APPENDIX C

Time Series Analysis of Discharge, Turbidity, and Juvenile Salmon Outmigration in the Susitna River, Alaska

TIME SERIES ANALYSIS OF DISCHARGE, TURBIDITY, AND JUVENILE SALMON OUTMIGRATION IN THE SUSITNA RIVER, ALASKA

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ABSTRACT

During the three years of study of juvenile salmon outmigration from the middle reach of the Susitna River, a correspondence has been noted between the peaks of river discharge and the peaks of outmigration. Further investigation of the relationship of outmigration to discharge was required because two large hydroelectric dams have been proposed for a region above the salmon rearing areas. These dams will markedly change the downstream discharge and turbidity regimes, factors which influence not only salmon outmigration, but almost all fish species and life stages including juvenile salmon rearing. Box-Jenkins models were developed for the 1983 and 1984 time series of river discharge, turbidity, and chinook and sockeye salmon fry outmigration rates in order to better understand the forces that shape the series and to statistically describe the natural conditions as a baseline against which future changes can be measured. The time series examined were described by relatively simple models, using mostly first-order autoregressive terms. About 85% of the variance in turbidity for one day was explained by the value for turbidity of the previous day. This figure was 44% for chinook salmon outmigration and 43% for sockeye salmon outmigration, the lower numbers indicating the effect of behavioral decisions on biological time series. Although the form of the time series plots of discharge and chinook salmon outmigration was different between the two years, the underlying stochastic processes which generated these series were the same. Bivariate transfer function models were constructed for turbidity and salmon outmigration rates which explain present values of these variables in terms of their own past values as well as past values of discharge.

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1.0 INTRODUCTION

While examining the plots of daily catch rate of outmigrating juvenile salmon at the Talkeetna Station outmigrant traps, an apparent correspondence was noted between the peaks of the time series of mean daily discharge and the time series of salmon outmigration (Hale 1983; Roth et al. 1984). Correlation analysis showed that there was a relatively strong relationship between discharge and the outmigration rates of various species/age classes of salmon during certain periods of time. The term outmigration rate is used here to mean the number of outmigrating fry captured at the traps per hour, not the distance travelled per hour. This relationship is not simply a matter of a greater volume of water being fished at higher discharges. The correlations of catch rate of age 0+ salmon with water velocity at the mouths of the traps were not significantly different from zero (Roth et al. 1984, Appendix A). There was in fact a greater number of fry per unit volume of water at high levels of discharge than at low levels.

A correspondence between discharge rate and salmonid outmigration has also been reported by other investigators (Cederholm and Scarlett 1982 - coho salmon; Congleton et al. 1982 - chum and chinook salmon; Godin 1982; Grau 1982; Solomon 1982b). The selective advantages of this behavior, according to Solomon (1982b), include easier passage over long distances or shallow areas and protection from predators provided by increased turbidity and by the large numbers resulting from a coordinated mass migration in response to an environmental cue.

There are probably two mechanisms which account for this relationship in the Susitna River. One is that the fish, which have gradually become physiologically ready for outmigration by growth and in response to photoperiod and temperature, are stimulated by a rise in mainstem discharge to begin that outmigration (Grau 1982). The second mechanism is that high flows physically displace the fish downstream. This latter mechanism may frequently occur for fry rearing in side sloughs, particularly for chum salmon (*Oncorhynchus keta*) and sockeye salmon (*O. nerka*). The natal sloughs for many chum and sockeye salmon have berms at the heads which prevent water from the mainstem from entering the site at low levels of discharge. When high flows occur, the slough heads are overtopped and the fry which had been rearing in low velocity water are subjected to a strong current.

Because two large hydroelectric dams have been proposed for the Susitna River in an area upstream of the rearing areas of the juvenile salmon (Fig. 1), and because these dams would markedly alter the natural discharge and turbidity regimes, it is necessary to quantify the relationship between the discharge and turbidity regimes and the outmigration patterns of the juvenile salmon. After the dams begin operation, the annual patterns of river discharge and turbidity level would be smoothed - both would be lower than normal in the summer and higher than normal in the winter. Also, the high frequency (daily) oscillations of these two time series would be dampened; there would be less day to day variation.

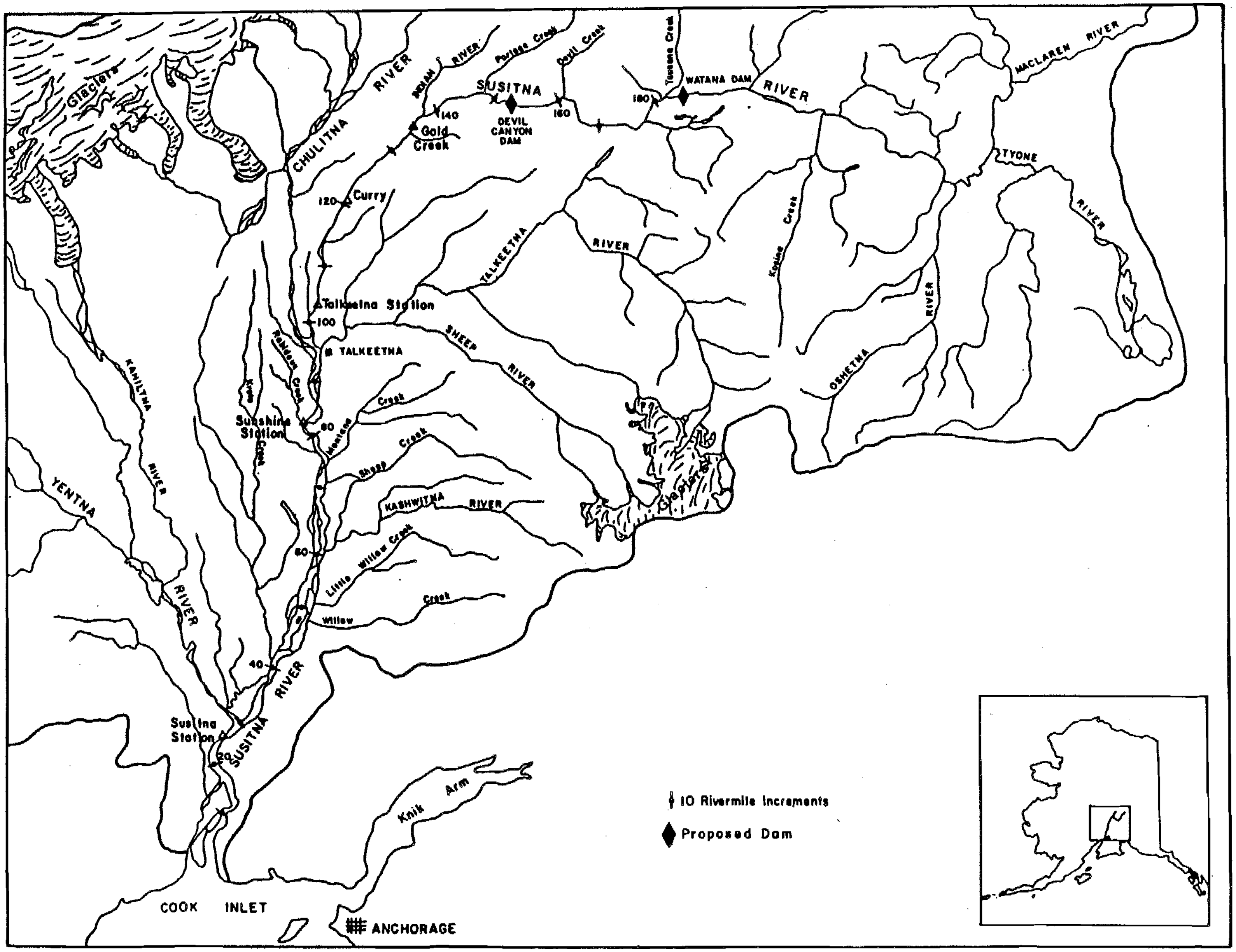


Figure 1. Map of the Susitna basin study region. (Source: Arctic Environmental Information Data Center).

There are many factors other than discharge and turbidity which affect the outmigration timing of juvenile salmon including time of year, size of fish, photoperiod, light intensity, and temperature (Brannon and Salo 1982); however, discharge and turbidity bear further investigation because of the changes in these two variables which would be caused by the proposed dams. Changes in river flow can affect the survival rate of young salmon (Stevens and Miller 1983). Potential negative effects of an altered flow regime include accelerated or delayed timing of outmigrations. Changes in outmigration timing may place the fish in their rearing areas at an unfavorable time from the standpoint of food supply, which could cause reduced survival (Hartman et al. 1967). Lower discharge levels can result in a shorter distance covered per day (Raymond 1968). Decreasing mainstem flows can lead to stranding of fish in pools which have been isolated from the mainstem (Solomon 1982a). Lower flows and clearer water than normal may also result in increased predation (Stevens and Miller 1983).

Turbidity level in the Susitna River probably does not have much direct effect on the daily number of fry which outmigrate or on the initiation of outmigration. In clear water streams, however, an increase in turbidity level can directly increase the number of outmigrating salmon by providing cover from predators (Solomon 1982b). Turbidity level in the Susitna River does change outmigration timing because fry in turbid water outmigrate during the day as well as during the night (Godin 1982; Roth et al. 1984). Clearing of the water could force the fry to shift to a nocturnal outmigration to avoid predators. However, this would be of marginal benefit for fry during the continuous daylight in June and July at 63° N latitude.

To avoid or alleviate the above problems, it is necessary to understand the mechanisms producing the present discharge, turbidity, and outmigration regimes. Knowledge of the discharge-outmigration relationships will be useful in trying to establish a post-project flow regime which will not interfere with the natural outmigration timing.

Also, because discharge and turbidity level are important variables affecting salmon life stages other than the outmigration phase as well as other species, it is necessary to statistically describe the natural discharge and turbidity regimes as a baseline against which future changes in these variables can be measured. Turbidity provides cover for salmon fry (Suchanek et al. 1984; Part 2 of this report) but also decreases primary production and affects the feeding, movement, and distribution of many of the fish species present in the river. Turbidity level after the dams begin operation will not only be influenced by a changed discharge regime, but will also be directly changed by the dams because settling of suspended sediment in the reservoir will create a turbidity regime substantially different from the present regime. Turbidity was included as a variable of interest in this paper more because of its effect on other life stages and species than because of its effect on salmon outmigration.

Further, discharge is the major variable in the extensive instream flow habitat modeling effort which has been conducted in the Susitna River; turbidity is also an important factor (Hale et al. 1984; Suchanek et al.

1984; Part 2 of this report). The current discharge and turbidity regimes that are driving these habitat models must be accurately described so that the models can be put into a proper perspective.

1.1 Time Series Analysis

The statistical methods collectively known as time series analysis are a logical choice for analyzing the natural discharge, turbidity, and outmigration regimes. A time series is a collection of observations ordered in time such as daily water temperature measurements. Time series analysis includes frequency domain (spectral analysis) and time domain problems. Spectral analysis is concerned with transforming a time series with a Fourier transform to a sum of sines and cosines (see Priestley 1981) and is appropriate with periodic series such as the classical example of the Canada lynx/snowshoe hare ten year cycle (Bulmer 1978). Methods for time domain problems (or Box-Jenkins models) are referred to as ARIMA (autoregressive, integrated, moving average) models (Box and Jenkins 1976). ARIMA models have been used extensively in economic forecasting (Nelson 1973; Granger and Newbold 1977).

Time series are shaped by both deterministic and stochastic (random) events. The series has a "memory" of the random events (or "shocks") operating on the series, that is, the effect of these disturbances may be apparent for several time units after the event occurred. One aspect of time series analysis consists of removing deterministic trends from a time series so that the values fluctuate around a mean level. A transformation may be necessary to ensure a constant variance. The random processes that generated the observed series can then be mathematically defined. The residuals left over after this model is fitted should be "white noise" (completely random) if the model is adequate.

Time series can be passed through a mathematical filter which changes the form of the input series. A "low pass filter" dampens high frequency perturbations and allows low frequency perturbations to pass unchanged. This is useful in smoothing noisy time series so that the basic pattern may be more readily observed. High pass filters are used when it is desirable to remove obvious (low frequency) trends in order to focus on the high frequency events.

Box-Jenkins models can be constructed using only the information contained in the time series itself. For example, although the discharge time series results from several independent variables including rainfall, air temperature, and solar insolation on the glaciers, it is not necessary to quantify these inputs in order to model the output (discharge). Information on the effects of all the inputs is already contained in the past history of the discharge record. However, information on the input series can be used in a transfer function model to obtain an equation with more predictive power. This is a model where an output series is a function of one or more independent input series as well as its own past history.

An observed series is one realization of all possible time series which could have been generated from a random process. Time series analysis examines the nature of the probablistic process that generated the observed series. The model should have similar properties to the generating mechanisms of the stochastic process (Granger and Newbold 1977). Then, one can form summary statistics about the series and make inferences about the nature of the stochastic process. After a model has been developed, it can be used to test some hypothesis about the generating mechanism of the time series, to forecast future values of the series, or to make decisions on how to control future values of the series (Granger and Newbold 1977).

1.2 Applications of Time Series Analysis

Time series analysis has been extensively used in examining physical data, particularly in oceanography. Salas and Smith (1981) demonstrated that ARIMA models can be used to model the time series of annual flows in streams. Srikanthan et al. (1983) analyzed the time series of annual flows in 156 streams in Australia. Time series models have also been used to examine the effect of the Aswan dam on the discharge of the Nile River and the effect of a hydroelectric dam on the discharge regime of the Saskatchewan River (Hipel et al. 1978).

Time series analysis methods have been also been used in examining time series of abundance and catch in marine fisheries (Van Winkle et al. 1979; Botsford et al. 1982; Peterman and Wong 1984; and Taylor and Prochaska 1984). These methods have been used by Saila et al. 1980, Mendelssohn 1981, Stocker and Hilborn (1981), Kirkley et al. (1982), and Jensen (1985) for forecasting future abundance or catch of marine fish stocks. Mendelssohn (1981) used transfer function models in addition to univariate Box-Jenkins models to forecast fish catch. Botsford et al. (1982) focused on searching for causal mechanisms of observed cycles in salmon fisheries in California rather than on defining models for the fisheries.

Applications to freshwater fish ecology problems are much more limited. Saila et al. (1972) used time series methods to cross correlate upstream migration activity of the alewife to solar radiation and water temperature. O'Heeron and Ellis (1975) considered a time series model for judging the effects of reservoir management on fish. Applications of spectral analysis to ecological problems have been reviewed by Platt and Denman (1975) and time series analysis in ecology was the subject of a symposium proceedings edited by Shugart (1978).

1.3 Objectives

The objective of this paper was to develop mathematical models for the times series of mean daily Susitna River discharge at the Gold Creek gaging station (river mile 136.7), daily turbidity level, and daily outmigration rates of chinook salmon (*Oncorhynchus tshawytscha*) and sockeye salmon (*O. nerka*) at the Talkeetna Station outmigrant traps (river mile 103.0) during the open water seasons of 1983 and 1984. Because time series analysis can provide an efficient summarization of a data set by a few parameters (Hipel et al. 1978), these models will be used to statistically describe the present conditions as a baseline against which future changes can be measured. The discharge and turbidity information will be useful for examining their relationship with salmon fry outmigration as well as with other species and life history stages. In addition, discharge was used as an input in transfer function models of discharge-turbidity, discharge-chinook outmigration and discharge-sockeye outmigration in order to describe the relationship between these variable and to be used as a possible technique to forecast future values or to examine the probable effects of the proposed dams.

Turbidity was chosen as a variable of interest because of its relationship with discharge and because of its importance in determining the distribution of rearing juvenile salmon (Suchanek et al. 1984; Part 2 of this report) and other species. It was selected more for this reason than for its effect on salmon outmigration, so it was not used as an input in a transfer function model with salmon outmigration. Chinook salmon were chosen because this species rears in sloughs and side channels affected by mainstem discharge and because chinook salmon have been selected as the evaluation species of the impact assessment study (EWT&A 1985). The sockeye salmon time series was chosen because mainstem discharge affects sloughs which are both natal and rearing areas for this species. While chinook salmon spawn mainly in tributaries in this system, sockeye salmon spawn mostly in mainstem sloughs.

2.0 METHODS

2.1. The Data

Mean daily discharge values for 1983 and 1984 (Fig. 2, Fig. 3) were obtained from the U.S. Geological Survey gaging station on the Susitna River at Gold Creek, river mile 136.7 (Still et al. 1984; U. S. Geological Survey provisional data, 1984). The time frame examined was May 18 to August 30 (105 observations). Discharge levels begin to decline in September when glacier melting decreases; hence, a longer series would not be stationary. Throughout this paper, the unit for discharge is one thousand cubic feet per second.

Daily water samples for turbidity (Fig. 2, Fig. 3) were taken at the outmigrant trap station and measured with an HF Instruments Model No. DRT-15B field turbidometer (Roth et al. 1984). Units are in nephelometric turbidity units (NTU). Only the 1984 turbidity series was examined.

