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STATISTICAL MODELLING OF TEMPERATURE VARIABILITY IN THE BARENTS SEA.

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ABSTRACT

During the latter years an effort has been made to find out more about the relations between environmental variation and recruitment, growth, distribution and migration of fish. The rationale has to a large degree been the needs from fisheries management. To utilize this knowledge for management purposes it is necessary to be able to make some kind of forecast of the environmental situation.

This work is an early attempt to quantify the future temperature development in the Barents Sea. We use three different methods, all applied to the ocean temperature time series from the Russian Kola-section. The first method uses the principle of least squares to fit a sum of Fourier components to the observations and construct a function which generates future values. We also apply Holt-Winters models with a linear trend and either an additive or a multiplicative seasonal component. The third procedure classifies the different years into a few categories according to temperature. Statistics on the historical temperature patterns can then be used for forecast purposes.

Our results indicate temperature conditions below the long term mean up to 1999. The uncertainty of the forecasts grows with the time-span, but we believe that the picture for the 2-3 first years is reasonably reliable. Our hope is that this work will help towards taking the environmental situation into consideration when evaluating the future fisheries resource situation.

Introduction

Since before the turn of the century one has sought for relations between environmental parameters and various population parameters of fish. From the early beginning one was concerned about finding the causes of the year to year variability of the yield and why the spawning migration could change from one period to the next. The recent years an effort has been put in to find the relations between environmental variation and recruitment, growth, distribution and migration of fish. The rationale for this has been that the results were to be used in the management of the fisheries. To be able to do so one must first be able to quantify such relationships and secondarily be able to make some kind of forecast of the environmental situation at least for the forthcoming two-three years. Assuming that temperature is an advective property, it would be possible to take temperature observations upstream and forecast the temperature development downstream like Helland-Hansen and Nansen (1909) did. They suggested a time lag of two years between Sognesjøen (southern Norway) and the Barents Sea. Elliot (1956) indicated a three year time-lag between changes in the sea level of the Gulf Stream outside Florida and changes in the heat transport to the Barents Sea. The problem is that not all temperature changes are a result of advection, some occur almost simultaneously over a large area (Loeng et al. 1992). We have for this reason chosen to look into methods which do not depend on upstream values.

This work is an early attempt to quantify the future temperature development in the Barents Sea. We use three different methods all applied to the ocean temperature time series from the Russian Kola section. One way to proceed is to assume periodicity in the temperature variability. Several authors have suggested periodicities of various lengths for the climatic variability in the Barents Sea, either based on oceanographical arguments or on different kinds of time series analysis (Bochkov 1982, Ottestad 1942, 1979, Izhevskii 1961, 1964, Loeng et al. 1992). The uncertainty of the forecast grows with the time-span, but we believe that the picture for the 2-3 first years is reasonably correct. At least we hope that this will be a first step towards taking the environmental situation into consideration when the future fisheries resource situation is evaluated.

Material

The longest ocean temperature time series in the Barents Sea is the Russian series from the Kola section ($33°30'E$, $70°30'N$ to $72°30'N$). This series goes back as far as 1900, holes in the observation series in the periods 1906-1919 and 1941-1944 have been filled by Bochov (1982). Monthly values are calculated by averaging along the section, in the vertical and in time. The data from recent years have been provided by PINRO, Murmansk.

The time series from Kola was analysed with other time series from the Barents Sea by Loeng et al. (1992). They found periodicities which were common to several of the time series. Their findings are presented in Table 1 together with results by other authors.

Table 1. Earlier described periodicities for different parameters in or close to the Barents Sea. S=salinity, T=ocean temperature, SST=sea surface temperature, AT=air temperature, AP= air pressure.

Period in years	*Parameter*	*Reference*
2.5	S / AT / AP	Loeng et al. (1992)
3.3	T / S / AT/ AP	Loeng et al. (1992)
4 - 5	T	Izhevskii(1961, 1964)
5	T / AT / AP	Loeng et al. (1992)
7.3	AP	Loeng et al. (1992)
8 - 10	T	Izhevskii(1961, 1964)
8.5	No. of cod caught in Lofoten	Ottestad (1942, 1979)
8.8	T / AP	Loeng et al. (1992)
11	No. of cod caught in Lofoten	Ottestad (1942, 1979) / Solar activity cycle
11.7 - 13.6	T / SST	Loeng et al. (1992)
17.5	T / AT	Loeng et al. (1992)
17.5	No. of cod caught in Lofoten	Ottestad (1942, 1979)
18-20	T	Izhevskii(1961, 1964)
18.6	No. of cod caught in Nor. Norway	Wyatt et al. (1993) / Nodal tide

Methods

Periodical fluctuations

In general a time series can be expressed as a sum av sines and cosines, the spectral decomposition of the series.

$$X_t = \mu + \sum_{k=1}^{m} \langle A_k \cos\omega_k t + B_k \sin\omega_k t \rangle + e_t \qquad (Eq.\ 1.)$$

where

X_t is random variable

μ is a constant parameter

A_k is the amplitude of the k-th cosine component

B_k is the amplitude of the k-th sine component

$\omega_k = \dfrac{2\pi}{\mathrm{period}_k}$ are the frequencies

e_t is a purely random process.

In matrix form this can be expressed as $X = A\theta + e$ or $E(X) = A\theta$ where

$$X^T = (X_1, \ldots, X_n) \ ,$$

$$\theta^T = (\mu, A_1, B_1, \ldots, A_m, B_m) \ ,$$

$$A = \begin{bmatrix} 1 & \cos\omega_1 & \sin\omega_1 & \ldots & \cos\omega_m & \sin\omega_m \\ 1 & \cos 2\omega_1 & \sin 2\omega_1 & \ldots & \cos 2\omega_m & \sin 2\omega_m \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ 1 & \cos n\omega_1 & \sin n\omega_1 & \ldots & \cos n\omega_m & \sin n\omega_m \end{bmatrix}$$

and E() expresses the expected value.

