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# VARIATION AND PREDICTION OF WATER TEMPERATURE IN YORK RIVER ESTUARY AT GLOUCESTER POINT, VIRGINIA

## A THESIS

## Presented to

The Faculty of the School of Marine Science
The College of William and Mary in Virginia

In partial Fulfillment

Of the Requirements for the Degree of

Master of Arts

by

Bernard B. Hsieh

1979

## APPROVAL SHEET

This thesis submitted in partial fulfillment of the requirements for the degree of

Master of Arts

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### **ACKNOWLEDGEMENTS**

The author wishes to express his sincere appreciation to his major professor, Dr. Bruce Neilson, without his encouragement, patience, guidance and continued support this study would not have been completed. I am sincerely grateful to Professor Haven for providing very valuable information and suggestions in Chapter V and Dr. Welch for his careful review of the Box-Jenkins technique. My thanks are also extended to Dr. Loesch, Mr. Lukens and the rest of my committee members for critically reviewing the manuscript and their many helpful comments. Particular thanks are also due to Mrs. Shirley Crossley for typing this long manuscript. The assistance of Mr. E. Lawrence from the VIMS Instrument Shop who provided the data and other sampling information is also acknowledged.

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#### ABSTRACT

A historical time series of daily water temperature measurements for Gloucester Point, Virginia (York River Estuary) during the period 1954 to 1977 is described by means of statistical techniques. A basic model which consists of trend, cyclical, seasonal, and irregular components is used to approach the nature of the water temperature variations. A simple sinusoidal curve is shown to describe the behavior of the annual component and accounts for more than 95 percent of the total variance either for an individual year or the 24 year mean record of water temperature. Consistent amplitude and phase angle were derived from Fourier analysis for the seasonal component of the water temperature. variance spectrum technique which is based on the frequency domain is used to express significant "hidden" cyclical components which may not be apparent in the Fourier Four significant cyclical components extracted from the non-seasonal water temperature readings, with 22 year, 26 month, 14 month and 6 month periods might be related to solar activity. Two periods with large fluctuations of water temperature occurred before and after the stable years 1962-1970. This also might result from the intensity of sunspot activity. The lunar period fails to be a significant factor. The trend component is not obvious because most of the long term variation during this study period is contributed by the 22 year cycle.

The first order autoregressive process gives the best fit for the daily residual data after the fundamental harmonic and the record mean are removed. This predictive model, which consists of a deterministic portion (annual cycle) and a stochastic portion (non-seasonal component), can forecast the daily water temperature 12 days ahead theoretically.

There was no direct relationship between monthly mean water temperatures and monthly condition index values for oysters in the York River Estuary. Other features of these two time series appear to be correlated, perhaps because water temperature is a dominant factor during parts of the year and other factors control during the remaining seasons.

# VARIATION AND PREDICTION OF WATER TEMPERATURE IN THE YORK RIVER ESTUARY AT GLOUCESTER POINT, VIRGINIA

### INTRODUCTION

The increasing concern for our living environment makes it necessary to understand the characteristics of water quality, especially its effect for our people. One of the most significant parameters is water temperature because it can affect the growth and health of the biota. Therefore, the analysis of water temperature variations can provide worthwhile information for us concerning the nature of an estuary.

Beaven (1960) calculated the daily temperature and salinity values of surface waters of the Patuxent River estuary at Solomons, Maryland, and presented tables of average values for the twenty year period, as well as the daily fluctuations shown graphically with monthly means and ranges. Ritchie and Genys (1976) extended Beaven's information to the next ten years, and also established a fourth degree polynominal regression equation which can be used to predict the water temperature for any given day. Ward (1963) demonstrated that an empirical sine curve equation closely fits the annual variation of temperature of a stream, and that the nature of the sine curve does not change much from year to year.

Others have examined the characteristic of the residual that results when the seasonal variation is subtracted from the actual time series record. The information gained from the analysis can be used to develop models to predict water temperatures.

For this study we have used as the basic model, the concept that there is a dominant annual cycle. Superimposed on this annual cycle can be a long term trend, other cyclic variations and random or irregular components. If all four independent components were put back together, the result would vary much like an actual water temperature time series.

W = A + T + C + 1

A = annual cycle

T = long term trend

C = cyclical variations

l = irregular or random component
and all of the terms are functions of time.

The purpose of this study is to use a 24 year record of water temperature in the York River Estuary to determine the nature of each of these components. The location of the sampling station, data processing methods and the basic statistical results (means, ranges, etc.) are presented in Chapter I.

Chapter II includes harmonic analysis of the data to determine the characteristics of the annual cycle. The importance of higher order harmonics also was considered.

In Chapter III, the variance spectrum was calculated and used to investigate the cyclical components of the time series. The Box-Jenkins technique to develop a predictive model was examined in Chapter IV. This technique needs only three simple parameters to determine the stochastic or irregular portion of the record, once the deterministic, annual cycle has been removed.

The information gained from these analyses can be applied to many fields. When values are missing from historical records these techniques are useful to supply the missing data, and also to provide more accuracy and limit errors in predicting future values. Above all, it can provide good information for scientists studying the variation of biological growth with temperature changes. This knowledge of water temperature variations should be useful for aquaculture too. The application of the water temperature analysis to oyster condition index trends is given in Chapter V.

And finally, a discussion of the study's findings and conclusions are presented in Chapter VI and Chapter VII.

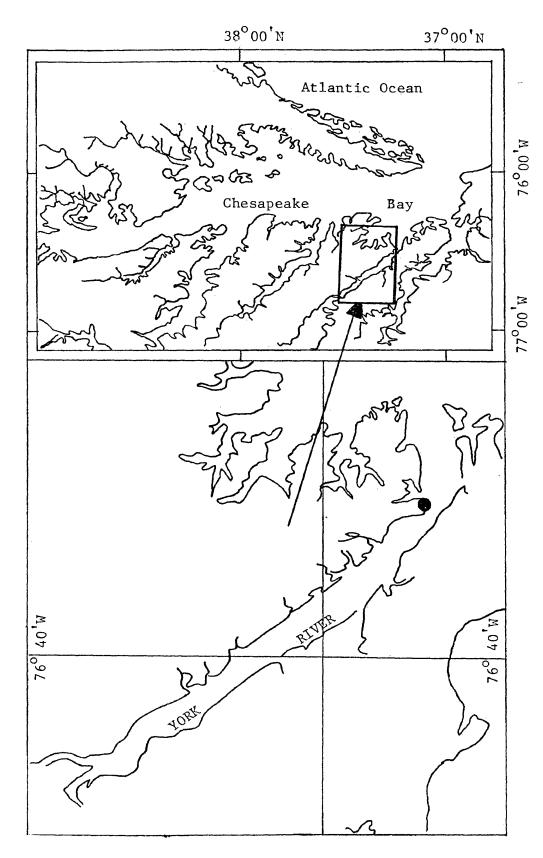
#### CHAPTER I

## DESCRIPTION OF THE DATA

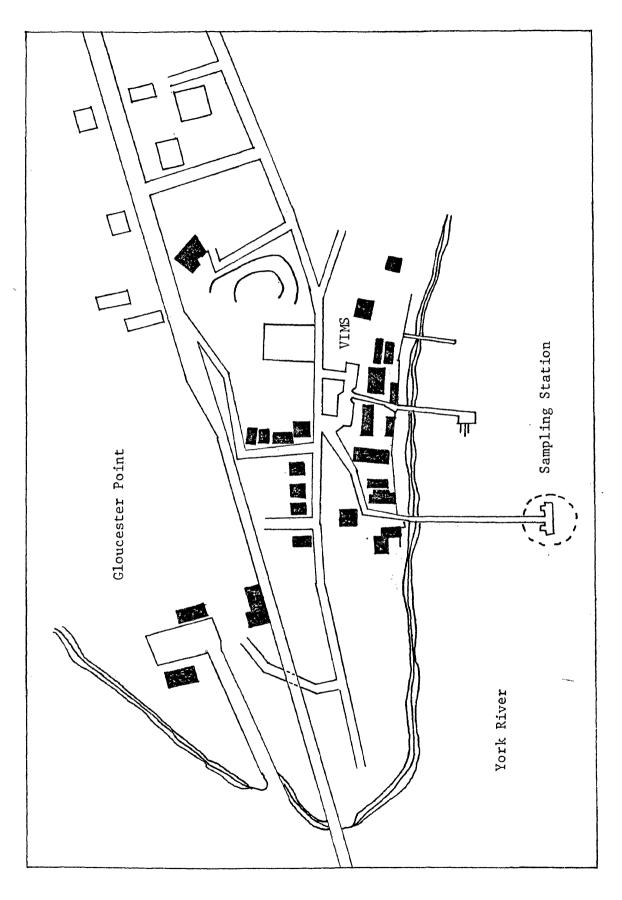
The York River is one of six major tributaries which enters Chesapeake Bay along its western shore (Fig. 1).

The drainage area of the York River is about 6900 square kilometres (km²) (Virginia Division of Water Resources, 1974) and lies entirely within the Commonwealth of Virginia. The York is formed at the town of West Point at the confluence of the Mattaponi and Pamunkey rivers. Tidal influences are observed over the entire length of the York River and extend about 96 kilometres (km) up the Mattaponi and 60 km up the Pamunkey. Its length from West Point to Chesapeake Bay is about 56 km. The average width of the York is about 3 km and the average depth about 6 metres (m), but depths range to over 26 m.

The Virginia Institute of Marine Science (VIMS) and
The School of Marine Science, College of William and Mary
is located at Gloucester Point on the north shore of the
York River about 9.6 km from Chesapeake Bay at a narrow
portion of the river channel. Water temperatures were
monitored by VIMS at the end of a pier which extends about
116 m from the shoreline. The river width from the pier to



Figuare 1. York River Estuary and its relatively posiyion in Chesapeake Bay.



Location of water temperature sampling station. Figure 2.

the Yorktown monument on the opposite side is about 3.2 km. The exact location of this station is latitude of  $37^{\circ}14.8$ ' N and longitude of  $76^{\circ}30.1$ 'W (Fig. 2).

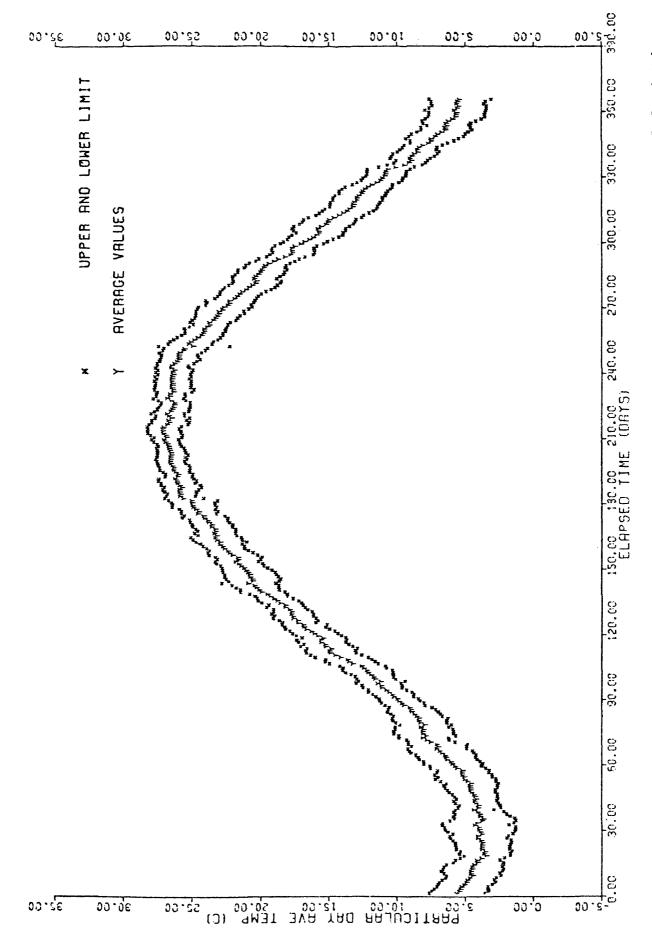
Water temperature readings have been made at this location since 1947. A mercury maximum and minimum thermometer was used to measure the daily extreme temperatures. Since 1972, an Interocean Model 513 CSTD probe has been This instrument was designed to accommodate a used. variety of situations which arise in oceanographic and estuarine studies. It incorporates sensors to provide in situ measurement of conductivity, salinity, temperature, The sensors are located 2.2 m below mean low water; the river bottom is 4.2 m below mean low water. Temperatures were read to the nearest 0.1 of a degree centigrade (C). In order that the surface water temperature may be more accurately estimated, the probe is checked once a week for agreement with a mercury thermometer which is placed at the same level of water as the instrument. The mercury thermometers have a rated accuracy + 0.25 C. It is estimated that the total error does not exceed + 0.5 C.

There have been only a few instances when the instrument was inoperative; the missing data was supplied by an interpolation method. If the temperature data were abnormal, data from another instrument, a Foxboro Temperature Recorder, were used. For more lengthy periods with missing values, the data gap was left in the record. Data gaps are greatest for the years 1964, 1968, and 1972.

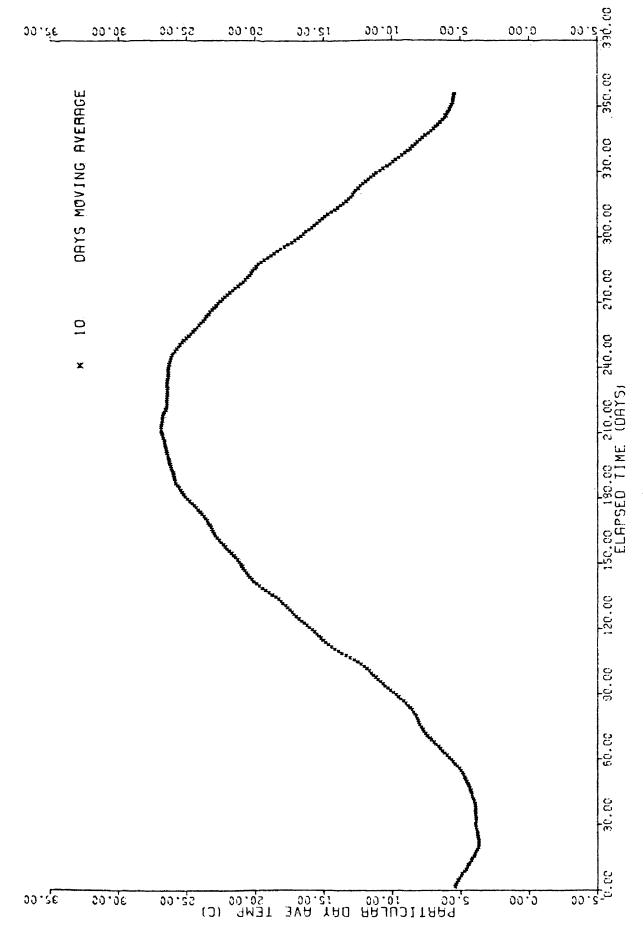
Although instantaneous readings were made prior to 1972, only the daily extremes were recorded. Since 1972, the average temperatures for each of 12 two-hour periods during that day are recorded as well. The daily extremes since 1954 and the two-hour average temperatures since 1972 are stored on punched computer cards at the VIMS Instrument Shop. Daily averages used in this study were the mean values for the daily extremes. The mean values for the 12 two-hour temperatures for the last six years also were calculated. Both were transferred to computer cards and stored in the William and Mary Computer Center library.

The daily average temperatures for the twenty-four years of record are given in tabular form in Appendix A. Statistics for each particular day of the year are given in tabular form in Appendix B. Normally, data for February 29 were ignored to simplify calculations. The twenty four year mean temperature for each day along with one standard deviation limits have been plotted (Fig. 3). Additionally, daily temperatures have been calculated using 7-day and 10-day moving averages of the twenty-four year means, and the 10-day moving average has been plotted (Fig. 4). The maximum and minimum daily temperatures, along with the year in which these occurred, have been listed in Appendix B.

The particular daily means of temperature ranged from 3.22 C to 26.92 C. Temperatures average around 3 C for



standard deviation. Н +1 Mean daily average temperatures for 1954 to 1977 and Figure 3.



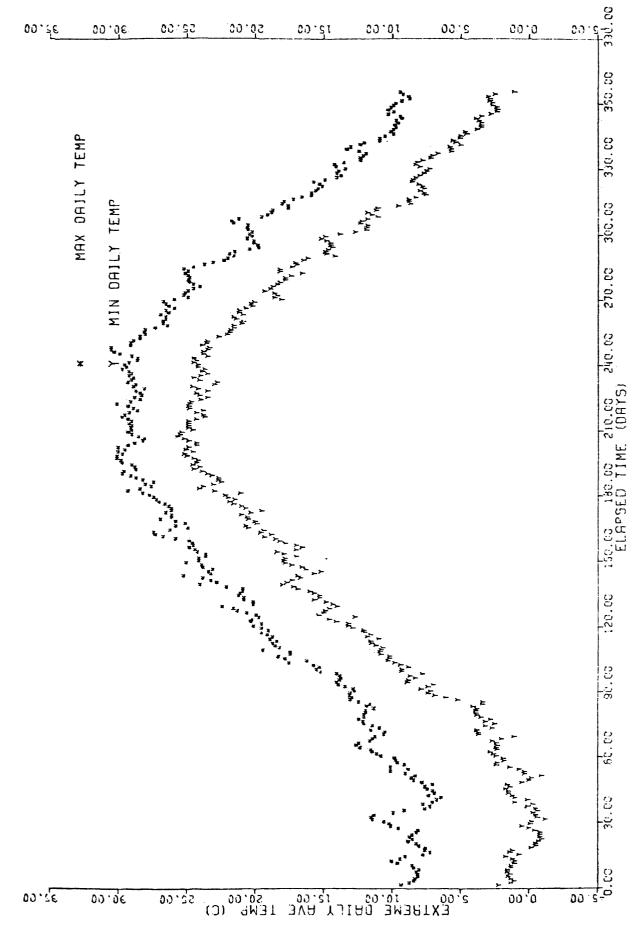
The 10 day moving average of 24 year mean daily average water temperatures. Figure 4.

about 25 days from January 15 to February 10. The coldest water temperatures occur during the middle or later part of January, and after six and one half months the warmest temperatures occur at the beginning of August.

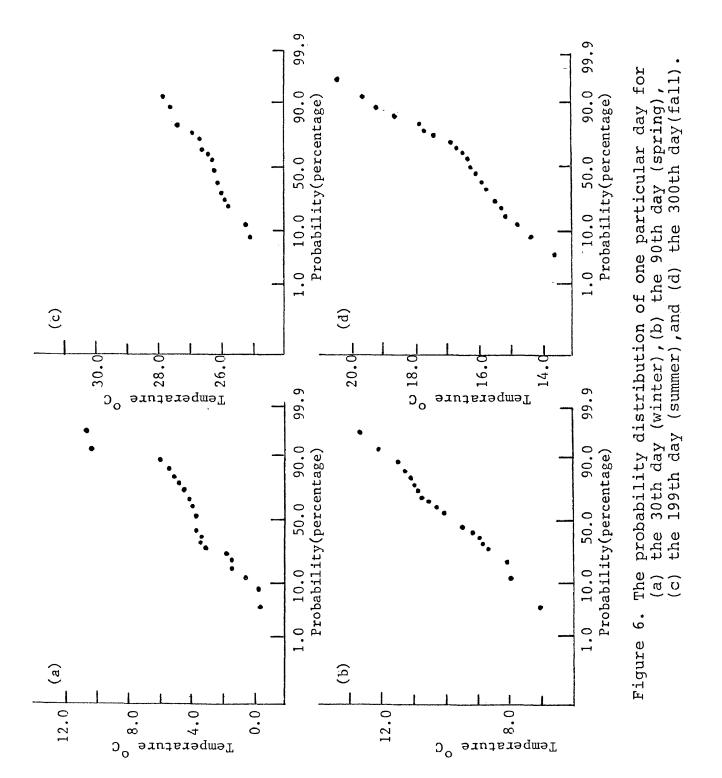
The standard deviation of the daily water temperature varied from 0.84 C to 2.58 C. Generally speaking, higher deviations occur during cold days and lower deviations occur during warm days (Fig. 3). However, highest value for the standard deviation occurred in the middle of September, although most days during that month have medium values.

The observed extreme daily average water temperatures ranged from a low value of -1.4 C on January 31 to a high value of 30.0 C on July 15 and 16 (Fig. 5). The days with highest extreme temperatures do not coincide with the days of the highest average temperature. The days with lowest temperature were a half month apart. From the middle of January through the middle of February, it is not uncommon for water temperatures to go below the freezing point. A few especially cold years, like 1977, produced many of the minimum values.

Sets of daily average temperatures were selected for each of the four seasons so that the probability distributions of values for the twenty-four years could be observed (Fig. 6). Generally, the data appear to be normally



The extreme water temperatures for each calendar day for the years 1954 to 1977. Figure 5.



distributed but there may be a few outlying points. Because the sample size (N equals 24) is not large, the distributions cannot be described in detail.

Both the time series for individual years and the twenty-four year mean record were used in the analysis which is described in the following chapters.

### CHAPTER II

### HARMONIC ANALYSIS AND THE ANNUAL CYCLE

The techniques called time series analysis may be applied to sets of observations if these sets are dependent statistically. If a time series exhibits a strong characteristic for a given frequency, or even a set of frequencies, one style of analysis which can emphasize this periodicity is called harmonic analysis or Fourier analysis. It can separate the time series data into a set of sine wave signals, each having a given period and amplitude. As frequently used for water quality data, harmonic analysis shows the physically meaningful harmonics, which then can be subtracted from the original series. It is not necessary to include each harmonic and all harmonics need not be consecutive.

The seasonal or annual component refers to the identical or nearly identical pattern which a time series appears to follow during successive years. In other words, this seasonal behavior is the pattern observed within each year. The trend component indicates the evolutionary change that occurs in a time series over long time intervals. It is revealed primarily as a changing mean level around

which the remaining components fluctuate with different degrees of regularity. The cyclical component describes successive advances and declines, and may include more than one cycle. In this chapter, the significance of these three components is investigated by harmonic analysis. The daily mean water temperature for each individual year is tested for the seasonal component. The twenty-four year daily mean series is examined to see if cyclical and trend components exist.

Kothandaraman (1971) reported that a single harmonic with a period of a year normally accounts for about 95% for the total variance of a water temperature record. Harmonic analysis can separate such cyclic variations from the observed record. If this is done, it is possible to investigate the nature of the non-cyclic variations, and it may be possible to construct a model which illustrates these non-cyclic variations. Thomann (1967) applied the general theory of Fourier and spectral analysis and presented the results of time variation for temperature and dissolved oxygen in the Delaware Estuary. The first harmonic included most of the total variance; the amplitude and phase angle were very similar for different transects through the whole estuary. Low-frequency phenomena dominated the residual spectra, especially for water temperature, with peaks in the area of 30 days. Long (1976) also did water temperature forecasting and estimation using Fourier

Series and Communication Theory techniques for a river with a constant thermal input from a power plant. He suggested that by using significant Fourier components he could make a meaningful prediction of daily average water temperature for up to 60 days ahead.

Other research has dealt with water temperature in the rivers or streams and the association with air temperature data. Kothandaraman (1971) investigated the nature of seasonal and non-seasonal variations in the daily mean river water temperature and developed a method to predict water temperature based on observed meteorological data. The resulting predictions had a standard error of estimate of about 1.1 C. Song (1973) postulated a model which includes variations due to atmospheric temperature fluctuation, and the seasonal variations of the water temperature as well as purely random fluctuations. Song and Chien (1977) analyzed some stochastic characteristics of the daily component of water temperature variations with respect to daily range, air temperature fluctuations, and watershed Linear regression models and autocorrelation and cross-correlation models were used.

Since it is already known that the annual water temperature cycle can be described roughly as a sine curve, it is reasonable to assume the Fourier analysis will provide meaningful information about the water temperature record.

Therefore, a fundamental formulation can be used to estimate amplitude and phase angle for the different components:

$$T = \overline{T} + \sum_{i=1}^{M} a_i \sin (b_i x + c_i)$$
 (2-1)

$$= \overline{T} + \sum_{i=1}^{M} A_i \sin b_i x + B_i \cos b_i x \qquad (2-2)$$

where 
$$A_i = a_i \cos c_i$$

$$B_i = a_i \sin c_i$$
then  $a_i = \sqrt{A_i^2 + B_i^2}$ 

$$c_i = \tan^{-1} \frac{B_i}{A_i}$$

in which  $\overline{\mathtt{T}}$  is the average of the record

a; = the amplitude of the ith harmonic

 $b_i$  = the frequency for the ith harmonic

c = the phase angle in radians for the
 ith harmonic

M = the number of harmonics

the phase angle c; can be adjusted as follows:

$$c_{i} = \begin{cases} \tan^{-1} \frac{B_{i}}{A_{i}} & A_{i} > 0 \\ \tan^{-1} \frac{B_{i}}{A_{i}} + \pi & A_{i} < 0 & B_{i} \ge 0 \\ \tan^{-1} \frac{B_{i}}{A_{i}} - \pi & A_{i} < 0 & B_{i} < 0 \\ -\frac{\pi}{2} & A_{i} = 0 & B_{i} < 0 \\ -\frac{\pi}{2} & A_{i} = 0 & B_{i} > 0 \\ \arctan & A_{i} = 0 & B_{i} > 0 \end{cases}$$
arbitrary
$$A_{i} = 0 & B_{i} = 0$$

The coefficients in Eq. 2-1 can be determined using the least-squares method which would make the sum of

deviations a minimum (after the harmonic coefficients  $A_i$  and  $B_i$  are calculated). These harmonic coefficients  $A_i$  and  $B_i$  may be given by:

$$A_{i} = \frac{2}{N} \sum_{x=1}^{N} Tx \sin b_{i}x \qquad (2-3-1)$$

$$B_{i} = \frac{2}{N} \sum_{x=1}^{N} Tx \cos b_{i}x \qquad (2-3-2)$$

where N = Total sample number

Tx = water temperature record at day x x=1,2,...,365 for yearly data

These two values ( $A_i$  and  $B_i$ ) can be estimated very accurately by the least-squares method, which saves some time compared to calculating the very big inverse matrix required to solve the set of linear equations if one needs to include higher frequency terms.

Harmonic analysis will be applied first to the twentyfour year mean record to show the variation of water temperature over the longer term. The second concern is to
examine the variation of phase angle and amplitude year by
year. Once the mean of the record and the amplitude and
phase angle for each harmonic have been calculated, we can
determine how many and which harmonics are needed. These
can be selected with a useful calculator index, the
variance accounted for by the given harmonic. From eq.
(2-2) it is known that the variance accounted for by each
given harmonic is equal to the half value of the amplitude

squared (Var<sub>i</sub> = A<sub>i</sub><sup>2</sup>/2). From the percentage of total variance accounted for by that harmonic we can decide whether it is significant or not. For instance, the mean record for the twenty-four years has a first harmonic which accounts for 99.68% of the total variance. The second harmonic accounted for only 0.21% of the variance and none of the next 10 harmonics includes a portion greater than 0.02%. So, for many purposes, the first harmonic is sufficient to explain the trend of the average data, probably because many variations have been damped out through the twenty-four year averaging.

From the result shown above, the mean water temperature at the VIMS pier roughly can be described by a simple sinusoidal curve with a 365 day period, a 240° phase lag, an average temperature of 15.57 C and an amplitude of 11.59 C. Fourier coefficients were calculated by equation 3-3 for the first to the thirteenth harmonic. The principal results from the Fourier analyses of the temperature time series are presented year by year in Table 1. The first harmonic for each year's record has very limited phase angle variation but this is not true for higher harmonics. The first five harmonics accounted for most of the variance (Table 2). It can be noted that the second through fifth harmonics account for an additional 0.8 to 3.0 percent of the variance. Because the phase angles are scattered for successive years, random phenomenon are probably included in the record.

Amplitude (C) and phase angle (radians) estimates for the first five harmonics of daily water temperature series for each year during 1954-1977. Table 1.

fth Amp.	4.09	9	$\infty$	3.43	0.	. 7	. 7	. 7	.5	$\infty$	Η.	4.	ω.	0.	ς.	6	.7	.2	7.	0	7.	ε,	0.	7.	. 7
Fif Amp.	0.43	5		0.99		<u>.</u>	7.	4.	7	.5	.5	4.	۲.	4.	٣,	9•	2	.2	.2	.2	5	7.	.7	₹.	0
ourth .   Pha.	8	0.	٣,	5.31	0.	٣.	9.	.5	.2	7.	4.	٣.	۲.	$\infty$	.2	.2	7	.2	7	٣.	4.	9	0	7	<b>!</b>
Four Amp.	0.34	4.	6	0.33	9•	<u>-</u>	9	.7	. 5	٣,	9•	7	۳,	5	4.	٣.	.5	7	7	. 4	٤,	6	9.	7.	0.
rd Pha.	1.	<b>.</b>	ω,	1.80	8	۲.	. 4	φ.	Ч.	. 4	∞.	0.	6.	4.	٣.	4.	۲.	٦.	5	9.	9•	$\infty$	۲.	φ.	. 7
Third	5	. 2	9	0.78	<b>.</b>	.5	-	ς,	9•	တ	. 2	$\infty$	. 4	0.	٦.	2	7	5	. 7	. 2	4.	9	٣.	7	
econd Pha.	7.	$\infty$	4.	4.95		.5	∞.	• 5	φ,	$\infty$	. 2	ω,	.5	. 2	۲.	. 5	$\infty$	. 2	. 7	9.	0.	<u>-</u>	4.	.2	. 3
Sec. Amp.	. E.	9	7	0.74	9.	.2	. 4	0	φ,	0	. 7	. 2	.2	. 7	0.	.5	0.	9	. 4	. 4	5	4.	ထ္	.5	.5
t Pha.	.2	. 2	۲.	4.24	۲.	. 2	۲.	Τ.	.2	?	۲.	٦.	٦.	7		. 2	۲.	٦.	⊣.	۲.	7	⊣.	٣.	.2	-
Firs Amp.	1.4	2.1	1.2	10.85	2.1	2.4	2.1	1.9	1.9	2.0	1.1	1.3	1.3	0.7	2.2	2.3	2.2	1.7	9.0	1.5	0.0	0.9	1.1	2.9	1.5
Average	5.6	5.5	5.1	15.46	4.6	9•9	5.4	5.5	5.1	5.0	5.3	5.1	4.7	4.7	5.2	5.0	5.4	6.4	5.5	6.5	9.9	6.8	5.3	6.3	5.5
Year	95	95	95	1957	95	95	96	96	96	96	96	96	96	96	96	96	97	97	97	97	97	97	97	97	еа

Table 2. Analysis of variance for water temperature data.