Outmigration rate (Fig. 2, Fig. 3) was measured by two outmigrant traps, one on each bank, located at river mile 103.0 (Roth et al. 1984). The rate is reported as number of fish per trap hour with catch from the two traps combined. Only age 0+ fry were used in the analysis because the traps were not efficient at capturing age 1+ fry and, consequently, the numbers were low. Further, age 1+ chinook and sockeye salmon have essentially completed their outmigration from this reach of river by the end of July so the time series are shorter.

The chinook salmon time series for 1983 runs from May 18 (shortly after ice-out) to August 30 (when outmigration is winding down), a total of 105 observations. The 1983 sockeye salmon data were not examined. There were six days during the 105 day series when the outmigrant traps were not fished - a one day, a two day, and a three day period. Although values for gaps in time series can be estimated by a spline method, the gaps in the outmigration series are short enough so that a simple interpolation of values is sufficient (Sturges 1983).

In 1984, the traps were continuously operated from May 14 to October 6. However, the series were cut off at the end of August in order to be comparable to 1983 and to achieve a stationary series. About 98% of the cumulative outmigration of age 0+ chinook and sockeye fry in 1984 had occurred by the end of August.

2.2. Identification and Estimation of Time Series Models

Univariate models were developed for the four time series: discharge, turbidity, and chinook and sockeye salmon outmigration. Methods for developing Box-Jenkins ARIMA and transfer function models are described in section 7.0. Basically, there are three steps in developing an ARIMA model: model identification, parameter estimation, and diagnostic checking (Box and Jenkins 1976). The autocorrelation (AC) and partial autocorrelation (PAC) plots for each series were examined to help identify possible autoregressive (AR) and moving average (MA) components. A tentative model was developed and the parameters estimated.

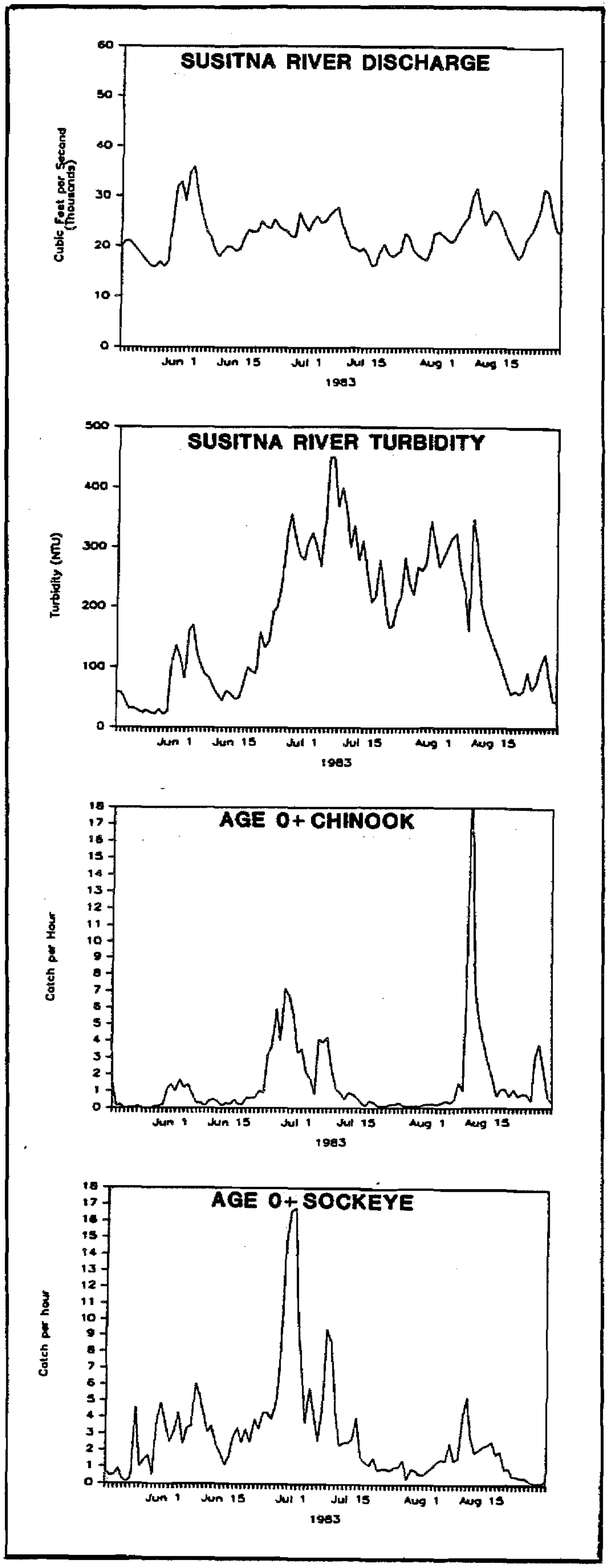


Figure 2. Discharge, turbidity, and chinook and sockeye salmon outmigration rate, 1983.

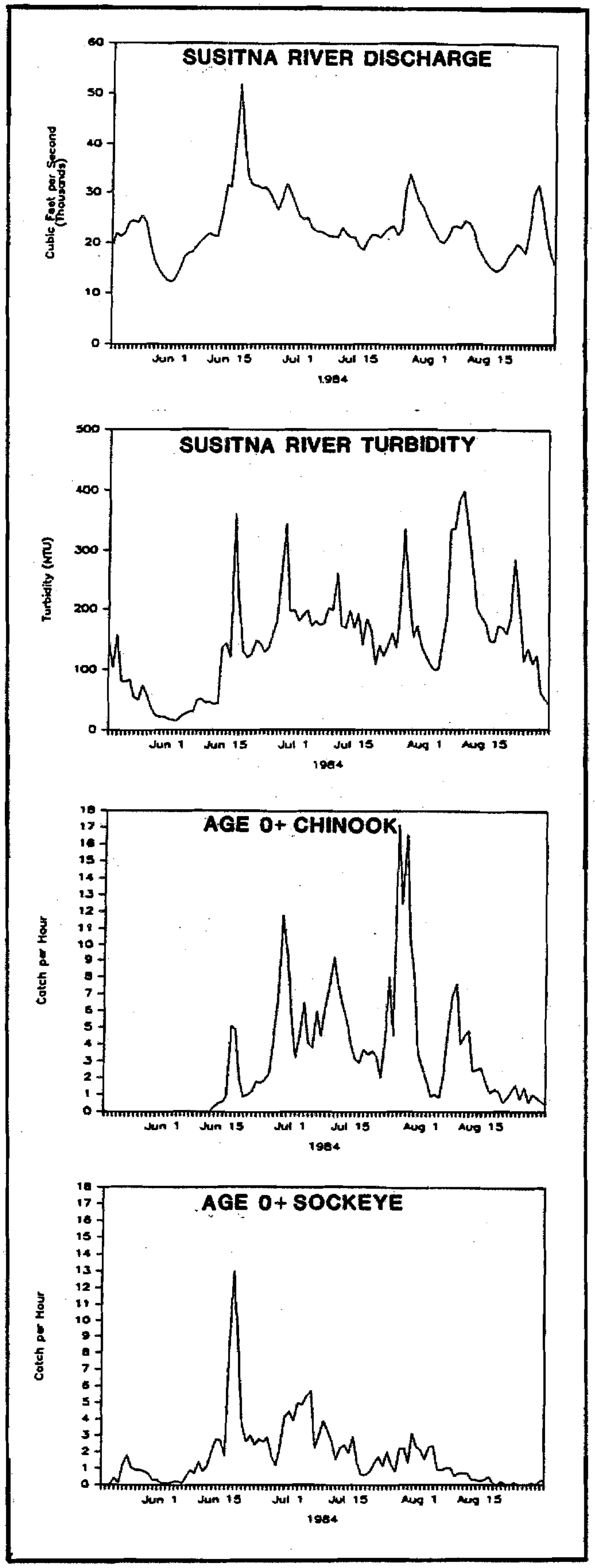


Figure 3. Discharge, turbidity, and chinook and sockeye salmon outmigration rate, 1984.

Insignificant components were removed from the model. The residuals were checked to see if there was significant departure from the assumption that they were white noise. If the residuals were white noise, the model was considered to be adequate. If not, a new model was identified and the process repeated until the residuals were reduced to a white noise process.

All of the time series work was done using the BMDP statistical package (Dixon et al. 1981). The BMDP Box-Jenkins program estimates parameters by both the conditional least squares method and the backcasting method. The estimates chosen for this paper were from whichever method gave the lowest residual mean square.

The time series of mean daily discharge from May 18 to August 30 appeared to be stationary so no differencing was done. A plot of the range of sub-groups of the series against the mean of the sub-groups (as suggested by Hoff (1983) indicated that a logarithmic transformation of the data would be helpful in stabilizing the magnitude of the fluctuations throughout the series; therefore, a model was also developed for the natural log of the raw data. As the turbidity time series was questionably stationary, models were developed for both the original series and for a differenced series.

Models were developed for the chinook and sockeye salmon outmigration rate time series on both the raw data and on data transformed by ln (x + 1). This transformation was used to avoid taking logarithms of zero; there was zero catch on some days.

2.3 Transfer Function Models

Transfer function models (see section 7.0) were developed for discharge/turbidity, discharge/chinook outmigration, and discharge/sockeye outmigration. Only one input (discharge) was used. Multiple input transfer function models (Liu and Hanssens 1980) or multivariate time series models (Mendelssohn 1982) can be developed, but are substantially more complex.

3.0 RESULTS

3.1. Univariate Model for Mean Daily Discharge

The time series of mean daily discharge during the summer of 1983 is shown in Fig. 4; the log-transformed data are in Fig. 6. Autocorrelation function (ACF) and partial autocorrelation function (PACF) plots for the raw data are given in Fig. 5 and for the log- transformed data in Fig. 7. In all the ACF and PACF plots, the "+" symbol on either side of the vertical axis indicates the 95% confidence interval. The first order autoregressive component was strong in both the raw and the transformed series. The ACF and PACF plots for the raw data indicated that a moving average component was required. Models containing various combinations of first and second order AR and MA terms were examined. Of the acceptable models identified, the model with the lowest standard errors on the parameter estimates and the least significant residuals was an ARMA(2,2). However, the ARMA(1,1) was nearly as good as the ARMA (2,2) so, in keeping with Box and Jenkins' (1976) advice that a parsimonious model (i.e., the one with the fewest possible parameters) is desirable, the ARMA(1,1) is considered the "best" model for the non-transformed data. Parameter estimates were:

$$\hat{\phi}_1 = .992 \text{ with std. error of } .0135$$

$$\hat{\theta}_1 = -.580 \text{ with std. error of } .0807$$

The model is:

$$y_t = 22.7 + .99\,(y_{t-1} - 22.7) - .58\,a_{t-1} + a_t$$

where: y_t is the discharge level at time t and

a_t is a white noise process at time t

Neither the mean nor any of the autocorrelations or partial autocorrelations of the residuals was significant; therefore, the model is considered to be adequate. This equation can be interpretted as: The discharge level for any given day is a function of (the mean level, 22.7 cfs, of discharge during the period) plus (most of the previous day's discharge level minus the mean level) minus (about half of the previous day's noise component) plus (the given day's noise component).

The plots of both the ACF and PACF on the residuals from this model showed a slightly significant spike at a lag of 15 or 16 days. This could indicate that the discharge time series has a periodicity of about 15 days, or slightly more than two weeks. This possibility was further examined by spectral analysis. The spectrum of discharge (Fig. 8) did in

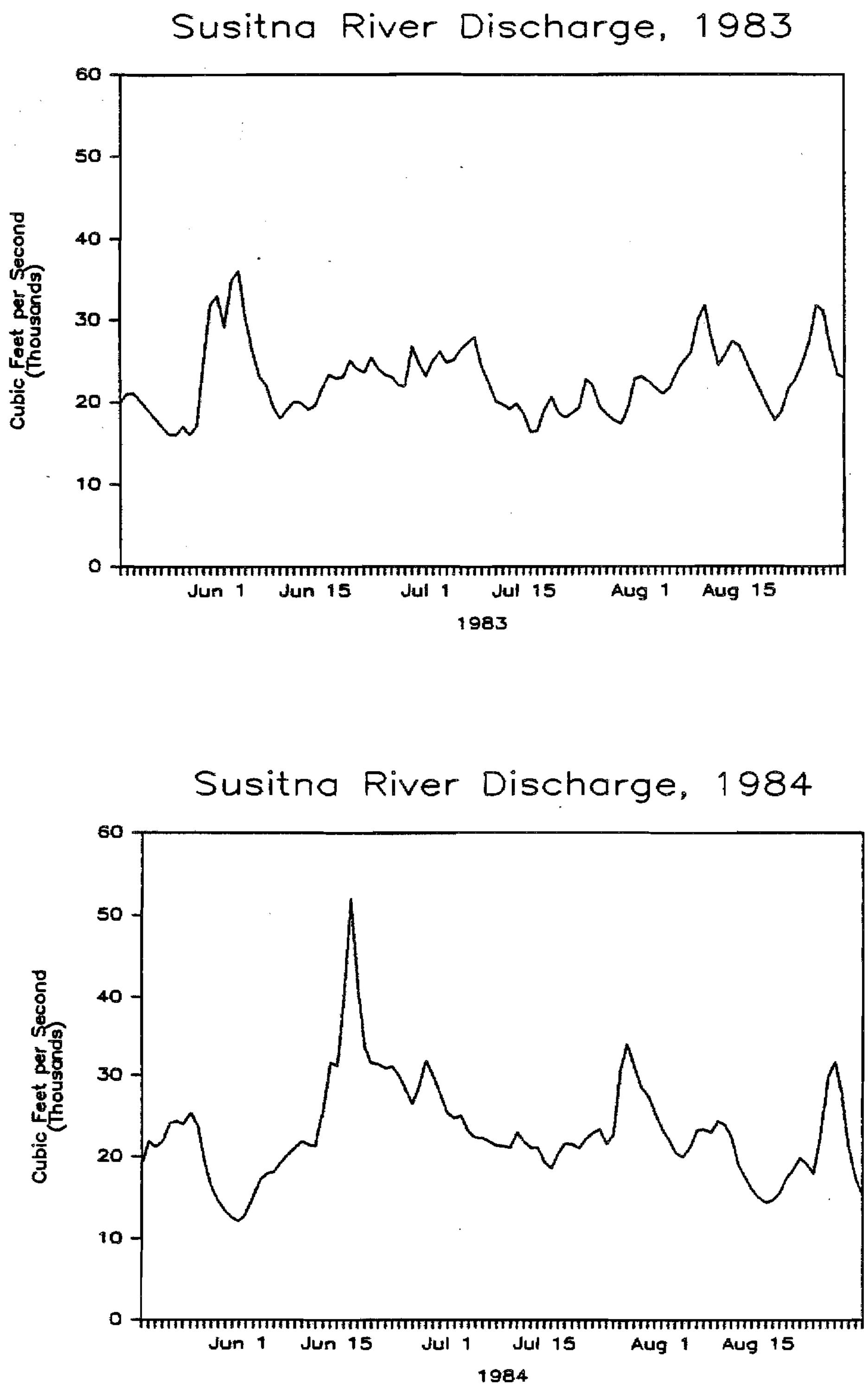
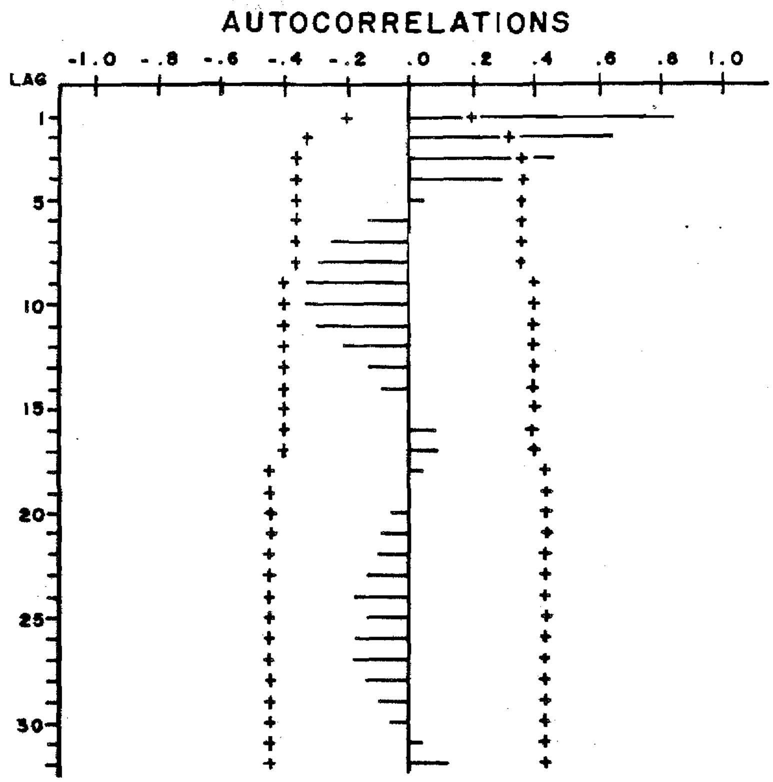


Figure 4. Susitna River discharge time series at the Gold Creek gaging station, 1983 and 1984.



