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Forecasting Fishery Performance for Northern Shrimp (*Pandalus borealis*) in NAFO Divisions 2HJ

by

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Abstract

The physical environment of the ocean is believed to have a major influence on pandalid shrimp populations and there are numerous studies that incorporate environmental variables to predict and forecast landings from the fishery and/or resource abundance. Cause-and-effect mechanisms are not clearly understood in many instances but the predictive nature of the relationships provides a potentially powerful forecasting tool. Meaningful indicators of the future prospects for shrimp stocks that support valuable commercial fisheries are necessary in a comprehensive stock assessment process.

In this paper, I use time-series analysis to construct an illustrative, predictive model for standardized, annual catch rates (an abundance index) in a shrimp fishing area off the Labrador coast (NAFO Divisions 2HJ). Environmental data (annual winter ice cover) are incorporated as an input series to improve predictive and forecasting power. Results support the hypothesis that cold conditions, which result in more extensive ice cover, are favourable for shrimp at early life-history stages. Predictions of annual catch rates fit the observed values well in most cases and a catch-rate forecast for several years is provided. Possible functional mechanisms are discussed.

Introduction

The importance of environmental (oceanographic) influences in affecting the dynamics of pandalid shrimp populations is widely accepted. Nevertheless, the statistical relationships seldom have been demonstrated adequately and the functional relationships, in most cases, have not been clearly explained. The decline of the *Pandalus borealis* resource in the Gulf on Maine during the 1970's was well-documented but opinion remains divided on the relative importance of natural and anthropogenic factors (see Apollonio et al., 1986; Clark, et al., this symposium). The collapse of the Alaskan fishery for *P. borealis* (renamed *P. eous* by Squires, 1992) during the late 1970's prompted an extensive review of the literature on the relationship between shrimp distribution and physical oceanographic parameters (Ippolito et al., 1980). The proceedings of the international pandalid shrimp symposium held in Kodiak, Alaska in 1979 (Frady, 1981) included research presentations and panel discussions on the environmental relations to pandalid shrimp. Subsequently, Nunes (1984) conducted major studies that included the effects of temperature on shrimp reproduction and larval survival. The recent NAFO symposium on Pandalid Shrimp Fisheries - Science and Management at the Millennium - devoted an entire session to environmental and trophic considerations, concluding that these factors "… must play an increasingly important role in the assessment and management of pandalid populations in the future." (NAFO, 1999).

Predictions of shrimp landings/abundance from perceived associations with environmental signals have taken a variety of forms. Driver (1978) used predictions of sunspot activity to forecast abundance of *Crangon crangon* in the Irish Sea for several years. Sheridan (1996) associated indices of fishing activity with surface and ground-water levels to make short-term predictions of *Penaeus duorarum* landings off southwest Florida. De Pasquier (1998), in conducting a stock assessment for white shrimp (*Penaeus schmitti*) in Lake Maracaibo, Venezuela, incorporated temperature as an environmental variable in a modified Schaefer model and concluded that catches can be predicted for more efficient fishery management.

There are numerous examples of forecasting abundance of pandalid shrimp. Dow (1966) suggested that sea water temperatures from Boothbay Harbour (Maine, U.S.A.) could be used to predict relative abundance of commercial-sized shrimp two years later. This was revised to a forecast using catch and mean seawater temperature four years earlier (Dow, 1977). Warren (1973) observed that, over a fifty-year period, annual mean water temperature in the Wash (U.K.) was inversely related to pink shrimp (*P. montagui*) landings in the following year. Lysy and Dvinina (1991) showed, that in areas of the Barents Sea, water temperatures in spring could be used to forecast the size of the *P. borealis* stock up to 3 years. Hannah (1993) demonstrated that sea height level off Oregon, U.S.A. was strongly negatively correlated with recruitment of ocean shrimp (*P. jordani*) to the fishery in the following year and speculated on a functional mechanism for the relationship (Hannah, 1999). A recent, unpublished study in the Gulf of St. Lawrence (Canada) showed that models of nitrate levels in surface water layers might be useful to predict commercial catch rates of *P. borealis* up to three years (personal communication, J. Plourde, Department of Fisheries and Oceans, Mont-Joli, Quebec).

