Recreational Fishery Fleet Dynamics Models

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Introduction

The presented models were developed to provide an estimate of recreational harvest and discards as they relate to fisheries management policies and stock status for summer flounder, black sea bass, and scup. The management alternatives presented are constructed in the context of their eventual application to the specification setting process for these species, and the model is being investigated by the Mid-Atlantic Fishery Management Council's (MAFMC) Fishery Management Action Team (FMAT) and the Atlantic States Marine Commission's (ASMFC) Plan Development Team (PDT) for use in the development and analysis of alternatives for the MAFMC and ASMFC Recreational Reform Initiative. The project is informed by extending work by Dr. John Ward (Ward 2015) on quantifying the historical effects of changes in management measures on discards and harvest based on the historical MRIP dataset, supplemented with information from stock assessments for these species. The management effects produced by this work could be integrated into a harvest control rule as a way of emulating fishery responses (and their uncertainty) to management measures, to demonstrate the implications of selecting various management configurations, and to understand the relative value of different management options.

The recreational harvest and discard models for summer flounder and black sea bass underwent peer review in September 2021 by a panel consisting of members of the MAFMC Scientific and Statistical Committee. Based on that review, several refinements were introduced to the recreational harvest and discard models which are reflected in the final model configurations presented here and discussed in the methods and discussion sections of this report. Full responses to peer review comments are included in this report as well, along with a summary table (Table 9).

Background

Given the current use of conservation equivalency (CE) and regional approaches in summer flounder, scup, and black sea bass management, which allow states or groups of states the ability to use differing recreational management measures provided that state specific harvest falls within pre-specified harvest targets, and the desire to explore new strategies for recreational management at the MAFMC and ASMFC, it is important to investigate new techniques that may be more effective than the yearly and somewhat ad hoc approach to recreational management that is currently used for setting management measures annually. Underlying the current process are the assumptions of similarity between years in the fishery for both fishing behavior and in the population dynamics of the targeted species. The process ignores many dynamic factors including implementation error in the new management procedure, changes to discard rates based on the new management regime, growth or decline in the population of fishers, and inter-annual changes in availability of the resource to anglers. It was noted during the process for Addendum XXVIII that current methods for developing CE measures each year are subject to variability and uncertainty, and the performance of this strategy has not been consistent historically. Additionally, the process rarely allows for a re-evaluation of the performance of the chosen management in the following year to quantify how the program is working, beyond accounting for harvest limit adjustments that are needed in the following year to meet new management objectives.

This project was designed to contribute to developing a new methodology that can perform better over time by accounting for more of the known population dynamics, allowing for transparency in the specification setting process and including the assessment of uncertainty in management choices. Having a quantification of uncertainty in the specification setting process allows for the application of risk tolerance to choices and could allow for more stability through time in the management program.

Moving from an ad hoc harvest-based approach for setting specifications to a model-based approach may allow for more inter-annual stability in recreational management by not being directly subject to single year swings in Marine Recreational Information Program (MRIP) harvest estimates. The MRIP survey is the method used to collect recreational catch information (see: https://www.fisheries.noaa.gov/topic/recreational-fishing-data). A model-based approach may also better account for important population dynamics that are currently being ignored, such as recreational discards and future changes in availability due to cohort strength. Proposed advantages of a model-based approach are that performance of projections will be enhanced as stability will be increased in specification-setting, thus improving buy-in and knowledge of regulations by the fishing public, and the inclusion of more factors in the model-based projections than the status quo conservation equivalency process, potentially impacting future performance.

The model-based strategies could offer value to managers by providing context of existing versus new management specifications for recreational harvest, thus allowing them to optimize the eventual management regime they select. Various options for management specifications will be reviewed at different regional configurations to provide trade-off information with regard to the management unit chosen. Variations of these approaches will also be explored that better use the inherent uncertainty in the system by translating this into uncertainty-based setting of the management program. In other words, an option could be used where the management system will only change if the recreational catch exceeds or underperforms relative to a threshold of uncertainty that exists in the output from the various models. These offer a potential for enhanced stability in management setting and these approaches better recognize the fact that the catch estimates and population information are both derived from statistical methods.

To model the effects of management specifications on recreational harvest, we originally selected an approach using Generalized Additive Models. Generalized Additive Models (GAMs) are extensions of generalized linear models in which the linear predictor incorporates the summation of smooth nonparametric functions of predictor variables (Wood 2006). Thus, the relationship between any of the smoothed predictor variables and the response variable may be nonlinear. As with other GLMs, the response variable may follow any from the exponential family of distributions (Wood 2006). The general structure of the model may be written:

$$g(\mu_i) = \mathbf{X_i} * \boldsymbol{\Theta} + f_1(x_{1i}) + f_2(x_{2i}) + f_3(x_{3i}, x_{4i}) + \ldots.$$

where

μ_i is the expected value of Y_i, the response variable, and Y_i ~ some exponential family distribution

$\mathbf{X_i^*}$ is a row of the model matrix for strictly parametric model components, $\boldsymbol{\Theta}$ is the vector of associated parameters, and the f_j are smooth functions of the covariates x_k. The smoothing functions are flexible and can use one of several bases including polynomials, cubic splines, thin plate regression splines, and P-splines. Estimation of the model is done via maximum likelihood, with a penalty term based on the second derivatives of the smoothing functions (e.g. penalizing the 'wiggliness' of the splines to avoid overfitting).

The advantages of using GAMs over other regression techniques include: straightforward interpretation of marginal effects of the predictors due to the additive structure of the model; the ability to capture nonlinear patterns by fitting smoothers to the data without *a priori* knowledge of their distribution; and the ability to control the wiggliness of the predictor functions to assess the tradeoffs between variance and bias.

To refine the modeling approach in response to peer review feedback, the model was converted to a shape constrained additive model (SCAM) (Pya and Wood 2015). The sole differentiation between SCAMs and GAMs is that the former incorporates user-specified restrictions on the shape of the smooth function for the relationship between one or more of the predictor variables and the response variable. For example, the relationship between a covariate and the response variable may be specified to be monotonically increasing or decreasing, convex, or concave. These constraints were introduced to our model so that the form of the smoothing functions for certain variables would reflect scientific intuition; these circumstances are explained in more detail in the methods section.

Methods

Recreational fishery fleet dynamics model

Crucial to short-term fishery forecasts is a consideration of how changes to recreational management measures such as minimum size, bag limits, and season length affect recreational harvest and discarding rates. A recreational fishery fleet dynamics model was developed that predicts both harvest and discards using the historical MRIP dataset along with an understanding of the management measures in place during the same period. To supplement this information, data from recent stock assessments for the species studied were also included such as spawning stock biomass and recruitment.