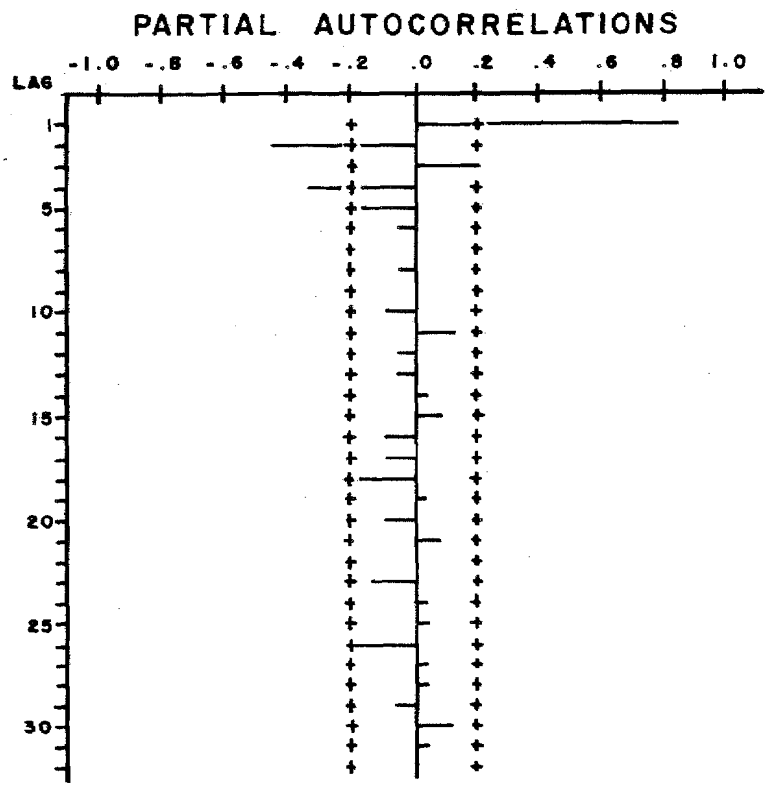


Figure 5. Plots of autocorrelations and partial autocorrelations for 1983 discharge time series.

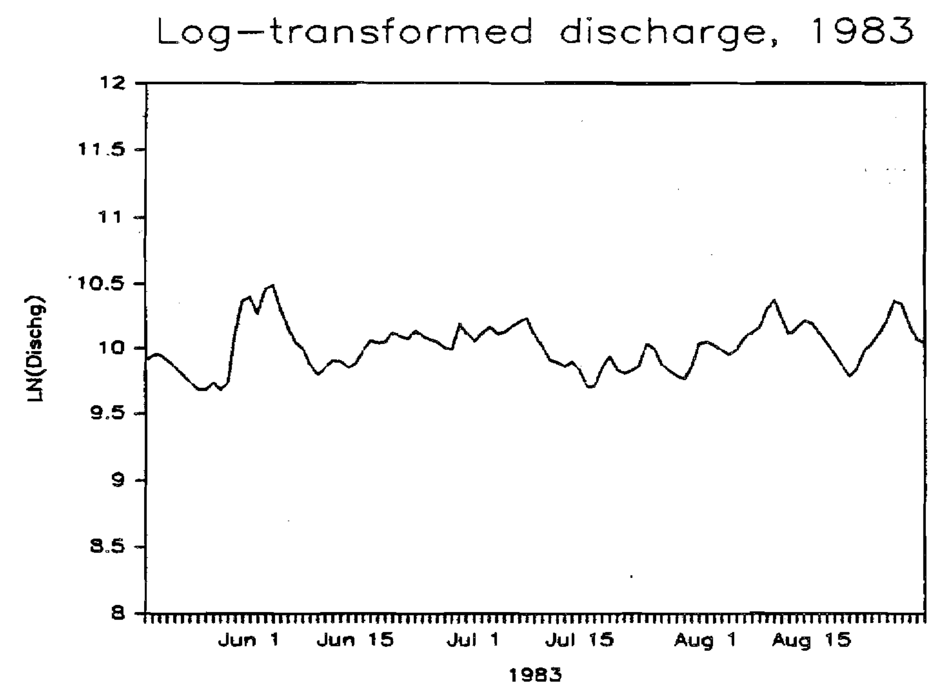


Figure 6. Log-transformed discharge time series, 1983 and 1984.

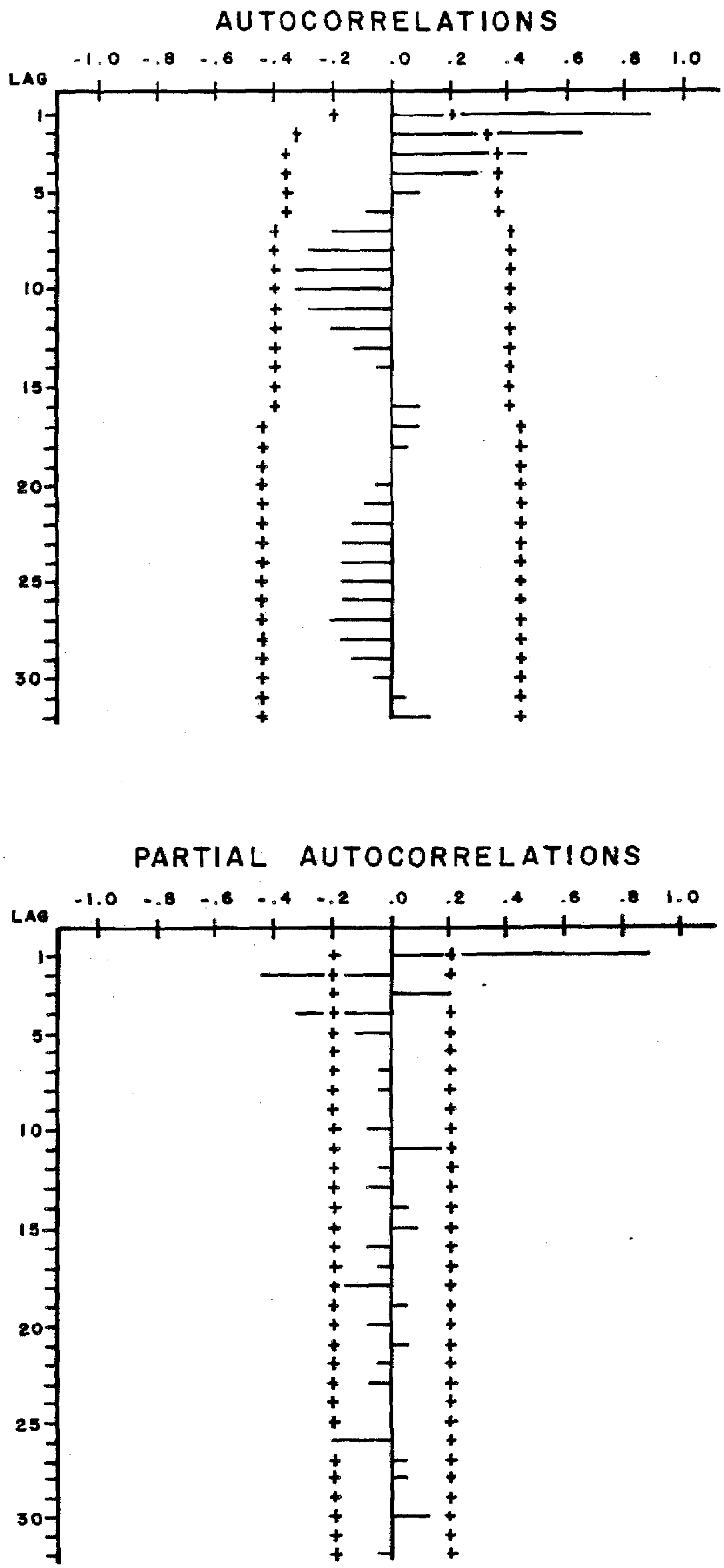


Figure 7. Plots of autocorrelations and partial autocorrelations for 1983 log-transformed discharge time series.

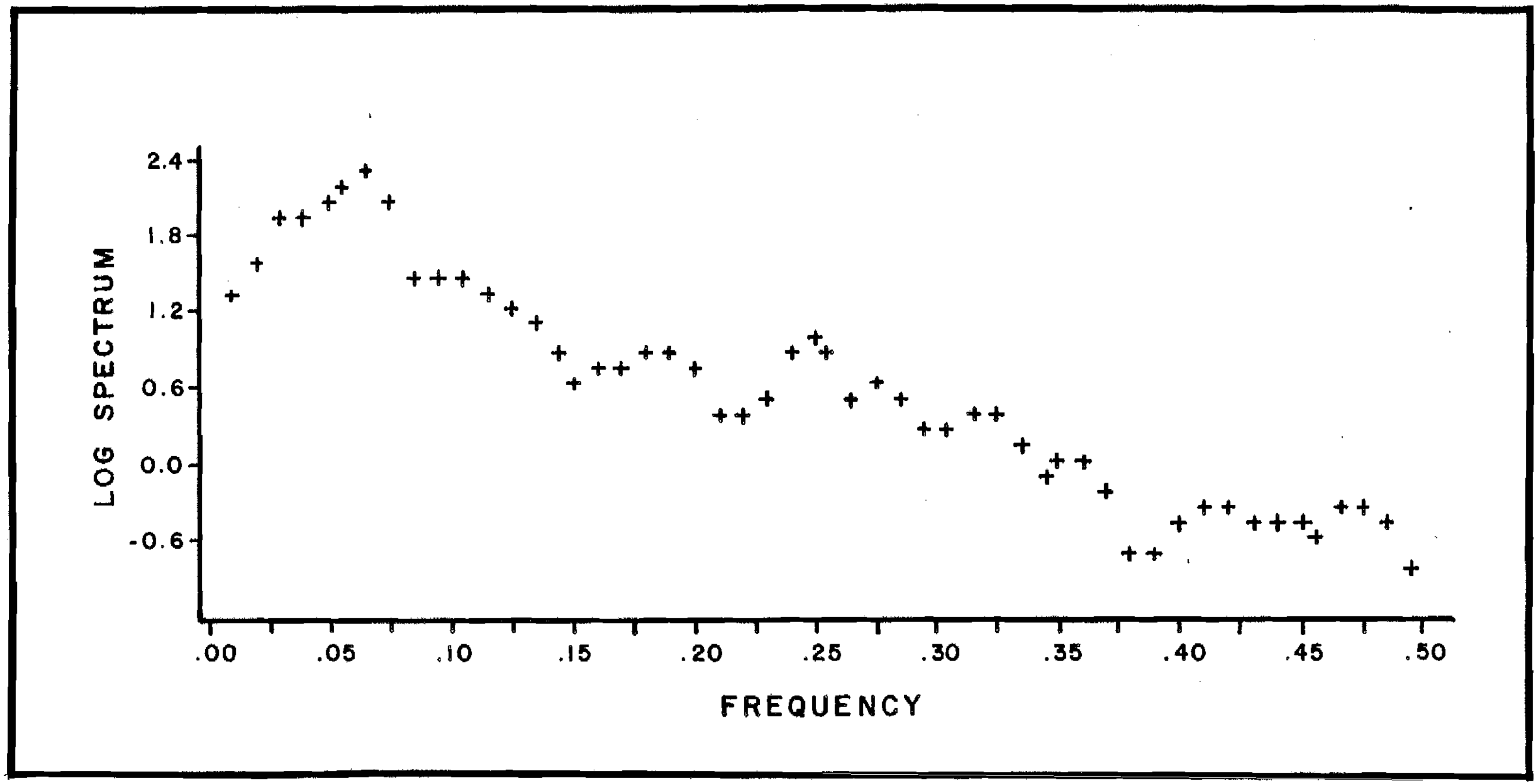


Figure 8. Spectrum of 1983 discharge time series.

fact indicate a peak at a frequency of .065 (a period of 15 days). It is not known at this time if this periodicity is "real". It may be related to weather patterns in the basin which control solar insolation (cloud cover) and rainfall. A much longer time series of discharge would have to be examined to answer this question. A periodic term could be added to the ARMA(1,1) model (Box and Jenkins 1976) but, given the low significance level of the periodicity, it does not seem appropriate at this stage of model development.

Carrying the idea of parsimony a step further, it can be seen that an ARMA(1,0) model using the log-transformed data is adequate and has the lowest number of parameters. The parameter estimates for this model were:

$$\hat{\phi}_1 = .994 \text{ with std. error of } < .00005$$

giving

$$\ln y_t = 10.0 + .99\,(\ln y_{t-1} - 10.0) + a_t$$

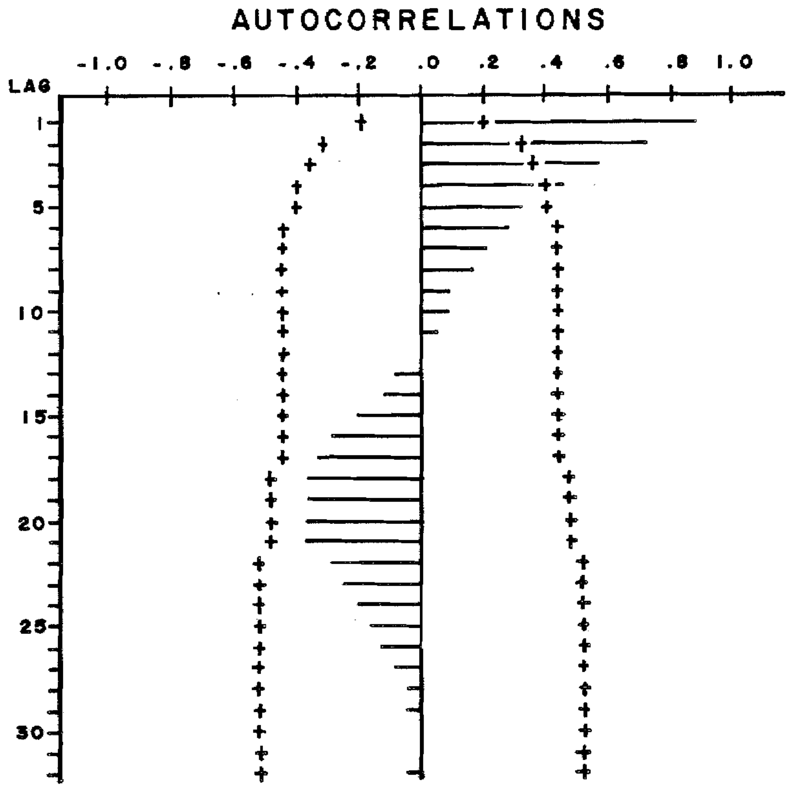
The parameter $\hat{\phi}_1$ was very close to unity. If $\hat{\phi}_1$ were equal to 1.000, the model would be reduced to a random walk model (Chatfield 1984). That is, the log of the discharge for today is the same as the log of the discharge for yesterday plus a random error term. When $\hat{\phi}_1$ approaches 1.000 in a model with only one AR term, the series could be non-stationary (Hoff 1983). To test this, the series was differenced. The residuals from an ARIMA(1,1,0) model showed significant spikes, so the differencing did not help; the ARIMA(1,0,0) model is better.

The AC's on the residuals of the ARMA(1,0) model were a little better than those of the ARMA(1,1) on the non-transformed data. However, the mean of the residuals was slightly significant, so the ARMA(1,1) model on the raw data is probably superior to this one.

The 1984 discharge time series is shown in Fig. 4 and Fig. 6. The ACF and PACF plots (Fig. 9) were similar to those of 1983. An ARMA(1,1) model on the 1984 raw data was adequate, as it was in 1983. Parameter estimates were: $\bar{y}$ = 23.2; $\hat{\phi}_1$ = .808 (std. error = .0638); and $\hat{\theta}_1$ = -.692 (std. error = .0750). An AR(1) model on the log-transformed data was also adequate but, again, had a slightly significant mean residual. The ACF and PACF plots, using log-transformed data (Fig. 10), were similar to those of 1983, but perhaps showed less indication of a moving average process. The estimate for $\hat{\phi}_1$ was .994 (exactly the same as the 1983 data), with a standard error of 0.0001, and the estimate for $\bar{y}$ was 10.0.

3.2. Univariate Model for Turbidity

The time series for turbidity in 1983 (Fig. 11) was more complex than that of discharge. The ACF and PACF plots (Fig. 12) indicated a strong AR(1) component. However, AR(1), AR(2), and ARMA(1,1) models were not adequate to explain the series.



