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A PRELIMINARY WESTERN ATLANTIC BLUEFIN TUNA INDEX OF ABUNDANCE BASED ON CANADIAN AND USA ROD AND REEL FISHERIES DATA: 1984-2014

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SUMMARY

Three indices of large western Bluefin tuna abundance are consolidated to form a single standardized index. This index is based on data from the Canadian rod and reel, tended line and harpoon fisheries and the USA rod and reel and hand line fisheries. The large number of trips with no catch result in overdispersion which is addressed using a Poisson model with an observation level random effect; a zero-inflated Poisson with an observation level random effect and a hurdle Poisson with an observation level random effect.

RÉSUMÉ

Trois indices d'abondance de grands thons rouges de l'Ouest sont consolidés pour former un seul indice standardisé. Cet indice est basé sur les données des pêcheries canadiennes opérant à la canne et moulinet, à la ligne tendue et au harpon et des pêcheries des États-Unis opérant à la canne et moulinet et à la ligne à main. Le grand nombre de sorties sans capture entraîne une surdispersion qui est traitée à l'aide d'un modèle de Poisson avec un effet aléatoire au niveau de l'observation ; un modèle de Poisson à inflation de zéros avec un effet aléatoire au niveau de l'observation et un modèle de Poisson "hurdle" avec un effet aléatoire au niveau de l'observation.

RESUMEN

Se consolidan tres índices de abundancia de atún rojo occidental grande para formar un único índice estandarizado. Este índice se basa en datos de las pesquerías canadienses de caña y carrete, de barrilete y de arpón y en las pesquerías estadounidenses de caña y carrete y liña de mano. El gran número de mareas sin capturas tuvo como resultado la sobredispersión, que se solucionó utilizando un modelo Poisson con un efecto aleatorio a nivel de observación, un modelo Poisson de ceros aumentados con un efecto aleatorio a nivel de observación y un modelo Poisson hurdle con un efecto aleatorio a nivel de observación.

KEYWORDS

Catch Rates, Bluefin tuna, Rod and Reel

1. Introduction

The western Atlantic bluefin tuna stock status is based on an age structured population model (Lauretta *et al.* 2015) fit using, mainly, fishery dependent catch/effort rates. Several of these relative abundance time series represent trends of the same sized fish in adjoining geographical areas and are possibly reflecting changes in the distribution of a stock component rather than changes in biomass (**Figure 1**). Given that the nature of the fishing is similar across these areas, consolidating the data would be more likely to yield a signal that was proportional to the true biomass of that stock component and be less sensitive to changes in stock distribution over time.

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The objective of this analysis was to combine the fishing data from the USA and Canada for bluefin tuna above 110 kg and provide a single standardized index for an area from Cape Cod to the Gulf of St. Lawrence. This would effectively meld three large fish indices into a single index, and resolve contradictory stock assessment model data inputs.

Description of the data source

The details of the Canadian fisheries are given in Andrushchenko and Hanke (2016, *in press*) and for the USA rod and reel fishery in Lauretta and Brown, 2015. The data from USA and Canada were combined according to the protocols outlined in Lauretta *et al.* 2016 (*in press*). The environmental covariates added to the data included sea surface temperature, ocean depth, seafloor gradient and forage habitat suitability. The source of the covariates is described in the document except for forage habitat suitability index which was provided by Druon *et al.* (2016 *in press*, SCRS/2015/P/002).

1.1 Description of the fishery and target species

Across the entire spatial domain of the data and for the fishing gears selected, bluefin tuna are the primary target species. The vessels tend to be small (<45') but will venture out to the Scotian Shelf break on trips as long as a week in some areas (e.g. Southwest Nova Scotia). The gear types and their and the way it is used are similar in each area.

1.2 Size, age range and condition of the fish that the index applies to

The analysis was limited to Bluefin tuna above 110 kg or 177 cm in straight fork length.

1.3 Changes in the fishery that might affect catch rates

In Canada, the mandatory submission of logbooks was instituted in 1996. Prior to this, the fishing data were submitted voluntarily and consequently the representativeness of the submissions was not known.

In 2004, the southwest Nova Scotia (SWNS) fleet moved from a competitive fishery to an Individual Transferrable Quota (ITQ) system. The main fleet fishing in the southern Gulf of St. Lawrence (GSL) adopted an ITQ-like system in 2011. Fishing within statistical area 4W (NENS) is subject to the same management structure of SWNS, except in area 4Wd where the fishery continues to operate in a competitive manner. Historical catches in 4V (NENS) are subject to the same restrictions as the GSL fleet. In the USA the vessels fish under a competitive system with individual trip limits based on size class categories.

According to industry feedback, market demand for a given size class of tuna has had some effect on the SWNS fishery's harvest decisions in 2014.

Fishermen from the GSL fleets have indicated that large bluefin tuna have moved north in the Gulf of St. Lawrence, while the smaller individuals remain in the region. This has been a concern for fishermen and managers over the past two fishing seasons. Frequency histograms of the catch in the GSL show that the prevalence of bluefin tuna less than 350 kg has been increasing since 2010. This may be evidence of a strong cohort but could also represent an increase of migrants from the eastern stock. Two 2015 tag recoveries in the GSL were from fish tagged in a Portuguese trap and another by French bait boats in the Bay of Biscay. This type of movement has never been reported and is in addition to discoveries of 2 GSL fish trailing eastern origin swordfish long line gear.

The GSL fleet is large in comparison to the SWNS fleet but their allocation is not proportional to the number of license holders. In the GSL, 695 license holders are allocated 54.37% of the Canadian bluefin tuna quota whereas in SWNS 42 license holders are allocated 21.7%. Thus, each SWNS fishermen has over 6.5x more quota per license compared with the GSL.

2. Methods

2.1 Data Exclusions and Rationale

The trip level data for the mid-Atlantic, Maine, Gulf of St. Lawrence and north east Scotian Shelf areas was aggregated to gear-port-days. In these areas, trips are under a day in length and catch is limited to one or two fish whereas in south west Nova Scotia, trips are many days in length and more fish are permitted per trip.

The Canadian fishery data was limited to catches made by tended line, rod and reel and harpoon, excluding catches made by the trapnet fleet in St. Margaret's Bay. USA used only hand line and rod and reel. The months with fishing included July through November and were limited to years 1984 – 2014.

2.2 Management Regulations

There have been two major changes in the management of the Canadian bluefin tuna fishery: 1) the introduction of mandatory log submissions in the mid-1990s and 2) the switch to an Individual Transferable Quota (ITQ) fishery in the early 2000s (SWNS, some 4W) and 2010s (sGSL). Starting in 1996, mandatory log submissions provided detailed information on all trips targeting bluefin tuna in Canadian waters, including trips with no catch; prior to 1996, this information was submitted on a voluntary basis.

As a consequence of ICCAT recommendations, which became effective in 1992, various regulatory changes were implemented for U.S. fisheries. Those measures included daily catch limits on anglers and/or vessels and fishery closures for various size categories of bluefin. The applicable fishery closures and catch limits, allocated by regulatory categories Angling (non-commercial) and General (commercial), have been documented by Ortiz *et al.* 1999, Brown *et al.* 1999, and Brown (2009).

2.3 Dataset used in the Analysis

The data span the period 1984 to 2014 and spatially from Cape Cod to the Gulf of St. Lawrence. It represents the fishing efforts of three gear types: rod and reel; harpoon and handline/tended line occurring seasonally. The seasons are defined as follows: early= {July, August}; mid= {September} and late= {October, November}. **Table 1** shows the distribution of the data by factor. The fishing domain was sub divided into 5 geographic units that also share similar fishing practices. In the U.S.A these were mid-Atlantic and Maine, with the former representing all fishing from states south of Maine to roughly Cape Cod (New Hampshire, Massachusetts, and Rhode Island). In Canada, these were Southwest Nova Scotia (SWNS), Northeast Nova Scotia (NENS) and the Gulf of St. Lawrence (GSL).

2.3.1 The effort and catch variables

Effort hours and count of bluefin tuna caught, aggregated to trip, were used to develop the standardized index.

2.4 Model Standardization and Diagnostics

All models were fitted in a Bayesian framework using Markov chain Monte Carlo methods in the R package MCMCglmm (Hadfield 2010, 2015). While many of the models could be fitted in a frequentist framework, only MCMCglmm provided the flexibility to model random effects and residual variance structures for zero inflated, hurdle and zero altered response distributions. Additionally, MCMCglmm converged quicker than JAGS and converged when glmer (R package lme4) failed.

Convergence of each parameter on the equilibrium distribution was monitored using visual inspection of the MCMC chain. Autocorrelation of successive MCMC estimates was also checked visually and assessed with estimates of effective sample size.

The checking of model adequacy is possible using residual diagnostics (e.g. Pearson residuals plotted against each covariate) for models with a single error term. For models that include random effects other than a residual term (hierarchical) checking of model adequacy is best assessed using posterior predictive checks. Both approaches were used whenever possible.

The Deviance Information Criterion (DIC) is computed by MCMCglmm and was used with caution in the model selection process given that when N is large, DIC tends to favour more complex models.

The factors available for the analysis included gear, area, season, year and continuous variables include hours fished and year. The only two-way interaction considered was that between season and area as it was conceivable that the seasonal trend in catch could vary by area. Gears were not expected to vary in their effectiveness seasonally nor do we expect the gears to perform differently in the different areas or across years. A potential year by area or year by season effect was not addressed at this point. Including a flag or fleet effect was considered but it is captured by the area effect under the current definition of area.

