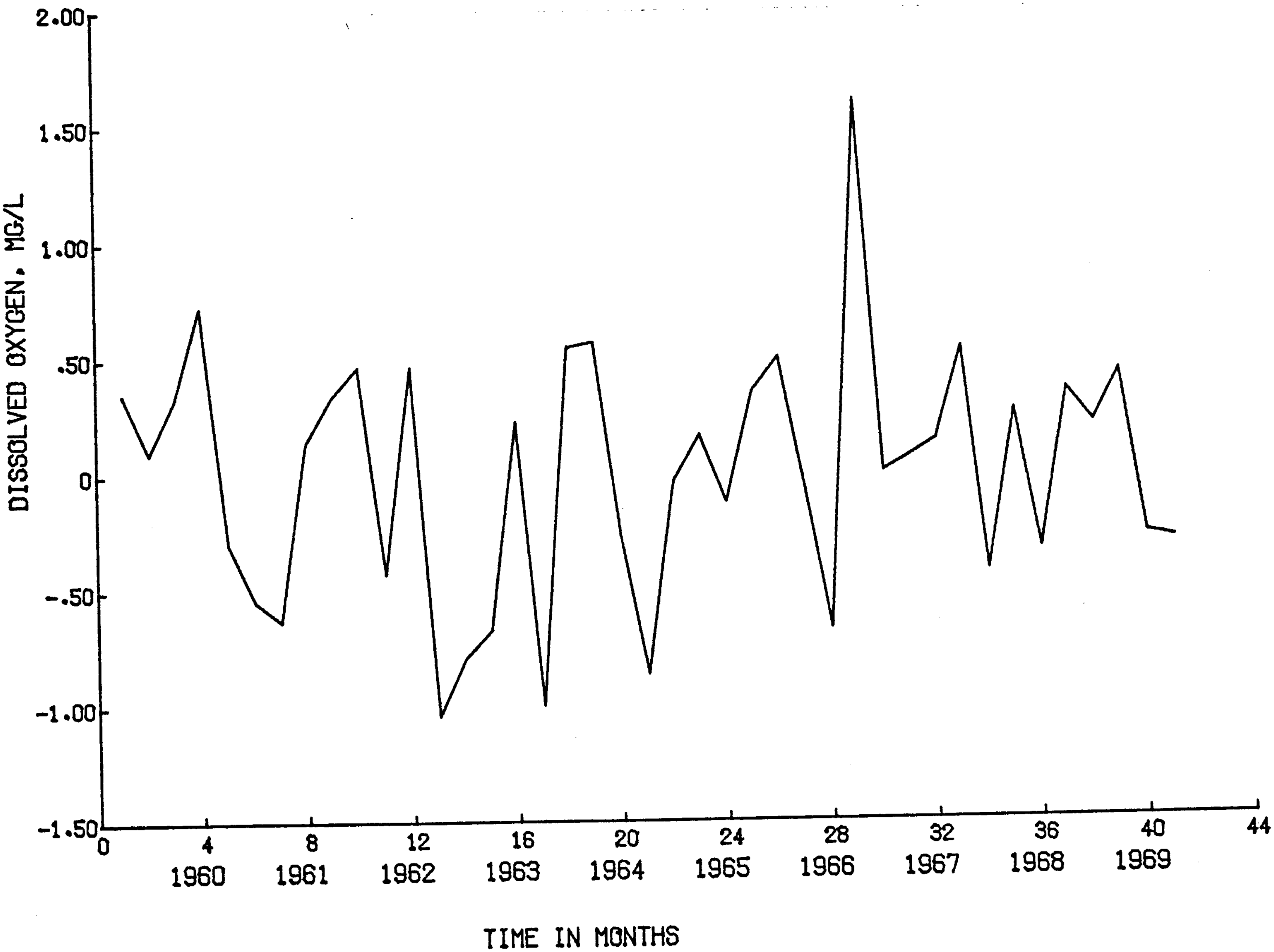

Figure II.12b Skagit River at Marblemount Deseasonalized Dissolved Oxygen

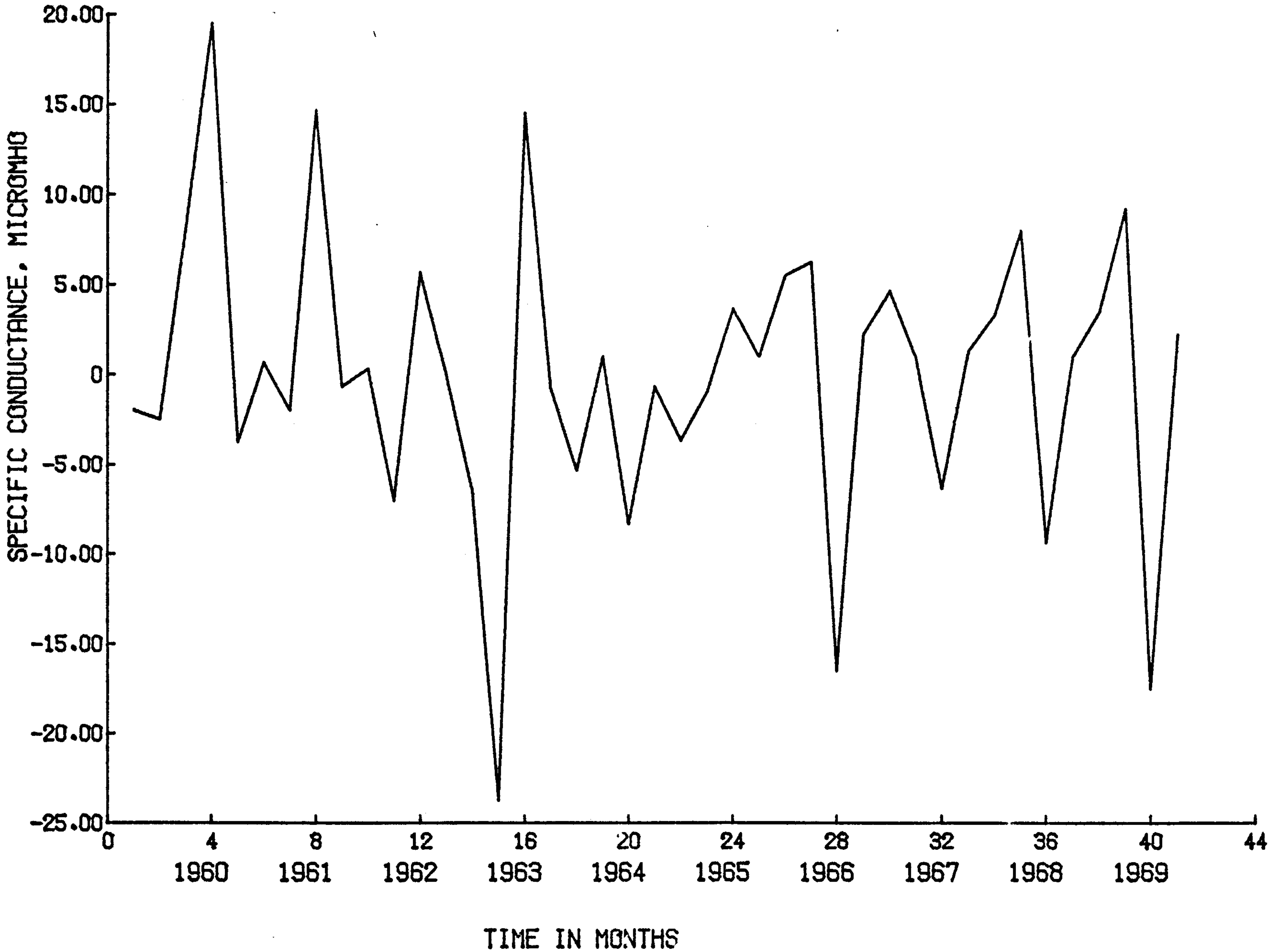

Figure II.12c Skagit River at Marblemount Deseasonalized Specific Conductance

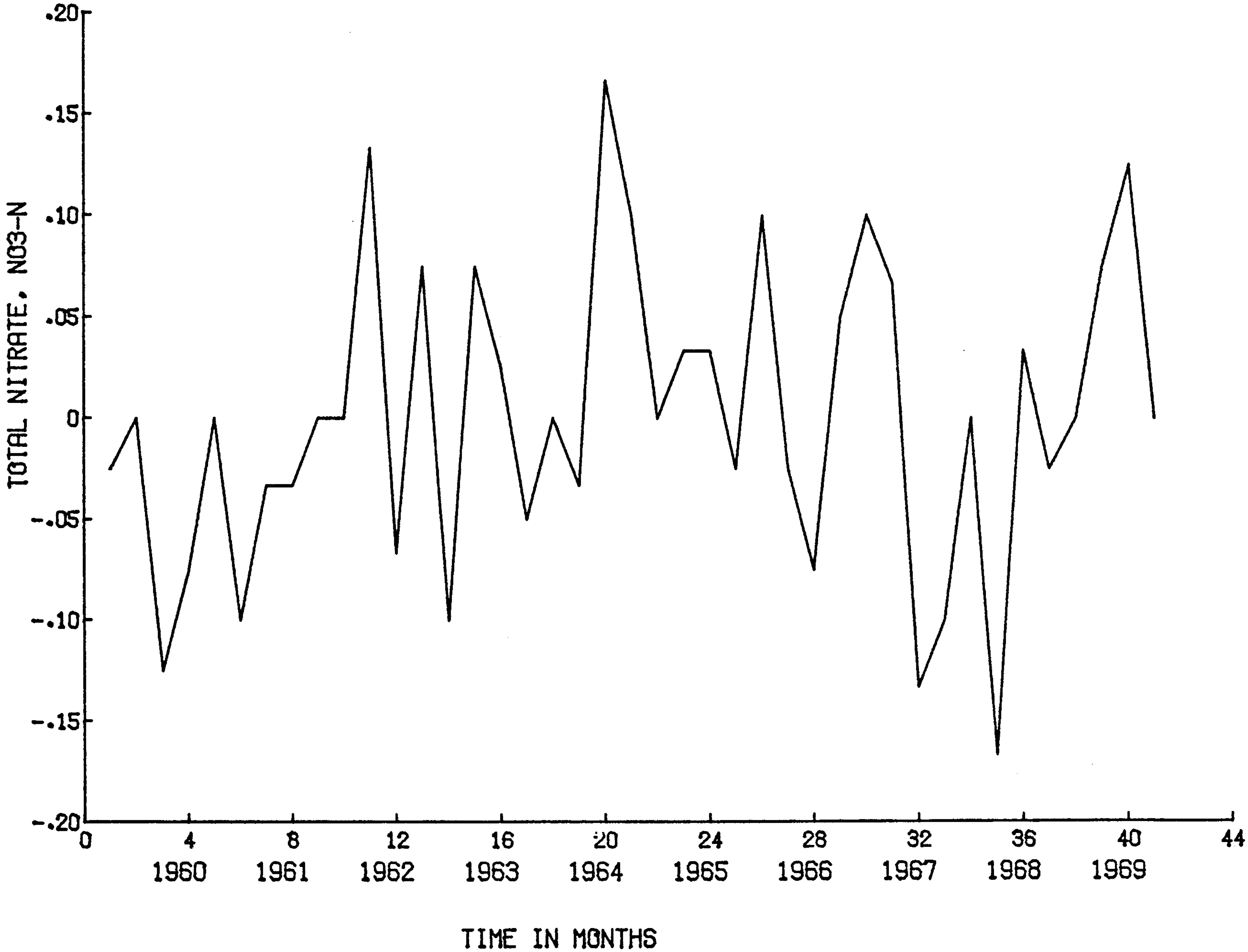

