Hierarchical analysis of a remote, Arctic, artisanal longline fishery

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This is the first paper to explore trends in catch per unit effort (cpue) through time of a Greenland halibut *Reinhardtius hippoglossoides* stock targeted by an artisanal, winter fishery in Cumberland Sound on southern Baffin Island, Canada. We modelled cpue data from 1987 to 2003, looking at two questions: what factors have driven cpue trends, and is cpue an accurate index of a stock's abundance? In the context of limited data availability, we used generalized linear models (GLMs) and hierarchical models to assess important predictors of cpue. Hierarchical models with multiple fixed environmental effects contained fishing location or individual fisher as random effects. A month effect showed greatest catch rates during February and March; the monthly North Atlantic Oscillation index was positively associated with catch rates; and a change from decreasing to increasing cpue after 1996 was linked to reduced fishery participation following a large storm. The best Akaike's information criterion-ranked GLM identified a negative relationship of cpue with shark bycatch. Although data limitations precluded conventional stock assessment, our models implicated the environment and fisher behaviour as drivers of cpue trends. Additionally, using multiple hierarchical models to predict cpue provided a more informative analysis for understanding trends in cpue than a GLM alone.

Keywords: catch per unit effort, Cumberland Sound, Greenland halibut, mixed effects models, North Atlantic Oscillation.

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Introduction

Despite the commercial importance of the Greenland halibut *Reinhardtius hippoglossoides* to indigenous communities, stocks in the eastern Canadian Arctic have been relatively unstudied to date, in part because of the remoteness characterizing the fisheries. The Greenland halibut is a deep-water flatfish, found up to 1500 m deep in the Davis Strait off Baffin Island (Templeman, 1973) and as deep as 2200 m off West Greenland (Boje and Hareide, 1993). Small halibut typically inhabit shallower water (0–600 m), and the abundance of older, larger fish often increases with depth (Atkinson *et al*., 1982; Bowering, 1982; Atkinson and Bowering, 1987). Davis Strait is considered to be an important spawning area for Greenland halibut in the Northwest Atlantic (Jørgensen, 1997; Simonsen and Gundersen, 2005), and the pelagic eggs and larvae are dispersed via currents. The distribution of juvenile Greenland halibut has been linked to the North Atlantic Oscillation (NAO; Albert and Høines, 2003), which is an atmospheric pressure difference controlling the North Atlantic Current. As variations in the NAO lead to changes in ocean circulation and climatic conditions in the North Atlantic (Dickson *et al*., 1999, 2000), these fluctuations can cause changes in spawning locations and concentrations, and larval dispersion. Moreover, increased Greenland halibut commercial landings in West Greenland waters have coincided with NAO-driven periods of colder water (Buch *et al*., 2004).

Studies of Arctic/Antarctic systems, where harsh conditions limit methods for evaluating deep-water fisheries, often suffer from a lack of data to assess stock status. Although the goal of fisheries managers is to promote the sustainable production of fish stocks through formal stock assessment, it is often impractical to collect fishery-independent data in isolated or harsh environments, so the information collected by a fishery is the main (or only) source of abundance data available (Maunder *et al*., 2006). An artisanal longline fishery in Cumberland Sound, Nunavut, represents such a site, where inhospitable Arctic conditions and the remoteness of the fishery necessitate the use of fishery-dependent data to evaluate catch trends. Complicating this reliance on fishery-dependent data is the self-reporting nature of the fishery: all data available have been voluntarily recorded by individual fishers since the inception of the fishery in 1987. Characterized by winter sea ice that extends seawards from the shore (called landfast ice), Cumberland Sound contains a seasonal Inuit fishery for Greenland halibut that is accessible from the town of Pangnirtung. The fishery can only operate during winter when the formation of landfast ice allows fishers access to deep water; currently, no summer fishery exists owing to a lack of boats. Peak catches for the winter fishery were in the early 1990s, reaching more than 400 t, but recent years have yielded reduced total catch (e.g. just 3 t in 2007), potentially because of the increasingly shorter sea-ice seasons, less stable ice conditions, and fewer fishers participating in the fishery.

In this study, we evaluate catch per unit effort (cpue) from 1987 to 2003 within the fished areas of Cumberland Sound to determine the social and environmental factors that have driven the observed catch trends, and whether the cpue from the Cumberland Sound fishery is an accurate index of abundance for Greenland halibut. Past reports assessing Cumberland Sound Greenland halibut stocks have suggested overharvesting as a potential explanation for the decreasing cpue (Pike, 1994) and weight-at-age (Mathias and Keast, 1996). Treble (2008) showed that a decline in mean length and reduced catch rates could be attributed to changes in fishing location, growth-overfishing, or the development of the fishery, because an initial decline in cpue is to be expected for a new fishery. Although these factors potentially drive cpue, other factors may have affected local catch rates, including the NAO and/or the fishing characteristics of individual fishers.

Available Department of Fisheries and Oceans (DFO) Canada fisher-specific logbooks presented an opportunity to account for some effects of individual behaviour in Cumberland Sound. Cpue is thought to be influenced by fisher behaviour, e.g. by decisions of where and when to fish and what to target, through information sharing or increased fishing power (*sensu* Branch *et al.*, 2006). Allen and McGlade (1986) demonstrated the importance of identifying the "actors" in a fishery and including their subjective responses/actions in a model rather than assuming a global desire of fishers for optimal efficiency. Here, we explore how cpue trends in Cumberland Sound reflect aspects of fisher behaviour, specifically who fishes and where they fish, and how these vary relative to the physical environment.

Material and methods

Fishery characteristics

Cumberland Sound is an inlet on the southeastern side of Baffin Island, some 250 km long and 80 km wide (Figure 1). The bottom topography, although variable, generally consists of shallow margins with central depths >1500 m. Characterized by the formation of seasonal landfast ice, the timing and the extent of ice development vary annually based on the latent heat of surface water and the weather conditions (Treble, 2008). The observed fishing locations from 1987 to 2003 were generally dependent on sea-ice conditions, so catch locations varied annually. Overall, fishing has been concentrated in the northern portion of the sound, within 70 km of Pangnirtung.

The Cumberland Sound halibut fishery depends on the formation of landfast ice for travel to the deep-water fishing grounds and as a substructure for fishing. The fishery uses bottom longlines set through a hole in the ice; a metal kite that uses currents stretches the line along the bottom. The longline is then anchored in place with a heavy stone, and it remains attached to the ice with rope that extends the depth of the water. On average, 100 hooks are placed on the longline at ~2 m intervals using rope gangions. Between 1987 and 1995, the fishery shifted from being hand-operated to using power winches, making it easier to fish multiple lines (typically 2–3) from one hole, although no data were collected to evaluate this transition. The time required to bait and set additional lines was generally longer than the 2–3 h set time when a single line was used, leading to an increase in the average duration of longline sets to 8–10 h. Because of the increase in abundance of larger halibut with depth, fishing effort was focused between 800 and 1200 m in Cumberland Sound when ice conditions allowed. Fishers were also aware of halibut preference for mud substrata, and as such, directed their fishing in such areas. No offshore gillnetting or trawling is permitted in the Sound.

