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Preliminary Results of a Spatial and Temporal Analysis of Haddock Distribution Applying a Generalized Additive Model

by

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ABSTRACT

The temporal and spatial trends in the distribution of haddock, *Melanogrammus aeglefinus*, from Nova Scotia and south, were examined using a generalized additive model (GAM). Spatial (latitude and longitude) and environmental (depth and temperature) covariates were used as predictor variables for the response variable (abundance). The preferred depth was less than 100m and the preferred bottom temperature was between 8°- 12° C. Estimates of mean abundance using the model results were more precise than the estimates normally derived from observed catch numbers.

INTRODUCTION

Data collected on annual groundfish surveys provide information on the spatial distribution of species and the environmental conditions at the time of capture. Typically, analyses of these data have been done using generalized linear models (GLMs), often with the addition of covariates. An alternative to a GLM is a generalized additive model or GAM (Hastie and Tibshirani 1986, Swartzman et al. 1992) that models the nonlinearity of the predictor variables. A GAM can be utilized as a predictive model or as an exploratory method to suggest possible transformations of the data or appropriate parametric models, such as a GLM. In this paper, a GAM was applied to catches of haddock, *Melanogrammus aeglefinus*, to explore trends in abundance related to spatial and environmental covariates. A step-wise GAM was performed to determine the best fitting model prior to applying the final GAM to the entire data set. Abundance indices of stratified mean number per tow and the associated variances were estimated for both the sample and fitted catch numbers.

METHODS

Data

Data from the NEFSC bottom trawl research surveys, described by Azarovitz (1981), were used in the analyses. Catch of haddock, in numbers, were obtained from the autumn surveys for the offshore strata only, from 1963-1994. Stations where haddock were not caught, ('zero tows'), were also included. The latitude, longitude, average depth, and bottom temperature observations recorded at each station were also used in the analysis. The range of occurrence of haddock within the 31 year time series defined the area of the study and was delineated by 63°W to 75°W longitude and 37°N to 45°N latitude. Catch numbers were adjusted for vessel and gear differences using the coefficients of 0.82 and 1.49, respectively, for the appropriate years (NEFSC 1991). Only acceptable tows were included (station type-haul-gear code of 136 or less), and stations without a bottom temperature observation were deleted.

Abundance indices of stratified mean number per tow, and the associated variances were estimated for both the observed and fitted values of catch number using the same methodology currently implemented by the NEFSC (Cochran 1977). The indices were derived from offshore strata 13-40, which is different from the NEFSC estimate derived from strata 13-25 and 29-30 presented in the current assessment (O'Brien and Brown 1995).

Model Description and Application

A GAM is a nonparametric analog to a GLM and can be described as:

$$Y=\alpha+\sum_{j=1}^{n} f_j(X_j)+\epsilon$$

where the usual linear function of a covariate, $\beta_j X_j$ is replaced with f_j, an unspecified smooth function. As in the GLM, it is necessary to specify the underlying error distribution of the model and the link function which relates the response variable to the predictors. The error distribution used for this application of the GAM is a Poisson, which is appropriate for describing random occurrences and count data (Zar 1974, Sokal and Rohlf 1981). The link function is the log of the response variable, which is catch in numbers. The candidate predictor variables are the spatial variables latitude and longitude, and the environmental variables depth and bottom temperature.

The GAM, in addition, requires specification of the smooth function using a scatterplot smoother such as loess, running mean, or a smooth spline. The scatterplot smoother used in this application is the cubic B-spline. The resulting 'smooth' characterizes the trend of the response variable as a function of the predictor variables. The degree of smoothing in a scatterplot smooth is controlled by the span, which is the proportion of points contained in each neighborhood (the set of x values within a defined distance of x_i). In S-PLUS, the software used for this analysis, the smooth functions of the GAM are solved by an iterative process of smoothing the partial residuals called the Gauss-Seidel iterative method or backfitting (Hastie 1992). The algorithm separates the parametric from the nonparametric part of the fit, and fits the parametric part using weighted linear least squares within the backfitting algorithm.

As an example, in a multiple predictor model with 2 variables, given an estimate $\hat{f}_1(x_1)$, $f_2(x_2)$ is estimated by smoothing the residual of $Y-\hat{f}_1(x_1)$ on x_2 . With the estimate $\hat{f}_2(x_2)$, an improved estimate of $\hat{f}_1(x_1)$ is obtained by smoothing $Y-\hat{f}_2(x_2)$ on x_1. Smoothing is continued until $Y-\hat{f}_1(x_1)$ on x_2 is $\hat{f}_2(x_2)$ and $Y-\hat{f}_2(x_2)$ on x_1 is $\hat{f}_1(x_1)$.

The fitting of the GAM is an iterative looping process involving the scatterplot smooth, the backfitting algorithm, and the local scoring algorithm, which is a generalization of the Fisher scoring procedure in a GLM. Each iteration of the local scoring algorithm produces a new working response and weights that are directed back to the backfitting algorithm which produces a new additive predictor using the scatterplot smoother (Hastie 1992, Hastie and Tibshirani 1986, Stat. Sci. 1993, Swartzman et al. 1992).

A step-wise GAM was performed to determine the best fitting model based on the criteria of the lowest Akaike Information Criterion (AIC) test statistic. AIC is a function of both the log likelihood function and the effective number of parameters being estimated. The AIC in the step-wise GAM (Hastie 1992) is calculated as:

$$\text{AIC} = \text{D} + 2df\,\phi\,,$$

where D=Deviance (residual sums of squares),
df = effective degrees of freedom, and
ϕ = dispersion parameter (variance).

The deviance estimated in the model, analogous to the residual sums of squares, is a measure of the fit of the model. The model with the lowest AIC is considered to have the best number of parameters to include in the final model. The spatial variables, latitude and longitude, and both the linear and the smooth functions for depth and temperature were among the possible variables in the step-wise GAM. A pseudocoefficient of determination, R^2, was estimated as 1.0 - the ratio of the deviance of the model to deviance of the null model (Swartzman et al. 1992). The effect of the environmental variables alone on abundance was examined by running a second model that did not include the spatial variables and comparing the R^2 values for the two models.

RESULTS

The step-wise GAM indicated that the model with the lowest AIC was:
Catch number=Intercept + s(average depth) + s(bottom temperature) + latitude + longitude, where s is a smoothing spline. This model, model 1, was used to run the GAM for the entire time series and model 2 used the same formulation without the spatial variables.

Distribution plots of observed and fitted catch numbers from model 1 for selected years, generally about every 5 years, are presented in Figures 1-9. The catch number, temperature, and depth data are interpolated in the plots to provide contour representation. The effect of the spatial and environmental variables on the distribution of abundance can be seen by comparison of the plots of observed and fitted catch numbers. In the earlier years, when the distribution of haddock was more widespread there is a noticeable shift in the fitted relative to the observed (1963,1965) abundance. In the latter years (1989,1994) when the population is relatively smaller, with a highly contracted range, there is little difference between the observed and fitted abundance.

Plots in Figures 10-18 represent the contribution of average depth and bottom temperature to the fitted additive predictor. The curves are drawn by connecting the points of the fitted values for each function against its predictor. The y-scale is not of importance given that there is an intercept in the model; the fitted values are adjusted to average zero (Hastie 1992). In all years, abundance is negatively correlated with depth and the preferred depth is generally less than 100 m. The preferred bottom temperature varied between years but was generally around 8° -12° C.

The pseudocoefficient of determination, or R^2, for each model and for the difference between models, is presented in Table 1. Model 1 always has an R^2 greater than model 2, indicating that model 1 is the better fitting model as previously determined by the AIC in the step-wise GAM. Small differences in R^2 between the two models indicates little additional information is provided by including latitude and longitude in the model (1963, 1969, 1977, 1987, 1990). When R^2 is greater than 50% in model 2 (1969, 1977, 1987, 1990), the environment appears to influence the spatial distribution of haddock. When the difference in R^2 is large between the two models (1983, 1994), some factor other than depth and temperature is most likely influencing the spatial distribution.

The observed and GAM fitted stratified mean number per tow index follow the same trend and, in general, the GAM fitted mean is less than the observed mean (Table 2, Figure 19). The GAM fitted index has a lower variance than that of the observed (Figures 20-22), which is also evident in the consistently lower coefficients of variation (Table 2).

A summary output of model 1 for the years corresponding to Figures 1-9 is presented in Appendix A.

DISCUSSION

The time series of distribution plots clearly indicates how the relative size and distribution of the haddock stock has declined and contracted, respectively, over time (Figures 1-9). The variability in R^2 values over the time series indicates that factors other than depth and temperature are influencing the spatial distribution of haddock. If depth and temperature preferences are different among age classes, variable recruitment and the age structure of the stock may be influential factors. Surficial sediment is also a likely spatial characteristic influencing distribution of haddock, particularly for juveniles avoiding predation.

The abundance indices derived from the GAM fitted catch numbers provide a more precise estimate compared to the observed catch numbers. Depth and temperature clearly influence the abundance of haddock, and additional predictor variables, such as bottom type, may further increase the precision of the estimate.

As is the case in preliminary, developmental work, this analysis could be improved and the model extended. The lack of temperature observations at some stations contributed to the loss of data in different years. This additional catch data can be incorporated into the GAM by using a supplemental temperature database. Application of the bootstrapping procedure to the GAM results would provide another approach to assess the significance of the smooth functions. The model could also be extended by transforming the predictor variables, investigating the interaction of the predictor variables, or by adding other covariates such as bottom sediment type, age classes, or length groups.

The GAM may be more informative for species that are inherently more coherent, such as schooling fish, e.g., herring or mackerel (Swartzman et al. 1994), or more aggregated species such as scup. Also, application of the GAM to a multi-species complex or group in the northwest Atlantic, such as flounders or gadids, would provide insight into the factors that influence spatial trends in distribution between species (Swartzman et al. 1992).

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Table 1. Annual pseudo-R^2 values for models 1 and 2[1], the difference in R^2 between the models, and the number of fish captured and number of stations with bottom temperature recorded for Georges Bank-Gulf of Maine haddock (strata 13-40), 1963-1994. A formulation of Model 1, without the year effect is presented as 1963-1994.

Year	Model 2	Model 1	Difference	Fish	Stations w/temperature	Catch stations w/o temperature
1963	0.39	0.45	0.06	21105	131	1
1964	0.36	0.48	0.12	15501	118	2
1965	0.35	0.54	0.19	10712	123	5
1966	0.24	0.54	0.30	5622	100	4
1967	0.28	0.44	0.16	2952	102	18
1968	0.30	0.51	0.21	1979	85	11
1969	0.53	0.62	0.09	1751	80	14
1970	0.20	0.50	0.30	1676	109	3
1971	0.32	0.53	0.21	2507	120	1
1972	0.50	0.67	0.17	3695	104	4
1973	0.54	0.63	0.09	3318	91	6
1974	0.32	0.53	0.21	2052	89	5
1975	0.21	0.45	0.24	5898	129	0
1976	0.59	0.74	0.15	7496	80	3
1977	0.54	0.62	0.08	9867	130	3
1978	0.06	0.38	0.32	7712	199	8
1979	0.42	0.59	0.17	18171	169	9
1980	0.11	0.39	0.28	8266	111	7
1981	0.40	0.71	0.31	3995	91	1
1982	0.60	0.73	0.13	3054	73	12
1983	0.46	0.81	0.35	3231	67	27
1984	0.55	0.80	0.25	1206	39	94
1985	0.49	0.66	0.17	598	30	54
1986	0.58	0.79	0.21	798	35	20
1987	0.65	0.70	0.05	3464	32	41
1988	0.71	0.88	0.17	301	15	30
1989	0.53	0.74	0.21	317	22	24
1990	0.93	0.99	0.06	88	4	40
1991	0.41	0.69	0.28	1155	39	1
1992	0.31	0.49	0.18	760	62	9
1993	0.58	0.81	0.23	1292	52	5
1994	0.41	0.90	0.49	2145	33	8
	mean	Mean	Difference	Total	Total	
1963-1994	0.16	0.29	0.13	152684	2664	

[1]

Model 2: Catch number = s(average depth) + s(bottom temperature)
Model 1: Catch number = s(average depth) + s(bottom temperature) + latitude +longitude

Table 2. Stratified mean number per tow and coefficient of variation (CV) for observed and GAM fitted catch numbers for Georges Bank-Gulf of Maine haddock (strata 13-40), 1963-1994.

	OBSERVED		GAM FIT	
Year	Mean	CV	Mean	CV
1963	145.77	0.16	127.38	0.04
1964	180.46	0.19	154.83	0.06
1965	101.56	0.15	89.78	0.08
1966	33.11	0.19	32.88	0.07
1967	16.17	0.31	14.50	0.04
1968	6.17	0.39	6.12	0.07
1969	3.45	0.31	6.71	0.22
1970	8.08	0.55	6.80	0.09
1971	4.13	0.22	6.14	0.10
1972	10.85	0.21	10.64	0.17
1993	15.98	0.35	9.44	0.18
1974	4.23	0.24	4.47	0.08
1975	30.74	0.24	23.91	0.05
1976	70.78	0.48	53.79	0.26
1977	23.41	0.33	21.77	0.16
1978	25.30	0.20	28.05	0.04
1979	57.07	0.59	48.45	0.15
1980	28.75	0.23	37.79	0.07
1981	13.38	0.31	12.52	0.11
1982	5.36	0.32	6.95	0.27
1983	7.97	0.38	8.40	0.21
1984	3.42	0.40	5.90	0.11
1985	10.77	0.38	11.22	0.28
1986	6.58	0.52	5.62	0.30
1987	4.91	0.36	3.16	0.05
1988	2.57	0.66	4.10	0.55
1989	6.33	0.46	6.76	0.33
1990	1.77	0.52	1.78	0.50
1991	6.98	0.38	7.21	0.14
1992	4.39	0.30	3.94	0.14
1993	6.33	0.30	6.62	0.20
1994	10.34	0.56	10.28	0.35

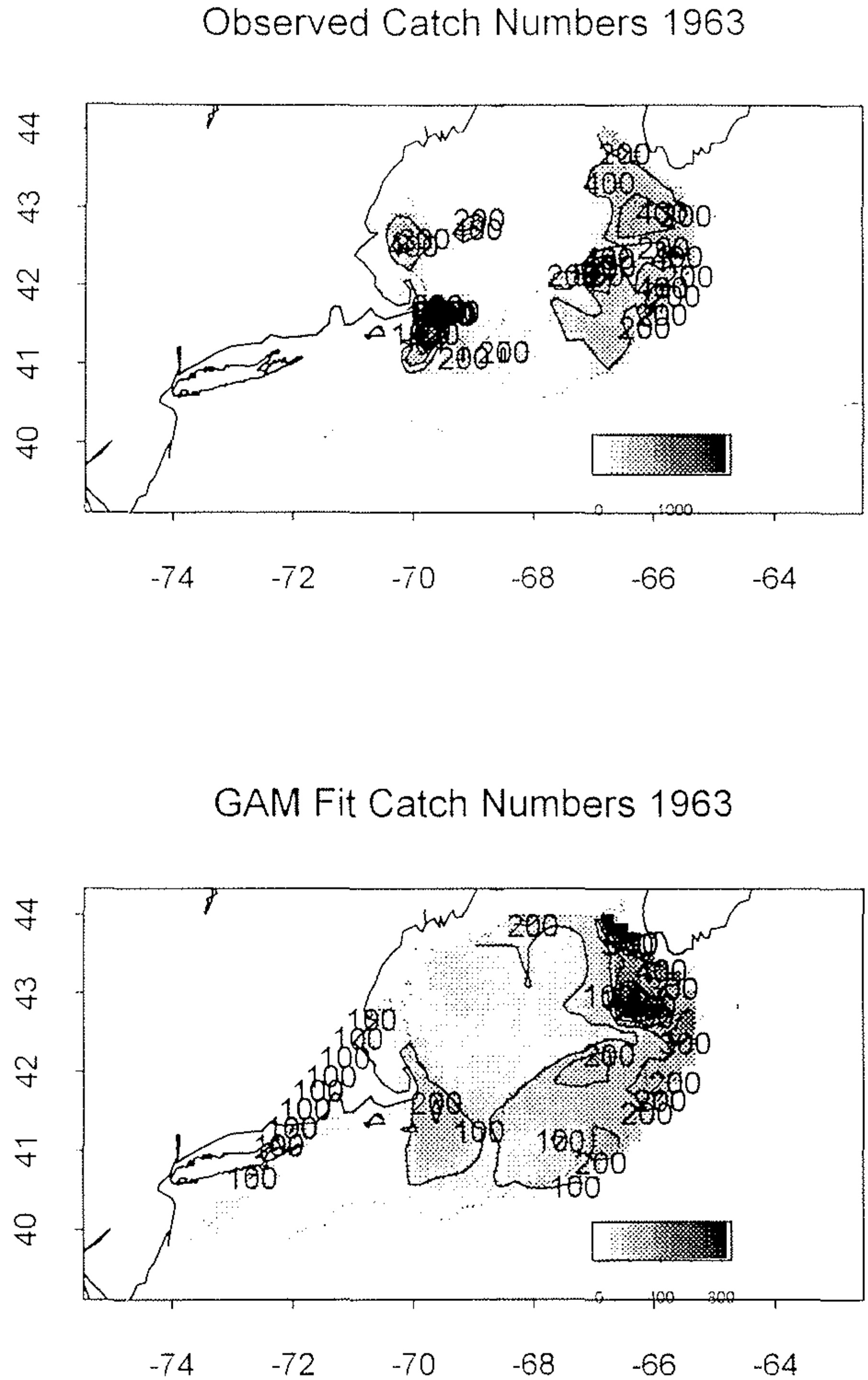
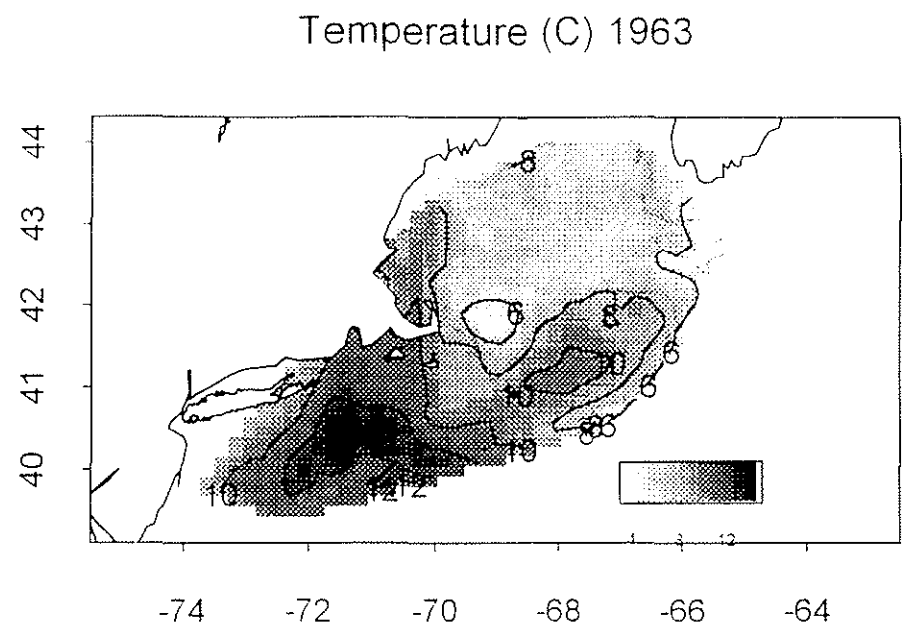


Figure 1. Interpolated observed and GAM fitted catch numbers of haddock and corresponding bottom temperature and average depth for 1963.