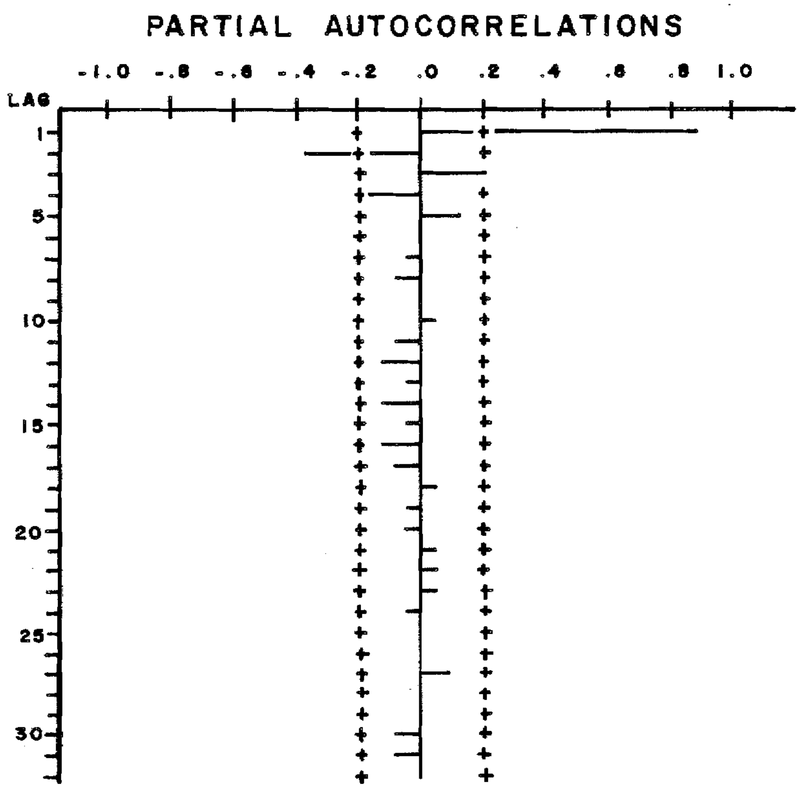
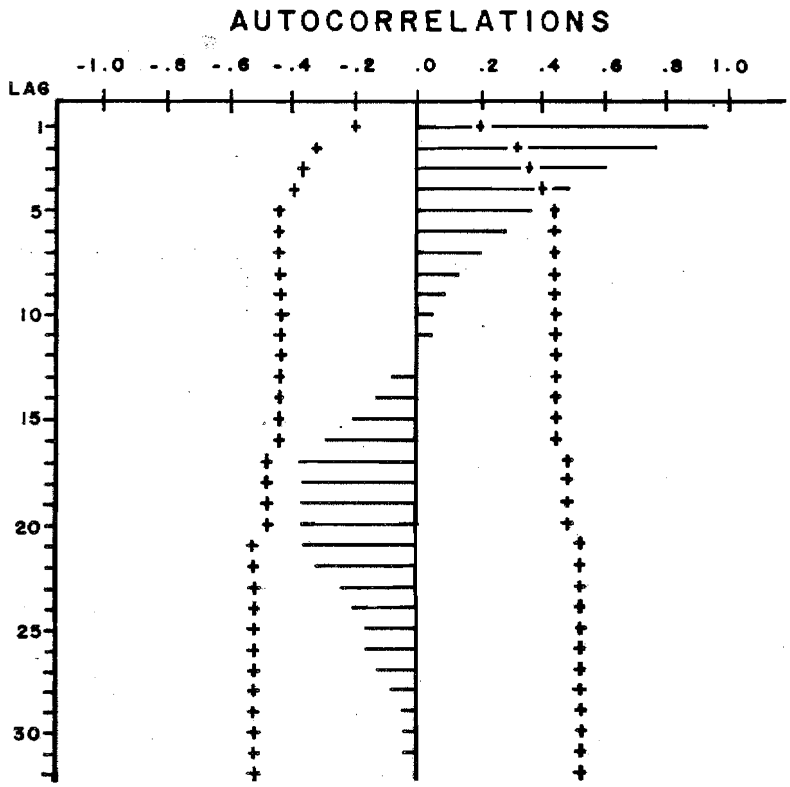


Figure 9. Plots of autocorrelations and partial autocorrelations for 1984 discharge time series.



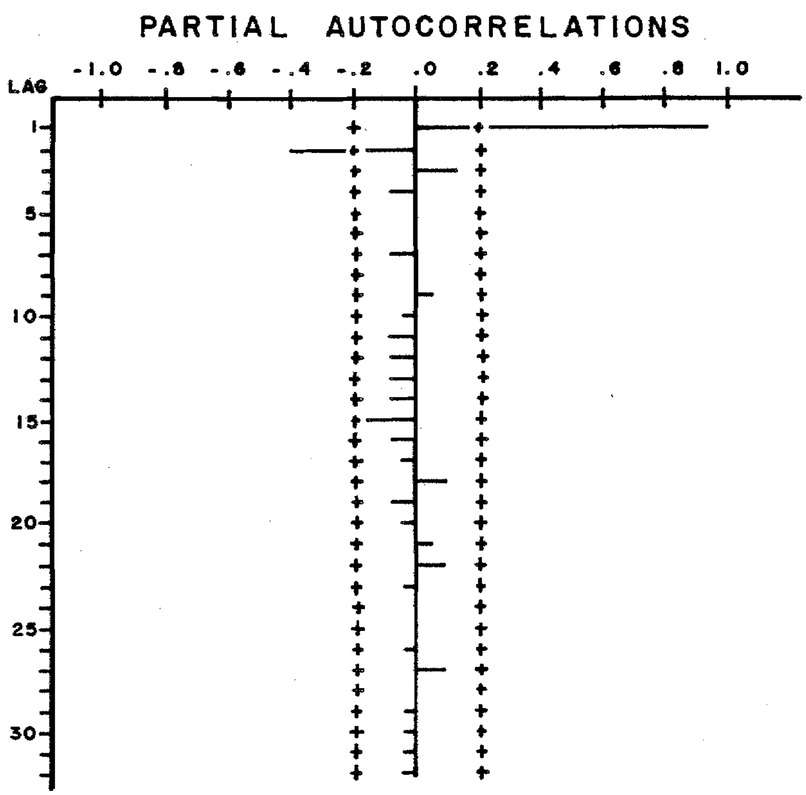


Figure 10. Plots of autocorrelations and partial autocorrelations for 1984 log-transformed discharge time series.

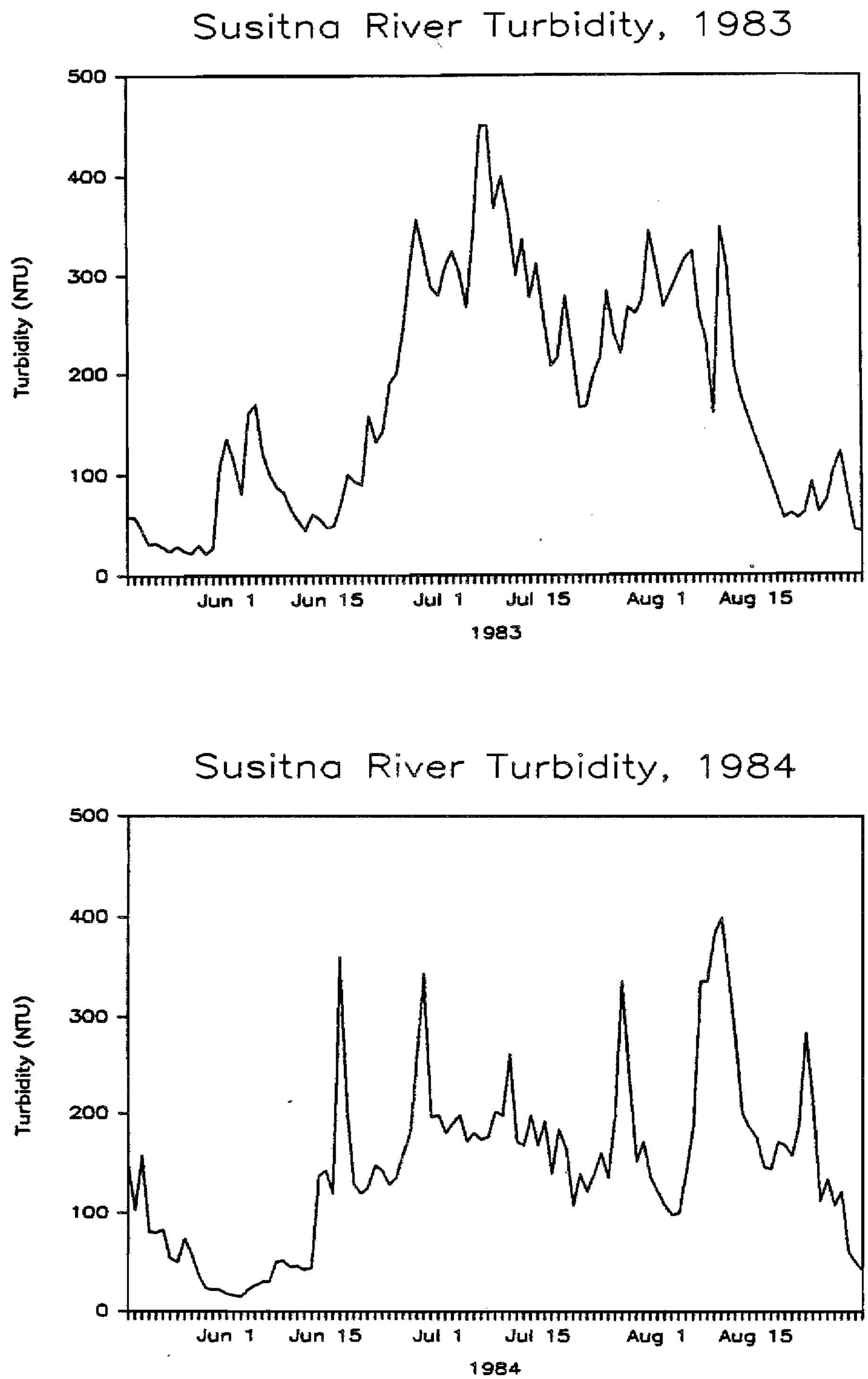


Figure 11. Turbidity time series at Talkeetna Station, 1983 and 1984.

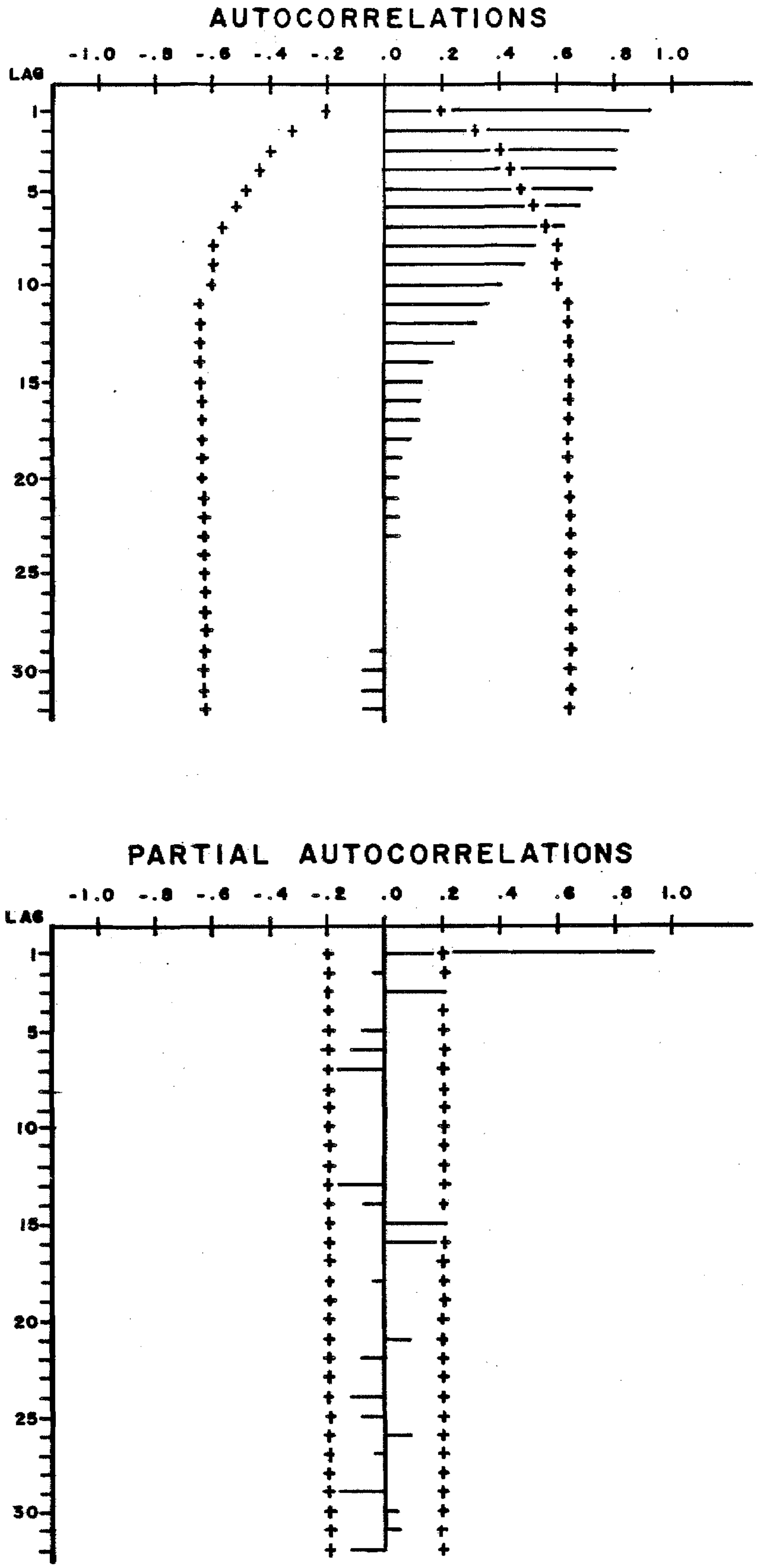


Figure 12. Plots of autocorrelations and partial autocorrelations for 1983 turbidity time series.

The series appears to border on being non-stationary because it increases in the spring as glacier melt increases and then declines in the fall. (This series would certainly be non-stationary over a longer time frame because the turbidity level is very low in the winter). The slow decay of the autocorrelations in the ACF (Fig. 12) also indicated non-stationarity.

Further investigation using the raw data showed that the series had a significant second order MA term, while the first order MA term was not significant. Both first and second order AR terms were significant. This gives the model:

$$y_t = 176.1 + .94(y_{t-1} - 176.1) + .06(y_{t-2} - 176.1)$$
$$+ .23\, a_{t-2} + a_t$$

with std. errors: on $\hat{\phi}_1$ = .0122

on $\hat{\phi}_2$ = .0234

on $\hat{\theta}_2$ = .0988

Note that even though the same notation is used, the white noise process (a_t) here is different from that in section 3.1.

While this ARMA model is adequate for the time frame examined, in general, an integrated model (i.e., one with a differencing operation) is probably more appropriate because of the suspected non-stationarity of the raw data. The differenced series (Fig. 13), which represents consecutive changes in the original series values, is clearly stationary with a mean close to zero. The ACF and PACF plots for the differenced series (Fig. 14) showed that the differenced series could be adequately modeled with just the second order MA term; the first order autoregression term was not significant in the differenced series. The equation is:

$$Z_t = .23\, a_{t-2} + a_t$$

$$\text{where: } Z_t = y_t - y_{t-1}$$

with std. error on $\hat{\theta}_2$ = .0972 and the mean of the residuals insignificant.