Fogarty (1989), in describing methods to forecast yield and abundance of invertebrates, distinguished between structural and heuristic models. The former deal with cause and effect in describing relationships within natural systems whereas the latter recognize recurrent patterns in time series without implying causality. Nunes (1984) stated that the correlation (heuristic) studies have only limited value since they do not explain the direct effects of environmental factors. Fogarty (1989) argued that it is often impossible to manipulate natural systems within strictly controlled experiments and, therefore, the only alternative is to investigate factors for which there is reason to suspect causal relationship. At risk of taking both authors out of context, I enter the "argument" from the viewpoint that, in addition to establishing current resource status, the stock assessment process for northern shrimp, *P. borealis*, must utilize forecasting tools to comment on future prospects for recruitment and spawning stock biomass. Heuristic models might not serve well in our understanding of natural processes but can provide accurate predictions and forecasts and, as stated by Fogarty (1989), serve as the foundation for future research. This was supported in part by Hannah (1993) who noted that, despite limitations, correlative studies could be important for shrimp to develop hypotheses about environmental recruitment mechanisms.

This paper was inspired by the notion of Fogarty (1989) that it may be possible to obtain accurate forecasts with heuristic models using an approach (Box and Jenkins, 1976) which provides a formal structure within an adaptable framework. I use time-series analysis to construct predictive models for standardized catch rates (an abundance index) in a northern shrimp (*P. borealis*) fishing area off the Labrador coast (NAFO Divisions 2HJ). Environmental data are incorporated as input series in transfer functions, thereby testing the hypothesis that "cold conditions" are favourable for shrimp at early life-history stages.

Materials and Methods

Study area

Two depressions (marginal troughs) in the mid-Labrador Shelf, known as the Hopedale and Cartwright Channels (Figure 1), have supported commercial, bottom-trawl fisheries for northern shrimp since the mid 1970's. The deepest, landward portions of these channels (>500 m) are connected to the seaward shelf edge by a saddle with depths greater than 200 m. Commercial concentrations of shrimp occur primarily in depths between 200 and 500 m in the channels and saddles and along the shelf edge. Initially, shrimp within each channels were treated as separate stocks but, beginning in 1994, were combined for assessment/management purposes. Fishing grounds throughout the area, especially within the channels, are largely ice covered in winter, spring and even early summer in some years. The shelf edge is accessible for fishing on a year-round basis when ice conditions are slack.

Fishery data

Catch (kilograms) and effort (hours fished) from commercial vessel log records were compiled for all years from 1977 to 1998 within the shrimp fishing area. Catch per unit effort (CPUE), expressed as kg per hour, was calculated by year. The raw CPUE data were standardized by multiple regression in an attempt to account for variation due to factors such as year, month, area and vessel (Parsons et al., 1999). The standardized, annual series (Figure 2) has been used as a measure of fishery performance and as an indicator of change in the fishable stock over time. Natural log (ln) CPUE values for each year, output from the regression analysis, were used in the current modeling exercise.

Environmental data

Several environmental variables, expressed as annual values, were examined during preliminary correlative studies of possible associations with trend in shrimp CPUE. These included bottom temperature at hydrographic Station 27 off St. John's, Newfoundland, volume of the cold intermediate layer off southern Labrador, location of the Gulf Stream front and several measures of ice cover in the northeast Newfoundland-southern Labrador areas. The series (1970 -1998) of annual estimates of winter ice cover ($km^2 \times 10^{-5}$), as provided in Drinkwater et al. (1999) (Figure 3), was chosen for two reasons. It provided the "best" indicators of significant correlation with CPUE during investigative exercises and was more "meaningful" than some others when speculating on possible functional relationships (see Discussion). Regarding the latter, shrimp eggs hatch in spring and larvae are believed to reside for several weeks near the surface water layers (< 50 m) under the ice cover within the study area.

Modeling procedures

The **a**uto**r**egressive, **i**ntegrated, **m**oving-**a**verage (ARIMA) procedure of SAS (1993) was used to derive predictive models for shrimp CPUE. These are also known as Box-Jenkins (1976) models. The SAS user instructions described three steps in ARIMA modeling:

1. ***Identify*** the autoregressive and/or moving-average process in the response series (i.e. CPUE);
2. ***Estimate*** to specify the model to fit to the variable and estimate its parameters; and
3. ***Forecast*** to generate future values of the response series and confidence intervals for the forecasts.