The contribution from one period has two degrees of freedom, A_k and B_k, or equivalently the amplitude and the phase. As we see the model is linear in the unknown parameters θ. The least squares method can then be used to estimate θ, that is to find the estimates $\hat{\theta}$, where $\hat{\theta}^T = \left(\hat{\mu}, \hat{A}_1, \hat{B}_1, \ldots \hat{A}_m, \hat{B}_m\right)$, that minimize

$$\sum_{t=1}^{n} \langle X_t - \langle \mu + \sum_{k=1}^{m} \langle A_k \cos\omega_k t + B_k \sin\omega_k t \rangle \rangle \rangle^2 \qquad \textit{(Eq. 2)}$$

The solution to this is $\hat{\theta} = \left(A^T A\right)^{-1} A^T x$ where x is the column vector consisting of the observations $x_1 \ldots x_n$.

The method of least squares can be considered as a linear multiple regression between **X** and the columns of A. Viewed in this way the linear regression routine of the SAS package (SAS Institute 1988b) can be used to find $\hat{\theta}$. We then also have a measure of how large a part of the total variation which is explained by the chosen frequencies. One must, however, be aware that this is a somewhat unusual form of linear multiple regression and that objections may be raised on the ground of the error terms, e_t, not being independent. The Durbin-Watson parameter was worked out for some cases and found to be much less than 2.0, confirming the above doubts. This made us not focus to strongly on the regression point of view and only use SAS's Reg procedure because this is a practical way to compute $\left(A^T A\right)^{-1} A^T x$. If periodic fluctuations at a few frequencies dominate, much of the variability in the time series will be caught in the sum of the sine and cosine components of these frequencies, that is a small number of selected ω_k 's. Even if a model with a large number of explanatory variables (many frequencies in our case) gives a better fit to the data set considered, the forecast need not be better (Shepherd et al., 1984). Stepwise regression is not suitable in our case. The reasons for this are that the e_t terms are correlated and not normal and also that we wish to include both the sine and the cosine component of the selected frequencies so as not to fix the phase. Instead we chose to use the periods with the largest amplitude $\sqrt{A_k^2 + B_k^2}$. The periods for temperature fluctuation in the Barents Sea considered have all been suggested for this area by other authors (Table 1).

Holt-Winters seasonal models

Holt-Winters forecasting models are a family of exponential smoothing procedures. Chatfield (1989) and SAS Institute (1988a, 1992) give an introduction. Two types of Holt-Winters models with linear trend are applied, one with an additive and one with a multiplicative representation of the seasonal variation. The models can be expressed as

$X_t = a_t + b_t t + s_t(t) + e_t$ (additive, *Eq. 3*) and

$X_t = (a_t + b_t t)\, s_t(t) + e_t$ (multiplicative, *Eq. 4*)

where a_t is the constant trend parameter

b_t is the linear trend parameter

$s_t(t)$ is the seasonal component for the season to which time t belongs and

e_t is the random error term.

This gives the predicted values for τ periods (months) forward

$\hat{X}_{t+\tau} = a_t + b_t(t+\tau) + s_t(t+\tau)$ (additive, *Eq. 5*) and

$\hat{X}_{t+\tau} = \langle a_t + b_t(t+\tau)\rangle s_\tau(t+\tau)$ (multiplicative, *Eq. 6*).

"One step ahead" predicted values are generated continuously as long as there are observed values. Based on the equation and parameter values at this time predicted values are calculated for as far into the future as requested. Estimated confidence intervals for the forecasted values are also given, in our case a 95% interval was chosen. The estimates for the parameters a_t, b_t and $s_t(t)$ are updated at each time step by updating functions. The stability of the analysed series, amount of noise, the influence of the newest observations and so on are decisive for the choice of weights for updating. If desired the weights are set automatically by the analysis program.

Combinations of temperature-classified years

If the temperature anomalies themselves are too hard to forecast it would perhaps be advantageous to reduce the level of precision and classify the temperatures in the Kola-section in a few discrete temperature classes. Statistics on the historical temperature patterns can then be used for forecasting purposes. For fisheries management a forecast of the next couple of years being warm, cold or average should be of interest, especially if the level of uncertainty is indicated.

The simplest case is a binary classification into warm (W) and cold (C) years. The straightforward approach is to compare the yearly mean with the total mean (3.90 degrees C) for the years 1900-1993. This gives the time series in Table 2.

Table 2. The years 1900-1993 classified as cold (C) or warm (W) according to the ocean temperature in the Kola section.

0 1 2 3 4 01234567890123456789012345678901234567890123456789 CCCCCWCWCCCCCCCCCCCCCWWWCCWCCCCWWCWWWWWWWCCCWWWWWCW
5 6 7 8 9 0123456789012345678901234567890123456789012 3 WWWCWWCWCWWWWCWCCCCCWCWWWWWCCCCCCWWCCCCWWWWW

Ternary classification categorises the years as warm (W), medium (M) or cold (C) according to the deviation of the yearly mean from the total mean. If the deviation is less then 0.2 degrees Celsius, the year is classified as medium. The corresponding ternary time series is given in Table 3.

Table 3. The years 1900-1993 classified as cold (C), medium (M) or warm (W) according to the ocean temperature in the Kola section.

0 1 2 3 4 01234567890123456789012345678901234567890123456789 CCCCCMMMMMMMCCMCCCCMWWMMCMCMMCWWCWWWMWWWMCCWWMMWMW
5 6 7 8 9 01234567890123456789012345678901234567890123 WWWMWWCWCWWWMCWMCMCCWCMWMWWCCCCCCWWCCCMWWWWM

Results

The fitting of Fourier components for the 9 frequencies given in Table 2 was done for monthly temperature values from the Kola section as well as 12 months moving averages of this series. The 12 months moving averages were calculated as

$$x_{t_{m12}} = \frac{1}{2}x_{t-6} + \sum_{i=-5}^{5} x_{t+i} + \frac{1}{2}x_{t+6} \qquad \textit{(Eq. 7)}$$

This was done for the period January 1921 to December 1993, a total of 876 months. The parameter estimates $\hat{\theta}$ found for the 1921-93 period were then used to forecast the temperature development until 1999. As a control of the methods forecasting abilities the fitting of Fourier components was also done based on data from 1921 to 1985 and from 1921 to 1989. The $\hat{\theta}$'s found in these cases were used to make forecasts for respectively 1986 to 1993 and 1990 to 1993. Note that these are true forecasts since no knowledge of the forecasted period is used. Charts of observed and predicted time series are given in Figs. 1-3. Similar calculations were also done for a subset of frequencies with large amplitudes. In Table 4 amplitudes, coefficients of determination, $R^2 = \dfrac{\sum\left(\hat{x}_i - \bar{x}\right)^2}{\sum\left(x_i - \bar{x}\right)^2}$, and adjusted coefficients of determination,

$R_a^2 = 1 - \left(1 - R^2\right)\frac{n-1}{n-m-1}$, are given for different cases. R_a^2 is included because the more common R^2 is an increasing function of the number of explanatory variables and thus only suited for comparison between models with the same number of variables.