3.3. Univariate Model for Age 0+ Chinook Salmon Outmigration

The time frame chosen for Age 0+ chinook salmon was the same as that of discharge (Fig. 15). The plots of the ACF and the PACF for 1983 (Fig. 16) showed a strong first order autoregresssive component. In fact, an ARMA(1,0) model, abbreviated as AR(1), adequately represents the data. Although the plot of the range of sub-groups against the mean of the

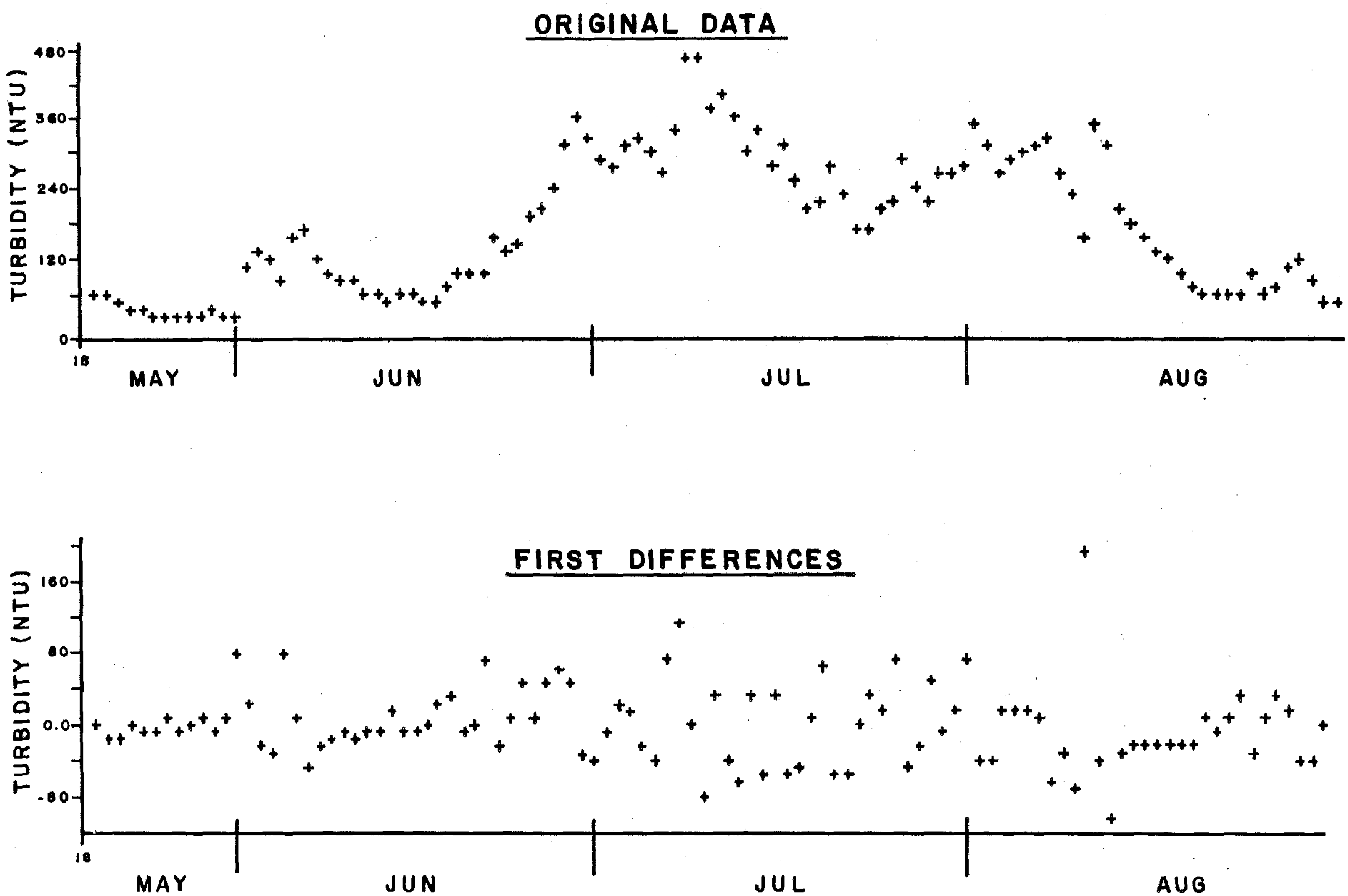
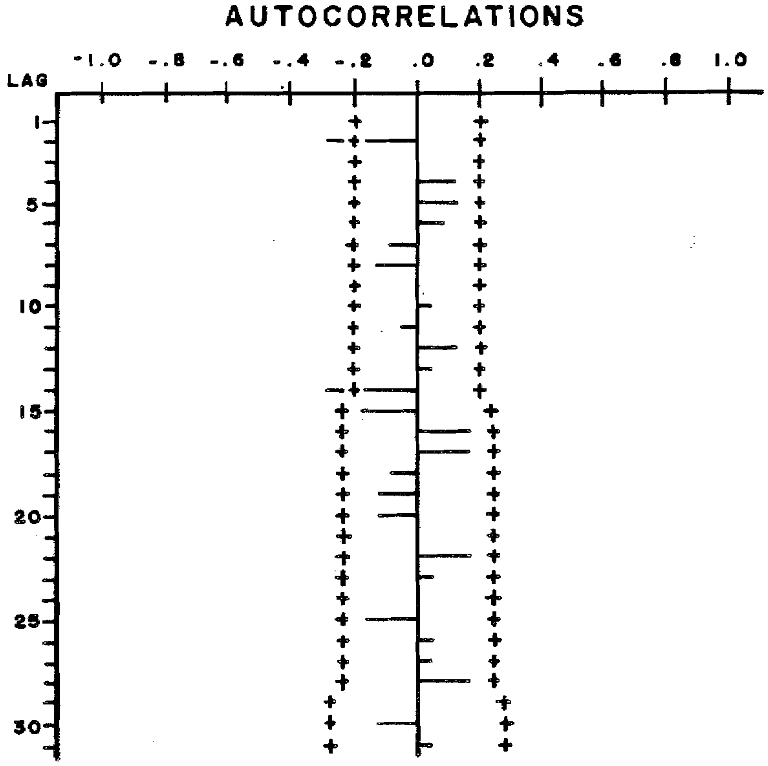


Figure 13. Differenced turbidity time series, 1983.



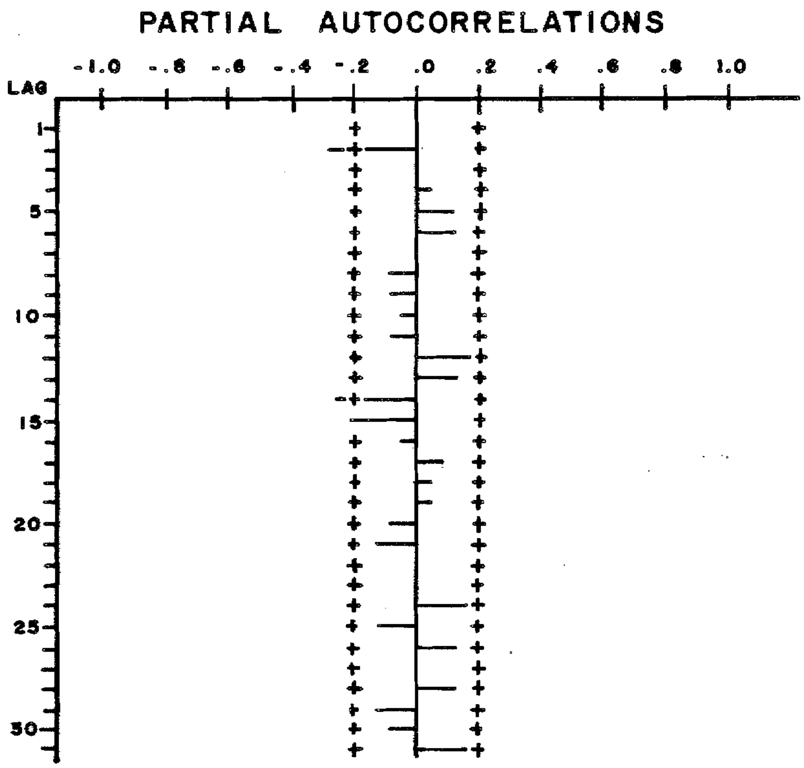


Figure 14. Plots of autocorrelations and partial autocorrelations for differenced 1983 turbidity time series.

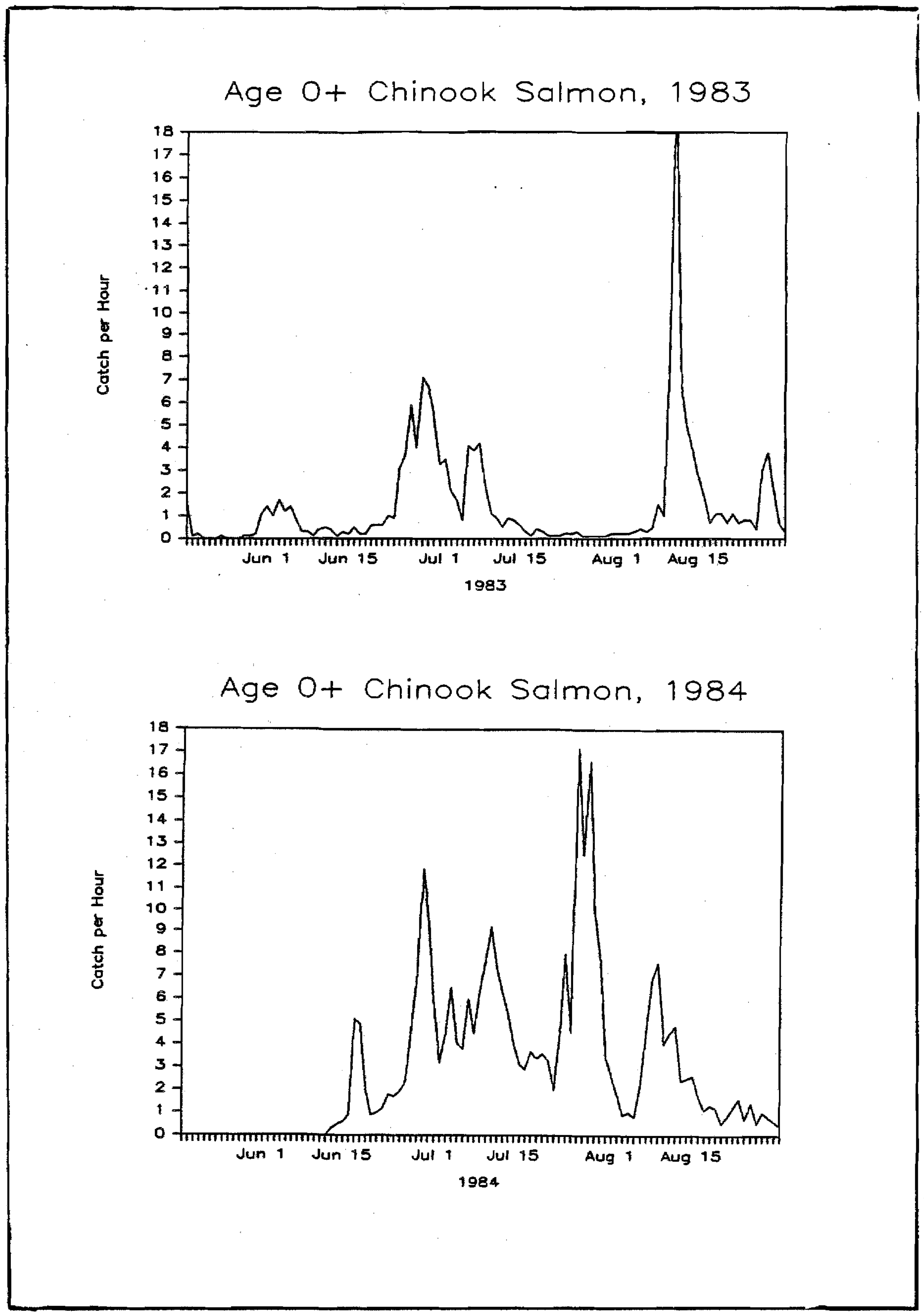
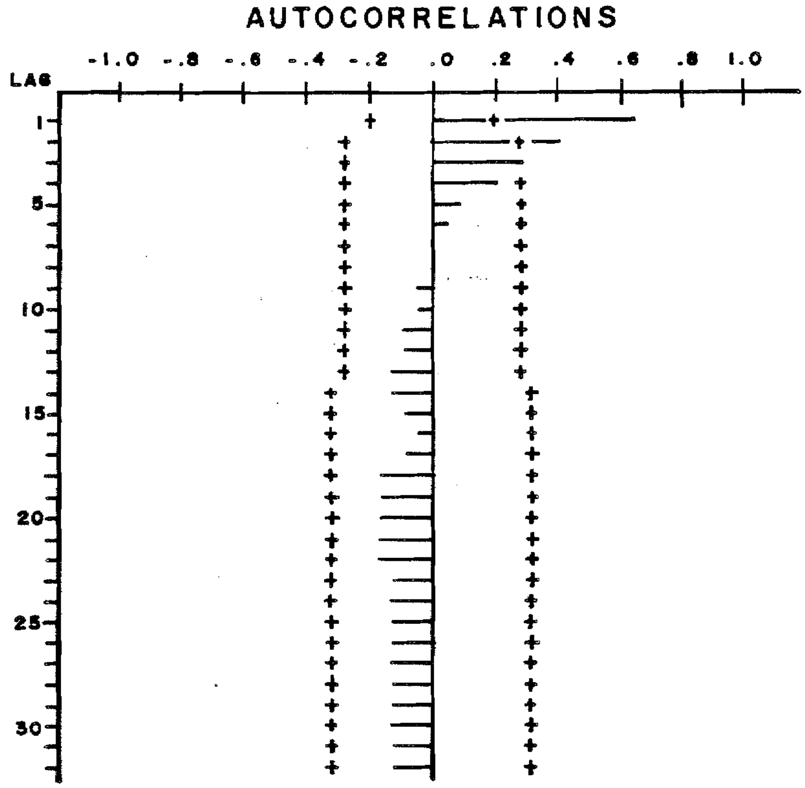


Figure 15. Age 0+ chinook salmon outmigration rate time series, 1983 and 1984.



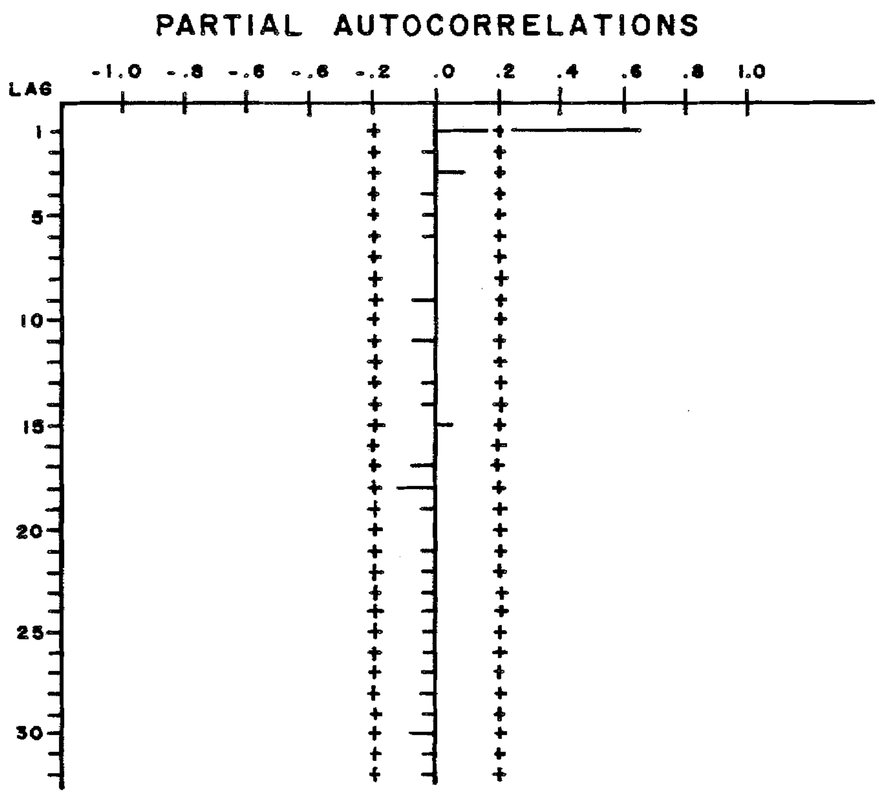


Figure 16. Plots of autocorrelations and partial autocorrelations for 1983 chinook salmon outmigration time series.

sub-groups indicated the need for a logarithmic transformation, the residual AC's of an AR(1) model on the log- transformed data (Fig. 17) were slightly larger (but still insignificant) than those of the AR(1) model on the raw data. The standard error on $\hat{\phi}_1$, however, was lower with the log-transformed data. ACF and PACF plots for the log-transformed data are shown in Fig. 18. The AR(1) model for the raw data is:

$$y_t = 1.52 + .66\,(y_{t-1} - 1.52) + a_t$$

with standard error on $\hat{\phi}_1$ = .0743.

The AR(1) model for the log-transformed data is:

$$\ln(y_t + 1) = .67 + .92\,(\ln(y_{t-1} + 1) - .67) + a_t$$

with standard error on $\hat{\phi}_1$ = .0363.

The mean of the residuals was not significant.

The time series plot for age 0+ chinook salmon outmigration in 1984 (Fig. 15) shows a different pattern from that of 1983. The fry did not begin to migrate in 1984 until about June 12. The low level of outmigration early in the season causes a time series which is non-stationary. To avoid this problem, the time frame selected for 1984 ran from June 12 to August 31 (79 cases). Analysis of this shorter series is not as strong as that of the longer series in 1983 but the series is long enough from a statistical point of view; Hoff (1983) suggests that about 40 or 50 observations is the minimum necessary for attempting an ARIMA model. Although logarithmic transformation did not appear to be strictly necessary for the 1983 data, it was required (to produce an AR(1) model) with the 1984 data, perhaps because of the shorter time series in 1984.