At the start of the fishery in 1987, voluntary logbooks were offered to fishers by DFO, and catch and effort trends have been monitored since the formation of the fishery. Because logbooks were voluntary, data are inconsistent in both frequency of records (how often the logbooks were submitted) and quality of records (how much information was recorded in each logbook). For example, we have records of the number of fishers who participated annually in the fishery, but no record of how many fishers our data cover annually, because fishers did not consistently record their names. Additionally, there has been no environmental monitoring or research conducted in Cumberland Sound, such as hydrographic records, climate studies, or an evaluation of the substratum. Other limitations to the data include a lack of fishery-independent surveys, no understanding of the local Greenland halibut catchability, and no estimates of total abundance. These restrictions in available data greatly limited the options available for stock assessment, leading us instead to focus on models that determine the processes driving cpue trends, e.g. social or environmental factors.

Logbook data included longline soak time, the number of hooks deployed, the number of fish caught, the number of sharks or skates caught as bycatch, fisher identification, and fishing locations (all terms are defined in Appendix 1, and tables of available data are provided in Appendix 2). Because fishers congregate for fishing (typically within sight of each other), location was reported based on the eight general areas, A–H, that they used annually (Figure 1). A monthly NAO index was taken from the Climate Analysis Section of the US National Center for Atmospheric Research (Hurrell, 1995). Further, based on our *a priori* expectations regarding the influence of fishers and the environment on catch rates, we utilized logbook information to generate several additional covariates: (i) the annual number of fishers, (ii) a pre-/post-storm dummy variable representing a storm in February 1996 that caused a 70% loss of fishing gear and subsequently led many fishers to stop fishing (and used to examine annual trends pre- and post-storm), (iii) a dummy variable representing the presence of shark bycatch, and (iv) a categorical variable for each surname reported in the logbook data, representing individual fishers, to structure a random-effects distribution of fisher effects (to maintain fisher anonymity, we assigned each of the 35 surnames a letter, A–Z, followed by AA–II). Again, the number of fishers who recorded their names varied annually and only represents a small portion of the total number of fishers participating in the fishery.

The response variable, cpue, was calculated as the number of Greenland halibut caught per 100 hooks per hour. As only a subset of the data had precise location or fisher name records, we created two subsets of data: (i) only observations associated with a location, and (ii) only observations associated with a fisher name. We visually compared the three datasets (all data included, location data only, and fisher data only) to ensure that they showed the same cpue trends through time.

Model structure

Following data exploration and organization, we established candidate models of cpue based on available explanatory data and highly correlated parameters. The models were built to incorporate all plausible combinations of variables, and all variables from the available data were included (NAO, month, number of

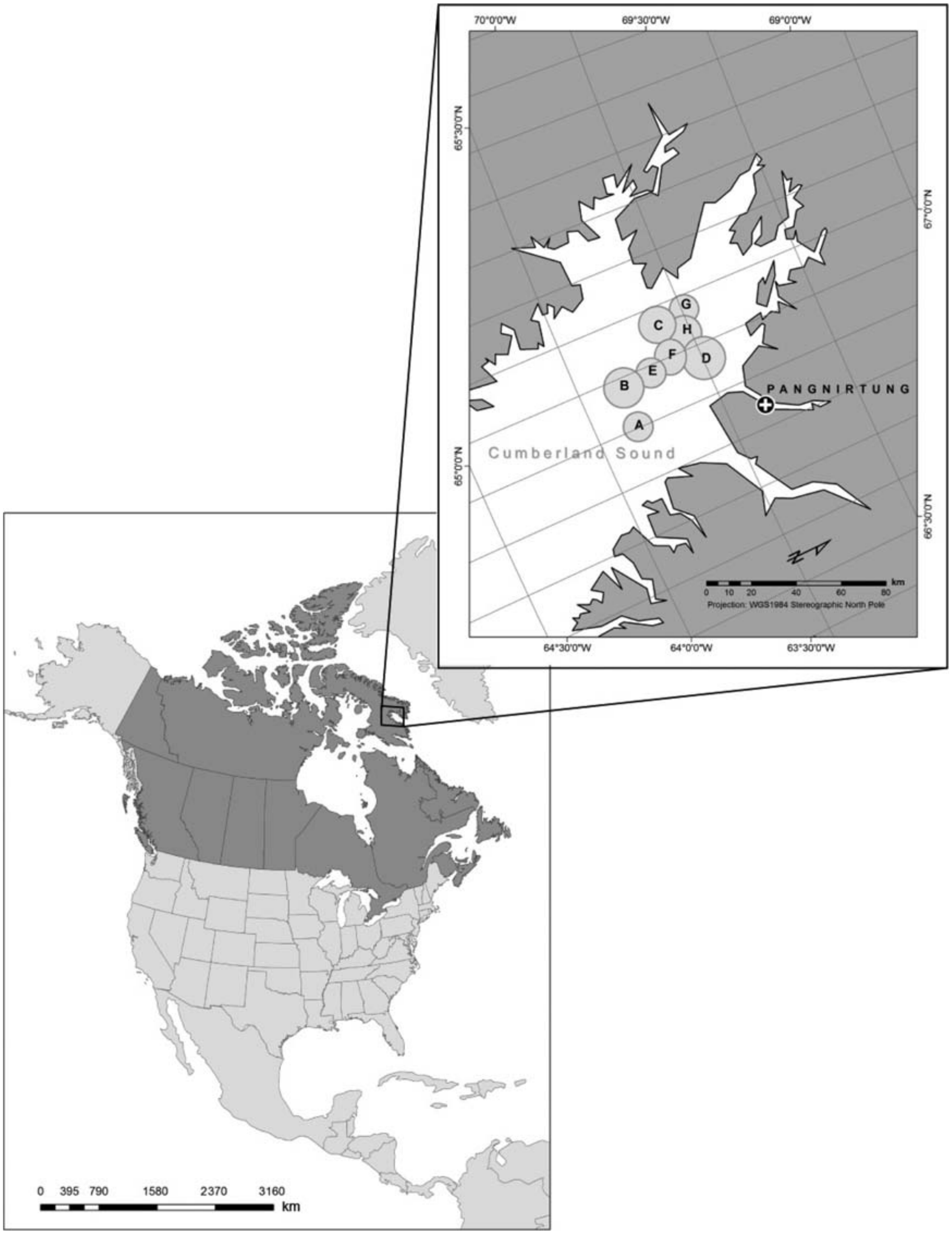

Figure 1. Location of the Inuit commercial fishery targeting Greenland halibut in Cumberland Sound, Nunavut, Canada. The letters A–H represent the fishing sites.