Data

The MRIP dataset uses the newly calibrated MRIP data timeseries (see: https://www.fisheries.noaa.gov/feature-story/fishing-effort-survey-calibrating-recreational-catch-estimates), and the data were queried to produced harvest and discards at a year-state-Wave level of granularity. This dataset of harvest and discards was overlaid with state-year-Wave specific historical management measures dating back to 1993 (the black sea bass dataset was started in 2009 after investigation). A "Wave" is a term used for two-month time periods within a year (e.g. January through February is Wave 1, March through April is Wave 2, etc.). The state regulations in place were refined to the Wave level. In cases where management plans did not line up well with the existing Wave structure of MRIP, the management that was in place for the majority of the wave was used. In other words, if the bag limit changed within a wave, the bag limit that was in place for the longest amount of time in that Wave was used.

The final dataset includes several metrics broken down by year, state, and Wave. Both landings and discards are in number of fish as estimated by MRIP. Bag limit, minimum size, and season length by year, state, and Wave (where applicable) were compiled from past fishery management plan review information. The recreational harvest limit (RHL) and spawning stock biomass (SSB) were pulled from past stock assessment reports. A lagged recruitment variable was also added to the analysis. To derive this value, age was estimated based on the minimum size of each state in each wave and year using a Von Bertalanffy growth curve. Values for the growth curve came from the most recent stock assessment documents (NEFSC, 2019).The stock assessment estimates recruitment (R) as the number of recruits at age 0 in a given year. The lagged recruitment for each row of data was the recruitment value counted back from the current year by the age at minimum size (rounded to the nearest whole year value). For example, if the minimum size of a fish was 18 inches in 2007, then the fish was estimated to be 6 years of age and the recruitment value used in year 2007 was the estimated number of age-0 recruits in 2003.

Model structure

From this survey generated catch information (MRIP), and the knowledge of the management structure in place in each state, a series of Shape Constrained Additive Models (SCAMs) were built to model the effects of management on harvest and discards. The “scam” function from the “scam” package (Pya 2021) was used in the statistical software R for the analysis (R core team 2021).

By using available information on recreational fishing to evaluate plausible alternatives for these relationships, we can account for uncertainty in the management responses of recreational fishery fleet dynamics. Since a statistical model was used, estimates of uncertainty can also be produced. The estimated uncertainty from these analyses can be used to describe alternate states of nature in the recreational fleet dynamics model when projecting a new series of management measures into the future.

The general form of the recreational fleet dynamics model is:

$$\begin{aligned} HarvestorDiscards \\ &= Year + s(Minimum\ Size) + s(Wave) + State + s(SeasonLength) + s(Bag) \\ &+ Recruitment + SpawningStockBiomass + RecreationalHarvestLimit \end{aligned}$$

Where an s indicates variables in the GAM that are smoothed, *Year* is the calendar year the harvest and regulations occurred in, *Minimum Size* is the regulatory minimum size in place for each year-state-Wave combination, $Wave$ is the two month period in which the catch occurred as defined by MRIP (waves go from 1 to 6 for the year), $State$ is the state in which the harvest occurred (states of MA – NC were used in the analysis), $SeasonLength$ is the length of the open fishing days in the specific Wave (e.g. days open can go from 1 to 61 or 62 depending on the Wave), Bag is the regulatory bag limit (or number of fish an individual angler is allowed to take on a trip) in a particular year-state-Wave combination. Other covariates were tested in the model including Recreational Harvest Limit (RHL), Recruitment (lagged by the number of years it would take for the recruit to enter the recreational fishery), and Spawning Stock Biomass (SSB) from the stock assessment (NEFSC 2019). These covariates were tested as elements that could provide information on availability of the stock to anglers, but not all were included in the final models because they did not significantly contribute to harvest and discard prediction ability.

A gamma distribution was selected for the model (with a log link) after model testing, with the gamma distribution performing the best relative to the existing data. Other distributions were considered including Poisson and negative binomial since the harvest and discards are in numbers of fish and therefore discrete, but the gamma distribution offered some of the same attributes such as not dropping below zero and flexibility in the shape of the distribution, and performed best during model testing, so this was the selected distribution for the model.

For the “scam” function, the “REML” method was used for the smoothness selection of the model. Also called “Restricted Maximum Likelihood”, this approach maximizes the scaled average of the likelihood over all possible values for the model parameters to find the variance parameters for the model (Wood 2017). Several bases were considered for the non-shape constrained smoothers included in candidate models, including cubic splines, P splines, and low-rank thin plate splines. Ultimately, low-rank thin plate splines (the default basis in the mgcv package for GAMs) were selected as the base for the smoothers, as this method does not require knots to be equidistantly placed over the range of the data (Wood 2006; Perperoglou et al. 2019). For shape constrained smoothers, shape constrained P-splines were used, which incorporate restraints on the functional form of the relationship between the covariate and the predicted value (Pya and Wood 2015).

Separate models were developed for harvest and discards. Future iterations may investigate a more synthetic way of modeling harvest and discards simultaneously, but to stay as close as possible to the models that were peer reviewed, two separate independent models were developed.

Given the level of refinement in the dataset, the general model can be applied to the coast, can be run as a stand-alone state specific model, and can be run as different regional configurations. It can also be run in a retrospective fashion to predict previous years to determine model performance. These all lead to flexibility in this model as a management tool, allowing for changes to occur through time, while allowing a consistent underlying method to be used even with these changes.

In addition to the estimated mean prediction, a function was used that samples from the uncertainty within the posterior of the model to produce an observation, or a single estimate within the envelop of uncertainty in the model. This function simulates data from a multivariate normal distribution conditioned on the covariance matrix from the SCAM model. This function is used to produce a single observation over multiple realizations for use in projecting the outcome of a specific regulatory set up (bag limit, minimum size, and season length set up) and helps to understand the uncertainty that is possible within this single management choice.

Model testing

A series of nested models based on the general model described above and all working from the same dataset were tested (Tables 3 - 8). In addition to various combinations of covariates, variations on the number of knots (the upper limit of the amount of complexity of model to be fitted) and smoothing methods were also tested. The models were all compared via Akaike information criterion (AIC) using the AIC function in R.

Evaluating performance

Several diagnostics were run on the models. The first was to examine the statistical table and the effect plots from the models. This was done to determine the statistical significance of the effects as well as examining that the effects were logical.

An additional set of diagnostics were run through the scam.check function in the mgcv package. This function plots four standard diagnostic plots, some smoothing parameter estimation convergence information, and the results of tests which may indicate if the smoothing basis dimension for a term is too low. The four plots are various residual plots. Please refer to the package documentation for the specifics on the various tests, but suffice it to say, the diagnostic analysis is less straight forward than traditional glm interpretation, therefore care is needed when interpreting these diagnostics.