2.4.1 Poisson models with observation level random effect

The catch was believed to be the product of a count process and over-dispersion is modeled using an observation level random effect. The *de facto* model for MCMCglmm always controls for over-dispersion and unlike GLM, which uses a multiplicative model of over-dispersion, it uses an additive model (Hadfield, 2012). Consequently, the linear predictor includes a 'residual' for which a residual variance is estimated. This over-dispersed Poisson model is functionally very similar to a negative binomial model (Atkins *et al.* 2013). The base Poisson model included fixed effects for year, season, area and gear with a log(Hour) offset and model 2 included a season by area interaction and is given by:

$$
\begin{aligned}
&Catch_{ijkl} \sim Pois(\exp(l_{ijkl}))\\
&l_{ijkl} = \eta_{ijkl} + \varepsilon_{ijkl}\\
&\eta_{ijkl} = \beta_1 + \beta_2 \times fYear_i + \beta_3 \times fSeason_j + \beta_4 \times fArea_k + \beta_5 \times fGear_l + \beta_6 \times fSeason : fArea_{jk} + \log Hours_{ijkl}\\
&\log(\mu_{jkli}) = \eta_{ijkl}\\
&\varepsilon_{ijkl} \sim N(0, \sigma_\varepsilon^2)
\end{aligned}
$$

Random components of a Poisson GLMM model with a non-identity link function do not have a mean of zero on the scale of the observations. Consequently, to avoid underestimates, predictions must include both fixed and random effects (Atkins *et al.* 2013, Breslow and Clayton 1993, Hadfield 2012). The unconditional mean and variance as given by Greene (2007, p130) are:

$$
\begin{aligned}
&E(Catch_i) = \mu_i \cdot \exp(\sigma^2/2)\\
&Var(Catch_i) = \mu_i \cdot \exp(\sigma^2/2) \cdot \{1 + [\exp(\sigma^2) - 1] \cdot \mu_i \cdot \exp(\sigma^2/2)\}
\end{aligned}
$$

This effectively provides the expectations after marginalizing the residual effect and can be extended to other random effects by letting σ^2 equal the sum of all variance components. The mean and variance are also given in Zuur *et al.* (2012) (citing Johnson *et al.* 1994) and though seemingly different, after some manipulation can be shown to be identical to that of Greene (2007):

$$
\begin{aligned}
&E(Catch_i) = \mu_i \cdot \exp(\sigma^2/2)\\
&Var(Catch_i) = \mu_i \cdot (\mu_i \cdot [\exp(\sigma^2) - 1] \cdot \exp(\sigma^2) + \exp(\sigma^2/2))\\
&\qquad\qquad = \mu_i \cdot \exp(\sigma^2/2) \cdot \{1 + [\exp(\sigma^2) - 1] \cdot \mu_i \cdot \exp(\sigma^2) / \exp(\sigma^2/2)\}\\
&where \qquad \exp(\sigma^2) / \exp(\sigma^2/2) = \exp(\sigma^2/2)
\end{aligned}
$$

2.4.2 Zero inflated Poisson models with observation level random effect on count portion

In this section the zero catches are believed to be the product of two processes. Firstly, the zeros may arise because the fish are present but are not caught. This results in false zeros. True zeros may arise because there are no fish present. In this two-component mixture model of the catch, the false zeros were modeled as originating from zero inflation using a binomial model while the counts and true zeros were modeled as originating from a Poisson process. The zero inflated GLMM for catch is given by:

$$
\begin{aligned}
&Catch_i \sim ZIPois(\exp(l_{1i}), \log it^{-1}(l_{2i}))\\
&l_{1i} = \eta_{1i} + \varepsilon_{1i}\\
&l_{2i} = \eta_{2i} + \varepsilon_{2i}
\end{aligned}
$$

Where in the base model the logistic component has an intercept only:

$$\eta_{1i} = \beta_1 + \beta_2 \times fYear_i + \beta_3 \times fSeason_i + \beta_4 \times fArea_i + \beta_5 \times fGear_i + \log Hours_i$$
$$\eta_{2i} = \gamma_1$$

And in model 2 the logistic component includes many of the same regressors as in the count portion:

$$\eta_{1i} = \beta_1 + \beta_2 \times fYear_i + \beta_3 \times fSeason_i + \beta_4 \times fArea_i + \beta_5 \times fGear_i + \log Hours_i$$
$$\eta_{2i} = \gamma_1 + \gamma_2 \times fSeason_i + \gamma_3 \times fArea_i + \gamma_4 \times fGear_i + \log Hours_i$$

And in model 3, both components are identical and include an interaction term:

$$\eta_{1i} = \beta_1 + \beta_2 \times fYear_i + \beta_3 \times fSeason_i + \beta_4 \times fArea_i + \beta_5 \times fGear_i + \beta_6 \times fSeason : fArea_i + \log Hours_i$$
$$\eta_{2i} = \gamma_1 + \gamma_2 \times fYear_i + \gamma_3 \times fSeason_i + \gamma_4 \times fArea_i + \gamma_5 \times fGear_i + \gamma_6 \times fSeason : fArea_i + \log Hours_i$$
$$\varepsilon_{1i} \sim N(0, \sigma^2_{\varepsilon 1})$$
$$\varepsilon_{2i} \sim N(0,1)$$

The mean and variance of a ZIP GLM are given by (Zuur *et al.* 2012):

$$E(Catch_i) = \mu_i \cdot (1 - \pi_i)$$
$$Var(Catch_i) = (1 - \pi_i) \cdot (\mu_i + \pi_i \cdot \mu^2_i)$$

However, for our ZIP GLMM the expectation and variance must account for the over-dispersion residual variance and possibly other variance components as described above. Here we have the added complication of marginalizing with respect to the over-dispersion residual variance of the binomial model. This cannot be done analytically but two approximations exist (Hadfield 2012). Here we use the approximation provided by Diggle *et al.* (2004):

$$E(Catch_{i,Binomial}) = \pi_i \approx logit^{-1}\left(\frac{\eta_{2i}}{c}\right), where\ c = \sqrt{1 + \left(\frac{16\sqrt{3}}{15\pi}\right)^2 \sigma_2^2}$$

And for the Poisson GLMM:

$$E(Catch_{i,Poisson}) = \mu_i = exp\left(\eta_{1i} + {\sigma_1^2}/{2}\right)$$

For the expected value of the ZIP GLMM we substituted the estimates of μ_i and π_i into the expectation and variance for the ZIP GLM above when calculating Pearson residuals. The residual variance for the zero inflated process is not observed and is fixed at 1 while the residual covariance between the zero inflated and Poisson process are set to zero because both processes cannot be observed in a single data point (Hadfield 2012).

2.4.3 Hurdle Poisson models with observation level random effect on count portion

As in the previous section, the catches are believed to be the product of two latent variables however the zeros are not the product of two processes. The catch is believed to be a function of one process causing the fish to be absent or present and a second process influencing the number that are caught when they are present. A binomial model was assumed for the distribution of the presence/absence data and a zero truncated Poisson model was used to describe the distribution of the non-zero count data. The hurdle GLMM for catch with an observation level random effect on the counts is given by:

$$Catch_i \sim ZAPois(exp(l_{1i}), logit^{-1}(l_{2i}))$$

$$l_{1i} = \eta_{1i} + \varepsilon_{1i}$$

$$l_{2i} = \eta_{2i} + \varepsilon_{2i}$$

Where in the base model both the logistic and zero-truncated components had identical regressors:

$$\eta_{1i} = \beta_1 + \beta_2 \times fYear_i + \beta_3 \times fSeason_i + \beta_4 \times fArea_i + \beta_5 \times fGear_i + log\ Hours_i$$

$$\eta_{2i} = \gamma_1 + \gamma_2 \times fYear_i + \gamma_3 \times fSeason_i + \gamma_4 \times fArea_i + \gamma_5 \times fGear_i + log\ Hours_i$$

$$\varepsilon_{1i} \sim N(0, \sigma^2_{\varepsilon 1})$$

$$\varepsilon_{2i} \sim N(0,1)$$

And in model 2 both components included the $fSeason \times fArea$ interaction. The mean and variance of a hurdle GLM with binomial and zero-truncated Poisson sub models are given in Zuur *et al.* (2012):

$$E(Catch_i; \pi_i, \mu_i) = c_i \times \mu_i, \qquad where\ \ c_i = \frac{1-\pi_i}{1-e^{-\mu_i}}$$

$$Var(Catch_i; \pi_i, \mu_i) = c_i \times (\mu_i + {\mu_i}^2) - (c_i \times \mu_i)^2$$

The scaling of μ_i and π_i by the observation level random effect is as given above and these were substituted into the expectation and variance for a hurdle GLM when calculating Pearson residuals.

3. Results

3.1 Nominal

The trend in non-zero catch per hour differed across regions (**Figure 2**). In the Maine region there is very little upward or downward trend evident while in the mid-Atlantic States, what little data is available shows a strong decline in catch since about 2005. Proceeding northwards we see that the SWNS region shows a positive trend in catch since 1995, NENS since 2000 and GSL since 2005.

A related metric tracks the proportion of non-zero catch trips per year (**Figure 3**). The year 2000 marks a turning point in the success of fishing for four of the 5 regions: Maine, SWNS, NENS and GSL. In the case of Maine it marks the beginning of a long decline in success that only recently has begun to increase. The success off the mid-Atlantic States fluctuate around a mean value of about 5%.