The models investigated in the current analysis included an input series (i.e. winter ice cover) in a transfer function. Transfer functions, in addition to modeling the response series using its own past values, incorporate current and past values of an input series. When delays are evident from valid crosscorrelations, inclusion of the input series can improve the forecasting power of the model.

The key to the identification step was matching theoretical autocorrelation functions of different autoregressive/moving-average processes with the sample functions obtained from the analysis. Diagnostic tools for the estimation step included significance tests for parameters, goodness-of-fit to compare the model to others and tests for "white noise" (uncorrelated) residuals. The white noise tests indicate whether the residual series contain additional information requiring more complex modeling. The procedural steps and guidelines described in SAS manuals (1984, 1993) were followed throughout the modeling exercise.

Results

The identification step for the CPUE data produced autocorrelations that decayed rapidly indicating stationarity (no trend) in the series (Table 1). Therefore, differencing (modeling the change in CPUE from year to year rather than the CPUE series itself) was not necessary. The autocorrelation functions (full, inverse and partial) also indicated a first-order, autoregressive process, characterized by significant autocorrelation at a lag of one year. The inclusion of an autoregressive parameter (1 year lag) in the estimate step achieved "white noise" residuals ($P > 0.15$) and no additional parameterization was required. This autoregressive model predicts the CPUE as an average, plus some fraction of the previous CPUE, plus a random error.

Similarly, the winter ice input series revealed a stationary, first-order, autoregressive process (Table 2). Again, the inclusion of a single, autoregressive parameter (1 year lag) reduced residuals to "white noise" ($P > 0.10$) and more complex modeling was not considered necessary.

In constructing the transfer function, which included crosscorrelation of the two autocorrelated series, both the input and response variables were filtered with a "prewhitening" model. Fogarty (1989) explained that a time series model (in this case an autoregressive model of order 1) is first fit to the input series so that residuals are independent (reduced to white noise). Then, using the same model, the input series is filtered followed by the response series. Residuals are crosscorrelated rather than the original series. These steps were followed in accordance with the SAS programming instructions. Crosscorrelations of the prewhitened series (Table 3) showed highest correlations at shifts of 0 and 6 years. With no shift, the relationship was negative (-0.42) whereas, with a shift of 6 years, the relationship was positive (0.39).

The simplest transfer function model with forecasting potential and in which residuals were reduced to white noise included a first-order autoregressive parameter for the CPUE series and an input winter ice series with a shift or pure delay of 6 years (Table 4). The input series, however, contributed far less to the model than either the mean term, which was most important, or the autoregressive parameter. Significant autocorrelation of residuals to lag 18 are not considered to be meaningful given the length of the time series. Model specifications were:

estimated intercept = 6.25733746
autoregressive factor: 1 - 0.9682 B(1)**
Input is winter ice with a shift of 6.
Overall Regression Factor = 0.112077.

Predictions of annual ln CPUE were close to the observed values in most cases and a six-year forecast beyond 1998 showed that catch rates, at best, would stabilize but, more likely, decline (Figure 4).

Discussion

The results of the above time-series analysis are more illustrative than interpretive. That is, they serve mainly to demonstrate techniques by which forecasting tools for shrimp can be developed. Generally, for these types of analyses, there should be at least 30 observations. With fewer (as in this example where there are only 22 values within the response series), parameter estimates may be imprecise and standard errors and *t*-ratios unreliable (SAS, 1993). This limitation brings into question the ability to identify with certainty the autoregressive (and/or moving average) processes, valid crosscorrelations and, ultimately, a representative transfer function. Nevertheless, during the investigative modeling phase that explored both unstandardized and standardized CPUE, different input series and several model formulations, an environmental signal was present consistently in the crosscorrelations at various shifts or delays. Regarding the CPUE, the unstandardized series produced first order, autoregressive diagnostics that were similar to those of the standardized series, allaying concern about making conclusions that might be influenced by the regression analysis of the latter (personal communication, S. Smith, Department of Fisheries and Oceans, Dartmouth, Nova Scotia). The standardized series was used in order to achieve stability during the ARIMA estimation procedure.