The ACF plot for 1984 on the log-transformed data (Fig. 19) was similar to that of 1983, although it did decay a little more quickly. The 1984 PACF plot (Fig. 19) was very similar to that of 1983 in indicating a strong AR(1) component. The estimated value of ϕ_1 in 1984 was 0.973 (very close to that of 1983), with a standard error of 0.0265. The 1984 model is:

$$\ln(y_t + 1) = 1.39 + .97\,(\ln(y_{t-1} + 1) - 1.39) + a_t$$

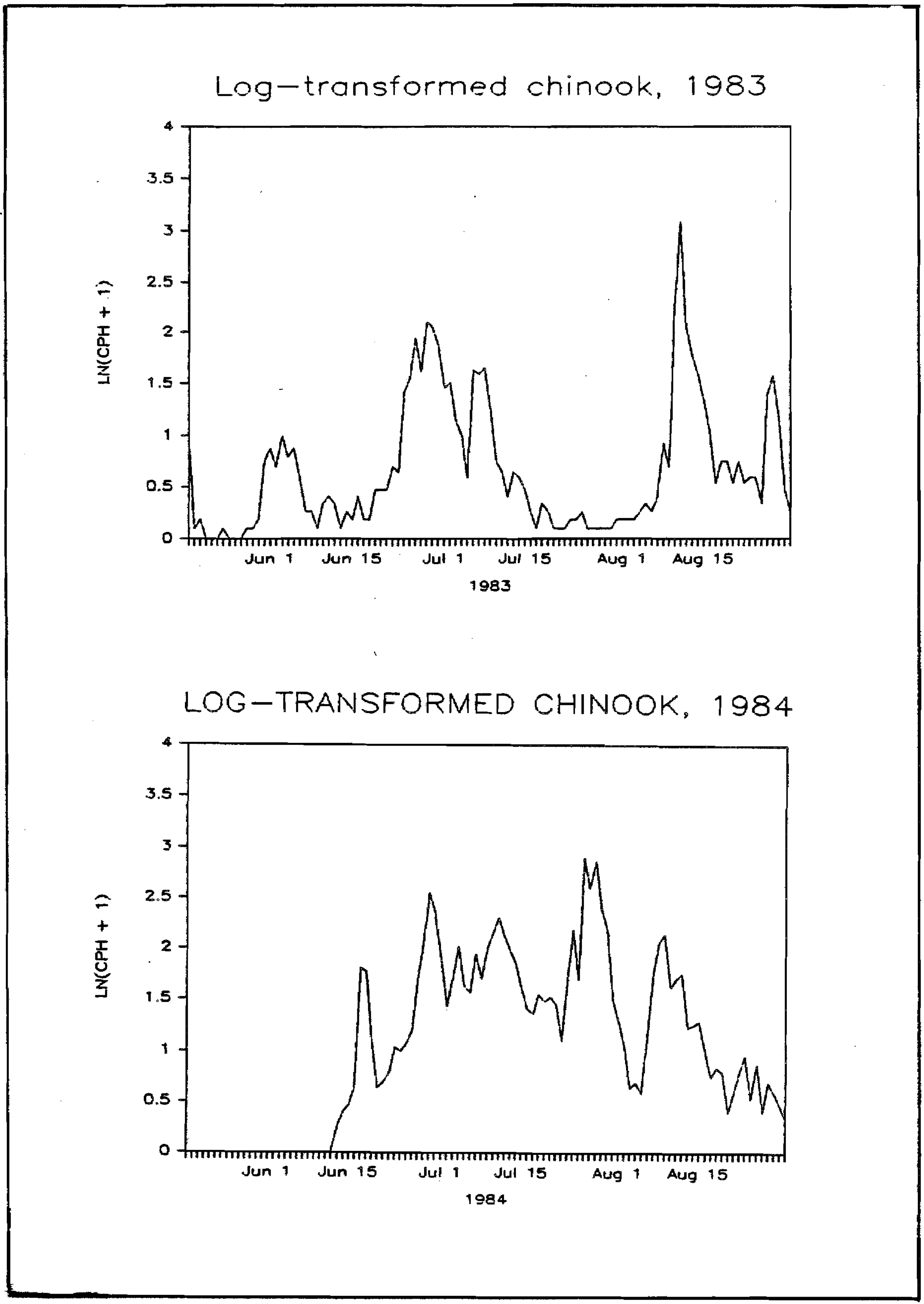
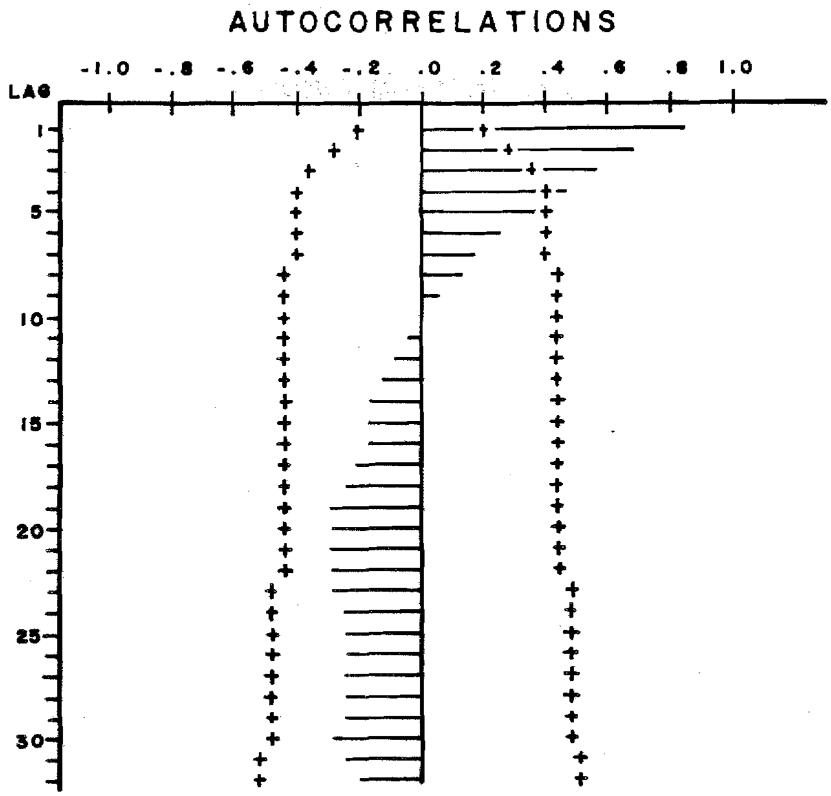


Figure 17. Log-transformed age 0+ chinook salmon outmigration rate, 1983 and 1984.



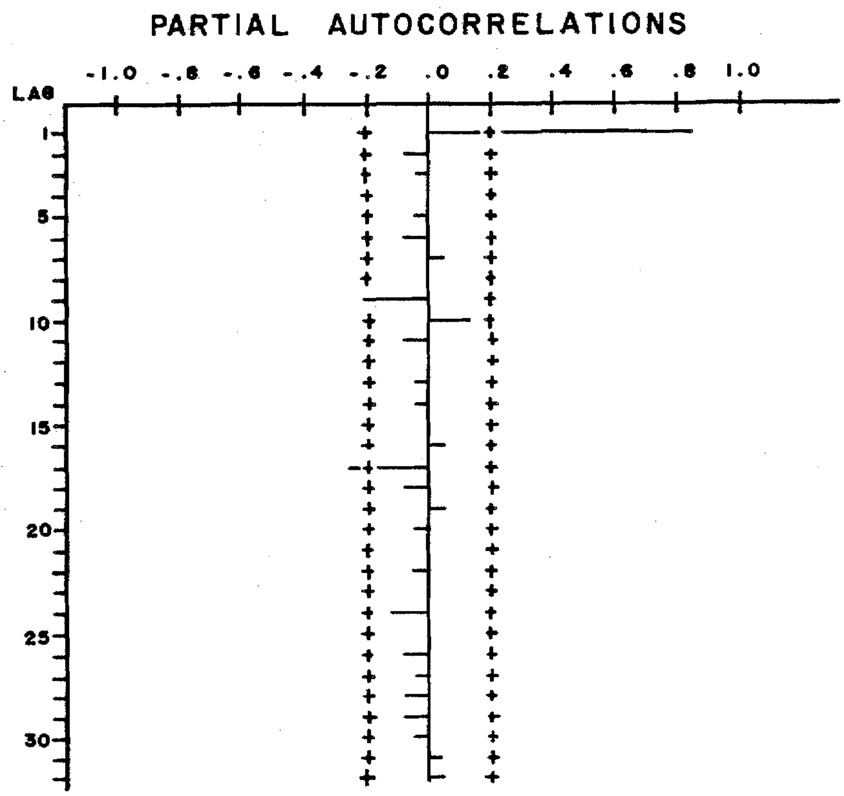


Figure 18. Plots of autocorrelations and partial autocorrelations for log-transformed 1983 chinook salmon outmigration time series.

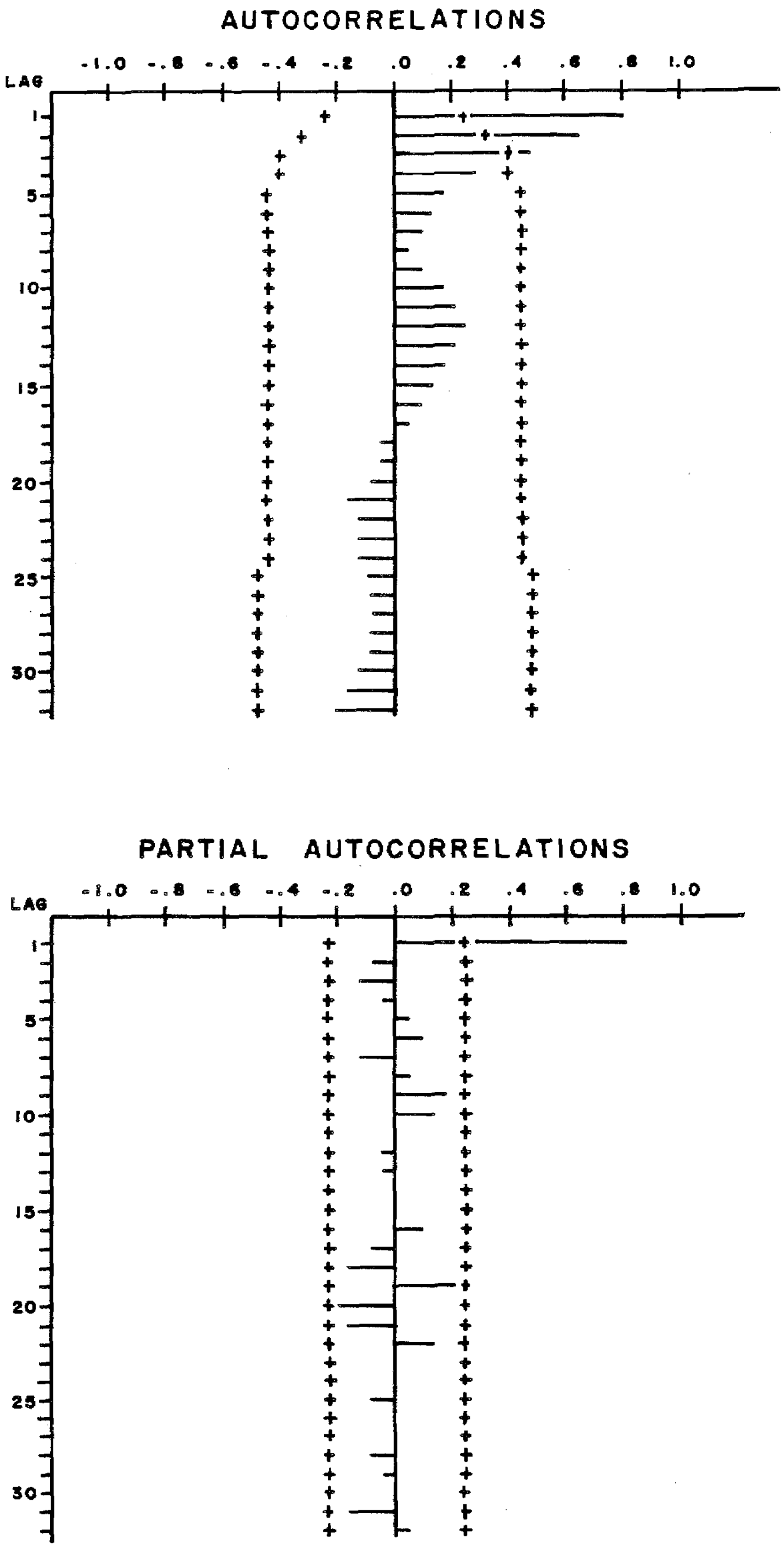


Figure 19. Plots of autocorrelations and partial autocorrelations for log-transformed 1984 chinook salmon outmigration time series.

The mean of the residuals was insignificant. This model does not differ from that of 1983, except that the mean level was higher. This was a result of a higher escapement of adult chinook salmon in 1983 than in 1982.

All three of the ACF plots for chinook fry outmigration (Figs. 16, 18, and 19) had AC's after lag 18 which did not appear to decay further. This may indicate the presence of a weak non-stationary or periodic element which should be explored with subsequent data sets.

3.4. Univariate Model for Age 0+ Sockeye Salmon Outmigration

Age 0+ sockeye salmon outmigration was examined from May 23 through August 31, 1984 (Fig. 20). This time series showed a strong AR(1) component (Fig. 21), similar to that of the chinook salmon time series. However, neither an AR(1) model on the raw data or on the log-transformed data was adequate. A MA(1) component was also significant in the raw data, leading to the model:

$$y_t = 1.76 + .78\,(y_{t-1} - 1.76) - .57\,a_{t-1} + a_t$$

The standard error on $\hat{\phi}_1$ (.775) was .0681 and on $\hat{\theta}_1$ (-.567) was .0883. Although the mean of the residuals was slightly significant, none of the autocorrelations or partial autocorrelations were, so the model is reasonable.

3.5. Discharge-Turbidity Transfer Function Model

The cross correlations for the residuals from the 1983 discharge series and the 1983 turbidity series, both filtered by the ARMA(1,1) model for discharge, had a significant spike at lag = 1 day (Fig. 22). This suggested a candidate model (Box and Jenkins 1976; McCleary and Hay 1980):

$$y_t = \frac{\omega_0 B}{1 - \delta_1 B} x_t + N_t$$

where: y_t is the output series (turbidity)

ω_0 and δ_1 are transfer function parameters

B is the backward shift operator

x_t is the input series (discharge)

N_t is the noise component, an ARIMA model

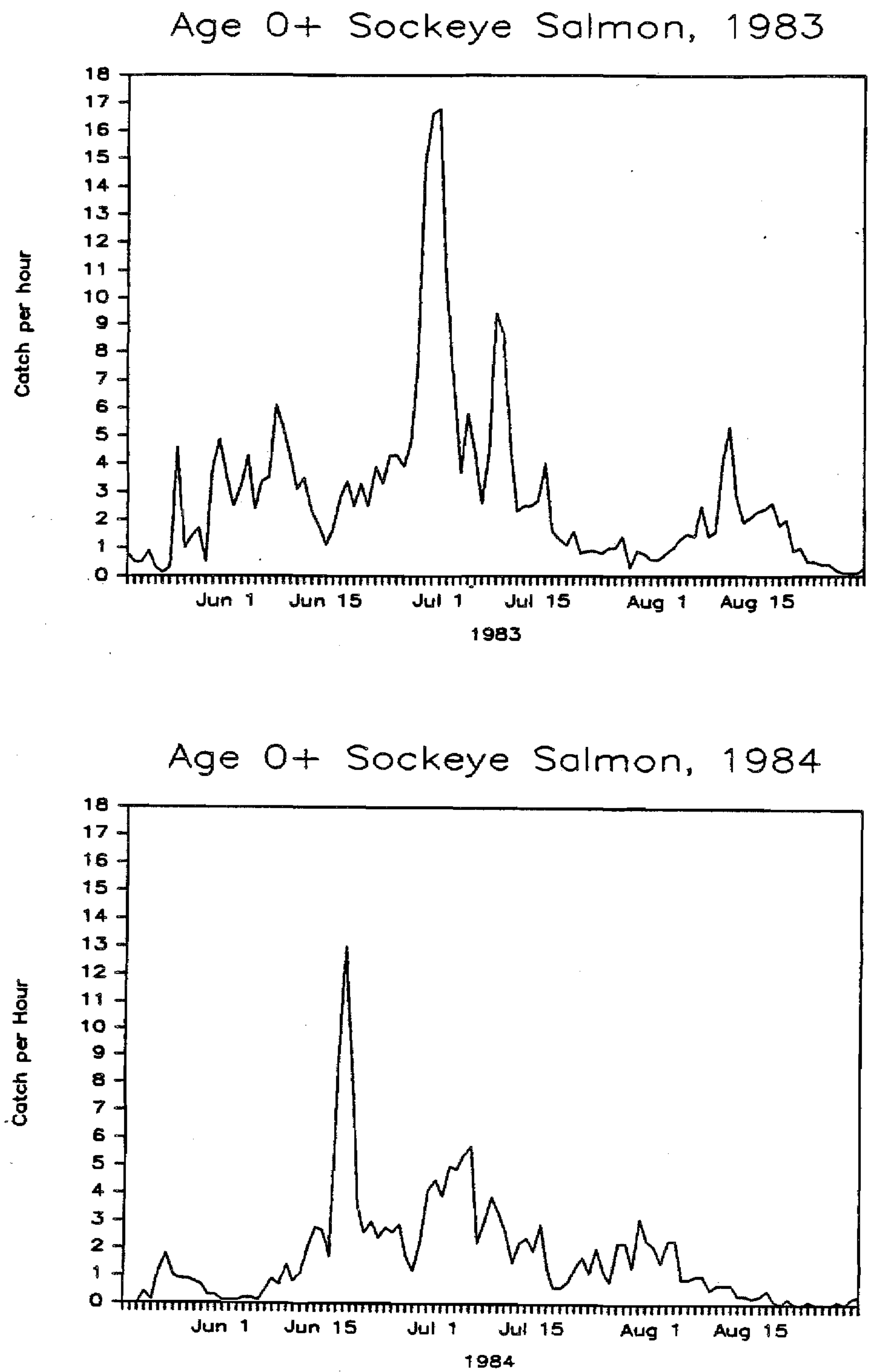
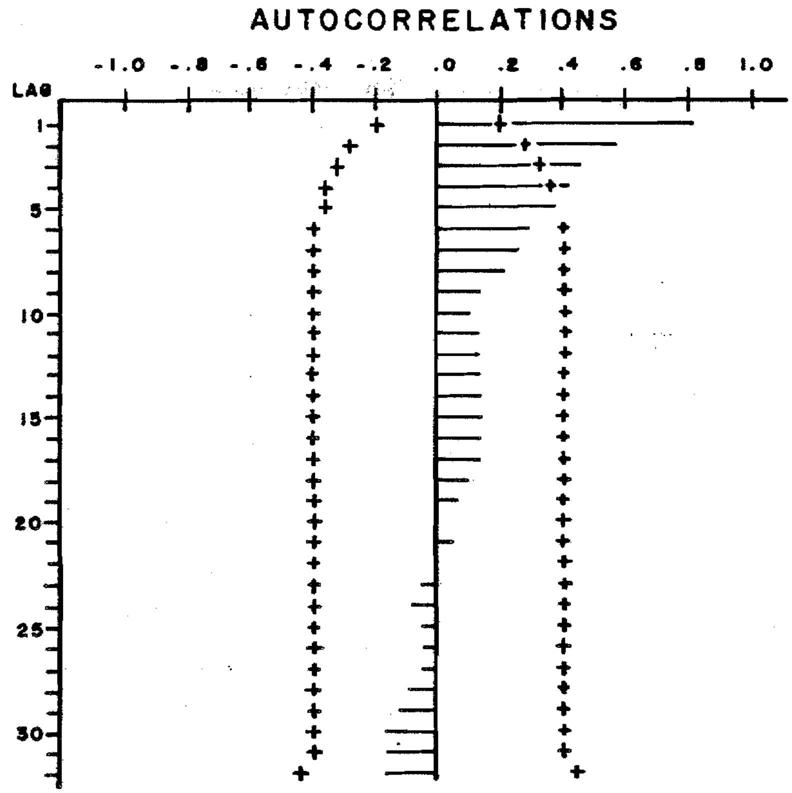