Table 4. Amplitude at 9 different frequencies for 3 different periods and 12 month moving average for the Kola section ocean temperature time series. Order of each period when ranked by amplitude size is given in parenthesis. R^2 and R_a^2 are shown for series estimated from all 9 frequencies and from respectively the 7 and 5 with largest amplitudes.

Period in years	*months*	*Amplitudes*			
		Monthly values until 1993	*Monthly values until 1989*	*Monthly values until 1985*	*12mth MA 1921 to 1993*
2.5	30	0.127 (6)	0.134 (5)	0.127 (6)	0.101 (7)
3.3	40	0.092 (8)	0.105 (7)	0.110 (7)	0.075 (9)
5.0	60	0.137 (4)	0.165 (3)	0.137 (5)	0.128 (5)
7.3	88	0.143 (3)	0.161 (4)	0.142 (3)	0.144 (2)
8.8	106	0.114 (7)	0.098 (8)	0.072 (8)	0.108 (6)
11.0	132	0.135 (5)	0.133 (6)	0.140 (4)	0.134 (4)
13.0	156	0.147 (2)	0.175 (2)	0.212 (1)	0.143 (3)
17.5	210	0.076 (9)	0.055 (9)	0.163 (2)	0.082 (8)
18.6	223	0.270 (1)	0.184 (1)	0.049 (9)	0.276 (1)
R^2 9 frequencies		0.12	0.13	0.13	0.48
R_a^2 9 frequencies		0.11	0.11	0.11	0.47
R^2 7 frequencies		0.12	0.12	0.12	----------
R_a^2 7 frequencies		0.10	0.10	0.10	----------
R^2 5 frequencies		0.10	0.10	0.10	----------
R_a^2 5 frequencies		0.09	0.09	0.09	----------

The Holt-Winters procedure was applied to the series of monthly ocean temperature values from the Kola section from January 1921 and onwards. Figs. 4,5 and 6 show observed values from January 1980 and examples of "one step ahead estimates" and forecasts. In Fig. 4

the forecast from March 1994 to January 1995 with an additive model and standard updating weights of 0.10557 for the constant and linear trend estimates and 0.25 for the seasonal parameter estimates is shown. Fig. 5. shows the corresponding plot for the case of a multiplicative model. To help evaluate the forecasting abilities of the scheme we also estimated the model parameters based on data from January 1921 to September 1989 and used them to forecast one year ahead. Fig. 6 shows the results of the forecast with additive model and low weights for both the linear trend parameter and the seasonal parameters (0.025). The estimated model parameters for 4 different models are given in Table 5. Note that the seasonal parameters of the multiplicative model are of a different nature than those of the additive. The sum of the additive parameters is zero while the average of the multiplicative is zero.

Table 5. Estimated model parameters for 4 applications of Holt-Winters models on monthly means of ocean temperature from the Kola section.

Models	*1*	*2*	*3*	*4*
Type	*Additive*	*Multiplicative*	*Additive*	*Additive*
Period of data	*Jan. 1921- Feb. 1994*	*Jan. 1921- Feb. 1994*	*Jan. 1921- Sept. 1989*	*Jan. 1921- Sept. 1989*
No. of observations	*878*	*878*	*825*	*825*
Type of weights	*Standard weights*	*Standard weights*	*Standard weights*	*Low weights*
Weight constant trend parameter	0.1055728	0.1055728	0.1055728	0.1055728
Weight linear trend parameter	0.1055728	0.1055728	0.1055728	0.0250000
Weight seasonal trend parameter	0.2500000	0.2500000	0.2500000	0.0250000
Standard deviation of the error term	0.4291867	0.4409953	0.4352710	0.3939055
Constant	3.7610632	3.7800313	4.3711730	4.1684029
Linear	-0.045321	-0.045526	0.0538488	0.0107658
January	-0.195076	0.9553909	-0.280028	-0.079426
February	-0.538934	0.8680779	-0.732667	-0.557172
March	-0.779176	0.8156868	-0.887444	-0.877065
April	-0.962078	0.7697345	-1.034705	-1.074106
May	-0.754538	0.8183174	-0.747413	-0.929109
June	-0.314042	0.9220591	-0.292620	-0.452601
July	0.2828132	1.0633550	0.2807891	0.2115741
August	0.7279513	1.1714532	0.7741122	0.7457025
September	0.9211953	1.2200389	1.0007168	0.9876995
October	0.8905396	1.2144475	0.9460686	0.9458446
November	0.5555064	1.1365969	0.7166889	0.7300045
December	0.1658577	1.0448418	0.2565016	0.3486525