3.2 Standardized indices

3.2.1 Poisson models with observation level random effect

The base model without a season by area interaction had a DIC of 69883.58 compared to a DIC of 69356.33 for a model with it. A difference of 8 to 10 is enough to indicate a better model (Zuur *et al.* 2013). The overdispersion was estimated to be 1.20 without and 1.23 with the interaction term and values less than 1.4 are considered acceptable. **Figure 4** compares the coefficients for the 2 models where values above zero increase the expected count while those below decrease it relative to the global mean. Seasonal effects within areas are observed where previously the effect of seasons across areas was negligible.

Residual plots for the 2 models are provided in **Figures 5 and 6**. Visually, there is not much difference between the two outputs. The residual versus fit plots showed a pattern for the smaller fitted values and could be an artifact of fitting using the observation-level random intercept (Zuur *et al.* 2013, pg. 218). It is also clear from the fit versus observed plot that we are dealing with very noisy data with most of the data residing with small values of catch or no catch. The residual pattern was also examined for the year effect within each season and area combination (**Figures 7 and 8**). This plot more clearly showed the trend in residuals and was used throughout the document as a tool to evaluate the fit of the models. In this case the effect of the interaction was a reduction in the range of residual values. In either model there is a tendency to underestimate the catch in recent years in the GSL and NENS and overestimate it in SWNS and Maine with the mid-Atlantic neutral. The magnitude varied by season as well. The residual difference across the whole time series was small (~1) and to address it may require a second or third order interaction involving year or a continuous effect of year.

The last figure relating to the Poisson models (**Figure 9**) showed the predicted catch within each area relative to the observed catch for the model with a season by area interaction. The estimates were marginalized with respect to the observation-level random intercept and reflect the rod and reel gear fishing in mid-season. Trends seemed reasonable for some of the areas, though the SWNS and mid-Atlantic predictions appeared to be outside the data in recent years.

3.2.2 Zero inflated Poisson models with observation level random effect on count portion

The base ZIPoisson model has two components. The portion describing the Poisson process was identical to the Poisson main effects model and the binomial portion modeling the zero inflation had only an intercept. The DIC was 72295.5, which was much larger than the Poisson models tested. Expanding the binomial portion of the model to include all main effects except year reduced the DIC to 72245.86. A further expansion of the model so that both the Poisson and binomial component models contained all main effects and the season by area interaction reduced the DIC 71609.88.

Qualitatively, the residuals plots from all three ZIPoisson models were similar and only the last one described above will be discussed in any detail. Careful examination of **Figure 10** revealed only marginal differences from the Poisson models. The residual trends across levels of the year effect with the area and season levels were also similar with a slight shrinkage of the range in the residuals (**Figure 11**). The predicted catch by area (**Figure 12**), was very similar to what we see in **Figure 9** except that the increasing trend for SWNS and the mid-Atlantic did not extend as far beyond the data. Much of the data lie along the baseline and by modeling the zero inflation the predictions are more in line with the observations.

3.2.3 Hurdle Poisson models with observation level random effect on count portion

The two hurdle models tested had the same regressors in both the zero truncated Poisson and binomial components of the model. The base hurdle model had the same regressors as the main effects Poisson and this was extended to include the season by area interaction in both submodels. The DIC in the first case was 92636.96 and in the second 92764.93. The summary table of coefficients for this second model (**Table 2**) indicated that some pruning of non-significant factors may be required.

Examining the second model in more detail we see that the pattern in the residuals for small fitted values of the count has decreased and that the fitted counts are lower in magnitude (**Figure 13**) relative to the extremes observed in the data. The residual trend across the levels of the year effect have the same pattern as described for the other models (**Figure 14**) and the range has increased slightly compared to the ZIPoisson model.

The annual trends in the predictions of catch by area are similar to the other models but notably they now have a closer relationship to the data (**Figure 15**). If we estimate the catch for every combination of the levels of the main effects and their interactions while marginalizing the effect of the random observation-level intercept, and then average these estimates for each year, we produce the relative trend in abundance shown in **Figure 16**. We can do this for every iteration of the MCMC sample yielding the posterior mean catch and 95% Highest Posterior Density intervals for each year. The resulting annual trend in catch related well to the nominal trend without following it exactly. Versions of this plot produced for the ZIPoisson model and the base hurdle model (not shown) did not provide reasonable estimates of catch from about 2009 to 2014. Values were well above the nominal. Also the nominal estimate for 1989, which was odd compared to adjacent years, was fit exactly by the other models whereas in **Figure 16** it is not.

Posterior predictive checks of the model fit of this and the other models related the lack of fit of the model for the actual data to the lack of fit of the model for ideal data. In the comparison of the residuals from the ideal and actual data, half the paired discrepancies should lie above a 1:1 line and half below if the fit is good. This balance was achieved with the final hurdle model.

4. Research Recommendations

The combined USA-Canadian western Atlantic bluefin tuna index addresses the limitations associated with the individual USA and Canadian fisheries indices, because it operates on a larger geographical scale and is more robust to individual fleet dynamics and stock distribution. Although a model was developed that described the observed catch fairly well, further model development is still possible. To that end we recommend exploring the following:

1. If we think that there is heterogeneity in the timing and location of the fishing effort, we could treat the season by area interaction as a random effect. This essentially allows us to make inferences for the potentially fished times and areas rather than just the realized ones, thereby improving the comparability of annual standardized CPUE estimates (Katara and Gaertner 2014). As Candy (2004) indicates, casting formerly fixed effects as random ones, will also result in efficiencies in the model fitting because, in a mixed-model approach, the fixed effects are estimated by generalized least squares while BLUP estimation of random effects and REML estimation of the random-effect variance occur separately. These operations are interleaved in the iterative fitting algorithm and because the estimation of the parameters is distributed, this makes the estimation feasible and stable. A solution, stable or not, is not always possible when all the parameters are fitted as fixed effects. He also noted that this approach is less susceptible to imbalance in the observations of the season by area cross-classification and the bias in variance it could introduce. The only caveat to this approach might be that we would not want to provide population-average estimates of the fixed effect parameters by integrating the season by area random effect out of the conditional predictions of catch if there were seasonal trends in the catch by area and we were interested in them. In this case we could use the BLUP estimates of the random effects to provide conditional catch estimates for reference levels of area and season.

2. In this and other catch standardization exercises, there are often imbalances in the data caused by fluctuating fishing patterns, for example, which could lead to biased estimates of variance and catch rates. The Bayesian hierarchical modeling framework proposed by Zhang and Holmes (2010) was shown to mitigate the effect of changing spatial coverage and it should be considered for the current standardization exercise. With it, it is possible to estimate specific interaction effects for areas and season combinations (or year by area combinations) which were not fished by borrowing the information from the likelihood contributions of all other effects.

3. Year by area or season interactions were not considered in this analysis, due to time constraints and yet it is reasonable to imagine that these effects would be important. If these interactions can be considered to have arisen because of random change in the distribution of the population, then it is possible to treat them as random effects and we can average out the random area by year or season by year interactions by ignoring these terms (Candy 2004). Our principle concern here is that the interaction is random and this can be verified by looking for tends in the area or season by year random effect across the years. If trends exist, obtaining standardized yearly estimates of catch for the whole fishery becomes a much more difficult problem involving a weighted averaging out of the area and /or season which is only really valid if the catch is temporally and spatially random within the seasons and areas, respectively.

4. Exploratory plots of the relation of catch to the forage suitability index were promising however many records could not be mapped to an index value. It needs to be resolved whether all the data can be mapped to an index value and what affect this and other environmental covariates have on the catch.

5. Though the data are generally very good, there are a few outstanding issues that deserve some attention. Consideration should be given to identifying changes in management and the effect on fishing; evaluating the influence of multiple target species on the bluefin tuna directed effort (Hanke *et al.* 2012) and older data should be validated to ensure that zero-catch trips and other information reporting is consistent with today.

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Table 1. Data availability by factor. The row totals within each factor are identical. GSL = Gulf of St. Lawrence; SWNS=South west Nova Scotia and NENS=North east Nova Scotia.

	Season			Gear			Area				
Year	Early	Mid	Late	Harpoon	HandLine	RodnReel	GSL	SWNS	NENS	Maine	MidAtlantic
1984	70	187	123	0	324	56	380	0	0	0	0
1985	155	194	99	0	448	0	448	0	0	0	0
1986	171	218	92	0	452	29	481	0	0	0	0
1987	76	67	23	0	166	0	166	0	0	0	0
1988	133	163	38	0	332	2	279	55	0	0	0
1989	225	173	77	0	467	8	244	231	0	0	0
1990	421	499	248	0	680	488	467	179	522	0	0
1991	358	303	230	0	503	388	281	248	362	0	0
1992	302	424	239	11	590	364	342	247	376	0	0
1993	521	757	443	155	1075	491	719	637	31	264	70
1994	822	737	97	51	1023	582	962	292	141	215	46
1995	862	729	417	70	1104	834	1102	351	69	463	23
1996	1210	1329	1157	189	1717	1790	1707	1657	160	165	7
1997	1092	1209	846	146	1113	1888	1509	1353	217	62	6
1998	1019	1153	808	136	619	2225	1102	1328	244	299	7
1999	787	901	225	73	353	1487	871	781	101	154	6
2000	965	687	569	46	341	1834	1103	614	119	334	51
2001	791	480	319	36	297	1257	981	388	68	131	22
2002	965	797	95	44	174	1639	890	462	56	408	41
2003	1039	276	107	31	129	1262	887	15	9	461	50
2004	676	590	132	44	133	1221	543	409	80	328	38
2005	836	628	180	18	120	1506	732	405	79	385	43
2006	648	463	119	17	89	1124	673	240	100	184	33
2007	383	245	367	15	53	927	353	273	95	255	19
2008	518	259	406	14	62	1107	461	198	169	323	32
2009	345	211	170	11	47	668	298	112	59	219	38
2010	242	218	133	9	22	562	66	118	55	326	28
2011	342	310	275	6	35	886	414	120	64	323	6
2012	432	375	298	8	38	1059	362	147	76	502	18
2013	319	489	259	19	60	988	408	166	52	423	18
2014	97	274	215	11	41	534	416	119	51	0	0

Table 2. A summary of the fit of the hurdle model with main effects and season by area interaction in both the zero truncated Poisson and Binomial sub models and a freely estimated observation-level random intercept in the Poisson sub model.