fishers, shark presence/absence, fisher name, location, pre-/post-storm dummy variable). Correlations between parameters were determined with the cor function in the statistical package R (R Development Core Team, 2008). All candidate models (Appendix 3) were run as generalized linear models (GLMs) or generalized mixed-effects (hierarchical) models. Essentially, each candidate model represented a hypothesis of the factors that were driving cpue and how those factors influenced cpue among the levels of location and fisher. Note that no "complete" dataset exists on which to build these models; only data recorded voluntarily exist for analysis. We checked the normality assumptions of our linear models by visual inspection of the residuals, leading to a natural log transformation of the response (cpue). As zero values posed a problem for natural log transformation, cpue was first modified by adding 0.1 fish per 100 hooks per hour to all observations.

After log transformation of the response, all candidate models assumed a normal distribution of errors, ε, run in the following form:

$$\log(\text{cpue})_i = \beta_0 + \beta_i x_{ki} + \varepsilon_i, \qquad (1)$$

where β_0 is the model intercept, and β_i is the model slope for any given covariate x_k. After original candidate models were formulated, the 8 location and 35 fisher levels led to overparameterization of the models. A mixed-effects route was followed. From the basic GLMs, we established a set of hierarchical models with location or fisher included as random effects. Because the same location or the same fisher will have multiple measurements of log(cpue), these measurements are correlated, an important aspect for a model to capture (Venables and Dichmont, 2004). Creating random effects in a generalized linear hierarchical approach accounts for the non-independence of observations (e.g. individual fishers) for predictors representing multiple levels (for further information on linear mixed models, see Robinson, 1991, and for further information on linear mixed models in fisheries research, see Venables and Dichmont, 2004).

Because only a subset of the data had precise location or fisher name records, we created two separate sets of hierarchical model. Therefore, we modelled a distribution of location and fisher via random effects that accounted for within-location and within-fisher dependence. Random effects allow us to build a distribution from localized, simple relationships available from the logbook data, and these distributions from the hierarchical models allow us to capture the broader, regional processes driving cpue. As not all years were represented in the subsets, shark bycatch records were too rare to include in the hierarchical models. Additionally, neither the full dataset nor the fisher hierarchical candidate models included the number of fishers and storm variables together in the same models because of a high correlation coefficient between the terms.

The candidate mixed-effects models were formed from

$$\log(\text{cpue})_{ij} = \beta_{0j} + \beta_{kj} x_{kij} + \varepsilon_{ij} + a_j, \qquad (2)$$

where β_{0j} is the model intercept, β_{kj} the model slope for any given covariate x_k of the jth location or fisher, ε_{ij} the normally distributed random error term, and a_j the random effect of either location or fisher, modelled as an independent and normally distributed variable. All candidate models were run using the glm and nlme packages in the statistical package R. Individual models were compared using Akaike's information criterion (AIC; Burnham and Anderson, 2002), and model goodness-of-fit (GOF) was assessed using likelihood ratio tests (LRTs) of each fitted model relative to a null (intercept-only) model (Zuur *et al.*, 2007).

Results

Data exploration

Pairwise plotting of explanatory variables showed no collinearity in the location subset, but in the fisher subset and the full dataset, a strong correlation existed between the number of fishers and the storm term ($r = -0.91$ and -0.79, respectively). The lack of correlation in the location subset results from the years represented: the location subset records only include 2 years following 1996, whereas the fisher and full datasets include all years after 1996. Therefore, the existence of the storm trend in the fisher and full datasets drives the correlation between the number of fishers and the storm. A plot of the complete dataset's raw log(cpue) data through time for Cumberland Sound demonstrated a clear drop in cpue since 1990–1992 (Figure 2a) to the lowest value in 1999, followed by an apparent increase in catch rates until 2002. The location and fisher subsets showed identical raw log(cpue) trends. A comparison of the complete dataset's raw log(cpue) plot (Figure 2a) with a plot of annual NAO index (Figure 2b) showed no obvious similarities, but comparison of a monthly NAO index plot for all years (Figure 2d) with a monthly log(cpue) plot for all years (Figure 2c) showed a parallel trend. Declines and increases in the NAO monthly index appeared to correspond to declines and increases in Cumberland Sound catch rates. A plot of fisher participation (Figure 2e) showed an increasing number entering the fishery after its onset, peak participation in 1995, then a sharp drop after the storm of 1996.

Generalized linear model

Although the use of different datasets can affect model parameter sizes, there was no way to determine which dataset most accurately represented Cumberland Sound reality, and discarding data for the covariates that were incompletely represented would have removed considerable information, forcing us to rely on the three separate datasets for modelling. The best AIC-ranked GLM (Table 1; MS11 in Appendix 3) included the fixed effects of year, NAO, month, shark presence/absence, and the interaction term of storm and year. The top-ranked GLMs and top-ranked hierarchical models all included the effects of year and NAO (Table 2). All three models selected showed strong correspondence between predicted and observed log(cpue) values (Figure 3). Model GOF LRTs for all top-ranked models verified the assumed normally distributed errors, and quantile–quantile plots also showed adequate model fit to normally distributed errors.

For GLM MS11, the predicted response when including all effects (combined model output) showed a decreasing trend in log(cpue), followed by a slight increase (Figure 4). The year effect indicated a general decrease in catch rates over time (Table 2), suggesting reduced abundance of Greenland halibut in the Sound through time. The NAO had a positive effect on log(cpue). Categorical month variables showed that February through May had higher log(cpue) than January, with the best catch rates in February and March. The interaction term between storm and year, shared by the best-fitting GLMs and fisher hierarchical models, reflected the change from declining catch rates before the 1996 storm to an increase in catch rates thereafter.

Because of the rarity of shark records within the data, only the GLMs could include the shark presence/absence variable, and it was identified as an important predictor of log(cpue). The negative value for shark presence indicated that the presence of a shark on the line reduced the predicted log(cpue).