A final analysis was done to determine the efficacy of the approach. Given that the model is conditioned on the existing historical dataset, a retrospective analysis can be done to determine if the model can recreate previous MRIP estimates. This was accomplished by creating a prediction data frame based on the exact bag limit, minimum size, and season length that were in place in the states during the year being analyzed. The final model was then run 1,000 times sampling from the posterior uncertainty in the model. The prediction and the actual summed landings for the year being analyzed were superimposed for examination of the model's efficacy in estimating harvest.

Results

Individual models were fitted to harvest and discards of summer flounder, black sea bass, and scup. The final models had the following forms:

Summer flounder:

Harvest= *Year(re) + s(Minimum Size) + s(Wave) + State + s(Season Length) + s(Bag Limit) + Recruitment + s(RHL)*

Discards= *Year(re) + s(Minimum Size) + s(Wave) + State + s(Season Length) + s(Bag Limit) + Recruitment + SSB*

Black sea bass:

Harvest= *Year(re) + s(Minimum Size) + s(Wave) + State + s(Season Length) + s(Bag Limit) + Recruitment + s(RHL)*

Discards= *Year(re) + s(Minimum Size) + s(Wave) + State + s(Season Length) + s(Bag Limit) + Recruitment + SSB*

Scup:

Harvest = *Year(re) + Mode + s(Minimum Size) + s(Wave) + State + s(Season Length) + s(Bag Limit) + SSB*

Discards= *Year(re) + Mode + s(Minimum Size) + s(Wave) + State + s(Season Length) + s(Bag Limit) + RHL*

Output from the recreational fishery fleet dynamics model generally indicated logical outcomes from the effects of the historical management measures. In general, harvest increased when regulations were liberalized (e.g., increased season length or RHL) and harvest decreased when regulations were made more restrictive (Table 1 and Figures 1, 4, 7, 10, 13, and 16). Generally, the final model effects appear to align with the understanding of what these various effects should be having on landings and discards.

Year was included as a smoothed numerical term in the initial models but was converted to be included as a random effect in the presented models in response to peer review feedback. We agree that conversion from a numerical to a categorical variable is appropriate to account for interannual variability in harvest estimates that is not accounted for by the other covariates in the model. By including year as a random effect, harvest predictions may be made without the need for assumptions regarding how future years will relate to historical years.

Multiple peer reviewers supported conversion of wave from a smoothed continuous variable to a categorical variable. While we acknowledge that wave is more aptly described as a factor, it was maintained as a continuous variable to account for the continuous seasonal pattern evident in recreational harvest seen across all three species. The wave effect is included in the harvest and discard models to account for changes in fishing behavior throughout the year that cannot be accounted for with the other management-related variables included. Because adjacent waves are expected to be more similar in harvest rate than waves that are separated by several months, wave was maintained as a continuous variable with a cyclical spline. This also gives flexibility for potential future models where waves are fragmented for management. In other words, if a partial wave is used in the future for management, reductions at the end of a wave will have a different effect than if changes are made at the beginning of the wave.

A retrospective analysis was done to look at the performance of each of the models relative to harvest and discards in years past. A multi-year retrospective analysis was performed where the management measures in place for each of the past years was used to predict the harvest in that same past year, and then this model prediction was compared to the actual harvest estimate produced by the MRIP program in that year. Figures 3, 6, 9, 12, 15, and 18 show the results of the retrospective analysis. What can be seen is that the model largely is able to predict, within the range of uncertainty in the predictions, the observed MRIP harvest or discard estimates for that year. In general, these predictions are most accurate from 2017 to 2019, perhaps reflecting closer coupling of management measures to harvest in most recent years or potentially an improvement in MRIP estimates of these data.

The effect of Wave within the model was also logical, increasing both harvest and discards from spring with a peak in the summer and then decreasing into the fall and winter. And finally, the effect of the different states on harvest and discards also made intuitive sense in that large states with high levels of fishing for these species had the strongest effect (e.g. NY and NJ) while smaller states with less fishing had negative effects (e.g. DE and MD), all of which were relative to the reference state of CT (Tables 1 and 2).

The model diagnostics are largely good for both the harvest and discard models. Residuals are generally normally distributed with a mean of zero, though there is some degree of a positive tail for both the harvest and discard models depending on the species. There is no patterning in the residuals, therefore they appear to be random with even variance across the range (Figures 2, 5, 8, 11, 14, and 17).

A shape-constrained smoothing function was used for the relationship between bag limit and harvest or discards for several of the models. In the first iteration of the recreational harvest models, bag limit produced a counterintuitive negative (yet insignificant) relationship with harvest. It was postulated that this negative relationship was an effect of a temporal trend wherein bag limits were reduced over the time series in response to increased fishing pressure due to increasing biomass and availability of the species. Thus, originally an interactive smoothing term including bag limit and RHL and/or SSB was introduced to allow the bag limit covariate to inform harvest in an intuitive manner. In response to peer review comment, this interactive term was removed and bag limit was instead fitted with a monotonically increasing shape constrained smoother in some cases. We recognize that there may have been changes in management approach over time that influenced the relationship between bag limit and harvest and cannot be fully accounted for within the model's parameterization. Previous conservation equivalency analyses of trip-level information indicate that year-to-year changes in bag limit produce the intended effect (although sometimes marginal) on recreational harvest so this shape-constrained smoother is assumed to represent expected real-world dynamics of possession limit changes.

Generally, the stock status variables of SSB, RHL, and recruitment (lagged to represent recruitment to the fishery) had a marginal impact on the model AIC for summer flounder, scup, and black sea bass. In cases where including these variables resulted in only a small change to the AIC (less than 2 points), preference was given to their inclusion.

Summer flounder

Season length was not significant in the summer flounder harvest model but was in the discard model (Tables 1 and 2) and generally had a positive effect on harvest and discards, meaning as season length increases, so do harvest and discards (Figures 1, and 4).

The recreational harvest limit was not included in the final summer flounder discard model but was included in the final harvest model. In theory, higher RHLs could be associated with higher summer flounder harvest, which seems to be indicated in the harvest model, for discards it is a more difficult effect to understand as discards could increase even with an increasing RHL due to cohort effects. This coupled with the fact that RHLs before 2019 were based on uncalibrated

MRIP data makes the link between this variable and eventual harvest and discards by anglers likely to be influenced by the uncalibrated MRIP estimated methods, adding variability to the effect in the model. This covariate may improve information to both models over time so should be kept for potential use moving forward.

The SSB covariate generally had an insignificant (P>0.05) effect on harvest and discards for summer flounder. This may be because regulations were set more conservatively in response to high fishing pressure in later years of the time series, when spawning stock biomass was generally at high levels. The covariate was kept in the discard model due to both the improvement in AIC as well as the desire to have either RHL or SSB as a stock status variable in each model if possible.

Recruitment was kept in both the discard and harvest models. It was only significant in the discard model; it was borderline in the harvest model, but in both cases the covariate improved the AIC score and had the intuitive effect of increasing harvest and discards as recruitment increased.