Observation level intercept	**post.mean**	**l-95% CI**	**u-95% CI**	**eff.samp**								
Count submodel	0.6544	0.6181	0.6886	682								
Binomial submodel	1	1	1	0								
Efects		**Count submodel**						**Binomial submodel**				
	post.mean	**l-95% CI**	**u-95% CI**	**eff.samp**	**pMCMC**		**post.mean**	**l-95% CI**	**u-95% CI**	**eff.samp**	**pMCMC**	
Intercept	-4.946317	-5.27989	-4.62844	1082.92	<5e-04	***	-1.0987	-1.19569	-0.99779	2000	<5e-04	***
logEffort	0.997311	0.995366	0.999363	2000	<5e-04	***	0.989425	0.987399	0.991326	2000	<5e-04	***
Year1985	-0.41166	-0.89544	0.059909	608.75	0.1	.	0.246114	0.092725	0.413214	2000	0.003	**
Year1986	-0.948794	-2.22687	0.119733	59.41	0.075	.	-0.4972	-0.80195	-0.1649	2000	<5e-05	***
Year1987	-2.553096	-6.69245	1.391782	11.09	0.32		-1.24051	-1.69662	-0.74301	2000	0.003	**
Year1988	1.449291	1.067332	1.829129	1238.97	<5e-04	***	-1.98382	-2.5913	-1.32112	2000	<5e-06	***
Year1989	1.73718	1.410393	2.079139	1131.64	<5e-04	***	-2.72713	-3.48597	-1.89923	2000	0.003	**
Year1990	1.258052	0.937326	1.588732	1034.67	<5e-04	***	-3.47044	-4.38065	-2.47735	2000	<5e-07	***
Year1991	1.197957	0.873622	1.539793	971.42	<5e-04	***	-4.21375	-5.27532	-3.05546	2000	0.003	**
Year1992	1.00164	0.666176	1.322081	1079.74	<5e-04	***	-4.95706	-6.16999	-3.63357	2000	<5e-08	***
Year1993	0.553346	0.244267	0.900682	1092.46	<5e-04	***	-5.70037	-7.06467	-4.21168	2000	0.003	**
Year1994	0.891528	0.57297	1.224845	1086.6	<5e-04	***	-6.44369	-7.95934	-4.78979	2000	<5e-09	***
Year1995	0.887655	0.566985	1.191595	1086.8	<5e-04	***	-7.187	-8.85402	-5.36791	2000	0.003	**
Year1996	0.094881	-0.2284	0.417737	1051.96	0.545		-7.93031	-9.74869	-5.94602	2000	<5e-10	***
Year1997	-0.11525	-0.41967	0.241009	1012.2	0.484		-8.67362	-10.6434	-6.52413	2000	0.003	**
Year1998	0.345621	0.015043	0.660141	1061.77	0.038	*	-9.41693	-11.538	-7.10224	2000	<5e-11	***
Year1999	0.964595	0.622407	1.279852	1074.49	<5e-04	***	-10.1602	-12.4327	-7.68035	2000	0.003	**
Year2000	0.132281	-0.20401	0.459366	904.21	0.433		-10.9036	-13.3274	-8.25847	2000	<5e-12	***
Year2001	0.71852	0.409446	1.069437	1058.94	<5e-04	***	-11.6469	-14.2221	-8.83658	2000	0.003	**
Year2002	0.962289	0.622189	1.275764	1074.46	<5e-04	***	-12.3902	-15.1167	-9.41469	2000	<5e-13	***
Year2003	0.62978	0.284018	0.953724	910.22	<5e-04	***	-13.1335	-16.0114	-9.9928	2000	0.003	**
Year2004	0.99997	0.673133	1.338592	1121.74	<5e-04	***	-13.8768	-16.9061	-10.5709	2000	<5e-14	***
Year2005	1.013039	0.675749	1.325852	1071.27	<5e-04	***	-14.6201	-17.8008	-11.149	2000	0.003	**
Year2006	0.97497	0.666164	1.316683	941.97	<5e-04	***	-15.3634	-18.6954	-11.7271	2000	<5e-15	***
Year2007	1.061537	0.698209	1.376027	1033.65	<5e-04	***	-16.1067	-19.5901	-12.3053	2000	0.003	**
Year2008	1.164415	0.801606	1.476676	1127.52	<5e-04	***	-16.85	-20.4848	-12.8834	2000	<5e-16	***
Year2009	1.522061	1.168462	1.848476	1044.16	<5e-04	***	-17.5934	-21.3795	-13.4615	2000	0.003	**
Year2010	1.635586	1.251942	1.952221	1143.98	<5e-04	***	-18.3367	-22.2741	-14.0396	2000	<5e-17	***
Year2011	1.748151	1.38825	2.064839	1091.31	<5e-04	***	-19.08	-23.1688	-14.6177	2000	0.003	**
Year2012	2.000004	1.662659	2.329074	1109.92	<5e-04	***	-19.8233	-24.0635	-15.1958	2000	<5e-18	***
Year2013	1.783526	1.446784	2.106771	1019.38	<5e-04	***	-20.5666	-24.9581	-15.7739	2000	0.003	**
Year2014	1.855706	1.504114	2.184756	1081.25	<5e-04	***	-21.3099	-25.8528	-16.352	2000	<5e-19	***
Season_mid	0.609681	0.506556	0.701977	992.1	<5e-04	***	-22.0532	-26.7475	-16.9301	2000	0.003	**
Season_late	0.930978	0.814924	1.041055	975.8	<5e-04	***	-22.7965	-27.6422	-17.5083	2000	<5e-20	***
Area_SWNS	2.105492	2.009965	2.19099	915.66	<5e-04	***	-23.5398	-28.5368	-18.0864	2000	0.003	**
Area_NENS	0.058687	-0.22654	0.302878	702.89	0.659		-24.2831	-29.4315	-18.6645	2000	<5e-21	***
Area_Maine	0.069298	-0.35746	0.477694	73.62	0.734		-25.0265	-30.3262	-19.2426	2000	0.003	**
Area_MidAtlantic	1.747484	0.781993	2.609882	136.49	0.006	**	-25.7698	-31.2209	-19.8207	2000	<5e-22	***
Gear_HL	-0.15851	-0.26261	-0.05676	1610.53	0.002	**	-26.5131	-32.1155	-20.3988	2000	0.003	**
Gear_RR	-0.30392	-0.41511	-0.19779	1655.36	<5e-04	***	-27.2564	-33.0102	-20.9769	2000	<5e-23	***
Season_mid:Area_SWNS	-0.653903	-0.76844	-0.54205	1308.88	<5e-04	***	0.640692	0.53572	0.741778	1724.2	<5e-04	***
Season_late:Area_SWNS	-1.24416	-1.39206	-1.0882	1104.85	<5e-04	***	1.355562	1.237227	1.477177	1731.68	<5e-04	***
Season_mid:Area_NENS	0.152169	-0.10932	0.475956	838.5	0.323		-0.33538	-0.48673	-0.20003	1686.02	<5e-04	***
Season_late:Area_NENS	-0.013609	-0.28901	0.294614	804.14	0.942		-0.62072	-0.76269	-0.4844	2381.93	<5e-04	***
Season_mid:Area_Maine	-0.297489	-0.85925	0.247189	104.42	0.29		-0.18647	-0.31636	-0.04637	1818.06	0.008	**
Season_late:Area_Maine	-0.344698	-0.93857	0.231654	128.12	0.214		-0.23426	-0.38666	-0.08009	1876.28	0.007	**
Season_mid:Area_MidAtlantic	-2.266376	-4.64446	0.227295	44.45	0.067	.	0.293517	0.112998	0.474076	2000	<5e-04	***
Season_late:Area_MidAtlantic	-6.599504	-11.7699	-1.01907	14.8	<5e-04	***	0.127994	-0.0647	0.307822	2000	0.175	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1												
Iterations = 6401:126341												
Thinning interval = 60												
Sample size = 2000												