The example presented showed that the mean of the CPUE series and its autoregressive parameter were important and that a first-order autoregressive model could fit the observed data adequately. A shrimp catch includes three or more year classes (ages 4 to 7+) and it is not surprising, therefore, that a significant autoregressive process was detected. (More surprising, perhaps, was the lack of significant, higher order parameters, given that a strong year class can contribute significantly to the catches for more than two years.) However, the forecast capability of such a model is limited to only one time period. Although the winter ice input series did not contribute greatly to the model fit (Table 4), it did improve the forecast given a delay of six years as indicated in the crosscorrelations.

The highest crosscorrelations between ln CPUE and winter ice at delays of 0 and 6 years can be discussed in relation to the effects of ice cover on fishing activity and stock productivity. The relationship with no delay was negative and it is reasonable to assume that heavy ice in a given year might adversely affect fishing activity and CPUE. Optimal fishing grounds, in whole or part, would be inaccessible and effort diverted to fishable but less productive areas resulting in lower CPUE. Extensive ice cover in cold years possibly contributes positively to survival of larvae and juveniles in the same year and the effect can be detected in the CPUE several years later (the mean age of animals in the catch is about 6 years). Mechanisms can be only speculated. Perhaps extensive ice cover serves simply to retain larvae and early juvenile stages within preferred areas (i.e. within the first 50 m) prior to settlement, thereby enhancing recruitment to the fishable stock. In a slack ice year, retention might be reduced and dispersal of larvae and juveniles to hostile environments (i.e. lower survival) could be extensive. A recent study by Ramseier et al. (this symposium) showed that the extent of localized sedimentation of particulate organic carbon (POC) can be derived from information about ice cover. Given that POC is known to be important to the distribution of shrimp (Butler, 1971) and likely plays an important role as a food supply, it is possible that the explanation of the functional relationship is related more to nutrient supply than temperature-related phenomena. This would help explain the apparent inconsistencies between *in situ* observations, which suggest "cold conditions" are favourable for shrimp, and laboratory studies, which indicate that larval growth and survival are enhanced at higher temperatures (e.g. Wienberg, 1982; Nunes, 1984).

Forecasting fishery performance and/or stock abundance for northern shrimp is a vital adjunct to the stock assessment process. Current methodology involves qualitative evaluation of the interpretation of multiple indicators of stock performance (Savard and Parsons, 1999; Koeller et al., this symposium) most of which reflect current status. Relatively few indicators address future prospects. Despite a lack of information on future trends in shrimp stocks, long-term expectations by "stakeholders" are immense. Shrimp resources respond to environmental perturbations. The model presented here addresses a possible reaction to the physical/biological environment but would be improved by the incorporation of an index of predator abundance, another important factor in shrimp population dynamics.

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Table 1. Autocorrelation functions for variable ln CPUE from SAS ARIMA Procedure; mean of working series = 6.266818, standard deviation = 0.403669, number of observations = 22.

```
                                                        Autocorrelations
                         Lag Covariance Correlation -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
Std
                           0   0.162949    1.00000  |                     |********************|
0
                           1   0.132454    0.81286  |           .         |****************    |
0.213201
                           2   0.100179    0.61479  |       .             |************.       |
0.324841
                           3   0.065325    0.40089  |     .               |********      .     |
0.374008
                           4   0.036653    0.22494  |    .                |****           .    |
0.393055
                           5   0.016168    0.09922  |    .                |**             .    |
0.398863
                           6 -0.0020284   -0.01245  |    .                |               .    |
0.399983
                           7 -0.0077439   -0.04752  |    .               *|               .    |
0.400001
                           8  -0.019571   -0.12010  |    .              **|               .    |
0.400257
                           9  -0.021107   -0.12953  |    .             ***|               .    |
0.401892
                          10  -0.034234   -0.21009  |    .            ****|               .    |
0.403785
                                                                                "." marks two standard
errors

                                                  Inverse Autocorrelations

                                    Lag Correlation -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
                                      1    -0.60796  |         ************|        .           |
                                      2     0.15448  |          .          |***     .           |
                                      3    -0.09667  |          .        **|        .           |
                                      4     0.12122  |          .          |**      .           |
                                      5    -0.14384  |          .       ***|        .           |
                                      6     0.20074  |          .          |****    .           |
                                      7    -0.24169  |          .     *****|        .           |
                                      8     0.28638  |          .          |******  .           |
                                      9    -0.26471  |          .     *****|        .           |
                                     10     0.11760  |          .          |**      .           |

                                                    Partial Autocorrelations

                                   Lag Correlation -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
                                      1     0.81286  |          .          |****************    |
                                      2    -0.13544  |          .       ***|        .           |
                                      3    -0.16945  |          .       ***|        .           |
                                      4    -0.03403  |          .         *|        .           |
                                      5     0.00742  |          .          |        .           |
                                      6    -0.09787  |          .        **|        .           |
                                      7     0.10209  |          .          |**      .           |
                                      8    -0.19267  |          .      ****|        .           |
                                      9     0.09393  |          .          |**      .           |
                                     10    -0.27711  |          .    ******|        .           |

                                              Autocorrelation Check for White Noise

                                  To    Chi                   Autocorrelations
                                 Lag  Square DF   Prob
                                   6   32.85  6  0.000  0.813  0.615  0.401  0.225  0.099 -0.012
```