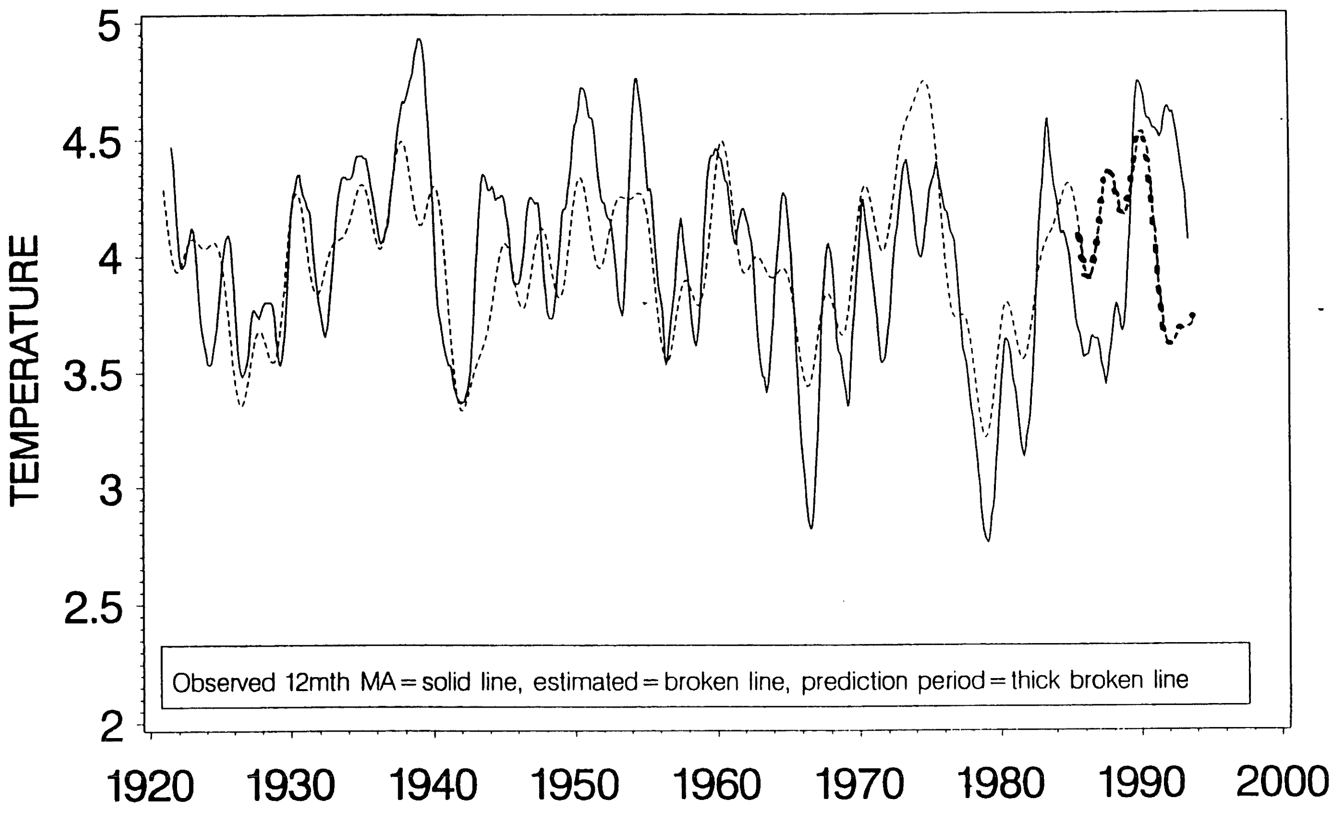

Fig 1. 12 months moving average of monthly means of observed ocean temperature at the Kola section 1921-93, estimated values 1921-1985 and values forecasted for 1986-93 by the 9 periods given in Table 1.

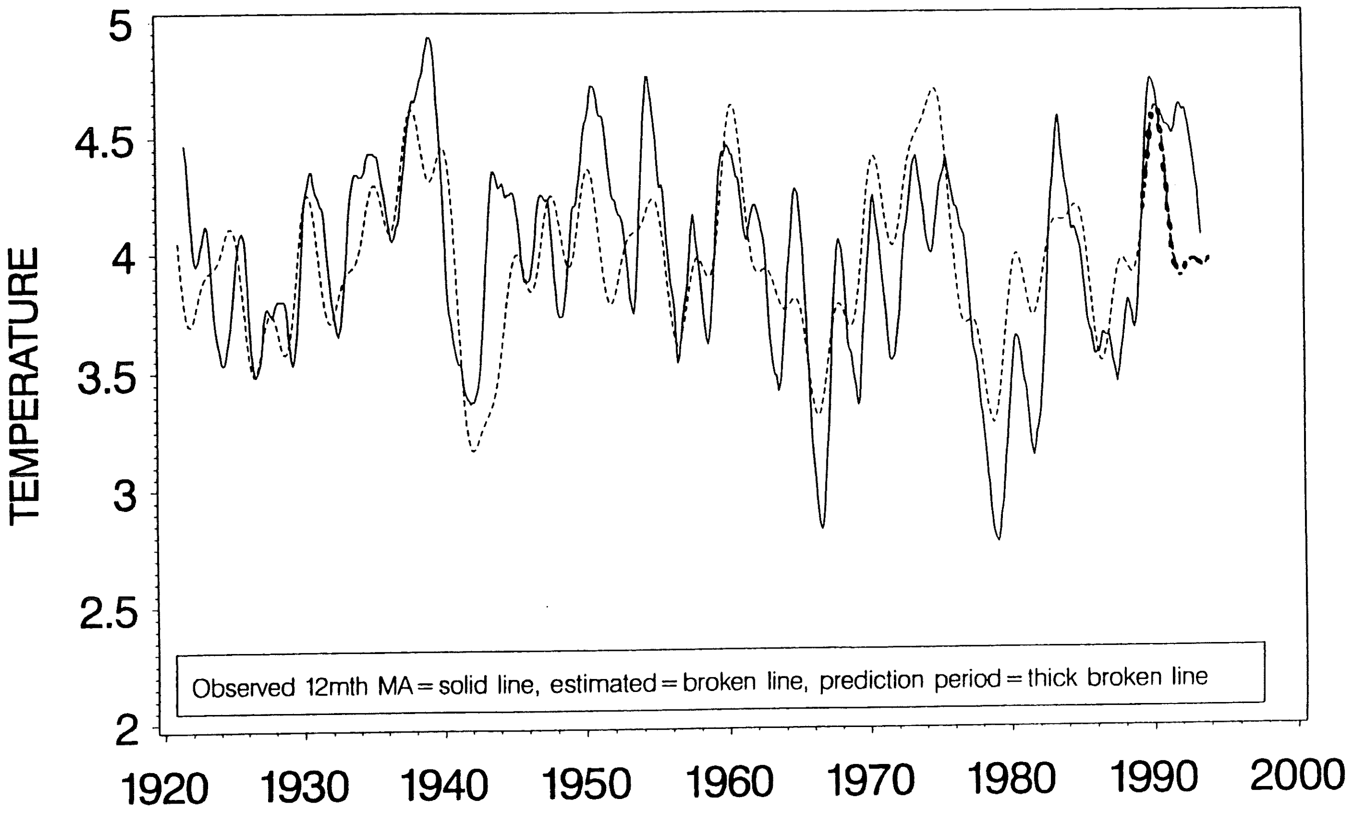

Fig 2. 12 months moving average of monthly means of observed ocean temperature at the Kola section 1921-93, estimated values 1921-1989 and values forecasted for 1990-93 by the 9 periods given in Table 1.