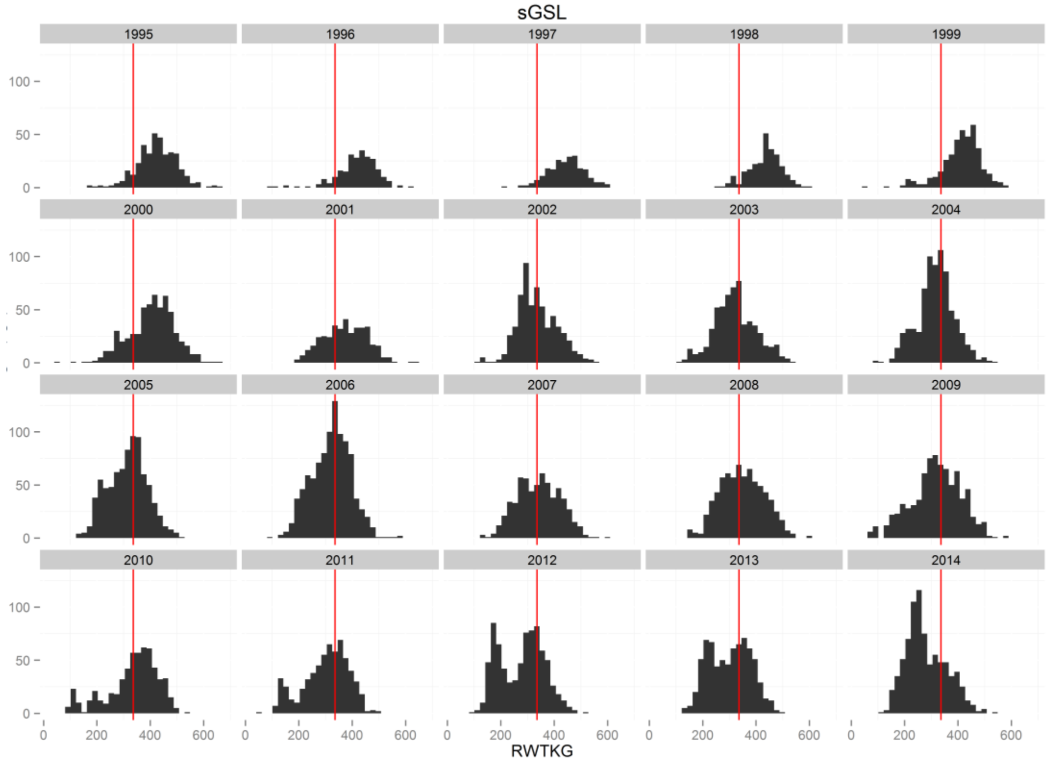

Figure 1. Catch composition for the Gulf of St. Lawrence fishery since 1995. Vertical line marks series mean 1981-2014) of 350 kg.

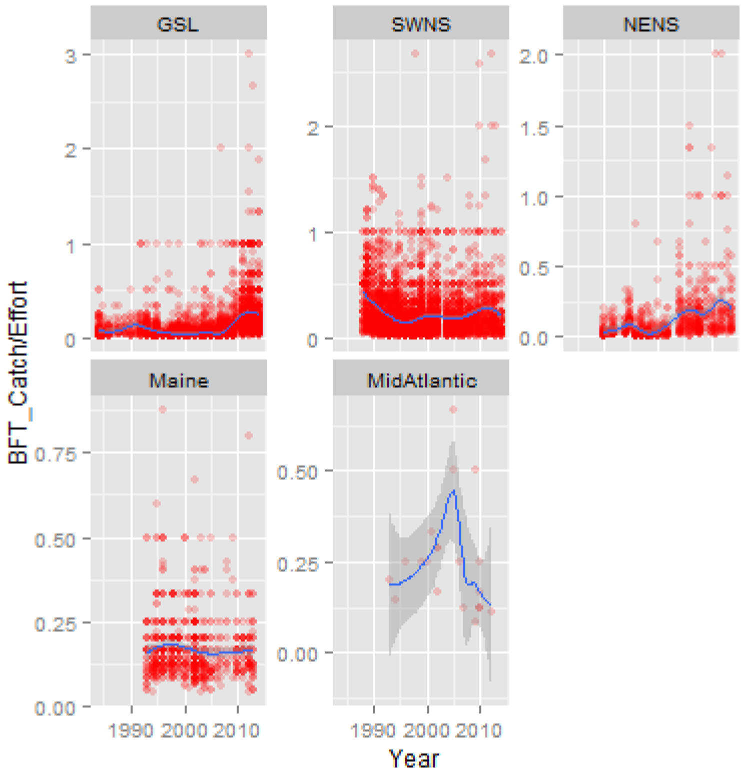

Figure 2. Non-zero Catch per hour fished for fleets using harpoon, handline and rod and reel in 5 areas ranging from mid-Atlantic in the south to GSL in the north.

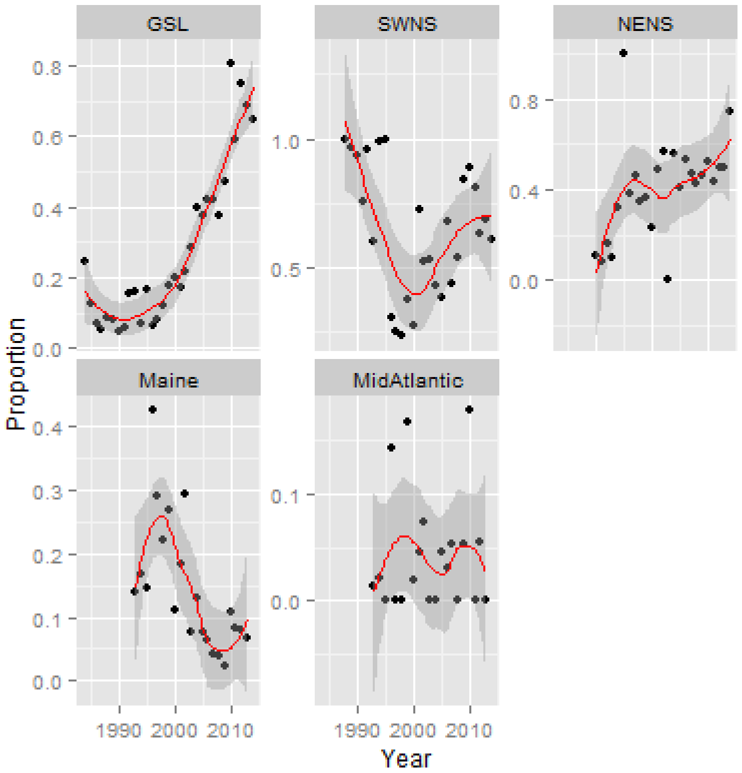

Figure 3. Proportion of trips fished with a non-zero catch for fleets using harpoon, handline and rod and reel in 5 areas ranging from mid-Atlantic in the south to GSL in the north.

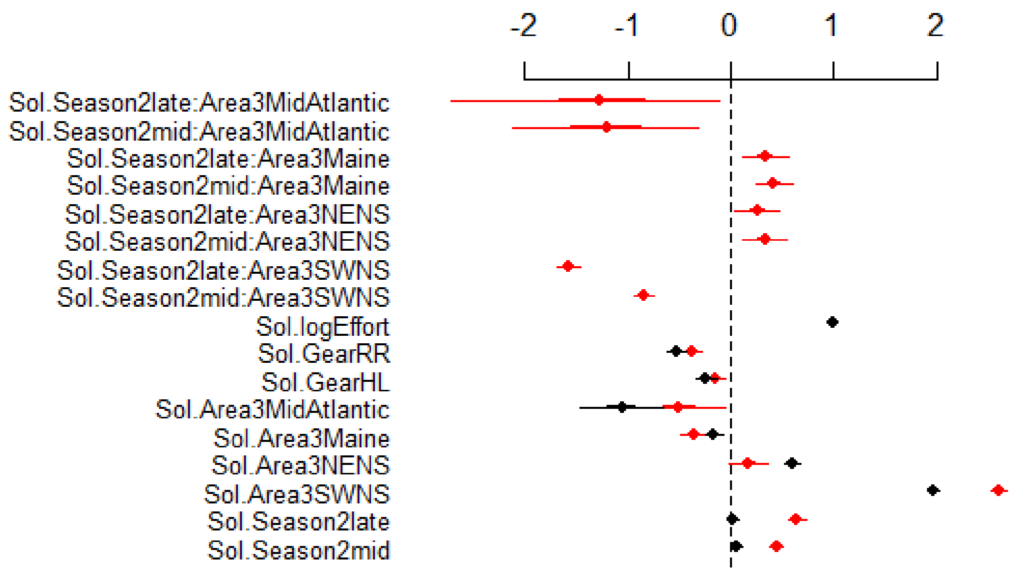

Figure 4. A comparison of coefficients from the Poisson model with (red) and without (black) a season by area interaction. The short crossbar represents the 95% credible interval and the longer whiskers represent the extremes of the posterior distribution for a coefficient. Note that the coefficient for logEffort was fixed at one in both models while all others were freely estimated.