Hierarchical models

Location

Based on the AIC values (Table 1), the best location model included the fixed effects of year, NAO, and the categorical month variable (LM7; Appendix 3). Combined model output indicated a steeper decline and increase in catch rates than GLM MS11 (Figure 4). The year effect, as in the GLM, showed a decrease

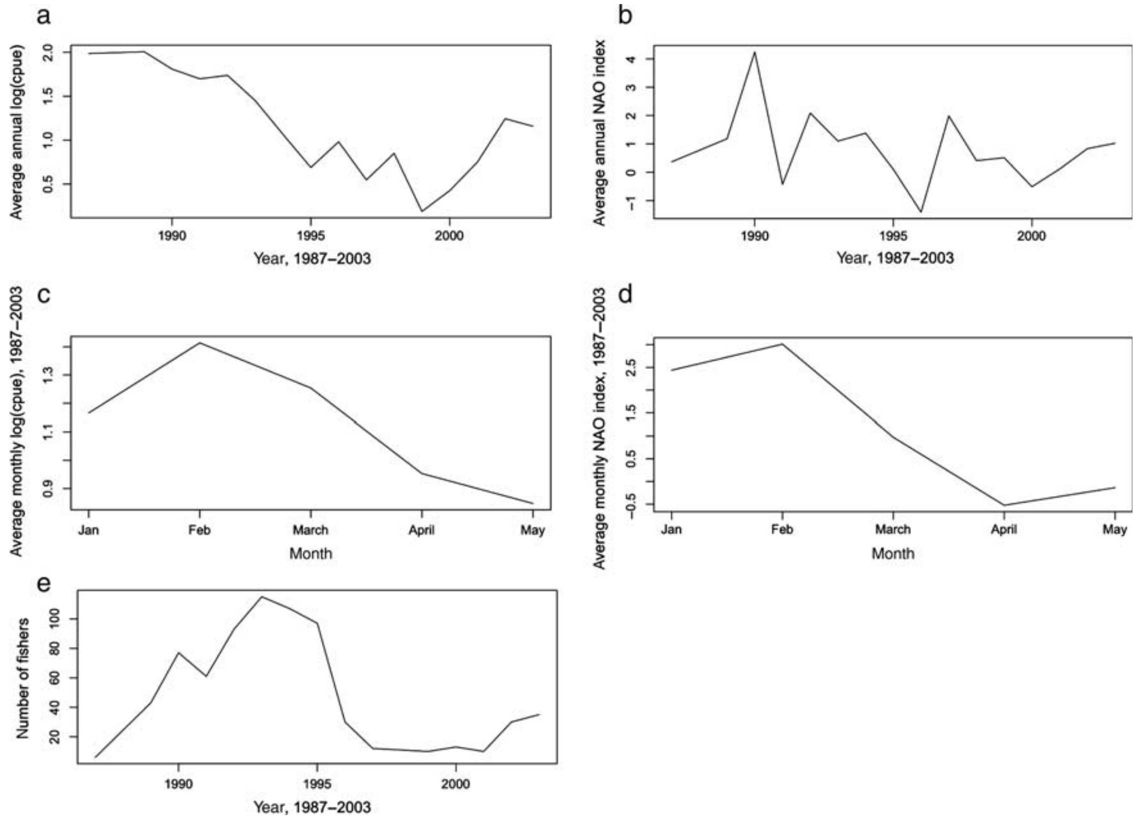

Figure 2. Trends in response and covariates. (a) Annual average log(cpue) through time, 1987 – 2003. (b) Average annual NAO index through time, 1987 – 2003. (c) Average monthly log(cpue) for all years, 1987 – 2003. (d) Monthly NAO index averaged for all years, 1987 – 2003. (e) Total number of fishers participating annually.

Table 1. AIC values for the best three AIC-ranked GLMs and hierarchical models.

Model	ID number	AIC value
Generalized linear model	11	33 927.47
	9	33 958.06
	8	33 960.80
Location hierarchical model	7	9 206.337
	14	9 215.101
	17	9 225.788
Fisher hierarchical model	7	13 507.86
	4	13 521.60
	5	13 555.21

in catch rates through time (Table 2), suggestive of reduced Greenland halibut abundance through time. The NAO effect on catch rates was positive, but the effect size was greater in the location hierarchical model than the GLM, suggesting that when location is accounted for, the estimated NAO effect on Greenland halibut increases. The categorical month variables showed best catch rates in March, followed by February. However, the magnitude of the effect of April was reduced more in the location hierarchical model than the GLM, whereas the effect of May became negative. This change to a negative month effect indicates that the GLM May effect is confounded by fishing location, so when locational variability has been accounted for in a hierarchical model, the May effect becomes negative.

Table 2. Parameter estimates and confidence intervals for the best-ranked GLM (MS11) and hierarchical models (location, LM7; fisher, FM7).

Parameter	GLM MS11	LM7	FM7
Intercept	1.2572 ± 0.05	0.7109 ± 0.24	0.7894 ± 0.89
Year	−0.1188 ± 0.01	−0.1146 ± 0.10	−0.2447 ± 0.03
NAO	0.0095 ± 0.01	0.0541 ± 0.02	0.0603 ± 0.02
Storm	−1.0773 ± 0.10	–	−1.1551 ± 0.14
Storm × Year	0.2303 ± 0.02	–	0.3719 ± 0.04
Month (February)	0.3128 ± 0.05	0.3077 ± 0.13	0.3417 ± 0.90
Month (March)	0.3951 ± 0.05	0.1751 ± 0.13	0.2106 ± 0.90
Month (April)	0.2502 ± 0.06	0.0710 ± 0.14	0.1758 ± 0.90
Month (May)	0.1700 ± 0.07	−0.6930 ± 0.17	−0.0416 ± 0.90
Shark presence	−0.1846 ± 0.04	–	–
Explained deviance	0.247	0.317	0.348

Fisher

The best AIC-ranked model for the fisher data (Table 1) included the fixed effects of year, NAO, month, and the interaction term of storm and year (FM7; Appendix 3). Combined model output also showed a steeper decline and increase in log(cpue) than GLM MS11. Year was negatively associated with log(cpue) (Table 2), but the year effect for FM7 was more negative than in the GLM and LM7; therefore, the decline in relative abundance was most pronounced when individual fishers were taken into account. A positive NAO paralleled positive log(cpue), but the