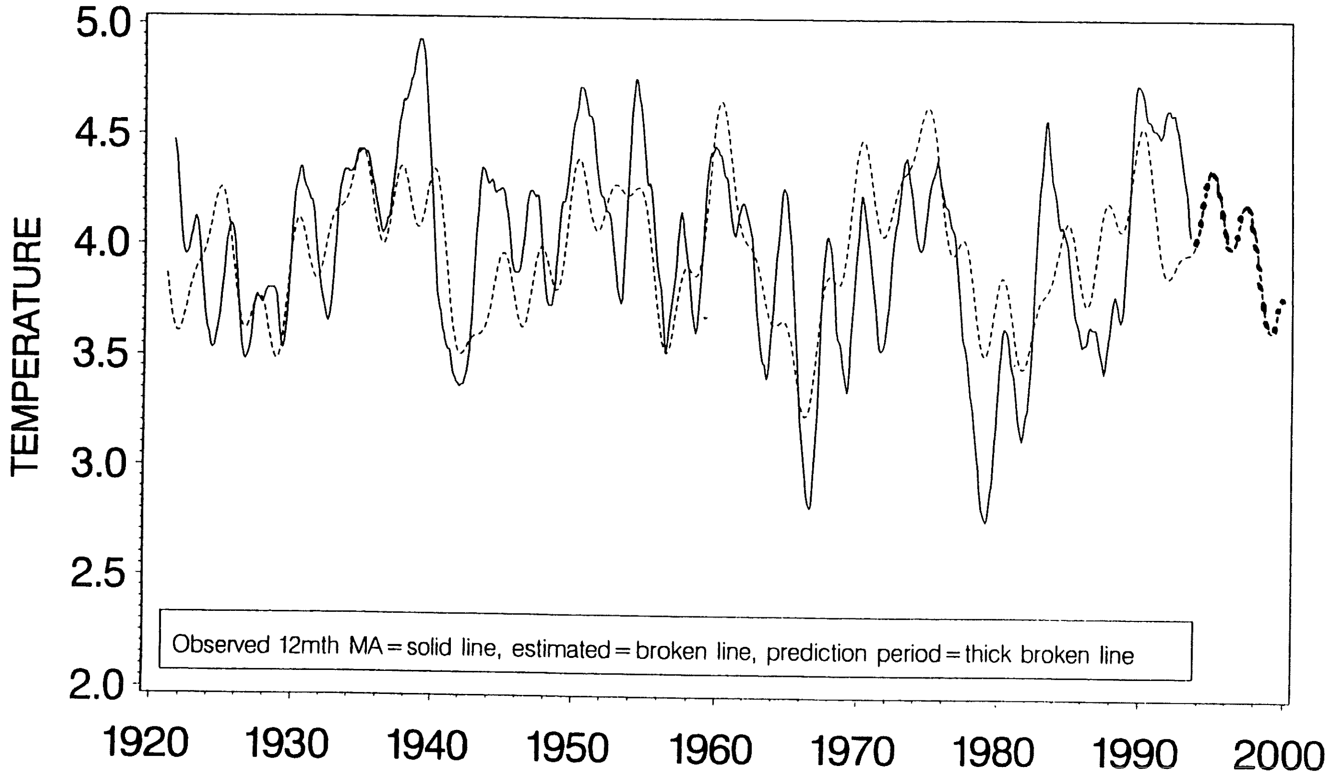

Fig 3. 12 months moving average of monthly means of observed ocean temperature at the Kola section 1921-93, estimated values 1921-1993 and values forecasted for 1994-99 by the 9 periods given in Table 1.