Figure II.12d Skagit River at Marblemount Deseasonalized NO_3-N

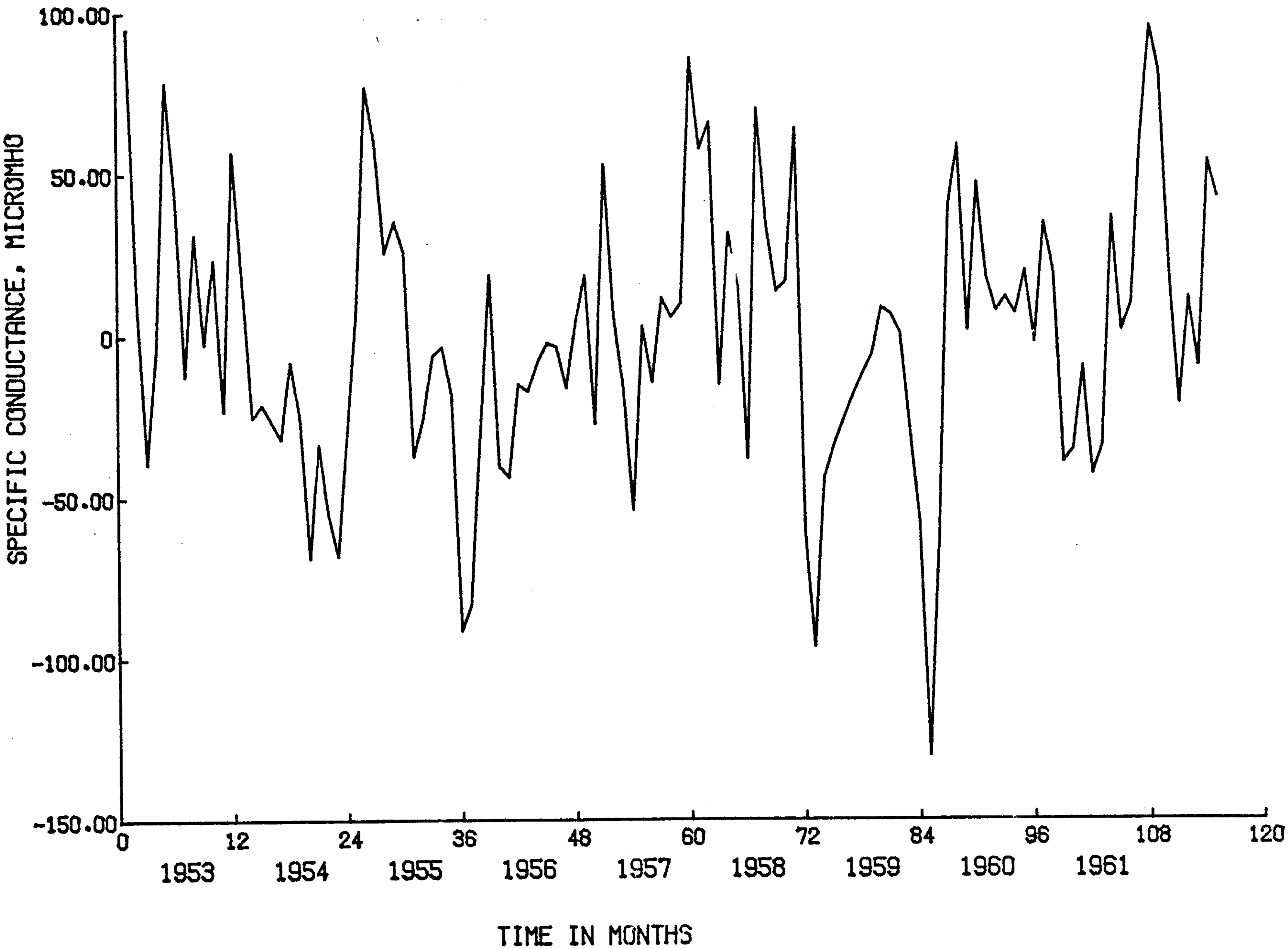

Figure II.13a Yakima River at Kiona Deseasonalized Specific Conductance

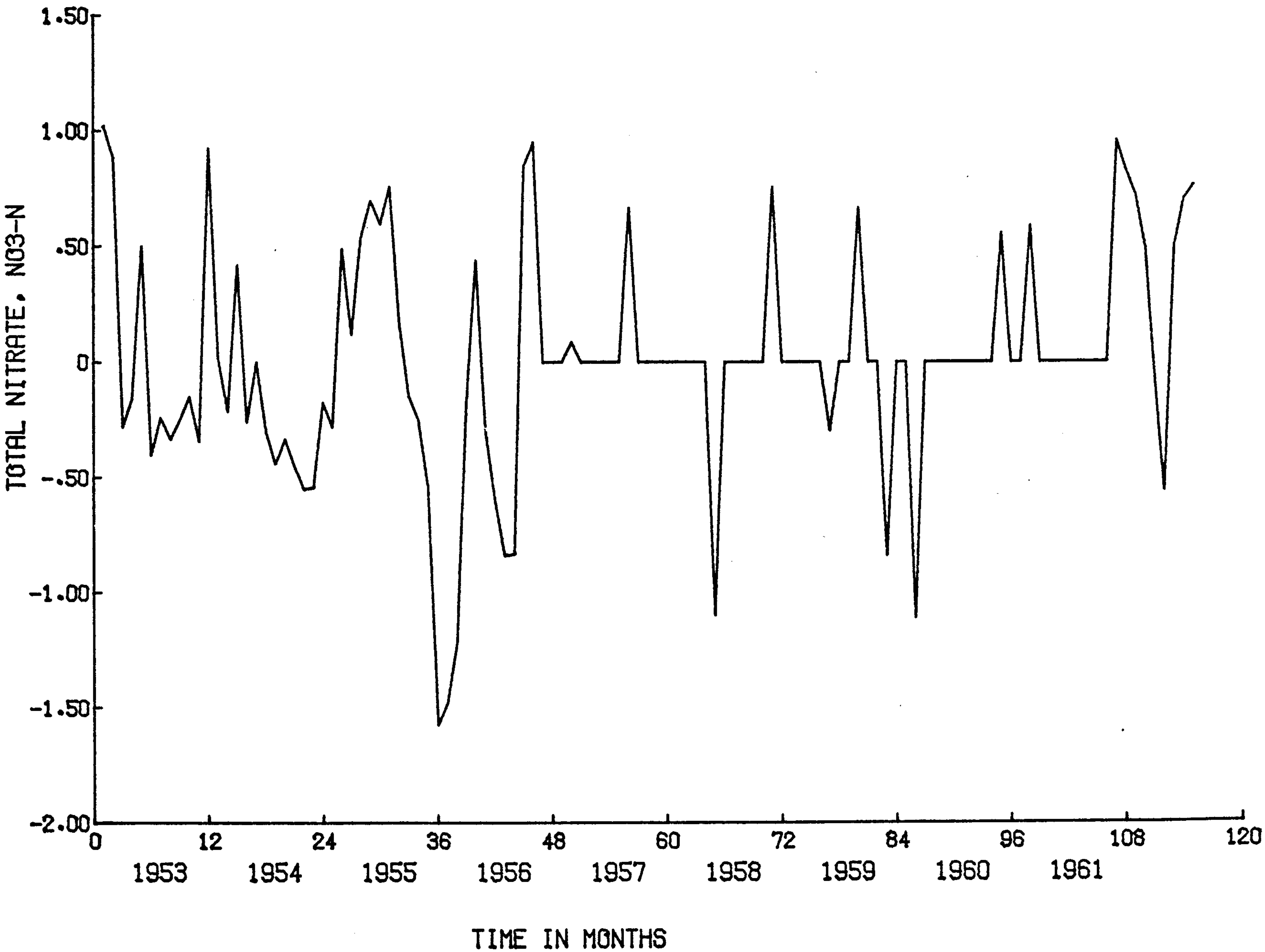

Figure II.13b Yakima River at Kiona Deseasonalized NO_3-N

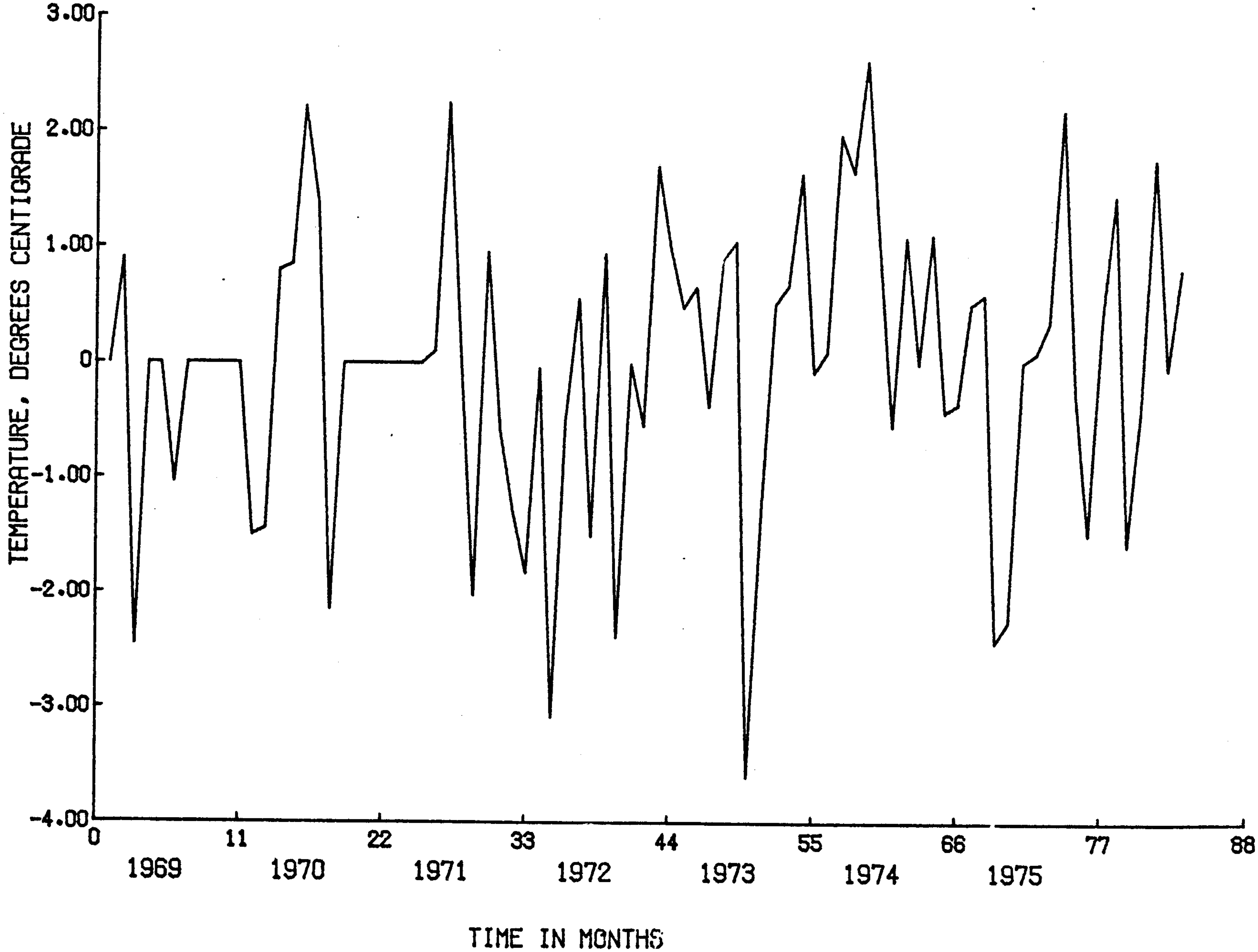