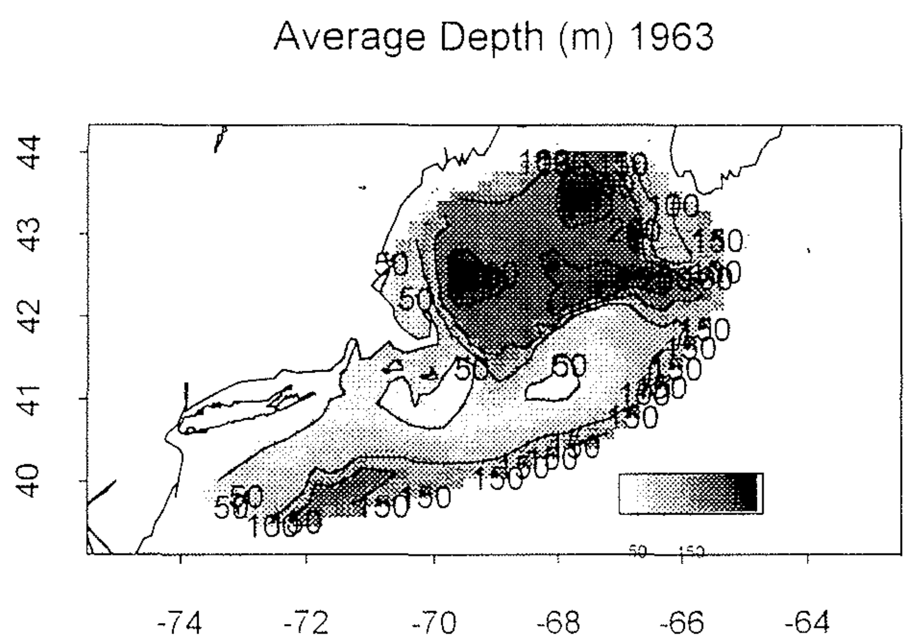


Figure 1 (Continued). Interpolated observed and GAM fitted catch numbers of haddock and corresponding bottom temperature and average depth for 1963.

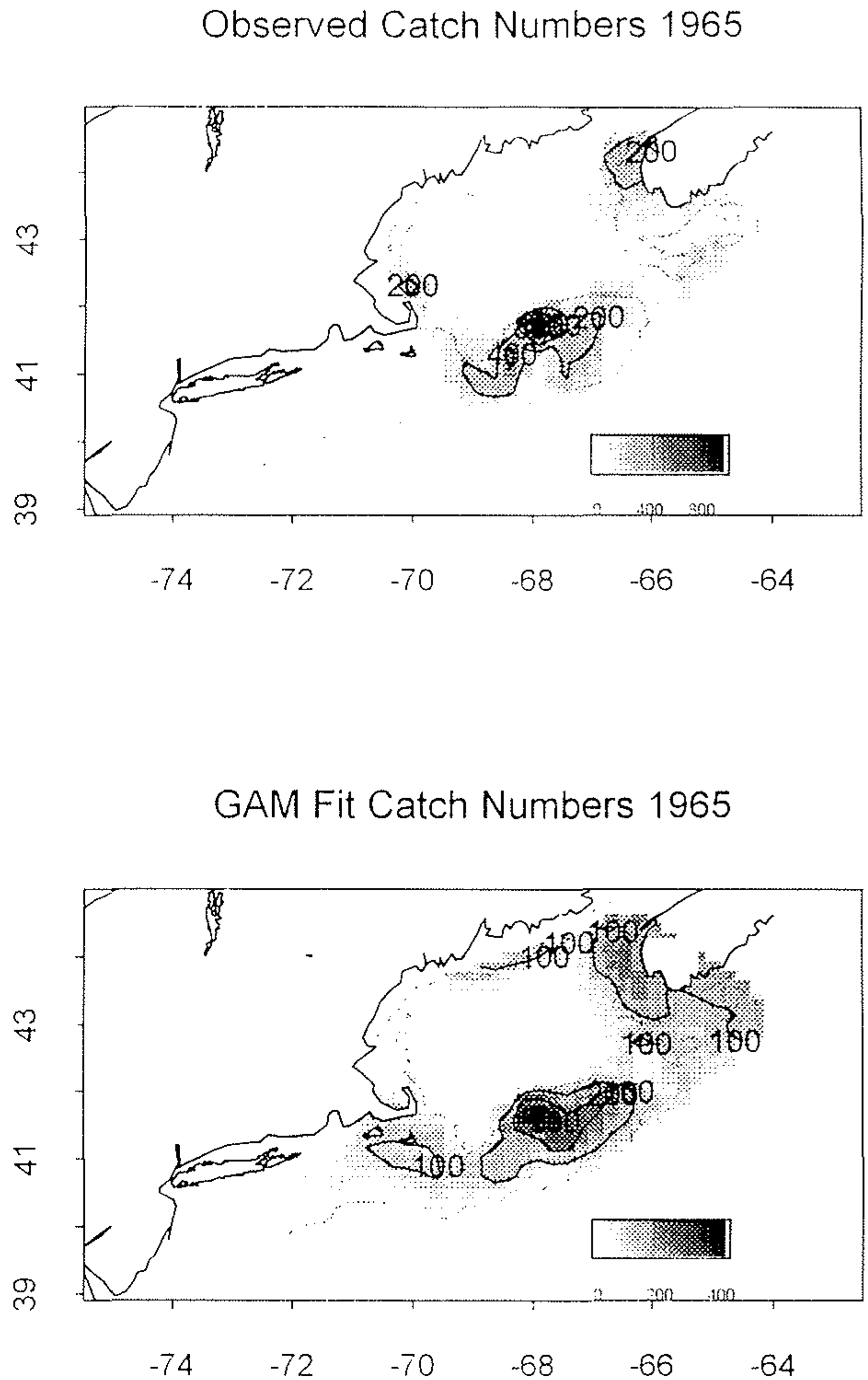
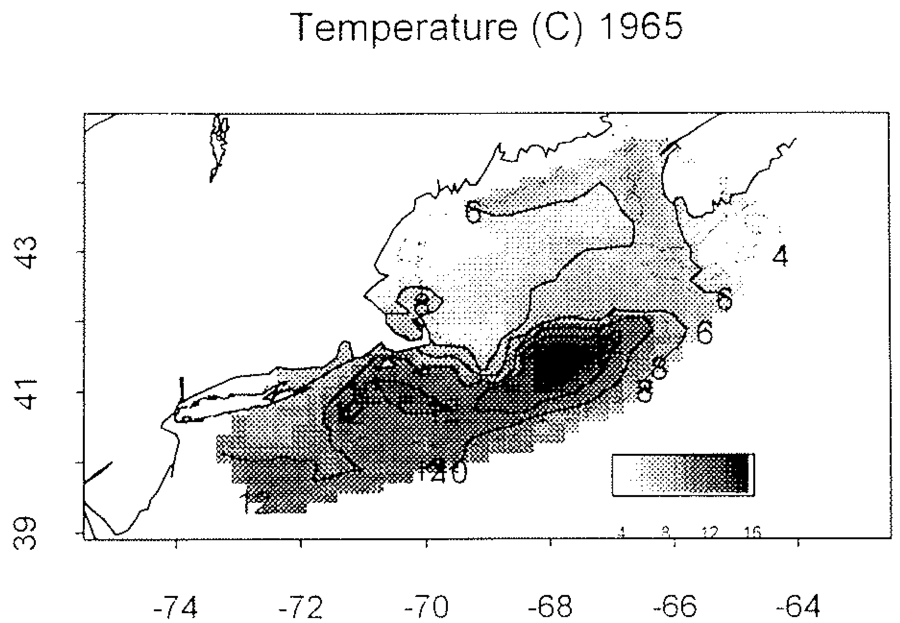
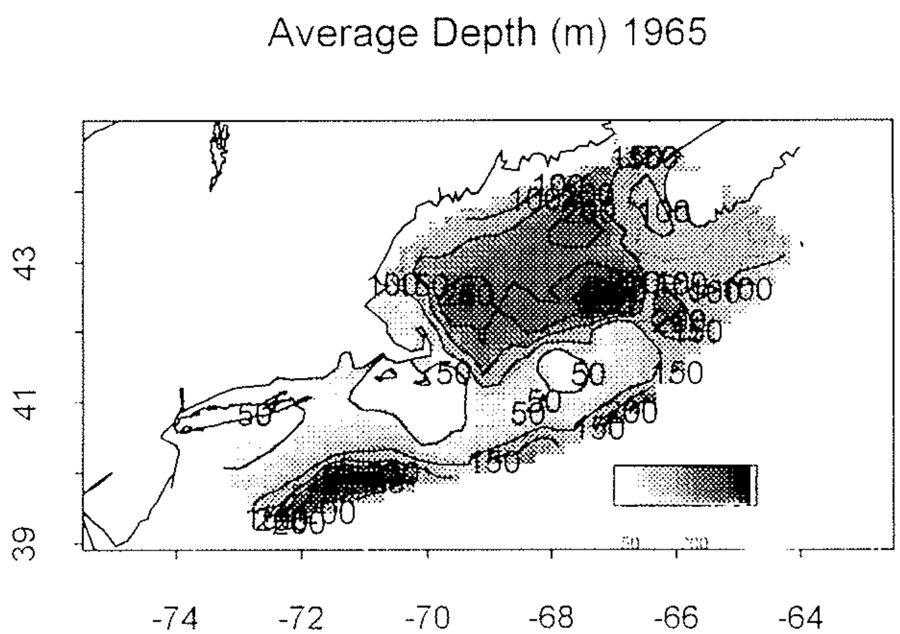


Figure 2. Interpolated observed and GAM fitted catch numbers of haddock and corresponding bottom temperature and average depth for 1965.





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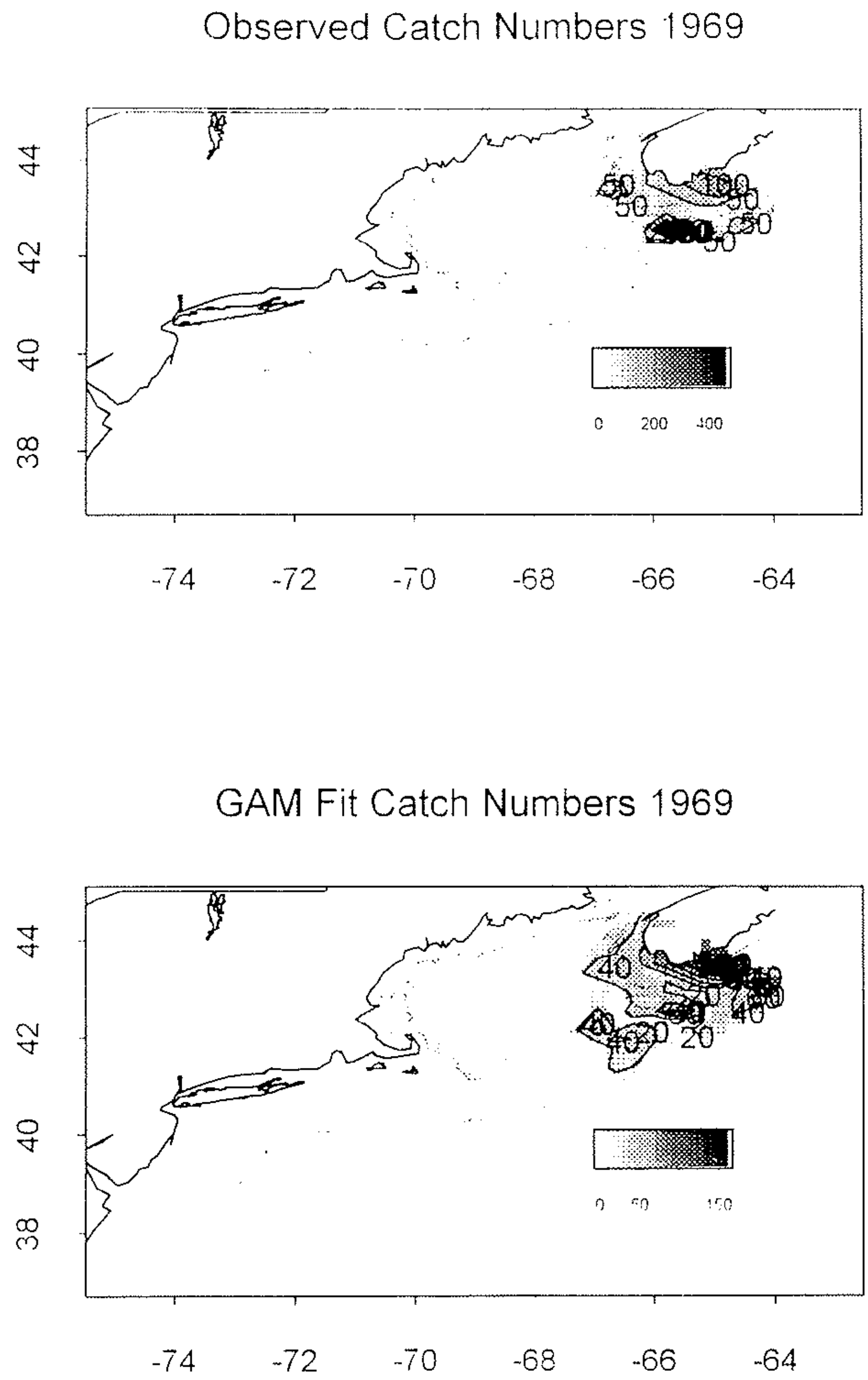
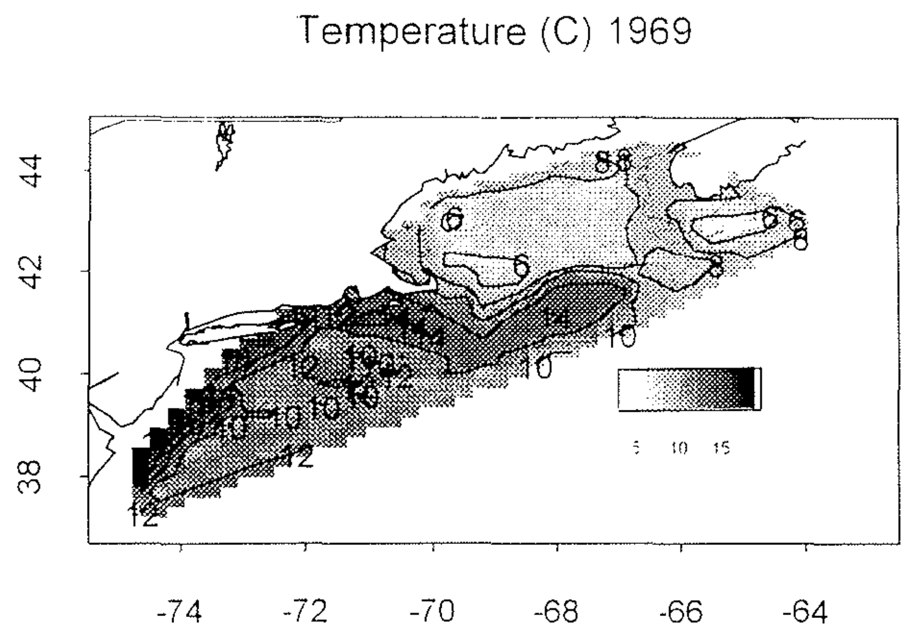


Figure 3. Interpolated observed and GAM fitted catch numbers of haddock and corresponding bottom temperature and average depth for 1969.