Figure 20. Age 0+ sockeye salmon outmigration rate time series, 1983 and 1984.



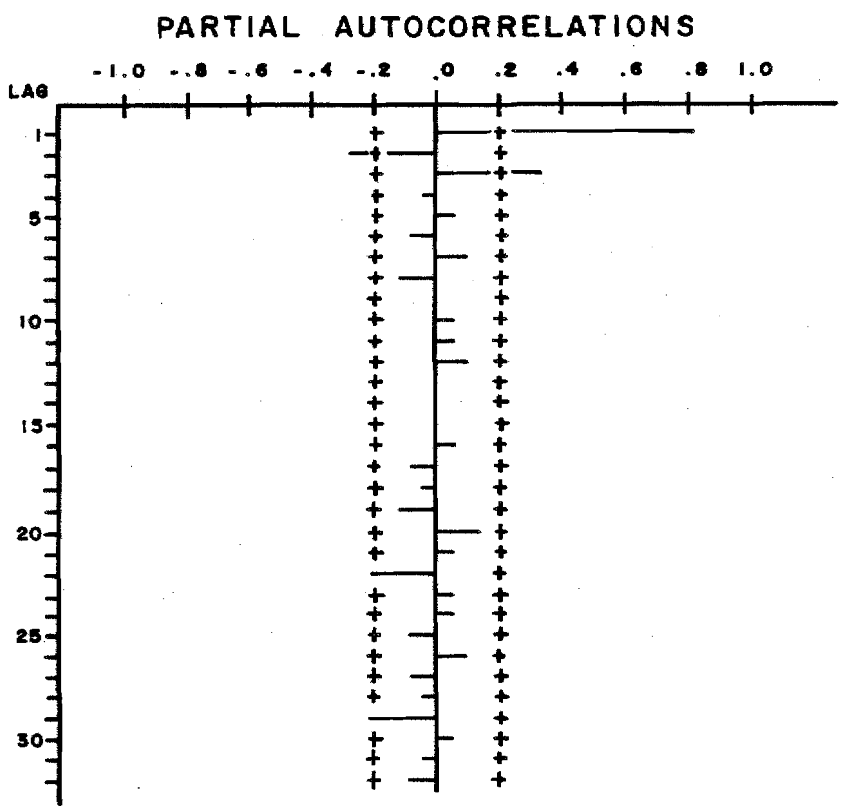


Figure 21. Plots of autocorrelations and partial autocorrelations for 1984 sockeye salmon outmigration time series.

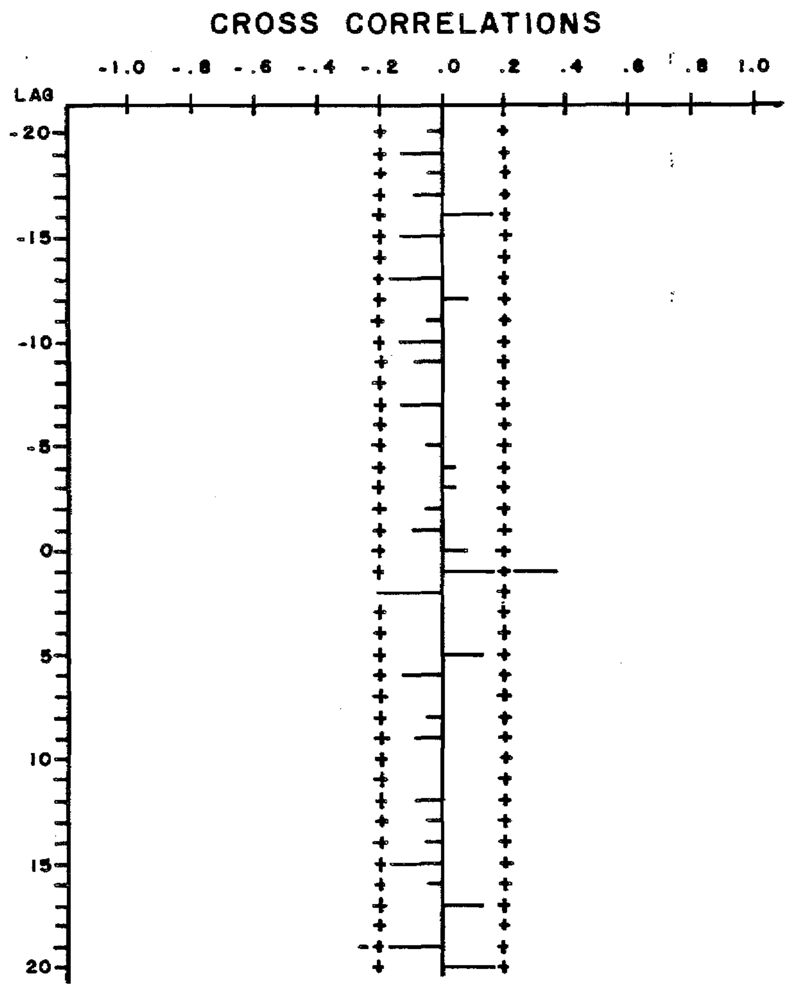


Figure 22. Plot of cross correlations between the residuals of the ARMA (1,1) discharge model and the prewhitened turbidity time series, 1983 data.

The assumption that the ARIMA component of the model was white noise led to significant AC's in the residuals series and was therefore rejected. The ACF and PACF plots on the residuals from this model suggested an AR(1) model for the N_t component, leading to the full model:

$$y_t = \frac{\omega_0 B}{1 - \delta_1 B} x_t + \frac{a_t}{1 - \phi_1 B}$$

Parameter estimates were:

$\hat{\omega}_0$ = 8.349 with std. error of 1.7044

$\hat{\delta}_1$ = -0.559 with std. error of 0.1718

$\hat{\phi}_1$ = 0.993 with std. error of 0.0009

The t statistic for each of these estimates was significant, leading to the conclusion that discharge and turbidity are related by the equation:

$$y_t = \frac{8.35 B}{1 + .56 B} x_t + \frac{a_t}{1 - .99 B}$$

The ACF and PACF plots on the residuals from this model showed no significant spikes; therefore, the model is adequate.

3.6. Discharge-Chinook Transfer Function Model

After both the input series (discharge) and the output series (chinook salmon outmigration rate) from 1983 were filtered by the ARMA(1,1) model for the discharge series and the residuals from both series were cross correlated, there was a significant correlation at lag = 1 day (Fig. 23). This suggested the transfer function model, as given by McCleary and Hay (1980):

$$y_t = \omega_0 x_{t-1} + N_t$$

or, using the backward shift notation of Box and Jenkins (1976):

$$y_t = \omega_0 B x_t + N_t$$

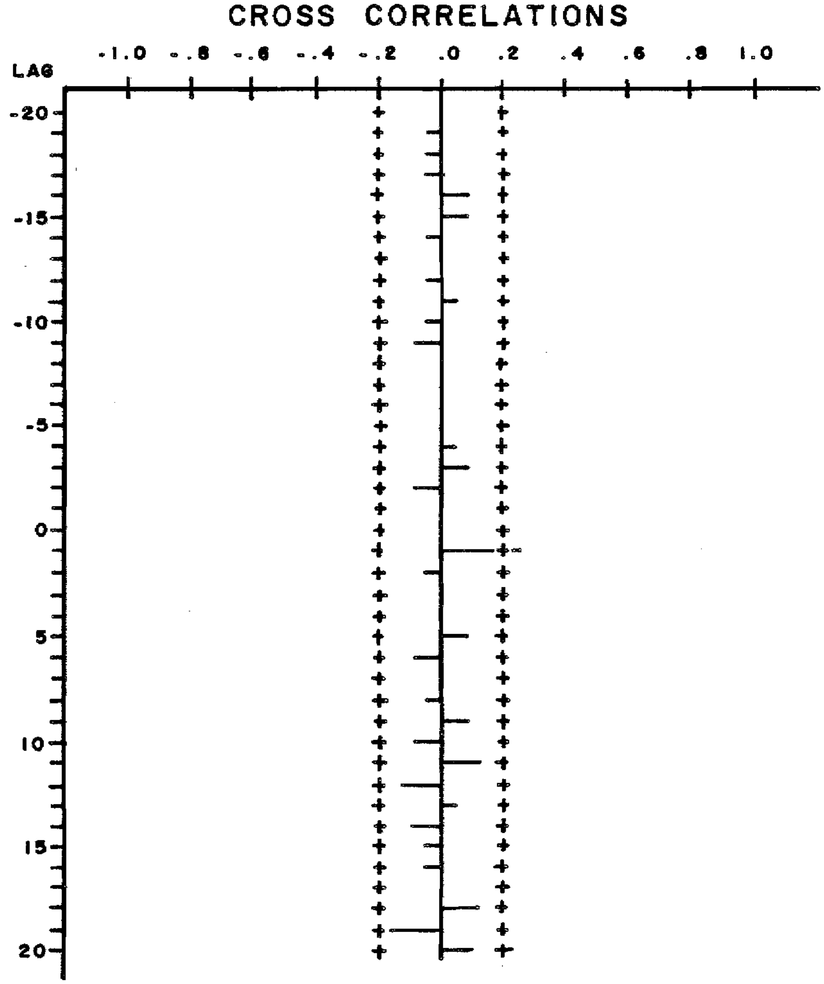


Figure 23. Plot of cross correlations between the residuals of the ARMA (1,1) discharge model and the prewhitened chinook salmon outmigration time series, 1983 data.

This model implies that the current day's discharge rate has an effect on the next day's outmigration rate. The estimate of ω_0 was 0.02. The residual ACF using this model suggested that the assumption of white noise for the N_t component was not valid; it appeared that an ARMA(1,0) model would be appropriate. The full model is:

$$y_t = \omega_0 B x_t + \frac{a_t}{1 - \phi_1 B}$$

The parameters for this model were estimated as:

$\hat{\omega}_0$ = .025 with std. error of .0249

$\hat{\phi}_1$ = .667 with std. error of .0751

The t statistic on the estimate for ω_0 was not significant. However, because the practice of prewhitening the output series with the model for the input series tends to underestimate the significance of the results (Botsford et al. 1982) and because there was a significant cross correlation between discharge and outmigration rate at a lag of one day, it seemed best to leave this term in the model. This would have to be verified with more years of data. The model is:

$$y_t = .025\, B(x_t) + \frac{a_t}{1 - .67 B}$$

The ACF and PACF for the residuals from this model showed no significant spikes so we may conclude that the model is adequate.

This model does not imply that the discharge series is a strong predictor for the outmigration series. But adding discharge does result in an expression which has more predictive value than would be obtained by looking at the outmigration series by itself.

3.7. Discharge-Sockeye Transfer Function Model

As with the discharge-chinook relationship, the cross-correlations of the 1984 discharge and sockeye series, filtered by an ARMA(1,1) model for discharge, showed a significant spike when the sockeye series was lagged one day behind the discharge series (Fig. 24). This spike was stronger for sockeye than it was for chinook. A candidate model (Box and Jenkins 1976; McCleary and Hay 1980) was:

$$y_t = \frac{\omega_0 B}{1 - \delta_1 B} x_t + N_t$$

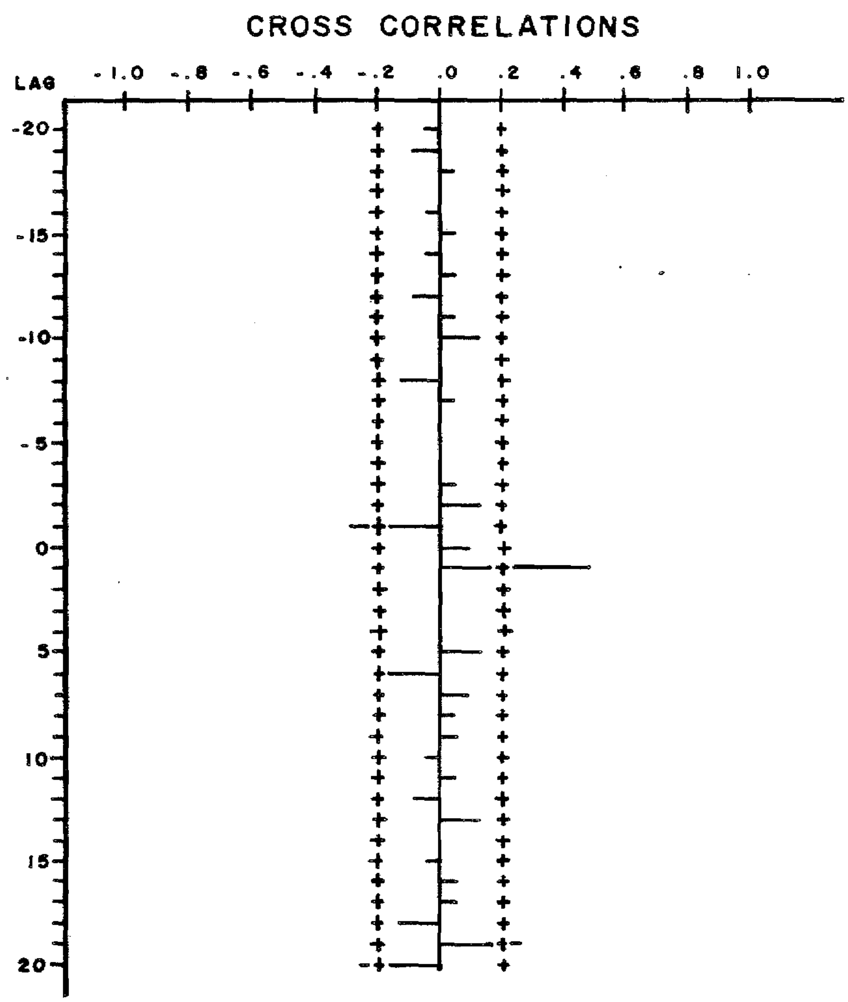


Figure 24. Plot of cross correlations between the residuals of the ARMA (1,1) discharge model and the prewhitened sockeye salmon outmigration time series, 1984 data.