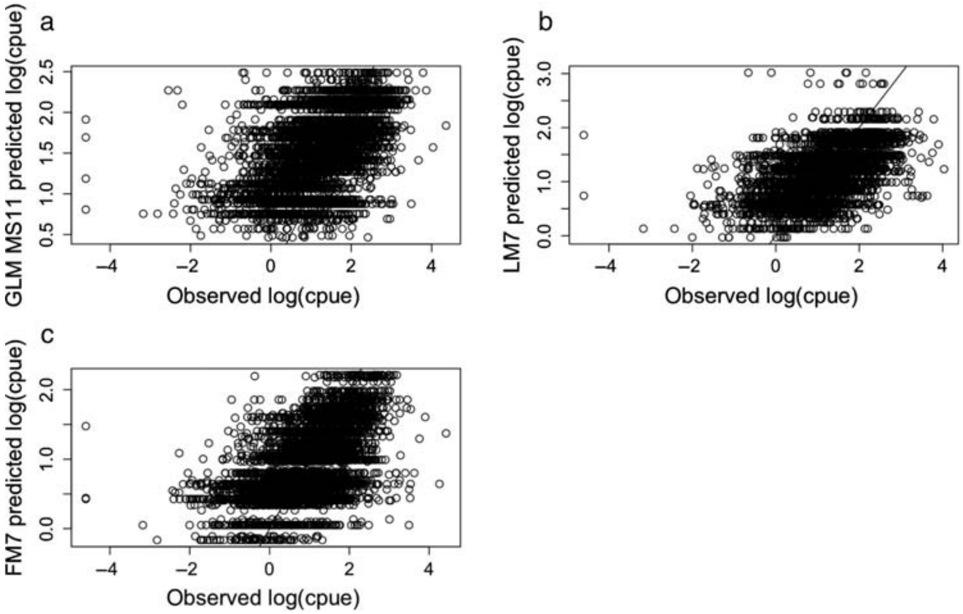

Figure 3. Comparison of predicted log(cpue) against observed log(cpue) for Greenland halibut in Cumberland Sound from (a) the best AIC-ranked GLM (MS11), (b) the location hierarchical model (LM7), and (c) the fisher hierarchical model (FM7).

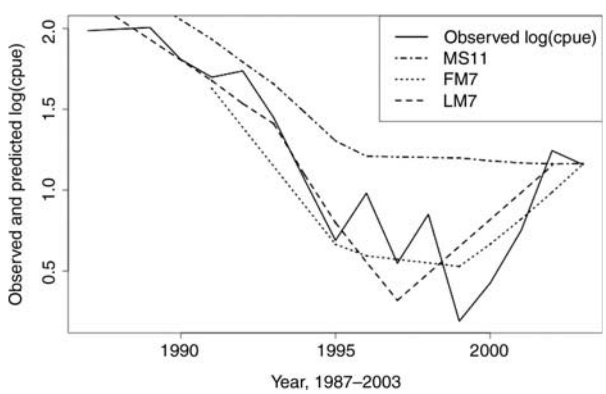

Figure 4. Observed log(cpue) through time with the predicted log(cpue) through time for the GLM (MS11), location hierarchical model (LM7), and fisher hierarchical model (FM7).

effect from the NAO was greatest for the fisher model (Table 2). Therefore, when individual differences between fishers were accounted for via a random effect, the effect of the NAO on catch rates increased. The categorical month variable mirrored the location hierarchical model with a negative effect of May, but the best catch rates were predicted for February, followed by March. For the interaction of storm and year, the predicted log(cpue) increased relative to the no-interaction model. The fisher model's storm effect size increased relative to the parameter estimate from the GLM, indicating a stronger change after 1996 from a declining to an increasing catch rate when individual fisher effects were taken into account.

Discussion

Annual trends in cpue are typically thought to reflect changes in annual abundance (Maunder and Punt, 2004), and negative trends are thought to represent decreases in relative abundance through time. However, the notion that cpue is often not proportional to abundance (Ultang, 1976; Garrod, 1977) demands explanatory data to standardize cpue and deal with the associated assumptions (e.g. constant catchability or random distribution of fishing effort relative to the fish; Maunder and Punt, 2004). As the data we analysed were insufficient to calculate stock biomass, we could not draw conclusions about trends in absolute abundance that may have driven some of the trends we observed. Yet, despite these data limitations, we have shown that raw cpue likely represented an inconsistent index of Greenland halibut relative abundance. Environmental factors such as the NAO and season appear to be driving trends in fish abundance, whereas aspects of the fishery, particularly individual fisher characteristics, affect the reported catch rates. Importantly, the magnitude of the environmental effects was altered when differences in catch rate among fishers were ignored.

In the GLM analysis of the full dataset (i.e. all years, 1987–2003), all available covariates, excluding the number of fishers, were identified as important predictors of Greenland halibut catch rates. The presence of Greenland sharks as bycatch, a variable only included in the GLM, affected catch rates negatively, demonstrating that sharks either prey on unhooked fish, scavenge hooked fish before being hooked themselves, or sever the longline. The tendency of Greenland sharks to entangle themselves in and/or break the longline is a major source of time and gear loss to Cumberland Sound fishers (Pike, 1994), and the negative relationship between sharks and catch rate could be due to a tendency of fishers to report sharks only when they foul their lines. The ability of a species to escape or avoid scavengers once hooked determines the catch actually brought to the surface, and the amount of time a baited hook is available on the bottom will influence how many fish are captured (Ward *et al.*, 2004). Although typically greater soak time allows for better catch rates, the risk of bycatch or scavenging also increases, and Greenland halibut may trade food for safety (McNamara and Houston, 1990) by avoiding longlines where sharks are present. Pike (1994) found a positive correlation between shark catch rates and set duration, which suggests that reducing set time would reduce Greenland shark bycatch, but since the transition to a power winch in these data, set times have actually increased. Unfortunately, records of the technology transition do not exist, preventing an assessment of bycatch about set time and the use of a power winch.

Both hierarchical models and the GLM identified two environmental factors associated with catch rates: the NAO index and month. Because of the lack of environmental records in Cumberland Sound, the NAO provided the best available proxy for capturing physical variability, because it is linked to changes in hydrographic characteristics, mixed layer depth, and circulation patterns (Drinkwater *et al.*, 2003). For example, fluctuations in the monthly NAO index have been linked to the timing of stratification in the North Sea (Sharples *et al.*, 2006), and the Davis Strait and Labrador Sea are mixing sites of both Arctic and Subarctic waters (Dunbar, 1951; Bailey, 1957). Changes in the boundaries of these waters have influenced the distribution of marine fauna in Cumberland Sound (Aitken and Gilbert, 1989).

The monthly NAO index has a significant positive effect on log(cpue) of Greenland halibut, consistent with observations from other fisheries in the North Atlantic (Bøgstad and Gjøsten, 1994; Friedland *et al.*, 1998; Dickson and Turrell, 1999). For example, the distribution of Greenland halibut in the Norwegian Sea was related to the hydrographic front between surface Atlantic water and colder, deeper water (Bakken *et al.*, 1975; Bergstad and Isaksen, 1987; Bergstad, 1990). The Faroe–Shetland Channel, which exhibits considerable interannual variability in currents and water temperature, has the highest Greenland halibut catch rates in intermediate waters originating in the Arctic (Bullough *et al.*, 1998). Therefore, NAO-mediated hydrographic changes could possibly influence the distribution of Greenland halibut within Cumberland Sound or their accessibility to fishers, or the positive relationship between the NAO and catch rates could be capturing local climatic and hydrographic changes that operate on a seasonal scale.