Black Sea Bass

One important note is that the dataset for black sea bass was truncated to start in 2009. This was done due to conflating signals and a rapidly changing population during the full time period, producing illogical effects in the model. This was done to respond to some of the critique from the peer reviewers. Truncating the time period to the past 10 years provided enough historical data for the model to generate parameters, while not pulling in data that confounded the analysis.

Season length was significant in the black sea bass harvest model but was not in the discard model (Tables 1 and 2) and generally had a positive effect on harvest and discards, meaning as season length increases, so do harvest and discards (Figures 7 and 10).

The recreational harvest limit was not included in the final black sea bass discard model but was included in the final harvest model. The logic for this is the same as noted in the summer flounder section. This covariate may improve information to both models over time so should be kept for potential use moving forward.

The SSB covariate generally had an insignificant (P>0.05) effect on harvest and discards for summer flounder. This may be because regulations were set more conservatively in response to high fishing pressure in later years of the time series, when spawning stock biomass was generally at high levels. The covariate was kept in the discard model due to both the improvement in AIC score as well as the desire to have either RHL or SSB as a stock status variable in each model if possible. In the case of black sea bass, the effect was a negative effect, meaning as SSB increased, discards increase. This could be due to the effects of cohorts moving into the population that take a while to reach harvestable size, so add more to discard totals than was seen for summer flounder.

Recruitment was kept in the harvest model but not in the discard model. It was not significant in the harvest model but improved the AIC score, therefore was kept. In the discard model it was also not significant and degraded the AIC score. In the harvest model recruitment had the intuitive effect of increasing harvest as recruitment increased.

<u>Scup</u>

Harvest and discard models for scup were fitted to data from 2003 to 2019, the most recent year for which stock status estimates are available. Scup is managed with different regulations for the private sector and the for-hire sector. The harvest and discard models for this species incorporated a “mode” term, which accounts for the higher magnitude of scup landings from the private/rental/shore mode compared with the for-hire mode.

Monotonically increasing and decreasing smoothers were fitted to bag limit for scup harvest and discards, respectively. As with summer flounder, temporal trends in the management approach may influence the relationship between bag limit and harvest; bag limits were more variable in the early years of the data and became relatively static during the last six years of the time series.

As with the summer flounder models, season length was marginally insignificant in the scup models (Tables 1 and 2) but had a positive effect on harvest and discards, meaning as season length increases, so do harvest and discards (Figures 13 and 16).

The SSB covariate had an insignificant ($P>0.05$) but positive effect on scup harvest and was included in the final harvest model. Similar to bag limit, this variable may be influenced by temporal shifts in the management approach, as fishing pressure increased in later years of the time series when scup spawning stock biomass was at high levels. For the discard model, RHL was included as a stock status variable and had an insignificant yet negative relationship with discards. The relationships between management and stock status variables and discards is less straightforward than those for harvest. As scup availability increases, fishing pressure could increase, which may result in higher discard rates corresponding to increased fishing effort. Another possibility is that increases in SSB and RHL may be driven by large cohorts coming into the population. This could increase discards in the short term as those age classes are still too small to be harvested by the fishery. However, the increased availability of scup to recreational harvesters via an increased RHL may also result in fewer regulatory discards as management measures are liberalized, reducing regulatory discards of the species.

Discussion

One of the key features of this work was the development of the recreational fleet dynamics models that can be used for management purposes. The models appear to perform well relative to being able to predict within the range of the MRIP estimates, and the output from the models is in line with the logical outcome of different management changes. The recreational fleet dynamics models have benefits to the overall management program for the recreational summer flounder, scup, and black sea bass fisheries in that this approach can be used as a new tool in the year-to-year management of these fisheries versus the current approach of independently analyzing the effects of the different management options (e.g., bag limit, season length, and minimum size). The modeling approach developed in this project could be preferred as it can more rigorously account for the interactions between these different measures in a more synthetic way; it is based off of empirical information not just from the most recent years but from all (or most) years in the time series, it is a single tool that can be used consistently by all states involved, and it has the attribute of generating uncertainty estimates, which is critical if the objective of regulatory stability is favored by managers. This tool can also be used in the evolution of the “Harvest Control Rule” approach to recreational management in that it can be used a priori to set the various steps in the management system in a way that accounts for uncertainty, and gets the fishery into a range that will align with the needed harvest limits given current stock status.

Changes will need to be made to the existing management process to accommodate the findings of this work. There is currently a need to adjust annually to make sure harvest is remaining under the RHL. In more recent time, there has been some move to incorporate some flexibility into the process by allowing for some subjective use of the uncertainty in the harvest estimate from MRIP, so there is some precedent to incorporating a technique like that highlighted by this work. The approach should be further refined and made more systematic by incorporating a control rule structure around the process. The following is an example of an approach that could be used as a control rule in the recreational fishery for summer flounder, scup, or black sea bass, and with proper development, could be extended to other similar recreational fisheries:

1. Determine spatial extent to be used (state-by-state, regional, coastwide)
2. Use the recreational fleet dynamics model to estimate harvest for the current fishing year (conversely, the direct estimate from MRIP could be used with its internally estimated uncertainty bounds)
3. If the RHL for the given spatial extent falls within the 95% confidence bounds of the estimated harvest in year t, do not change regulations, otherwise,
4. If the RHL for the given spatial extent falls outside of the 95% confidence bounds of the estimated harvest in year t:
    a. Generate a harvest estimate for year t+1 using the recreational fleet dynamics model for the appropriate spatial extent
    b. Modify the regulatory parameters in the model until the estimated year t+1 harvest includes the RHL within its 95% confidence bounds
5. Set the result from step 3 or 4 as the management program in year t+1, and repeat the process at the end of year t+1

This control rule maintains an annual process, however regulations may or may not change in any given year based on the current year’s harvest and uncertainty estimates. Modifications could include increasing or decreasing the 95% confidence bounds to some other value based on the Councils risk tolerance, increasing the time step to something other than 1 year to enact the process, and changing from harvest estimates to catch estimates in an effort to account for mortality that includes discards rather than only harvest.

Overall this approach appears to be effective and can provide a better alternative to the current management strategy being used for summer flounder, scup, and black sea bass. The application could be extended to other fisheries as well, namely bluefish.

References

Northeast Fisheries Science Center. 2013. 57th Northeast Regional Stock Assessment Workshop (57th SAW) Assessment Report. US Dept Commer, Northeast Fish Sci Cent Ref Doc. 13-16; 967 p. Available from: National Marine Fisheries Service, 166 Water Street, Woods Hole, MA 02543-1026, or online at http://nefsc.noaa.gov/publications/

R Core Team (2021). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Terceiro M. 2015. Stock assessment update of summer flounder for 2015. US Dept Commer, Northeast Fish Sci Cent Ref Doc. 15-13; 18p. Available from: National Marine Fisheries Service, 166 Water Street, Woods Hole, MA 02543-1026, or online at http://www.nefsc.noaa.gov/publications/

Northeast Fisheries Science Center (NEFSC). 2019. 66th Northeast Regional Stock Assessment Workshop (66th SAW) Assessment Report. US Dept Commer, Northeast Fish Sci Cent Ref Doc. 19-08; 1170 p.