Figure II.13c Yakima River at Kiona Deseasonalized Temperature

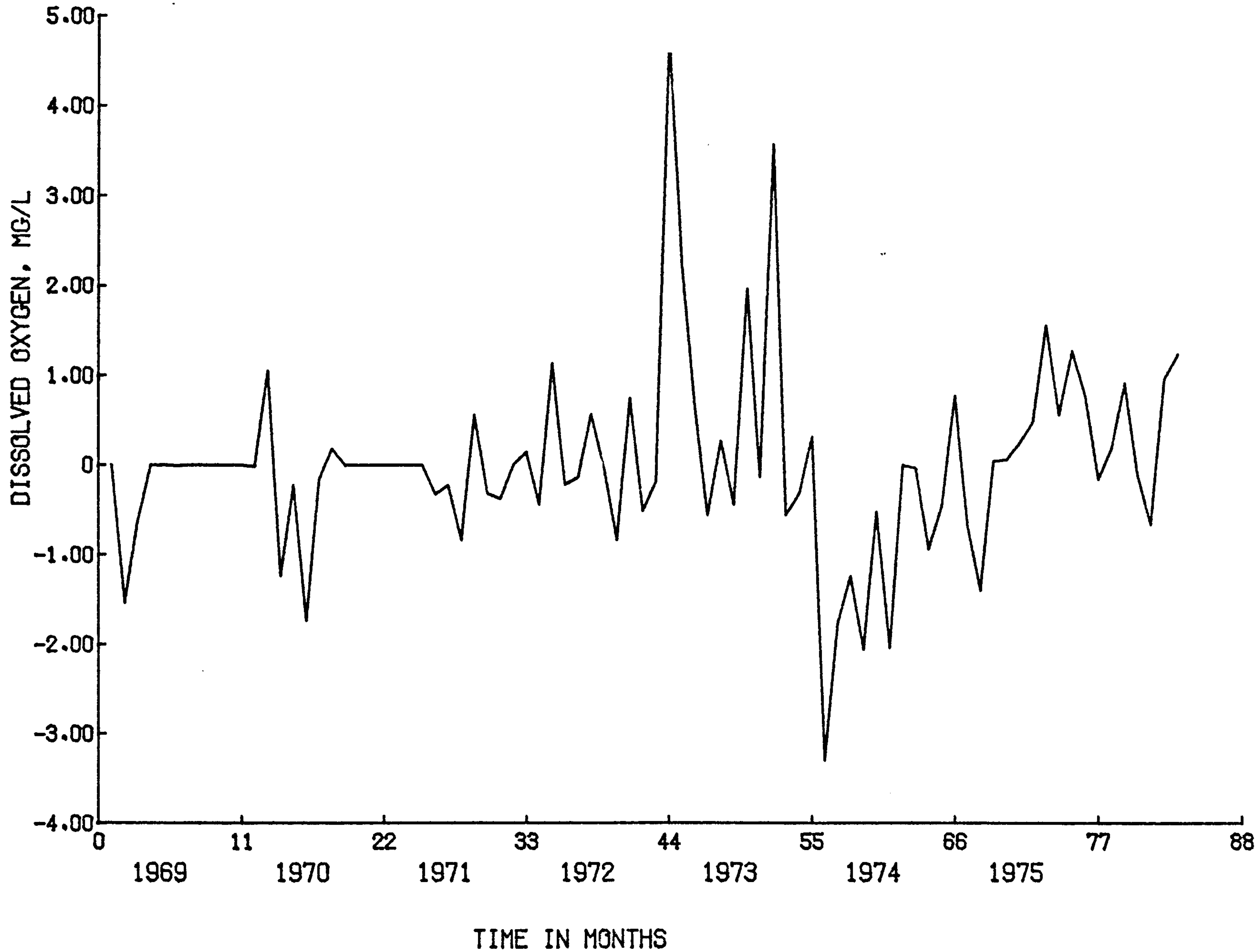

Figure II.13d Yakima River at Kiona Deseasonalized Dissolved Oxygen

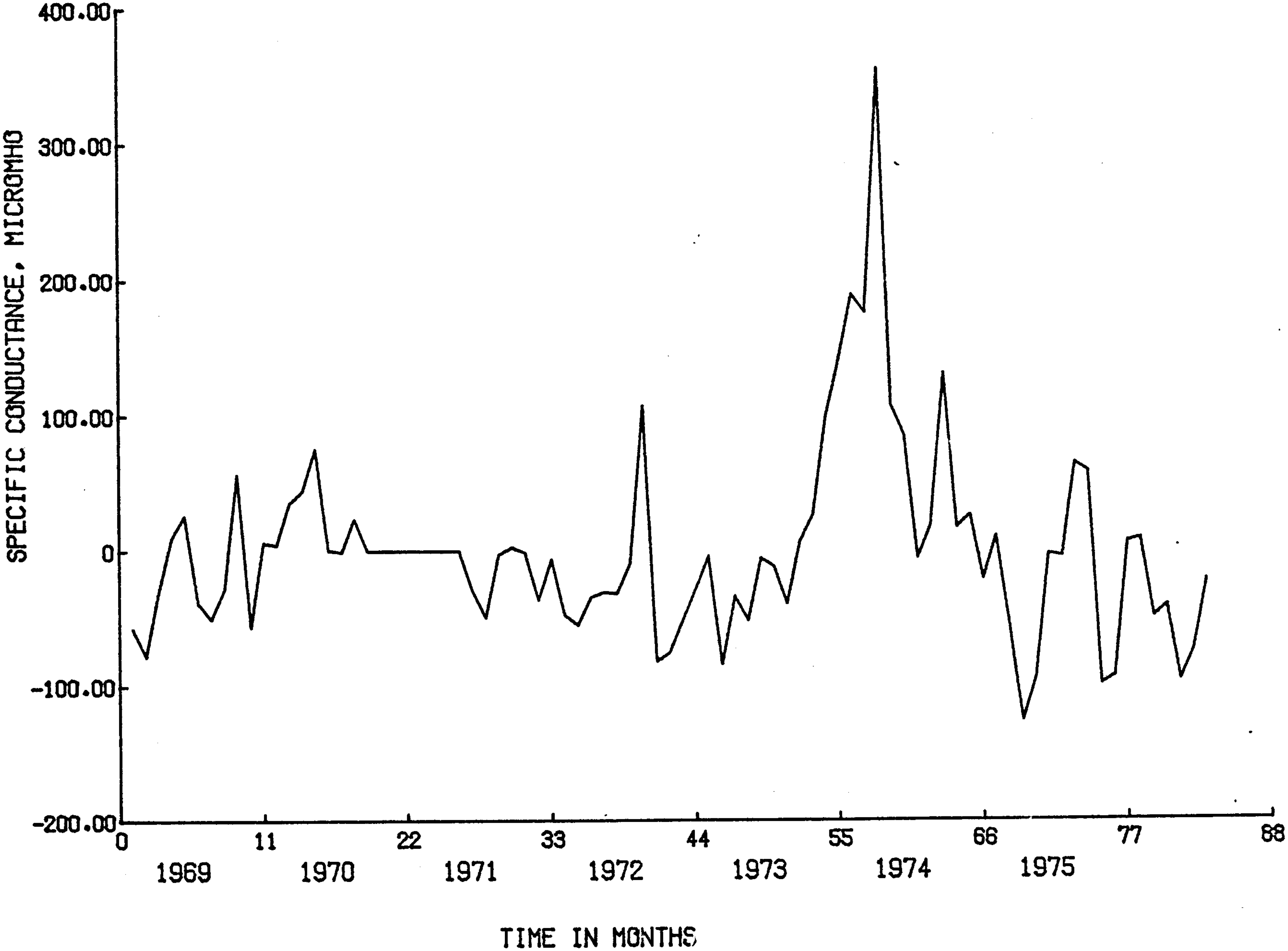

Figure II.13e Yakima River at Kiona Deseasonalized Specific Conductance