Year	Total Variance	l Harm	st	2nd to Harmo		6th & Higher Harmonic			
	variance						8**		
		Var.*	응**	Var.*	응**	Var.*	8 ^ ^		
1954	67.97	65.39	96.20	1.21	1.79	1.37	2.01		
1955	75.93	73.98	97.43	0.74	0.95	1.23	1.62		
1956	66.00	63.51	96.22	0.73	1.13	1.76	2.65		
1957	61.71	58.92	95.48	1.14	1.84	1.65	2.68		
1958	76.27	74.40	97.55	0.52	0.70	1.32	1.75		
1959	79.27	77.09	97.25	0.99	1.23	1.19	1.52		
1960	76.91	74.29	96.59	1.23	1.60	1.39	1.81		
1961	74.07	71.60	96.67	1.06	1.44	1.39	1.89		
1962	72.76	70.85	97.37	0.71	0.99	1.20	1.64		
1963	74.84	72.86	97.41	1.06	1.44	0.88	1.17		
1964	63.86	62.42	97.74	0.62	0.97	0.82	1.29		
1965	65.35	63.92	97.81	0.51	0.78	0.92	1.41		
1966	65.62	64.01	97.55	0.21	0.30	1.41	2.15		
1967	59.03	57.60	97.58	0.38	0.64	1.05	1.78		
1968	76.82	75.19	97.88	0.75	0.97	0.88	1.15		
1969	77.26	76.16	98.58	0.47	0.61	0.63	0.87		
1970	76.09	74.45	97.85	0.73	0.96	0.91	1.19		
1971	71.20	69.20	97.19	0.61	0.85	1.39	1.96		
1972	57.65	56.37	97.78	0.41	0.79	0.87	1.49		
1973	67.94	66.40	97.73	0.24	0.36	1.30	1.91		
1974	51.70	50.10	96.91	0.49	0.95	1.11	2.15		
1975	62.27	59.95	96.27	1.26	2.03	1.06	1.70		
1976	65.21	62.41	95.29	2.21	3.40	0.86	1.31		
1977	88.64	84.32	95.13	2.33	2.62	1.99	2.25		

<sup>\*</sup> The variance attributed to the specified harmonic

<sup>\*\*</sup>The portion of the total variance attributed to the specified harmonic

It is interesting to see whether the 2-hour data would produce the same result. In order to better understand the variations derived from the different samples, one of the most complete data sets was chosen. There are measurement every 2 hours through the entire year 1974 except for July 23 & 24. Harmonic analysis was done for the daily averages (the mean value of the daily maximum and minimum), the 2hour values, and the daily average of the 2-hour values. The last time series has a smaller portion of the total variance contributed by the first five harmonics and greater It is apparent that more variance is distritotal variance. buted to the higher harmonics (Table 3). Daily averages calculated in the two different ways showed similar results for each harmonic. This result gives us confidence that we needn't be concerned with the method of calculating the daily average values if we want to observe the long term tendency.

The harmonic analysis has been applied to the entire twenty-four year record. The period, amplitude, phase angle, variance and percent of total variance for all harmonics which have a percentage of variance more than 0.05 are shown in Table 4. Except for the first two, the lower order harmonics account for small variances. The 24th harmonic, the annual cycle, includes most of the variance of the record.

Table 3. The comparison of harmonic analysis for different sampling intervals of water temperature in 1974.

	1974	Daily Average (mean of max. and min.)	** Daily Average (2 Hr Value Avg.)	*2 Hr Values		
	avg.	16.64	16.60	16.57		
	total variance	51.70	51.48	52.23		
Н	amp.	10.01	9.99	10.04		
rst Har.	phase angle	4.23	4.23	4.24		
Fir	variance	50.10	49.97	50.41		
Har.	amp.	0.53	0.52	0.52		
	phase angle	0.04	0.09	0.02		
Second	variance	0.14	0.13	0.13		
Har.	amp.	0.48	0.46	0.43		
Third Ha	phase angle	0.64	0.65	0.59		
	variance	0.11	0.10	0.09		
Har.	amp.	0.37	0.37	0.42		
Fourth	phase angle	4.43	4.45	4.50		
P <sub>O</sub>	variance	0.07	0.07	0.08		
Har.	amp.	0.55	0.53	0.55		
ifth Ha	phase angle	5.75	5.78	5.74		
면	variance	0.15	0.14	0.15		

<sup>\*\* 365</sup> daily averages are calculated by each 2 hr value for that day

<sup>\*</sup>There are 365x12=4320 each 2 hr values for that year

The harmonic analysis of 24 year daily mean water temperature record. Table 4.

Percentage of Variance	0.21	0.15	0.07	0.10	0.08	90.0	0.13	0.06	0.07	95.84	0.05	0.05	0.20
Variance (C <sup>2</sup> )	0.14	0.10	0.05	0.07	0.05	0.04	0.09	0.04	0.04	67.22	0.03	0.03	0.14
Phase Angle (radians)	2.15	3.78	2.35	0.13	2.73	2.72	4.37	5.88	6.01	4.19	4.30	5.42	4.40
Amplitude (C)	0.53	0.45	0.31	0.38	0.33	0.38	0.43	0.30	0.31	11.59	0.25	0.26	0.53
Period (day)	8760	4380	1095	876	730	674	420	398	381	365	195	186	183
Number of Harmonic	П	2	œ	10	12	13	21	22	23	24	45	47	48

Another way to use harmonic analysis to determine the relative importance of different periodic components is to use the corresponding amplitudes. The half value of the sampling number multiplied by the corresponding amplitude squared is named the "intensity" for that frequency  $I(f_i) = \frac{N}{2}$  (amplitude)<sup>2</sup>. When those intensities are plotted against their corresponding frequencies, the figure is called a "periodgram", which shows the relative amount accounted for by a frequency band. This method was applied to the residual daily water temperature record (original series minus the annual cycle) to find the important cycles. In Figure 7, the intensities for the first 50 frequencies are Some obvious peaks occur in this figure. the very strong fluctuation in this figure makes it hard to distinguish which ones are important. Many isolated peaks may or may not show their significance in a practical situation. Fishman (1969) has pointed out that this method was inadequate for estimating the relative importance of periodic components for a wide variety of phenomena. The two principal reasons for this inadequacy were first, the departure of the fixed period from reality. Many phenomena do exhibit recurrent behavior, but few show any regular periodic appearance. second reason the periodgram failed stems from the inordinately large number of periodic components that are suggested as being important. It was hardly possible to reconcile all these peaks with what was actually observed. This implies

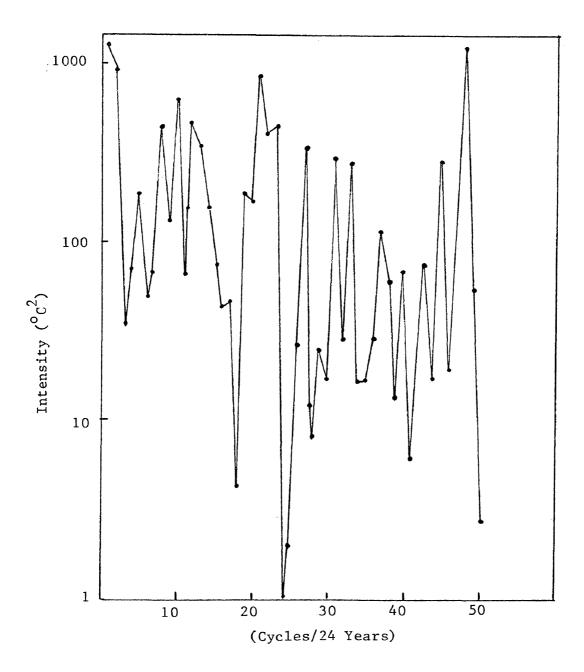


Figure 7. Periodgram for the water temperature residual series (mean and first harmonic removed).

that if some phenomenon is not an integer harmonic of the fundamental period, the calculated intensity peak will disappear. Therefore, the variance spectrum is needed to make up for these disadvantages.

In summary, the harmonic analysis has shown that the annual cycle of water temperature accounts for more than 95 percent of the total variance for either an individual year, the twenty-four year record or the twenty-four year mean. The amplitude and phase angle for the yearly harmonic were stable from year to year. The higher order harmonics (second or higher) show great variation in both amplitude and phase angle from one year to another. However this technique fails to explain the importance of phenomena for which the period is not an integer harmonic of the fundamental period of the record. This is especially true when a band of frequencies, rather than a single frequency, is important.

#### CHAPTER III

# THE CYCLICAL AND TREND COMPONENTS OF WATER TEMPERATURE VARIATIONS

It is desirable to know the importance of the cyclical and trend components. The trend component indicates the evolutionary change that occurs in a time series over long time intervals. It is revealed primarily as a changing mean level around which the remaining components fluctuate with different degrees of regularity.

The cyclical component describes successive advances and declines, and may include more than one cycle. Because cycles may be superimposed, it is difficult to observe them by visual inspection of the time series. They may or may not follow exactly similar patterns after equal intervals of time.

In this chapter, those significant components will be described by variance spectrum. In addition, after some significant components have been found, we will seek to define the causal relationships with some physical phenomena such as solar activity. Such a study may lead to an improved understanding of the different physical processes and their role in determining the variation of water temperature.

Finally, a table will show the intensity of those components which contribute to this twenty-four year record.

In the last chapter some relationships between the various harmonics and water temperature variations were presented. But if there are important frequencies which are not harmonically related to the length of the series, then we must find another method to analyze those variations. An appropriate tool to solve this problem is called power spectrum or variance spectrum. The power spectrum curve shows how the variance is distributed with frequency. The way from the time domain of the variance to the frequency domain is the Fourier transform of the autocovariance function. In other words, the variance spectrum is the transformation from a time-based to a frequency-based distribution through the autocovariance-function. Low frequency pass filters or high frequency pass filters can be used to choose the frequency needed.

In statistical theory, the correlation between neighbors with different spacing plays an important role and describes the behavior of a time series. The covariance between  $\mathbf{Z}_{t}$  and  $\mathbf{Z}_{t+K}$ , the values separated by K intervals of time, is called the autocovariance of lag K and is defined by

$$R(K) = \sum_{t=1}^{N-K} \frac{(Z_t - \overline{Z})(Z_{t+k} - \overline{Z})}{N-K}$$
(4-1)

where R(K) = autocovariance coefficient at lag K

 $\overline{Z}$  = the mean value of record

 $Z_t$  = the record value at time t  $Z_{t+K}$  = the record value at time t+K

The autocovariance coefficient plotted against the corresponding lags is called the autocovariance function. Zero lag (K=0) indicates the autocovariance coefficient is equal to the total variance (i.e.,  $R(o) = \sigma_a^2$ ). The ratio of autocovariance coefficient and total variance is called autocovariance coefficient. If both functions are positive, it means that the physical process described has a degree of positive tendency. If it has a negative value, it implies that opposite tendency will follow with a time lag of K units. If the first autocovariance value is positive this indicates that high (or low) values of temperature will tend to persist on the following day. If the autocovariance is negative, high values of temperature would be followed by low temperature values one day later, and vice versa.

Wastler (1963) described the mathematical basis for an application of spectral analysis. He states that the Fourier cosine transform is computed as

$$V_r = \Delta \tau (R(o) + 2 \sum_{g=1}^{m-1} R(g) \cos \frac{gr\pi}{m} + R(m) \cos r\pi)$$

where r = 0,1,2,...m

$$\Delta \tau = \begin{cases} \frac{2}{m} & r=0, m \\ \frac{1}{m} & 1 \le r \le m-1 \end{cases}$$

where  $V_r$  = the estimated power spectrum

R(m) = the autocovariance function with m day lags.

When these estimated values are plotted against the frequency, it makes apparent the dominant periods for this time series. The area under this curve equals the total variance of the record. Actually the estimated function is not always the best approach of the spectrum. It usually is transformed by a linear filter to smooth it and focus on the low frequency or high frequency values which one The highest frequency of estimate which limits the needs. events seen by a given sampling frequency is known as the Nyquist frequency (i.e.,  $f_N = \frac{1}{2} \Delta t$ ). In other words, the highest frequency cannot exceed half the sampling frequency. Although power spectrum has a characteristic to discover a hidden significant frequency, it is not able to measure the phase angle for that frequency.

Figure 8 indicates the autocovariance function of the twenty four year record after removing the 24th harmonic and record mean. The 24th harmonic, the annual cycle, removed 95.84 percent of the total variance. This figure shows the relationships for the first 720 lags. The first 80 autocovariance coefficients have decreasing positive values with an exponential decay. After that the autocovariance coefficients show approximately a sine wave form with damped amplitude and with increased lag. Since the autocovariance function has big positive values every 180 lag number (e.g., 180,360,540,etc.), the record probably contains a half year cycle. The first 217 autocovariance

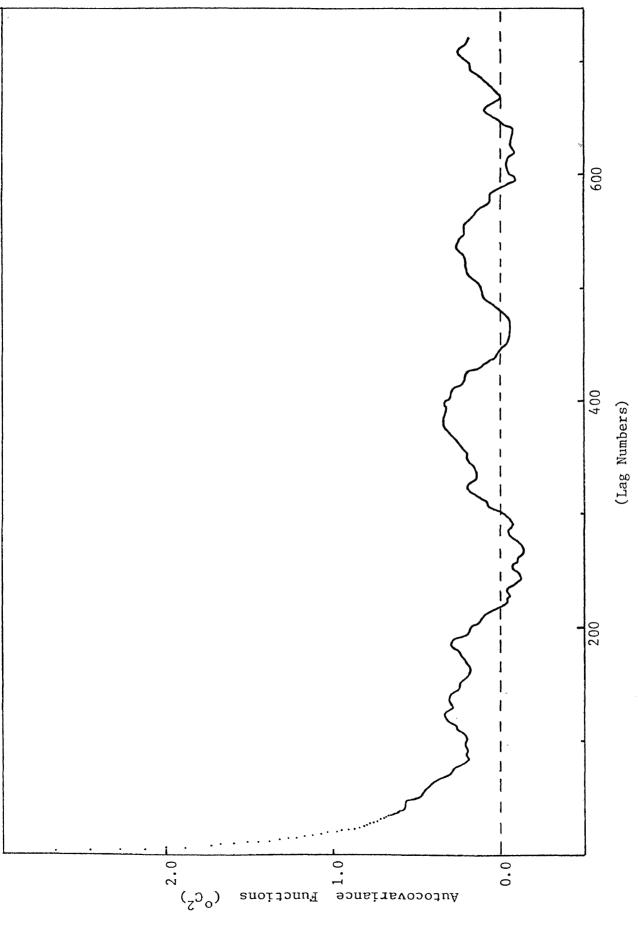


Figure 8. The autocovariance function of the 24 year daily mean series with the annual harmonic and record mean removed.

coefficients have positive values which means that temperature readings will follow the same tendency for these lags. The highest values of the later autocovariance coefficients appear at 378 day lag (positive) and 268 day lag (negative). This figure provides useful information to point out the relative tendency of water temperature residuals series.

With the variance spectrum technique it is possible to determine weak cyclical components for a particular time series record. If these cycles express sufficient regularity in their respective periods of oscillation, one would expect to observe local peaks and large values of variance in the vicinity of their corresponding frequencies. The narrower the peak, the more regular and discernible the cycle will be. The cyclical component often is so irregular that the corresponding spectrum shows only a concentration of variance over the entire low frequency range (Fishman, 1969).

In order to determine the significant peaks and periods with period less than two years, the maximum lag number is chosen as 365. In other words, the residual variance (annual component removed) will contribute over a frequency from 0 to 365 for this twenty-four year record. Gunnerson (1966) stated that significant values at zero frequency are a measure of the variance associated with secular variations which are revealed as long term increases or decreases. In addition, he mentioned that some random of nonrecurring

phenomena are contained in the zero frequency variance.

Therefore, it is highly significant that variance at zero frequency is in accord with the presence or absence of significant trends.

The variance spectrum of the residual daily temperature series for periods less than 2 years is shown in Figure 9. The dashed line represents the original estimated spectrum and the solid line indicates the smoothed estimation. log paper is used so that the high frequency band can be exhibited more clearly. Several peaks (182.5, 60-66, and 23.5 days) are apparent. However, a significance test with the 95 percent probability limits indicates that only the semiannual cycle is important. It should be mentioned that the absence of the peak at a very low frequency (i.e. period longer than half-year) doesn't mean the absence of a cyclical phenomenon for that range. To increase the resolution, one must either increase the maximum lag number (i.e. a wider range is observed) or filter out the high frequencies. second approach (Thomann, 1967) was used to compute the monthly residual mean, which results in a new residual series of 288 months (24 years).

In order to gain more information from this record, the variance spectrum of the monthly mean of the residual series was computed with the maximum lag number equal to 144. In other words, the first value has the period of twenty-four years. The results (Fig. 10) show only four peaks above

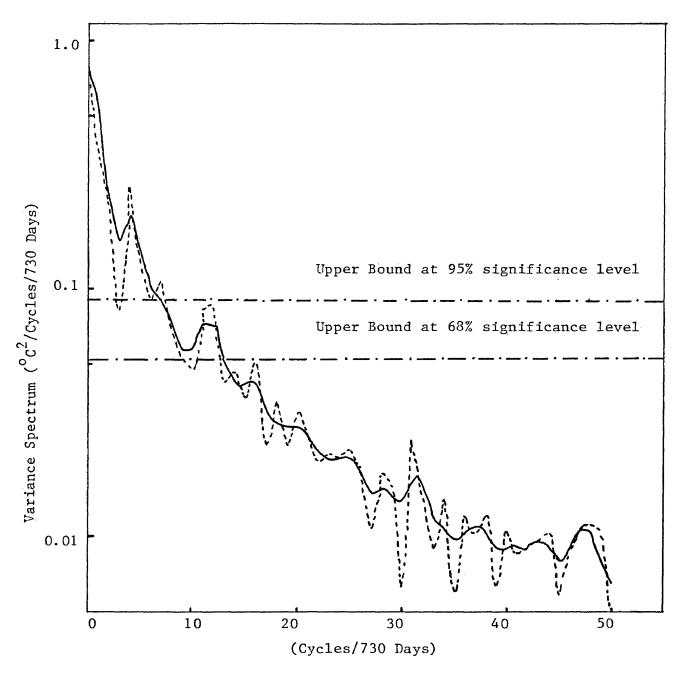
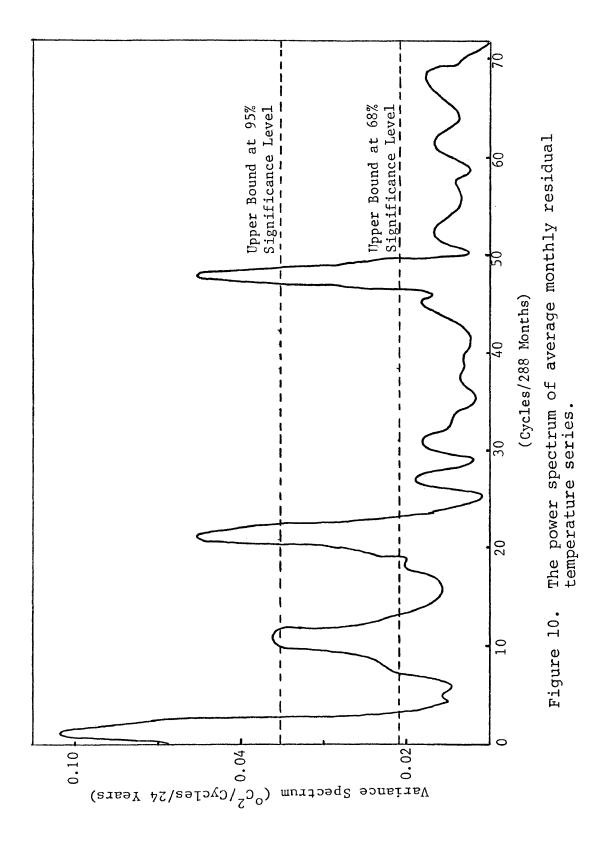


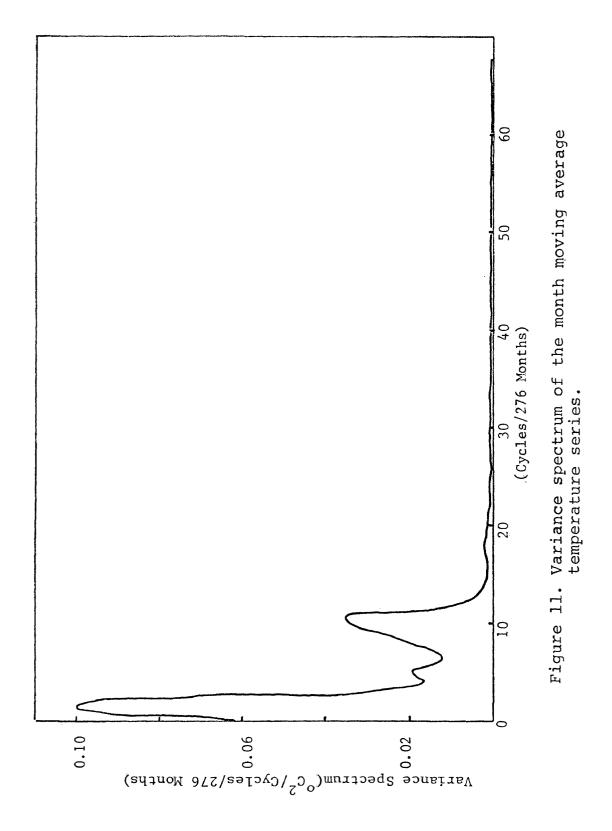
Figure 9. The power spectrum of the residual temperature series (annual cycle and mean removed) for periods less than 2 years.

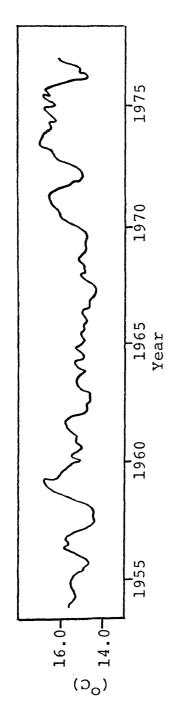


the 95 percent significance level with periods of 24 years, 26 months, 14 months and 6 months. Note that the biggest peak of this figure has no definite period since the second frequency (i.e. 12 year period) also accounted for a large portion of the variance.

The trend component is not obvious in this long-term cycle if it does exist. The variance accounted for by the zero frequency has a nonsignificant value (less than 0.1 percent of total variance). Therefore, it can be concluded that most of variance at very low frequency is contributed by the cycle with an approximate 24 year period. The trend component almost can be ignored in this record or it can be regarded as a very slight increase in the mean value.

Another simple and fast method to show this long-term cycle is to use the 12 month moving average to filter out short term cycles; the variance spectrum was calculated for the new series (Fig. 11) and only 2 peaks remained after this process. In Figure 12 the 12 month moving average and its smoothed curve are shown. Except for the mid-portion of the series, strong apparent variations of water temperature occur. From the end of 1972 to the middle of 1976 is seen as a relatively hot period. A feature of the period from 1962 to 1970 is a mean temperature about 0.5 C below the overall record mean of about 15.5 C.





The 12 month moving average for the monthly mean water temperature series. Figure 12.

In summary, the variance spectrum has shown that there are several important cyclical components of water temperature and that the trend component is very weak. Those results are summarized in Table 5.

#### Factors Controlling the Cyclical Components

Since some important signals have been noted in the variance spectrum, it is possible to seek some physical phenomena which might cause this behavior. The sunspot cycle often is regarded as one of the basic mechanisms which can affect phenomena such as the air temperature on earth. The lunar cycle might be another factor which produces In this study, we have concentrated on those fluctuations. "external" factors of recurring nature which may affect the The stages of investigation which water temperature record. follow will be: 1) the periodic behavior of sunspot numbers, 2) sunspot and/or solar cycle effects on the variability of water temperature, and 3) fluctuations on lunar cycle expected to be seen in the water temperature record.

## (1) Sunspot Behavior

A sunspot is "A temporary cool region in the solar photosphere that appears dark in contrast to the surrounding hotter photosphere" (Kaufmann, 1975). Counts of the number of sunspots visible at any given time have been recorded since the time of Gallileo (1610). By the mid-1800's, it had become clear that the number of sunspots varies periodically. The

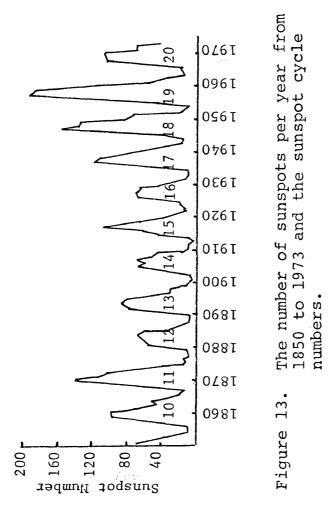
Table 5. The total variance of 24 years water temperature series contributed by the trend, cyclical, seasonal, and irregular components.

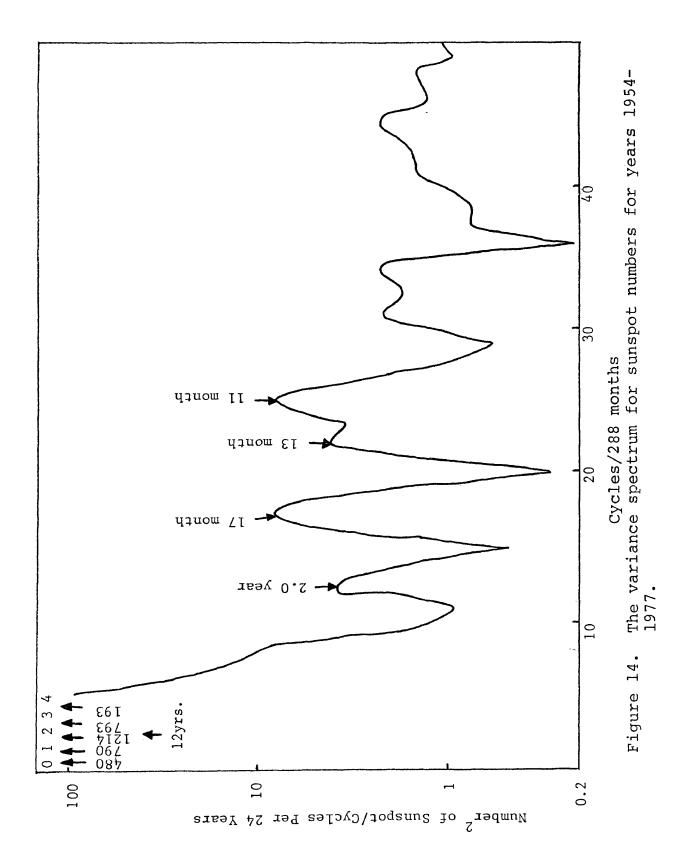
Component	Period (year or month)	Intensity (percentage of total variance)	
trend	not obvious	less than 0.10	
cyclical	around 24 years	0.44	
	26 months	0.21	
	13-14 months	0.30	
	6 months	0.24	
	around 2 months	0.06	
seasonal	12 months	95.84	
irregular		2.81	

sunspot cycle is defined as being from one minimum to another for the sunspot number. The yearly mean sunspot number for years 1850 to 1973 is shown in Figure 13. An 11 year period has occurred, and the number reached a record high value in 1959. However, the occurrence of maxima is not strictly periodic and there often is a delay in the maximum (or minimum) based on the distribution of sunspots in solar latitude and the magnetic field characteristics (Zirin, 1966). Some scientists believe the solar cycle has a 22 year period because the magnetic field reverses each 22 Each sunspot cycle may express different activity; therefore each has been given a number beginning with the middle 1800's. Recently, the sunspot maxima have occurred in 1948, 1959 and 1970, and the minimum values in 1954, 1964 and 1976.

The periodicity of sunspots number is of interest to many researchers. Sugiura (1977) analyzed the Zurich sunspot record for the years 1800-1975 using the power spectrum method. Several apparent peaks for this record were at periods of 10.9, 5.1, 3.4, 2.0, 1.8 and 1.3 years. Some additional minor peaks were noted from monthly data of sunspots for years 1954-1977 (Fig. 14) at 2.0, 1.4 (17 months), 1.1 (13 months) and 0.96 (11 months) year periods.

Many investigators have described the solar-terrestrial relationship using air-temperature records. Shan (1966) used the power spectrum analysis to show that for the air





temperature series at three different cities which had monthly records for over 50 years, the only significant energy in these spectrum appears at the period of 12 months. No significant energy was found corresponding to any known sunspot periodicity. Currie (1974) found the solar cycle signal in power spectra surface air temperature data from the North American continent, and showed that the period of  $10.6 \pm 0.3$  years did exist. Gerety (1977) pointed out that crossspectral computations, using the time series of Zurich sunspot numbers and seasonal temperature and precipitation records, indicate that these series are uncorrelated at individual stations with short-term records and when grouped together into latitude bands. Recently researchers have been concerned that volcanic dust might affect the temperature record (Schneider 1975, Mass 1977).