Perperoglou, A., W. Sauerbrei, M. Abrahamowicz, and M. Scmid. 2019. A review of spline function procedures in R. BMC Medical Research Methodology 19(1):1-16.

Pya, N. and S.N. Wood. 2015. Shape constrained additive models. Statistical Computing 25:543-559.

Pya, N. 2021. Scam: Shape Constrained Additive Models. R package version 1.2-12. https//CRAN.R-project.org/package=scam

Ward, J. 2015. Recreational Summer Flounder Fishery Assessment. Report to the Mid-Atlantic Fishery Management Council, as presented June 16, 2015. 196p.

Wood, SN. 2006. Generalized Additive Models: An introduction with R. Chapman and Hall/CRC. Pp 392.

Table 1 – Model output and diagnostics from the recreational fishery fleet dynamics GAM for the harvest models.

Summer Flounder:

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Family: Gamma 
Link function: log 

Formula:
x ~ s(Year, k = 5, bs = "re") + s(MinLen, k = 6) + s(Wave, k = 5, 
    bs = "cc") + State + s(SeasonLen, k = 4) + s(Bag, k = 5, 
    bs = "mpi") + LagRecr + s(RHL, k = 4)
<environment: 0x0000012524c1c9f0>

Parametric coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  9.755e+00  3.877e-01  25.164  < 2e-16 ***
StateDE     -5.155e-01  1.541e-01  -3.346 0.000859 ***
StateMA     -1.395e-01  1.650e-01  -0.846 0.397973    
StateMD     -4.276e-01  1.647e-01  -2.596 0.009610 ** 
StateNC      1.971e-01  1.740e-01   1.133 0.257518    
StateNJ      2.288e+00  1.588e-01  14.414  < 2e-16 ***
StateNY      1.723e+00  1.580e-01  10.905  < 2e-16 ***
StateRI      3.605e-02  1.606e-01   0.225 0.822412    
StateVA      1.145e+00  1.581e-01   7.247    1e-12 ***
LagRecr      8.715e-06  4.786e-06   1.821 0.069000 .  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
                edf  Ref.df       F  p-value    
s(Year)      18.208 25.0000   2.293 4.08e-05 ***
s(MinLen)     1.163  0.9549   1.615  0.21473    
s(Wave)       3.188  3.0000 169.448  < 2e-16 ***
s(SeasonLen)  1.132  0.9256   2.059  0.16783    
s(Bag)        1.161  1.0637   6.610  0.00934 ** 
s(RHL)        2.126  2.1391   1.847  0.15394    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.7687   Deviance explained = 66.2%
GCV score =  1.008  Scale est. = 0.96299   n = 840
```

Black Sea Bass:

```
Family: Gamma
Link function: log

Formula:
x ~ s(Year, k = 5, bs = "re") + s(MinLen, k = 5) + s(Wave, k = 5,
    bs = "cc") + State + s(SeasonLen, k = 4) + s(Bag, k = 4) +
    LagRecr + s(RHL, k = 4)
<environment: 0x00000125190a0288>

Parametric coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)          1.107e+01  2.866e-01  38.633  < 2e-16 ***
StateDELAWARE       -9.693e-01  4.023e-01  -2.410  0.01658 *
StateMARYLAND       -9.604e-01  3.944e-01  -2.435  0.01548 *
StateMASSACHUSETTS   1.040e+00  3.435e-01   3.029  0.00267 **
StateNEW JERSEY      1.504e+00  3.799e-01   3.958 9.47e-05 ***
StateNEW YORK        1.521e+00  3.253e-01   4.677 4.45e-06 ***
StateNORTH CAROLINA -3.088e+00  4.230e-01  -7.301 2.68e-12 ***
StateRHODE ISLAND   -2.225e-02  3.041e-01  -0.073  0.94173
StateVIRGINIA       -1.081e+00  3.918e-01  -2.760  0.00614 **
LagRecr              7.415e-07  2.353e-06   0.315  0.75288
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
                edf Ref.df      F  p-value
s(Year)      0.0000 7.0000  0.000 0.694368
s(MinLen)    1.0353 0.8786  6.917 0.014251 *
s(Wave)      3.1649 3.0000 15.517 6.56e-09 ***
s(SeasonLen) 2.3066 2.2435  8.261 0.000209 ***
s(Bag)       1.1277 0.7695  0.796 0.434560
s(RHL)       0.9316 0.9778  1.978 0.165327
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.4152   Deviance explained = 56.5%
GCV score = 1.5774  Scale est. = 1.4803    n = 314
```

Scup:

```
Family: Gamma
Link function: log

Formula:
x ~ s(Year, k = 5, bs = "re") + Mode + State + s(Wave,
    k = 3) + s(MinLen, k = 4) + s(SeasonLen, k = 4) + s(Bag,
    k = 5, bs = "mpi") + SSB

Parametric coefficients:
                           Estimate Std. Error t value Pr(>|t|)    
(Intercept)               9.127e+00  5.754e-01  15.863  < 2e-16 ***
ModePrivate/Rental/Shore  2.707e+00  1.491e-01  18.154  < 2e-16 ***
StateDELAWARE            -6.300e+00  5.591e-01 -11.268  < 2e-16 ***
StateMARYLAND            -6.578e+00  5.807e-01 -11.327  < 2e-16 ***
StateMASSACHUSETTS        9.745e-01  2.510e-01   3.883 0.000115 ***
StateNEW HAMPSHIRE       -4.211e+00  1.555e+00  -2.709 0.006948 ** 
StateNEW JERSEY          -1.198e+00  2.797e-01  -4.285 2.13e-05 ***
StateNEW YORK             9.808e-01  2.149e-01   4.564 6.09e-06 ***
StateNORTH CAROLINA      -6.699e+00  5.458e-01 -12.273  < 2e-16 ***
StateRHODE ISLAND        -3.891e-01  2.168e-01  -1.795 0.073223 .  
StateVIRGINIA            -4.934e+00  5.482e-01  -9.000  < 2e-16 ***
SSB                       8.919e-07  1.420e-06   0.628 0.530142    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
                edf  Ref.df      F  p-value    
s(Year)      0.0001 15.0000  0.000  0.49158    
s(Wave)      2.5164  1.2707 15.605 2.93e-05 ***
s(MinLen)    1.5360  1.9762  1.667  0.18928    
s(SeasonLen) 1.8998  2.0241  1.151  0.31674    
s(Bag)       1.1977  0.8663 10.995  0.00212 ** 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.2507   Deviance explained = 62.4%
GCV score = 2.2421  Scale est. = 2.1685    n = 618