The increased NAO effect in the hierarchical models demonstrates that a high NAO index is associated with higher cpue, independent of fisher or catch location. Because the parallel trends in the NAO index and cpue were unrelated to fishery aspects such as fisher or location, NAO-mediated or NAO-related environmental changes likely affected Greenland halibut distribution. Distribution changes have been observed in other fish too, e.g. Atlantic salmon (*Salmo salar*), whose thermal habitat size shrunk during years of positive NAO index and expanded during negative phases (Friedland *et al.*, 1998; Dickson and Turrell, 1999). A high NAO could also expand thermal habitat size for Greenland halibut in Cumberland Sound and make them more available to fishers, thereby increasing catchability.

Separate from the monthly NAO index, both hierarchical models and the GLM contained an effect from the categorical variable month. We included the months January–May as factors, and in both types of models, February and March had the highest cpue relative to January. Some variation among months could possibly be attributed to the NAO, but the medium correlation strength between NAO and month ($r = -0.58$) suggests only a partial influence of NAO on the monthly variation in catch rates. Fishing location varied temporally based on formation and break-up of sea ice, but when fishing location was included as a random effect, the variation in monthly cpue became more pronounced. In the GLM, the fishing location and fishers participating were confounded with month and caused a positive May effect, but when variation in location or fisher was accounted for with hierarchical models, the May effect was negative. This difference in the May effect between the GLMs and the hierarchical models suggests that the likely mechanism for reduced May catch rates was an environmental effect associated with month. This result is consistent with previous findings from exploratory summer longline catches in Cumberland Sound, where catch rates were reduced relative to winter longline catches (Northlands Consulting, 1994; Mathias and Keast, 1996) and only trawl and gillnet gear fishing at deep-water stations within Cumberland Sound produced catches (Northlands Consulting, 1994). Observed changes in catchability with season suggest that environmental factors could be influencing fish distribution.

One possible reason for a change in distribution could be migration associated with the onset of maturity in Greenland halibut. Distribution and size data from a trawl survey suggest a late summer movement of Greenland halibut to spawning grounds in the deep waters (>1000 m) of Davis Strait (Jørgensen, 1997). Additionally, seasonal migration between feeding and spawning areas has been observed for Greenland halibut in the Gulf of St Lawrence (Bowering, 1982) and Icelandic waters (Sigurdsson, 1979). However, if Greenland halibut migrate seasonally, catches between Cumberland Sound and Davis Strait would be expected; an exploratory fishery in Cumberland Sound caught no Greenland halibut at the Sound's mouth during August/September 1994 (Northlands Consulting, 1994). This absence suggests that if the fish leave, they do so before late summer or their behaviour reduces their catchability to near zero. Additionally, reduced catch could also result from a general dispersal within Cumberland Sound as opposed to an outmigration to Davis Strait. Nonetheless, parasite fauna on Cumberland Sound fish could not be distinguished from the fauna on fish from Hawke Channel in the Labrador Sea, implying movement to/from the Sound (Arthur and Albert, 1993).

The most important conclusion from the present analysis for future assessments in Cumberland Sound and other self-reporting, artisanal fisheries is that incorporation of random effects in fishery-dependent data analysis is critical for unbiased interpretation. Because fishers can increase fishing power, share information, move location, and, as in Cumberland Sound, report cpue themselves, it is the data source most likely to be influenced by their behaviour (Branch *et al.*, 2006), and teasing apart the effects of behaviour from other potential covariates is therefore an important step in analysing fishery-dependent data. In our study, because who fishes and where they fish make cpue observations non-independent, assessing their individual decisions is necessary for understanding cpue trends. The voluntarily recorded names and locations within this dataset allowed us to explore fisher behaviour and demonstrate that, at a small scale, individual decisions can affect raw cpue trends.

For Cumberland Sound, participation in the fishery rapidly increased after the initial successful years. The commercial popularity of Greenland halibut and the introduction of power winches to increase fishing efficiency attracted new individuals each year until a storm in 1996 caused gear loss, preventing any subsequent return of many fishers. As evidenced by large variation in fisher catch rates relative to the mean and consistent with predictions from behaviour theory (Branch *et al.*, 2006), differences in longlining skills varied widely among fishers, causing distorted trends in GLM environmental covariates.

Included as a dummy variable in both the GLM and the fisher hierarchical model, the 1996 storm changed the predicted cpue slope from declining to increasing. For the GLM where fisher differences were not considered, such a transition could represent the behaviour of fishers remaining after 1996, i.e. the fishers who most likely remained or re-entered the fishery after a gear loss of 70% were skilled, risk-taking fishers (*sensu* Allen and McGlade, 1986; Holland and Sutinen, 2000). However, the significance of the storm effect in the fisher hierarchical model suggests that fisher skill was not linked to the increased cpue after 1996. The size of the storm effect was increased in the hierarchical model, demonstrating that the storm effect captured a change in cpue unrelated to fisher behaviour because variation within individual fishers was accounted for through a random effect term.

As the hierarchical model in effect removed personal behaviour effects, the storm effect must represent something separate from fisher decisions and skill. One possibility is that increased cpue following 1996 was a result of reduced fishing pressure that led to a greater abundance of Greenland halibut. In fact, although the models predict increased cpue following 1996, the raw cpue data show the slope change in 1999 (Figure 4), consistent with the time-delay needed for a fish population to increase abundance. Without incorporating random effects, however, the exclusion of fisher skill as a possible explanation for the storm effect would not have been possible. As such, the application of hierarchical modelling provided a coherent approach for incorporating individual fisher decisions in fishery-dependent data analysis and for more accurately interpreting cpue trends.

Conclusion

The self-reported cpue in the Cumberland Sound fishery reflects a considerable influence of individual fisher behaviour and location, and we suggest that trends in the abundance and distribution of Greenland halibut, as represented by catch rates, result from both variations in the environment as well as the stock itself. Essentially, the trends in cpue have been driven by the NAO and month, and the variation in fisher presence (as represented by the storm variable) could have caused the change from declining to increasing cpue. The influence these factors have on raw cpue suggests that future stock assessments of Greenland halibut in Cumberland Sound must account for fisher behaviour influencing reported catch rates if they are to assess relative fish abundance accurately. The time-series, multilevel, nature of fishery-dependent data make such data inherently hierarchical, so the utilization of random effects in a hierarchical model is a more appropriate approach to structure fishery-dependent data analysis than conventional GLMs.