After Kalinin (1954) mentioned that a quasi-periodic geometric variation with a period of about 2 years, and the discovery of an oscillation of the zonal wind component in the equatorial stratosphere of slightly more than 2 years in length by Reed and Rogers (1962), many researchers began to reexamine the periodic behavior of sunspot cycle.

Shapiro and Ward (1962) pointed out the possibility of a spectral peak at the period of 25 months and suggested this cycle might be attributed to the solar ultraviolet radiation. Shan and Godson (1966) have shown the existence of the 26 months oscillation in the equatorial stratosphere. Currie

(1973) interpreted the spectral peak near 2.15 year, as the ninth and fifth harmonics of the double solar cycle and the sunspot cycle in the geomagnetic horizontal and vertical components. Sugiura (1977) demonstrated the existence of highly correlated quasi-biennial variations in the geomagnetic field and in solar activity.

According to above information, it can be concluded that the solar activity, such as the double sunspot, sunspot and quasi-biennial cycles, might affect terrestrial features.

(2) The Sunspot Cycle and its Effect on Water Temperature(a) Double-Sunspot Cycle: 22 years

It has been shown that the water temperature residual record for years 1954-1977 has a significant component with period around 24 years. This relation is examined by calculating the correlation coefficient between yearly mean water temperature and sunspot number (Fig. 15). The coefficient is so low (-0.223) that it is concluded that there is no direct influence from sunspot activity on water temperature. More precisely, there is no strong linear correlation between these yearly data, although it is possible that the non-linear effects exist. Perhaps, as Schneider (1975) noted solar radiation does not have a linear relationship to sunspot number. He emphasized that solar radiation increases with sunspot number, but eventually reaches a maximum and subsequently decreases.

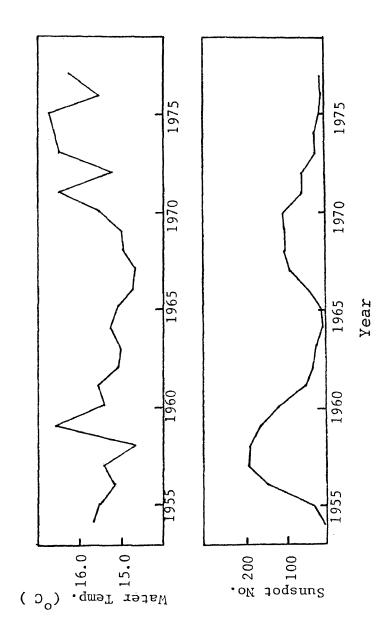


Figure 15. Yearly mean water temperature and sunspot number. (The correlation coefficient is -0.223).

In order to define the variation of water temperature at the same period as the solar cycle (22 years), the variance spectrum method again is used to examine the significance of the water temperature oscillation. The variation of water temperature for years 1954-1975, 1954-1964, and 1964-1975 is shown in Figure 16. Those peaks thought to be significant in sunspot records exist during all three periods. The size of the 22 year peak suggests that the solar cycle can effect water temperatures. In fact the variance accounted for by the 22 year peak is more than that accounted for by the 24 year peak previously.

Water temperature variations might be related to the double-sunspot cycle. Chernosky (1966) suggested that the last half of an even-numbered sunspot cycle is more active than the first half, and that the converse is true for the odd-numbered cycles. The years 1962-1969 had more stable behavior of water temperature and, perhaps, this might be attributed to reduced sunspot activity.

(b) Sunspots Cycle: approximately 11 years

In Figures 10 and 16a, the second frequency (period around 11 years) has high values. With the limited length of record, though, it is hard to determine whether it contains both long cyclical component or not. However, as an additional tool in evaluating the reality of the result, the 24 year record was re-analyzed by variance spectrum in 10 and 12 year segments. Those 2 segments of water temperature

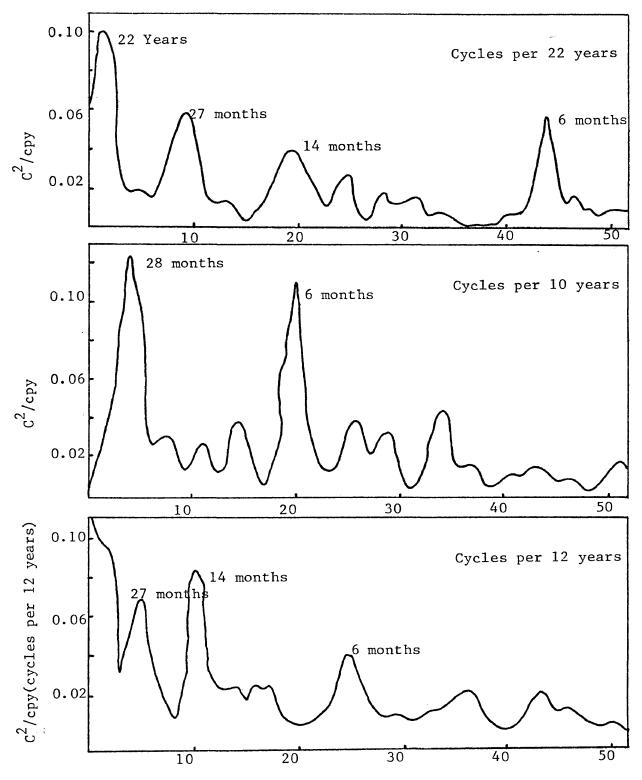
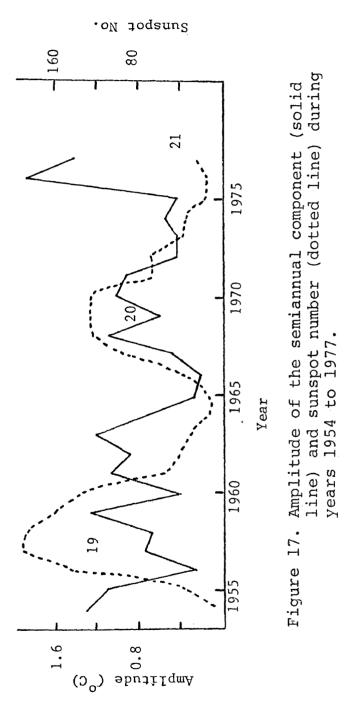


Figure 16. The variance spectrum of water temperature residual series for years (a) 1954-1975, (b) 1954-1964 and (c) 1964-1975.

record are chosen to correspond with the sunspot cycles in 1954-1963 and the following 12 years. If in both records the first frequency accounted for significant variance, it means that those two sunspots cycles affect the water temperature individually. Non-significant variance was accounted for by the first frequency for the first 10 year period (Fig. 16) but the first frequency accounted for more variance during the second segment of the record. Therefore, apparently there is no significant variation of water temperature corresponding to individual sunspot cycles.

### (c) Semiannual Variation: 6 months

The semiannual variation is not explained well by the spectrum of sunspot numbers. Chernosky (1966) investigated the effect of double sunspot cycles on terrestrial magnetic activity during 1884-1963. He stated that the semiannual maxima in geomagnetic activity may be due either to the earth's heliographic latitude or to the sun's geographic latitude. He suggested that the semiannual variation is very little in evidence at the odd-even number minimum (such as occurs between the 19th and 20th sunspot cycles) but is well developed at the even-odd number minimum. If the water temperature is affected similarly, this semiannual variation should be greater during the years 1954 and 1976 than around the years of 1964-1966. The amplitude of the semiannual variation of water temperature and the annual sunspot number for years 1954-1977 are presented in Figure 17. The semiannual

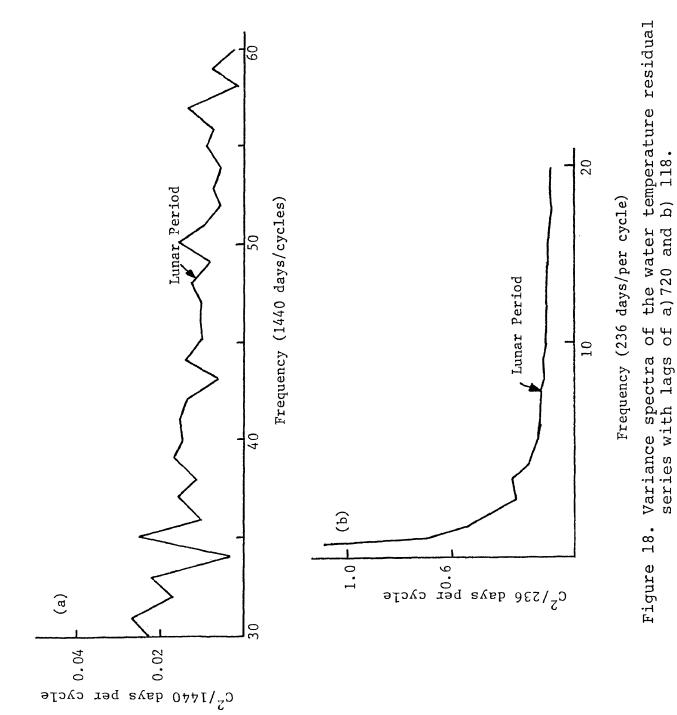


component was stronger in the years of 1954, 1955, 1976, and 1977 than the years of 1965 and 1966. But this fails to explain the variation for rest of years. Chernosky (1966) also suggested that in general, the odd-number sunspot cycle has more semiannual variation than even-number sunspot cycle. Perhaps this provides a partial explanation as to why the half-year variation of water temperature appears bigger during the 19th sunspot cycle than during the 20th sunspot cycle (see Fig. 16).

# (3) The Lunar Cycle.

Since the earth's rotation around the sun has a large impact on the water temperature record, perhaps the lunar cycle affects the water temperature, too. The lunar month is defined as the "synodic period which starts at new moon and ends approximately 29.53 days later at the next moon". Here, the variance spectrum is again used to examine this effect (Lund, 1965). A segment of the variance spectrum showing the frequency ranging from 30 to 60, with lag number equal to 720 fails to show any significant peak corresponding to the lunear period (see Fig. 18). The lunar period again fails to be important when the maximum lag number is chosen to be 118.

In summary, the cyclical portion of the water temperature record contains a 22 year cycle, a 26 month 'quasi-biennial'



variation, a 14 month variation and semiannual oscillations. All of those variations might be attributed to solar activity which shows similar cyclical variations. However, the daily water temperature series does not show any significant oscillation with the lunar period.

#### CHAPTER IV

#### THE IRREGULAR COMPONENT AND A PREDICTIVE MODEL

In Chapter I the long term, average values for each calendar day were presented. In Chapter II, harmonic analysis was used to demonstrate that most of the total variance for yearly series and the mean long term record is due to the annual cycle (the first harmonic). changed slightly from year to year, because the first harmonic cannot account for random events. Also because the cyclical components discussed in Chapter III have not been defined explicitly, one cannot predict the influence of these components on future water temperature readings. One solution is to make a mathematical model which contains as many components as possible. However, the result can be very complicated and confusing. In this chapter, a simple formulation of the non-seasonal component (after the annual component and record mean are removed from the original series) will be described.

This formulation is based on the Box-Jenkins (1970) technique and provides a structured stochastic model to simulate the annual trend and the irregular components of the water temperature variation. This kind of model possesses

a minimum number of parameters, may describe the stochastic process with maximum simplicity, and can include most of the total variance. The ability of this simple model to incorporate the variance of the York River water temperature time series record will be determined.

Many researchers have used stochastic and/or deterministic processes to describe the characteristics of water quality data sets. Almost all of the methods emphasize the behavior of past time series. But we also are concerned about the future readings for time dependent data. The Fourier series and the power spectrum techniques express the behavior based on the frequency domain of the time series. The Box-Jenkins method attempts to fit a model by expressing the time series as an output function which has a random input and consists of several transfer functions. This model not only can tell us something about the nature of the system generating the time series but also can be used to obtain forecasts of the future values.

The autoregressive, integrated, moving average model (ARIMA) used in the Box-Jenkins method will be explained in a later section of this chapter. We also will examine water temperature forecasts for 3 days or longer and evaluate extending the forecast to one year. The reliability of the predictions which have specified probability limits will be discussed.

Carlson and Watts (1970) have illustrated the method of identifying the appropriate form of the general autoregressive moving average model (ARMA) by use of the same autocorrelation function (ACF) used in the Fourier series analysis. this technique the values of the parameters for the suggested model of each series are estimated and the results checked to suggest further modification of the model. McMichael and Hunter (1972) developed a model for temperature and flow in rivers using the Box-Jenkins method. This kind of model divides each data set into a deterministic and a stochastic portion. From the viewpoint of numerical analysis, it is preferable to either a purely stochastic or a purely deterministic model. It is noted that a small number of parameters in this model can substitute for and contribute a greater portion of the response than a large number of amplitude and phase angle parameters in a Fourier series. Albert and Yu (1976) examined the stochastic structure of some water quality time series. They found that the ARIMA model could provide very satisfactory results and that a first order autoregressive model produces a 99 percent reduction in the variance of the original data. A mixed first order autoregressive and first order moving average model was preferred for this data set. Huck (1974) used the Box-Jenkins method to model chloride and dissolved oxygen data. was found that the best representation for the chloride data was an autoregressive model and dissolved oxygen was best described by a moving average process.

In this study, the York River water temperature data have been used to establish a deterministic-stochastic model using the Box-Jenkins parametric model. The deterministic portion was decided first; this portion was assumed to be the fundamental annual harmonic plus the record mean. It is necessary then to specify the order of the autoregressive model and the moving average model after observation of the autocorrelation function values and the changes in the variance of the residual series. The ARIMA process was used to fit the stochastic process. The three stage iterative procedure consisted of identification, estimation and evaluating the accuracy of model (Box and Jenkins, 1970).

Model identification includes use of the data and information on how the series was generated, and evaluating the appropriateness of the several kinds of parametric models available. Model estimation includes obtaining sets of coefficients, using different methods to approach the real data, and making the sums of square errors as small as possible.

The last step is to check the adequacy of the model and determine how it can be improved and corrected if it is inadequate. Each of these steps is described in detail in Appendix C.

Four models were selected as ones which can reasonably simulate the data. The choice was based on 1) highly

similar coefficients, 2) very close values of the ratio of the sum of the residual to the initial sum of squares, 3) approximately the same Q value, and 4) inclusion of about the same amount of total variance. The characteristics of the four models are summarized in Table 6 and described in greater detail in Appendix C. Considering the principle of simplicity, Occan's Razor, the best choice is the (1,0,0) model.

ARIMA Type	Parameters	Fitted Model	Percentage of Total Variance
(1,0,0)	φ <sub>1</sub> =0.91875	(1-0.91875B) z = a <sub>t</sub>	99.4179
(2,0,0)	$\phi_1 = 0.91019$ $\phi_2 = 0.00919$	(i=0.91019B- 0.00919B <sup>2</sup> ) z = a <sub>t</sub>	99.4180
(1,0,1)	$\phi_{1} = 0.9199$ $\theta_{1} = -0.008$	$(i-0.9199B)\tilde{z}_{t}$ =(i+0.008B) $a_{t}$	99.4179
(0,2,1)	θ <sub>1</sub> =0.99	$\nabla^2 \tilde{z}_t = (1-0.99) a_t$	99.4259

Table 6. The Final Estimation for Each Possible Model.

The behavior of the (1,0,0) model can provide some understanding of the stochastic processes affecting water temperature. It implies that the deviation from the annual cycle is dominated by the deviation for antecedent neighbors and those residuals have decreasing correlation from near to far neighbors. In mathematical words, deviations from the annual cycle will decrease with exponential decay.

Once the best fit model has been selected, the forecast function can be derived using relations between present and past observed values. The minimum square error is expected to explain how accurate this model is.

One of the basic concepts of the forecast model is that the present disturbance value,  $\tilde{z}_t = y_t - \tilde{y}_t$ , might be expressed as a set of linear functions of weighted present and previous shocks that is:

$$\tilde{Z}_{t} = \overline{\psi}_{0} \quad a_{t} + \overline{\psi}_{1} \quad a_{t-1} + \overline{\psi}_{2} \quad a_{t-2} + \dots$$
 (4-1)

The coefficient of  $a_t$ ,  $\overline{\psi}_o$ , is always regarded as 1. If  $\widetilde{Z}_{t+\ell}$  is the value observed  $\ell$  days ahead and  $Z_t(\ell)$  is the forecast value with  $\ell$  day lead time, the purpose of this exercise is to reduce the error between  $\widetilde{Z}_{t+\ell}$  and  $Z_t(\ell)$ . That is:

$$\widetilde{Z}_{t+\ell} = a_{t+\ell} + \overline{\psi}, \ a_{t+\ell-1} + \overline{\psi}_{2} \ a_{t+\ell-2} + \cdots$$

$$= (a_{t+\ell} + \overline{\psi}, \ a_{t+\ell-1} + \cdots + \overline{\psi}_{\ell-1} a_{t+1})$$

$$+ (\overline{\psi}_{\ell} \ a_{t} + \overline{\psi}_{\ell+1} a_{t+1} + \cdots)$$

$$= e_{t}(\ell) + Z_{t}(\ell) \qquad (4-2)$$

If the series of equation (4-2) is divided into two portions, that is the part of the shocks that have not happened yet and those shocks which have happened, then the disturbance & units ahead is composed of the forecast function corresponding to the lead time &. The forecast error can be regarded as the output from a set linear filter,

whose input is a set of white noise with  $\ell$  shocks. (See Appendix C-1 for details).

From equation (4-1), since each current disturbed value can be expressed as weight  $\overline{\psi}$  on a set of shocks.

$$\tilde{Z}_{\pm} = \overline{\psi}(B) a_{\pm}$$
 (4-3)

where  $\overline{\underline{\psi}}$  (B) =  $\overline{\underline{\psi}}_{o}$  +  $\psi_{1}$ B +  $\overline{\underline{\psi}}_{2}$ B<sup>2</sup> + ...

The ARIMA model is:

$$\phi(B) \nabla^{d} \tilde{Z}_{t} = \theta(B) a_{t}$$
 (4-4)

If equation (4-3) is substituted into equation (4-4) the result is:

$$\phi(B) \nabla^{d} \overline{\psi}(B) = \theta(B) \tag{4-5}$$

For a (1,0,0) model, based on equation (4-5)

$$\nabla^{d} = 1 \quad \theta (B) = 1 \quad \cdot \cdot \cdot \phi (B) = (1 - \phi B)$$

$$(1 - \phi B) \left(1 + \frac{\overline{\psi}}{1}B + \frac{\overline{\psi}}{2}B^2 + \ldots\right) = 1 \tag{4-6}$$

Comparison of equations (4-5) and (4-6) shows that the same power of B has the same coefficients on both sides.

$$\frac{\overline{\psi}_{1} - \phi = 0}{-\overline{\psi}_{1} \phi + \overline{\psi}_{2} = 0} \qquad \frac{\overline{\psi}_{1} = \phi}{\overline{\psi}_{2} = \overline{\psi}_{1} \cdot \phi = \phi^{2}} \\
-\overline{\psi}_{2} \phi + \overline{\psi}_{3} = 0 \qquad \overline{\psi}_{3} = \overline{\psi}_{2} \cdot \phi = \phi^{3} \\
\cdot \cdot \overline{\psi}_{j} = \phi^{j} \quad j \geq 1$$

The  $\ell$  term ahead for (1,0,0) model is:

$$\begin{array}{lll} & (1-\varphi_B) & \tilde{Z}_{t+\ell} = a_{t+\ell} \\ & \tilde{Z}_{t+\ell} - \varphi_{t+\ell-1} = a_{t+\ell} \\ & \text{when } \ell=1 & \tilde{Z}_{t+1} - \varphi_{t+\ell-1} = a_{t+1} & \tilde{Z}_{t+1} = e_t(1) + \hat{Z}_t(1) \\ & = a_{t+1} + \hat{Z}_t(1) \\ & & \cdot \cdot \hat{Z}_t(1) = \varphi_{t+1} = a_{t+2} = \tilde{Z}_{t+2} - \hat{Z}_t(2) - \varphi_{t+1} \\ & = \hat{Z}_{t+2} - \hat{Z}_t(2) - \varphi_{t+1} - \varphi_{t} \\ & \cdot \cdot \hat{Z}_t(2) = \varphi_{t+1} = \varphi_{t+1} + \varphi_{t+1} = \varphi_{t+1} + \varphi_{t+1} \\ & = \hat{Z}_{t+2} - \hat{Z}_t(2) - \varphi_{t+1} - \varphi_{t+1} + \varphi_{t$$

Therefore, it could be concluded that this forecast model might be expressed in the following form for different lead time but with the same origin:

$$\hat{Z}_{t}(1) = \phi \hat{Z}_{t} \tag{4-7}$$

$$\hat{Z}_{\pm}(\ell) = \phi^{\ell} \tilde{Z}_{\pm} = \phi^{\ell-1} \hat{Z}_{\pm}(\ell-1) \qquad \qquad \ell \ge 2$$
 (4-8)

Thus, tomorrow's water temperature can be predicted as:

$$\begin{split} \hat{Z}_{t}(1) &= \phi \tilde{Z}_{t} \\ \hat{Y}_{t}(1) &= \tilde{Y}_{t+1} + 0.91875 \cdot (\tilde{Y}_{t} - Y_{t}) \\ &= (\alpha_{1} + \alpha_{0} \sin(w(t+1) + 4.1956) - 0.91875 \\ &\cdot \sin(wt + 4.1956)) + 0.91875 Y_{t} \\ &= 1.264 + 11.5953 \cdot \sin(w(t+1) \\ &+ 4.1956) - 0.91875 \cdot \sin(wt + 4.1956)) + 0.91875 Y_{t} \end{split}$$

where,  $y_t$  = today's temperature reading

y
t+1 = annual harmonic corresponding value at
day t+1

 $\tilde{y}_{t}$  = annual harmonic corresponding value at day t

Because the forecast error is expected to have minimum mean square, an expected value equal to zero is the best. The theoretical error for  $\ell$  lead time is:

$$\nabla = (\overline{\psi}_0^2 + \overline{\psi}_1^2 + \overline{\psi}_2^2 + \dots + \overline{\psi}_{\ell-1}^2) \delta_a^2$$

where  $\delta_a^2$ : the residual variance after model was fitted

 $\overline{\underline{\psi}}_{j}$ : the coefficients of weight on j, j=0, ...,  $\ell$ -1

Thus the difference between the observed disturbance and forecast function  $\ell$  days later is bounded within the square root of  $\nabla$  times  $\epsilon$ , the corresponding value of the normal distribution (e.g. for the 50 percent probability limit,  $\epsilon=1.96$  etc.)

$$\widetilde{Z}_{t+\ell} = \widehat{Z}_{t}(\ell) + \varepsilon \left( (\underline{\psi}_{0}^{2} + \underline{\psi}_{1}^{2} + \dots + \underline{\psi}_{\ell-1}^{2}) \delta_{a}^{2} \right)^{\frac{1}{2}}$$

$$\delta_{a}^{2} = 0.4879 \quad \underline{\psi}_{0} = 1 \quad \underline{\psi}_{1}^{2} = (0.91875)^{2}, \dots$$

$$(4-10)$$

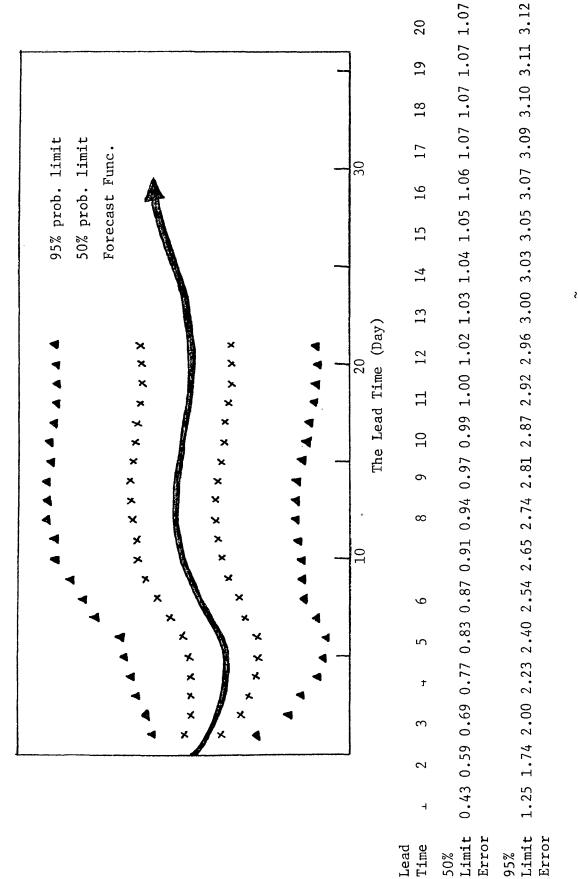
The square root of forecast error variance actually can be indicated as the summation of a geometric series with  $\phi^2$  factors.

$$\frac{\overline{\psi}_{0}^{2} + \overline{\psi}_{1}^{2} + \dots + \overline{\psi}_{\ell-1}^{2} = 1 + \phi^{2} + \phi^{4} + \dots + \phi^{2(\ell-1)}$$
(4-11)

Table 7 includes the first 20 forecast errors for water temperature data. The forecast error will increase with forecast lead time. It is found that the rate of increase approaches zero at about the fifteen days lead time. Actual temperature data and 1 day, 2 day, 3 day forecasts for 1976 are compared in Figures 19 to 21. These figures show that there is little difference between the forecast series and the actual function.

It is worthwhile to note that with a longer forecast period, the "shift" phenomenon is more obvious. deterministic portion (seasonal component) of this model is assumed to be a sine curve when the corresponding value of the sine function is decreasing, the predicted value is bigger than the actual value, and the contrary result occurs when the slope of the sine function is increasing. The reason might be that the water temperature annual cycle is not perfectly described by a sine curve. So, we can modify the short term forecasts by this general from July 20 to January 20, the forecast value should rule: be reduced a bit to approximate actual values more closely. During the other half of the year, prediction should be modified in the other direction. In the summer, the variation of water temperature is quite small, thus the prediction then is superior to other seasons.

In Chapter III examination of the autocovariance function has shown that the water temperature record includes



= a<sub>t</sub> model of water The first 20 forecast errors for (1-0.91875 B)  $\tilde{z}_{t}$ temperature prediction. Table 7.

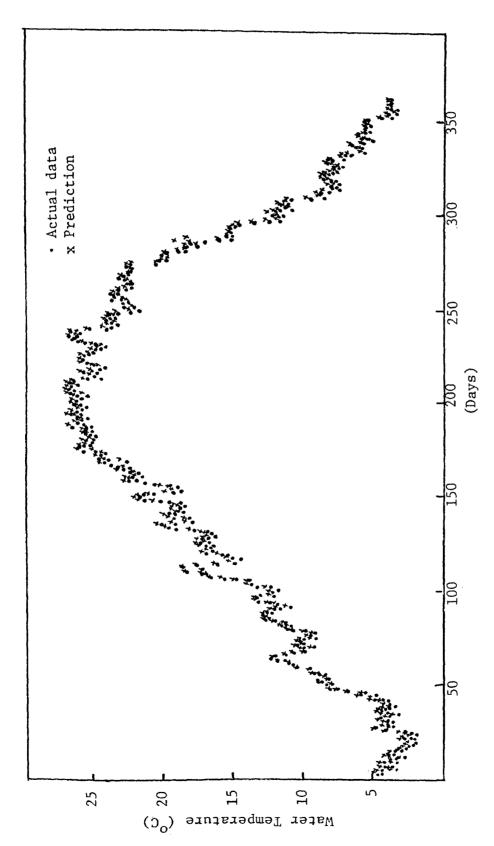


Figure 19. One day ahead prediction versus actual water temperature data in 1976.

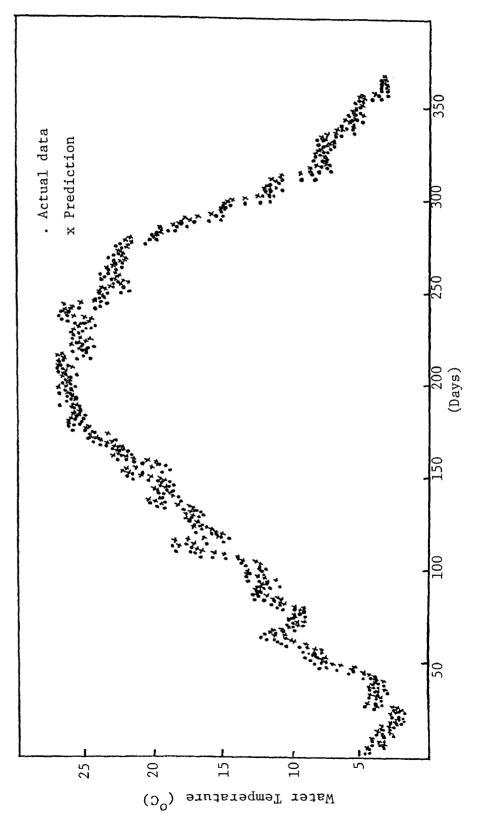
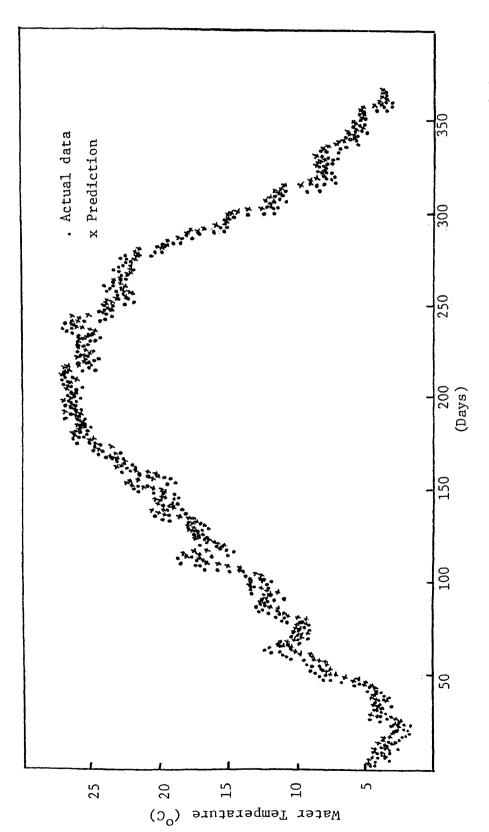


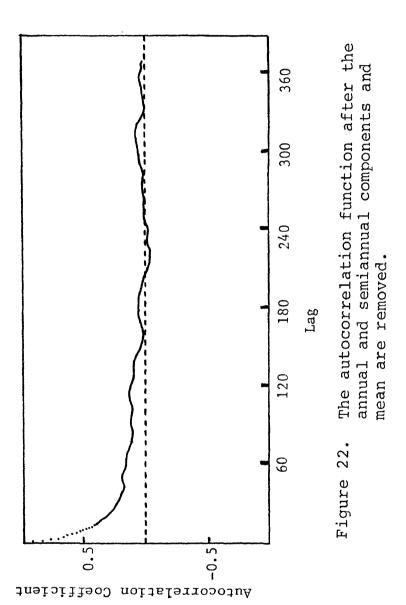
Figure 20. Two day ahead prediction versus actual water temperature data in 1976.