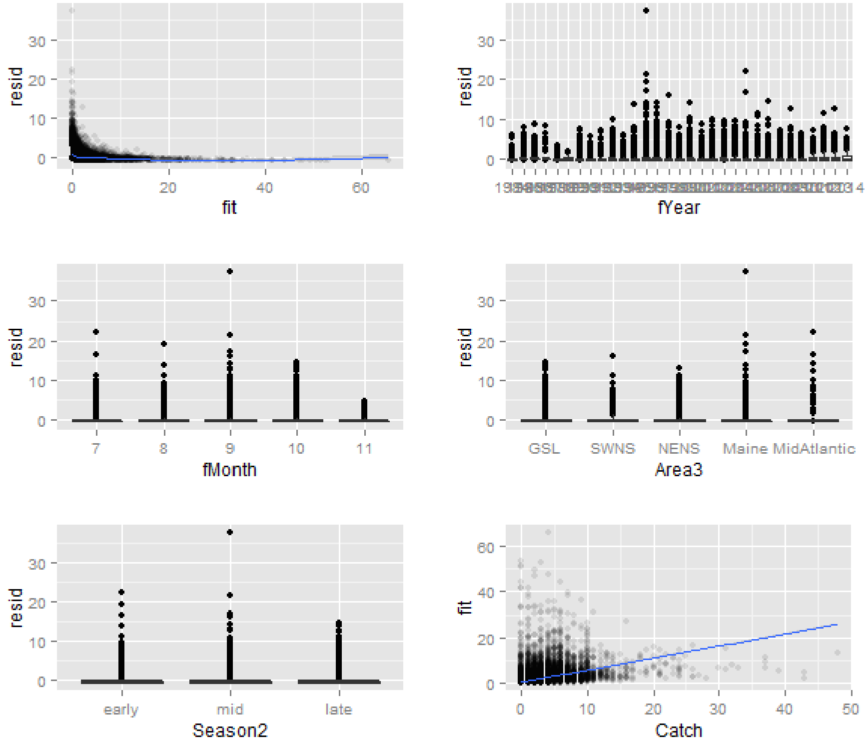

Figure 5. Residual plots for the Poisson model without a season by area interaction.

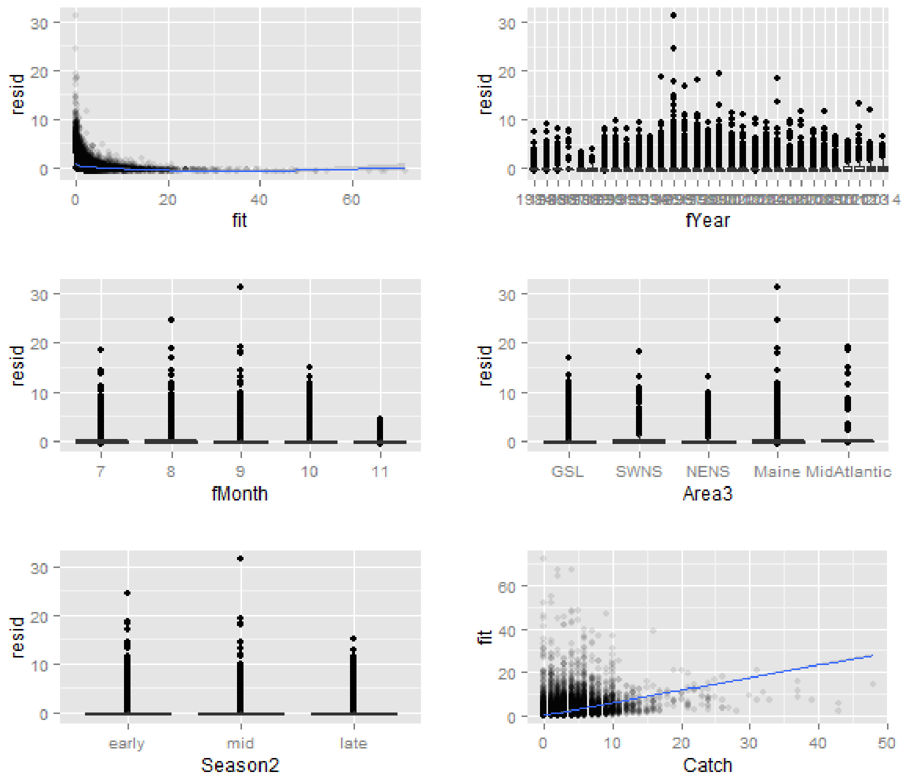

Figure 6. Residual plots for the Poisson model with a season by area interaction.

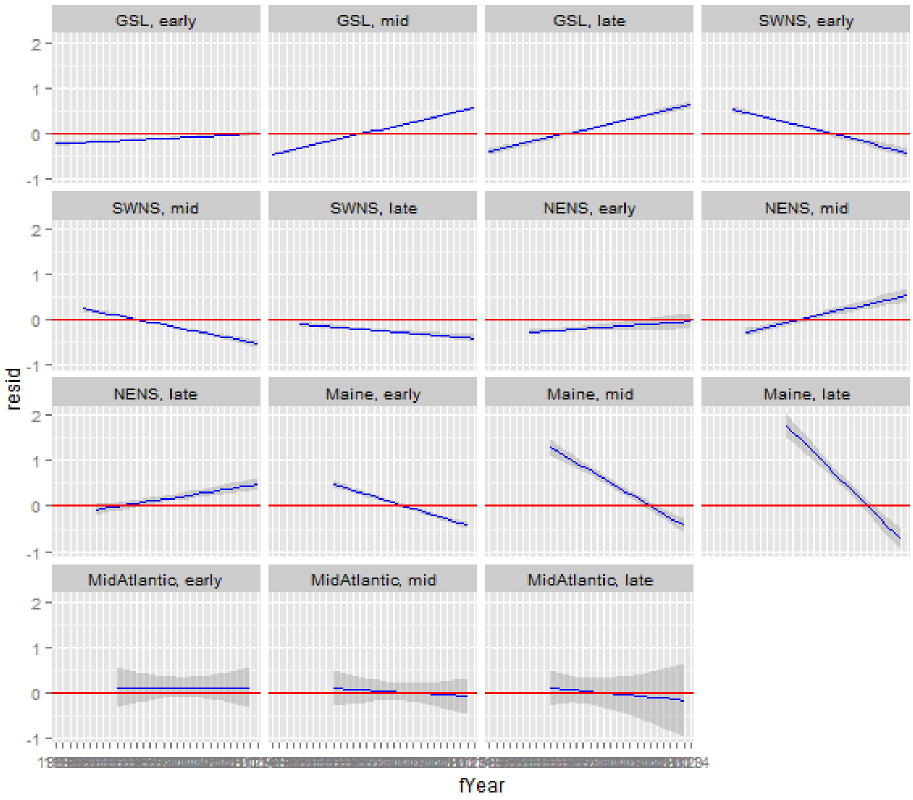

Figure 7. Pearson residual trends across levels of the year effect for the Poisson model without a season by area interaction.

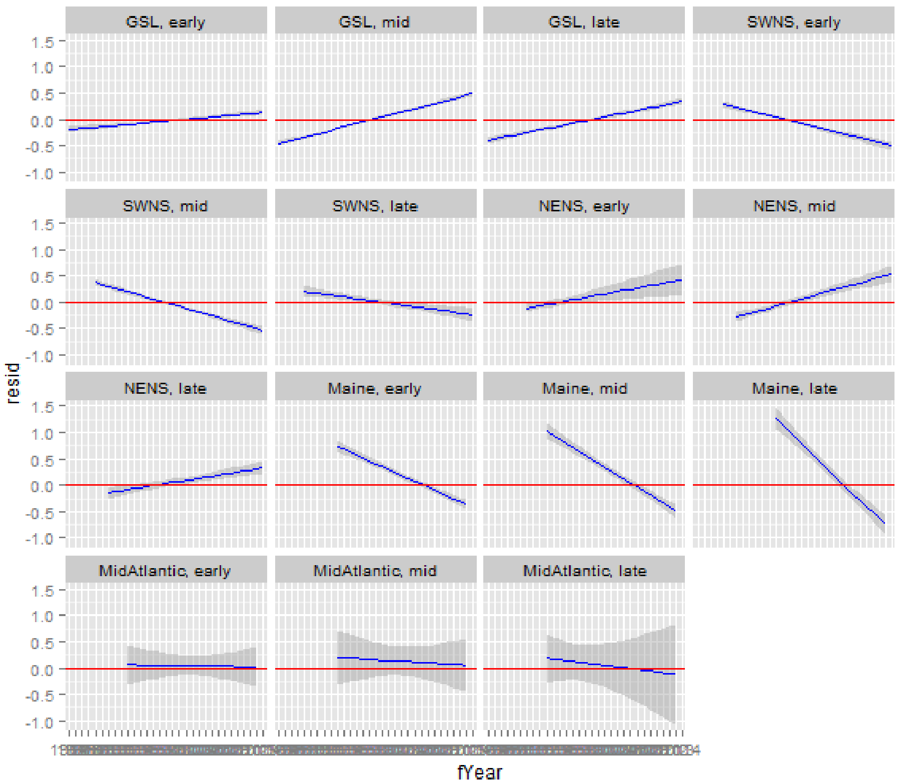

Figure 8. Pearson residual trends across levels of the year effect for the Poisson model with a season by area interaction.