Method: GCV   Optimizer: bfgs
Number of iterations of smoothing parameter selection performed was 29 .
Full convergence.
Gradient range: [-5.67844e-07,2.183899e-08]
(score 2.2421 & scale 2.1685)
The optimal smoothing parameter(s): 8644312 0.42785 1.70039 0.22757 8058.058 .
```

Table 2 – Model output and diagnostics from the recreational fishery fleet dynamics GAM for the discard models.

Summer Flounder:

```
Family: Gamma
Link function: log

Formula:
x ~ s(Year, k = 5, bs = "re") + s(MinLen, k = 5) + s(Wave, k = 5,
    bs = "cc") + State + s(SeasonLen, k = 4) + s(Bag, k = 4) +
    SSB + LagRecr
<environment: 0x0000012521c81920>

Parametric coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  8.526e+00  2.930e-01  29.100  < 2e-16 ***
StateDE      1.905e-01  1.611e-01   1.183  0.23724    
StateMA     -5.085e-01  1.851e-01  -2.747  0.00619 ** 
StateMD      9.744e-01  1.756e-01   5.548 4.31e-08 ***
StateNC     -2.244e+00  2.165e-01 -10.364  < 2e-16 ***
StateNJ      3.000e+00  1.516e-01  19.791  < 2e-16 ***
StateNY      2.311e+00  1.565e-01  14.770  < 2e-16 ***
StateRI     -2.807e-01  1.681e-01  -1.670  0.09541 .  
StateVA      2.118e+00  1.692e-01  12.515  < 2e-16 ***
SSB          7.892e-06  5.180e-06   1.524  0.12811    
LagRecr      1.141e-05  3.681e-06   3.099  0.00203 ** 
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
             edf Ref.df       F  p-value    
s(Year)      4.563 25.000   0.430   0.1218    
s(MinLen)    4.083  3.803   9.900 2.32e-07 ***
s(Wave)      3.366  3.000 180.338  < 2e-16 ***
s(SeasonLen) 2.501  2.593   9.658 1.68e-05 ***
s(Bag)       2.956  2.915   3.701   0.0127 *  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.8283   Deviance explained = 75.9%
GCV score = 0.89702  Scale est. = 0.85651   n = 638
```

Black Sea Bass:

```
Family: Gamma
Link function: log

Formula:
x ~ s(Year, k = 5, bs = "re") + s(MinLen, k = 5) + s(Wave, k = 5,
    bs = "cc") + State + s(SeasonLen, k = 4) + s(Bag, k = 4) +
    SSB
<environment: 0x000001251a2c2980>

Parametric coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)          1.196e+01  4.223e-01  28.316  < 2e-16 ***
StateDELAWARE        4.671e-01  3.449e-01   1.354  0.17664
StateMARYLAND        8.964e-01  3.422e-01   2.620  0.00923 **
StateMASSACHUSETTS   1.022e+00  3.142e-01   3.251  0.00127 **
StateNEW JERSEY      2.738e+00  3.421e-01   8.004 2.40e-14 ***
StateNEW YORK        1.630e+00  2.553e-01   6.383 6.28e-10 ***
StateNORTH CAROLINA -7.589e-01  3.393e-01  -2.236  0.02603 *
StateRHODE ISLAND   -1.053e-01  2.432e-01  -0.433  0.66534
StateVIRGINIA        1.145e+00  3.403e-01   3.365  0.00086 ***
SSB                 -7.255e-06  1.637e-05  -0.443  0.65793
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
               edf Ref.df      F p-value
s(Year)      4.583 8.0000  1.730  0.0280 *
s(MinLen)    3.719 3.7008  6.046  0.0002 ***
s(Wave)      3.090 3.0000 76.382  <2e-16 ***
s(SeasonLen) 1.111 0.9658  1.650  0.2078
s(Bag)       1.283 0.9021  0.042  0.8454
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.5584   Deviance explained = 63.7%
GCV score = 1.0884  Scale est. = 1.01      n = 336
```

Scup:

```
Family: Gamma
Link function: log

Formula:
x ~ s(Year, bs = "re") + Mode + State + s(Wave, k = 3) +
    s(MinLen, k = 4) + s(SeasonLen, k = 3) + s(Bag, k = 4, bs = "mpi") +
    LagRecruit

Parametric coefficients:
                           Estimate Std. Error t value Pr(>|t|)
(Intercept)               7.477e+00  7.862e-01   9.511  < 2e-16 ***
ModePrivate/Rental/Shore  3.755e+00  1.437e-01  26.133  < 2e-16 ***
StateDELAWARE            -3.940e+00  4.236e-01  -9.301  < 2e-16 ***
StateMARYLAND            -4.233e+00  4.333e-01  -9.769  < 2e-16 ***
StateMASSACHUSETTS        1.455e+00  2.367e-01   6.144 1.44e-09 ***
StateNEW JERSEY          -3.590e-01  2.655e-01  -1.352  0.17680
StateNEW YORK             1.191e+00  2.077e-01   5.736 1.51e-08 ***
StateNORTH CAROLINA      -6.141e+00  6.290e-01  -9.764  < 2e-16 ***
StateRHODE ISLAND        -5.443e-01  2.089e-01  -2.606  0.00939 **
StateVIRGINIA            -3.741e+00  4.040e-01  -9.259  < 2e-16 ***
LagRecruit               -5.724e-07  7.362e-07  -0.777  0.43716
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
               edf  Ref.df      F  p-value
s(Year)      0.000 16.0000  0.000  0.52085
s(Wave)      2.421  1.5892 48.693 1.11e-15 ***
s(MinLen)    1.305  1.6877  0.268  0.72715
s(SeasonLen) 1.362  1.4660  0.553  0.52205
s(Bag)       1.370  0.7855 11.689  0.00254 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.0646   Deviance explained = 65.8%
GCV score = 2.1393  Scale est. = 2.0777    n = 639
```