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Appendix 1
Variables in catch record data

Year	Year of catch observation
Julian day	Julian day of catch observation
Date	Date of catch observation
Month	Month of catch observation (1, January; 2, February; 3, March; 4, April; 5, May)
Set	Time of day line was set
Hauled	Time of day line was hauled
Duration	Soak time (h)
Hset	Number of hooks set on line
Hlost	Number of hooks lost during soak
Hfished	Number of hooks returned when line hauled
Greenland halibut	Number of Greenland halibut caught
Greenland halibut/100 hooks	(Greenland halibut caught per hooks fished) × 100
Greenland halibut/100 hooks/h	Greenland halibut caught per 100 hooks per duration
Shark	Number of Greenland sharks caught
Shark/100 hooks	(Sharks caught per hooks fished) × 100
Shark/100 hooks/h	Sharks caught per 100 hooks per duration
Ray	Number skates or rays caught
Location	Sites fished, A–H
Fisher	Full name of fisher for observation
Family	Surname of fisher for observation
NAO	North Atlantic Oscillation index (monthly)
Storm	Dummy variable (0, before February 1996 storm; 1, after February 1996 storm)
SharkPres	Dummy variable (0, shark not captured; 1, shark(s) captured)
NumFish	Total number of fishers participating in fishery for year of observation (not the number of fishers who turned in the voluntary logbooks)

Appendix 2
Number of catch records in each dataset by year

Year	All years	Location	Fisher
1987	108	108	0
1988[a]	0	0	0
1989	797	0	0
1990	1 361	0	0

Continued

Continued

Year	All years	Location	Fisher
1991	1 256	821	1 096
1992	489	223	0
1993	491	448	0
1994	689	429	0
1995	1 723	1 296	1 639
1996	127	49	83
1997	861	339	855
1998	522	0	0
1999	322	0	322
2000	93	0	626
2001	184	0	184
2002	563	208	563
2003	377	0	377
Total	9 963	3 921	5 745

[a]No records exist for 1988.

Annual total number of fishers in the fishery by year and the annual number of fishers who recorded their names (note that there is no record of how many fishers submitted logbooks, because not all recorded their names)

Year	Annual total	Recorded names
1987	6	0
1988	9	0
1989	43	0
1990	77	0
1991	61	27
1992	93	0
1993	115	0
1994	107	0
1995	97	18
1996	30	2
1997	12	10
1998	Unknown	0
1999	10	2
2000	13	5
2001	10	1
2002	30	6
2003	35	4

Annual total harvest and length of season

Year	Total harvest (t)	Season length (weeks)
1987	4	9
1988	11	7
1989	180	14
1990	255	18
1991	147	12
1992	430	21
1993	425	18
1994	400	18
1995	285	18
1996	60	18
1997	60	16
1998	63	13
1999	34	14
2000	45	13
2001	78	12
2002	106	11
2003	242	14

Appendix 3
Candidate cpue general linear models for all years, 1987–2003

MS0 $\log(\text{cpue})_i$	$= \beta_0 + \varepsilon_i$
MS1	$= \beta_0 + \beta_1\text{Year}_i + \varepsilon_i$
MS2	$= \beta_0 + \beta_1\text{Year}_i + \beta_2\text{Month}_i + \varepsilon_i$
MS3	$= \beta_0 + \beta_1\text{Year}_i + \beta_2\text{Month}_i + \beta_3\text{NAO}_i + \varepsilon_i$
MS4	$= \beta_0 + \beta_1\text{Year}_i + \beta_2\text{Month}_i + \beta_3\text{NAO}_i + \beta_4\text{SharkPres} + \varepsilon_i$
MS5	$= \beta_0 + \beta_1\text{Year}_i + \beta_2\text{NAO}_i + \varepsilon_i$
MS6	$= \beta_0 + \beta_1\text{Year}_i + \beta_2\text{NAO}_i + \beta_3\text{SharkPres}_i + \varepsilon_j$
MS7	$= \beta_0 + \beta_1\text{Year}_i + \beta_2\text{Month}_i + \beta_3\text{SharkPres}_i + \varepsilon_j$
MS8	$= \beta_0 + \beta_1\text{Year}_i + \beta_2\text{Storm}_i + \beta_3\text{Year}_i \times \text{Storm}_i + \beta_4\text{Month}_i + \varepsilon_i$
MS9	$= \beta_0 + \beta_1\text{Year}_i + \beta_2\text{Storm}_i + \beta_3\text{Year}_i \times \text{Storm}_i + \beta_4\text{Month}_i + \beta_5\text{NAO}_i + \varepsilon_i$
MS10	$= \beta_0 + \beta_1\text{Year}_i + \beta_2\text{Storm}_i + \beta_3\text{Year}_i \times \text{Storm}_i + \beta_4\text{NAO}_i + \varepsilon_i$
MS11	$= \beta_0 + \beta_1\text{Year}_i + \beta_2\text{Storm}_i + \beta_3\text{Year}_i \times \text{Storm}_i + \beta_4\text{Month}_i + \beta_5\text{NAO}_i + \beta_6\text{SharkPres}_i + \varepsilon_i$
MS12	$= \beta_0 + \beta_1\text{Year}_i + \beta_2\text{Storm}_i + \beta_3\text{Year}_i \times \text{Storm}_i + \beta_4\text{NAO}_i + \beta_5\text{SharkPres}_i + \varepsilon_i$
MS13	$= \beta_0 + \beta_1\text{Year}_i + \beta_2\text{Storm}_i + \beta_3\text{Year}_i \times \text{Storm}_i + \varepsilon_i$
MS14	$= \beta_0 + \beta_1\text{Year}_i + \beta_2\text{Storm}_i + \beta_3\text{Year}_i \times \text{Storm}_i + \beta_4\text{SharkPres}_i + \varepsilon_i$
MS15	$= \beta_0 + \beta_1\text{Year}_i + \beta_2\text{Storm}_i + \beta_3\text{Year}_i \times \text{Storm}_i + \beta_4\text{Month}_i + \beta_5\text{SharkPres}_i + \varepsilon_i$
MS16	$= \beta_0 + \beta_1\text{Year}_i + \beta_2\text{NumFish}_i + \varepsilon_i$
MS17	$= \beta_0 + \beta_1\text{Year}_i + \beta_2\text{NumFish}_i + \beta_3\text{Month}_i + \varepsilon_i$
MS18	$= \beta_0 + \beta_1\text{Year}_i + \beta_2\text{NumFish}_i + \beta_3\text{NAO}_i + \varepsilon_i$
MS19	$= \beta_0 + \beta_1\text{Year}_i + \beta_2\text{NumFish}_i + \beta_3\text{Month}_i + \beta_4\text{SharkPres}_i + \varepsilon_i$
MS20	$= \beta_0 + \beta_1\text{Year}_i + \beta_2\text{NumFish}_i + \beta_3\text{SharkPres}_i + \varepsilon_i$
MS21	$= \beta_0 + \beta_1\text{Year}_i + \beta_2\text{NumFish}_i + \beta_3\text{Month}_i + \beta_4\text{NAO}_i + \beta_5\text{SharkPres}_i + \varepsilon_i$
MS22	$= \beta_0 + \beta_1\text{Year}_i + \beta_2\text{NumFish}_i + \beta_3\text{NAO}_i + \beta_4\text{SharkPres}_i + \varepsilon_i$
MS23	$= \beta_0 + \beta_1\text{Year}_i + \beta_2\text{SharkPres}_i + \varepsilon_i$