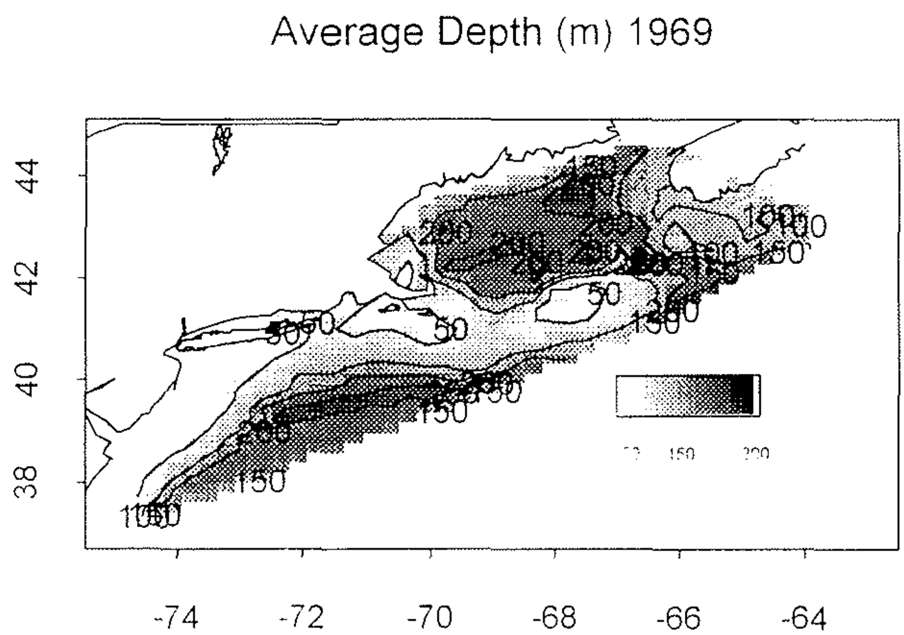
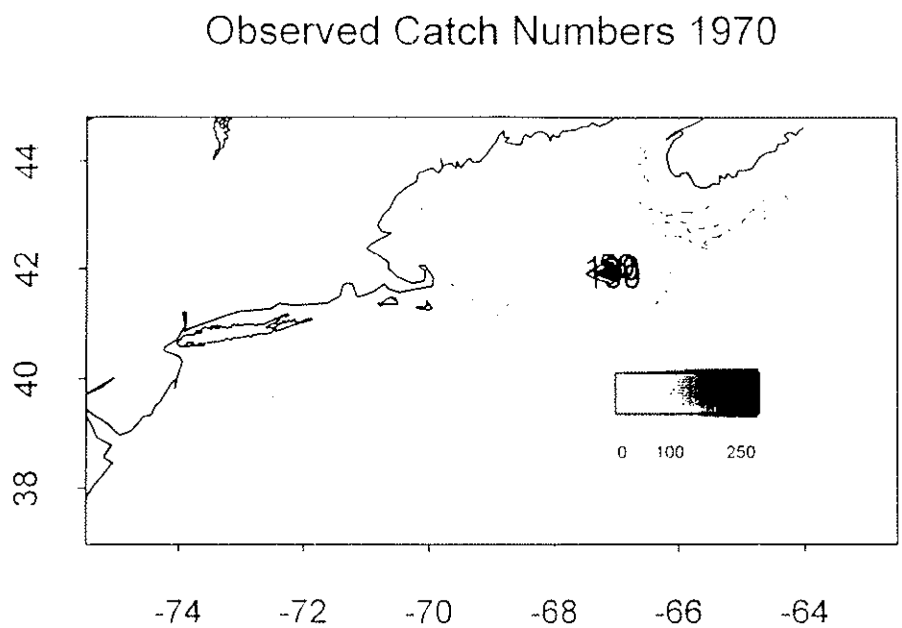


Figure 3 (Continued). Interpolated observed and GAM fitted catch numbers of haddock and corresponding bottom temperature and average depth for 1969.



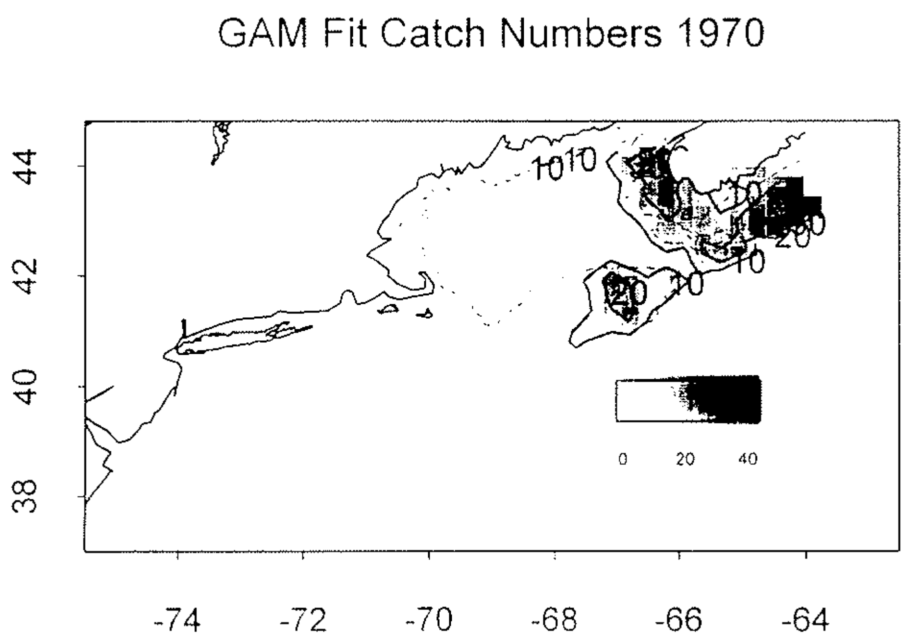
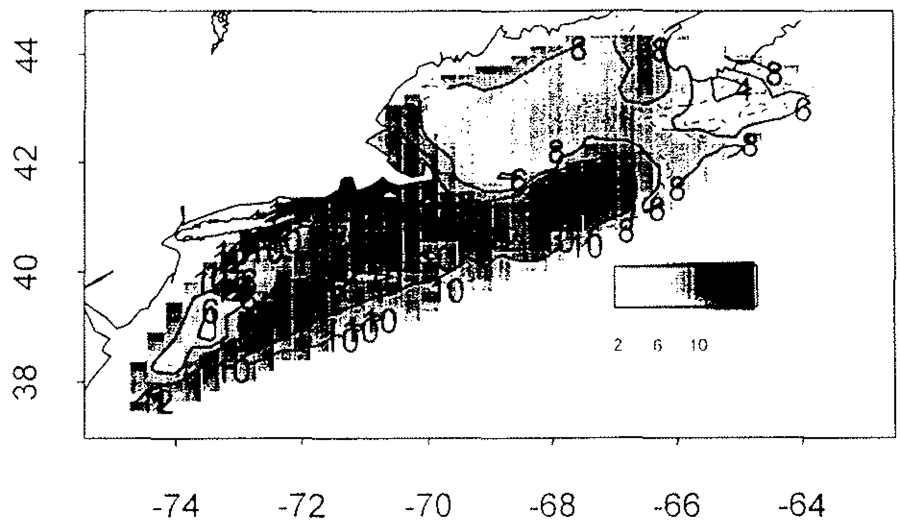


Figure 4. Interpolated observed and GAM fitted catch numbers of haddock and corresponding bottom temperature and average depth for 1970.

Temperature (C) 1970



Average Depth (m) 1970

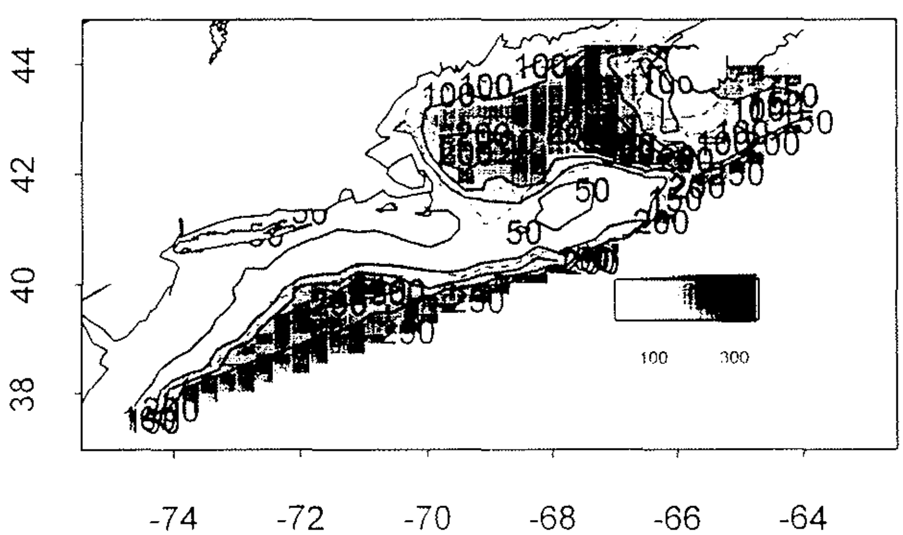
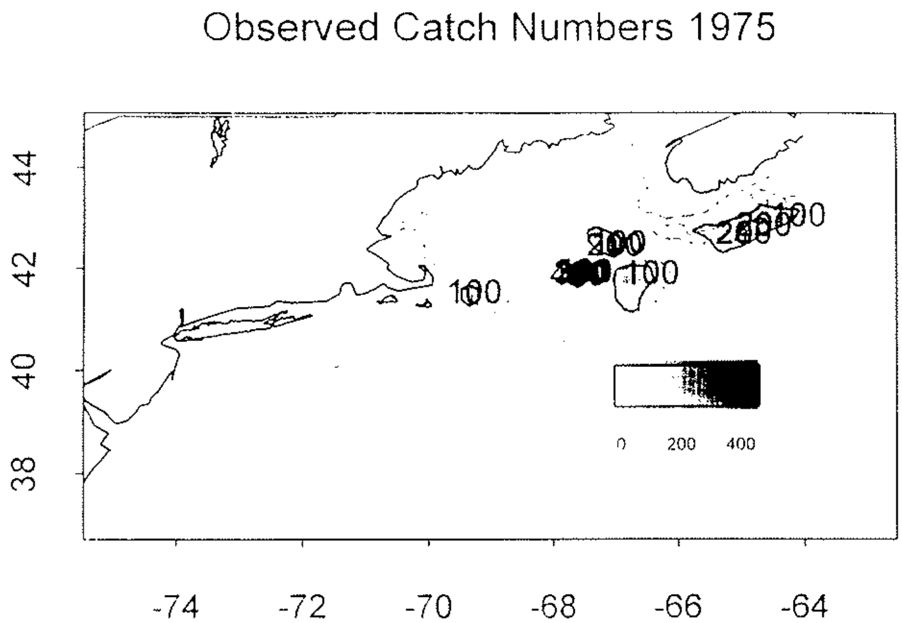


Figure 4 (Continued). Interpolated observed and GAM fitted catch numbers of haddock and corresponding bottom temperature and average depth for 1970.



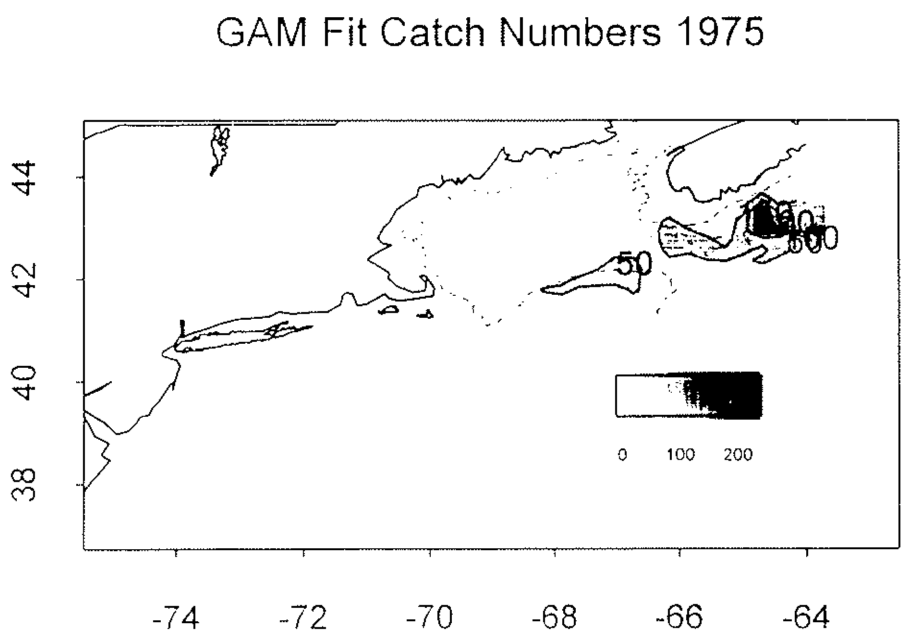
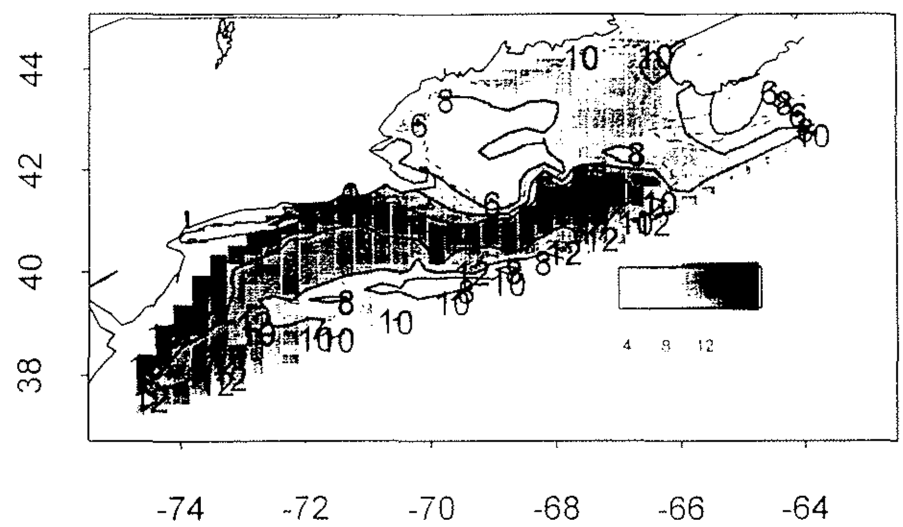
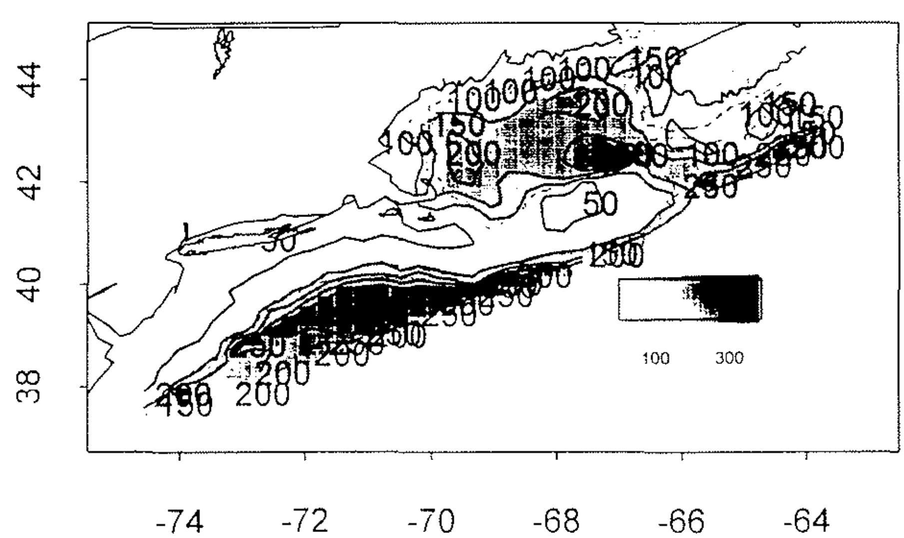


Figure 5. Interpolated observed and GAM fitted catch numbers of haddock and corresponding bottom temperature and average depth for 1975.