```
Method: GCV   Optimizer: bfgs
Number of iterations of smoothing parameter selection performed was 30 .
Full convergence.
Gradient range: [-4.353858e-07,2.194484e-07]
(score 2.1393 & scale 2.0777)
The optimal smoothing parameter(s): 53451640 0.03843 4.66137 0.3964 4440.23 .
```

Table 3 – Model testing configurations with associated AIC scores for the summer flounder harvest model

Model	Yr	Min Size	Wave	State	Open Days	Bag	SSB	Recruit	RHL	AIC
1	X	X	X	X	X	X	X	X	X	20833
2	X	X	X	X	X	X	X	X		20835
3	X	X	X	X	X	X		X	X	20835
4	X	X	X	X	X	X	X			20833
5	X	X	X	X	X	X				20834
6	X	X	X	X	X					20834
7	X	X	X	X						20837
8	X	X	X							21490
9	X	X								21780
10	X									21839
Final	X	X	X	X	X	X		X	X	20835

Table 4 – Model testing configurations with associated AIC scores for the summer flounder discard model

Model	Yr	Min Size	Wave	State	Open Days	Bag	SSB	Recruit	RHL	AIC
1	X	X	X	X	X	X	X	X	X	14642
2	X	X	X	X	X	X	X	X		14641
3	X	X	X	X	X	X		X	X	14641
4	X	X	X	X	X	X	X			14645
5	X	X	X	X	X	X				14645
6	X	X	X	X	X					14647
7	X	X	X	X						14669
8	X	X	X							15474
9	X	X								15695
10	X									15711
Final	X	X	X	X	X	X	X	X		14641

Table 5 – Model testing configurations with associated AIC scores for the black sea bass harvest model

Model	Yr	Min Size	Wave	State	Open Days	Bag	SSB	Recruit	RHL	AIC
1	X	X	X	X	X	X	X	X	X	7503
2	X	X	X	X	X	X	X	X		7503
3	X	X	X	X	X	X		X	X	7500
4	X	X	X	X	X	X	X			7501
5	X	X	X	X	X	X				7499
6	X	X	X	X	X					7496
7	X	X	X	X						7513
8	X	X	X							7750
9	X	X								7762
10	X									7799
Final	X	X	X	X	X	X		X	X	7500

Table 6 – Model testing configurations with associated AIC scores for the black sea bass discard model

Model	Yr	Min Size	Wave	State	Open Days	Bag	SSB	Recruit	RHL	AIC
1	X	X	X	X	X	X	X	X	X	9185
2	X	X	X	X	X	X	X	X		9184
3	X	X	X	X	X	X		X	X	DNC
4	X	X	X	X	X	X	X			9183
5	X	X	X	X	X	X				9182
6	X	X	X	X	X					9181
7	X	X	X	X						DNC
8	X	X	X							9437
9	X	X								9540
10	X									9554
Final	X	X	X	X	X	X	X	X		9183

Table 7 – Model testing configurations with associated AIC scores for the scup harvest model

Model	Yr	Mode	State	Wave	Min Size	Open Days	Bag	SSB	Recruit	RHL	AIC
1	X	X	X	X	X	X	X	X	X	X	14485
2	X	X	X	X	X	X	X	X	X		14482
3	X	X	X	X	X	X	X		X	X	14483
4	X	X	X	X	X	X	X	X			14480
5	X	X	X	X	X	X	X				14479
6	X	X	X	X	X	X					14488
7	X	X	X	X	X						14507
8	X	X	X	X							14517
9	X	X	X								14511
Final	X	X	X	X	X	X	X	X			14480