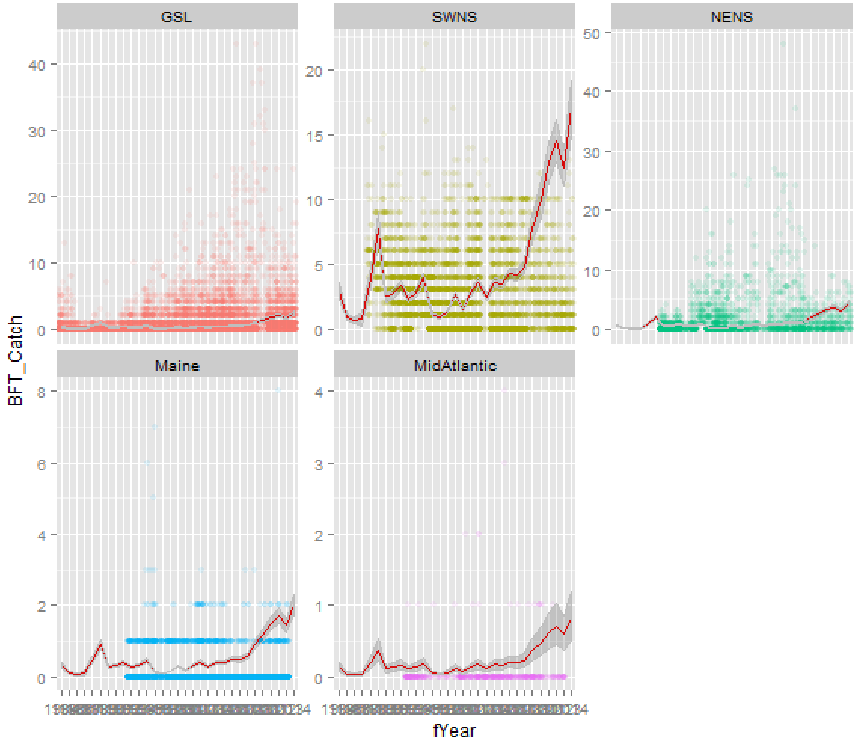

Figure 9. Predictions of the catch after marginalizing over the observation level random intercept and holding gear at RR and Season at mid. Poisson model without the season by area interaction.

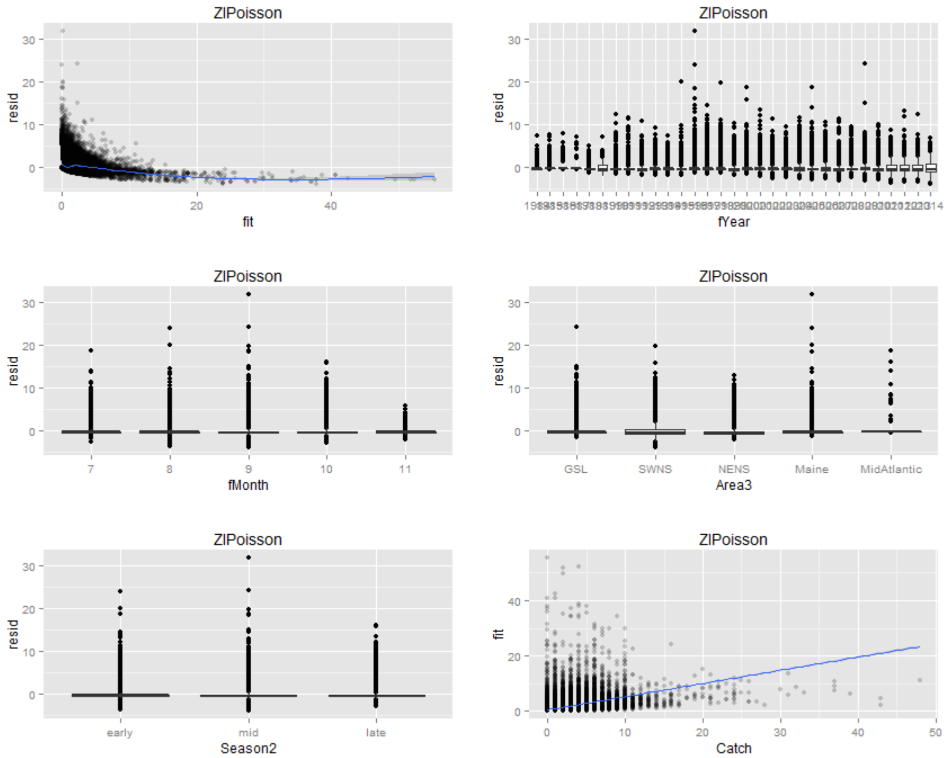

Figure 10. Residual plots for the ZIPoisson model with a season by area interaction.

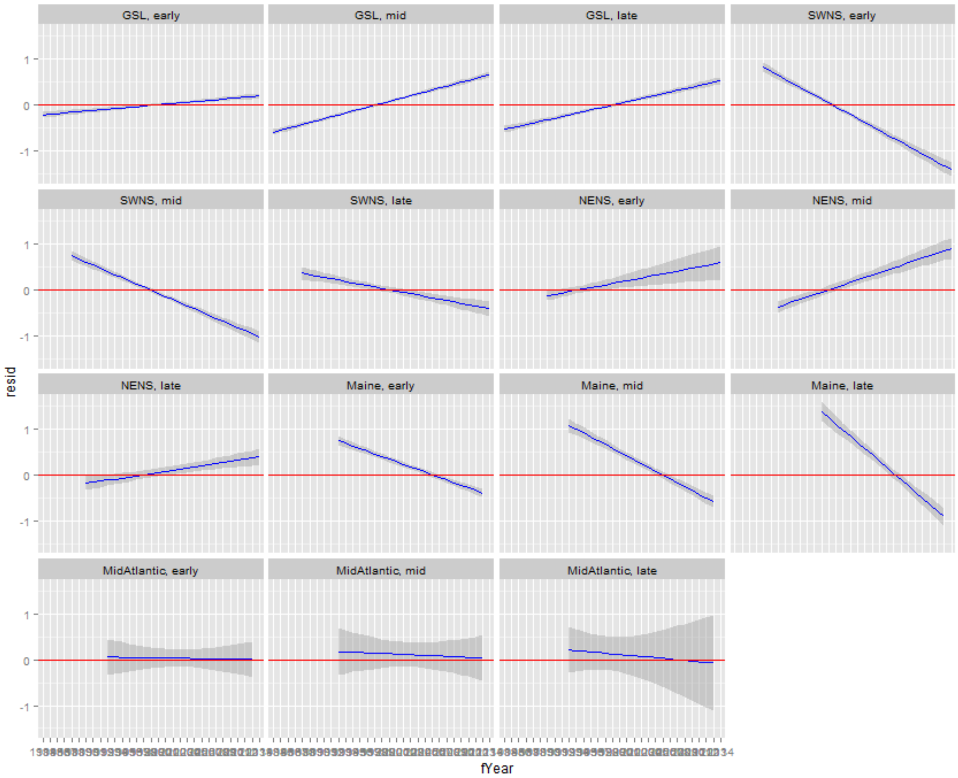

Figure 11. Pearson residual trends across levels of the year effect for the ZIPoisson model with a season by area interaction.

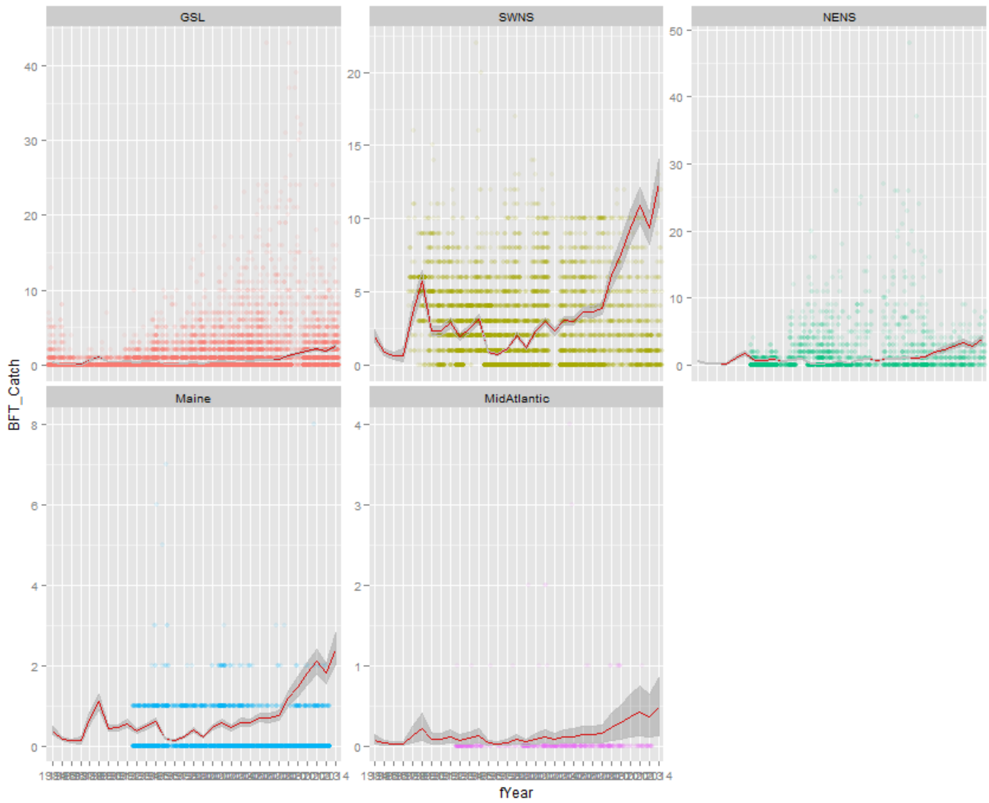

Figure 12. Predictions of the catch after marginalizing over the observation level random effect and holding Gear at RR and Season at mid. ZIPoisson model with the season by area interaction in both parts of the model.