Table 2. Autocorrelation functions for winter ice input variable from SAS ARIMA Procedure; mean of working series = 2.292069, standard deviation = 0.694036, number of observations = 29.

```
                                   Autocorrelations
Lag Covariance Correlation -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1         Std
 0   0.481685    1.00000  |                     |********************|          0
 1   0.290065    0.60219  |              .      |************        |   0.185695
 2   0.054421    0.11298  |           .         |**       .          |   0.243909
 3  -0.083943   -0.17427  |           .      ***|         .          |   0.245707
 4  -0.109749   -0.22784  |           .    *****|         .          |   0.249933
 5  -0.149025   -0.30938  |           .   ******|         .          |   0.256996
 6  -0.140523   -0.29173  |          .    ******|          .         |   0.269533
 7  -0.061925   -0.12856  |          .       ***|          .         |   0.280210
                                                   "." marks two standard errors

                            Inverse Autocorrelations
           Lag Correlation -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
            1   -0.58364  |       ************|      .             |
            2    0.07812  |             .     |**    .             |
            3    0.25028  |             .     |***** .             |
            4   -0.25449  |             . *****|     .             |
            5    0.13601  |             .     |***   .             |
            6    0.03646  |             .     |*     .             |
            7   -0.02905  |             .    *|      .             |


                            Partial Autocorrelations

           Lag Correlation -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
            1    0.60219  |             .     |************        |
            2   -0.39169  |            ********|     .             |
            3   -0.06132  |             .    *|      .             |
            4   -0.01974  |             .     |      .             |
            5   -0.31201  |             .******|     .             |
            6    0.02117  |             .     |      .             |
            7    0.05718  |             .     |*     .             |


                     Autocorrelation Check for White Noise

              To   Chi                   Autocorrelations
             Lag  Square DF   Prob
            6   21.90  6   0.001  0.602  0.113 -0.174 -0.228 -0.309 -0.292
```

Table 3. Correlation of ln CPUE and winter ice from SAS ARIMA Procedure. Both series have been prewhitened. Variance of transformed series = 0.041778 and 0.276015. Number of observations = 22.

```
                                  Crosscorrelations

 Lag Covariance Correlation -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
0  -0.045073   -0.41973  |           .********|        .           |
1 -0.0047923   -0.04463  |           .       *|        .           |
2   0.021928    0.20420  |           .        |****    .           |
3   0.029301    0.27286  |           .        |*****   .           |
4   0.032694    0.30446  |           .        |******  .           |
5   0.034805    0.32412  |           .        |******  .           |
6   0.042201    0.39299  |           .        |********.           |
7   0.026467    0.24647  |           .        |*****   .           |
8  0.0046350    0.04316  |           .        |*       .           |
9 -0.0048585   -0.04524  |           .       *|        .           |
10 -0.0062760  -0.05844  |           .       *|        .           |
                                    "." marks two standard errors

                    Crosscorrelation Check Between Series

        To   Chi                     Crosscorrelations
       Lag  Square DF  Prob
        5  10.83  6  0.094 -0.420 -0.045  0.204  0.273  0.304  0.324


           Both variables have been prewhitened by the following filter:

                              Prewhitening Filter

                             Autoregressive Factors
                          Factor 1: 1 - 0.69304 B**(1)
```

Table 4. Estimation of transfer function model parameters from SAS ARIMA Procedure.