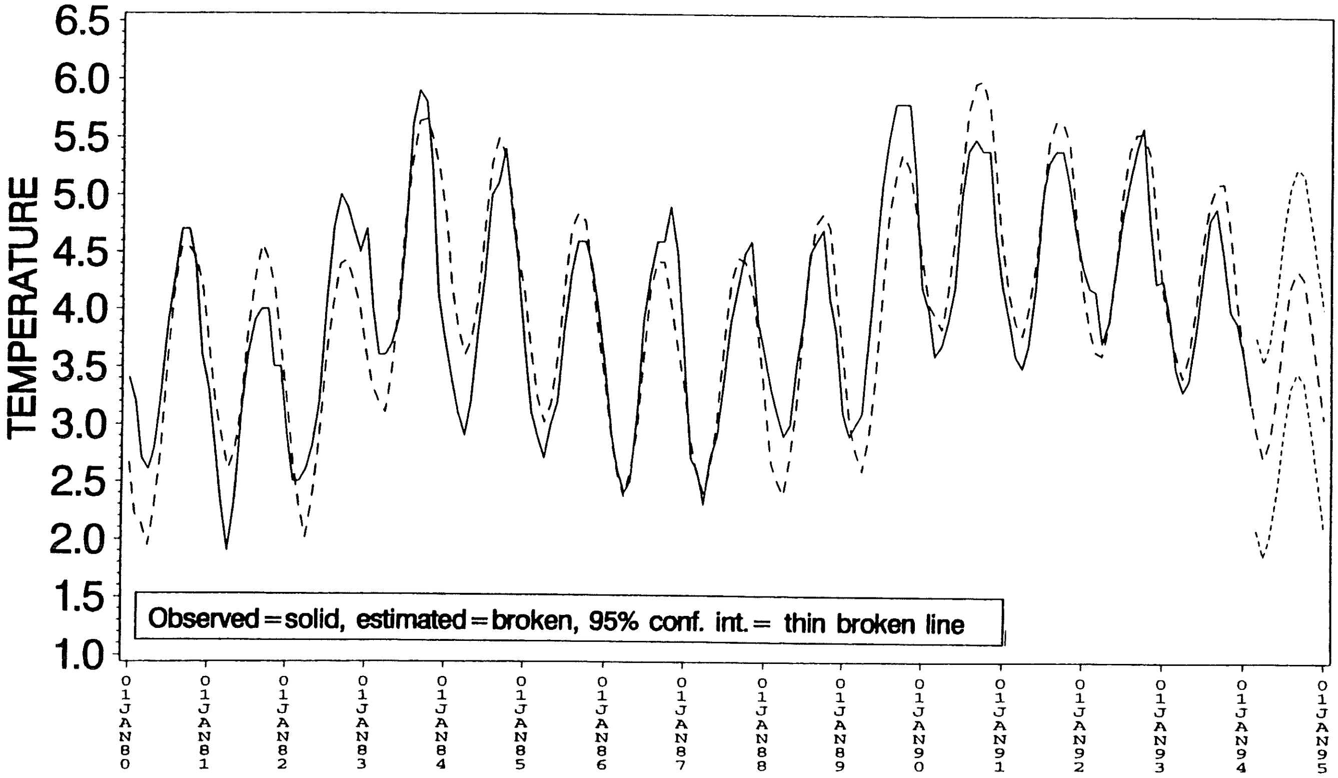

Fig. 4. Observed monthly means of ocean temperature in the Kola section for January 1980 to February 1994 and values estimated by an additive Holt-Winters modell applied to data from the period January 1921 to February 1994. The models "one step ahead" forecasts until February 1994 and further forecasts until January 1995 are given by the broken line. Upper and lower limits for the 95% confidence interval for the forecast are given by the thin broken line. Model 1 in Table 5.

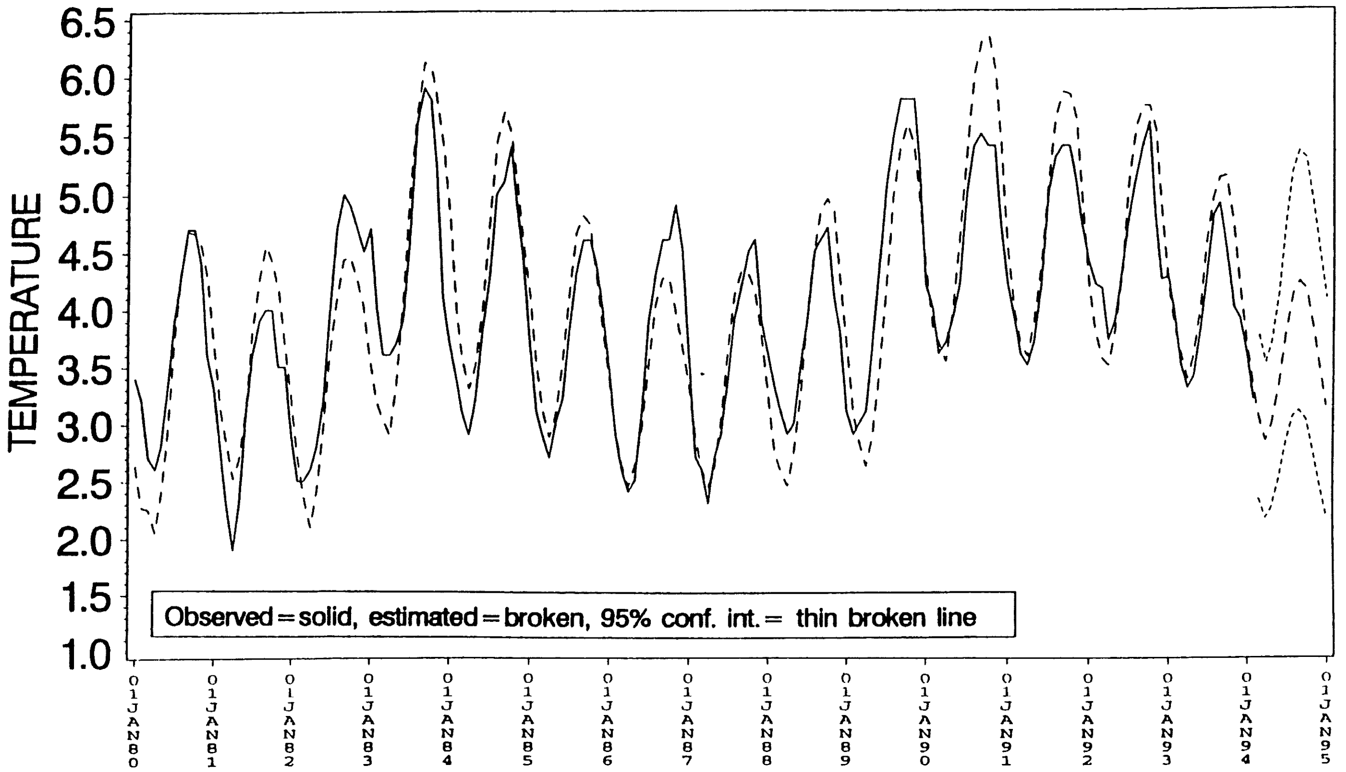

Fig. 5. Observed monthly means of ocean temperature in the Kola section for January 1980 to February 1994 and values estimated by a multiplicative Holt-Winters modell applied to data from the period January 1921 to February 1994. The models "one step ahead" forecasts until February 1994 and further forecasts until January 1995 are given by the broken line. Upper and lower limits for the 95% confidence interval for the forecast are given by the thin broken line. Model 2 in Table 5.