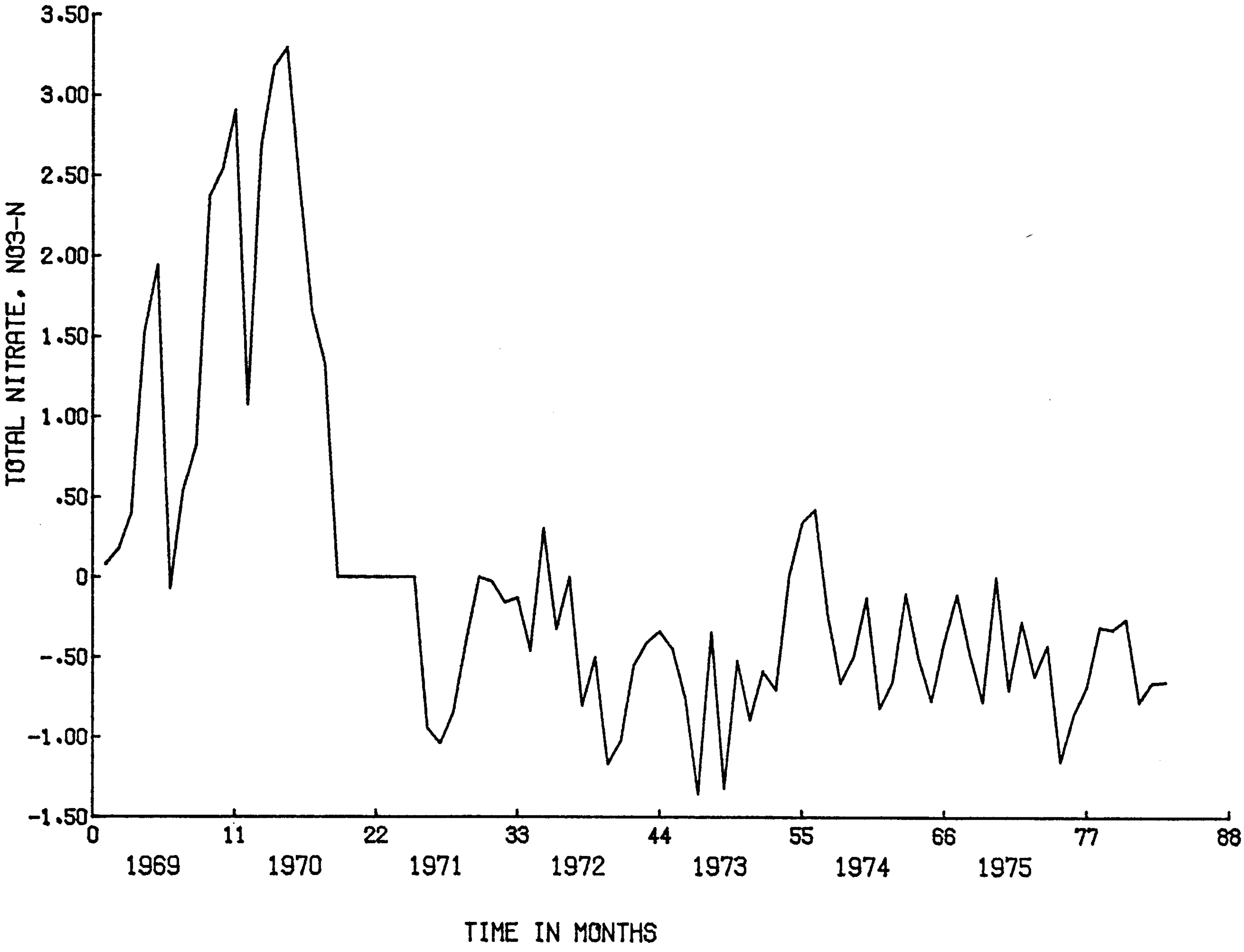

Figure II.13f Yakima River at Kiona Deseasonalized NO_3-N

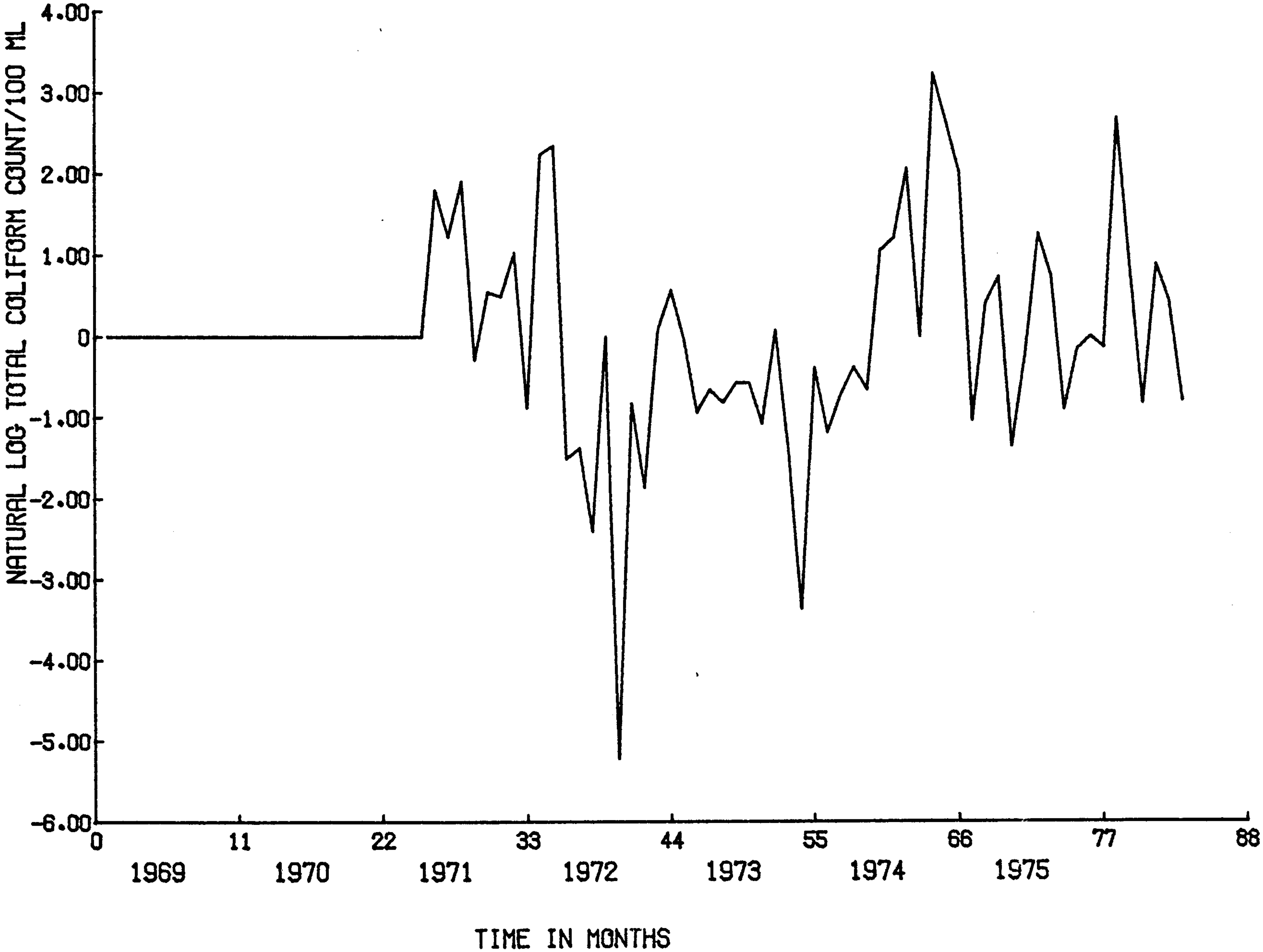

Figure II.13g Yakima River at Kiona Natural Log Total Coliform Count

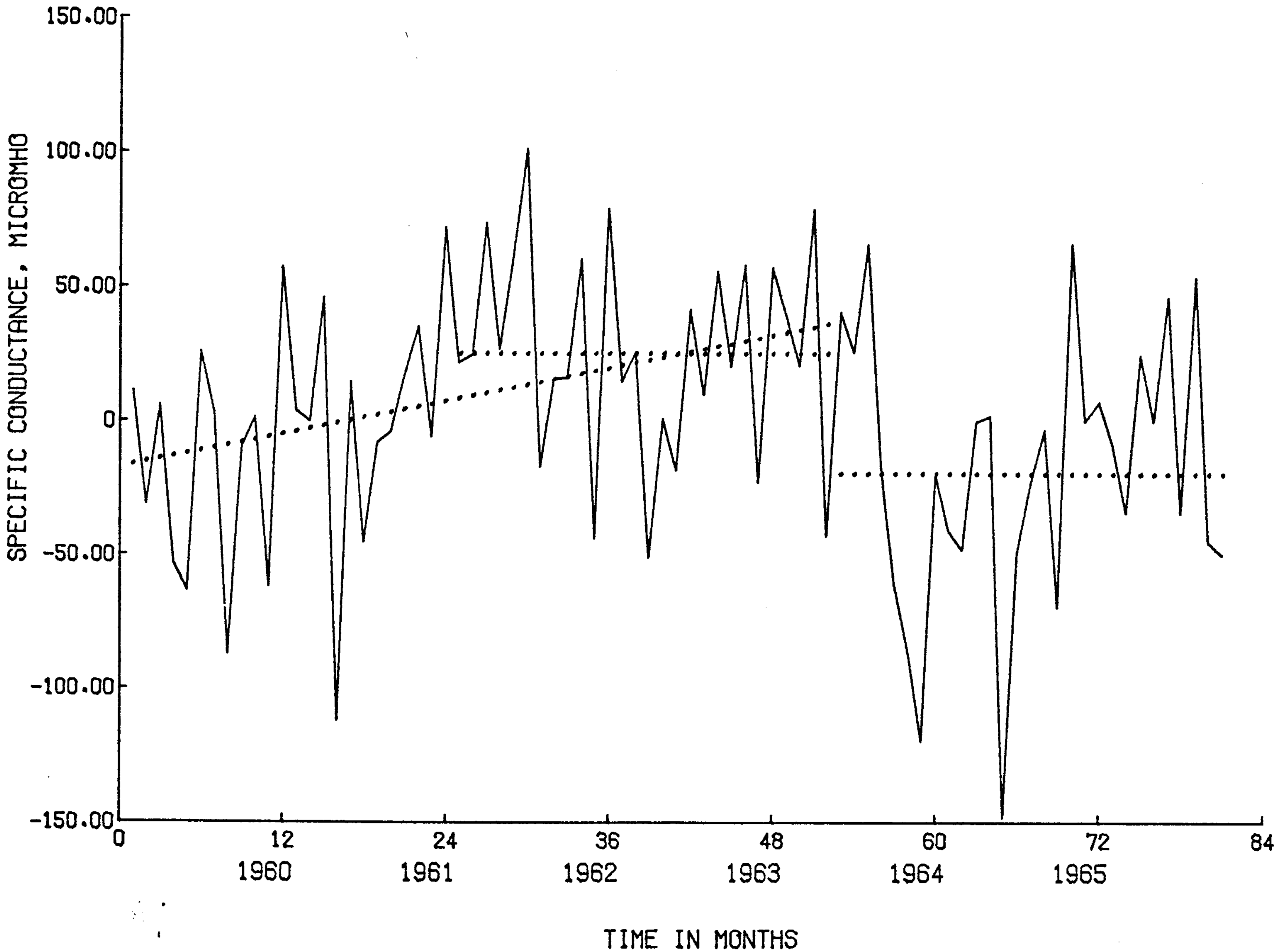

Figure II.14a Palouse River at Hooper Specific Conductance with Possible Trends