Temperature (C) 1975



Average Depth (m) 1975



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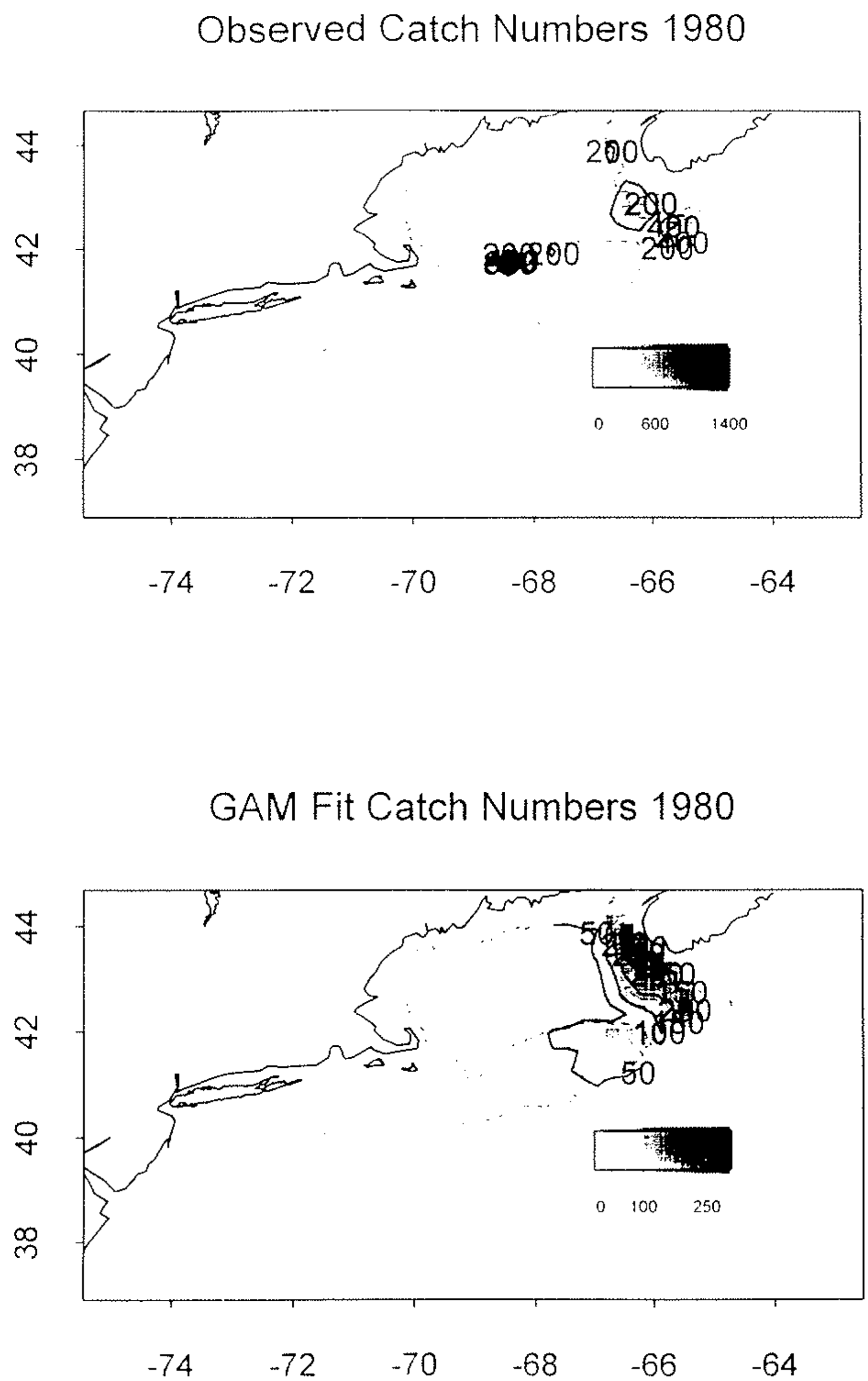
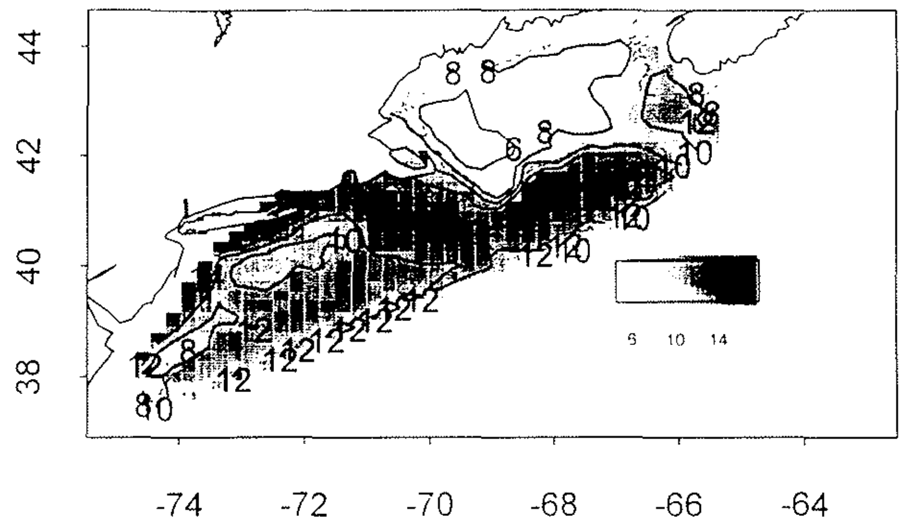


Figure 6. Interpolated observed and GAM fitted catch numbers of haddock and corresponding bottom temperature and average depth for 1980.

Temperature (C) 1980



Average Depth (m) 1980

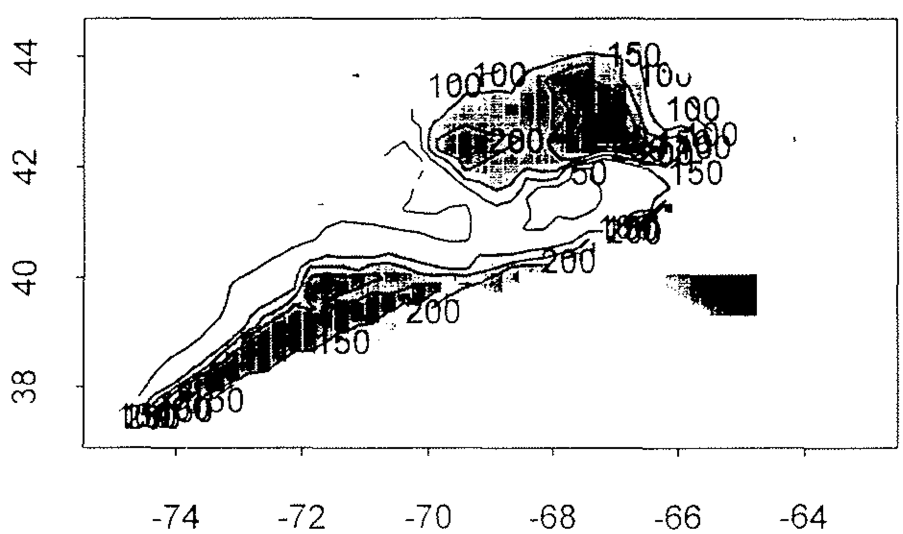
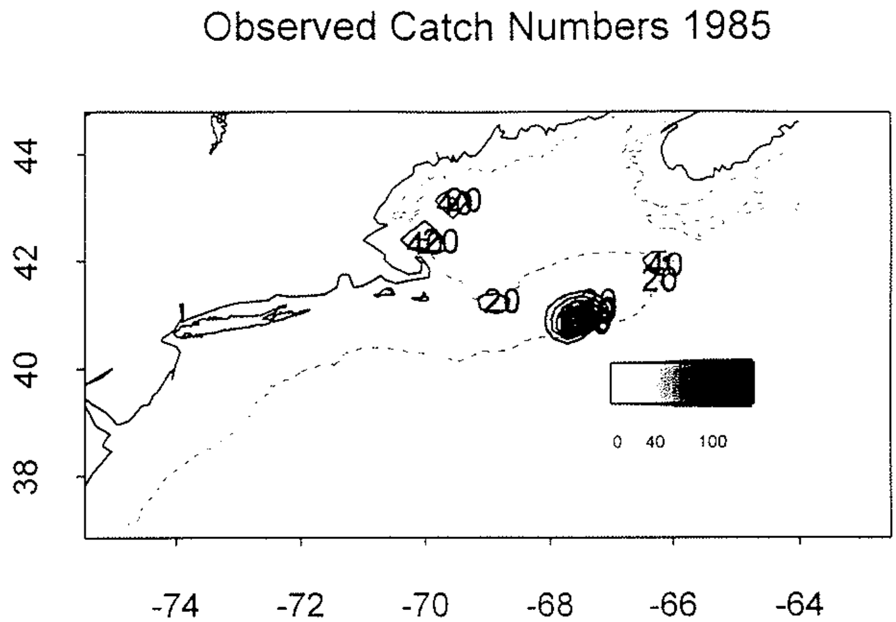


Figure 6 (Continued). Interpolated observed and GAM fitted catch numbers of haddock and corresponding bottom temperature and average depth for 1980.



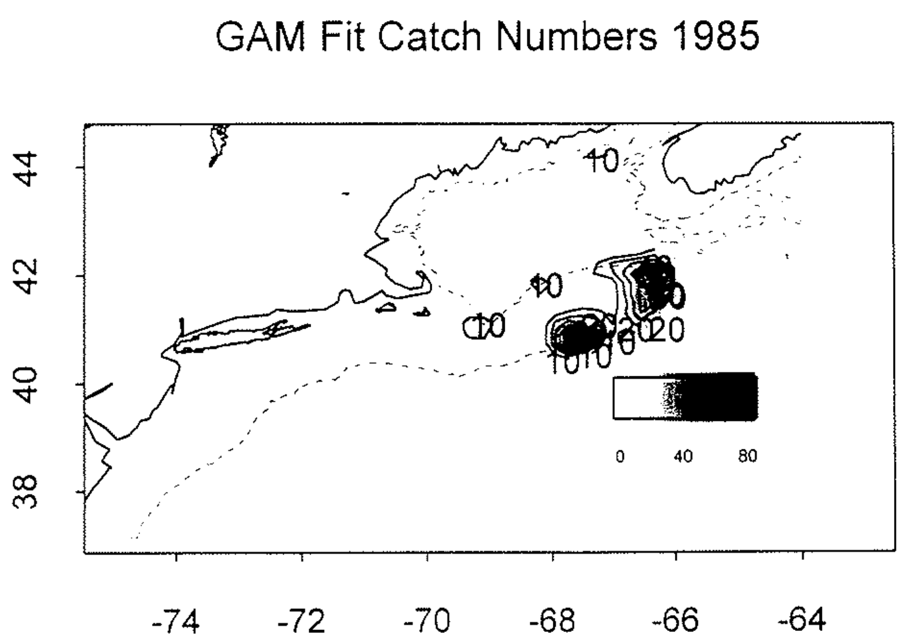
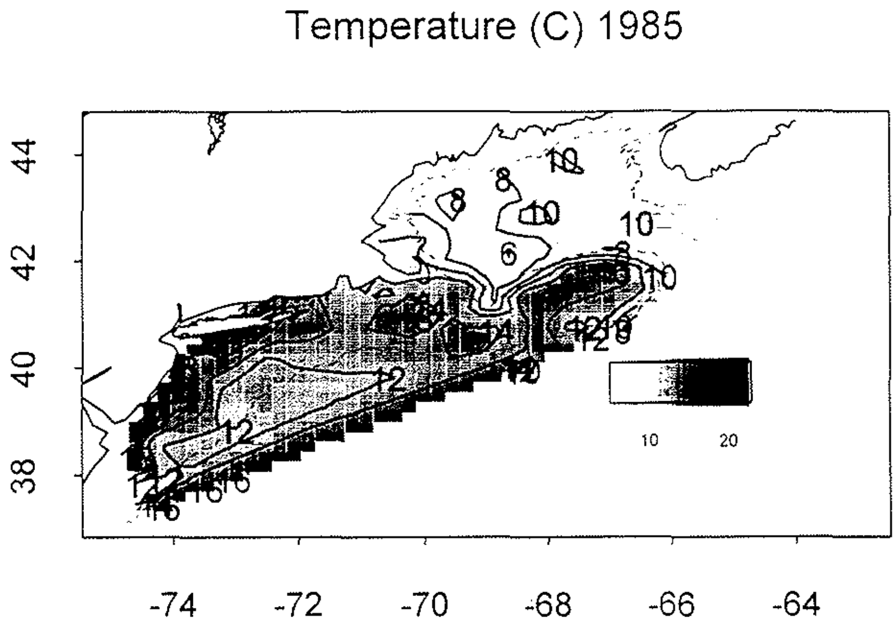


Figure 7. Interpolated observed and GAM fitted catch numbers of haddock and corresponding bottom temperature and average depth for 1985.



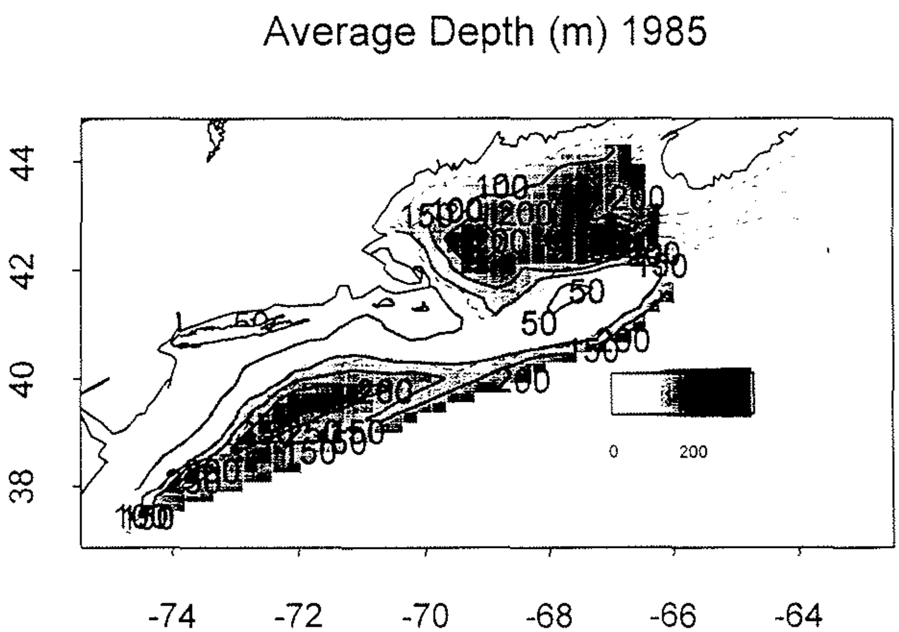
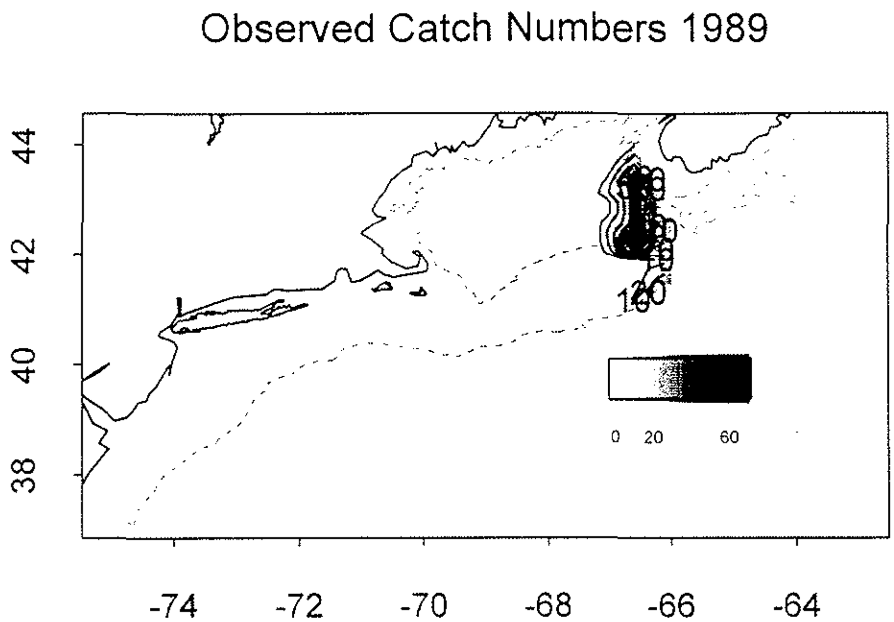


Figure 7 (Continued). Interpolated observed and GAM fitted catch numbers of haddock and corresponding bottom temperature and average depth for 1985.