Three day ahead prediction versus actual water temperature data in 1976. Figure 21.

the half-year cycle and this phenomena might be explained by geomagnetic field variation. Perhaps then the deterministic portion ought to contain both the annual and the semiannual variation. However, from Chapter II, it is seen (Table 1) that the amplitude and phase angle varies yearly for semiannual component. In other words, the semiannual component will change with time. This might conflict with the purpose of a deterministic function, which is to define a response function which is easy to calculate and accurate for any point in the time interval. Another reason why this shift phenomenon occurred is that the actual data used to compare with the predictions have a large fluctuation of semiannual nature. Table 1 indicates that the year which was used (1976) had the largest semiannual fluctuation (amplitude=1.8°C) for the period 1954-1977.

In order to improve the predictions when the semiannual fluctuation is strong, the deterministic portion of the model of water temperature can be modified to contain both the annual and semiannual cycles. The autocorrelation function for the residual series when the half-year cycle is eliminated is a function with exponential decay (see Fig. 22). The best fit model is still the first order autoregressive process (1,0,0) except the coefficient is changed to 0.91231. That model is:



$$\hat{y}_{t}(\ell) = \hat{y}_{t+\ell} + \phi^{\ell}(y_{t} - \hat{y}_{t})$$

$$= \alpha_{0} + \alpha_{1} \sin(w(t+\ell) + \alpha_{2}) + \alpha_{3} \sin(2w(t+\ell) + \alpha_{4})$$

$$+ (0.91231)^{\ell}(y_{t} - \alpha_{0} - \alpha_{1} \sin(wt + \alpha_{2}) - \alpha_{3} \sin(2wt + \alpha_{4}))$$

where

 $\ell$  = the number of  $\ell$  days ahead of prediction

 $\phi$  = the coefficient of the first order autoregressive process

 $\alpha_3$  = the amplitude of semiannual variation

 $\alpha_{\Lambda}$  = the phase angle of semiannual variation

The rest of parameters are the same as mentioned previously.

For this modified model, 1) two more parameters need to be estimated, 2) the residual variance only changes 0.01 (0.40971 to 0.39984), and 3) the ratio of the variation is large (480:1). Hence, due to the simplicity and the above tiny differences, it is suggested that this semiannual variation can be ignored for most predictions.

The relationship between actual data and the predictive function are summarized in Table 8. The total variance for actual data and predictions are very close. The one day prediction error is bounded by the 50 percent and 68.28 percent probability limits, while the other two predictions have errors near to one standard error. In addition, although the predictions have greater total difference than actual data for the entire year, the sums of those predictions

are almost the same. Therefore, for short term predictions, the deviation between actual data and the sine curve usually can be ignored.

Predictions for three arbitrarily selected original points are shown in Figure 23. None of the values for the first fifteen days is outside the 95 percent probability limit and only a few are near the 50 percent probability limit. The predictions are for winter, spring and summer.

Longer simulations of water temperature data using one known data point are shown in Figure 24. Because the forecast error will be constant after about 15 days lead time, the predictive function will follow the harmonic curve. The equations (4-8) and (4-9) explain this phenomenon.

$$\hat{z}_{t}(1) = \phi \tilde{z}_{t}$$

$$\hat{y}_{t}(1) = \tilde{y}_{t+1} + \phi (y_{t} - \tilde{y}_{t})$$

$$\hat{z}_{t}(\ell) = \phi^{\ell} \tilde{z}_{t}$$

$$\hat{y}_{t}(\ell) = \tilde{y}_{t+\ell} + \phi^{\ell-1} (\hat{y}_{t}(\ell-1) - \tilde{y}_{t})$$

$$= \tilde{y}_{t+\ell} + \phi^{\ell} (y_{t} - \tilde{y}_{t})$$
(4-13)

From equation (4-13), today's prediction is the deterministic value plus  $\phi$  times the difference between yesterdays reading and its harmonic value. With an increasing prediction period, the power of  $\phi$  will increase too (equation 4-14). But if  $\phi$  is less than 1, somedays later this exponential term will equal or be very close to

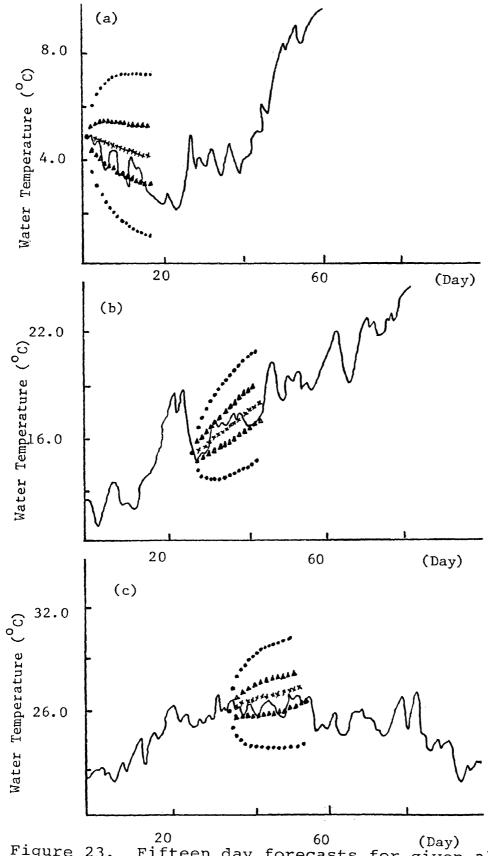
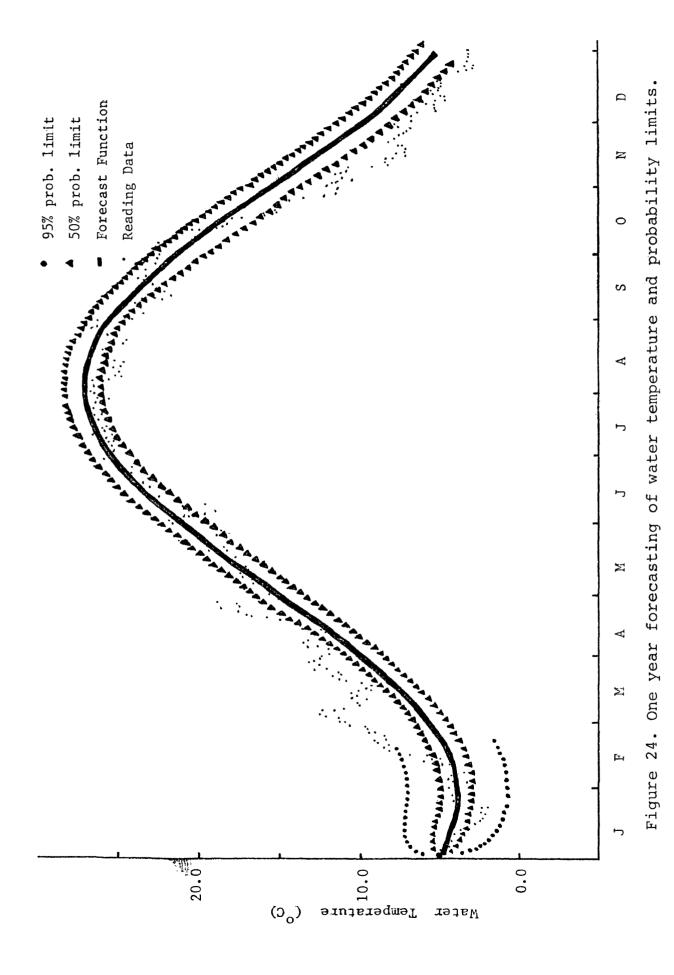


Figure 23. Fifteen day forecasts for given a) winter,b) spring and c) summer days.



zero. That means the predicted value is dominated by the deterministic portion of the model and the influence of the autoregressive operator disappears. Thus for long term predictions when the temperature readings are not modified by future shocks, the predictions will return to the deterministic routine sooner or later. For higher order autoregressive operators, the function goes back more slowly.

In summary, the Box-Jenkins technique can provide a daily water temperature predictive model. The best fit for the non-seasonal component of the York River water temperature record is the first order, autoregressive process. This model gives good results for short term predictions up to about 15 days ahead.

### NOTATIONS FOR CHAPTER IV

 $a_{+}$ : white noise process at time t (shocks at time t)

B: backward shift operator

d : order of differencing operator

e<sub>+</sub>: normal random deviate

L: lead time for forecast

P: order of autoregressive process

Q: estimate of statistic

q: order of moving average process

 $\gamma_{\kappa}$ : estimate of autocorrelation coefficients at lag K

ε: normal deviate corresponding to probability level

 $y_+$ : series of daily mean water temperature at time t

yt: annual harmonic corresponding value for day t's water temperature

F: forward shift operator

Z<sub>+</sub>: observed value of series at time t

the deviation from mean of a series (or from a defined deterministic function) at time t

 $z_{t(L)}$ : forecast at time t of  $z_{t+L}$  (L unit forecast ahead from time t)

θ: moving average coefficient

 $\delta_a^2$ : sample variance of a time series

φ: autoregressive coefficient

 $\phi_{KK}$ : kth-order partial autocorrelation function

j: jth weight when autoregressive process is expressed as weight infinite sum of previous shocks

∇<sup>d</sup>: dth-order backward shift operator

u: mean of the entire series

jth weight when moving average process is expressed as weighted infinite sum of previous disturbances

 $\boldsymbol{\theta}_{_{\mathbf{C}}}(\mathbf{B}):$  polynomials of order q for a moving average process

 $\boldsymbol{\varphi}_{D}\left(\boldsymbol{B}\right)$  : polynomials of order p for a autoregressive process

ACF: autocorrelation function

PACF: partial autocorrelation function

 $S(\phi,\theta)$ : sum of square when a series does exist autoregressive process with coefficient  $\phi$  and moving average process with coefficient  $\theta$ 

N: the number actually accounted for estimate coefficient

 $\alpha_n$ : series mean of water temperature

amplitude of water temperature series is fitted to annual sine curve

α<sub>2</sub>: phase angle of water temperature series is fitted to annual sine curve

w: frequency (in here,  $w = \frac{2\pi}{365}$  of water temperature data is fitted to a annual sine curve

#### CHAPTER V

AN APPLICATION: THE RELATIONSHIP BETWEEN
WATER TEMPERATURE AND THE CONDITION INDEX OF OYSTERS

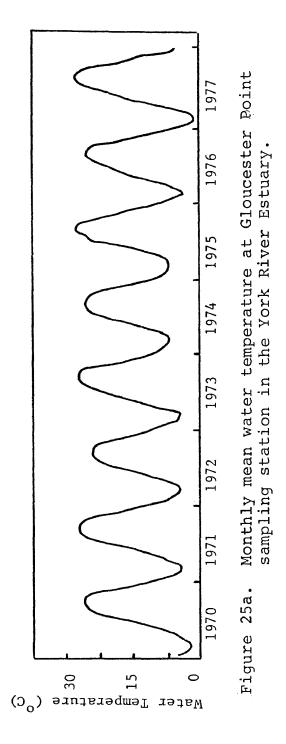
The variability of water temperature plays a very important role in maintaining the normal existence and the growth of aquatic biota. Many different impacts have been documented for changing water temperature (Arnold, 1962). It is known that temperature requirements are different for each stage of the growth cycle. In addition, natural reactions, such as diseases and competition, can become more important when coupled with water temperature stress. Because organisms can be affected by the variation of water temperature in these many ways, it attracts us to investigate the relationship between these factors and daily mean water temperature.

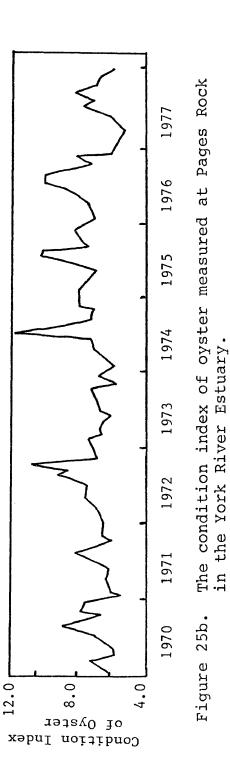
The oyster is one of the most important seafood products of the York River estuary. If we pay attention to the quality of the oysters, this will show us the best time for harvesting. Scientists have designed a method to express the meat quality of oysters termed the Condition Index (CI). This relative value can compare changes in yield from time to time or location to location for oysters. It is defined as the ratio of dry weight of the oyster meats in grams to

the size of the shell cavity in cubic centimeters. It is known that the higher values for condition index indicate greater amounts and quality of meats for any given bushel (Haven, 1962). The C.I. of oysters ranges from 3.0 to 12.0 and is classified by three groups based on quality. A "poor yield" is classified as values between 3.0 to 5.5 and "good yield", 7.6 and over. Values between those two classes are regarded as average quality. Meat quality of York River oysters has been average or below average, if all stations are considered. The average was 6.2 for the years 1955-1971.

Monthly C.I. of oysters have been measured since the end of 1969 to the present for three important estuaries in Virginia. The seasonal and long term tendency of that index number can provide information for the harvest of the future. The Pages Rock sampling station in the York River is near Gloucester Point and a complete data set exists for this station. The C.I. of oysters measured at Pages Rock for years 1970-1977 is shown in Figure 25. Two apparent peaks occur, one in late spring and the second in early fall. The yearly average increased in the period 1974-1976 but dropped back to a low level in late 1976. An especially low average of C.I. of oysters occurred in 1973.

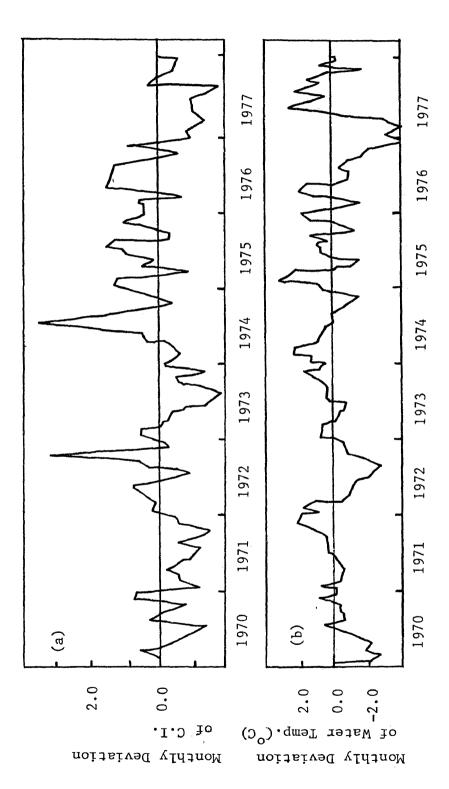
Water temperature might be one factor which affects growth and mortality of oysters. Hence, in order to know the relationships between the temperature and C.I. series, the cross-correlation function was used.





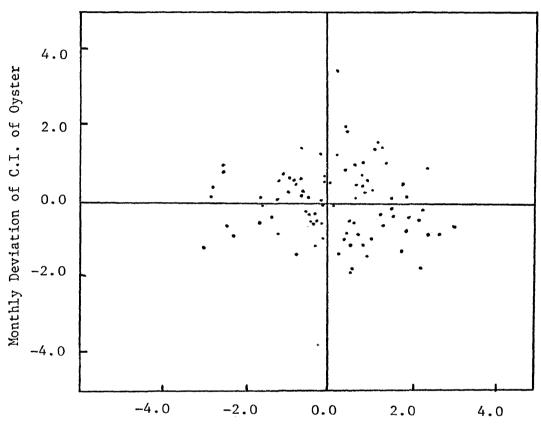
One can observe (Fig. 25) that the trend of the former is more regular than the latter. Since both trends are expressed as annual cycles, the monthly deviation from particular monthly mean of this period can more clearly reveal this relative relation (see Fig. 26). There appears to be no significant corresponding relationship through the entire trend. Plots of pairs of corresponding temperature and index deviations (Fig. 27) show that each section has almost the same number of pairs. That means that even if a direct relationship does exist, the coefficient will be very low. Besides, it is necessary to consider that the water temperature might affect the C.I. several months later. Cross correlations for lags of 0 to 3 months are 0.053, 0.114, 0.146 and 0.182 respectively. Even though there is an increasing tendency, they are all so small that it is not reasonable to make a regression equation. Values increased to about 0.33 for lags up to 12 months, although such long term influences do not appear to be reasonable. In conclusion, monthly mean water temperatures are not good indicators of monthly C.I. of oysters.

Arnold (1962) also has pointed out that aquatic organisms can acclimate to higher or lower water temperature and the former is easier than the latter. The sensitivity or tolerance of aquatic organisms to temperature changes (or levels) also varies with age, size and season. Hence, it is possible to seek some relative variations of water temperature through



at Pages Rock from the particular monthly mean during 1970-1977 and (b) Monthly deviation of water temperature Shows (a) Monthly deviations of condition index of oyster at VIMS pier from the particular monthly mean during 1970-1977. Figure 26.

ø



Monthly Deviation of Water Temperature ( $^{\circ}$ C)

Figure 27. The monthly deviation of water temperature and the corresponding monthly deviation of condition index of oysters for 1970-1977.

two successive index numbers. Several general rules are:

- The obvious peak of this index always occurs in June or July when the monthly mean water temperature is around 24C. This was true in the years 1970, 1974, 1975 and 1976 for which the index number was over 9 (Fig. 25). The years 1971, 1973, and 1977 did not have the high peak, perhaps because of hotter weather in July (average temperature over 26C). Day to day fluctuations also might affect the C.I.. The change in condition index of oyster from March to July versus the number of days when water temperature was in the range of 21C-25C is shown in Figure 28. The purpose is to see whether the increase of C.I. during late spring and early summer is related to the accumulated reaction of water temperature in a given water temperature The correlation coefficient is moderate (0.561). Slow acclimatization of the oyster to increased water temperature might be the reason for this moderate correlation.
- 2. Some minor peak usually occurs in September or October when the water temperature has dropped back to the range around 20C but this increase is slight.
- 3. Each major peak is very sharp. This might be explained that the oysters acclimate more easily to increasing water temperatures. However, the oysters require more dissolved oxygen at higher water temperatures. This may

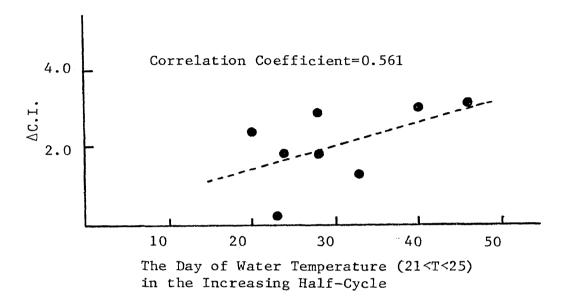
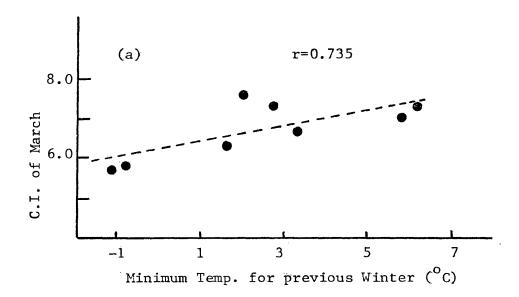


Figure 28. The change in C.I. of oyster versus the number of days the water temperature ranged from 21C to 25C for the months March to July.

control the upper temperature which can be tolerated by oysters and explain why there is a marked drop of the C.I. in late summer.

- 4. The C.I. during the winter does not always decrease after the oysters have acclimated to the lower temperatures. The C.I. value may increase slightly, e.g. years 1970, 1971, 1972, 1974, and 1977.
- The water temperature of around 10C is critical for oysters. If the spring is cold (water temperature less than 10C-11C through March), the C.I. will decrease. This indicates that for the oyster to be kept in cold water is disad-The relationship between water temperature during vantageous. the previous winter and the condition index in March is shown in Figure 29. If this relationship does exist, one would expect a warm winter to result in a higher C.I. value in In Figure 29-A the minimum water temperature observed during the previous winter is plotted versus the March C.I. A correlation coefficient of 0.735 was calculated. number of days with temperature below 10C and "degree-days" for T<10C were examined. The better correlation, r=0.723, was for the degree-days (Figure 29-B). However the small number of data points (8 points) does not allow us to define these relationships as clearly or precisely as we might like. The correlations are reasonably good for both indicators of the previous winter's coldness.



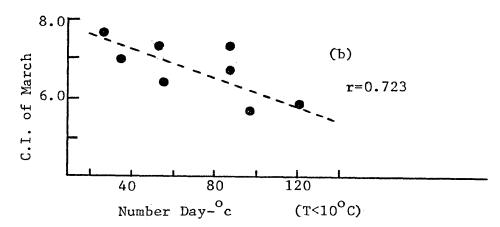


Figure 29. March Condition Index versus
a) minimum temperature for the
previous winter and b) number of
degree-days below 10C for the
previous winter.

In summary, there is no direct relationship between the monthly variation of water temperature and condition index of oyster. It might be because those relations between the acclimatization of the oyster and water temperature are not linear. Besides, many other factors, such as dissolved oxygen levels, quantity and quality of food available, also affect the health and growth of oysters. However, the ideal conditions to maintain high value of C.I. seem to follow this rule: warm winter, early spring, short summer and long autumn. More frequent sampling for C.I. value is needed to define the relationship with water temperature precisely.

### CHAPTER VI

#### DISCUSSION

(a) How to achieve a more satisfactory result using the basic model.

The four basic components of the water temperature time series (annual, trend, cyclical and random) have been derived. However, in order to reach a more satisfactory result for any given time series, some characteristics of the techniques used in this study need to be discussed and specified. Note that all of these four components will not occur for every time series, depending on the length of the record and the sampling interval. In this discussion it is assumed that a time series is long enough to contain all four components.

In general, the presence of a trend in a time series usually makes it difficult to examine the behavior of the remaining cyclical, seasonal and irregular component, especially for economic time series (Fishman 1969). If some obvious trend can be seen from the plotting of the time series, this component needs to be extracted first. The difference operator usually is used to solve this problem. The effect of this operator is to reduce a process from non-stationary sequences to a stationary process. The order of

the difference operator which is required to eliminate the trend component is related to the degree of the polynomial equation which best describes this trend behavior. In general, if the nth differences are zero on the average, then the trend will follow a polynomial of degree (n-1). For instance, if a straight line gives the best description, then the first differences (difference operator used once) will have a non-zero average, but the second differences will fluctuate around zero. In this study, a very strong annual cycle does exist, but the yearly mean doesn't show any apparent trend, (slope=0.072). Besides, it was found that the average nearest to zero occurs at the first difference.

The next step is the choice of an appropriate function which can present the general behavior of the seasonal and cyclical components. Fourier analysis usually is suitable because many periodic functions share, more or less, the properties of sinusoids. Another advantage of Fourier analysis is that the amplitude doesn't change with the initial point of the sampling interval. The disadvantages were noted at the end of Chapter II. It appears that if the Fourier analysis is performed before the variance spectrum is calculated, more information can be extracted.

More detailed knowledge of the cyclical behavior of a time series, however, can be reached solely by variance spectrum. Once an especially strong cyclical component

occurs, it will "block" the rest of the recurring behavior which may or may not be significant. In order to be certain of the regularity of a seasonal component or cyclical component, an analysis of segments of the time series is required to show the consistency of each cyclic component. The broad features of a cyclical component can be seen from each segment from Fourier analysis or the variance spectrum. It is not necessary to expect that each cyclical behavior will be repeated and have the same magnitude. However, this analysis can tell us if each component changes with different time intervals. If so, one might seek the cause of this change. For instance the approximately equal amplitudes and phase angles show the annual component of the water temperature record to be stable. However the first 12 years of the record behave differently at low frequency than the following 12 years of this 24 year record, although both the 24 year period and the 12 year period express high values in the variance spectrum.

The moving average and seasonally adjusted method also can be used to eliminate the effect of cyclic behavior in a time series. But the disadvantages for both is that the intensity of that cyclical behavior is not always known. Except for definite recurring phenomena that are known, the weighted moving averages or filters must be chosen correctly. Besides, big errors can occur when the time series is short.

Even with an increased understanding of a time series, sometimes it is hard to understand its nature totally.

Another, or a longer, time series might provide an explanation for the behavior of this series. "Multiple time series analysis" seems to be necessary for a very thorough and complete investigation.

(b) The advantages of a deterministic-stochastic model over a purely stochastic model

The Box-Jenkins technique can provide predictions from a simple parametric model which is generated by the ARIMA process and is suitable for many time series. This method can reduce effectively most of the total variance from a time series. However, few investigators have discussed the question of the limits of the predictions and the structure of the model. In order to explain this, it is necessary to indicate the advantages of a deterministic-stochastic model.

Many time series do not have an obvious deterministic function. Therefore, a predictive model can be made only if the whole series is regarded as the stochastic process. The ARIMA process still can provide a satisfactory result. However, this kind of model might be related more to previous disturbances than the combined deterministic-stochastic model. For instance, McMichael and Hunter (1972) derived a stochastic model using the daily mean water temperature. The characteristic of their model is that today's disturbance (here, the

disturbance is the reading subtracted from the mean value of the series) is related not only to yesterday's disturbance but also with that for the same day last year. In practice, the disturbance which occurred last year is unlikely to have any affect this year. The strong yearly cycle needs to be substituted, otherwise this series will remain non-stationary. A serious disadvantage of purely stochastic models is that the forecasting error is related to the standard deviation of the time series. Especially for recurring time series, the forecasting error will be large. The prediction also is limited by different situations (such as seasonal fluctuations) and affected by too many terms.

This should be taken as the deterministic function.

Then a model can be selected for the remaining, stochastic component. The stochastic model will provide information on the behavior of the time series.

#### CHAPTER VII

#### CONCLUSIONS

The basic conceptual model of the water temperature record which has been used in this study consists of a trend component, a cyclical component, a seasonal component and an irregular component each of which has been described. The important findings are as follows:

### (a) Long term trend component:

This component is not strong enough to express its behavior in this 24 year, daily mean water temperature series. It is known that the degree of difference operator and the variance accounted for by the zero frequency in the variance spectrum show the strength of this trend component. With a zero order difference operator, the trend component accounted for less than 0.1 percent of the total variance. Most of the variance at low frequency is contributed by a cyclical component with a period of 22 years.

### (b) Cyclical components:

Recurring cycles have been found in this daily mean water temperature record with the major periods being 22 years, 26 months, 14 months and 6 months. All four periods are characteristic of solar activity. The lunar period

(29.53 days) was not significant for this series. If these recurring phenomena are due to solar activity, an interesting exercise would be to derive a rule which can describe roughly the behavior of water temperature within a double-sunspot cycle. It is important to emphasize that the cyclical components do not always have the same intensity throughout a long time series period. For example the greatest semiannual variation of water temperature occurs around the even-odd sunspot minimum. The activity of quasi-biennial oscillation is similar. The 14 month oscillation is stronger during an even-numbered than during an odd-numbered sunspot cycle. In fact, its intensity during an even-numbered sunspot cycle is stronger than the biennial and semiannual variations.

The suggested interaction between sunspots and water temperature is as follows:

- 1) Solar activity is greatest during the first and last five or six years of the 22 year solar cycle. Correspondingly, the water temperatures will show greater variation during those periods (e.g. 1954-1959 and 1971-1976 of this series) than during the rest of the cycle (e.g. 1960-1970).
- 2) At the even-odd minimum in the sunspot cycle both the biennial and the semiannual variations tend to a maximum (e.g. years 1954, 1976, 1977).
- 3) The 14 month oscillation of water temperature has a stronger behavior during an even-numbered sunspot cycle.

## (c) Seasonal or annual component:

This component is so stable that it shows almost identical amplitude (11.59 c) and phase angle (240 degree) year by year. Over 95 percent of the total variance is accounted for by this component for individual years and the 24 year mean series. The higher order harmonics (periods less than one year) do not show consistent amplitude or phase angle. For this reason, the annual component needs to be extracted first; then the more information can be extracted from the residual water temperature record.

(d) Irregular (random) component: The remaining component which is left after removing the above three components from the original series is regarded as the irregular component. This component has no observable pattern and is regarded as the purely random phenomena.

# (e) Non-seasonal component:

In order to predict the future reading accurately (especially for the short term future), the non-seasonal component can be assumed as the stochastic portion. Using the Box-Jenkins technique a first order autoregressive process was found to give the best fit predictive model for this time series. Both portions, deterministic and stochastic, accounted for over 99.5 percent of the total variance of the original water temperature series. Reasonable prediction can be made for 12 days ahead using this model, if one standard deviation is taken as the termination point for the forecasting error.

Appendix A: Daily average water temperature at VIMS pier for years 1954-1977.