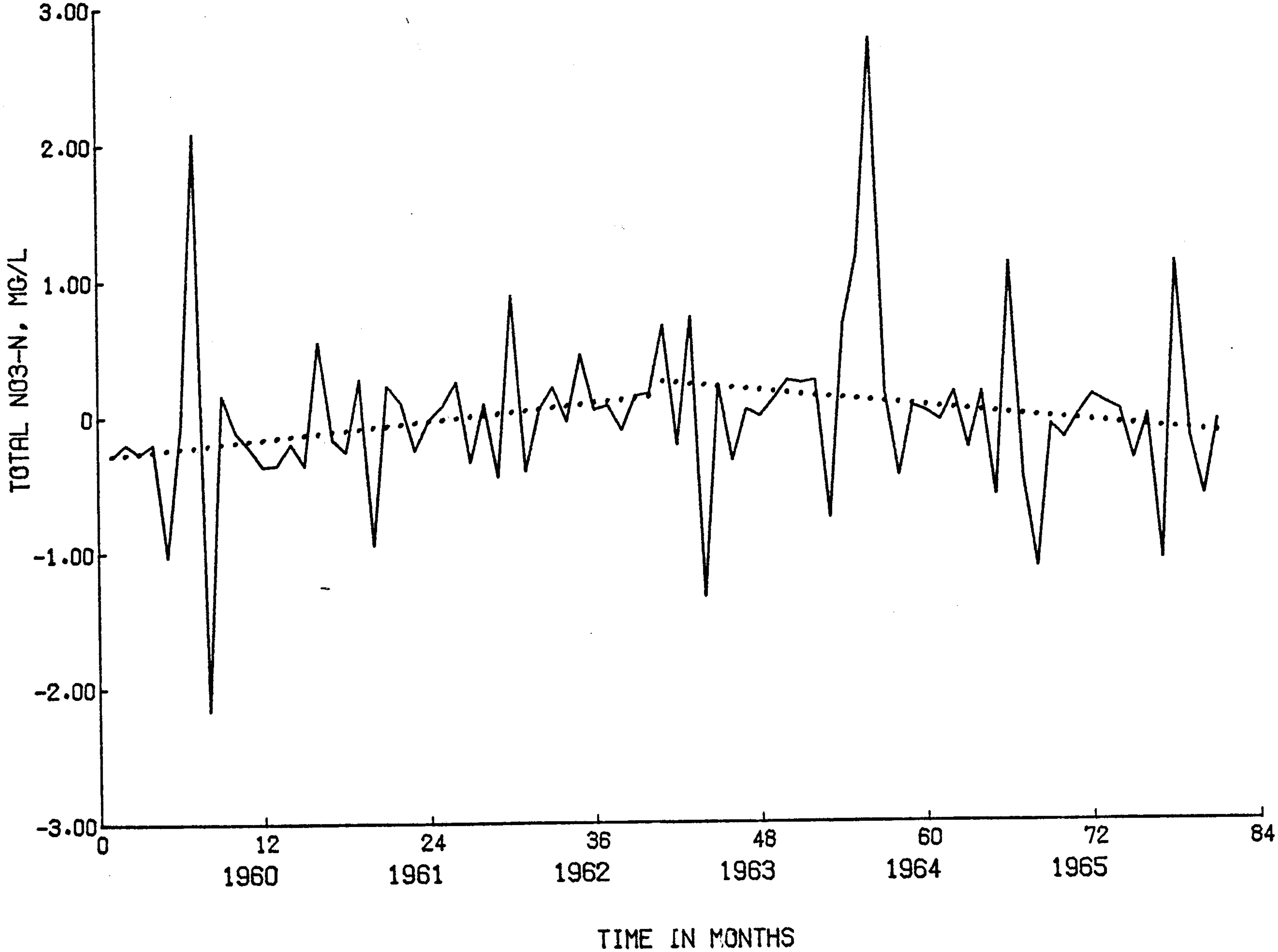

Figure II.14b Palouse River at Hooper Total Nitrate with Possible Trends

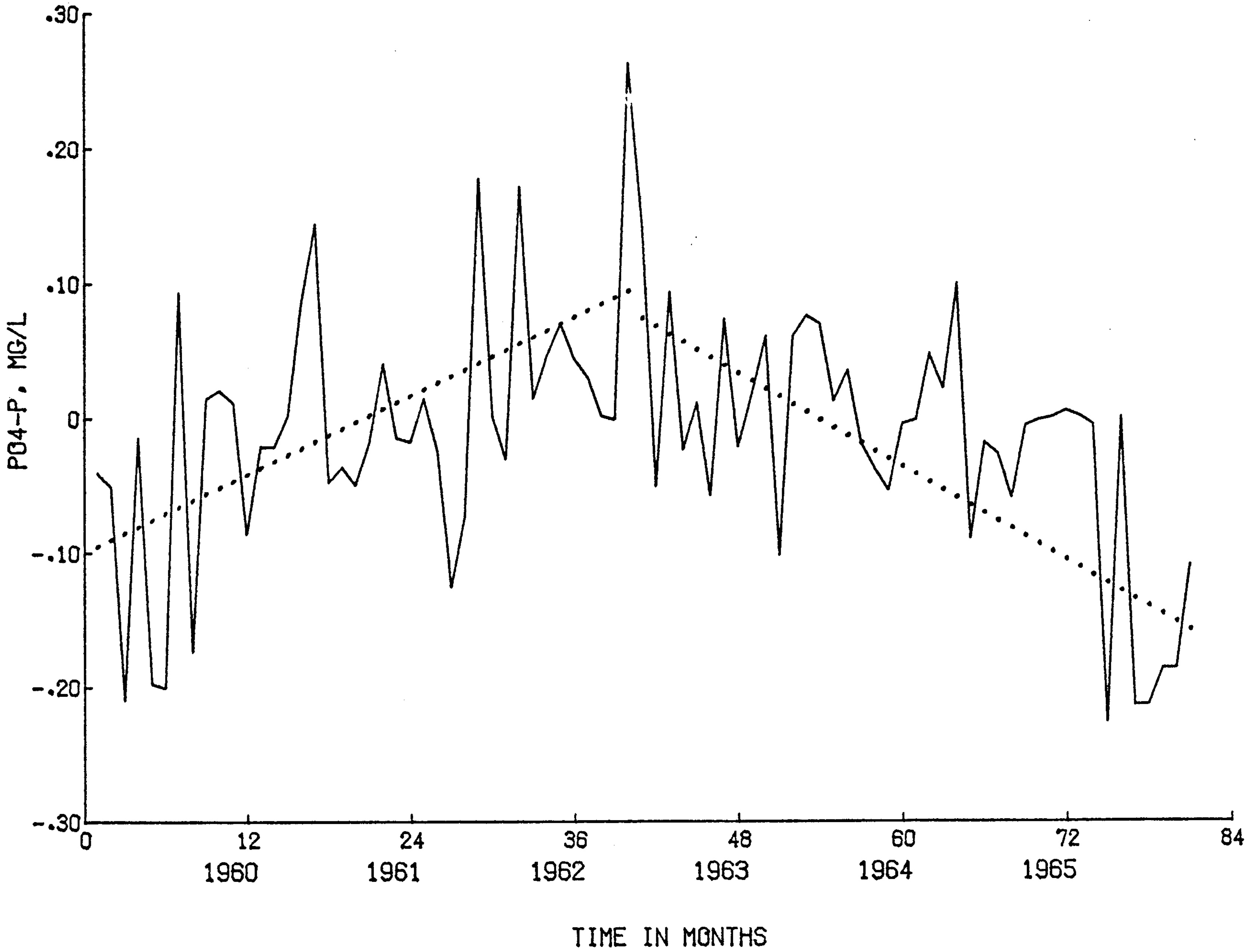

Figure II.14c Palouse River at Hooper Orthophosphate with Possible Trends

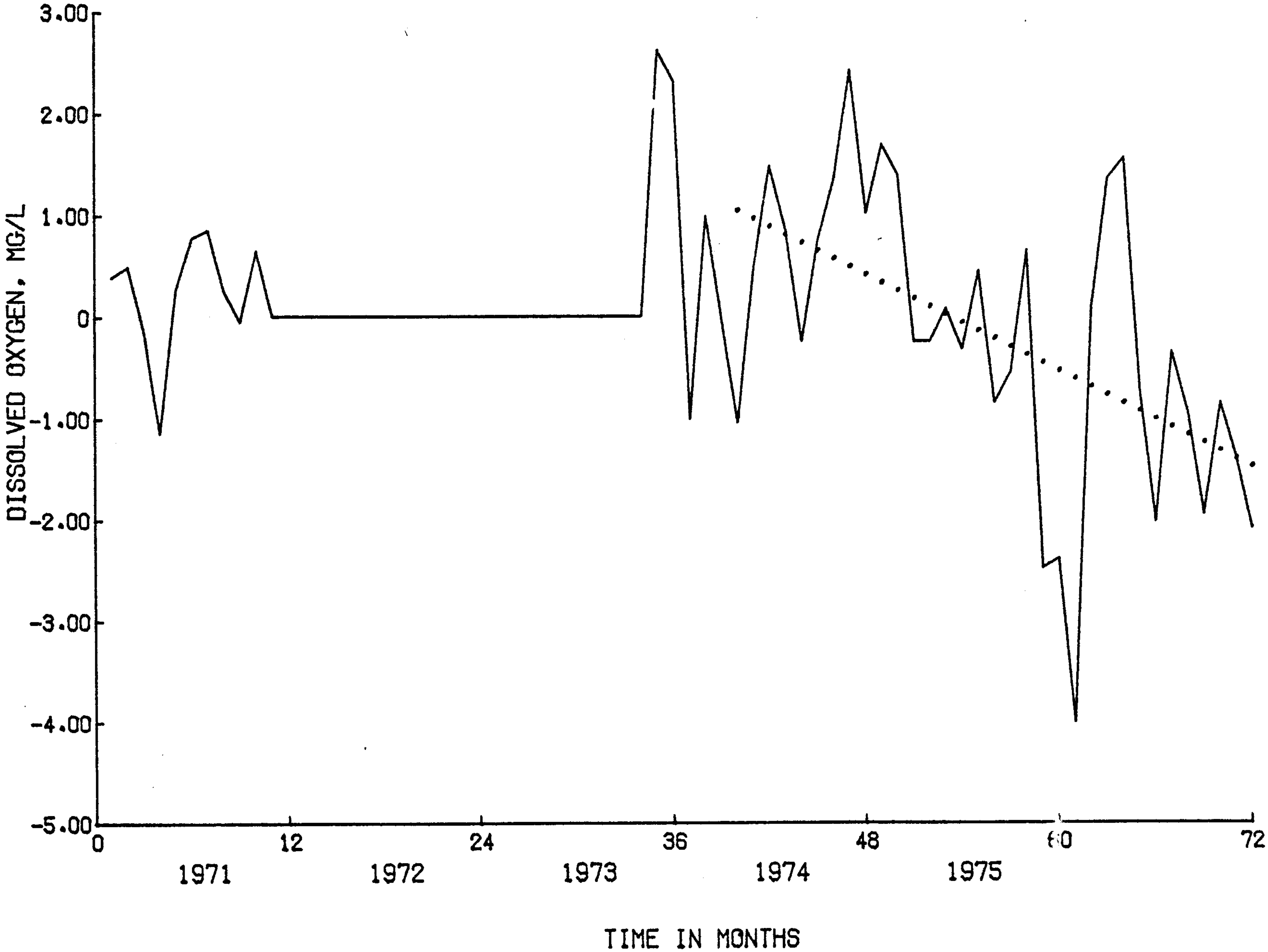