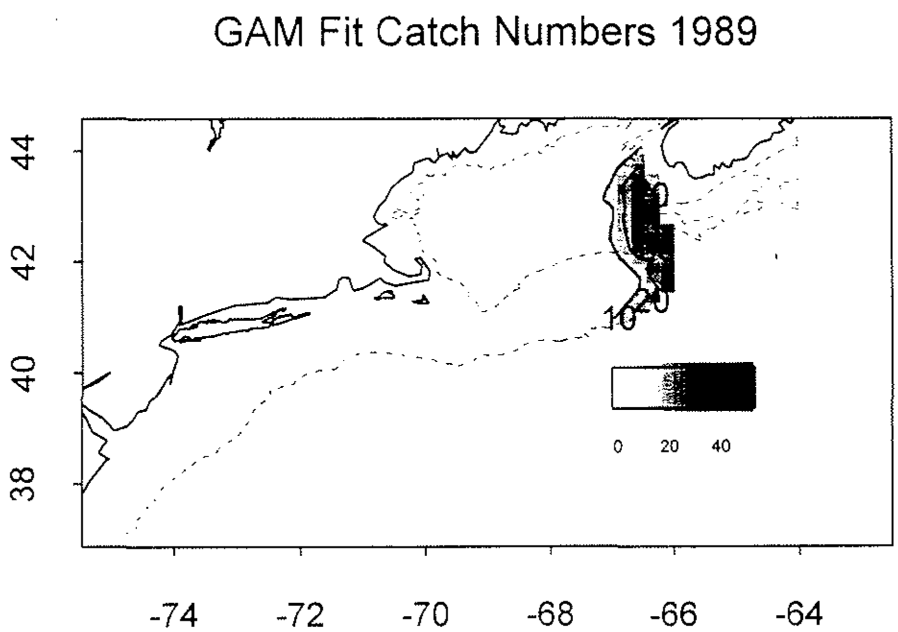
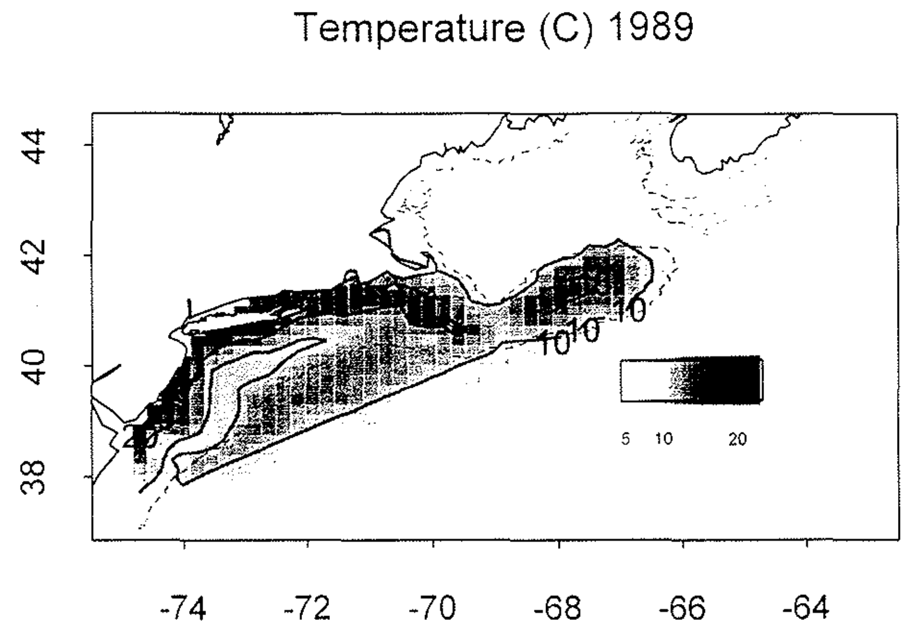


Figure 8. Interpolated observed and GAM fitted catch numbers of haddock and corresponding bottom temperature and average depth for 1989.



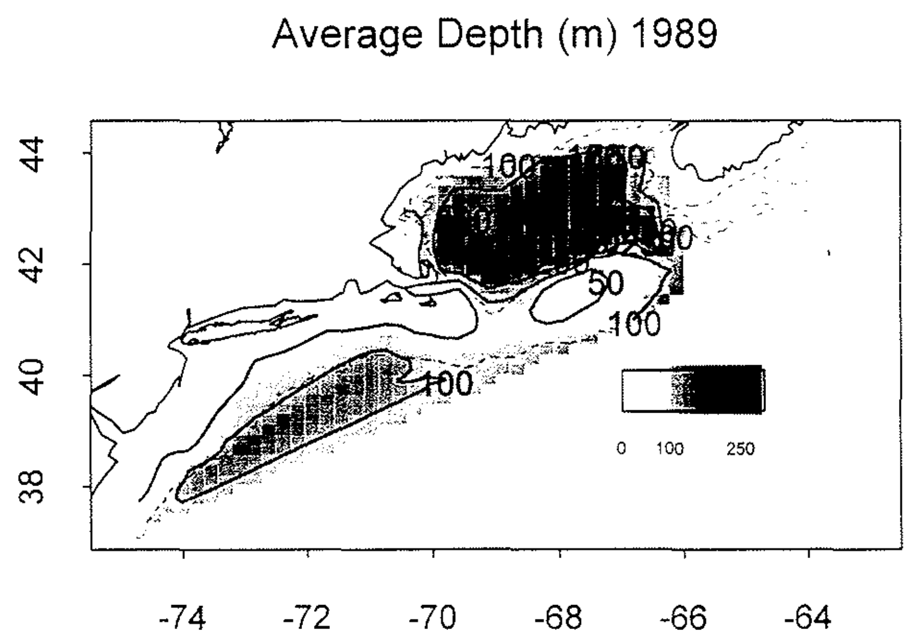
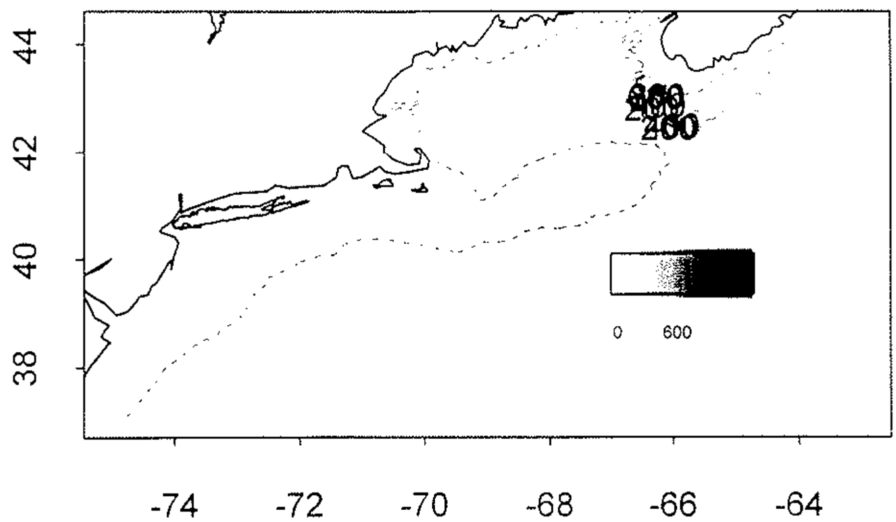


Figure 8 (Continued) Interpolated observed and GAM fitted catch numbers of haddock and corresponding bottom temperature and average depth for 1989.

Observed Catch Numbers 1994



GAM Fit Catch Numbers 1994

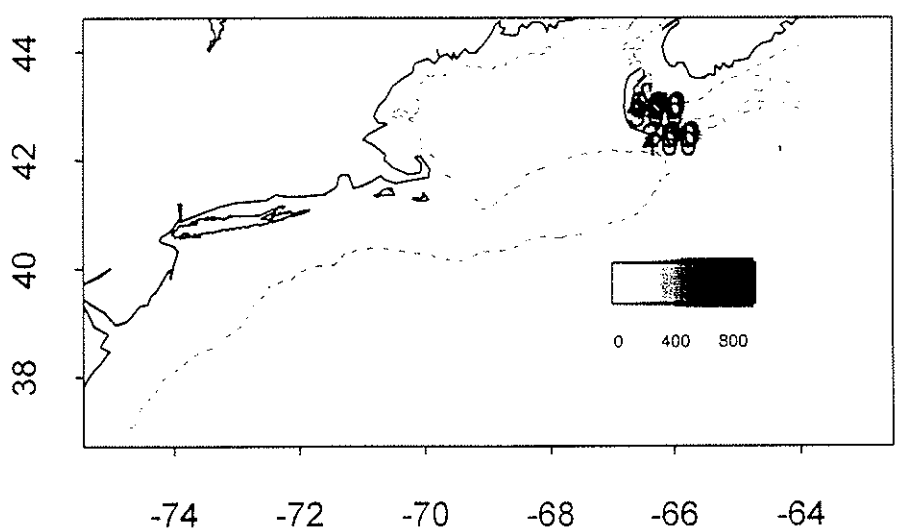
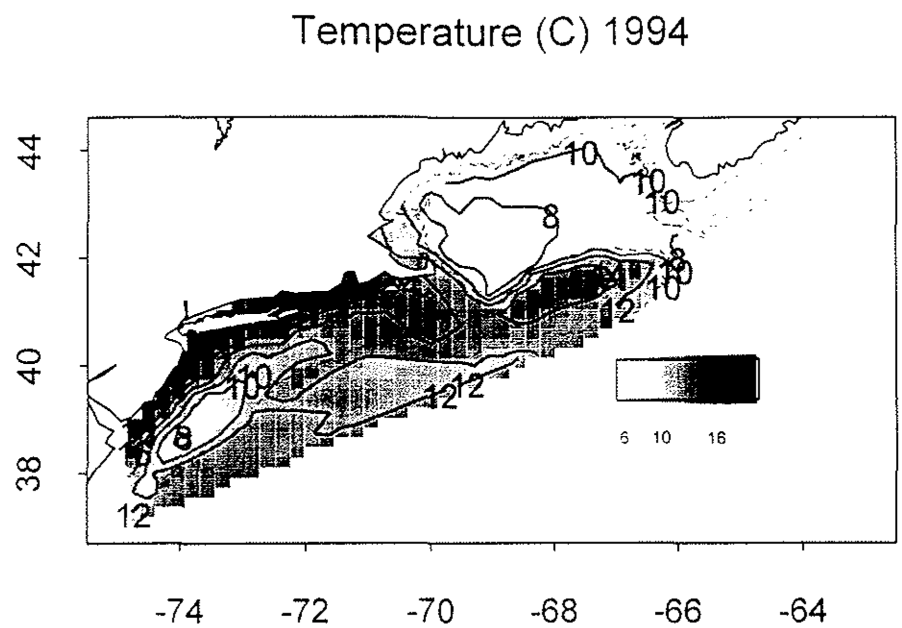


Figure 9. Interpolated observed and GAM fitted catch numbers of haddock and corresponding bottom temperature and average depth for 1994.



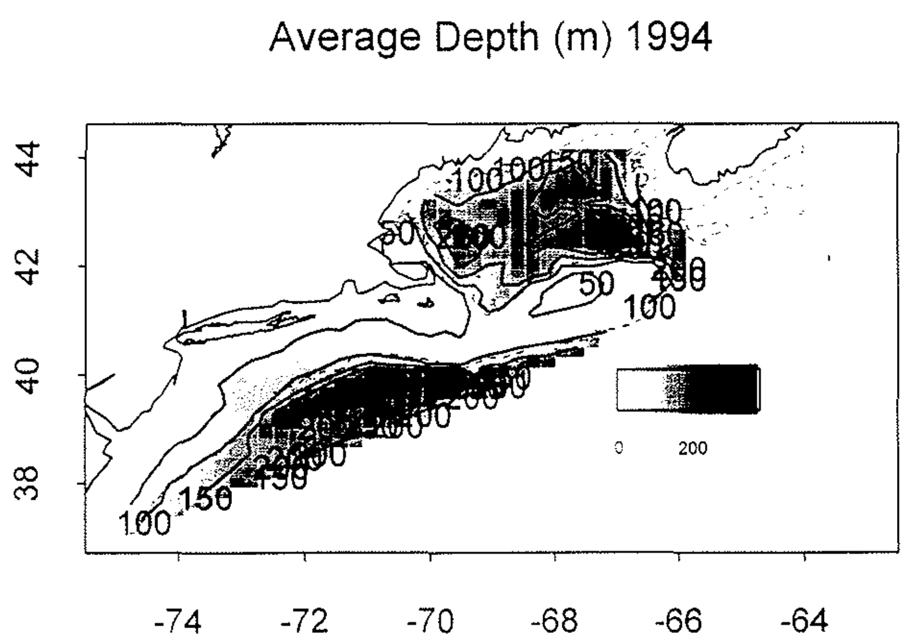


Figure 9 (Continued) Interpolated observed and GAM fitted catch numbers of haddock and corresponding bottom temperature and average depth for 1994.

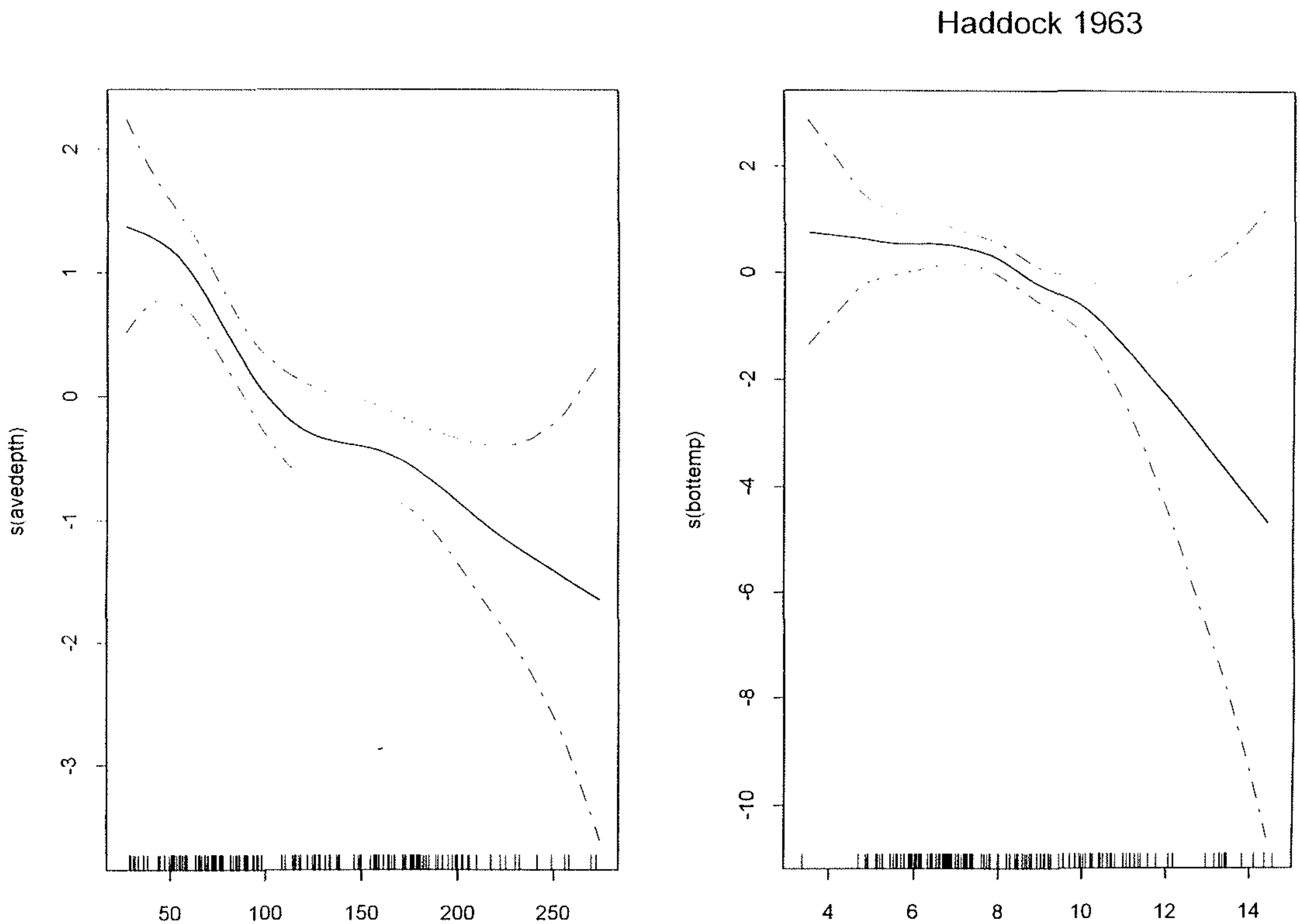


Figure 10. Scatterplot smooths of average depth (avedepth) and bottom temperature (bottemp) for model 1 with 95% confidence intervals (dotted line), autumn 1963. Y-axis is scaled to zero, rugplot along x-axis indicates number of observations.

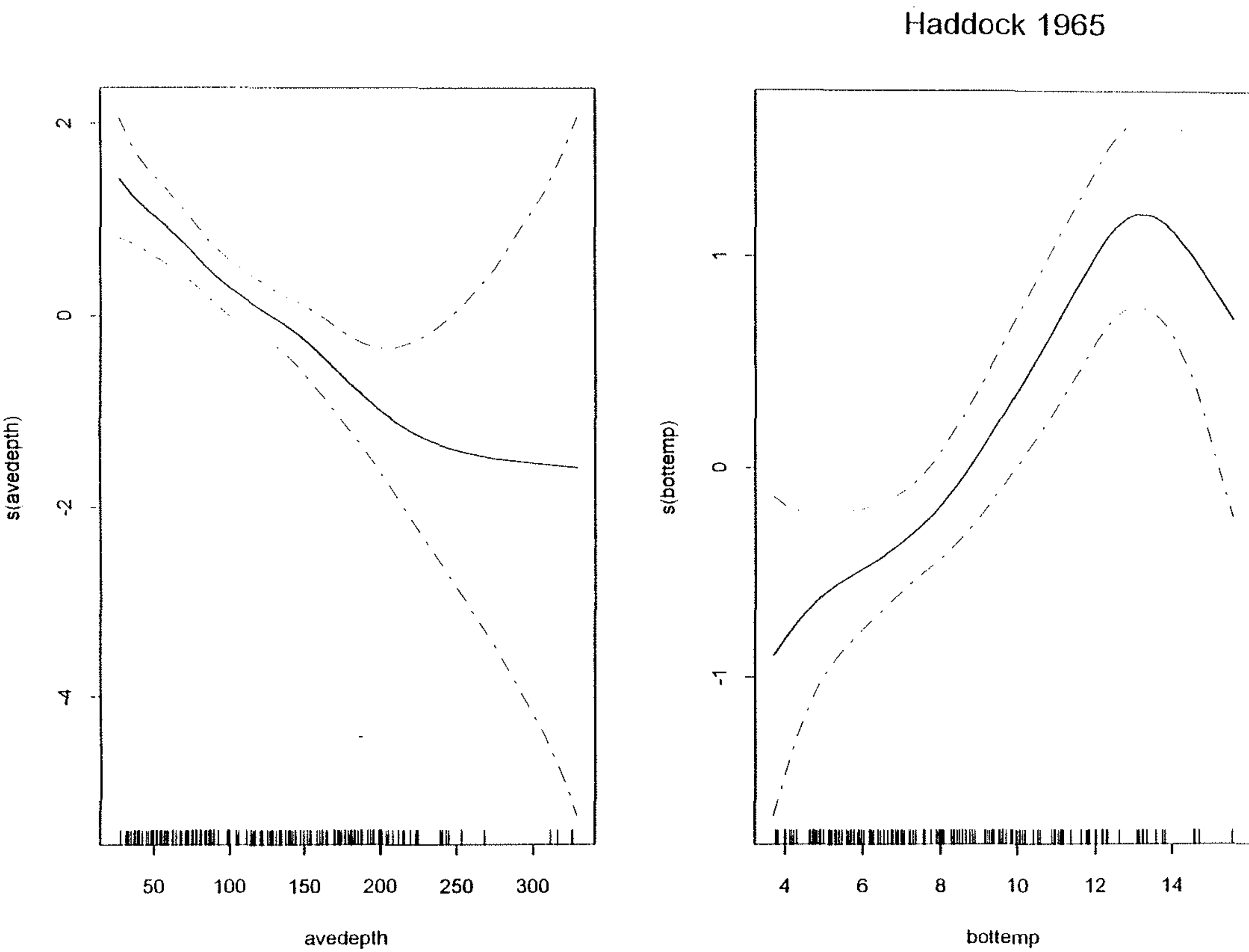


Figure 11. Scatterplot smooths of average depth (avedepth) and bottom temperature (bottemp) for model 1 with 95% confidence intervals (dotted line), autumn 1965. Y-axis is scaled to zero, rugplot along x-axis indicates number of observations.