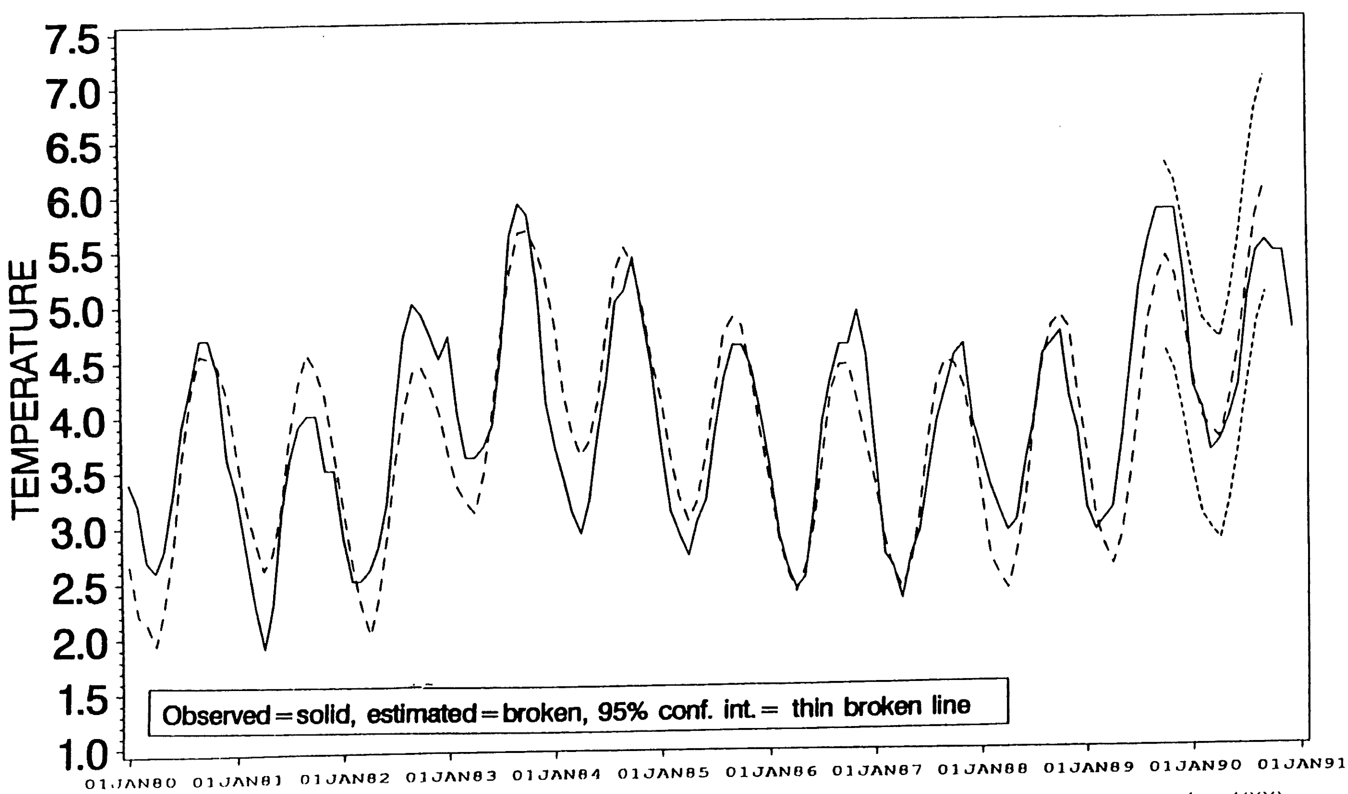

Fig. 6. Observed monthly means of ocean temperature in the Kola section for January 1980 to December 1990 and values estimated by an additive Holt-Winters modell applied to data from the period January 1921 to September 1989. The models "one step ahead" forecasts until September 1989 and further forecasts until September 1990 are given by the broken line. Upper and lower limits for the 95% confidence interval for the forecast are given by the thin broken line. Model 4 in Table 5.

Using the pattern statistics of binary temperature classification for the years 1900-1993 there has been 49 cold and 45 warm years in the Kola section. The 2-patterns are given in Table 6. Persistence can be defined as the continuation of the temperature class from one year to the next, that is the patterns WW or CC. In the Kola data persistence occurs in 62 of the 93 2-patterns, this gives a frequency of 66.7 per cent. In comparison, if the yearly temperature classes were statistically independent, the Kola series would be a binomial series. With the probability $p = 45/93 = 0.48$ of W, the expected frequency of persistence would be 50.1 per cent. The 3-patterns are given in Table 7. Persistence is clear in this case too as the patterns CCC and WWW have the highest frequency.

Table 6. Number of occurrences and frequency in percent of 2-patterns of cold (C) and warm (W) years according to the ocean temperature in the Kola section.

Temperature combination	*Number of occurrences*	*Frequency in percent*
CC	33	35.5
CW	16	17.2
WC	15	16.1
WW	29	31.2

Table 7. Number of occurrences and frequency in percent of 3-patterns of cold (C) and warm (W) years according to the ocean temperature in the Kola section.

Temperature combination	*Number of occurrences*	*Frequency in percent*
CCC	25	27.5
CCW	8	8.8
CWC	6	6.6
CWW	10	11.0
WCC	7	7.7
WCW	8	8.8
WWC	9	9.9
WWW	18	19.8

A cold period can be defined as a sequence of C's preceded and followed by W's, and warm periods similarly. Leaving out the incomplete initial and final periods, there have been 15 periods of each type in the time span 1900-1993. The length distributions of these periods are given in Table 8. Neglecting the high number of one-year "periods", we see that periods typically have a length of 3-5 years. There was an extreme long cold period in the years 1908-19.

Table 8. The number of warm, respectively cold periods classified by the length of the periods in years.

Length in years	1	2	3	4	5	6	7	8	9	10	11	12
Warm period	6	3	1	2	2	0	1	0	0	0	0	0
Cold period	8	1	1	2	1	1	0	0	0	0	0	1

For the ternary classification there has been 33 cold years, 27 medium and 34 warm years in the Kola section in the time span 1900-1993. Table 9 shows the ternary 2-pattern statistics. Persistence is evident in this case too, as the combinations WW and CC are the most frequent. On the other hand, there is no tendency for persistence in medium years, following an M all temperature classes are approximately equally probable.

Table 9. Number of occurrences and frequency in percent of 2-patterns of cold (C), medium (M) and warm (W) years according to the ocean temperature in the Kola section 1900-1993.

Temperature combination	*Number of occurrences*	*Frequency in percent*
CC	17	18.3
CM	8	8.6
CW	8	8.6
MC	9	9.7
MM	9	9.7
MW	8	8.6
WC	6	6.5
WM	10	10.8
WC	18	19.4

Using the pattern statistics, predictions for the coming years can be made. The simplest forecast strategy is to use persistence. If the temperature is warm one year the prediction for the following year is warm and correspondingly a cold forecast from a cold year. As seen from Table 6 this strategy is quite good, it gives the correct prediction in 2 out of 3 cases. Using the statistics we are able to do slightly better than persistence. For instance in a WC situation (warm last year, cold this year) Table 7 shows that persistence holds in 7 of 15 cases while nonpersistence holds in 8 cases.