Figure II.14d Palouse River at Hooper Dissolved Oxygen with Possible Trend

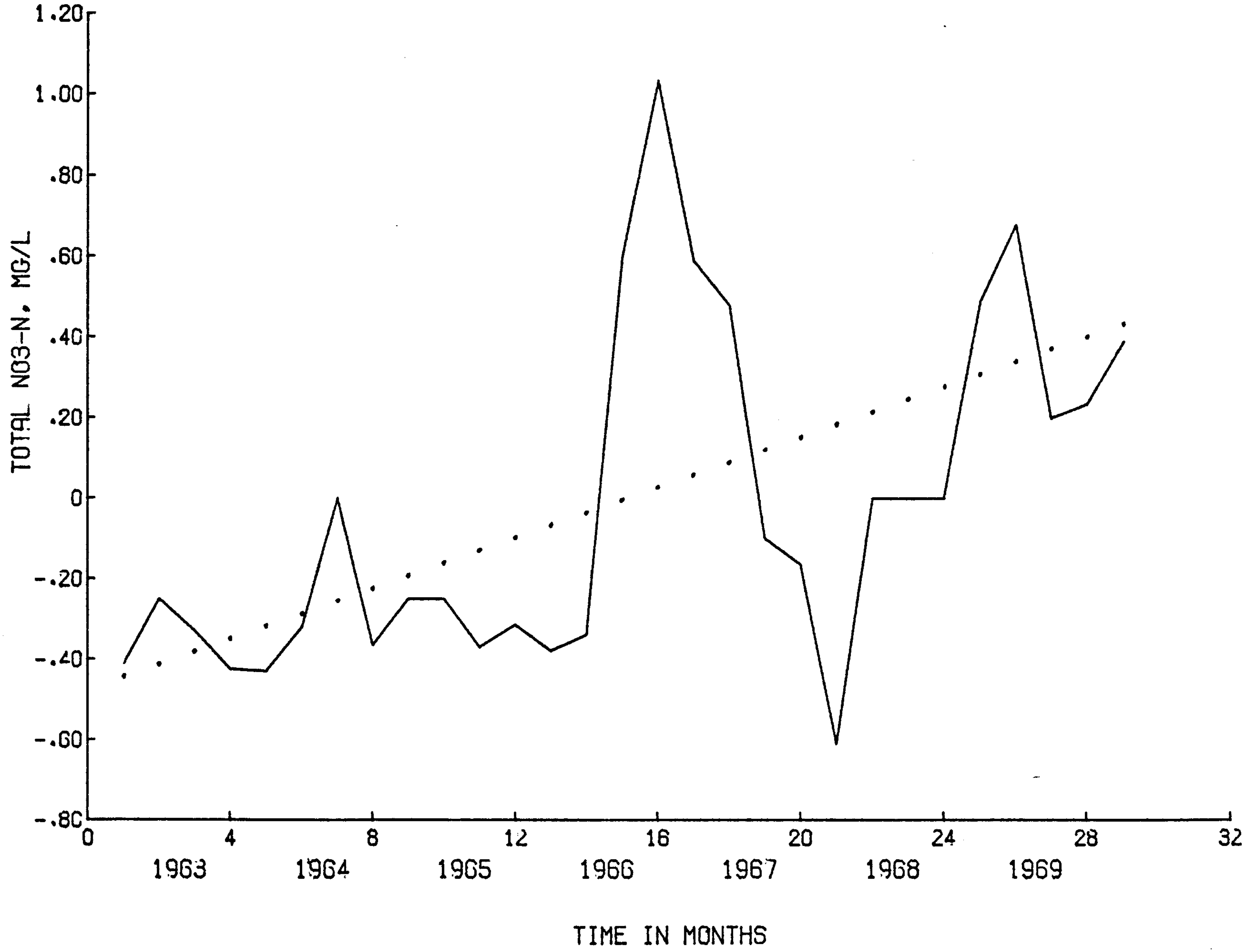

Figure II.15 Deschutes River at Tumwater NO_3-N with Possible Trend

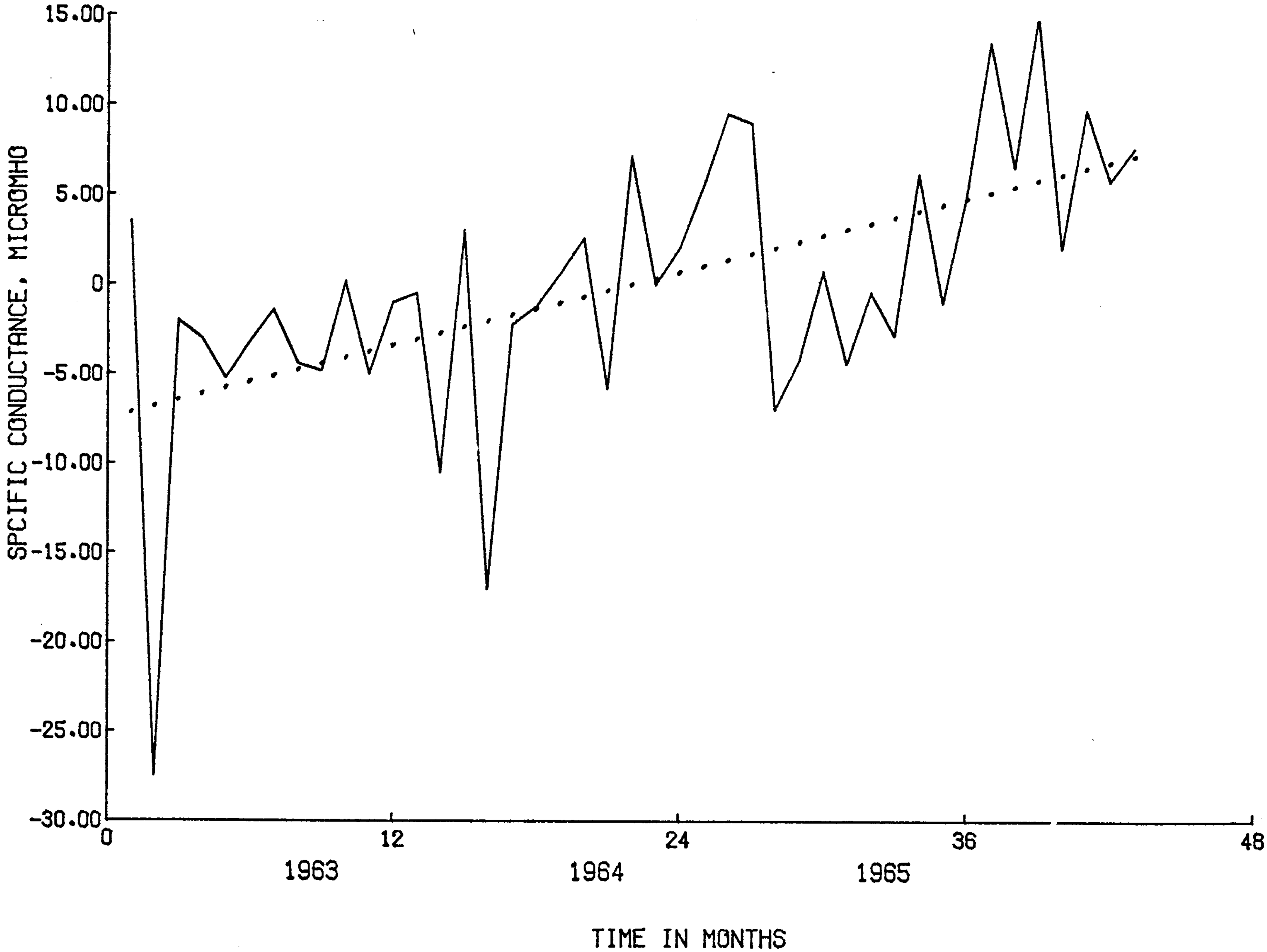

Figure II.16 Chambers Creek Near Steilacoom Specific Conductance with Possible Trend