Parameter	Estimate	Std Error	T Ratio	Lag	Variable	Shift
MU	6.25734	0.21298	29.38	0	LNCPUE	0
AR1,1	0.96820	0.08234	11.76	1	LNCPUE	0
NUM1	0.11208	0.06538	1.71	0	WICE	6

Autocorrelation Check of Residuals

To Lag	Chi Square	DF	Prob	Autocorrelations					
6	8.56	5	0.128	0.298	0.409	0.067	-0.061	0.070	-0.215
12	13.23	11	0.279	0.037	-0.243	0.153	0.118	0.110	0.068
18	29.82	17	0.028	-0.168	-0.156	-0.211	-0.168	-0.200	-0.157

Autocorrelation Plot of Residuals

```
 Lag Covariance Correlation -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1           Std
0   0.027400    1.00000   |                    |********************|           0
1  0.0081572    0.29771   |           .        |******  .           |    0.213201
2   0.011219    0.40945   |           .        |********.           |    0.231326
3  0.0018476    0.06743   |          .         |*        .          |    0.262208
4 -0.0016691   -0.06092   |         .         *|          .         |    0.262995
5  0.0019062    0.06957   |         .          |*         .         |    0.263635
6 -0.0058876   -0.21488   |         .      ****|          .         |    0.264468
7  0.0010108    0.03689   |         .          |*         .         |    0.272288
8 -0.0066558   -0.24291   |         .     *****|          .         |    0.272515
9  0.0041833    0.15268   |         .          |***       .         |    0.282186
10 0.0032272    0.11778   |         .          |**        .         |    0.285916
                                                    "." marks two standard errors
```

Inverse Autocorrelations

```
 Lag Correlation -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
1    -0.19896  |           .    ****|        .           |
2    -0.38733  |           .********|        .           |
3     0.03729  |           .        |*       .           |
4     0.30998  |           .        |******  .           |
5    -0.18099  |           .    ****|        .           |
6    -0.10567  |           .      **|        .           |
7     0.02913  |           .        |*       .           |
8     0.27954  |           .        |******  .           |
9    -0.15555  |           .     ***|        .           |
10   -0.08156  |           .      **|        .           |
```

Partial Autocorrelations

```
 Lag Correlation -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
1     0.29771  |           .        |******  .           |
2     0.35202  |           .        |******* .           |
3    -0.14573  |           .     ***|        .           |
4    -0.24268  |           .   *****|        .           |
5     0.21495  |           .        |****    .           |
6    -0.19487  |           .    ****|        .           |
7     0.02986  |           .        |*       .           |
8    -0.14986  |           .     ***|        .           |
9     0.34340  |           .        |******* .           |
10    0.13254  |           .        |***     .           |
```

Crosscorrelation Check of Residuals with winter ice input

To Lag	Chi Square	DF	Prob	Crosscorrelations					
5	0.40	6	0.999	0.075	0.064	-0.005	-0.049	-0.112	0.012
11	3.60	12	0.990	0.293	0.271	0.041	-0.058	-0.148	-0.119