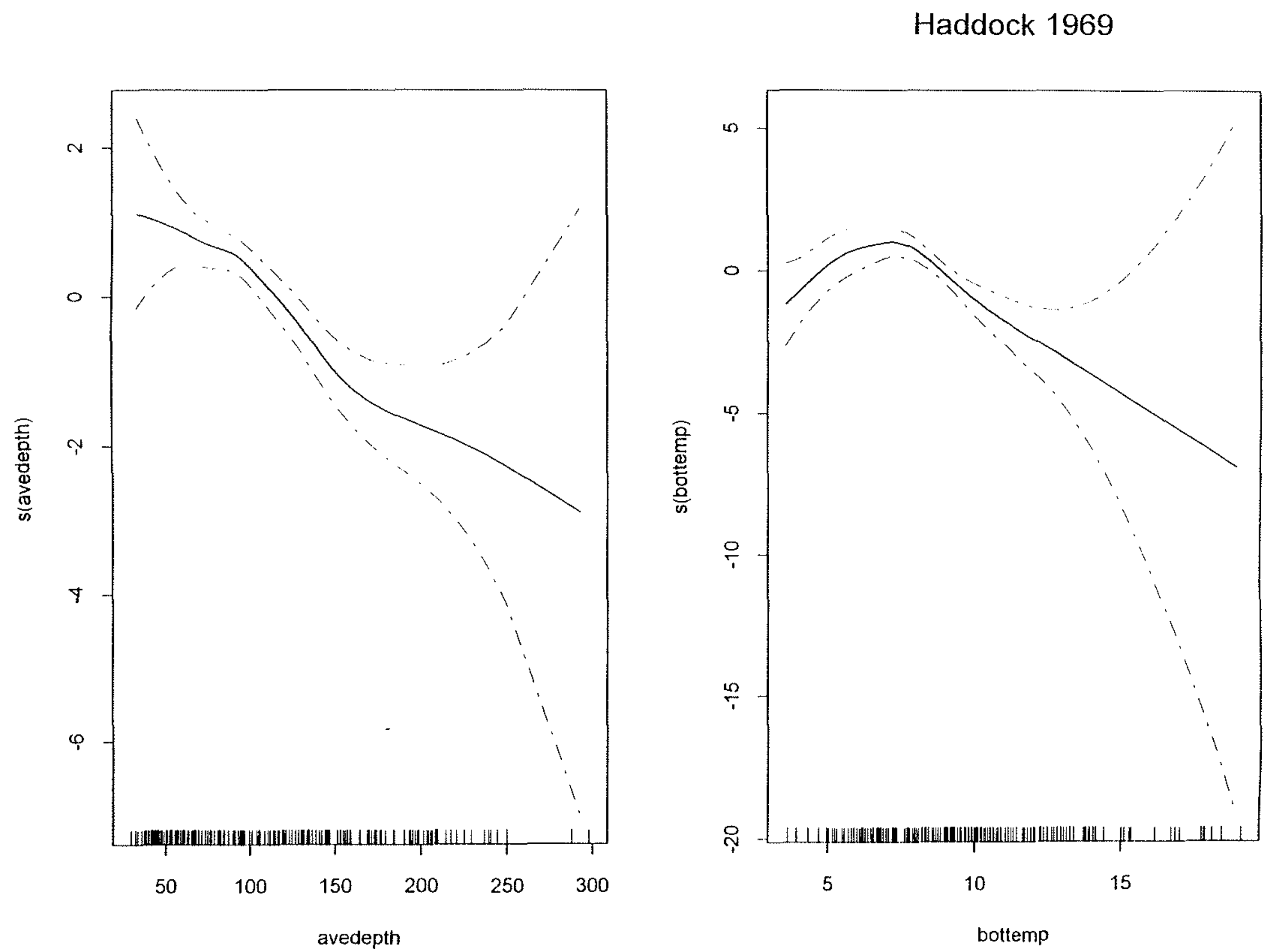


Figure 12. Scatterplot smooths of average depth (avedepth) and bottom temperature (bottemp) for model 1 with 95% confidence intervals (dotted line), autumn 1969. Y-axis is scaled to zero, rugplot along x-axis indicates number of observations.

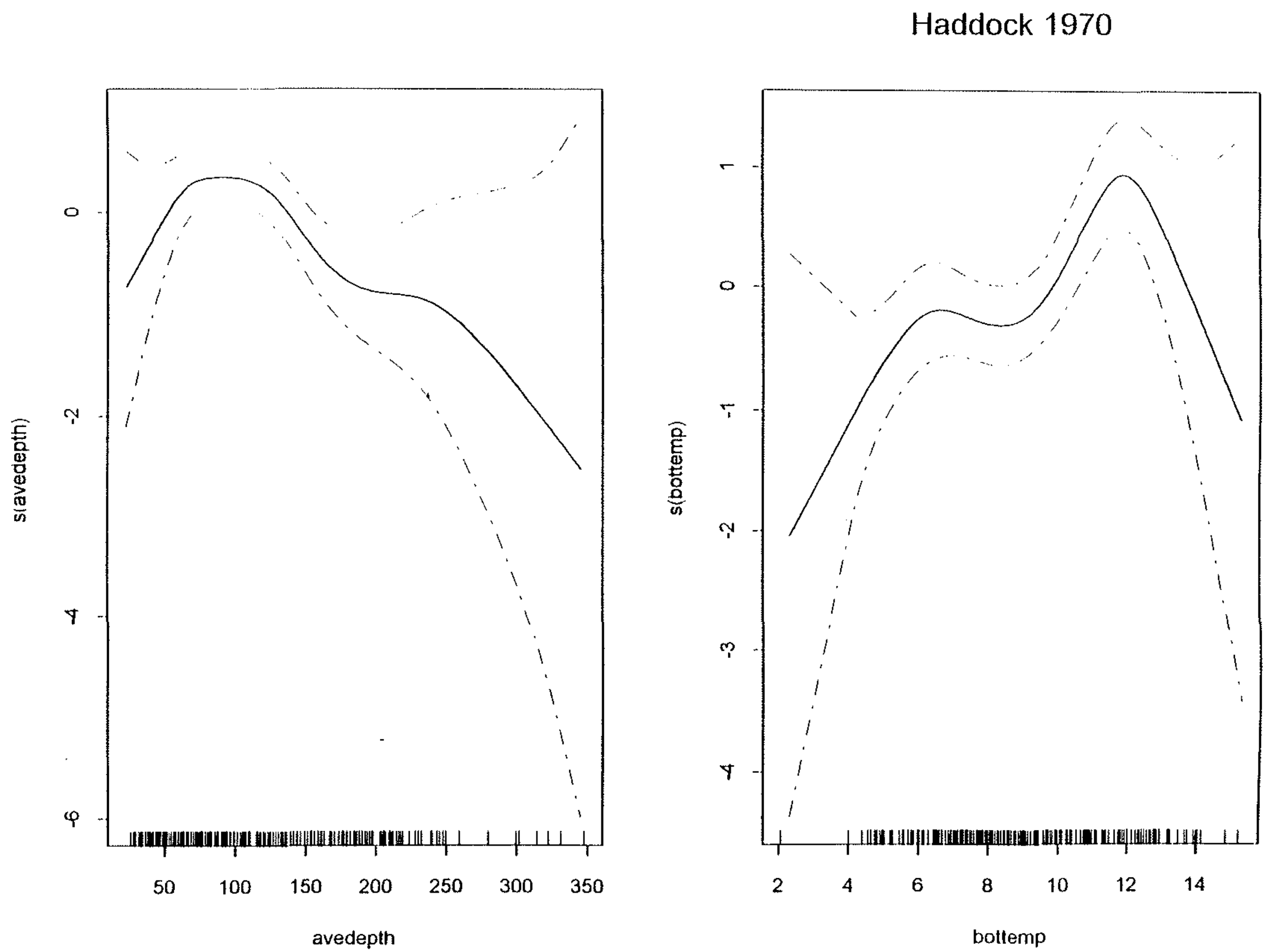


Figure 13. Scatterplot smooths of average depth (avedepth) and bottom temperature (bottemp) for model 1 with 95% confidence intervals (dotted line), autumn 1970. Y-axis is scaled to zero, rugplot along x-axis indicates number of observations.

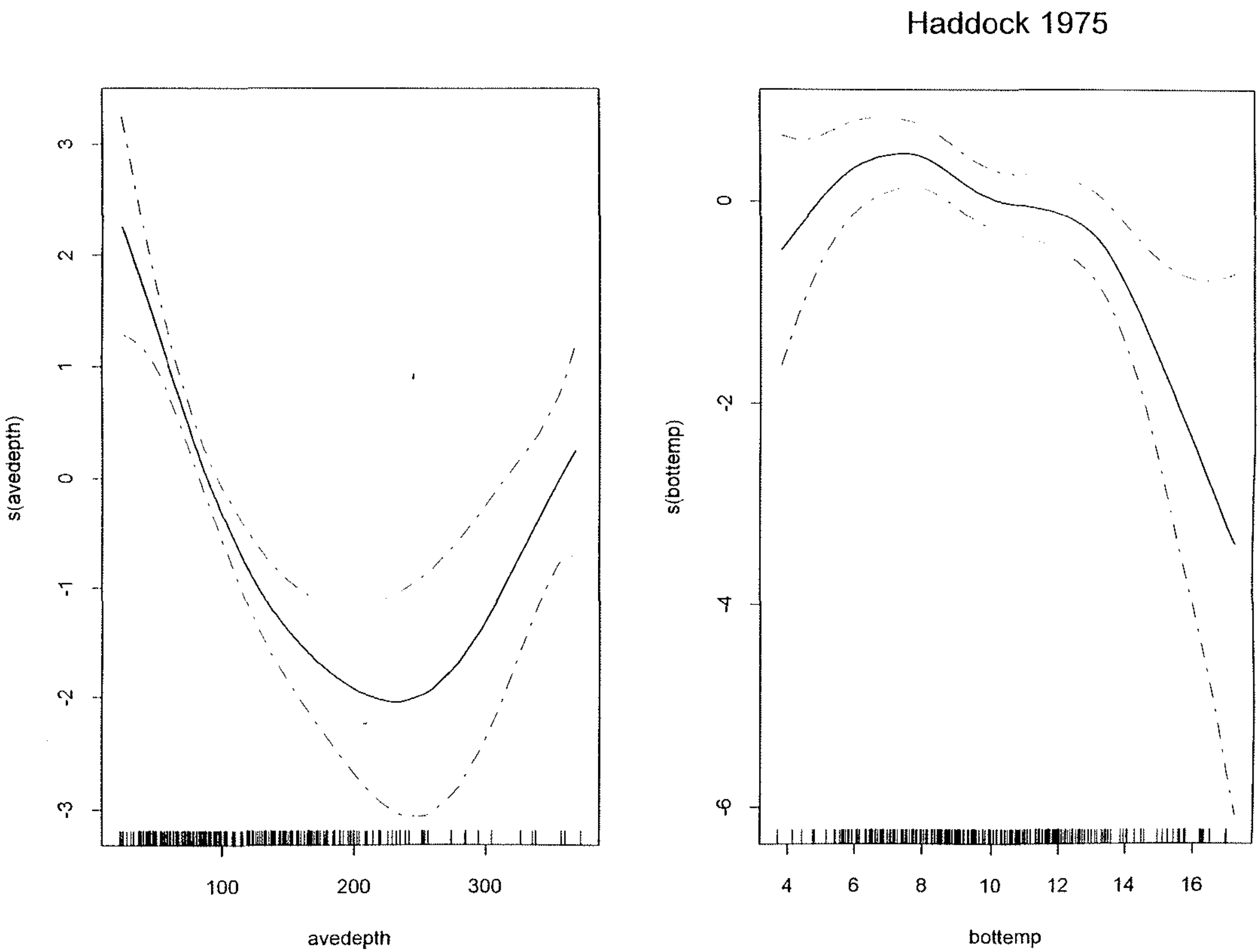


Figure 14. Scatterplot smooths of average depth (avedepth) and bottom temperature (bottemp) for model 1 with 95% confidence intervals (dotted line), autumn 1975. Y-axis is scaled to zero, rugplot along x-axis indicates number of observations.

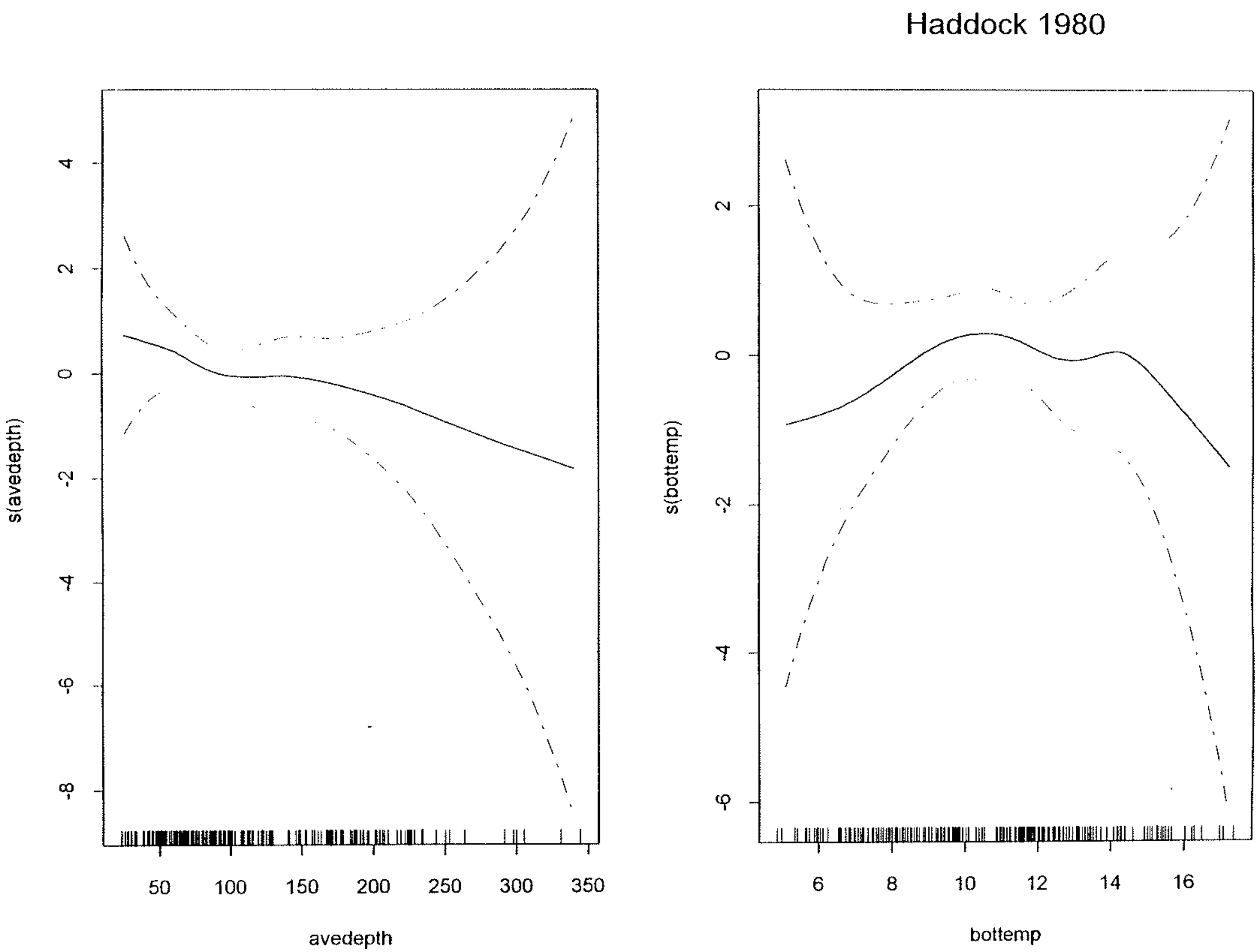


Figure 15. Scatterplot smooths of average depth (avedepth) and bottom temperature (bottemp) for model 1 with 95% confidence intervals (dotted line), autumn 1980. Y-axis is scaled to zero, rugplot along x-axis indicates number of observations.