DAILY AVERAGE WATER TEMPERATURE AT VIMS PIER IN 1954

DEC	0.6	•	•	•		•	•	•			•	•	•		•	•		•		•	•	•	•	•		•	•	•	•	•	•	5.3
NON	14.4	4.	2.	2.	2.	2.	-	-	-	-	-		-	1.	-	1.	-	2.	2.	2.	2.	-	-	-	•	0	6	•	6	•		11.6
100	24.3	3	3.	3.	4.	4.	2.	0	-	-	-	2.	2.	2.	6	*	*	*	6	æ	7	7	7.	-	7.	7.	7.	9	• 9	Š	4•	20.0
SEP	25.4	Š	4.	ŝ	3	9	۲	7.	7.	9	5.	4.	4•	4.	4.	4.	4.	. 4	4.	4.	4.	3.	3	3.	2.	2	2.	2.	3.	4.		24.7
AUG	26.6	7	9	• 9	9	• 9	5.	6.	5	6.	5.	4.	4•	5.	4.	5.	5.	5.	5	9	9	5.	4.	5.	9	• 9	• 9	•	•	5.	5.	25.7
JUL		• 9	5.	5.	9	5.	5.	5.	4.	4	4.	3	4•	5	4.	5.	5.	5.	5	5.	5.	5	5	5.	5.	• 9	• 9	6.	7	7	~	25.6
NOC	23.0	2.	2.	2.	-	-	-	2.	3	3	3.	4.	4.	4.	Š	4.	3	2.	-	3.	+	<b>*</b>	4.	4.	4.	4.	5.	3.	3.	3		23.5
MAY	œ	0	0	6	8	8	8	æ	8	ö	7.	7	9	5.	5.	• 9	7.	-	-	7	7.	-	<b>&amp;</b>	<b>&amp;</b>	8	6	•	-	-	-	22.1	18.6
APR	10.7	0	0	9.	0	0	2.	2.	2.	3.	2.	3.	3.	3.	4.	3	4.	4.	5.	2	-	-	-	8	8	9.	6	8	7	<b>α</b>		14.6
MAR	8.7	•			•	•		•	•	•	•	•	•		•			•	•	•	•		•				0	ċ	•	-	•	8.2
FEB	3.8	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•		•	•	•	•	•	•	•	•		•				5.4
NAU	5.5	•	•	•			•	•	•		•		•	•	•	•			•	•	•	•	•	•	•		•	•	•	•	•	4.3
	7	7	m	4	ß	9	_	∞	6											20												AVG

DAILY AVERAGE WATER TEMPERATURE AT VIMS PIER IN 1955

DEC	7.2	•	•	• (	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	3	•	•	•	•	•	•	•	•	•	5.0
NON	15.5		•	ין פּ	2	2.	3.	2.	-	2.	2.	2.	2.	1.	6	2.	-	-	0	<u>Ф</u>	0	0	ċ	6	0	6	•	•	•		11.8
OCT	22.4	<u>:</u> -	• -	-	•	-	-	0	-	°	•			0	0	6	8	<b>φ</b>	ф (С)	دعتراً @	•	-	7	•	9	6.	6.	9	-	9	19.3
SEP	26.5	V 1	• n u	י ער	, 10	4	4.	4.	<u>(1)</u>	3.	4.	3	2.	3.	4.	4	3	3	3	8	3	2.	2.	3.	-	-	2.	2.	2.		23.8
AUG	29.1		•	• 0	6	8	8	7	7.	7.	• 9	5.	5.	7.	7.	• 9	5	9	7.	8	8	7.	7.	7	9	• 9	• 9	9	9	• 9	27.4
JUL	24.8	٠ د	, r	ي :	• •	*	4.	•	7.	7	•	• 9	•	9	7.	7	-	7	-	8	Φ	<b>ж</b>	7	7	œ	8	6	8	-	8	27.1
NO S	21.4	<u>,</u>	ų c	• -	2	-	1.	•	0	0	•	ċ	0	0	-	2	3.	3.	S.	4.	4.	5	4.	*	4.	4.	<b>.</b>	5.	5		22.6
MAY	15.7	•	0 P	• a	. &	6	8	7	8	8	6	6	8	8	8	7.	7.	8	6	•	0	0	0	-	-	2.	3	ä	2.	Ϊ.	19.3
APR	9.5	•	•	. 0	•	0	6	•	-	2.	4.	4.	4.	60	5	5	4.	5	5.	5.	6.	.9	9	•	5	5.	5.	5.	5		13.5
MAR	6.0	•	•	• (	•	•	•		•		•	•	0	•	6	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	8
FEB	2-1	-	7 -0	 	6.1	•	•	3.0	•	•		•	*	2.6	•	•	•	•	•		•	•			•	4.9	•				3.2
JAN	* *	0.0	•	• (		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•		•	•	•	•	•	•	•	•	•	4.0
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23.2 18.1 13.2

25.5

25.9

1.9 5.2 7.6 11.0 17.5 23.5

AVG

## DAILY AVERAGE WATER TEMPERATURE AT VIMS PIER IN 1956

DEC	8.1		•	•	•	•	•		•	•	•		•	•	•	•	•		•		•	6	0	0	6	•	•	•	•	•	•	
N0 V	17.5	æ	7.	7.	9	9	•	6.	5.	*	3.	2.	3.	3.	3.	4.	2	2.	2.	2.	2.	5.	0	9.	•	•	•	•	•	•		
OCT	16.1	6	0	0	6.	6	6	6	9	8	8	<b>~</b>	<b>-</b>	-	8	8	7	7.	7.	7.	7.	7	7	7.	7.	9	• 9	•	5	•	7	
SEP	27.3	7	9	9	7	7	• 9	5.	4.	3.	3.	3	3	3.	4.	4.	4•	3	3.	2.	-		2.	-	-	•	7	8	<del>ф</del>	<b>ө</b>		
AUG	25.3	Š	5.	4.	4.	4.	4.	4.	Š	5.	9	5.	• 9	9	• 9	7.	7.	7.	9	9	5.	4.	4.	4.	4.	4.	5.	5.	5.	• 9	9	
JUL	26.5	7.	-	-	-	.9	5.	9	5.	4	5	5	5.	5	5.	5.	Š	5.	5.	5.	5	5	9	4.	5.	9	• 9	9	5	5	5	
NOC	20.1	o	0	0	-	-	-	2	2.	2.	2.	3.	<b>6</b>	4.	4.	4.	4.	5	3	1.	2.	4.	5.	5.	Š	9	7.	• 9	6.	9		
MAY	13.0	<b>†</b>	4.	2.	• 9	6.	9	5.	9	5.	9	7.	-	8	<b>ө</b>	œ	æ	8	æ	<b>&amp;</b>	8	8	9	8	æ	9.	9	9.	9.	9	0.	
APR	8.3	•	•	•	-	-	2.	6	6	-	6	6	•	0	0	-	0	0	•	0		-	_	•	.=4	-	-	3.	4.	4.		
MAR	9.9	•	•	•	•	•	•	•		•		•	•	•	•		•	•	•		•	•	•	•	•	•		•		•	•	
FEB	2.8	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•		•	•				
NAU	2.0		•	•			•	•	•	•	•				•	•	•	•	•	•	•	٠	•		•	•	•	•	•		•	
	<b>,</b> 4 (	7	m	4	S	9	7	<b>&amp;</b>	6												21											

16.8

24.8

25.5

26.3

20.2

20.1

13.9

AVG

DAILY AVERAGE WATER TEMPERATURE AT VIMS PIER IN 1957

DEC	•	•	•	•		ç	•	•	•		•	•	•	•	•			•	•	, ●,	●	•	•	•	, •	•	•	•	•	<b>6.</b> 8	•
NON	3.	3	3.	3.	*	13.2	2.	3°	2.	1.	1.	•	-	-	2.	2.	2.	2.	3.	2.	2.	1.	1.	1.	•	0	0	0	-	-	
100	0	•	6	6	8	-	-	7	8	8	8	-	8	9	7.	• 9	•	7.	9	•	5.	•	5.	9	9	5.	4.	3.	3	12.7	3
SEP	4	Š	5	5.	Š	4.	5	•	4.	Š.	Š	• 9	9	5.	6.	• 9	Š	5	4•	5.	5.	5.	5.	4.	4.	3	2.	ω. •	0	•	
AUG	7	7.	æ	8	7.	9	9	7.	6.	9	9	7.	9	• 9	5.	9	5.	'n	2.	2.	3.	4.	3.	ä	3.	3.	4.	4.	4.	24.6	5
10 <b>L</b>	5	5.	5	5	9	4.	9	9	9	9	5.	9	9	9	7	-	• 9	9	5.	• 9	7.	•	• 9	9	9	• 9	9	9	9	26.8	•
ND C	-	2	8	•	• 9	16.8	7.	8	8	9.	8.	9.	9.	-	-	0	0	-	0	•	0	6	-	2.	2.	3.	-	3.	2.		
MAY	9.	6	<b>ж</b>	9	• 9	• 9	-	8	8	9.	8	9.	9.	-	-	•	•	-	3.	ċ	•	6	-	2.	2.	3	L.	3.	2.	20.9	-
APR	•	0	-	0	-	-	-		0	-	2.	3	1.	•	-	-	3.	3.	4.	5	9	4.	9	•	-	8.	6	8	ري د	20.0	
MAR	•	•	•	•	•	•	•		•	•		•	•	•	•	•	•		6	•			•	•	•	•	·	•		9.4	•
FEB	•	•	•		•	5.2		•	•	•	•	•	•	•	•				•	•	•	•		•	•	•	•	•			
JAN	•	•	•	•	•	•	•	•	•	•	•	•	•		•	•	•	•		•	•	•	•	•	•	•	•	•	•	4.7	•
	<b>=</b>	7	m	4	2	9	7	<b>&amp;</b>	6	10	11	12	13	14	15	16	17	18	19	20	21	22	23	54	25	56	27	28	53	30	31

DAILY AVERAGE WATER TEMPERATURE AT VIMS PIER IN 1958

DEC	•	8.0	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	2.1
NOV	4 4	13.9	3.	4	4.	<b>6</b>	3	3.	3	2.	2.	3.	3.	3.	4.	4.	4.	5.	4.	4.	3	3.	3.	3.	ü	2.	-	-	•		13.6
OCT	21.3	, 6	6	6	8	8	8	6	6	9.	8	8	7.	<b>&amp;</b>	æ	8	8	7.	7	9	• 9	•	7.	9	9	9	5	2.	5.	÷	17.7
SEP	5	24.5	4.	Š	5		4.	4.	3	3	2.	2.	2.	2.	3	3	3.	3.	3	5.	5	3.	3.	3.	4.	4.	2.		-		23.5
AUG	7	26.3	9	•	7.	2.	•	• 9	7.	7	8	7.	9	•	9	5.	• 9	5.	5.	• 9	• 9	• 9	6.	6.	5.	4.	4.	4.	5.	5.	26.3
JUL	4	24.3	5	5.	5.	4	4.	3.	5.	4.	4.	5.	5.	• 9	5.	5.	• 9	5.	5	5.	5.	5	5.	5	9	7	7	7	<b>&amp;</b>	æ	25.7
NOC			0	•	-		0	-	1.	2.	3.	3.	3.	3.	2.	2.	2.	3.	2.	2.	-	1.	-	2.	3.	2.	3.	3.	3		22.3
MAY	4 u	15.8	7.	•	5.	5.	5.	5	•	7	<b>&amp;</b>	•9	8	8	<b>ф</b>	9.	•	<b>&amp;</b>	9.	0	6	5.	9.	•	6	0	ċ	æ	0	<b>.</b>	18.4
APR	•	6.8	•		•	•	•		•	•	•	6	0	2.		-	•	8	4.	4.	4.	2.	4.	5.	5.	4.	4.	4	5		11.5
MAR		5.1	•			•		•	•	•		•	•	•	•		•	•	•		•	. ●	•	•	•	•	•			•	5.3
FEB	4.0	0 W	•	•	•	•	•		•	•	•	•		•	•	•	•	•	•		•										1.8
NAL		υ 0 0 0	•	•		•	•	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	3.4
	٦ ر	N W	4	S	9	_	<b>&amp;</b>	6									18														AVG

DAILY AVERAGE WATER TEMPERATURE AT VIMS PIER IN 1959

DEC		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	6.8	•	•	•	•	•	•	•	•	•	S.	*	7.0	
NOV	7.	•	5	5	•	•9	5.	4.	4•	3.	3.	3	3.	4.	3.	3.	e.	-	°	10.5	0	0	ċ	-	Ϊ.	0	0	-	9.	•		12.9	
OCT	4•	4.	3	4.	4.	4.	4.	4.	5.	4.	5.	+	3.	3.	2.	0	0	0	6		9.	8	6	6	<b>ө</b>	æ	7.	-	• 9	9		21.4	
SEP	æ	-	8	<b>&amp;</b>	-	7.	•	<b>-</b>	7	7	7.	•9	9	5	5.	5	5.	4.	3.	23.4	3.	3.	<b>*</b>	4.	4.	5.	5.	4.	5	5.		25.9	
AUG	8	7.	7.	• 9	•	5.	5.	9	•	• 9	•	9	7	7.	8	8	• ω	7.	8	29.0	8	8	6	8	9.	6	6	6	9.	ф Ф	æ	27.9	
JUL	6	8	7.	7	•9	•9	7.	7.	• 9	• 9	• 9	5.	6.	•9	5.	6.	9	• 9	7.		• 9	•	7.	7.	7.	<b>⊕</b>	<b>ф</b>	8	æ	6	28.9	27.3	
NO C	3	3	8	3	4.	4	4.	*	Š	9	7	-	9	3.	2.	3.	2	2.	2.	23.0	3.	4.	4.	5.	5.	5.	9	7	7	8		24.8	
MAY	7.	7.	9.	8	6	6	9	8	2.	9.	0	0	6	6	6	8	6	· &	9.		-	-	2.	<u>-</u>	2.	2.	2.	3.	3.	3.		20.5	
APR	•	•		0	-	2.	3.	3	5.	5.	Š	3.	3.	2.	2.	8	4.	Š	5.	15.9	•	ις.	4•	4.	Š	5.	9	5.	• 9	7.		14.1	
MAR	•	•	•	•	•	•	•	•	•	•	•	•	•	9	•	•	•	•	•		•	ф Ф	•	0	-	0	•	6	6	6	10.2	8.4	
FEB	•	•	•	•	•	•		4.6		•	•	•	•	•	•	•	•	•	•	5.0	•	•	•	•	•	•	•	•				5.3	
JAN		•	•	•	•	•	•	2.3	•	1.8	•	•	•	•	•	•	•	•	*	2.8	•	•	•		•		•	•	•	•	•	3.3	
		2	3	4	5	9	7	80	6	10	11									20												AVG	

DAILY AVERAGE WATER TEMPERATURE AT VIMS PIER IN 1960

DEC	10.8			•	•	•	•	•	•	•	•	•		•	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	5.5
NON	14.4	• 5	3	3.	3.	3.	-	-	2.	-	-	-	-	-	2	w.	2.	2.	-	-	-	2	-	-		7	2.	2	-		12.4
100	21.8	• -	0	•	-	-1	0	6	•	0	0	•	-	-	-	•	•	0	0	6	8	7.	• 9	• 9	5	9	5.	4.	4.	4.	19.2
SEP	26.4	9	• 9	• 9	7.	5.	5.	5.	• 9	•9	5.	4.	4.	4.	3.	8	4•	4•	4•	4.	3.	3.	3.	2.	2.	-	-	-	-		24.5
AUG	25.3	; <b>~</b>	-	-	7.	<b>.</b>	9	8	7	•9	• 9	9	7.	• 9	7.	9	5.	ۍ.	Š	• 9	5.	9	5.	4.	4.	4.	5.	9	9	• 9	26.4
<b>1</b> 0 <b>r</b>	25.7	, 50	5.	6.	9	5.	5	5.	5.	5.	5	9	9	5.	5.	•	6.	6.	6.	9	9	9	-	7.	9	9	9	5.	5.	5.	26.1
NO T	22.6	. ~	3	3	4.	3.	3.	2.	2.	2.	2.	4.	4.	4.	4.	5	4.	4.	5.	5.	5.	5	5.	4.	4.	9	5.	5.	ŝ		24.3
MAY	16.1	9	8	-	8	8	<b>∞</b>	• 9	7.	-	• 9	7.	•	7.	8	9.	9.	•	0.	-	-	-	0	-	2.	-	-	2.	3.	2.	19.3
APR	8.0	• •	0	•	9.	•	•	0	•	•	0	2.	2.	ä	4.	4.	÷,	4.	4.	4.	5.	5.	•	5	• 9	-	9	-	•		13.1
MAR	4.7			•		•		•	•	*	*	*		•	•	•	•	•	•			•	•		•	•		•	•	•	3.6
FEB	4.4	• •	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•			•	•	•	•	•	•	•	•				4.6
NAC	5.5	• •	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•		•	•	•		•	•	•	5.3
	<b>-1</b> °	u n	4	5	9	7	<b>&amp;</b>	6	10	11	12	13	14	15	16	11	18	19	20	21	22	23	24	25	92	27	28	53	30	31	AVG

DAILY AVERAGE WATER TEMPERATURE AT VIMS PIER IN 1961

DEC		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	5.0	•	•	7.1
NON	~	<b>-</b>	7	8	8	8	-	9	5.	4•	4.	4.	4.	4.	5.	4.	4.	3.	3.	3.	-	1.	-1	-		•	0	•	•	6		14.0
OCT	2	2	2.	-	0	0	Ξ.	-		-	-	-	7	0	6	æ	8	9.	6	8	æ	7	7.	7	7	•	•9	9		•		19.3
SEP	•	7	8	<b>&amp;</b>	8.	9.	• 6	8	8	8	7.	8	7.	7.	5.	4.	2.	2.	-	2.	2.	2.	3	3.	3.	4.	8	3	23.0	2.		25.6
AUG	-	7	2	7	9	9	7	7.	8	7.	7	•	6.	9	•	• 9	9	9	5.	4.	4•	5.	5.	•	9	9	9	7.	27.6	7.	-	26.7
JUL	4.	5	4.	*	4.	3.	4.	5.	4.	3.	4.	5.	5.	5	5	5.	4.	5.	9	4.	5.	9	-	<b>&amp;</b>	æ	7.	8	8.	28.1	8	8	25.8
NOC	6	•	0	0	-	-	2.	3.	3	2.	4.	5	5.	4.	3.	2.	2	3.	3	3.	3.	2.	4.	3.	3	2.	2.	-	22.2	2.		22.8
MAY	3	33	4.	4.	5	4.	5.	• 9	7	<b>~</b>	8	8	9.	0	0	0	•	0	•	•	6	0	•	6	•	6	0	-		8	8	18.2
APR	•	•	•	•		ċ	•	6	0	0		0	9.	ċ	-	-	0	0	-	-	-	2.	4.	4.	3.	4.	4.	4.	13.3	3		11.4
MAR	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•		•	•	•	•	•		•	•		•	0	0	_	-	10.7	8.9
FEB		•		•	Ħ	•	•	•	•	•	•	•	•	•	•	•	3.4	•	•	•	•		•		•	•	•					3.3
JAN	3.6	•	•	•	•	•	•	•		•		•	•	•	•	•	•	•	•		•	•	•	•	•	•	•			•	•	2.8
	~	7	m	4	7	9	_	æ	6																				53			AVG

## DAILY AVERAGE WATER TEMPERATURE AT VIMS PIER IN 1962

DEC	•	6		•	•		•	•			•		•	•	•		•	•		•	•	•	3.5		•	•	•		•	•	•	5.5
NOV	ന	3	$\sim$	$\sim$	$\sim$	*	¥	¥	*	*	¥	*	¥	×	*	*	×	***	0	σ	¥	**	8.1	0.6	**	9.3	9.1	9.1	<b>5.6</b>	1.6		10.5
100	o	0	•	. 6	ċ	•	0	•	•	•	•	-	0	*	•		•	6	•	6	6	6	18.6	8	*	*	•	5	¥	*	•	19.5
SEP	• 9	• 9	4.	4.	15	4.	3	3.	3	δ.	4.	÷	4.	5	4.	9	4.	3.	4	3.	-	-	20.7	0	*	•	0	0	9	9		23.1
AUG	•	6.	Š	\$	• 9	9	5	9	7.	9	5	Š	5	5	5	•	5	• 9	5	Š	6.	5	25.4	Š	5	•	5	5	4.	3.	25.9	25.8
JUL	3.	5	3	2	2	3	5	• 9	5	5.	5.	S.	S	9	9	9	5	5.	4	9	5.	.9	5	• 9	'n	9	5	5.	5	ŝ	25.8	25.3
NO C	3		8	2	•	2	2	6	3	4	3.	2	٠ د	-	2.	3.	3.	•	5	4.	3.	4	24.8	*	4		Š	•	3.	3.		23.4
MAY	æ	7	7.	7	8	8	8	6	æ	8	8	8	7	0	0	0	0	0	2.	-	2.	2.	3	3	2.	2.	2.	-	0	-	23.0	20.3
APR	0	0	9.	•	0	-	2	1.	2.	2.	2.	-	•	-	1.	1.	0	0	-	l.	•	2.	12.6	3.	4.	5.	9	.9	~	7.		12.5
MAR	•			•						•	•	•				•	•		•		•				•	8		•	•	0	11.2	6.5
FEB	•	•	•		•	•	•	•	•			•			•	•		•	•	•	•		4.7	•	•	•	•	•				3.9
JAN	•		•	•	•	•	•			•	•		•		•		9	•	•			•	4.6	•				•	•	•	•	3.9
	<b>~</b>	7	m	4	2	9	7	80	6														23									AVG

DAILY AVERAGE WATER TEMPERATURE AT VIMS PIER IN 1963

DEC	1 11	5.9
NOV	0.000 0 1 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1	13.3
100	220 220 200 200 200 200 200 200 200 200	18.9
SEP	00000000000000000000000000000000000000	22.6
AUG	22222222222222222222222222222222222222	26.4
JUL	2222225665 222225665 222225665 222225665 222225665 222225665 222225665 22225665 22225665 22225665 22225665 22225665 22225665 222256665 22256665 22256665 222566666666	26.3
NO C	8 8 8 8 5 7 7 8 8 8 8 8 8 7 9 8 9 8 9 9 9 9 9 9 9	23.1
MAY	11 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	18.1
APR	11111111111111111111111111111111111111	13.5
MAR	11110000110001100110011001100110011001	7.1
F EB		2.02
JAN	* HOHHHHUNDA4400000000000000000000000000000000000	2.5
	33038765543010987654821 33028765543010987654821	AVG

DAILY AVERAGE WATER TEMPERATURE AT VIMS PIER IN 1964

DEC	8.9	•	•	0	•	0	•	•			•	•	•	•	•	•	•	•	•	•	•	•	•	•	· •	•	•		•	•	•	8.4
ACN ACN	5.	5.	4.	4.	4•	4.	4.	4.	4.	4.	4.	4.	4.	4.	4	4.	<b>.</b>	4.	4.	14.7	4.	2.	2	2.	2.	2.	2.	2.	3.	-		14.0
0C T		¥	*	*	9.	9.	8	7.	9	*	¥	*	9	6.	9	9	9	7.	7.	16.2	5	5	4.	4.	*	5.	5	'n	4.	S.	5.	16.3
SEP	25.4	Š	5	5.	5.	δ.	5.	5	5.	5.	• 9	5.	3.	2.	2.	2.	2.	2.	3.	2.	•	_	-	-	•	-	¥	*	**	*		23.7
AUG	25.1	5.	9	5	4.	5.	5.	4.	5.	4.	5.	5.	5.	4.	4.	3.	4.	4.	4.	4.	5	5.	5.	• 9	9	5	5	5.	5	3	5.	25.2
JUL	*	**	*	*	***	¥	*	*	*	#	*	女	*	*	S	•	Ð	S	S	25.9	S	S	9	S	S	S	S	S	S	•	rU.	25.8
NOF	#	***	*	*	*	*	*	*	*	* *	*	*	**	**	*	*	* *	*	*	* *	**	**	*	*	*	**	*	*	*	**		*
	*	*	*	*	*	*	*	*	*	*	*	#	#	#	*	¥	¥	#	#	*	*	*	¥	*	*	¥	*	*	¥	*		¥
MAY	* * *	*	**	**	**	松林林	**	**	* *	* *	* *	* *	* *	* *	* *	* *	*	*	* * *	* ***	* * *	* *	*	**	* **	*	* **	* **	* **	* **		* * * * * * * * * * * * * * * * * * * *
APR MAY	**** /	.2 ***	****	****	· 6 ***	• 1 * * * * *	**** 0.	**** 9.	<b>****</b> 8 • 0	计	计序段 存代代数	** **	***	** **	计算 存存存录	***	计分子 计分子计	**	**	安存 安存	外女女 母女母母	女女女 女女女女	计分子 计分子	* **	女女女 女女女女 妆	计计算 计计算计	女子子子 女子子	* **	* **	女子女女 女女女	*	*
P. 8. ₹	•7 7.7 ×***	·8 7·2 ***	****	**** 0°6 0°	•6 8•6 ***	<b>4.4 8。1 4.4.4.4.4.4.4.4.4.4.4.4.4.4.4.4.4.4.4.</b>	**** 0°6 9°	·8 9.6 ****	.5 10.8 ****	• O ***	• O ****	· 3 * * * * * * * * * * * * * * * * * *	· 3 4444 4444	**** **** 0 •	·3 杂异林辛 安华谷安	**** **** 0.	**** **** [	女子子子 子子子子 6.	· 5 4444 4444	计分类 计分类	• 0 本本本本 本本本本	***	· · · · · · · · · · · · · · · · · · ·	井穴长 华谷安华 华华华本	•3 华安林林 存谷安长 茶	***	· 计分类符 存存条件 典	• 2 头棒状体 各种特殊 斧	•3 安安存存 存存存货 吞	* **** **** **	**	* **** 1.
APR	.0 3.7 7.7 ****	•7 4•8 7•2 ****	• 5 5.4 8.6 ****	3 6.0 9.0 ****	** 6.6 8.6 ***	母称 安存各条 8。1 安存各条	*** 7.6 9.0 ***	.6 7.8 9.6 ****	.4 8.5 10.8 ****	• 3 9 • 0 本本本本 本本本本	· 7 8 · 0 * * * * * * * * * * * * * * * * * *	· 0 8 · 3 * * * * * * * * * * * * * * * * * *	·3 8·3 4+4+ ++4+	· 8 · 0 · 4 · 4 · 4 · 4 · 4 · 4 · 4 · 4 · 4	*** *** ***	**** **** 0 · 8 · 8 ·	·2 7.7 **** ****	4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4	-0 7-5 井本本本 本本本本	7.9 ***	·7 8.0 **** ****	**** **** 0.8 6.	· 7 8 · 0 · 8 · 4 · 4 · 4 · 4 · 4 · 4 · 4 · 4 · 4	• 2 安安尔安 安安安安 安安存存	·3 10·3 **** **** *	· 5 8 · 8 · 8 · 8 · 8 · 8 · 8 · 8 · 8 ·	* **** **** [ • 6 • 5 •	·3 9.1 **** **** *	•3 安安存存 存存存货 吞	* **** **** **	**	* **** 2.8 8.
EB MAR APR M	.5 4.0 3.7 7.7 ****	.7 3.7 4.8 7.2 ****	.0 3.5 5.4 8.6 ****	·7 3.3 6.0 9.0 ****	·3 **** 6.6 8.6 ****	· 9 **** **** 8 · 1 ****	·1 **** 7.6 9.0 ****	·1 4.6 7.8 9.6 ****	.7 4.4 8.5 10.8 ****	·6 4.3 9.0 **** ***	·0 4·7 8·0 ****	·3 5.0 8.3 ****	·0 4·3 8·3 4***	-2 3.7 8.0 本本本本 存本本本	· 4 3.6 8.3 **** ****	·2 3.8 8.0 **** ***	.4 4.2 7.7 **** ****	· 3 3.6 7.9 本华本本 本本本本	·8 4·0 7·5 #### ####	9 4.0 7.9 ****	·2 3.7 8.0 ****	·0 3.9 8.0 ***	• 0 3.7 8.0 本本本本 本本本本	•6 3.2 每年於在 存在於存 每年存存	·4 3.3 10.3 **** *	**** **** ****	* * * * * * * * * * * * * * * * * * *	*	开於 8.3 异异异异 存存存件 存	4 <del>**</del> ** <del>**</del> ** <del>**</del> ** <del>**</del>	8.8 **	* **** Los 8°7 ***

PIER IN 1965 DAILY AVERAGE WATER TEMPERATURE AT VIMS

DEC						6666	7.7
NON	~ ~ ~ ~ ~	,	n m n m m	22.7	*	10.5 10.8 111.0 10.5 10.5	12.2
UCT		• • • • • • • • • • • • • • • • • • •		<b>α α α α</b>	2 - 6 - 6 - 6 - 6	17.8 16.8 15.9 15.7 15.7 14.6 14.0	18.0
SEP	4004	* • • • • • • •	4 4 M W 4	4444	, v v v v v v	25.5 24.3 23.7 22.7 22.7	24.3
AUG	4000	, 6 6 6 9	666.	6.0	66.50	26.0 25.5 26.1 26.5 26.1 24.7 24.7	25.9
JUL	4464	* 4 4 10 4 1	y w w 4 w	6.00	, , , , , , , , , , , , , , , , , , ,	25.9 25.9 25.9 25.5 24.4 24.7	25.3
NOC	- 000	22.	- m m ~ ~ ~	9.00		233 233 233 233	21.9
MAY	₩. 4. 4.	0	9.	9.00 9.00	2	20.9 21.4 21.5 22.1 21.8 21.3 20.7	19.2
APR			, 00 - 0	1.00.	1224621	12.6 12.5 12.5 12.9 13.2	11.2
MAR	• • •						4.9
FEB.					44 8 8 4 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8	• • • •	3.8
NAL	• • •					W W 4 4 W 4 W W W 0 4 0 0 4 8 0 4 0 0 0 0	4.9
	-264	4 N O F ® (				25 25 27 27 29 30 31	AVG