Candidate location hierarchical models

LM0 $\log(\text{cpue})_{ij}$	$= \beta_{0j} + \varepsilon_{ij} + \text{Location}$
LM1	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \varepsilon_{ij} + \text{Location}$
LM2	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{Month}_{ij} + \varepsilon_{ij} + \text{Location}$
LM3	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{NAO}_{ij} + \varepsilon_{ij} + \text{Location}$
LM4	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{Storm}_{ij} + \beta_{3j}\text{Year}_{ij} \times \text{Storm}_{ij} + \varepsilon_{ij} + \text{Location}$
LM5	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{NumFish}_{ij} + \varepsilon_{ij} + \text{Location}$
LM6	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{NumFish}_{ij} + \beta_{3j}\text{Month}_{ij} + \varepsilon_{ij} + \text{Location}$
LM7	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{NAO}_{ij} + \beta_{3j}\text{Month}_{ij} + \varepsilon_{ij} + \text{Location}$
LM8	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{Month}_{ij} \times \text{NAO}_{ij} + \varepsilon_{ij} + \text{Location}$
LM9	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{NumFish}_{ij} + \beta_{3j}\text{NAO}_{ij} + \varepsilon_{ij} + \text{Location}$
LM10	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{NumFish}_{ij} + \beta_{3j}\text{Month}_{ij} \times \text{NAO}_{ij} + \varepsilon_{ij} + \text{Location}$
LM11	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{NumFish}_{ij} + \beta_{3j}\text{NAO}_{ij} + \beta_{4j}\text{Month}_{ij} + \varepsilon_{ij} + \text{Location}$
LM12	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{Storm}_{ij} + \beta_{3j}\text{Year}_{ij} \times \text{Storm}_{ij} + \beta_{4j}\text{NAO}_{ij} + \varepsilon_{ij} + \text{Location}$
LM13	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{Storm}_{ij} + \beta_{3j}\text{Year} \times \text{Storm}_{ij} + \beta_{4j}\text{Month}_{ij} + \varepsilon_{ij} + \text{Location}$
LM14	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{Storm}_{ij} + \beta_{3j}\text{Year}_{ij} \times \text{Storm}_{ij} + \beta_{4j}\text{Month}_{ij} + \beta_{5j}\text{NAO}_{ij} + \varepsilon_{ij} + \text{Location}$
LM15	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{Storm}_{ij} + \beta_{3j}\text{Year}_{ij} \times \text{Storm}_{ij} + \beta_{4j}\text{NAO}_{ij} + \beta_{5j}\text{NumFish}_{ij} + \varepsilon_{ij} + \text{Location}$
LM16	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{Storm}_{ij} + \beta_{3j}\text{Year}_{ij} \times \text{Storm}_{ij} + \beta_{4j}\text{Month}_{ij} + \beta_{5j}\text{NumFish}_{ij} + \varepsilon_{ij} + \text{Location}$
LM17	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{Storm}_{ij} + \beta_{3j}\text{Year}_{ij} \times \text{Storm}_{ij} + \beta_{4j}\text{Month}_{ij} + \beta_{5j}\text{NAO}_{ij} + \beta_{6j}\text{NumFish}_{ij} + \varepsilon_{ij} + \text{Location}$

Candidate fisher hierarchical models

FM0 $\log(\text{cpue})_{ij}$	$= \beta_{0j} + \varepsilon_{ij} + \text{Fisher}$
FM1	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \varepsilon_{ij} + \text{Fisher}$
FM2	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{Month}_{ij} + \varepsilon_{ij} + \text{Fisher}$
FM3	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{NAO}_{ij} + \varepsilon_{ij} + \text{Fisher}$
FM4	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{Storm}_{ij} + \beta_{3j}\text{Year}_{ij} \times \text{Storm}_{ij} + \beta_{4j}\text{NAO}_{ij} + \varepsilon_{ij} + \text{Fisher}$
FM5	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{Storm}_{ij} + \beta_{3j}\text{Year}_{ij} \times \text{Storm}_{ij} + \beta_{4j}\text{Month}_{ij} + \varepsilon_{ij} + \text{Fisher}$
FM6	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{Month}_{ij} + \beta_{3j}\text{NAO}_{ij} + \varepsilon_{ij} + \text{Fisher}$
FM7	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{Storm}_{ij} + \beta_{3j}\text{Year}_{ij} \times \text{Storm}_{ij} + \beta_{4j}\text{Month}_{ij} + x_{5j}\text{NAO}_{ij} + \varepsilon_{ij} + \text{Fisher}$
FM8	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{Storm}_{ij} + \beta_{3j}\text{Year}_{ij} \times \text{Storm}_{ij} + x_{4j}\text{Month}_{ij} \times \text{NAO}_{ij} + \varepsilon_{ij} + \text{Fisher}$
FM9	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{NumFish}_{ij} + \varepsilon_{ij} + \text{Fisher}$
FM10	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{NumFish}_{ij} + \beta_{3j}\text{Month}_{ij} + \varepsilon_{ij} + \text{Fisher}$
FM11	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{NumFish}_{ij} + \beta_{3j}\text{NAO}_{ij} + \varepsilon_{ij} + \text{Fisher}$
FM12	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{NumFish}_{ij} + \beta_{3j}\text{NAO}_{ij} + \beta_{4j}\text{Month}_{ij} + \varepsilon_{ij} + \text{Fisher}$
FM13	$= \beta_{0j} + \beta_{1j}\text{Year}_{ij} + \beta_{2j}\text{NumFish}_{ij} + \beta_{3j}\text{Month}_{ij} \times \text{NAO}_{ij} + \varepsilon_{ij} + \text{Fisher}$

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