The ACF and PACF plots on the residuals from this model suggested an ARMA(1,1) model for the N_t component, leading to the full model:

$$y_t = \frac{\omega_0 B}{1 - \delta_1 B} x_t + \frac{(1 - \theta_1 B)}{(1 - \phi_1 B)} a_t$$

Parameter estimates were:

$\hat{\omega}_0$ = .206 with std. error < .00005

$\hat{\delta}_1$ = -.190 with std. error .1848

$\hat{\phi}_1$ = .952 with std. error .0483

$\hat{\theta}_1$ = -.318 with std. error .1078

The t statistic for each of these estimates except $\hat{\delta}_1$ was significant, giving:

$$y_t = .21 B (x_t) + \frac{(1 + .32 B)}{(1 - .95 B)} a_t$$

where x_t = discharge X 10^{-3}

The ACF and PACF plots on the residual series from this model showed no significant spikes and the mean of the residuals was barely significant; therefore, the model is deemed adequate.

4.0 DISCUSSION

Time series analysis is a useful method for dealing with time ordered data sets, including ones that do not appear to make much sense at first glance because they are too noisy or because they drift as a result of random events. The modeling effort helps us to understand why the plots look as they do and what factors shape them. It also is useful in trying to understand what effect a change in the controlling factors might produce.

The influence of discharge level on turbidity and chinook and sockeye salmon outmigration is clearly seen upon inspection of Fig. 2 and Fig. 3. Of course, these latter three series are shaped by several factors other than discharge, so the correlation coefficient between them and discharge is not normally expected to be high, unless a relatively short section is examined. For example, the discharge peak in early June of 1983 is reflected in the other three series (Fig. 2). The bimodal discharge peak in August of 1983 is reflected in the turbidity and the chinook outmigration series, but only the first August peak is shown by the sockeye outmigration series. This was because most age 0+ sockeye salmon in the reach above the traps had left by the middle of August. Similarly, the late August discharge spike in 1984 had no effect on the sockeye series (Fig. 3). However, the high discharge peak in mid June of 1984 is strongly reflected in the sockeye series because this was a time when many age 0+ sockeye salmon were present in the reach.

Another example of a change in the relative effect of a discharge spike is shown by the 1984 chinook salmon series. The high discharge peak is mid-June had less effect on chinook outmigration than did the lower discharge peak in late July, a time when more age 0+ chinook fry were ready, because of physiological and behavioral reasons, to outmigrate.

The segments of the time series examined (discharge, turbidity, chinook and sockeye salmon outmigration) were described by relatively simple Box-Jenkins models, using mostly first-order terms. The usefulness of Box-Jenkins models is shown by the relative simplicity of the models developed for the salmon outmigration series; a visual inspection of the plots of the raw data for these series (Figs. 15 and 20) gives the impression of an erratic series of events. None of the series appeared to require differencing (although turbidity was on the borderline) to achieve stationarity nor did they appear to have a periodic component (discharge being a possible exception) which would require seasonal differencing. However, this should be re-examined when subsequent seasons of data are available. All of the series showed a strong first order autoregressive term, indicating that the value for any one day is greatly influenced by the value for the previous day. Similar results for the flow regimes of several streams in Australia was reported by Srikanthan et al. (1983), who found that most of the discharge series which were not white noise had a first order autoregressive term.

Examination of the autocorrelation coefficients of the four time series at lag = 1 day (adjacent values) gives an idea of the smoothness of the time series. Typically, the coefficient for physical/chemical variables is higher than that of biological variables and the time series for discharge (Fig. 4) and turbidity (Fig. 11) are less jagged than those for chinook salmon outmigration rate (Fig. 15) and sockeye salmon outmigration rate (Fig. 20). Saila et al. (1972) reported similar results for the autocorrelations of alewife upstream migration activity in relation to incident solar radiation and water temperature.

The square of the autocorrelation coefficient at lag = 1 gives a measure of the percentage of the variance of the value for today which is explained by what was measured yesterday (Murray and Farber 1982). In 1983, $(.86)^2 = 74\%$ of the variance of discharge for one day was explained by the value for discharge on the previous day. The percentage for turbidity was $(.92)^2 = 85\%$ while, for chinook salmon outmigration rate, it was only $(.66)^2 = 44\%$, and, for sockeye salmon, $(.65)^2 = 42\%$.

So, although fish tend to move in pulses more so than water or suspended sediments, fish outmigration is far from being a random event. That is, when an outmigration pulse occurs, the impetus has affected many fish and the phenomenon extends over a three or four day period. When we look at an outmigration time series, we are seeing the integrated results of several factors operating on sub-groups of the population in different locales. The fry in one slough may have emerged two weeks earlier than those of another slough because of a higher intragravel temperature. Or the head of one slough may have overtopped at a lower discharge level than the head of another slough, thus providing an environmental cue to the two groups at different points in time. But there is also a behavioral effect in that fry are stimulated to migrate when they see other fry migrating. This is particularly true for those species that form schools during outmigration.

The turbidity time series was the only one examined which included a second order term. The second order moving average term is likely related to the random "shock" caused by a rising discharge (which is in turn caused by rainfall) which resuspends sediment. It takes a few days after the rainfall is over for this perturbation in turbidity level to drop to the pre-rainfall level.

The discharge-turbidity transfer function model does not necessarily imply that discharge level is a strong causal factor for turbidity. These two variables are correlated largely because when glacial melting is high, both discharge and turbidity are high. This phenomenon provides the seasonal trend of the two series; the discharge of clear water tributaries such as Portage Creek and Indian River (which increases discharge but not turbidity) is a noise component. However, discharge does in fact have some direct causal effect on turbidity by resuspending sediments and other particles during a rapid rise in discharge level. Certainly turbidity is not a cause of discharge, so it makes sense to take discharge and noise as the input and turbidity as the output of a transfer function model. The value of the model is that it allows levels of turbidity for a few days ahead to be predicted from past values of both turbidity and discharge.

Turbidity level after the dams begin operation will not only be influenced by a changed discharge regime, but will also be directly changed by the dams because of settling of suspended sediments in the reservoir.

By building Box-Jenkins models for these four time series, a better understanding of the processes which control these variables was developed in that the structure of the random processes which generate an observed series has now been specified. Also, we have statistically described the natural time series as a baseline against which future changes can be assessed. This description of the discharge and turbidity regimes is important not only because of their effects on salmon outmigration, but also because of their effects on other life stages and species. It is important to explore the effect on salmon outmigration of a construction project which will change the basic rules, that is, change the underlying physical processes. Whereas the present discharge regime can be described as a mixed first order autoregressive and moving average process, the discharge regime under a post-project scenario could include entirely different terms.

An important point is that the underlying processes (the autoregressive and moving average components) were essentially the same in 1983 and in 1984 even though the actual time series, or "realizations," looked very different between the two years. This was true for both discharge and for chinook salmon outmigration; only a single year of turbidity and sockeye salmon outmigration was examined. Even though the discharge peaks do not match between the two years and the mean levels between years may have been different, the process which generated these peaks in both years was the same and can be described by an ARMA(1,1) model with similar parameter estimates for both years.

In a sense, the proposed dams would operate like a gigantic low pass filter on the discharge regime, dampening out the high frequency perturbations and letting the low frequency (annual cycle) events pass, but at a reduced amplitude. In other words, there are two effects of introducing a reservoir into this system: 1) the day-to-day changes in discharge would be smoothed and 2) the general discharge level would be higher than normal in winter and lower than normal in summer. However, this is an oversimplification because a new element would be present if the dams are built - namely, power demand. Power demand is not in phase with the natural discharge fluctuations, so dam operation to accommodate power demand will change the mechanisms which generate the current discharge regime.

The important question is, how would the salmon outmigration rates be affected if these discharge spikes were not present, as with a dam-regulated discharge regime? Further, what effects would these changes have on the population survival rate? Relatively high levels of discharge, and possibly four or five day peaks, in the late spring and early summer may be necessary to facilitate normal outmigration timing of juvenile salmon. On the other hand, very high discharge levels at this time of year, which occur naturally, may be harmful to juvenile chinook salmon if these floods displace the fry downstream from what would otherwise be their rearing areas.

Time series analysis is a statistical tool which has many potential applications to the Susitna River Aquatic Studies Program. It would be useful to build Box-Jenkins models for the 36 year record of discharge at Gold Creek gaging station. Because this information is continuous, it can be digitized as monthly, weekly, daily, or even hourly means. Turbidity, temperature, and dissolved gas time series could also be modeled in this manner. Developing time series models for the proposed post-project discharge regime to see whether the post-project discharge regime is also an ARMA(1,1) process would be informative in assessing dam-related effects. Intervention analysis, which is an extension of Box-Jenkins models concerned with a natural or human caused change to a system, would be an appropriate method to use (Box and Tiao 1975; Hipel et al. 1978; Thompson et al. 1982). One could determine if the intervention (construction of the dams) would have a significant effect on the time series processes. This method has been used to model the effects of the Aswan dam on the Nile River and of the Gardiner dam on the South Saskatchewan River in Canada (Hipel et al. 1978). Before and after mean levels can not be compared using normal analysis of variance because the observations are serially correlated.

Developing forecast models for the annual return of adult salmon or the annual total number of outmigrants would be an excellent use of time series analysis. The adult salmon return of a particular year is strongly related to the return of the previous year (that is, when catch is high one year, it tends to be high for several years) and there is probably a periodic component based on strong year classes. With such a model, one could predict the size of next year's adult salmon return, a piece of information which would be very useful to both fishery and hydroelectric dam managers. However, the time series of adult salmon return to the Susitna River is not long enough (only seven or eight years of data) to develop Box-Jenkins models. A minimum of about 40 or 50 observations is necessary (McCleary and Hay 1980; Huff 1983), although the method has been applied by Jensen (1985) to fish catch data with as few as 32 observations. The annual abundance of adult chinook and coho salmon in the California marine fishery has been successfully examined with time series analysis by Botsford et al. (1982) and Peterman and Wong (1984) have looked at sockeye salmon cycles in British Columbia and Bristol Bay. For the present, analysis of salmon time series in the Susitna River will have to be restricted to daily rates of a single year.

5.0 ACKNOWLEDGEMENTS

I thank Kent Roth, who has run the outmigrant operation since its beginning in 1982, and Dana Schmidt, former Project Leader of the Resident and Juvenile Anadromous Fish project, for their valuable discussions on some of the ideas in this report. Allen Bingham, Paul Suchanek, and Dave Bernard also made helpful comments on a draft copy of the report.

Much of this work was done as a project for a course on time series analysis taught by J. Horowitz of the Department of Mathematics and Statistics, University of Massachusetts. His assistance with the time series analysis and review of this paper are appreciated.

I am grateful to Mary Ferber of the Alaska Resources Library for conducting a computerized literature search on ecological and fisheries applications of time series analysis. Drew Crawford and Andy Hoffmann helped compile this report, the figures were drafted by Carol Hepler, and Skeers Word Processing Services did the typing.

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7.0 BOX-JENKINS ARIMA AND TRANSFER FUNCTION MODELS

Box-Jenkins models can be summarized as follows (Box and Jenkins 1976; McCleary and Hay 1980; Chatfield 1984). Suppose there is a time series y_t, t = 1..N. Then y_t is a moving average process of order q (or an MA(q) process) if

$$y_t = \theta_0 a_t + \theta_1 a_{t-1} + \theta_2 a_{t-2} + \ldots + \theta_q a_{t-q}$$

where θ_i are constants and $\theta_0 = 1$. The term a_t is a white noise process. White noise consists of a series of random shocks, each distributed normally and independently about a zero mean with a constant variance. The series y_t is an autoregressive process of order p (or an AR(p) process) if

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + a_t$$

where ϕ_i are constants. This is similar to a multiple regression model except that y_t is regressed not on independent variables but on past values of itself. A first order autoregressive process, AR(1), has the form:

$$y_t = \phi_1 y_{t-1} + a_t$$

Box and Jenkins (1976) define a backward shift operator B as:

$$B^m(Y_t) = Y_{t-m}$$

For m = 1,

$$BY_t = Y_{t-1}$$ or, the previous value.

Using B, the AR(1) equation can be written:

$$y_t = \frac{a_t}{1 - \phi_1 B}$$

Time series resulting from a mixture of AR and MA processes are called ARMA(p,q) models and have the form:

$$y_t = \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} + a_t + \theta_1 a_{t-1} + \ldots + \theta_q a_{t-q}$$

Using the backward shift operator B, an ARMA (1,1) may be written as:

$$y_t = (1 - \phi_1 B)^{-1} (1 - \theta_1 B) a_t$$

ARMA (p,q) models are appropriate only when the time series is stationary. Stationary in an ARMA model means that there is no systematic change in the mean or the variance over time and that there are no strictly periodic variations (Chatfield 1984); in other words, the mean, variance, and autocovariance are not dependent on time. Time series which are not stationary can sometimes be handled by "differencing" the series. Taking the difference of adjacent values gives a differencing order, d, of one:

$$\nabla^d Y_t = Y_t - Y_{t-d} \quad , \quad d = 1$$

Such models are said to be "integrated" and are denoted by ARIMA(p,d,q) where p is the order of the autoregressive component, d is the order of differencing, and q is the order of the moving average component.

Time series with seasonal variations, such as would occur in a multiple year series of daily water temperature measurements, can be made stationary by seasonal differencing. For example, the value for April 15 of one year is subtracted from the value for April 15 of the following year, and so on for all days of the year.

It has been assumed above that the time series had a mean value of zero. With stationary time series which have a non-zero mean, the mean has to be subtracted from every y_i term. For example, the form of an AR(1) model would be:

$$y_t = \mu + \phi_1 (y_{t-1} - \mu) + a_t$$

The autocorrelation function plays a major role in identifying and building time series models. A regular correlation coefficient measures the correlation between N pairs of observations on two variables. The autocorrelation coefficient is somewhat similar except that it measures the correlation between all observations of the same variable at a given distance apart in time (that is, between Y_t and Y_{t-k} for all values of t, where k = time lag). Also, the covariance is estimated only over N-k pairs of observations (McCleary and Hay 1980). Autocorrelation coefficients at different lags indicate the extent to which one value of the series is related to previous values and can be used to evaluate the duration and the degree of the "memory" of the process. The autocorrelation function (ACF) is the set of autocorrelation (AC) coefficients at different lags associated with a time series; a plot of the ACF is called a correlogram (Chatfield 1984).

The ACF is defined as:

$$ACF_k = \frac{\text{covariance}(Y_t, Y_{t+k})}{\text{Variance}(Y_t)}$$

and is estimated by:

$$ACF_k = \frac{\sum_{t=1}^{N-k} (Y_t - \bar{Y})(Y_{t+k} - \bar{Y})}{\sum_{t=1}^{N} (Y_t - \bar{Y})^2} \cdot \frac{N}{N-k}$$

A partial autocorrelation (PAC) coefficient measures the excess correlation at lag k which is not accounted for by an autoregressive model of order k-1. The set of PAC's at different lags associated with a time series is called the partial autocorrelation function (PACF).

There are three steps in developing an ARIMA model: model identification, parameter estimation, and diagnostic checking (Box and Jenkins 1976). ARIMA model building is an iterative process. The first thing to do is to look at a plot of the time series. Time series that are not stationary must be made so by trend removal which can be accomplished by such methods as differencing the series or by polynomial (or other) regression. Examination of the autocorrelation function (ACF) and the partial autocorrelation function (PACF) of a stationary series helps to identify a possible ARIMA model. The next step is to estimate the parameters of the model and again examine the ACF and PACF plots, this time on the residuals from the model. This process is repeated until the residuals show no significant AC's or PAC's at any lag, which indicates that the residuals consist of only a white noise process.

When there is an independent variable which is also a time series, a transfer function model can be developed. This model consists of the transfer function component from the independent variable as well as the ARIMA component (or noise component) from the dependent variable (McCleary and Hay 1980) and can be represented as:

$$Y_t = f(X_{t-b}) + N_t$$

where: Y_t is the output time series

X_t is the input time series

$f(X_{t-b})$ is the transfer function component

N_t is the noise or ARIMA component

Transfer function models can be bivariate (when there is one independent variable) or multivariate (more than one independent variable).

The steps to take in developing a transfer function model (Box and Jenkins 1976; McCleary and Hay 1980; Dixon et al. 1981) are: (1) develop an ARIMA model for the input series, obtaining the pre-whitened input (residuals), (2) filter the output series by the model for the input series, (3) cross-correlate the residuals from the first two steps, (4) identify the form of the transfer function component from the cross correlation function, (5) assuming the errors are white noise, estimate the values for the parameters, (6) identify an ARIMA model for the residuals, (7) if the ARIMA component is not white noise, combine the ARIMA component with the transfer function component to form a new model, (8) estimate the parameter values, and (9) examine the ACF and PACF plots on the residuals from the new model to see if the model is adequate.

Appendix C
Time Series Analysis of Discharge,
Turbidity, and Juvenile Salmon Outmigration
in the Susitna River, Alaska

ALASKA DEPARTMENT OF FISH AND GAME

SUSITNA RIVER AQUATIC STUDIES PROGRAM

REPORT NO. 7

RESIDENT AND JUVENILE ANADROMOUS FISH
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PARTS 1 AND 2

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334 W. Fifth Avenue, Second Floor
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July 1985