DAILY AVERAGE WATER TEMPERATURE AT VIMS PIER IN 1966

	DEC	•		•	•	•	•	7.0	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•		3.6	9.9
<b>,</b>	NON	4.	5.	4	3.	3.	3	12.7	2.	3	3	4.	3.	3	<del>'</del>	2.	-	-	2.	2.		-	0	0	0	0	-	-	•	•	6		12.3
	OCT	6	æ	6	9.	6	8	$\infty$	8	8	8	<b>ф</b>	7.	å	8	å	8	7.	<b>-</b>	-	9	9	5	7	7.	• 9	9	5.	5.	3	5.	14.0	17.5
	SEP	9	•	• 9	5.	9	5.	25.1	4.	3.	3.	4•	3.	2.	2.	2.	2.	-	<u>-</u>	-	0		1.	-	-	ċ	0	ċ	Ö	0	0		22.7
	AUG	S	4.	4.	ä	3.	4.	23.6	4.	4.	4.	4.	4•	4.	+	4.	5.	4	5.	9	• 9	•9	9	9	9	5	5	5.	9	9	9	• 9	25.2
: :	JUL	•	6.	Š	•	•	• 9	26.2	5	• 9	•	•	-	8	æ	7.	6.	9	9	5.	•	5.	5	5.	5.	5.	9	7.	•9	9	5.	•	26.3
	NOC	6	6	9.	0	-	-	21.7	1.	-	-	0	9.	0	0	-	-	• 0	-	-	-	\$	2.	2.	3.	3.	4.	4.	4.	4.	5.		21.7
	MAY	5	4.	Š	4.	5	5.	16.9	9	9	5.	• 9	5	•	• 9	9	• 9	7.	8	8	6	0	6	9.	•	6	9.	0	•	0	•	9.	17.6
	APR	•		•				0.6	0	•	6	ċ	-	0	0	0	<b>-</b>	-	2.	2.	3	•	4.	4.	3	*	4.	•	3	4.	•		11.8
	MAR	•	•	•	•	•	•	5.5	•	•	•	•	•	•	•	•	•	•	•	•			•	0		•	•	•	•	•	•	•	7.7
	FEB				-0.8	-0.7	-0.1	-	*	*	•	•	•		•	•	•	•	•		•	4.1	•	•	•	•	•	•	•				2.6
	NAU	•	•	•	•	•		7.5	•	•	•	•			•	•	•	•	•	•	•	•	•	•	•		•	•	•	•	•	•	4.3
		-	2	Ų	4	Ŋ	9	~	ω	6	10	11	12									21											AVG



DAILY AVERAGE WATER TEMPERATURE AT VIMS PIER IN 1967

.7 10.
.5 11.
.2 11.
.7 11.1
.3 10.
.8 11.
.5 11.
6.4 11.8
.8 11.
.4 11.
.8 12.
.2 11.
.3 11.
.6 12.
.1 12.
•6 13•
.6 14.
.5 13.
•6 13.
•4 13•
.4 13.
•6 13•
•6 13•
•6 12•
.2 13.
.3 12.
.2 12.
.4 11.
.3 12.
.2 13.
0.
6.9 12.3

DAILY AVERAGE WATER TEMPERATURE AT VIMS PIER IN 1968

DAILY AVERAGE MATER TEMPERATURE AT VIMS PIER IN 1969

DEC	8.8		•	•	•	•	•	*	¥	*	*	女	*	₩	*		•	•	•			•	•	•	•	•	•	•	•		•	5.2
NON	4	4.	5.	5.	4.	8	3.	2.	2.	2.	•	-	-	-	*	*	*	*	*	¥	¥	*	*	*	*	*	•		•	•		12.3
100	0	•	1.	-	0	•	0	•	0	•	20.1	•	•	•	9.	6	æ	<b>α</b>	7.	8	8	<b>&amp;</b>	7.	\$	5.	5	• 9	5	4.	3.	4.	18.4
SEP	26.0	ŝ	3	• 9	9	5	9	5.	5.	4•	3	3.	3	3.	3	4.	4.	3	2.	-	-	-	-	0	•	-	-	1.	•	•		23.1
AUG	• 9	9	5	5.	5.	9	9	9	9	5	25.8	5.	5	5.	•9	• 9	•	•	9	5.	4.	5.	Š	5	5.	9.	5	5.	5.	5	5.	25.8
JUL	9	9	9	9	9	7.	ф Ж	9	5	5	25.8	9	5.	• 9	9	9	9	7.	7.	7	•	7.		9	6.	• 9	• 9	9	9	9	• 9	26.7
NO C		3	2	2.	2.	2	3.	3.	3.	3.	23.3	+	5.	4.	4.	女女	¥	*	*	*	4.	3.	4.	4.	4.	4.	5.	9	.9	7.		24.1
MAY	4.	5	•	9	-	8	8	8	8	-	17.2	9	-	7	8	<b>α</b>	6	6	6	0	6	6	0	0	0	0	0	0	•	-	•	18.7
APR	9.	0	•	0	0	0	•	2.	2.	2.	12.8	3.	ë.	3	4.	4.	5.	5.	5.	3	4.	*	3.	<i>ب</i>	3,	5.	ŝ	5.	3	5		13.3
MAR	•	•	•	•	•	•				•	3.5	•	•	•	•	•	•		•	•		•	•	•	•	•		•	•	•	•	S. 53
FEB	•	•	•		•	•	•	•	•	•	3.8	#	*		*	*	•	•	2.5	•		•		•	•	•	•	•				<b>6</b>
JAN	•			•	•		•	•	•		2.5	•	•	•	•	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	2.9
	-	2	m	4	Ŋ	•	_	<b>∞</b>	6		11																					AVG

## DAILY AVERAGE WATER TEMPERATURE AT VIMS PIER IN 1970

DEC	10.1	•	0	9.	•	•	•		•	•	•	•	•	•	•	•	•	•	•	•	•		•	•	•	•	*	*	*	*	8.2
NON	15.8	9	5.	Ŝ	4.	各	¥ ₩	*	4.	4.	5	4•	4.	4.	4.	3.	2.	2.	2	3.	2.	2.	0	0	6	•	•	•	•		13.2
0C T	21.5	2.	-	1.	0	0			2.	2.	2.	2.	2	2.	-	6	æ	<b>ө</b>	7	7.	8	8	8	<b>*</b>	æ	2	9	5.	5	5.	19.7
SEP	26.5	50	5	5	¥	¥	¥	4.	4.	4.	4.	4.	4.	5	5.	5.	5	*	长 长	*	5.	5.	9	9	•	5.	¥	¥	4.		25.4
AUG	27.2	7	9	• 9	• 9	9	• 9	9	5.	4.	5.	5.	5	7	7.	7	<b>-</b>	9	7	9	9	9	9	9	9	• 9	9	9	7	-	26.5
70 <b>r</b>	25.1	5.	5.	4•	4.	5.	Š	Š	5.	4	4.	5.	5.	5.	4	9	5.	9	5	4.	4.	4.	4.	5.	5.	9	-	7.	6.	-	25.5
N D T	22.3 22.7	W.	2.	2.	-	-	3.	'n	3	3.	4.	5.	3.	3.	3	4.	4.	Š	5	5.	4.	4.	4.	4.	4.	4.	4.	4.	4.		23.8
MAY	16.8 17.7	• 9	5	9	5.	4.	• 9	7.	• 9	• 9	6.	<b>α</b>	9.	0	0	6	ထီ	8	9.	0	-	-	*	<b>ķ</b>	2.	2.	_	1.	-		18.7
APR	8.3	•	•	•	6	•	•	•	0	•	-	-	-	•	•	-	2.	2.	2.	6	4.	4.	4•	4	4.	4.	5.	5	5		12.0
MAR	4.8 5.0	•	•	•		•		•	•	•	•		•	•	•	•	•		•	•	•				•		•	•	•	•	9.9
FEB	3.0	•		•	•	•	•	•	•		•	•		•		•	•	•	•	•	•			•	•	•	•				3.
JAN	3.7	3.6	•	•	•	•	•	•	***	ij	•	•		•	**	•		•	•	•		•	•	•	#∤	1.5	•	•	•	•	1.9
	1 2	33	4	3	9	7	<b>&amp;</b>	6							16																AVG

DAILY AVERAGE WATER TEMPERATURE AT VIMS PIER IN 1971

DEC	8.8	7.2	9.9	9•9	8•3	8.0	0.6	8.6	*	*	₩	*	*	¥	*	* * * *	*	8.3	8.6	8.0	6.9	7.5	7.7	7.7	8.6	8.6	8•3	8.6	8.6	8.1
NOV	21.5 21.6 21.6	6	9	8	8	• 9	•	5.	5.	3.	4.	5.	禁	5	5	5	5	5	<b>*</b>	3.	2.	-	-	-	•	•	•	0		15.1
100	22.9 22.9	2.	3.	2.	2.	-1	1.	-	*	*	0	0	•	-		-	0	6	6	9		0	0	0	0	•	0	0	•	21.1
SEP	26.5 26.4	• •	9	¥	*	-	7	7.	7	<b>!</b>	9	9	9	6.	6.	•	•	9	5	5.	4.	4.	4.	3	4.	4.	<del>ن</del>	3.		25.9
AUG	27.0	• • •	7	7	9	9	<b>.</b>	• 9	9	7	9	•	<b>-</b>	7.	9	9	• 9	• 9	7.	7.	-	-	9	*	茶	*	*	7.	•	27.1
JUL	27.4	9	7.	•9	•9	7.	7.	7.	9	•9	9	•	•	• 9	• 9	-	7	9	9	Š	6.	9	9	. 9	9	7.	9	9	9	26.7
ND T	20.6	· · · · · · · · · · · · · · · · · · ·	2.	3.	<b>.</b>	3.	3.	3.	3.	ä	3	3	3.	2.	2.	2.	3	4.	5.	5	4.	5.	• 9	5	• 9	~	7.	7.		24.1
MAY	16.3 15.6	5.	5	• 9	9	9	7.	8	8	6	6	6	9.	8	8	6	0	2.	-	0	0	-	1.	-	-	6	9.	6	9.	18.9
APR	9.1	•	2.	0	•	•		-	2.	4.	<b>6</b>	3.	3.	3	3	3.	4.	'n	4.	4.	3.	4.	4.	4.	4.	5	5	5.		3.
MAR	& & & & & & & & & & & & & & & & & & &	• •	•	•	•	•	•		•	•			1.	0	•	9	•	•	●.	•	•	•	•	•	•	•	•		•	8.5
FE8	3.0		•	•	•	•	•	•	•	•		•	•	•	•	•	•	•	•		•	•	•	•	•	•				<b>9*</b>
JAN	* * * * * * * * * * * * * * * * * * * *	• 9	•	•	•	•	•	•		. •	•	•	•	•	•	. •	. •	•	•	•	•	•	•	•	•	•	•	•	•	4.4
	12"	7	2	9	7	ထ	6								17															AVG

DAILY AVERAGE WATER TEMPERATURE AT VIMS PIER IN 1972

DEC	0.6	8.7	9.1	•	•		•	•	•	•		•	•	•	•	•		•	•	•	<b>6.</b> 8				•	•	•	•	•	•	•	8.4
NOV	•	•	•	•	•		•	*	¥	•			•	•		•	•	•	•	•	11.6	•	•	•	•	•	•	•	•	•		12.8
100		2.	-1	2.	•	-	•	ċ	•	6	9	9.	9	9	9	<b>\$</b>	8	~	7.	\$	15.2	5	50		5		5	5	5	5	5	18.4
SEP	* * *	#	*	*	*	**	***	*	* * *	***	**	*	外外外外	* * *	**	*	***	***	**	**	*	**	**	* * *	**	**	*	**	**	*		*
AUG	***		**	* * *	**	*	***	**	**	**	*	* * *	*	*	**	**	*	*	**	*	*	***	**	*	*	*	**	**		**		*
JUL	22.8	23.9	24.2	23.9	23.6	22.5	22.5	23.0	23.3	**	*	* * *	**	* * *	**	***	**	**	***	**	**	***	计计计	**	**	<b>长</b> <b>长</b> <b>长</b> <b>长</b>	***	***	¥	*	¥	23.3
NO C	ဆ	œ	0	•	-	<u>-</u>	-	-	-	0	9.	0	6	o	-	-	-	2.	3	3	23.0		0	0	-	-	2.	3.	2.	2.		21.3
MAY	9	7.	7.	9	9	7.	7.	7	9	• 9	• 9	9	7.	7	7.	8	8	9.	9.	8.	18.8	• 6	8	œ	<b>α</b>	• 9	6.	8.	9.	•	•	17.9
APR	•			•	ċ	•	ó	6			0	0	0	-	-	2.	2.	3	3.	5	14.7	4.	4.	4.	4.	4.	*	4.	Š	•		12.2
MAR	•						٠							•			•		•		1.6		•	•		•	•	•	9.1		•	8.0
FEB	•	•	•	•	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	3.8	•	•	•	•	•	•	•				4.4
AA	•	•			•	•					•	•	•	•	•	•	•	•	•	•	5.8		•		•		•	•		•	•	6.7
	-	2	ĸ	4	S	9	7	æ	6												21											AVG

DAILY AVERAGE WATER TEMPERATURE AT VIMS PIER IN 1973

DEC	12.2	-	2.	3.	2.	2.	-	•	0	6	•	•	•	•	•	•	•	•	•	•	•	•	•		•	•	•	•	•	9	8.9
NON	17.2	•	•	5.	4.	3	4.	3	2.	-	2.	-	-	2.	2.	-	-	-	-1	-	2.	2.	2.	3	3.	4.	4.	3.	2.		13.3
OCT	23.3	3.	3	3.	2.	2.	2.	2.	2.	2.	-	-	ļ	-	-	1.	6	9.	8	<b>&amp;</b>	æ	æ	8	æ	8	æ	8	8	7	-	20.7
SEP	28.9	8	8	8	<b>&amp;</b>	8	<b>&amp;</b>	7.	•9	9	•	•	ŝ	5.	5.	S	5.	4.	4.	4.	4.	5.	ŝ	4•	4.	4.	4.	4.	4.		26.2
AUG	27.6		7.	7.	8	8	8	6	•	8	7.	7.	7.	9	7.	7.	-	9	9	9	9	5	•	9	9	7.	7.	5	8	æ	27.4
JUL	25.8	9	7.	7.	9	-	7	8	-	-	6.	9	• 9	• 9	5	5.	9.	9	9	Š	5.	• 9	•	•	9	• 9	• 9	7	7	7.	26.7
NO C	21.6	2	2.	3.	4.	3.	3	4.	4.	S.	3	ë.	4.	5	4.	3.	3.	3.	4.	4.	5.	3.	5.	5.	5	5.	5	5.	5		24.1
MAY	16.0	7	9	9	9	7.	-	7.	*	6	ó	0	9.	7	8	6	æ	æ	æ	7.	<b>α</b>	8	8	œ	7.	8	6	9.	0	-	18.3
APR	12.0	0	-	0	-	7.	•	-	•	•	•	•	ċ	-	2	2.	3.	3.	4.	5.	4.	5.	5.	9	9	5	3.	4.	5		12.8
MAR	6.2	•	•	•	•	•				•	•	•	•	0	-	•	6	6	6	6	¥ ¥	•	*	*	.6		6	•	0	0	8.7
FEB	5.8				•	•	•		•				•	•	•		•	•	•	•	•		•	•		•	•				5.1
JAN	88 60	•	•		•		•	•	•	•		. •	•	•	•	•		•		•	•	•		•	•	•	•	•	•	•	5.5
	~	ı m	4	'n	9	~	89	6	01	11	12	13	14	15	91	17	18	19	20	21	22	23	<b>54</b>	25	97	27	28	53	30	31	AVG

DAILY AVERAGE WATER TEMPERATURE AT VIMS PIER IN 1974

DEC		•	•	•	•	•		•	•	•	•	•	•	•	•	•	•	•	•	8.0	•	•	•	•	•	•	•	•	•	•	•	8.5
NON	_	7	-	1.	-	7	9	5	5.	5.	4.	4.	4.	3	3	3.	3	2.	2.	12.7	2.	2.	2.	2.	7	2.	-	0	6	•		13.9
100		0	8	<del>.</del>	8	8	8	8	7	8	8	8	8	8	8	8	8	8	7	16.2	4.	4.	4.	5.	Š	5.	5.	5.	5.	9	9	17.3
SEP	е В	7.	7.	•	5.	4.	4.	3.	4	4.	4	5.	6.	5.	4.	4•	4.	4.	4.	25.3	5	4.	3.	-	-	1.		1.	2.	*		24.5
AUG	8	-	-	9	9	5.	4	5	5	5	4.	S	9	7.	• 9	9	• 9	7	9	26.4	6.	<b>6</b> *	• 9	7	7.	7.	-	-	7.	7.	7.	26.6
JUL	3.	4.	5	5.	Š	4.	5.	9	• 9	9	9	5.	5	5.	9	7.	9	9	9	26.4	9	9	5	Š	5.	5.	5.	9	¥	¥	-	25.9
NOC	-	-	* 2	2.	2	3	2	2.	3.	4.	*	4.	3.	4.	4.	4.	4.	4.	5	25.3	4.	5	5	4.	3.	3.	2.	3	4.	4.		23.8
MAY	7	-	7	8	-	9	•	9	2	<b>~</b>	7.	8	8	6	6	0	0	2.	-	_	-	0	-	-	-	7.	ċ	0	0	7	21.7	19.5
APR	•	-	2.	3.	ij	3.	3	2.	2.	2.	3.	3.	3	4.	2.	4.	5.	4.	4.	15.3	Š	5	5.	4.	4.	4.	5.	5	7.	-		14.1
MAR	•	•	•	•		•	0	-	_	-	•	6	9	•	•	•	•	9.	0	10.0	0	0	9	9.	6	æ	6	°	0	0		8.6
FEB	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•		•	7.3	•	•	•	•	•	•	•					7.4
JAN	•	•	•	•	•	•	•	•	•	•	•		•	•	•				•	8.1	•		•	•	•	•		0		0		7.8
		2	m	4	Ŋ	9	1	<b>&amp;</b>	6											20												AVG

DAILY AVERAGE WATER TEMPERATURE AT VIMS PIER IN 1975

DEC	-	*	*	¥	*	. •	6	•	•	8.9	•		•	•	•	•	•	•	•	•	•	•	•		•		•	•	•	•	4.4	7.4
NON	•	7	-	7.	7.	7	7	~	7	17.9	<b>?</b>	7.	9	5.	5.	4.	3.	3	4	4.	3	3.	3	2.	2	2.	1.	-	-	-		15.0
OCT	2.	2.	•	0	0	-	-4	-	0	0	0	0	0	•	-	-	0	0	0	6	9.	6	0	0	0	0	6	6	6	8		20•3
SEP	5.	5.	5.	5.	9	• 9	6.	5.	5.	25.3	5.	4.	4.	ه	2.	2.	2.	2.	2.	6	3	2.	2.	2.	3.	3	3	2.	2.	2。		24.0
AUG	8	æ	9.	6	6	<b>&amp;</b>	7.	7.	7		7.	7.	-	7.	7	7	8	8	8	6	<b>ө</b>	8	8	1.	8	8	8	8	<b>ф</b>	<b>&amp;</b>		28.2
JUL	5.	5.	6.	•	5	9	5.	9	• 9	27.0	9	5.	5	5	5.	5.	5	9	6.	9	7.	7.	5	<b>ө</b>	7.	-	-	7.	7	-	7.	26.4
JUN	2.	3	4.	4	4.	'n	2.	ن •	3.	23.5	2.	2.	3	4.	Š	5.	5	• 9	• 9	6.	9	9	9	9	9	•	9	Ŝ	5.	*		24.8
MAY	4.	4.	5.	•	5.	• 9	•	-	œ	18.2	<b>.</b>	6	ф Ф	9.	6	0	6	•	0		-	2.	3.	3.	3	2.	3.	3.	3.	4.	4.	6*61
APR	Ö	-		•	•	•	•	•	•	10.1	9.	•	9	0	•	0	ô	-	1.	•	2.	3,	4.	4.	un.	5.	Š	5	4.	4.		11.6
MAR	•	•	•	•	•	•	•	•	•	0.9	•	•	•		•	•	•	•	•	•	•	•	0	0	0	0	•	6	0	0	•	8.1
FEB	•	<b>;</b>	•	•	•	•		•		6.3	•	•	•		•	•	•	•	•	•	•	•	•	•	•	•	•					7.5
JAN	•		•	•	•	•	•		•	8.4	•		•	•	•	•		•	•	•	•	•	•	•			•			•	e-med	8.0
	cad	7	m	4	ĸΩ	9	_	<b>&amp;</b>	6	10	11									20												AVG

DAILY AVERAGE WATER TEMPERATURE AT VIMS PIER IN 1976

DEC	$\begin{matrix} \begin{matrix} $	
NOV	100000000000000000000000000000000000000	80
1 00	0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	
SEP	103008818003301153614 5333555552533355335153615	23.3
AUG	00000000000000000000000000000000000000	25.7
JUL		
NOC	\$\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\	22.9
MAY		18.4
APR	11111111111111111111111111111111111111	14.5
MAR	10000000000000000000000000000000000000	prosed
FEB	44m4444m444mm0m0ramaaaaaaaaaaaaaaaaaaaaa	<b>6.</b> 4
JAN	4444m444m804m8m202020202020202044m4m4 • • • • • • • • • • • • • • • • • • •	ູ້
	336846666666666666666666666666666666666	AVG

DAILY AVERAGE WATER TEMPERATURE AT VIMS PIER IN 1977

DEC	10.4	9.	0	6	0	8	•	•		•	•		•	•	•	•		•	•	•	•			•	•	•			•	•	7.1
NO V	14.3	5.	9	9	7.	7	9	7.	1	5.	3.	3.	2.	2.	Š	3.	å	2.	2.	2.	2.	2.	2.	2.	-	0	0	0	9.		13.7
1001	24.3	2.	-	1.	-	0	6	6	ж ж	ж Э	.6	8	7	9	9	4.	4.	<b>*</b>	4•	4.	5.	5	5.	5.	Š	5.	5	5	5.	<b>.</b>	17.5
SEP	28.9	0	•	•	8	7	-	5.	9	9	5.	5.	5	5	٠ <u>.</u>	9	9	6.	9	5.	Š	5.	5.	5.	5.	Š	4.	4.	4.		26.4
AUG	27.8	့ ဆ	8	8	8	æ	<b>œ</b>	ф ж	ဆီ	9.	<b>ω</b>	<b>ө</b>	ဆီ	<b>α</b>	8	ъ Ж	• Э	7.	9	\$	9.	• 9	7	6.	9	• 9	9	9	~	ထီ	27.7
JUL	26.8	9	• 9	7	<b>α</b>	8	6	6	6	8	<del>.</del> ھ	<b>.</b>	6	6	0	0	6	6	6	6	Ċ,	å	æ•	<b>~</b>	• 9	• 9	6.	-	7	7.	28.4
N C C	22.9	3	3	ω •	3.	2.	-		1.	ö	2.	2.	$\ddot{\mathbf{e}}$	s.	ال •	4•	,†	<b>*</b>	3.	\$	5.	5.	5.	3.	5.	δ.	7.	6.	9		23.9
MAY	17.4	6	9	• 5	0	-	<u>.</u>	ж ж	7	1.	-	-	9.	9.	9.	ö	•	7	2.	3.	3.	3	3.	2.	2.	3	3.	4.	3.	2	20.9
APR	12.7	6	m	6	2.		÷	2.	2.	4.	Ŋ	-	္ခ်	7	<b>.</b>	-	7	5	ထိ	<del>•</del> ဆ	$\overset{\bullet}{\infty}$	8	φ •	6.	<b>!</b>	ڼ	9	7	<b>?</b>		15.5
MAR	6.7		•		•	•	•	•	•		<b>.</b>	-	0	0	-	2.	2.		-	-	•	•	•	ċ	·	·	0	•	-	္ပံ	6.6
F EB	-0.8	-0.5	•	•	•	•	46	-0.1	•	•	•	•		•	•	•	•	•	•	•	•	•	•			•					2.0
JAN	2.7	•	•	•	•	•		1.1	•	•	**	*	**		**	¥	<b>5.</b> 0-	•	•	•	•	-1.C	•		•		•	•	•	•	0.4
	1 0	m	4	2	9	_	80	6	10	11	12	13	14	15	91	11	18	19	2 C	21	22	23	54	25	56	27	28	58	30	₩ 100	ΔVG

MONTHLY AVERAGE WATER TEMPERATURE AT VIMS PIER

	JAN	<b>F</b> E 8	M A R	APR	Y A Y	NO C	JUL	AUG	SEP	100	NON	DEC
5 2	•	•		•	•	9	Ŋ	5	4	0	•	•
62		•	•			2.	<b>-</b>	-	3	•	•	•
<b>\$</b> 5		•	•		7.	•	5	5	3	8	•	
55	•	•	•	•	0	0	9	5	•	• 9	•	
95		•	•	•	္ဆံ	2.	Š	9	3.	7.		•
1959	3.3	5,3	8.4	14.1	20.5	24.8	27.3	27.9	25.9	21.4	12.9	7.0
95	•	•	•	•	6	4•	9	9	4.	6	•	•
96		•	•	•	8	2	5	•	5.	6	4	
95	•	•	•	2.	0	3	5	5.	3	9.	•	•
96		•	•	•	ээ •	3	9	9	2	æ	3.	•
95		•		•	ф	2.	5	5	3	• 9	4.	•
56	9	•	•		6	-	5.	5.	•	8	2.	•
95	•		•	-	7	-	• 9	5.	2	7.	2.	•
95	•	•	•	2.	5	2.	5	5.	2.	8	-	•
Ŝó	•	•	•	•	-	3.	26.0	9	3	9.	2.	•
95	•		•	3.	20	4•	26.7	ري •	3	æ	•	•
15		•	•	2.	ů,	3.	5	9	٠ ک	6	3,	
67	•	•	•	3.	ဆံ	4.	26.17	27.	5	•	•	•
15	•		•	•	-	-	3.3	24.	4.	8	. •	•
97	•	•	•		ဆိ	4.	٥	7	9	0	•	•
25	•	•	•	•	5	3.	25.9	9	4.	-	•	•
25	•	•	•	•	5	4	9	8	24.0	0	•	•
16		•	•			2.	26.1	Š	3.	9	•	•
16	•	•	•	•	20.3	3	28.4	-	9	7	13.7	7.1

Appendix B. Long term water temperature statistics for each calendar day of the year at Gloucester Point.