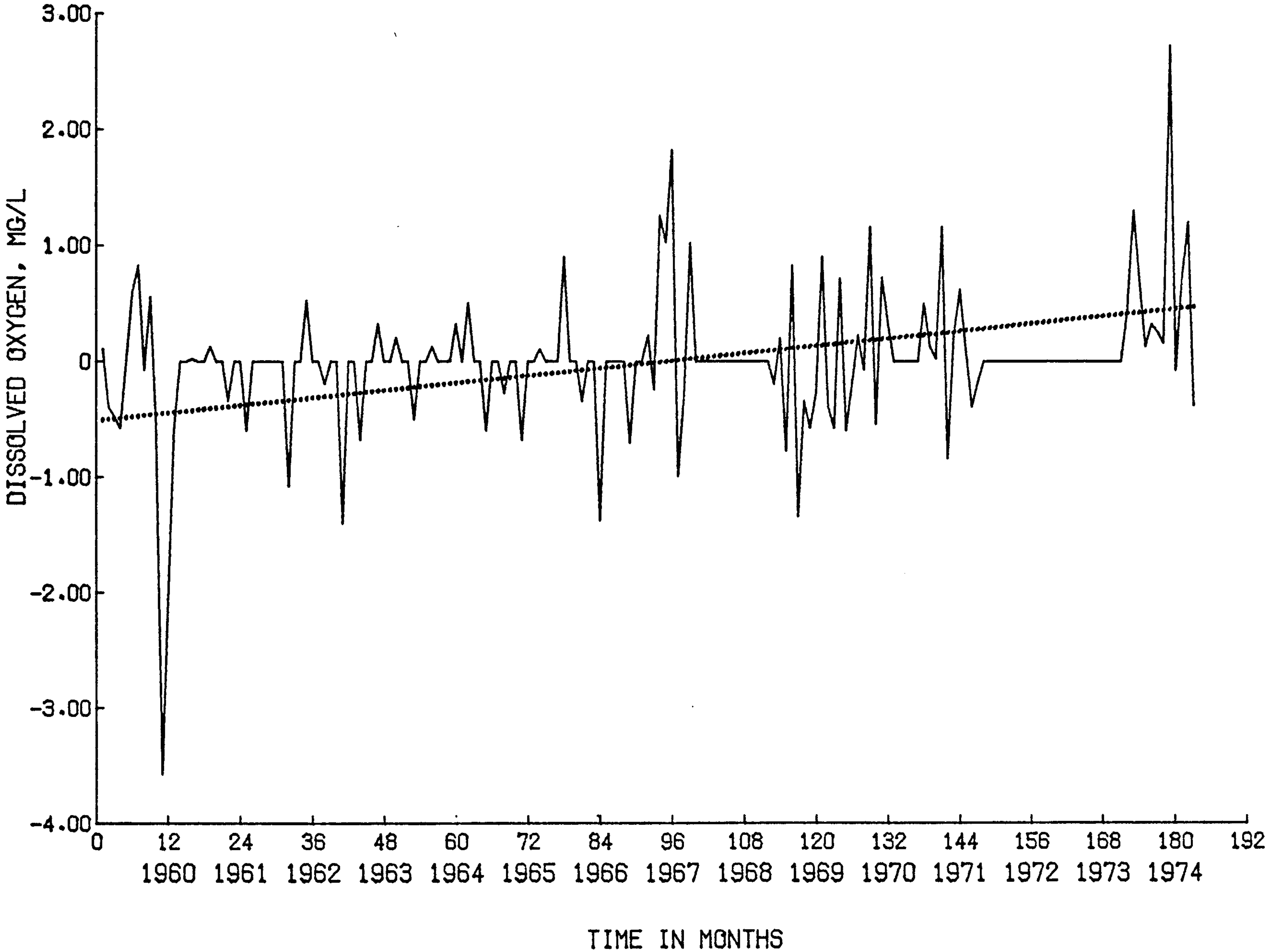

Figure II.17a Samish River Near Burlington Dissolved Oxygen with Possible Trend

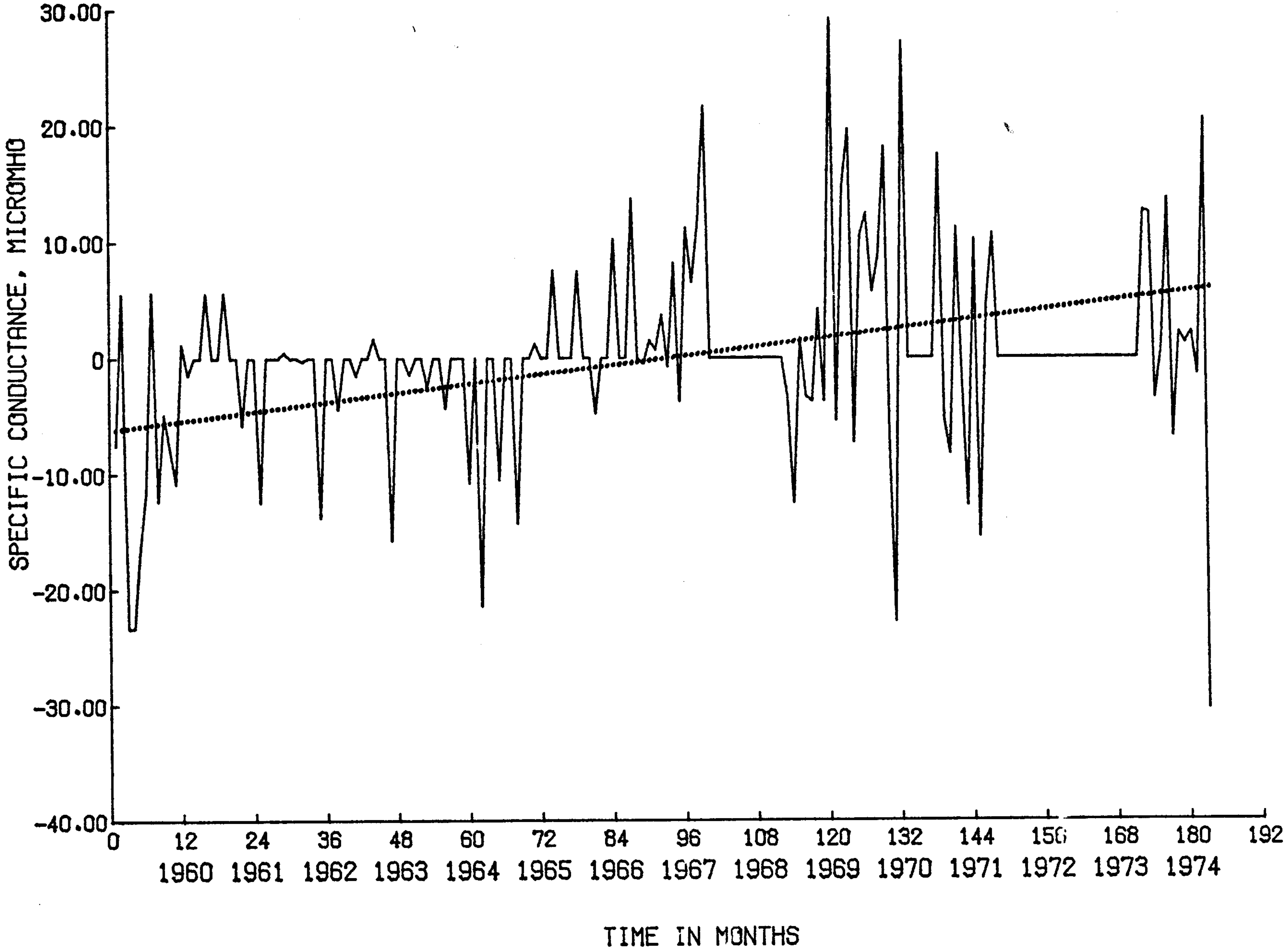

Figure II.17b Samish River Near Burlington Specific Conductance with Possible Trend