So far the year 1994 is slightly warmer than average. For the purpose of making predictions for 1995 and 1996 it is assumed that 1994 is W binary and M ternary. The statistics are based on the years 1900-1993. Binary the situation in 1994 is CWWWWWW. Using persistence the prediction should be W. On the other hand, the length distribution (Table 8) shows that long warm periods seldom occur. Using different pattern lengths the probability that 1995 should be a warm year is given in Table 10. The results depend on the combination length. Using short lengths the prediction is essentially persistence, in this case W. With longer patterns the probability of a warm year is close to 0.5 and no clear prediction can be made.

Table 10. Conditional probabilities of 1995 becoming a warm year based on temperature patterns of different lengths. Binary classification of years.

Pattern length	*Pattern*	*Frequency*	*Probability*
0	W	45/93	0.48
1	W|W	29/44	0.66
2	WW|W	19/28	0.68
3	WWW|W	12/18	0.67
4	WWWW|W	6/11	0.55
5	WWWWW|W	2/5	0.40
6	WWWWWW|W	1/1	1.00

The probabilities of 1996 becoming a warm year are given in Table 11. Here "?" denotes the unknown temperature class of 1995. In this case too the tendency is "W", especially for short pattern lengths. The probabilities are, however, closer to 0.5.

Table 11. Conditional probabilities of 1996 becoming a warm year based on temperature patterns of different lengths. Binary classification of years.

Pattern length	*Pattern*	*Frequency*	*Probability*
0	?|W	45/93	0.48
1	W?|W	27/43	0.63
2	WW?|W	17/27	0.63
3	WWW?|W	9/17	0.53
4	WWWW?|W	5/10	0.50
5	WWWWW?|W	2/4	0.50
6	WWWWWW?|W	0/1	0.00

Using ternary classification the situation in 1994 is CMWWWWWMM. Table 12 summarises the temperature of the following year in earlier situations with the same combinations. A prediction for 1995 can be based on Table 12 and for 1996 on Table 13.

Table 12. Ternary combinations for the 1994 situation with statistical frequency distribution of temperature class for the following year.

Temperature combination	*Number of occurrences*	*Following year*		
		C	*M*	*W*
MM	9	3	5	1
WMM	2	1	0	1

Table 13. Ternary combinations for the 1994 situation with statistical frequency distribution of temperature class two years ahead. "?" denotes the unknown temperature class of 1995.

Temperature combination	*Number of occurrences*	*2 years ahead*		
		C	*M*	*W*
MM?	9	2	6	1
WMM?	2	0	2	0

Based on this ternary information it is quite unlikely that 1995 or 1996 will be warm years. The best prediction is medium temperature for both years.

Discussion

Due to the periods which make up the estimated series being 2.5 years or longer it was not to be expected that we would be able to capture more than a relatively small part of the total variation in the observed series of monthly values. The smooth estimated series can for instance not resolve the seasonal variation which dominates the observed series. This is reflected by the low values of R^2 and $\bar{R}_a^2$ in Table 4. But our aim is to deal with variations on the time scale of years and the explanation of the 12 months moving average series is seen to be substantially better.

Figs. 1, 2 and 3 show attempts to forecast the temperature development in the Barents Sea. The forecast from 1986 to 1993 (Fig. 1) is not good. The estimated series is clearly out of phase with the observed series. The forecast from 1990 (Fig. 2) is better. The warming in the beginning of the forecasted period is included, even if the warm period is too short. A fundamental difference in the past history of these two predictions is revealed when studying how well the estimated curve coincides with the observed one at the starting point of the prediction period. While the agreement was quite good in 1990, the series were in phase and the values similar, the situation in the beginning of 1986 was quite different. The curves were in opposite phase and the difference between estimated and observed values large. From this it follows that in 1985, solely based on the situation before the prediction was done, one could determine that the reliability of the forecast would be low, while one in 1989 had reason to be more optimistic. This indicates that one in general should take into consideration if the estimated series is in phase or not with the observations at the start of the prediction period.

Even though the difference between the values forecasted until January 1995 by an additive (Fig. 4) and a multiplicative model (Fig. 5) is not large, the two different types of Holt-Winters models may in general give estimates quite far apart. While an additive model (Eq. 3) has a seasonal variation which is independent of the level of the series, the seasonal effect in a multiplicative model (Eq. 4) is proportional to the mean value. Since we have no empirical reason to expect the seasonal variation to be larger in warmer years, we have an a priori reason to doubt if a multiplicative model is well suited for our case. The reason we applied also this kind of model was mostly to have something to compare the additive forecast with.

The method based on temperature pattern statistics looks promising for predictions one to two years ahead. However, the results are very sensitive to the choice of classification scheme (binary or ternary) and pattern length. A theoretical study is needed to figure out which choice gives the most reliable prediction. The possibility of extending the discretised series further back in time by other climate series should also be examined.

Both the additive and the multiplicative Holt-Winters forecasts support the results based on periodic fluctuations of a temperature decline. The results based on pattern statistics are less conclusive. While persistence gives us a continuing warm period, Table 8 shows that long warm periods are unusual. The probability of 1995 or 1996 becoming a warm year depends on the length of the combination used. The frequency distribution in Table 13 based on a ternary classification indicates that 1995 and 1996 most likely will be years of medium temperature and least likely warm.

Earlier we argued for the use of our univariate methods based on the fact that an important part of the Barents Sea temperature variation is of non-advective origin. Another such approach is the class of models described by Box and Jenkins (1970) dealing in terms of auto-regressive (AR) and moving average (MA) processes. But also multivariate methods are depicted by Box and Jenkins. To try to account for both the advective and non-advective part of the temperature variation a future approach might be to combine knowledge of periodicities in the Barents Sea temperature and cross correlations with upstream time-series.

Although more work is necessary we believe this paper to be a useful effort towards forecasting of the Barents Sea ocean temperature. Admittedly there are uncertainties and all our results do not point in the same direction, but the overall conclusion must be that we are entering a period with temperatures lower than that of the latest years. Temperature values below the long time average must be expected.

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