POINT		≺R	95	96	96	96	9	96	1977	16	16	95	16	26	96	96	16	96	16	16	-	16	67	16	16	16	16	~	16	96	~	6	9
	ES	LOW	0	~	• 9	7	3	•2	1.40	• 4		7	δ	8	0	.5	3	2	0.	• 4	-0.70	١.	• 9	$\boldsymbol{\dashv}$	0	0.	0.	9	•2	6	-0.30	4.	-1.40
GLOUCESTER	XTREM		97	16	-	16	16	16	1975	16	16	97	16	16	4	16	97	16	16	67	7	16	16	16	16	16	16	97	16	16	_	6	~
JAN AT G		HI 6H	• 2	• 6	3	•2	0	0.	8.10	6.	.3	•4	5	• 9		6.	9.	7.	5	•4	6.	7	<b>1</b>	4.	• 6	•4	₹	0	4.	0.0	0.1	.5	1.3
ICS FOR	AVG	2		7.	0	6	8	-	4.63	5	4.	6	•2	₹	0	6	8	1	.7	9.	5	• 5	• 5	•5	5	.5	9.	• 6	•	2.	1	-1	7
STATISTI	MOVING	7DAYS	• 2	-	0.	6.	4.85	1		4.	4		2	.2	7.	0	<b>ω</b>	.7	• 6	.5	•5	• 4	4.	• 4	.5	• 6	•	•	• 6	. 7	1	3.79	7.
ERATURE S	COEFF	AR	3	• 4	.3	3	• 4	•4	0.41	4.	• 4	• 4	5	5	5	• 5	• 4	4.	• 4	5	.5	5	÷5	• 5	S.	5	5	.5	•5	• 6	• 6	• 6	•
EMPERA	STD	w	0	0	6.	8	6.	0	1.91	8	0.	0	• 2	• 2	-	0.	ω.	9.	• 6	9	œ	8	6.	6•	0.	0	7.	0	-	2.	• 4	S	•
M WATER T	24YEAR	ERAG	4.	5		0.	$\infty$	9.		4.	• 2	,	L.	.2	• 2	7	8	9	5	• 2	3	3	S.	5	5	•5	• 6	8	8	.5	• 6		7.
TER	DAY		-	7	κij	4	S	9	7	ထ	6																					30	
LONG	DAY		-	7	m	4	'n	9	~	Φ	6																					0	

LONG TERM WATER TEMPERATURE STATISTICS FOR FEB AT GLOUCESTER POINT

			_																									
YR	97	96	16	96	96	96	16	96	16	16	16	16	95	95	95	95	95	95	95	95	95	95	95	95	96	96	1963	96
ES LOW		-	5	0.8	7.		5	8	7	æ	Ö	.3	w.	5	.2	4.	e.	0.2	4.	1.1	7	7	Š	2	2	Ä	1.60	7.
XTREM YR	97	16	67	16	16	16	16	16	16	16	96	16	16	16	16	95	16	16	16	16	16	16	16	16	16	16	9261	16
е н16н	4.	.2	φ,	0		7.	• 6	6.	•		-2	8	6.	,	3	6	.7	3	5	.2	6.	0	1	0	0	5.	09.6	1.
G AVG 10DAYS	. 7	.7	1.	7.	1		1.	æ	8	6.	9.	0	0		7	•2	3	<b>.</b> .	•4	•5	• 6	1.	ထ	6	~	-2	5.40	ij
MOVING 7DAYS	. 7	.7	1.	1.	1.	1		8	6.	6.	6.	6.	0	7	-	.2	•2	3	4.	5.	• 6	7.	8	6.	0	2.	5.36	5
COEFF VARI	• 6	• 6	•	• 6	5	5	• 4	3	4.	4.	6	.3	.3	3	4.	3	4.	*	4.	4.	4.	• 4	4.	4.	3	3	0.37	3
STD	4.	• 6	• 4	•2	0.	80	8	• 4	Š	S	• 5	r.	.5	٠ ک	• 6	• 6	1	6.	6.	6.	0	•2	6.	0	80	φ.	2.02	8
24YEAR AVERAGE	0	6.	5	4.	9.	9.	8		7.	7.	0	0.	9	0	7.	3	3	• 4	• 4	• (J)	•6	8	8	6.	0	6.	5.40	3
DAY																											58	
D A Y	pref	7	3	4	S	9	7	ထ	6																		27	

LONG TERM WATER TEMPERATURE STATISTICS FOR MAR AT GLOUCESTER POINT

- -		X X	96	96	96	96	96	96	96	1960	96	96	96	96	96	96	96	96	96	96	96	96	96	96	96	96	96	96	96	96	95	95	95
אורא ייטוא	ES	LOW	. 2	4.	• 6		.2	7	• 2	2.50	8	6.	5	.5	• 6	5	0	.3	0	• 6	6	• 6	.7	1	• 6	6.	• 2	• 2	0	• 9	1	• 2	•
96.000	EXTREMI	YR	161	197	197	161	197	197	161	1974	197	197	161	161	197	161	197	197	161	197	197	197	197	197	197	197	197	197	197	197	197	197	161
- 1 - 1 - 1 - 1 - 1 - 1 - 1 - 1 - 1 - 1		HI GH	0.7	1.0	3	1.4	• 2	2.5	.3	11.50	.3	1.1	0.5	0.4	1.4	0.8	3	1.9	2.0	2.3	6.	6.	<b>&amp;</b>	<b>ω</b>	•2		5	2.3	6.	8	0	6.	• 6
<b>1</b>	AV	LODAYS	•6	8	0	-	ن	4.	•6	6.80	•9	7.	•2	• 4	č	• 6	.7	8	• 9	6	0	~	7.	•2	4.	5.	٠,	88	0	4	S.	3	7.
)	OVIN	7DAYS 1	• 6	8	0		3	• 4	5.	6.75	6.	~	• 2	• 4	.5	-	8	8	φ,	6.	0	0	7.	• 2		3	• 6	8	0	7.	63	•5	7.
	L L	VARI	6	£.	Ü	3	J.	• 3	3	0.31	3	• 3	• 2	• 2	• 2	• 2	• 2	•2	• 2	• 2	• 2	•2	•2	• 2	• 2	• 2	• 2	•2	7.	-	7	7.	7
	STD	DEV		0	<b>~</b>	-	2.	33	3	2.14	0	-	. 7	5	8	0	7.		7	6.	<b>ω</b>	<b>6</b> 0	6.	0	. 7	8	•	. 7	•5	• 4	5	4.	4.
ENE MAIEN	4YEA	AVERAGE	.7	8	7	.2	2,	• 5	•6	06.9	1.	8	3	• 5	8	• 6	8	6.	8	0	2.	0.	• 2	t		5	1.	1.	8	•2	• 4	• 6	. 7
	DAY	<b>≺</b>	9	61	62	63	99	65	99	29	<b>6</b> 8	69	70	11	72	73	74	75	91	11	78	7.9	80	81	82	83	84	85	86	87	88	89	06
	⋖	N O N	-	7	w	4	Ŋ	9	_	ထ	6																					30	

LONG TERM WATER TEMPERATURE STATISTICS FOR APR AT GLOUCESTER POINT

DAY	24YEAR	STO	COEFF	MOVIN	G AVG	ш 101 111	XTREM	ES.	α >
_	CKAG	U	Ł	C P C	LODAL	2		•	
	0.0	6.3	-	6.	6.	2.7	16	1.	96
٥i	0.1	5	-	0.1	1.0	3.3	16	• 2	96
~	0.3	5	7	0.3	0.3	3.8	16	<b>Ф</b>	95
.+	0.5	• 4	7.	0.5	0.5	3.9	16	.7	95
۰.	6.0	4.	~	0.7	1.0	3.7	16	• 6	96
'n	6.0	4.		0.8	0.8	3.6	96		96
_	1.1	• 6		1.0	1.0	3.7	96	.5	16
ക	6.0			1.2	1.2	3.9	95	• 6	95
G.	1.3	4.	7.	1.3	1.3	5.1	95	7	16
0	1.5	4.	-	1.5	I.5	5.4	95	~	16
_	1.6	.5	-	1.6	1.7	5.2	95	• 6	95
N	1.8		-	1.8	1.9	5.6	16	.2	95
m	1.9	<b>Φ</b>		2.0	2.1	7.4	16	• 6	95
.+	2.1	S	4	2.3	2.3	6.1	16	0.1	96
in	2.3	• 6	-	2.5	2.6	7.7	16	0.0	16
<b>~</b>	3.0	1		2.8	2.9	8.2	16	0.0	16
_	3.2	φ.	-	3.2	3.2	7.3	16	0.6	16
æ	3.3	• 6	-	3.5	3.5	7.3	16	0.7	95
6	3.8	• 9		3.8	3.7	9.3	16	0.6	95
0	4.3	8		4.1	4.0	8.1	16	0.5	95
_	4.6	φ,	7	4.3	4.3	8.4	16	1.0	95
2	4.7	8	7	4.6	4.5	8.6	16	1.3	95
m	4.6	8	-	4.8	4.7	8.3	16	1.4	95
4	6.4	6.	-	4.9	4.8	8.8	16	0.8	95
S	5.0	•		5.0	5.0	8.6	95	1.6	95
9	5.3	7.	-	5.1	5.2	9.0	95	1.4	95
~	5.3	8		5.3	5.3	9.4	95	1.8	95
œ	5.2	•	<del>سا</del>	5.4	5.5	8.9	95	1.9	96
61	15.56	1.66	0.11	15.68	15.72	19.40	1957	12.70	1961
0	5.8	• 6	-	5.8	5.9	0.0	95	3,0	96

<u> </u>	<b>≺</b>	S	9	9	5	9	S	10	9	9	9	9	9	9	9	S	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9
POINT								19																								
	ES LOW	3.0	3.9	4.	2.5	5.2	4.8	14.70	4.4	3.8	4.1	4.6	5.5	5.1	5.1	5.5	5.8	6.7	7.0	7.8	7.5	7.1	6.5	6.7	5.5	5.0	1.9	6.4	7.1	• 6	7.7	7 ° 6
GLOUCESTER	EXTREM YR	9.5	95	95	16	16	16	1977	16	95	6	95	16	16	95	95	96	16	16	95	16	16	16	95	26	16	95	16	16	~	97	97
MAY AT (	HIGH	9.4	0.2	0.1	9.6	9.8	0.5	21.20	1.5	2.3	0.0	0.0	0.7	0.7	1.1	1.0	⊕ 0•8	0.8	2.0	3.9	2.7	3.1	3.7	5.1	3.1	3.3	3.0	3.7	3.8	6.4	4.0	4.0
CS FOR	IG AVG	0.9	6.2	6.4	6.7	6.8	7.0	17.20	7.3	7.5	7.6	7.8	8.0	8.1	8.3	8.6	8.8	9.0	9.3	9.5	9.7	6.6	0.1	0.2	0.3	0.4	0.5	0.7	0.8	6	1.0	T • T
STATISTIC	MOVING 7DAYS 1	0	<b></b>	.5	1.	6	0	17.22	4	5	•	- 7	1.9	8.1	8.3	8.5	8.8	9.1	9.3	9.5	9.8	0.0	0.1	0.3	0.4	0.4	0.5	9.0	0.7	<b>ω</b>	1.0	T
ш	COEFF VARI		7.	0	7.	0	0.	0.09	0	0	0.	0	0.	0	0	0.	0	0.	0	0	0	0	0	7	0	~	~	0.	0	0.	0.	0.
EMPERATUR	STD		9		9.	•2	• 4	1.57	4.	\$	4.	•2	• 4	•2	4.	• 5	r.	7	£.		• 4	• 5	. 7	• 9	8	0	• 9	6	6.		•	'n
WATER T	24YEAR AVERAGE	6.0	6.4	6.6	9.9	7.0	7.0	17.37	7.4	7.5	7.5	7.6	8.0	0	8.3	8.5	8 8	0.6	8.5	1.6	6.6	0.0	0.2	0.7	0.3	0.3	0.5	0.5	9.0	8	1.0	1.2
G TERM	DAY YR	2	2	2	Ò	2	Ñ	127	7	2	3	3	3	3	(	3	3	3	3	3	4	4	4	4	4	4	4	4	4	\$	S	5
LONG	DAY	~	7	'n	4	2	9	7	ω	6																				58		

LONG TERM WATER TEMPERATURE STATISTICS FOR JUN AT GLOUCESTER POINT

LONG TERM WATER TEMPERATURE STATISTICS FOR JUL AT GLOUCESTER POINT

	¥ >	16	16	96	96	96	16	16	1972	16	96	6	95	95	96	96	96	96	95	96	96	16	16	16	16	96	96	96	96	96	96	96
ES.	LOW	2.8	3.9	3.6	2.9	2.3	2.5	2.5	23.00	3.3	3.7	4.3	3.9	4.4	4.1	4.0	4.3	4.8	5.0	4.4	4.9	4.7	4.1	4.1	1.4	5.0	5.5	5.3	5.5	4.4	4.7	4.7
EXTREM		95	95	95	95	95	16	16	1977	16	16	16	16	16	16	16	16	16	16	16	16	97	16	16	16	96	95	95	98	95	95	95
	нын	9.2	8.3	7.5	7.9	7.3	8.1	8.6	29.00	9.6	9.5	8.6	8.7	8.9	9.6	9.7	0.0	0.0	9.6	6.6	9.6	6.6	9.2	8.7	8.1	8.0	8.4	8.9	9.2	8.9	0.6	8.9
AVG	00 V	5.2	5.3	5.4	5.5	5.5	5.7	5.7	25.77	5.8	5.8	5.9	5.9	6.0	6.0	6.1	6.1	6.2	6.2	6.2	6.3	6.3	6.4	4.9	6.4	6.5	6.5	9.9	9.9	6.7	6.7	<b>6.7</b>
MOVING	7DA YS	5.2	5.3	5.4	5.6	5.6	5.7	5.7	25.78	5.7	5.8	5.9	5.9	5.9	0.9	6.1	6.2	6.2	6.2	6.3	6.3	6.3	6.3	6.4	6.4	6.5	6.5	9.9	9.9	6.7	2.9	6.8
COEFF	AR	0	0	0	0	0	0	0	0.05	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
STD	W	4.	0	0	-	3		• 4	1.24	63	• 2	6.	5	6.	0	7	7.	0	0.	7.	0.	7	0	0	0	8	8	6.	6.	0.		•2
24YEAR	ERAG	5.4	5.6	5.6	5.7	5.6	5.5	5.6	25.86	5.8	5.9	5.8	5.7	5.9	6.1	6.1	6.1	6.3	6.4	6.3	6.3	6.2	6.3	6.3	6.4	6.4	6.5	9.9	6.8	9.9	6.6	6.8
DAY		α	$\infty$	œ	8	$\infty$	œ	œ	189	9	6	6	6	9	6	9	δ	δ	9	0	0	0	0	0	0	0	0	0	0	-		-
DAY		-	2	m	4	ĸ	9	~	80	6																				53		

LONG TERM WATER TEMPERATURE STATISTICS FOR AUG AT GLOUCESTER POINT

۲x	96	96	96	96	96	9961	96	95	96	96	6	96	96	96	96	96	96	96	95	95	95	95	95	95	95	95	95	98	95	96	96
ES LOW	4.7	4.7	4.1	3.5	3.6	24.10	3.6	4.6	4.7	4.6	4.5	3.8	3.3	3.9	4.1	3.3	4.0	4.4	2.8	2.6	3.9	4.3	3.8	3.3	3.7	3.5	4.0	4.0	4.3	4-1	4 • 3
EXTREM H YR	195	197	195	195	197	0 1955	195	197	197	197	197	195	161	197	195	195	195	197	195	197	195	195	195	196	195	195	195	195	195	195	197
HI G	9.1	8.9	9.2	9.6	9.4	29.10	8.5	8.8	9.2	0.0	9.0	8.3	8.7	8.2	8.3	8.6	8.0	8.8	8.6	9.2	8.9	8.8	9.1	8.9	9.1	9.6	9.3	9.4	9.1	8.5	8.5
G AVG 10DAYS	6.7	6.7	9.9	6.6	6.6	26.62	6.5	6.4	6.4	6.3	6.3	6.3	6.4	6.3	6.3	6.3	6.3	6.3	6.3	6.3	6.3	6.2	6.2	6.2	6.2	5.9	6.2	6.2	6.1	6.1	6.1
MOVING 7DAYS	6	6.7	6.7	9.9	9.9	9.9	6.5	4.9	6.4	6.3	6.3	6.3	6.3	6.3	6.3	6.3	6.3	6.3	6.3	6.2	6.2	6.2	6.2	6.2	6.2	6.2	6.2	6.2	6.2	6.1	7
COEFF VARI	0	0	0	0	0	0.05	0.	0	0.	0	0	0	0	0	0.	0	0	0	0.	0	0	0.	0.	0	0.	0	0	0.	0	0.	0
STD	•2	7	•2	• 4	ů	1.28	•2	0	•2	w.	•2	•	~·	7	0		0.	0	2.	4.	•2	•2	•2	4	7.	<b>رن</b>	~	•2	•2	•2	prod Q
24YEAR AVERAGE	6.9	6.9	6.9	9.9	6.4	26.58	6.3	6.5	6.7	6.4	6.3	6.2	6.1	6.1	6.3	6.6	6.4	6.4	6.1	6.1	6.2	6.2	6.2	6.3	6.2	6.2	6.1	6.1	0.9	6.3	6.3
DAY YR	-	-		_	-	218	-	2	7	2	7	2	2	2	2	2	2	3	3	3	رئ	3	3	36	(L)	38	(1)	4	4	4	4
DAY	-	2	m	4	S	9	7	ω	6									18													

LONG TERM WATER TEMPERATURE STATISTICS FOR SEP AT GLOUCESTER POINT

α >		96	96	96	96	96	96	96	96	96	16	16	96	96	96	96	96	96	96	96	96	96	96	96	96	96	95	95	95	1956	95
ES		3.3	3.6	3.6	3.3	3.2	3.7	3.4	3,3	5.0	2.5	1.9	1.7	1.6	1.4	1.4	0.8	0.7	1.2	1.4	0.7	1.0	1.0	0.5	0.0	0.1	6.6	7.9	8.4	18.20	8.4
EXTREM YR		16	16	16	16	16	96	96	16	96	96	96	96	96	96	95	95	16	16	16	16	96	96	96	16	16	16	16	95	1959	6
ם ב	2	8.9	9.8	0.2	0.4	0.4	9.0	9.0	8.8	8.3	8.3	7.9	8.0	7.9	7.2	6.3	9.9	9.9	6.4	6.4	6.8	6.2	4.9	5.8	6.2	6.4	6.6	5.8	4.8	25.10	5.0
G AVG		6.0	6.0	5.9	5.8	5.7	5.5	5.4	5.3	5.1	4.9	4.7	4.5	4.4	4.3	4.1	4.0	3.8	3.7	3.6	3.5	3.3	3.2	3.1	2.9	2.8	2.6	2.5	2.3	22.17	6.1
MOVIN		6.1	6.0	6.0	5.9	5.7	5.6	5.4	5.3	5.1	4.9	4.7	4.5	4.4	4.2	4.1	3.9	3.8	3.7	3.6	3.5	3,3	3.2	3.1	2.9	2.8	2.6	2.5	2.3	22.20	2.0
COEFF	Č.	0	0	0	0	0	0	0.	0	7.	0	0.	0	0.	0	0	0	0	0.	0	0	0	0	0	0	0	0.	0.	0.	0.08	0
STD	į	4.	3	• 6	9•	.5	• 6	• 5	S	r.	is,	.5	3	'n	• 4	£.	• 4	'n	• 4		2	• 6	• 5	• 6	8	8	6.	\$	• 6	1.74	æ
24YEAR		6.1	6.0	5.9	5.9	5.9	5.8	5.5	5.3	4.7	5.0	6.4	4.6	4.4	4.1	4.0	3.9	3.9	3.7	3.6	3.6	3.3	3.2	3.0	2.9	5.9	2.7	2.5	2.3	22.20	2.1
DAY		4	4	4	4	4	4	5	5	S	S	5	S	Š	5	S	5	9	9	9	9	9	9	9	9	9	9	~	~	272	_
MOAY	)		7	m	4	5	9	7	ထ	6																				58	

LONG TERM WATER TEMPERATURE STATISTICS FOR OCT AT GLOUCESTER POINT

<b>≻</b>	95	96	16	16	16	95	95	96	96	16	95	95	96	95	16	16	16	16	16	16	16	16	97	96	16	16	16	16	1976	16	16
ES LOW	9.1	8.7	8.5	8.2	8.0	7.6	7.6	7.2	6.4	8.0	8.0	7.1	6.8	6.9	6.3	0.9	4.0	4.6	4.7	4.5	4.2	4.3	4.3	4.6	5.0	4.7	3.6	2.5	11.70	1.7	1.6
EXTREME YR	95	95	6	95	95	95	95	95	95	95	95	95	95	95	95	16	16	96	96	96	16	96	16	16	16	16	16	16	1971	16	16
H16H	4.8	4.4	3.9	4.4	4.7	4.8	4.7	4.8	5.0	4.8	5.1	4.4	3.6	3.0	2.2	1.9	1.5	1.8	1.4	0.3	9.6	1.6	0.0	0.0	0.5	0.1	0.3	0.1	20.40	0.5	0.4
3 AVG LODAYS	1.7	1.5	1.3	1.1	6.0	0.7	0.5	4.0	0.2	0.0	6.6	9.8	9.6	9.5	9.3	0.6	8.7	8.5	8.3	8.0	7.8	7.6	7.3	7.1	6.8	9.9	4.9	6.2	16.09	5.8	5.6
MOVING 7DAYS 10	1.7	1.5	1.3	1.1	0.8	9.0	0.4	0.3	0.2	0.0	6.6	9.8	1.6	9.5	9.3	9.1	8.8	8.5	8.2	1.9	7.7	7.5	7.3	7.1	6.9	6.7	6.5	6.2	15.98	5.8	5.6
COEFF	0	0.	0	0	0	0.	0.	0.	0	0.	0.	0.	0	0.	0.	0.		0	0.	0,	0.	0	0	0	0	0.			0.11	7	• 1
STD	t)	'n	\$	• 6	1	8	. 7	7.	1	•	. 7	1	١.	8	•	• 6	<b>8</b>	• 6	• 6	.5	• 6	ι, Σ	• 6	.5	5	.5	• 6	• 6	1.79	8	-
24YEAR AVERAGE	1.8	1.6	1.3	1.1	0.8	9.0	0.4	0.1	0.0	0.2	0.1	6.6	1.6	9.6	9.4	9.3	8.9	8.6	8.3	7.8	7.4	7.3	7.3	7.3	7.1	6.7	6.5	6.1	15.90	5.6	5.4
DAY YR	~	7	~	~	7	~	8	8	$\infty$	$\infty$	$\boldsymbol{\omega}$	$\boldsymbol{\omega}$	œ	8	$\boldsymbol{\omega}$	$\boldsymbol{\omega}$	6	6	6	6	9	9	6	Ş	6	ĝ,	0	0	302	0	0
DAY		2	ĸ	4	ß	9	7	ထ	6																				59		

LONG TERM MATER TEMPERATURE STATISTICS FOR NOV AT GLOUCESTER POINT

≺ R	76 79 79	76 76 76 76	76 76 76 76 76 76 76 76 76 76 76 76 76 7	76 79 79 70 70	1000	1976 1976 1976 1976 1976
ES Low	2.0.2.0.1.6		0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	4 4 10 10 10 4	004690	7.30 7.30 7.80 8.10
EXTREME YR	97 97 97	160	97 97 97 70 70	10000	997	1958 1973 1958 1973 1973
н16н	1.5	9.0 9.0 8.7 8.6	7 7 7 7 7 Y Y Y Y Y Y Y Y Y Y Y Y Y Y Y	ָ ממטעמט ממעמרט	0 W W 4 W W 0	13.90 13.80 13.30 14.00 13.40
AVG ODAYS	~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~	0 4 4 4 4 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6	. W W W W W W	77777		11.21 11.01 10.76 10.49 10.23 10.00
MOVING 7DAYS 1	4.05.0 5.03.4	4 4 4 4 4 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6	2 2 3 4 1 C	22223	2252	11.16 10.96 10.78 10.58 10.05
COEFF VAR I	7777			4 m m m m m		000000000000000000000000000000000000000
STD DEV	800		0000-		0, 1, 0, 4, 0, 1	1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
24 YEAR Average	10 10 10 10 10 10 10 10 10 10 10 10 10 1	0 0 0 7		20.000	2222	110.03 10.68 10.57 10.55 10.55
DAY YR	0000	00		4	12222	9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9
DAY	- 2 6 3	+ 10 0 M &				32222 3222 3084 3084 3084 3084

LONG TERM WATER TEMPERATURE STATISTICS FOR DEC AT GLOUCESTER POINT

YR	1976 1976 1976	16	2	95	5	95	96	96	46 95	95	95	96	95	95	96	96	9	96	96	9	96	70
ESLOW	7.00	. r. r.	• 6	• 4	φ. φ.	4.6	9	رس ر		5	. 7	6	• 6	2.	7.	5	3	1.	1	<b>ω</b>	3	0
EXTREM YR	1973	16	16	~ ~	76	76	95	76	35 95	95	95	95	95	95	ر د و	95	95	96	95	95	16	07
н16н	12.20 12.00 11.80	2.3	2.9	1.9 0.8	0.8	9.8	9.8	9.	- 4.	• 6	• 2	6.3	• 2	9.8	7.0	9.8	• 6	• 2	9.	1.	~	~
G AVG 10DAYS	9.57	6.9	4.60	1.6.	.5	6.	6	~	0.4	4		0	6.	ا څ	•	.5	4.	4.	• 4		$\hat{\boldsymbol{\varepsilon}}$	~
MOVING 7DAYS	9.54	8 9	5.	1.6.	5.	£ -	ω.	1.	٠ ب	•	7	0	6	φ, ι	و د	.5	4.	4.			3	?
COEFF VAR I	0.13			7.		2,0	.2	5.	2.	•2	• 2	• 2	£.	ų,	٠, در	3	4	3	.3	.3	٤,	7
STD DEV	1.27	5	• 6	w 4	mm	n, o	6.	6.		. 7	• 5		• 9	0	<b>5 C</b>	0	-	0	5.	æ	6.	. 2
24YEAR AVERAGE	9.29 8.97 8.80	6.	• 6	.1.	8.	•2	6.	ω,	. 2	• 2	•	• 2	0		٠. ر. در	3	•	63	•2	63	e.	.2
CAY YR	335 336 337	mm	4 4	サセ	4 4	4 4	. 4	7	S	S	S	S	5	S	n n	S	\$	9	9	9	9	9
DAY MON	H 27 K	14 W	9	8 6	10	2 5	14	15	97	18	61	20	21	22	23 24	25	97	27	28	59	30	31

## Appendix C: The Box-Jenkins Technique

- C-1. The fundamental operators used in the Box-Jenkins method
- C-1-1. The deterministic and stochastic models

One might consider that a model or formulation called the deterministic model, can be fitted exactly to the behavior of a phenomenon. For example, we can calculate the route of a ship navigated in known direction with known velocity. However, it is hard, almost impossible, to predict future behavior precisely because there exist unknown factors which can affect the final result, such as variable wind velocity and current direction can move a boat off course. Therefore, it is assumed that no behavior can be predicted exactly, but that it is possible to look for the probability limits within which it would be. This kind of process is said to be a stochastic process. physical phenomena can be decomposed into two portions. The first component is described by a true response function which is easy to calculate for any instant of time. second portion is the stochastic process which can be approached only by statistical theory.

C-1-2. Stationary and non-stationary processes

If a stochastic process is in statistical equilibrium about a constant mean level over long periods, this is called a stationary process. On the contrary, a stochastic process in an uncontrolled situation or one which has different mean level with time changes (such as stock prices frequently exhibit) exhibits non-stationary behavior.

C-1-3. Backward, forward and backward difference operators

Three operators are introduced to simplify the relation between data. The first is the backward operator, B, which is defined by  $BZ_{+} = Z_{+-1}$ . The current value multiplied by a factor B is equal to the previous value. Hence  $B^2Z_+ =$  $BZ_{t-1} = Z_{t-2}$  and furthermore  $B^nZ_t = Z_{t-n}$ . The second operator, the inverse order for past operator  $(F = B^{-1})$ , is the forward operator which is given by  $FZ_t = Z_{t+1}$ ; therefore  $F^{n}Z_{+} = Z_{++n}$ . The present value times the nth power of F is to be estimated by the value n intervals in the future. The third operator is the backward difference operator " $\nabla$ " which can be written in terms of B;  $\nabla Z_t = Z_t$ -  $Z_{+-1} = (1-B) Z_{+}$  (the first difference);  $\nabla^{2}Z_{+} = (1-B)$  $(z_t - z_{t-1}) = z_t - 2z_{t-1} + z_{t-2} = (1-B)^2 z_t$  (the second difference); hence  $\nabla^n Z_+ = (1-B)^n Z_+$  (the nth difference). In this study, it will be seen that the backward difference operator is a useful tool to distinguish a non-stationary process from a stationary process.

#### C-1-4. The ARMA process and the ARIMA process

Shocks are random drawings from a fixed distribution, usually assumed normal and having a mean of zero and variance  $\delta_a^2$ . Such a sequence of random variables  $a_t$ ,  $a_{t-1}$ ,  $a_{t-2}$ , ... is called a white noise process. (Box & Jenkins, 1970, p. 88). One concept of white noise is that the next value for this process may not be predicted even though one knows all of the previous values. One tries to have the residual autocorrelation function of a time series exhibit a random process as closely as possible; in this way the model will be selected.

Each shock,  $\tilde{Z}_t$  (where  $\tilde{Z}_t$  is the deviation from the mean or some other origin) can be estimated by the present shock plus the weighted sum of either all previous random shocks or all previous deviations.

They are 
$$\tilde{Z}_t = a_t + \overline{\psi}_1 a_{t-1} + \overline{\psi}_2 a_{t-2} + \cdots$$

$$= a_t + \sum_{j=1}^{\infty} \overline{\psi}_j a_{t-j}$$

$$\tilde{Z}_t = a_t + \pi_1 \tilde{Z}_{t-1} + \pi_2 \tilde{Z}_{t-2}$$

$$= a_t + \sum_{j=1}^{\infty} \pi_j \tilde{Z}_{t-j}$$
(C-1)

From equation C-1, if a set of weighted values is given, the current disturbance  $\tilde{Z}_t$  can be expressed by the sum of previous shocks plus the present shock. This process is said to be a moving average model.

Hence, the first order of moving average process is defined by

$$\tilde{z}_{t} = a_{t} - \theta a_{t-1} = (1 - \theta B) a_{t}$$
 (C-3)

The moving average model of order 2 is given by

$$\tilde{z}_{t} = (1 - \theta_{1}B - \theta_{2}B^{2}) a_{t} = a_{t} - \theta_{1}a_{t-1} - \theta_{2}a_{t-2}$$
 (C-4)

and the moving average model of order q is given by

$$\tilde{z}_{t} = a_{t} - \theta_{1} a_{t-1} - \theta_{2} a_{t-2} - \cdots \theta_{q} a_{t-q}$$

$$= (1 - \theta_{1} B - \theta_{2} B^{2} - \cdots - \theta_{q} B^{q}) a_{t}$$
(C-5)

equation C-5 may be written as

$$\tilde{z}_t = \theta_q$$
 (B)  $a_t$ 

 $\theta_{\rm q}({\rm B})$  is called the moving average operator with order q. Similarly, equation C-2 also can be taken with the number of weighted values depending on the practical situation. This process is called the autoregressive model of order p.  $\phi_{\rm p}({\rm B})$  is the autoregressive operator with order p. The first order of autoregressive model is obtained by

$$\tilde{Z}_{t} = \phi \tilde{Z}_{t-1} + a_{t}.$$

$$(1 - \phi B) \tilde{Z}_{t} = a_{t}$$
(C-7)

The pth order of the autoregressive model is given by

$$(1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p) \tilde{z}_t = a_t$$

$$\phi_p(B) = (1 - \phi_1 B - \dots - \phi_p B^p)$$
(C-7)

$$\dot{\bullet} \quad \phi_{p}(B) \quad \tilde{Z}_{t} = a_{t}$$
 (C-8)

It sometimes will be necessary to include both autoregressive and moving average terms in the model.