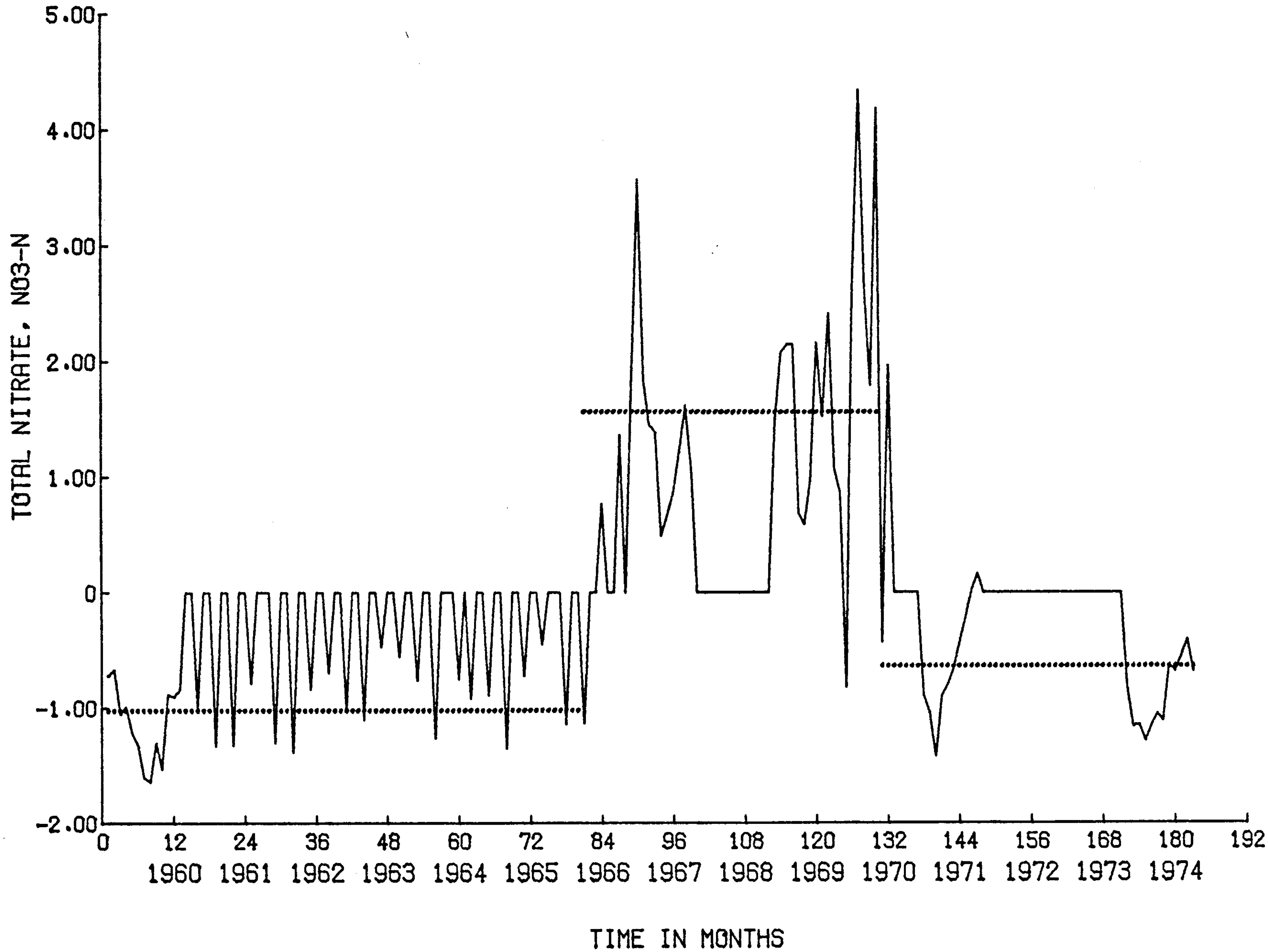

Figure II.17c Samish River Near Burlington Total Nitrate with Possible Trends

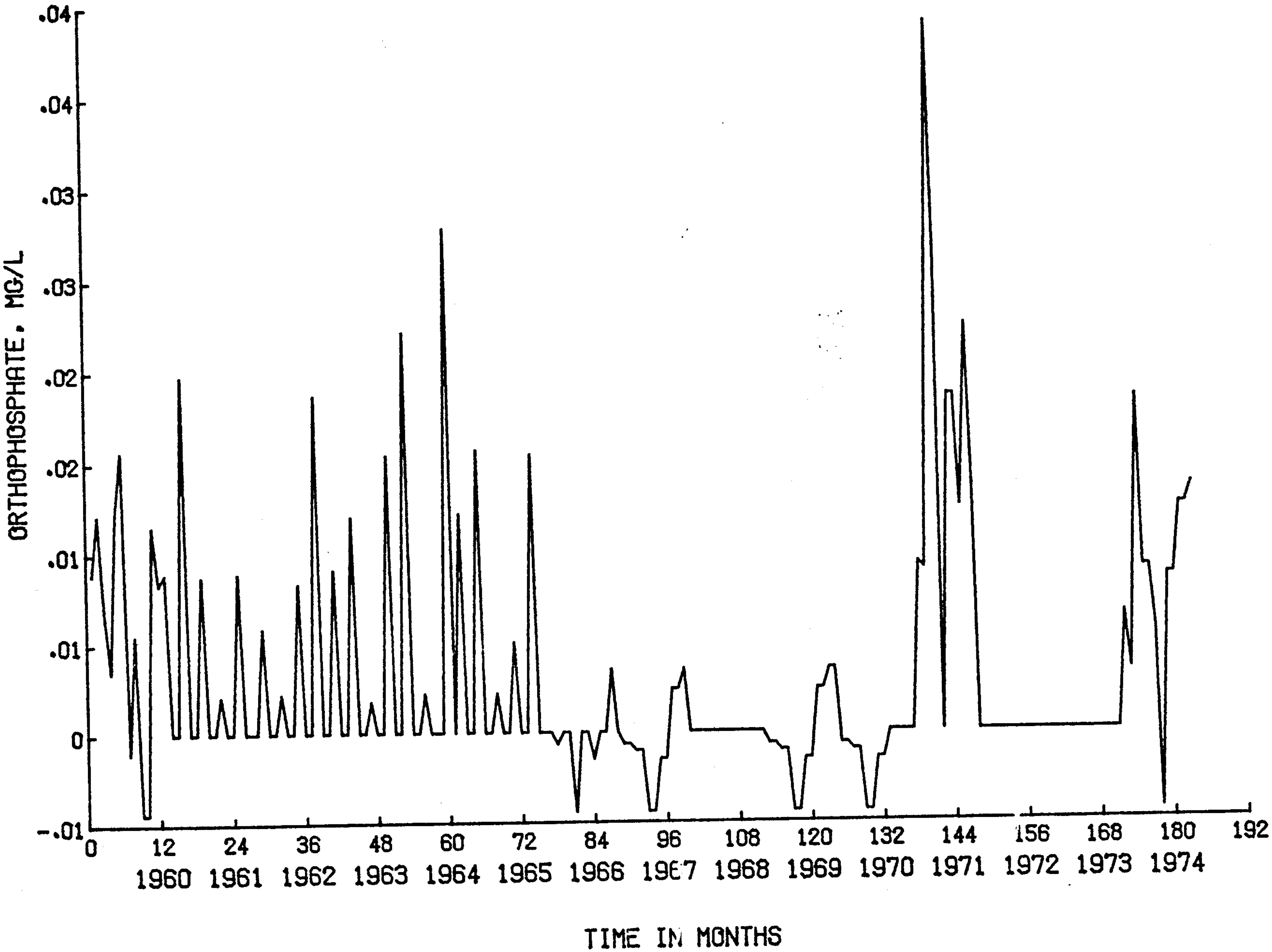

Figure II.17d Samish River Near Burlington Orthophosphate

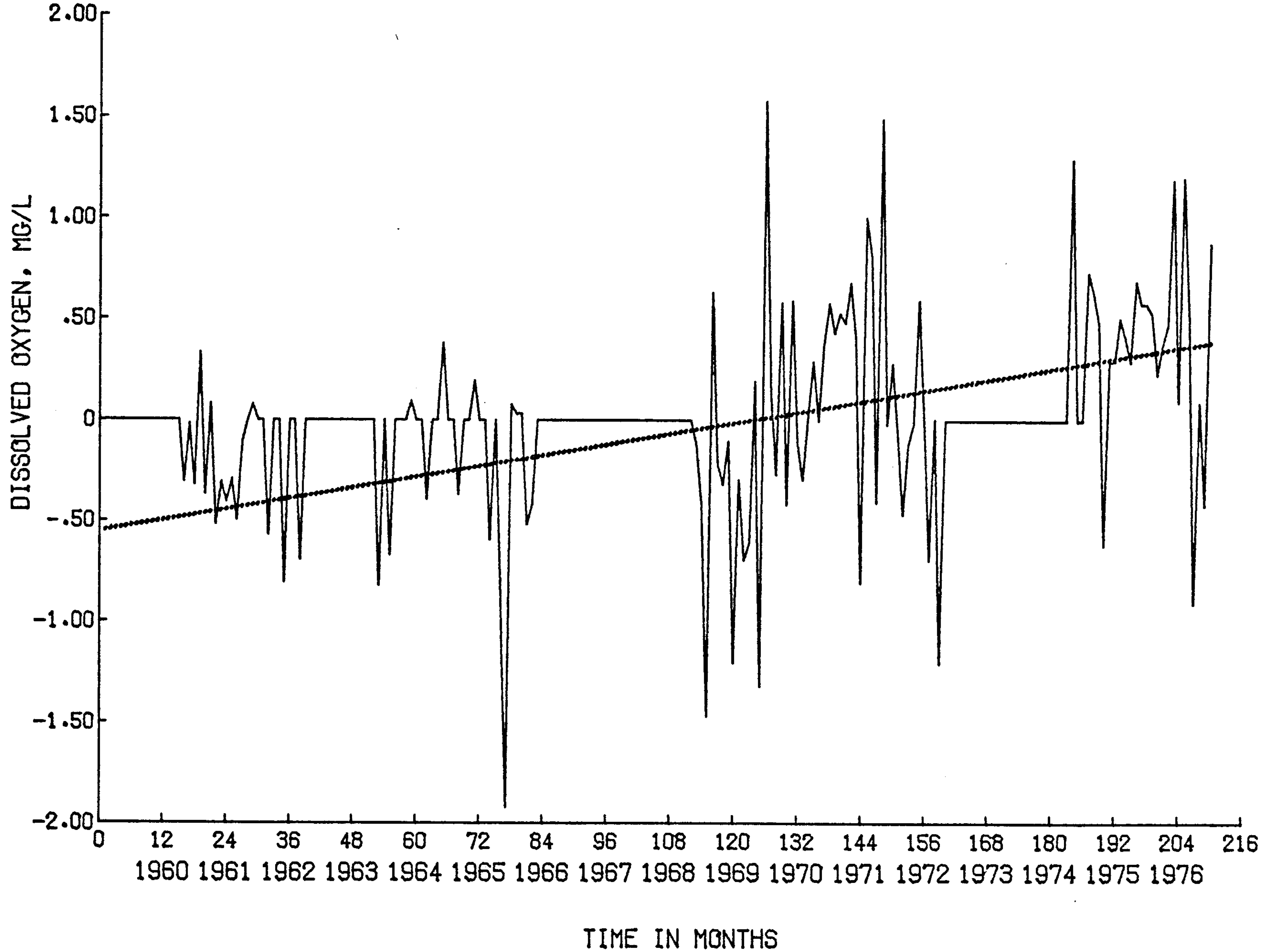

Figure II.18 Puyallup River at Puyallup Dissolved Oxygen with Possible Trend