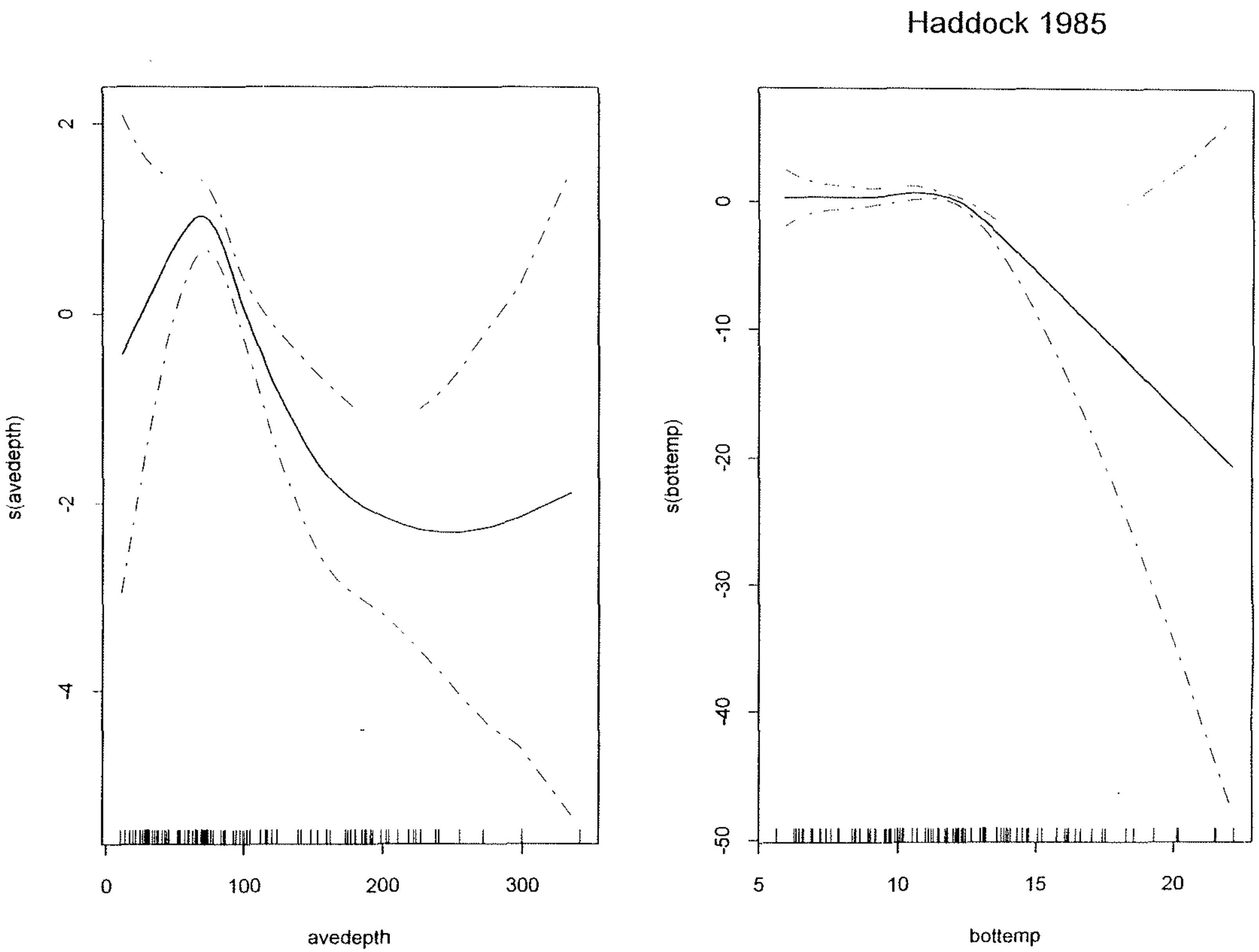


Figure 16. Scatterplot smooths of average depth (avedepth) and bottom temperature (bottemp) for model 1 with 95% confidence intervals (dotted line), autumn 1985. Y-axis is scaled to zero, rugplot along x-axis indicates number of observations.

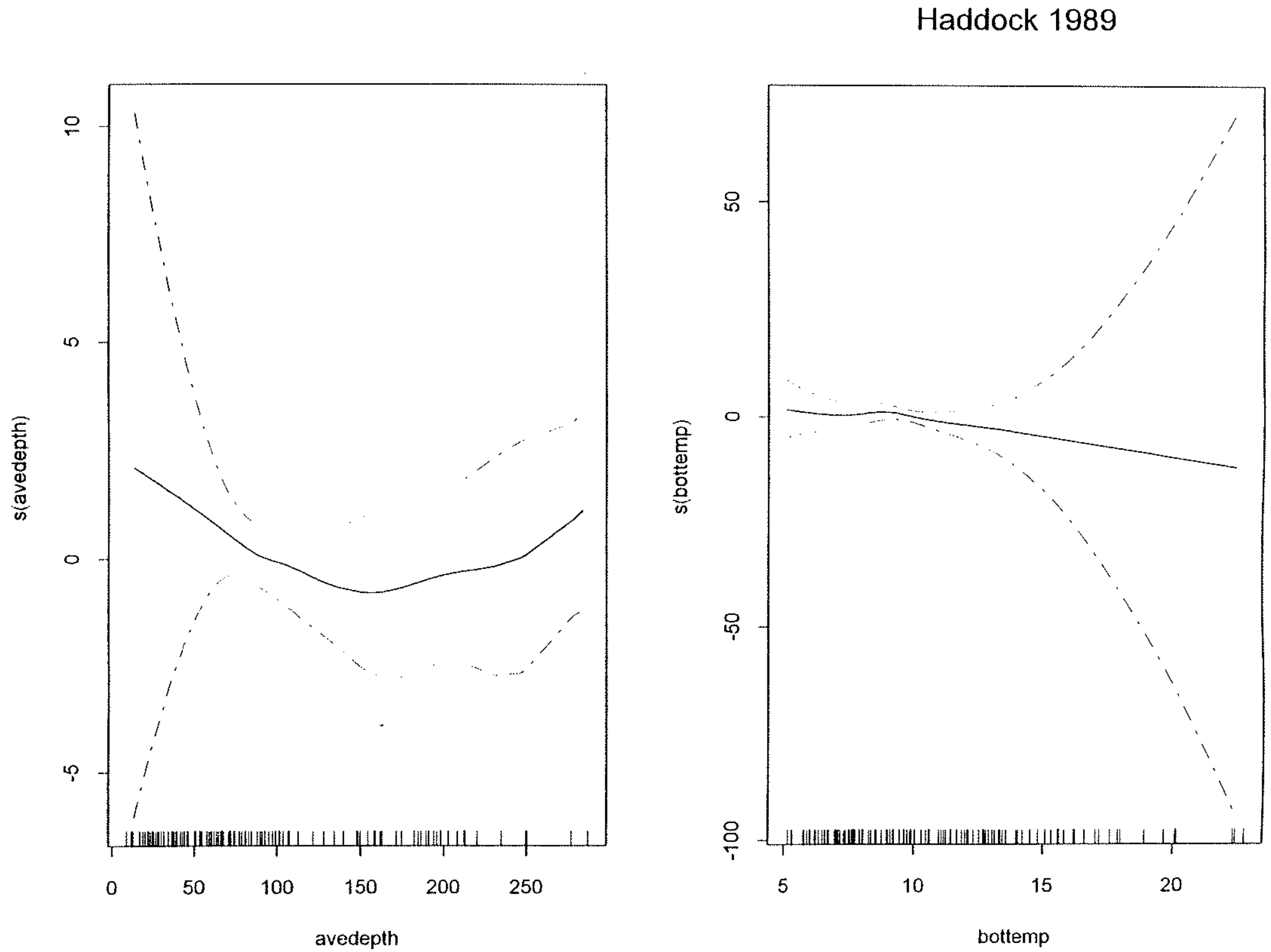


Figure 17. Scatterplot smooths of average depth (avedepth) and bottom temperature (bottemp) for model 1 with 95% confidence intervals (dotted line), autumn 1989. Y-axis is scaled to zero, rugplot along x-axis indicates number of observations.

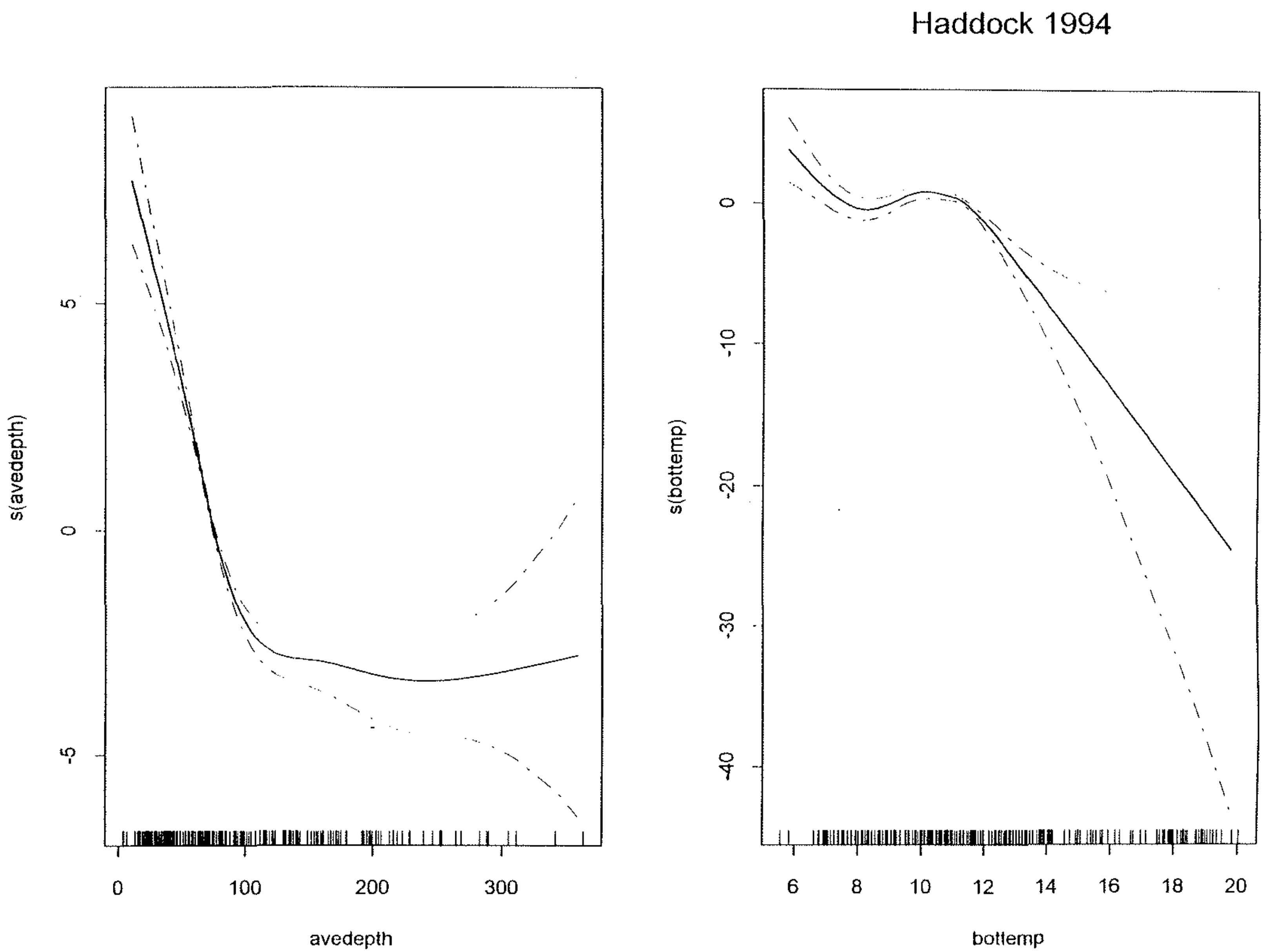


Figure 18. Scatterplot smooths of average depth (avedepth) and bottom temperature (bottemp) for model 1 with 95% confidence intervals (dotted line), autumn 1994. Y-axis is scaled to zero, rugplot along x-axis indicates number of observations.

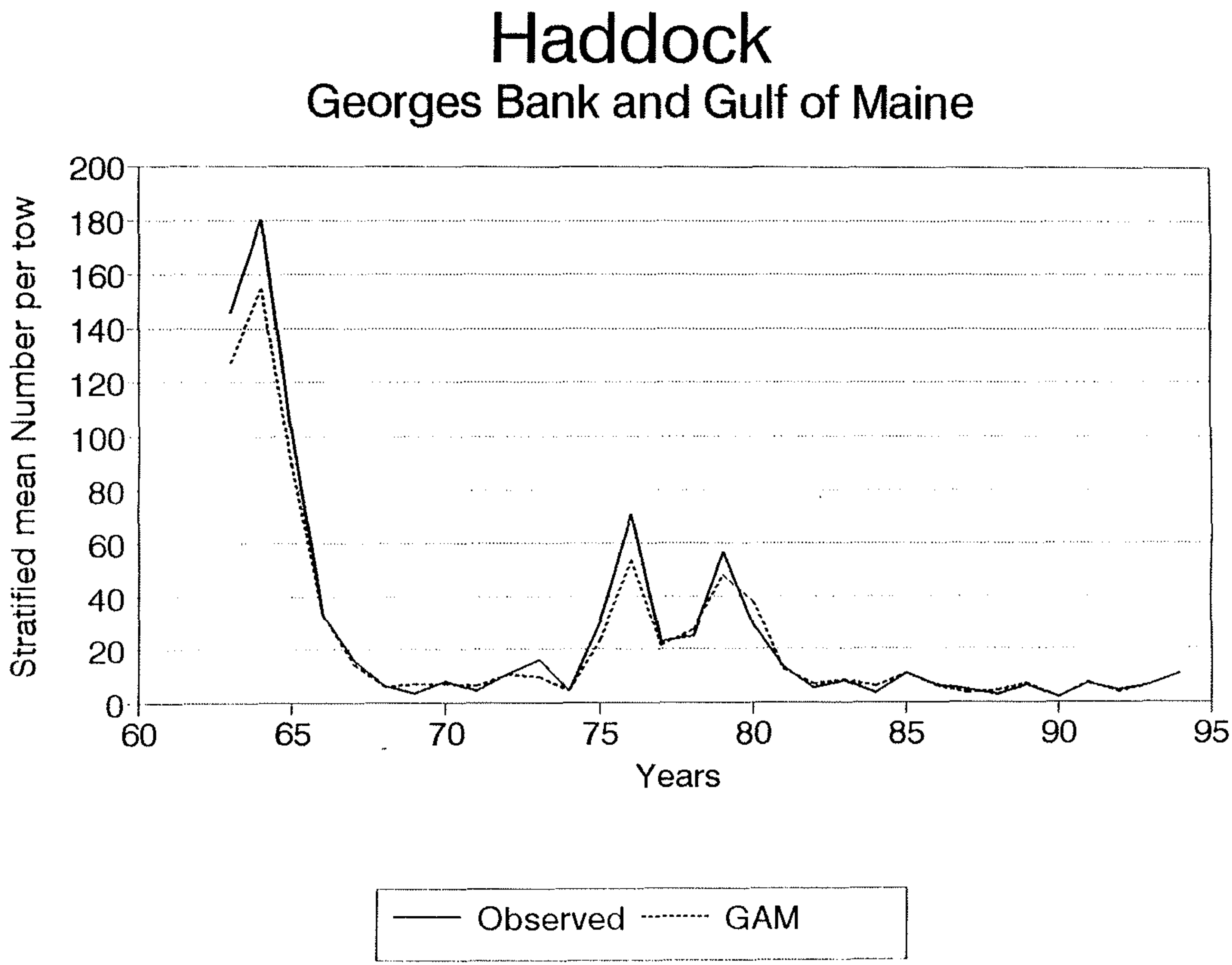


Figure 19. Stratified mean number per tow for observed and GAM fitted catch numbers for haddock, 1963-1994.