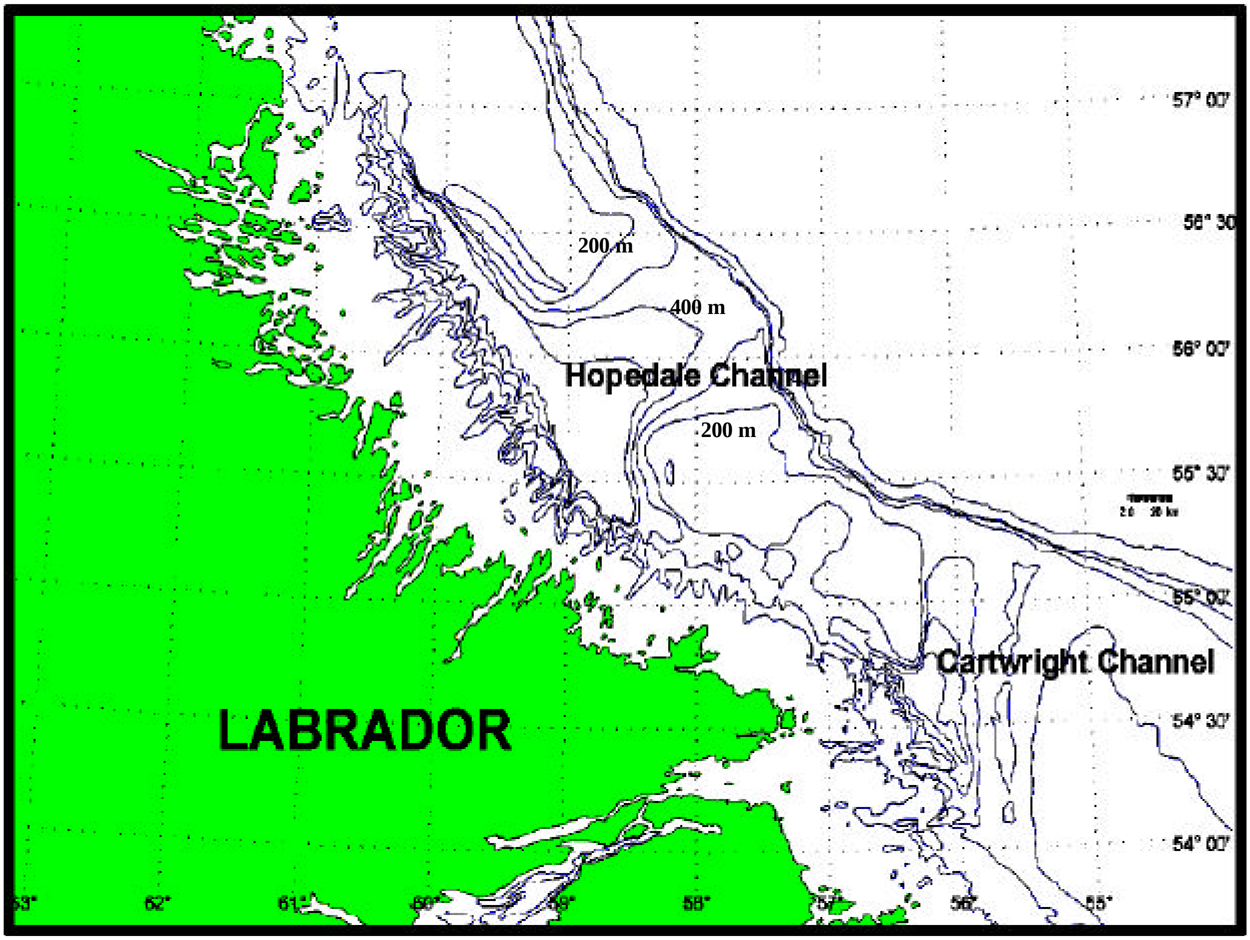

Figure 1. Location of Hopedale and Cartwright Channels off Labrador (Divisions 2HJ).

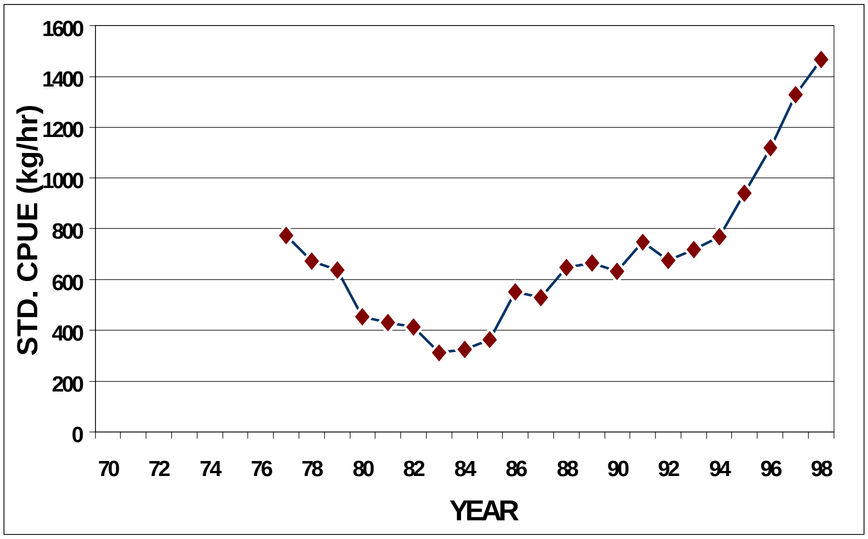

Figure 2. Standardized catch per unit effort (kg/hr) in Hopedale and Cartwright Channels, 1977 - 1998 (from Parsons *et al*., 1999).