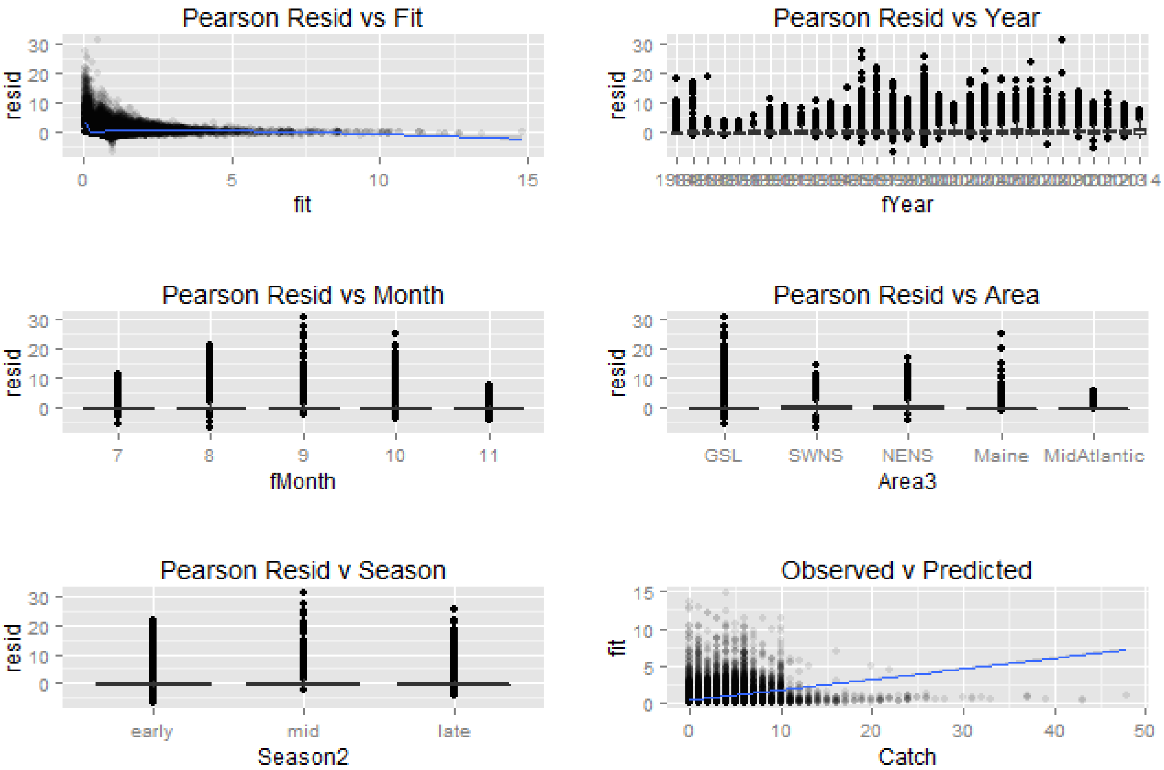

Figure 13. Residual plots for the hurdle model with a season by area interaction.

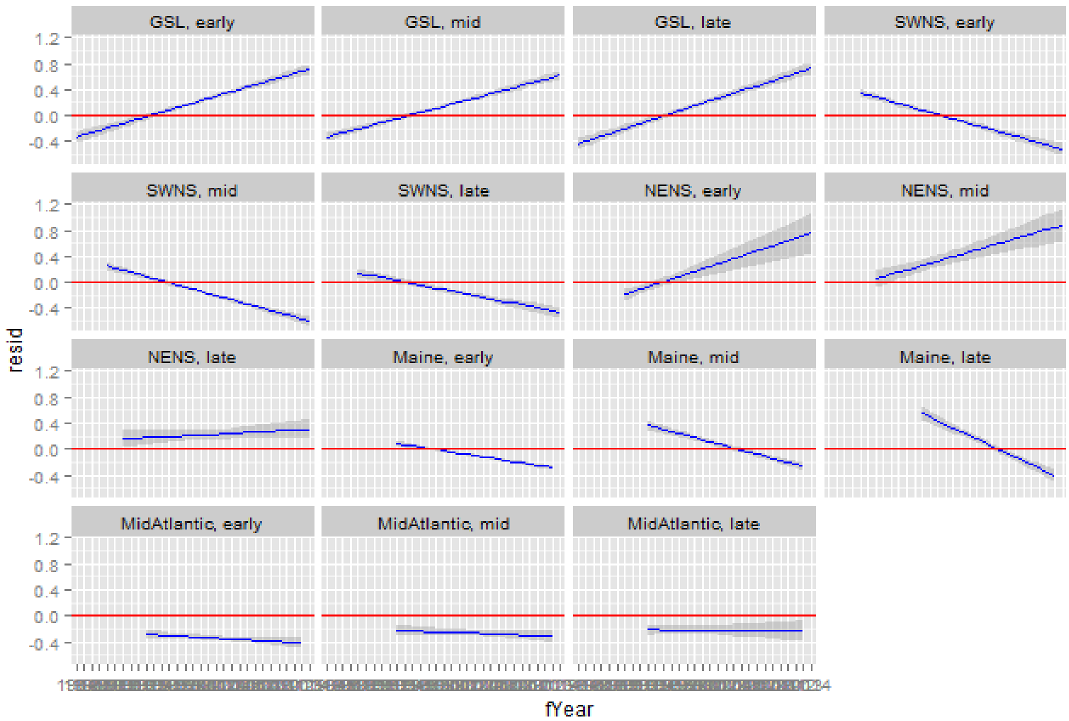

Figure 14. Pearson residual trends across levels of the year effect for the hurdle model with a season by area interaction.

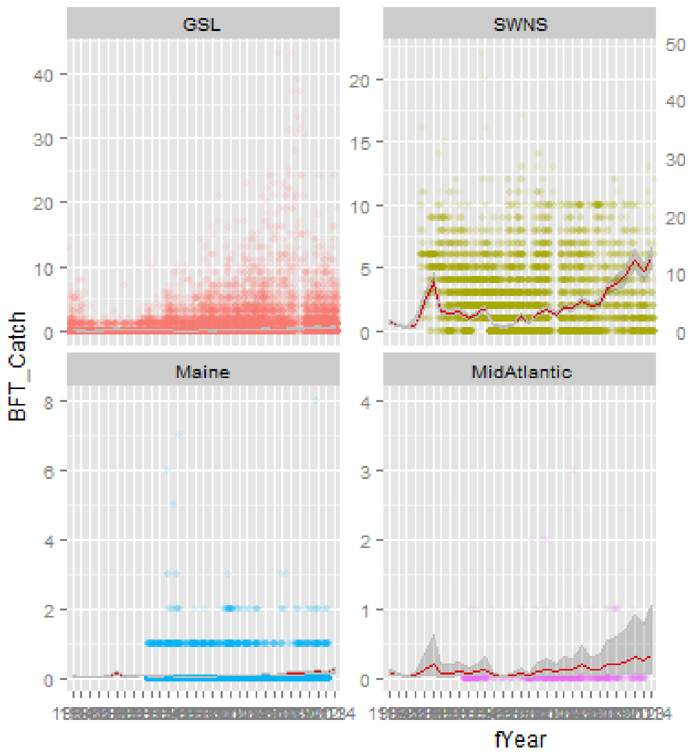

Figure 15. Predictions of the catch after marginalizing over the observation level random effect and holding Gear at RR and Season at mid. The hurdle model has the season by area interaction in both parts of the model.

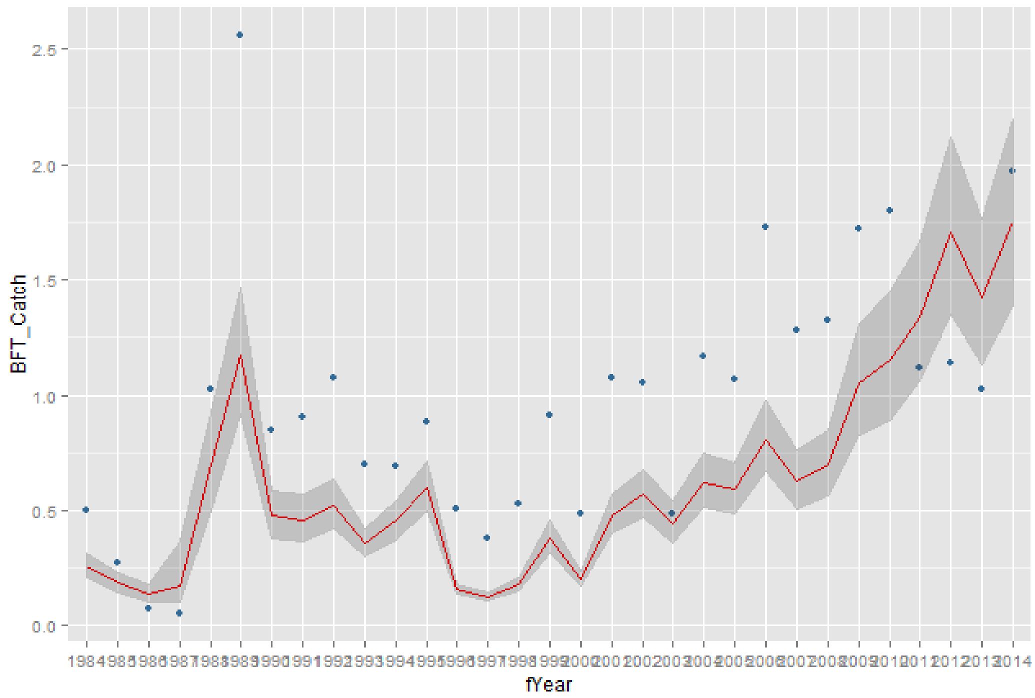

Figure 16. Predictions of the catch after marginalizing over the observation level random effect and averaging over the levels of the fixed effects. The hurdle model has the season by area interaction in both parts of the model.