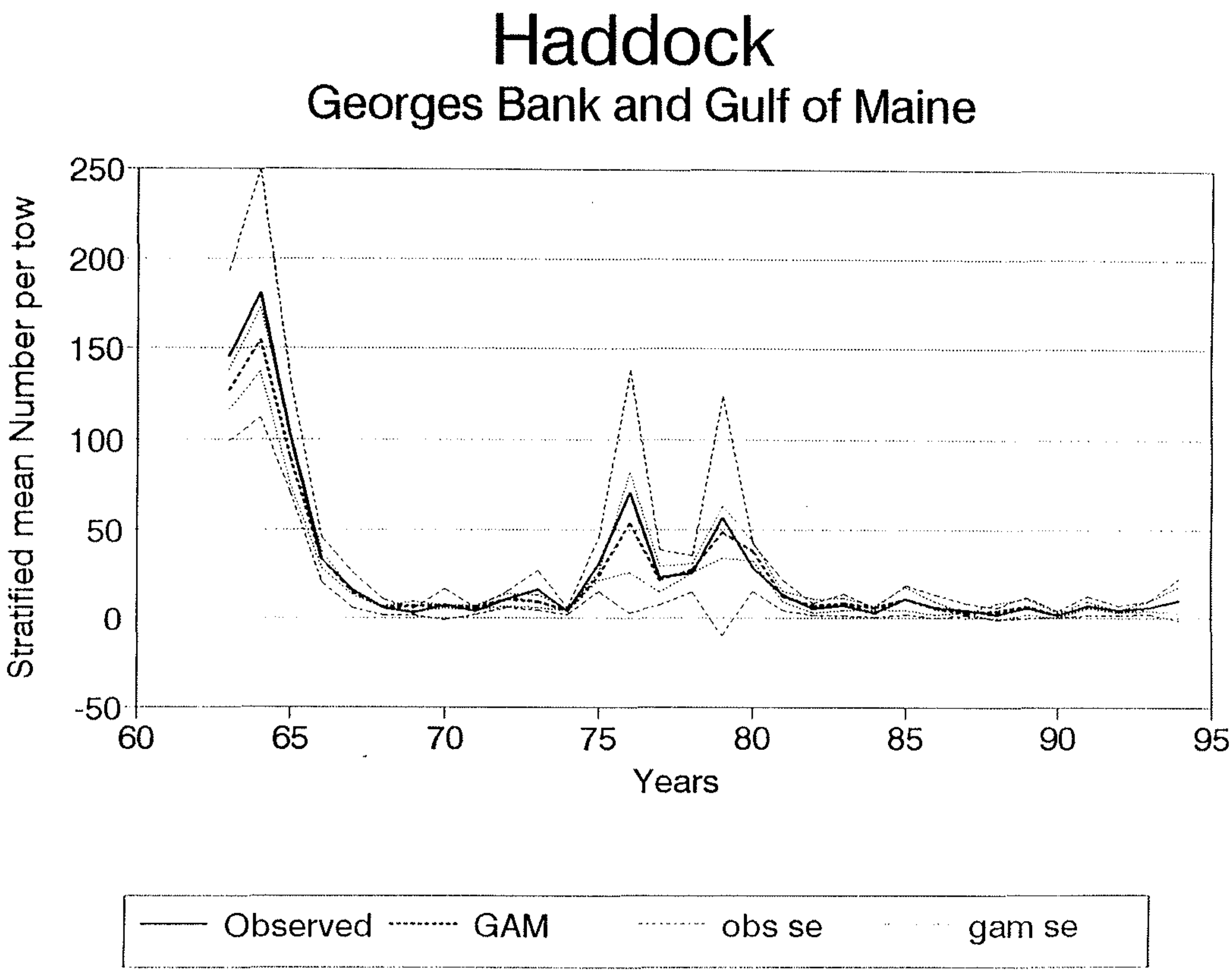


Figure 20. Stratified mean number per tow with standard errors for observed and GAM fitted catch numbers for haddock, 1963-1994.

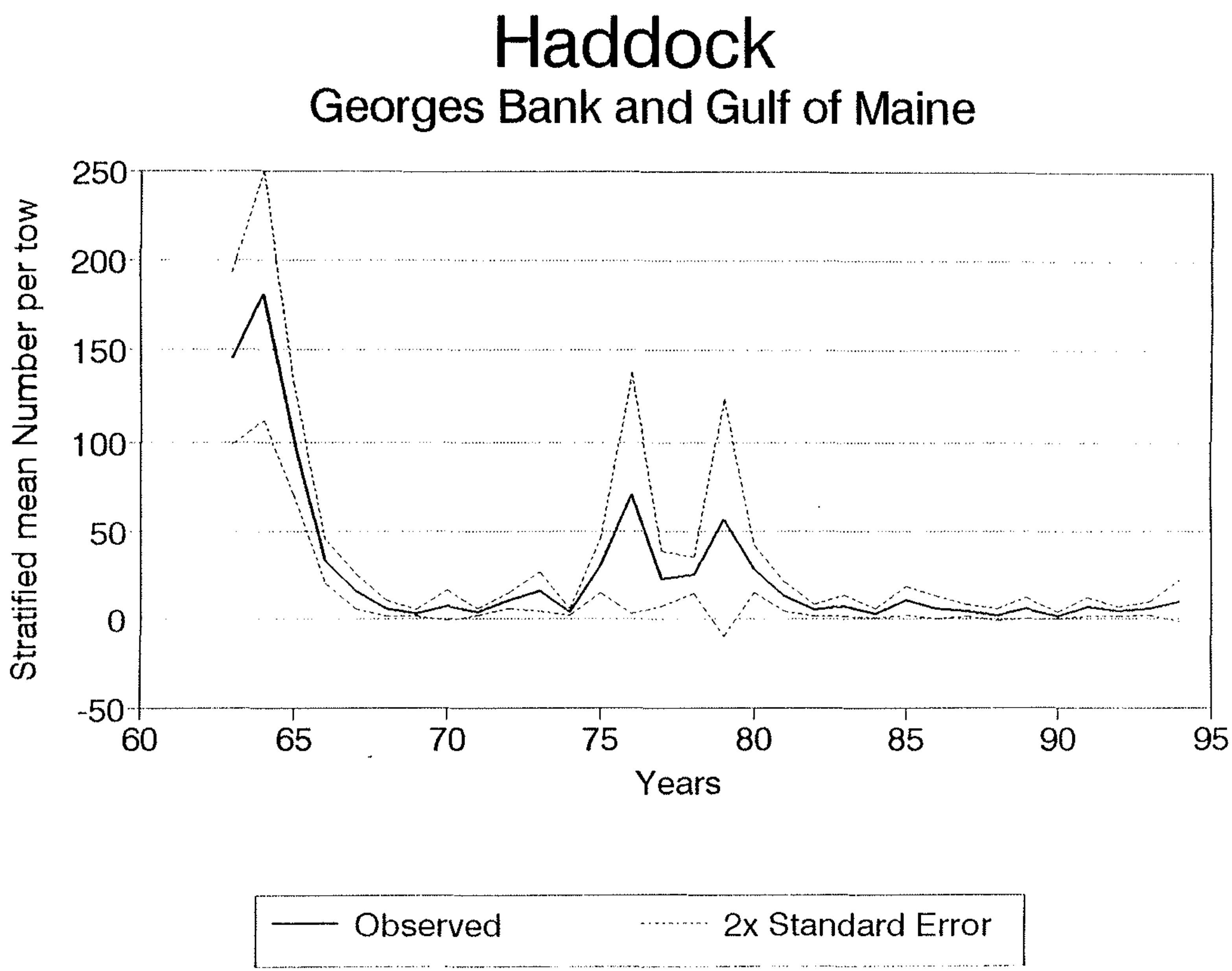


Figure 21. Stratified mean number per tow with standard errors for observed catch numbers for haddock, 1963-1994.

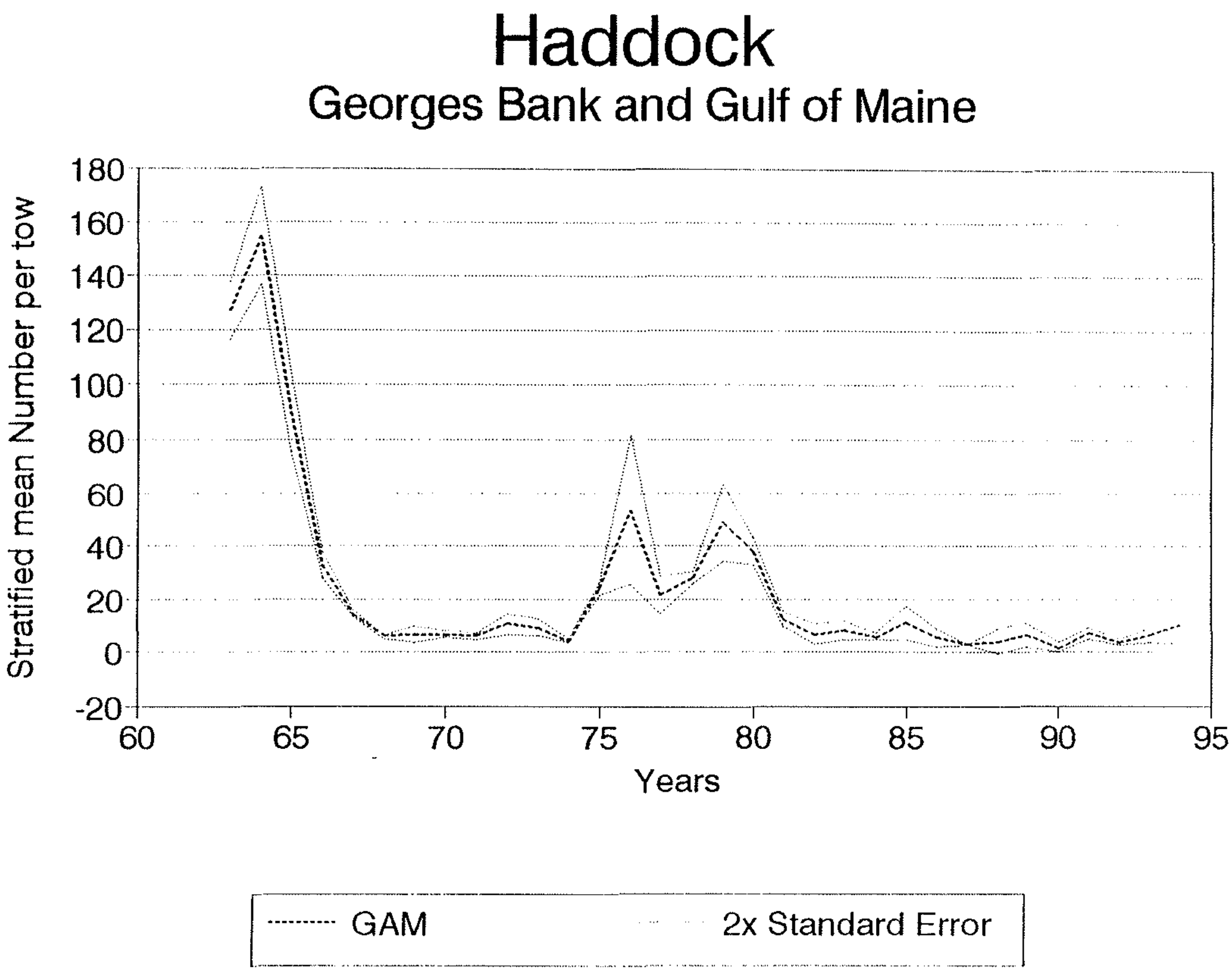


Figure 22. Stratified mean number per tow with standard errors for GAM fitted catch numbers for haddock, 1963-1994.

Appendix Table A. Summary of GAM statistics for model 1.

1963
Summary of h63s2

```
Call: gam(formula = form2, family = poisson, data = h63, na.action = na.omit)

Deviance Residuals:
       Min        1Q    Median        3Q      Max
 -23.70334 -9.257201 -3.440912 0.1306106 60.68097

(Dispersion Parameter for Poisson family taken to be 1 )

    Null Deviance: 42950.02 on 180 degrees of freedom

Residual Deviance: 23480.34 on 170.0727 degrees of freedom

Number of Local Scoring Iterations: 7

DF for Terms and Chi-squares for Nonparametric Effects

            Df Npar Df Npar Chisq P(Chi)
(Intercept)  1
s(avedepth)  1     3.0   1195.835      0
 s(bottemp)  1     2.9   1110.979      0
        lat  1
        lon  1
```

1965
Summary(h65s2)

```
Call: gam(formula = form2, family = poisson, data = h65, na.action = na.omit)

Deviance Residuals:
       Min        1Q    Median       3Q      Max
 -14.92645 -5.793921 -3.368031 1.277742 27.86504

(Dispersion Parameter for Poisson family taken to be 1 )

    Null Deviance: 24432.84 on 188 degrees of freedom

Residual Deviance: 11173.43 on 178.1817 degrees of freedom

Number of Local Scoring Iterations: 6

DF for Terms and Chi-squares for Nonparametric Effects

            Df Npar Df Npar Chisq P(Chi)
(Intercept)  1
s(avedepth)  1     3.0   148.3583      0
 s(bottemp)  1     2.8   686.6302      0
        lat  1
        lon  1
```

1969
Summary(h69s2)

```
Call: gam(formula = form2, family = poisson, data = h69, na.action = na.omit)

Deviance Residuals:
       Min        1Q     Median         3Q      Max
 -14.16375 -1.774192 -0.8154677 -0.150751 26.97446

(Dispersion Parameter for Poisson family taken to be 1 )
```

```
    Null Deviance: 7371.993 on 209 degrees of freedom

Residual Deviance: 2791.303 on 199.0142 degrees of freedom

Number of Local Scoring Iterations: 7

DF for Terms and Chi-squares for Nonparametric Effects

            Df Npar Df Npar Chisq P(Chi)
(Intercept)  1
s(avedepth)  1       3    92.7616      0
 s(bottemp)  1       3   869.5796      0
        lat  1
        lon  1
```

1970
Summary(h70s2)

```
Call: gam(formula = form2, family = poisson, data = h70, na.action = na.omit)

Deviance Residuals:
       Min        1Q     Median         3Q      Max
 -7.195061 -2.322113 -0.9872909 -0.1218674 27.88095

(Dispersion Parameter for Poisson family taken to be 1 )

    Null Deviance: 5680.571 on 259 degrees of freedom

Residual Deviance: 2827.305 on 249.1798 degrees of freedom

Number of Local Scoring Iterations: 7

DF for Terms and Chi-squares for Nonparametric Effects

            Df Npar Df Npar Chisq P(Chi)
(Intercept)  1
s(avedepth)  1     3.0   175.5272      0
 s(bottemp)  1     2.9   354.7190      0
        lat  1
        lon  1
```

1975
Summary(h75s2)

```
Call: gam(formula = form2, family = poisson, data = h75, na.action = na.omit)

Deviance Residuals:
       Min        1Q    Median         3Q      Max
 -21.10518 -4.336802 -2.435916 -0.7235324 31.33545

(Dispersion Parameter for Poisson family taken to be 1 )

    Null Deviance: 20087.14 on 280 degrees of freedom

Residual Deviance: 10971.52 on 270.3134 degrees of freedom

Number of Local Scoring Iterations: 7

DF for Terms and Chi-squares for Nonparametric Effects

            Df Npar Df Npar Chisq P(Chi)
(Intercept)  1
s(avedepth)  1     2.9   3056.350      0
 s(bottemp)  1     2.8    849.076      0
        lat  1
```

```
       lon  1
```

1980
Summary(h80s2)

```
Call: gam(formula = form2, family = poisson, data = h80, na.action = na.omit)

Deviance Residuals:
       Min        1Q    Median         3Q      Max
 -18.26041 -6.866505 -2.713142 -0.5729098 85.2113

(Dispersion Parameter for Poisson family taken to be 1 )

    Null Deviance: 34989.46 on 246 degrees of freedom

Residual Deviance: 21436.25 on 236.2112 degrees of freedom

Number of Local Scoring Iterations: 9

DF for Terms and Chi-squares for Nonparametric Effects

            Df Npar Df Npar Chisq P(Chi)
(Intercept)  1
s(avedepth)  1     3.0    259.648      0
 s(bottemp)  1     2.8   1037.916      0
        lat  1
        lon  1
```

1985
Summary(h85s2)

```
Call: gam(formula = form2, family = poisson, data = h85, na.action = na.omit)

Deviance Residuals:
       Min        1Q     Median          3Q      Max
 -8.393346 -2.069827 -0.9312267 -0.02706914 12.20916

(Dispersion Parameter for Poisson family taken to be 1 )

    Null Deviance: 2883.124 on 115 degrees of freedom

Residual Deviance: 1030.41 on 105.223 degrees of freedom

Number of Local Scoring Iterations: 7

DF for Terms and Chi-squares for Nonparametric Effects

            Df Npar Df Npar Chisq P(Chi)
(Intercept)  1
s(avedepth)  1     2.9   166.3630      0
 s(bottemp)  1     2.9   231.3585      0
        lat  1
        lon  1
```

1989
Summary(h89s2)

```
Call: gam(formula = form2, family = poisson, data = h89, na.action = na.omit)

Deviance Residuals:
```

```
      Min         1Q     Median          3Q      Max
 -6.115248 -0.8356205 -0.2329611 -0.01670546 8.019467

(Dispersion Parameter for Poisson family taken to be 1 )

    Null Deviance: 1607.183 on 120 degrees of freedom

Residual Deviance: 407.267 on 110.1224 degrees of freedom

Number of Local Scoring Iterations: 7

DF for Terms and Chi-squares for Nonparametric Effects

            Df Npar Df Npar Chisq P(Chi)
(Intercept)  1
s(avedepth)  1     2.9   116.4413      0
 s(bottemp)  1     2.9   151.2236      0
        lat  1
        lon  1
```

```
1994
Summary(h94s2)

Call: gam(formula = form2, family = poisson, data = h94, na.action = na.omit)

Deviance Residuals:
     Min         1Q     Median            3Q      Max
 -16.4313 -0.6643988 -0.0686757 -0.0002249396 14.96985

(Dispersion Parameter for Poisson family taken to be 1 )

    Null Deviance: 17354.96 on 279 degrees of freedom

Residual Deviance: 1780.679 on 269.1192 degrees of freedom

Number of Local Scoring Iterations: 9

DF for Terms and Chi-squares for Nonparametric Effects

            Df Npar Df Npar Chisq P(Chi)
(Intercept)  1
s(avedepth)  1     2.8   2116.289      0
 s(bottemp)  1     3.0    937.258      0
        lat  1
        lon  1
```