Thus, 
$$\tilde{Z}_{t} = \phi_{1}\tilde{Z}_{t-1} + \phi_{2}\tilde{Z}_{t-2} + \dots + \phi_{p}\tilde{Z}_{t-p} + a_{t}$$

$$- \theta_{1}a_{t-1} - \dots - \theta_{q}a_{t-q}$$

$$\phi_{p}(B) \tilde{Z}_{t} = \theta_{q}(B) a_{t} \qquad (C-9)$$

is called the mixed autoregressive-moving average process of order (p,q) which is sometimes abbreviated to ARMA (p,q). However, for non-stationary processes, the ARMA model is not capable of covering the entire series. The complementary method to be added is the difference operator "V" which is required to acquire stationarity. (Box & Jenkins, 1970 chapter 4 & 6). Normally, it has a priority over the autoregressive and moving average processes. Accordingly, the ARMA model is modified as follows:

$$\phi_{p}(B) (1-B)^{\tilde{d}} \tilde{z}_{t} = \theta_{q}(B) a_{t}$$
or 
$$\phi_{p}(B) \nabla^{\tilde{d}} \tilde{z}_{t} = \theta_{q}(B) a_{t}$$
(C-10)

- C-2. Model identification
- C-2-1. The ACF and PACF and their behavior as indicators of ARMIA processes

To identify the model which should be built up, one must determine the type of model which might be used and obtain an initial estimate of the model parameters. In practice, it is not necessary to know exactly which type has the greatest probability of describing a given time

series because there are different ways to investigate model types. Eventually those different ways produce a set of very similar coefficients after the model is checked. It should be mentioned that in preference to a model which has small residual variance but a high order, we would choose a lower order model with a somewhat larger residual variance. For instance, if the difference of residual variance between (1,0,1) and (2,0,0) models is one percent, the simpler (1,0,1) model is preferred. This criterion is an important factor in making the final selection from several similar models.

The techniques which are used to identify the type of model utilize the autocorrelation function (ACF) and partial autocorrelation function (PACF). Before being described by the ARIMA process, a time series should be modified to remove the non-stationary situation, thus becoming a stationary stochastic process. Those two techniques can provide information which indicates which series include non-stationary process. The characteristic of the ACF for non-stationary series which is most apparent is that moderate values continue and are not damped relative to the first few values of the function. An alternative method is to construct the first one or two differences of the original time series and then examine the corresponding ACF until an obvious stationary process is shown (i.e. the ACF dies out quickly). Therefore, if the estimated ACF does not die

out quickly, this will be a signal for a non-stationary stochastic process. Box & Jenkins (1970) mentioned that generally it is sufficient to inspect the stationary process for the 0th, 1st or 2nd order of the difference operators used.

The partial autocorrelation function (PACF) is a minor tool to assist in examining series. For the ARMA model system the ACF and PACF have symmetric solutions to illustrate the same series. For example, the ACF for the first order autoregressive model can be described as an exponential decay with increasing lag value and the ACF for the first order moving average model will tail off after the first value. (i.e. the PACF for the first order autoregressive model will tail off after the first value and the PACF for the first order moving average model can be explained as an exponential decay with increasing lag value).

If the ACF is expressed by the same formulation as previously

$$\left(\gamma_{K} = \sum_{t=1}^{N-K} (Z_{t} - \overline{Z}) (Z_{t+K} - \overline{Z}) / \sum_{t=1}^{N} (Z_{t} - \overline{Z})^{2}\right)$$

then the PACF is defined as

$$\gamma_{j} = \phi_{K1}\gamma_{j-1} + \phi_{K2}\gamma_{j-2} + \phi_{K3}\gamma_{j-3} + \cdots$$

$$+ \phi_{K(K-1)}\gamma_{j-K+1} + \phi_{KK}\gamma_{j-K} \qquad (C-11-A)$$

here K=1,2,... j=1,...K

 $\gamma_j$  is autocorrelation coefficients  $\phi_{KK}$  is the partial autocorrelation coefficients  $\phi_{Kj}$  is the jth coefficient in an autoregressive process of order K

The PACF can be expressed directly as:

$$\phi_{\ell,\ell} = \begin{cases} \gamma_1 & \ell = 1 \\ \gamma_{\ell} - \sum_{j=1}^{\Sigma} \phi_{\ell-1,j} \gamma_{\ell-j} \\ \frac{j=1}{1 - \sum_{j=1}^{\Sigma} \phi_{\ell-1,j}} & \ell = 2,K \end{cases}$$
 (C-11-B)

where 
$$\phi_{\ell j} = \phi_{\ell-1,j} - \phi_{\ell \ell} \phi_{\ell-1,\ell-j}$$
  $j=1,2,\ldots,\ell-1$ 

Some common characteristics for the basic ARIMA model types and forms of the ACF distributions are represented in Table C-1. The (1,d,0) model means the current disturbance  $\mathbf{Z}_{+}$  equals a fixed proportion  $\phi_{1}$  of the previous disturbance  $Z_{t-1}$  plus the present shock  $a_t$ . The autocorrelation function decays exponentially to zero when  $\phi_1$  is positive, but decays exponentially to zero and oscillates in sign when  $\boldsymbol{\phi}_1$  is negative. Yet the (o,d,1) model indicates the current disturbance  $Z_{t}$  equals the present shock  $a_{t}$  subtracted from a fixed proportion  $\theta_1$  of the previous shock  $a_{t-1}$ . The ACF for this process has a cutoff after lag 1. In other words, except for the one neighboring value, no relationship exists for the first order moving average process. models might be composed of these two basic types. The most important terms for the (2,d,0) model are the two previous

order	behavior	the styl	e of dis.	range
(1.d.1)	decays exponentially	ф, > o	\$,<0	-ι<φ,<1
(o,d,1)	only the first a.c.f. non-zero	0,70	0,<0	- I< 0 <sub>1</sub> < 1
(2,d,0)	mixture of expo- -nential or damped sine curve	φ <sub>1</sub> 7 ο φ <sub>2</sub> > ο		-1< \$\psi_2<1\$ \$\phi_2+\phi_1<1\$ \$\phi_2-\phi_1<1\$
(0,d,2)	only the first a.c.f. non-zero	θ,70 θ <sub>2</sub> 70	θ <sub>1</sub> >ο θ <sub>2</sub> <ο	-1<02<1 02+0.<0 02-0.<0
(1,d,1)	decays exponen- -tially from the first lag	 	1	-1<0,<1
	11136 108	         	الم الم	-1<0,<1

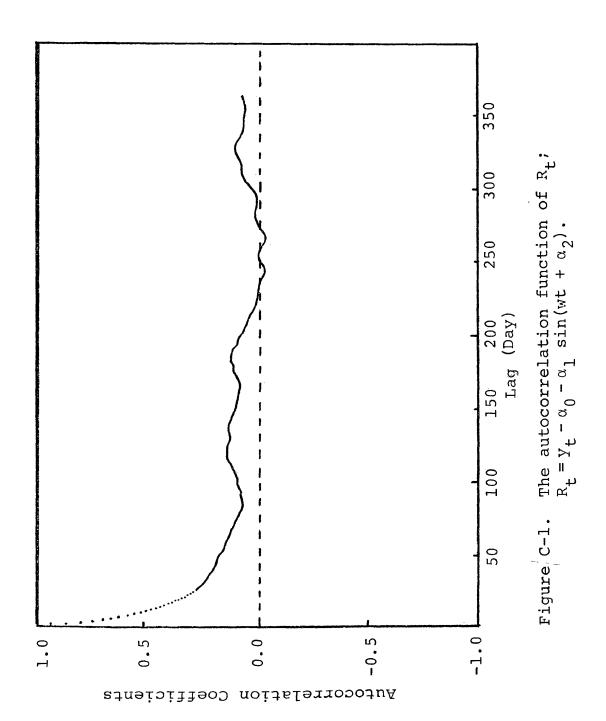
Table C-1. The teeoretical behavior of the autocorrelation functions for some low order ARIMA processes.

neighbor values etc. In addition, it is easy to see the neighboring relation between disturbances for an autoregressive process is stronger than for a moving average process at the same order.

It is useful to know the nature of the ACF for both simple and mixed models, so that this knowledge will aid in interpreting real situations. It is necessary to emphasize that the behavior is for theoretical situations; these distributions normally will not coincide absolutely with real data. Box & Jenkins (1970) showed that after the theoretical ACF has damped out, for real time series moderatively large estimated autocorrelation coefficients can occur and some ripples and trends are expected to occur too. It also is suggested that closely related models need to be included and identified at the same time because the result of such comparisons is more accurate.

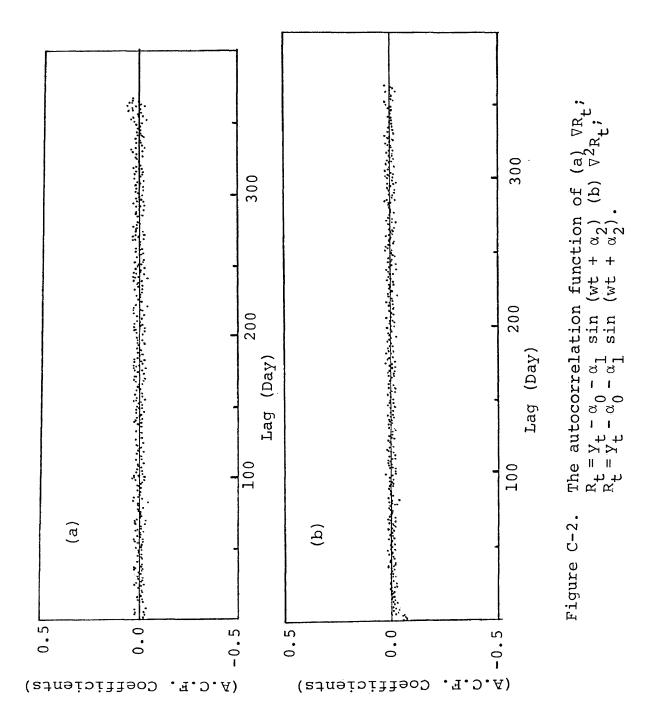
# C-2-2. Computed ACF's for Z, $\nabla$ Z, and $\nabla$ <sup>2</sup>Z

The estimated autocorrelations of Z,  $\nabla Z$  and  $\nabla^2 Z$  for water temperature residuals after removing the most significant harmonic for the yearly cycle and record mean are shown graphically in Figures C-1 and C-2. From Figure C-1, it is observed that the values for the first 80 autocorrelations die out with an exponential decay; then follows what looks like a sine wave with diminishing amplitude. The mean level is at approximately 0.05 unit. This stochastic process may



be fitted by a mixture of exponentials and damped sine curves, as has been revealed by Box & Jenkins' work. Some imaginary roots might be included in this process, in which case they contribute a sine term solution to the ACF for the characteristic equation  $\phi_p(B)=0$  and the resulting ACF will follow a damped sine curve. Of course, the real root portion for this characteristic equation could be indicated as a damped exponential.

It should be remembered that the estimated ACF will differ somewhat from the theoretical values. Considering this idea, the series can be fitted by the (1,0,0) model or the (1,0,1) model which only slightly changes the relative coefficients of the (2,0,0) model. For Figure C-2, the first difference operator is used to modify the series and the new ACF value computed again. Surprisingly, no values greater than 0.05 function units occur after the first 4 lags. The new series already approaches "white noise". first 4 values of ACF are not enough to construct a model. If we check the second difference series of the ACF, it is described well by a (0,2,1) model because the first value is approximately equal to 0.5, and subsequent variations are all less than 0.04 and around the zero line. It should be noted that the higher order of the difference series can make those shocks disappear. But a (0,2,1) model will be investigated to determine its adequacy.



The PACF is computed to confirm the nature of this series. In Figure C-3, one notes that the first function value is large, but none of the second to fifth values is over 0.04 function units. That is strong evidence that the first order autoregressive model is appropriate. In summary, the water temperature series can be represented by the (1,0,0), (2,0,0), (1,0,1), or the (0,2,1) model.

#### C-3. Model estimation

C-3-1. Estimating parameters for the autoregressive model

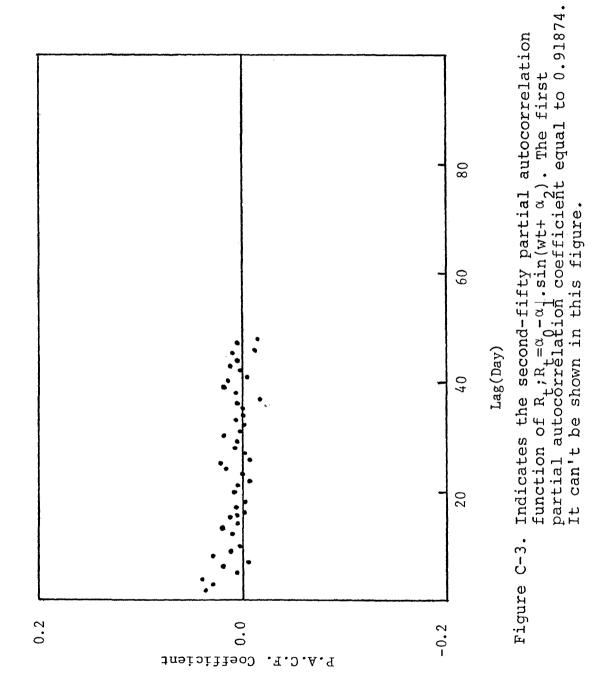
The autoregressive model belongs to a linear process, thus the least square estimate method is available. The general form of the autoregressive model is:

$$\tilde{z}_t = \phi_1 \tilde{z}_{t-1} + \phi_2 \tilde{z}_{t-2} + \dots + \phi_p \tilde{z}_{t-p} + a_t$$
 (order=p)

The least square method is expected to reduce the magnitude of the sum of squares between the observed and estimated values as small as possible.

$$S(\phi_1, \dots, \phi_p) = \sum_{t=p+1}^{n} (\widetilde{z}_t - \phi_1 \widetilde{z}_{t-1} \dots - \phi_p z_{t-1})^2 = \min m$$
(C-15)

With differentiations of the sum of squares, a set of linear equations can be obtained with respect to  $\phi_1,\ldots,\phi_p$ ; each equation is set equal to zero.



If the order is 1, equation C-15 becomes

$$S(\phi_1) = \sum_{t=2}^{n} (\tilde{z}_t - \phi_1 \tilde{z}_{t-1})^2 = minimum$$

and

$$\frac{\partial S}{\partial \phi_1} = -2 \sum_{t=2}^{n} \tilde{z}_{t-1} (\tilde{z}_t - \phi_1 \tilde{z}_{t-1}) = 0$$

$$\cdot \cdot \cdot \phi_1 = \sum_{t=2}^{n} \tilde{z}_{t-1} \cdot \tilde{z}_t / \sum_{t=2}^{n} \tilde{z}_{t-1} \cdot \tilde{z}_{t-1}$$

Thus, the autoregressive model of order 1 is fitted to the water temperature variation model. Its coefficient is 0.91875.

For (2,0,0) model, the sum of squares is

$$S(\phi_1, \phi_2) = \sum_{t=3}^{n} (\tilde{z}_t - \phi_1 \tilde{z}_{t-1} - \phi_2 \tilde{z}_{t-2})^2 = \min_{t=3}^{n} (\tilde{z}_t - \phi_1 \tilde{z}_{t-1} - \phi_2 \tilde{z}_{t-2})^2$$

$$\frac{\partial S}{\partial \phi_1} = -2 \sum_{t=3}^{n} \tilde{Z}_{t-1} (\tilde{Z}_t - \phi_1 \tilde{Z}_{t-1} - \phi_2 \tilde{Z}_{t-2}) = 0$$

$$\frac{\partial S}{\partial \phi_2} = -2 \sum_{t=3}^{n} \tilde{z}_{t-2} (\tilde{z}_t - \phi_1 \tilde{z}_{t-1} - \phi_2 \tilde{z}_{t-2}) = 0$$

The above equations can be arranged in a matrix form:

Then  $\phi_1$  and  $\phi_2$  can be determined by multiplying the inverse matrix of the 2x2 matrix on the left side by the matrix on the right side. The result is

$$\phi_1 = 0.91039$$
  $\phi_2 = 0.00919$ 

If only one parameter needs to be estimated, one can alter the original equation to another form, then insert the assumed value to find the region which has the minimum square value of residuals. When this inserted value of accuracy increases, the result is approached.

For instance, for the first order of autoregressive model:

$$\widetilde{Z}_{t} = \phi \widetilde{Z}_{t-1} + a_{t}$$

$$\widetilde{Z}_{t} = \widetilde{Z}_{t-1} + a_{t}$$

values can be chosen to determine under which value the summation of shocks square is minimum. In Figure C-4,  $\phi$  is about 0.919 when the computed region is between 0.91 to 0.93.

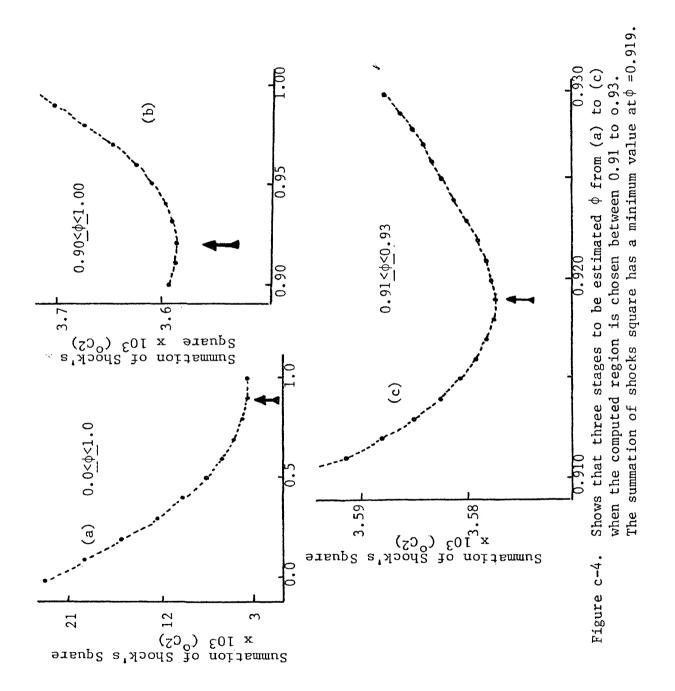
C-3-2. Estimating parameters for the moving average model

Since it is hard to express the sum of squares in explicit form, the moving average process also needs to have the type of equation changed. For example, the first order moving average model is expressed as:

$$\tilde{Z}_t = \theta_q(B) \cdot a_t \qquad (q=1)$$

$$\dot{z}_{t} = a_{t} - \theta a_{t-1}$$

Since the expected value of the residuals  $\mathbf{a}_{\mathsf{t}}$  is equal to zero, therefore  $\mathbf{a}_{\mathsf{0}}$  can be assumed zero.



$$a_0 = 0 a_1 = \tilde{z}_1$$

$$a_2 = \tilde{z}_2 + \theta a_1 \dots$$

$$a_n = \tilde{z}_n + \theta a_{n-1}$$

$$s(\theta) = \sum_{t=1}^{n} (a_t)^2$$

The sum of squares, can be obtained for different values of  $\theta$ . For a higher order moving average process, this approach can be followed but the final value will depend on two or more corresponding values.

#### C-3-3. Estimating parameters for mixed models

The equations for the autoregressive-moving average model also need to be transformed (Carlson 1970). The first order mixed model is:

$$\tilde{Z}_t = \phi_1 \tilde{Z}_{t-1} + a_t - \theta_1 a_{t-1}$$

If a value of  $\theta_1$  is assumed, then the data  $z_1,\ldots,z_t$  may be converted to a new data set  $t_1,\ t_2,\ \ldots,\ t_n$ 

$$t_1 = \tilde{z}_1$$

$$t_2 = \tilde{z}_2$$

$$t_n = \tilde{z}_n + \theta_1 t_{n-1}$$

This set of t can be described as an autoregressive model

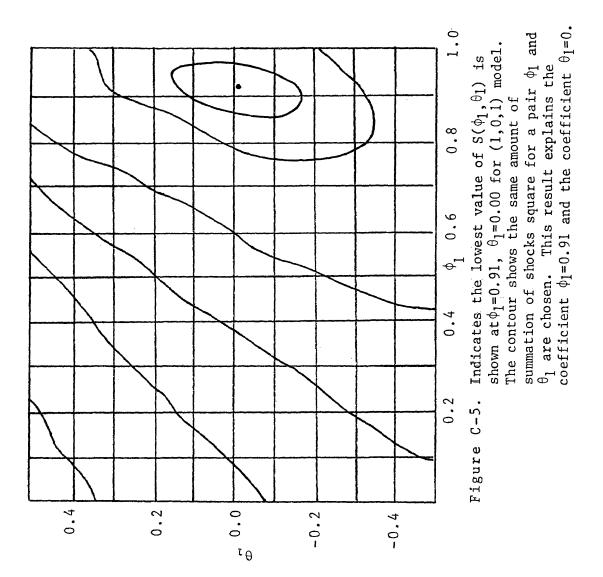
$$t_{+} = \phi t_{+-1} + a_{+} \tag{C-16}$$

From equation C-16, parameter  $\phi$  can be estimated as previously mentioned for autoregressive model which normally uses the least square method. The results are  $\phi_1$  = 0.919 and  $\phi_2$  = -0.008. The sum of squares computed from a pair of  $\phi_1$  and  $\theta_1$  values can be shown on the  $(\phi_1, \theta_1)$  plane.

If the contours of constant sum of squares are sketched, the lowest center can be observed as in Figure C-5. The observed values are approximately equal to  $\phi_1$  = 0.9 and  $\theta$  = 0.00. The parameters for the four possible models are summarized in Table C-2.

### C-4. Checking the adequacy of the models

Four models have been identified, and the parameters which are used to fit that model also have been estimated. Coefficients for some of the models are highly similar to each other, such as the parameters for the (1,0,0) models, since 6 = 0.00. This seems to tell us that both these models can express the same behavior if both are under the standard error which is permissible for the estimated autocorrelation function. However, for each model tested, the most important step is to determine whether this model is adequate. If it is not adequate, how can this model be altered to present the true behavior. Thus, the checking process not only will move us toward a complete model but also will give us more confidence in the model chosen.

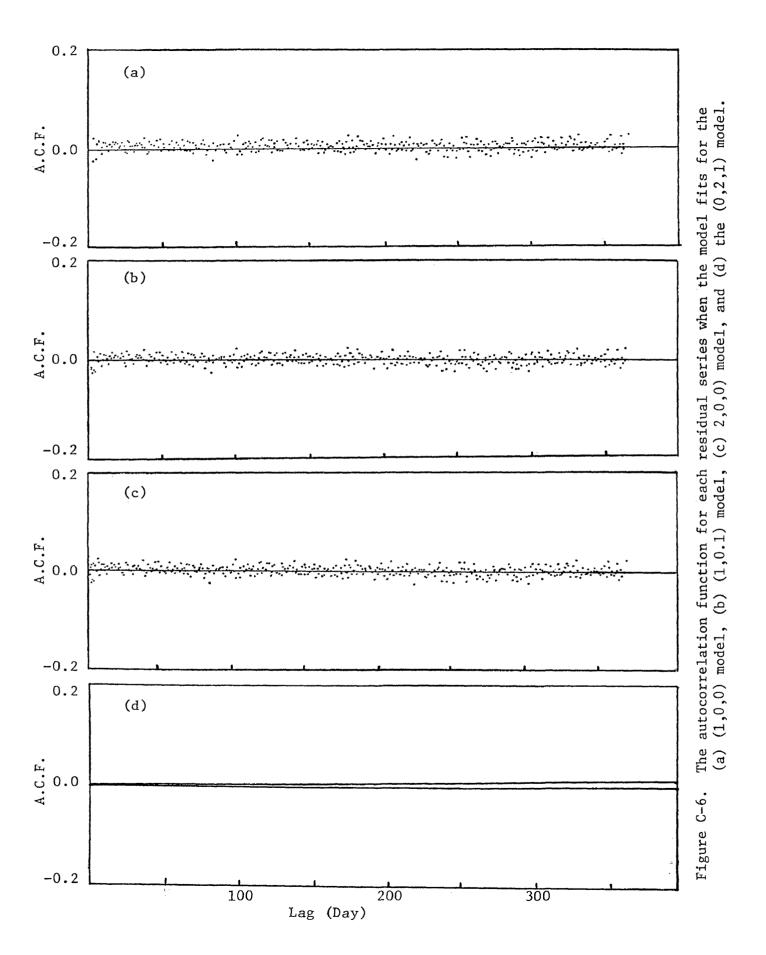


The final estimates for each possible model. Table C-2.

ARIMA Process	Parameter Values	The Type of Model
(1,0,0)	$\phi_{1} = 0.91875$	$\tilde{Z}_{t} - 0.91875  \tilde{Z}_{t-1} = a_{t}$
(2,0,0)	61016 <b>°</b> 0 = <sup>Τ</sup> φ	$\tilde{z}_{t-2}$ 0.91019 $\tilde{z}_{t-1-0.00919}$
	$\phi_2 = 0.00919$	$\tilde{Z}_{t-2} = a_t$
(1,0,1)	$\phi_{1}=0.9199$	$\tilde{z}_{t} - 0.9199\tilde{z}_{t-1} = a_{t}^{+} 0008a_{t-1}$
	$\theta_1 = -0.008$	
(0,2,1)	$\theta_1 = 0.99$	$\nabla^2 \tilde{z}_t = a_t - 0.99 a_{t-1}$

#### C-4-1. The ACF for residual series

The most common method used to check an assumed model is to observe the distribution of the residuals using the statistical behavior. The probability distribution may produce a straight line such as was used in Chapter II. The ACF again can play this important role for checking the residual series. As we know, the theoretical autocorrelation function is distributed around zero values for each lag after a model is fitted completely. But due to slight differences, the estimated ACF may be distributed approximately normally about zero with variance  $n^{-1}$  based on Baretetts' approximation. That means if the estimated ACF is within the upper or lower bounds with a standard error of  $n^{-1/2}$  (one standard deviation) one can still regard this process as "white noise" behavior. However, at low lags a reduction of variance can occur and the residual ACF can be highly correlated. Those relations disappear quickly at high lags (Box & Jenkins, 1970). Therefore, one can use  $n^{-1/2}$  as the standard error to examine the distribution at low lags. According to the above assumption, the standard error is about 0.0213 for the 95 percent (two standard deviation) confidence limit. In Figure C-6 the individually computed and fitted models are shown. Apparently, except for the first couple values at low lags, the estimated ACF have only about one tenth the values outside the bound. This result is associated with the length of series and the choice as to whether a lag value is regarded as moderate or high.



C-4-2. Q value and the residual variance checking

Usually, the Q=N  $\Sigma$   $r_i^2$  which is calculated by summing the residual ACF multiplied by the number, N = n-d. If the fitted model is acceptable, then this value, say Q, is approximately distributed as Chi-square distribution with degree of freedom (k-p-q), the maximum calculated lag value subtracted from the order of the autoregressive process plus the order of the moving average, and will fall between the corresponding confidence limits for the Chi-square distribution. Normally the 95 percent limit is to be expected as the standard if this model is appropriate. Table C-3 the Q value is equal to 475.32 while the 5 percent point for x<sup>2</sup> with 364 degrees of freedom is 407.207. question to be considered is whether this sample is so large that the maximum lag number, 365, is too low. fore, we extend the lag values to 1095, and then calculate the sum of residual ACF squared. It was found that even though the value tripled, the Q value still cannot prove that this model is adequate, because the Q value tripled In Table C-3 are listed the Q values for each fitted Unfortunately, none of them is less than the 90 percent limit value. It is worthwhile to observe whether

Q value testing is the method which can check whether a model is adequate or not from the residual ACF of distribution.

The Q value (Chi-squares) for each residual series and the ARIMA process is fitted. Table C-3.

Model Style	r, 2	Q	06.00	p-N=u	Degree of Freedom
(1,0,0)	0.0542	475.32	409.21	8760	364
(1,0,1)	0.05411	474.00	408.15	8760	363
(2,0,0)	0.05350	468.66	408.15	8760	363
(0,2,1)	0.10061	881.14	409.21	8758	364
		-			

the moving Q value converges or not. A (0,2,1) model residual ACF, which increases constantly, is shown in Figure C-6d. This phenomenon indicates that high correlations probably will appear for large lags. However, especially low correlation values occur at low lags.

Now, we must pay attention to one of the most important processes of this study, which is to find a model that minimizes the sum of squares and produces a minimum total variance. The variance of the original data is 70.14 c<sup>2</sup>. The ratio of the sum of squares of the residual for each model to the initial sum of squares is a good indicator of the best model. Table C-4 presents some of the statistical results to aid in the final decision. The (1,0,0), (1,0,1)and (2,0,0) models still have very similar solutions. percentage of total variance is reduced to less than 0.06. The best choice is the (1,0,0) process which has the most simplicity and lowest order. The final question to be considered is how to modify the model when it is inadequate. Box & Jenkins (1970) suggested that making another ARIMA model from the residual series, then combining this model with the original model.

For example, suppose that  $b_{\mathsf{t}}$  is the residual from the model C-17 and this model appears to be nonrandom.

$$\phi_{\mathbf{b}}^{\mathbf{d}}(\mathbf{B}) \nabla^{\mathbf{d}} \tilde{\mathbf{z}}_{\mathbf{t}} = \theta_{\mathbf{b}}^{\mathbf{d}}(\mathbf{B}) B_{\mathbf{t}}$$
 (C-17)

The residual analysis for each possible model. Table C-4.

Model Style	Sum of Residuals	Total Squares of Residuals	Percentage of Total Variance	The ratio of $s_{\rm r}/s_{ m o}$
	-151.15	23023.25	4.52	 
	-12.41	3588.71	0.58	0.15587
	-12.12	3,589.38	0.58	0.15590
	-12.67	3588.13	0.58	0.15585
	-99.64	3826.68	0.67	0.16621

= the summation of squares for the residual series (model is fitted) = the summation of squares for water temperature series after annual cycle and mean record are removed. တ္ဝ

Using the ACF of  $b_{\mathsf{t}}$ , it can be used to build a model for which the residual is random.

$$\phi_{a}(B) \nabla^{a} b_{t} = \theta_{a}(B) a_{t}$$
 (C-18)

Substituting C-18 into C-17, we have a new model:

$$\phi_{b}(B) \cdot \phi_{a}(B) \nabla^{d_{b}} \nabla^{d_{a}} \tilde{z}_{t} = \theta_{b}(B) \cdot \theta_{a}(B) a_{t}$$
 (C-19)

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