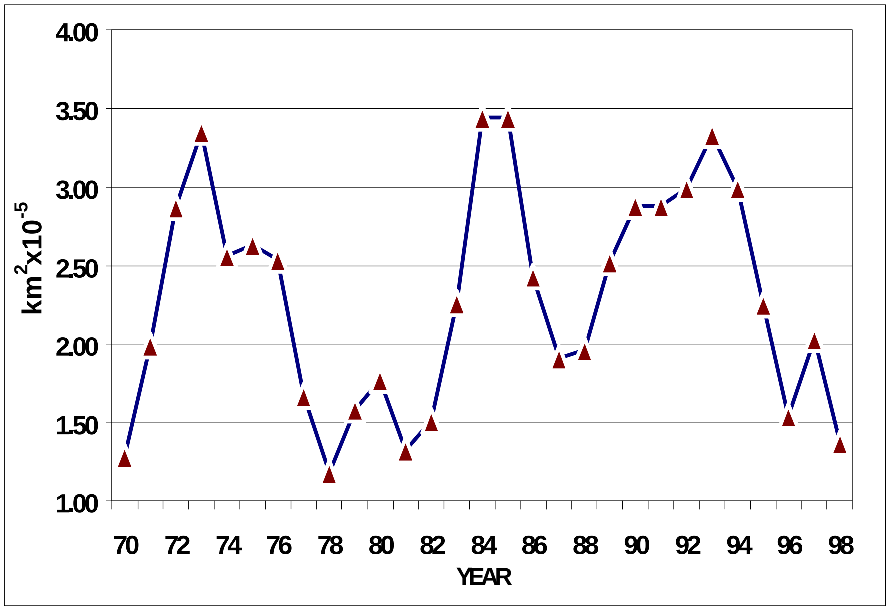

Figure 3. Area of winter ice cover (km^2 x 10^{-5}) off Newfoundland-Labrador, 1970 - 1998 (from Drinkwater *et al*., 1999).

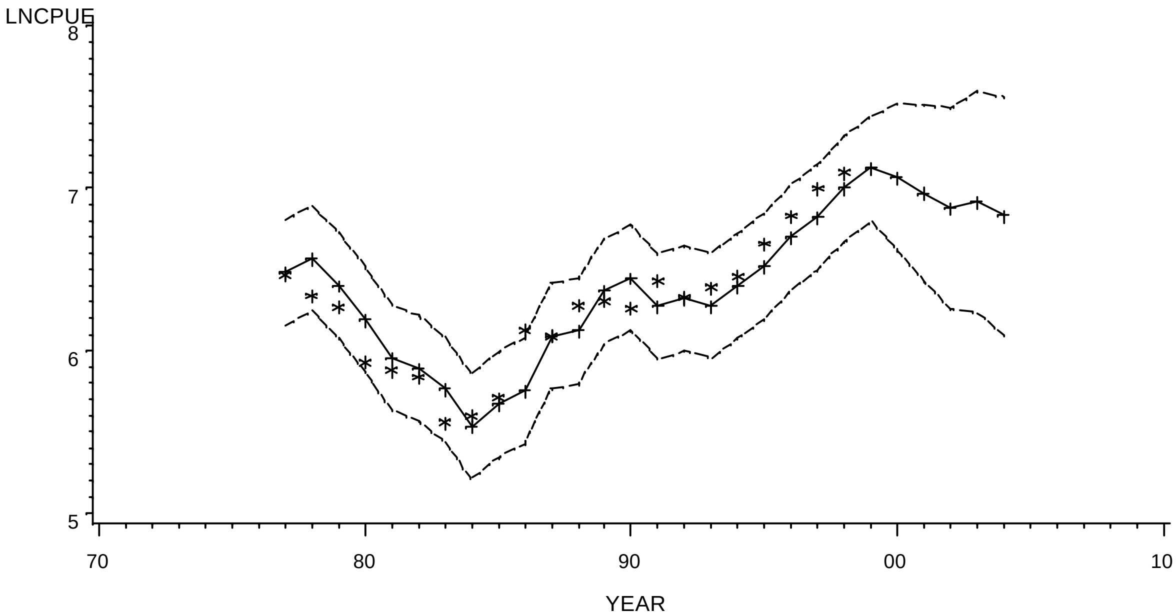

Figure 4. Transfer function model for ln CPUE and winter ice input series with six-year forecast. Observed = '*', predicted = '+', and broken lines = 95% confidence intervals.