Table 8 – Model testing configurations with associated AIC scores for the scup discard model

Model	Yr	Mode	State	Wave	Min Size	Open Days	Bag	SSB	Recruit	RHL	AIC
1	X	X	X	X	X	X	X	X	X	X	15150
2	X	X	X	X	X	X	X	X	X		15148
3	X	X	X	X	X	X	X		X	X	15148
	X	X	X	X	X	X	X		X		15146
	X	X	X	X	X	X	X			X	15147
4	X	X	X	X	X	X	X	X			15147
5	X	X	X	X	X	X	X				15145
6	X	X	X	X	X	X					15155
7	X	X	X	X	X						15159
8	X	X	X	X							15157
9	X	X	X								15232
Final	X	X	X	X	X	X	X		X		15146

Table 9 – Responses to peer review comments.

Issue	Page(s) of peer review report	Resolved?	Notes
Model selection process unclear	pg. 1-2, 5-6	Y	Tables above and text should clarify
Should use same variables for harvest and discards	pg. 5	N	Felt it was logical that the variables might be different between the models
Investigate performance of modeling harvest and discards together		N	Future work
Year should be categorical variable	pg. 3	Y	Included as a random effect
Should be able to predict zero harvest during fishery closure	pg. 4, 6	N	Even when fisheries are closed, there are often landings that occur
Wave should be categorical variable	pg 7	N	We expect there to be some sort of seasonal trend in the wave covariate (ie adjacent waves should be more similar than distant waves)
Out of sample predictions at the state level should be shown	pg. 6	Y	Could be done as additional diagnostic
Name of the model should be revised, as it does not capture behavior of anglers or the fleets	pg. 1, 3	N	Happy to discuss a new name with the MC
Selection of interaction terms should be revisited	pg 5-6	Y	Interactions were removed
Counterintuitive relationship between bag and harvest	pg. 5-6	Y	Subsequent work resolved this issue

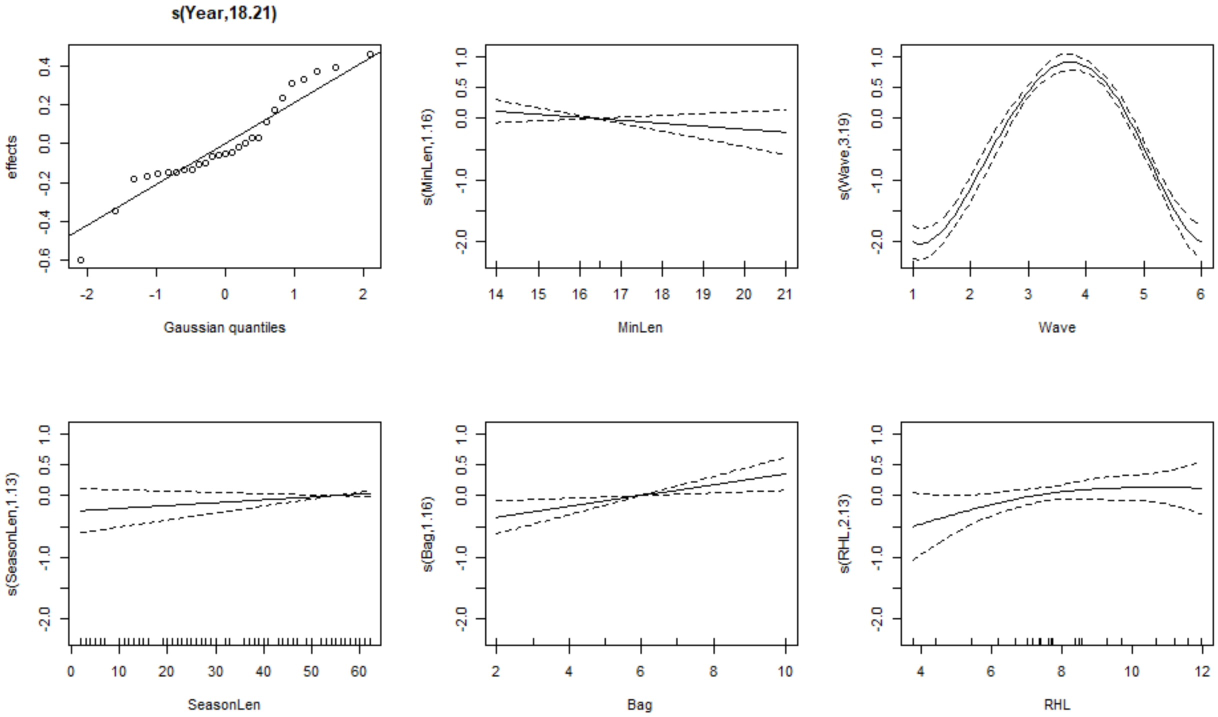

Figure 1 – Output on the covariate effects from the recreational fishery fleet dynamics GAM for the summer flounder harvest model.

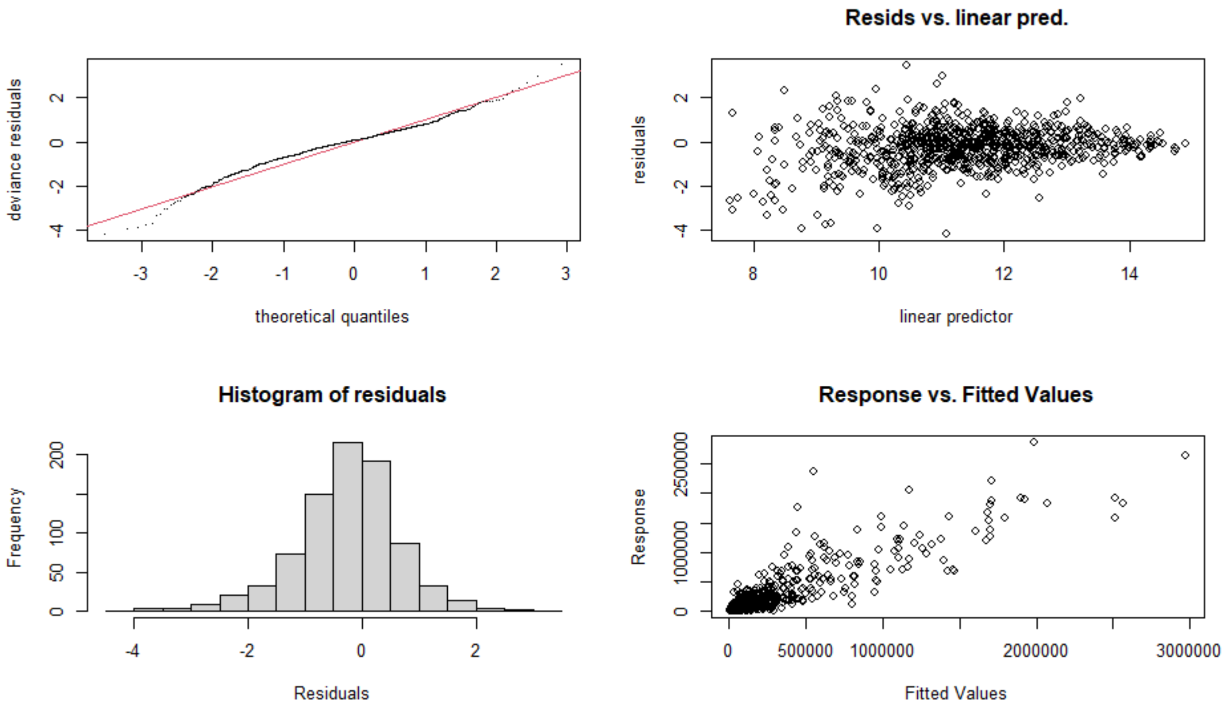

Figure 2 – Model diagnostics for the recreational fishery fleet dynamics GAM for the summer flounder harvest model.

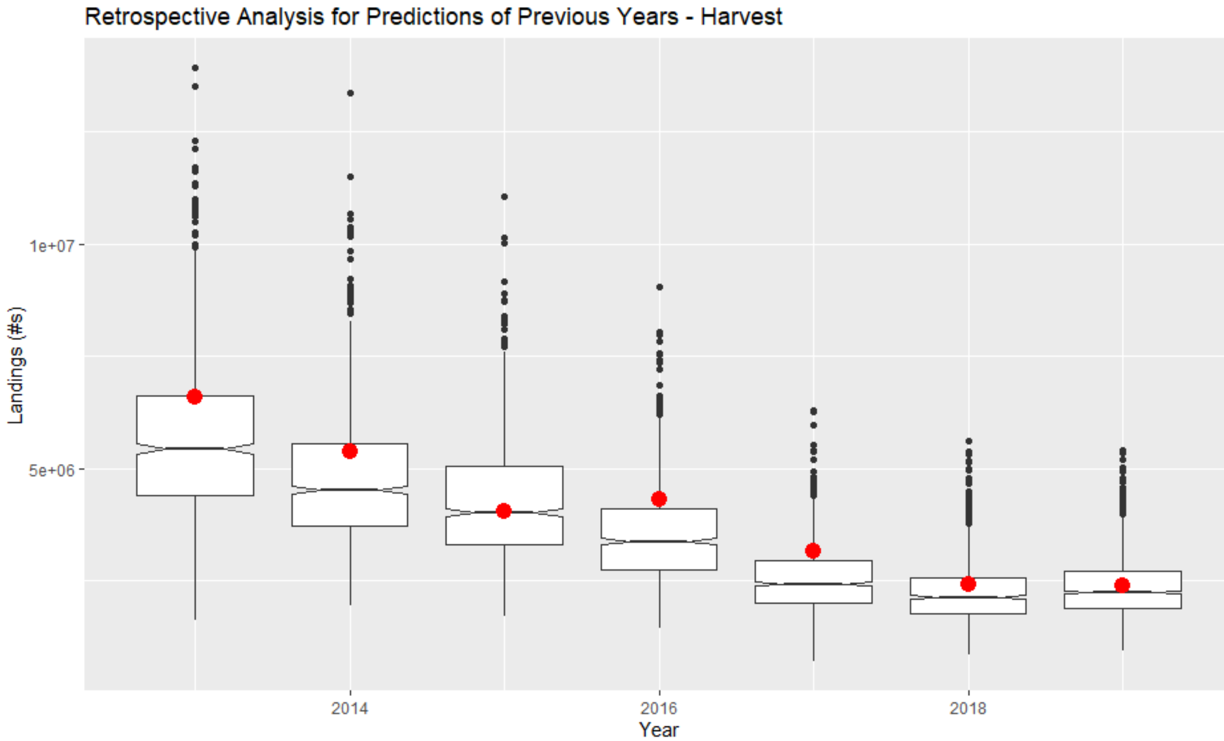

Figure 3 – Retrospective analysis using simulated data from the summer flounder SCAM and comparing it to MRIP summer flounder harvest estimate for years 2014 - 2019. The box and whisker plot is the model estimate with uncertainty and the red dot is the “observed” MRIP estimate.

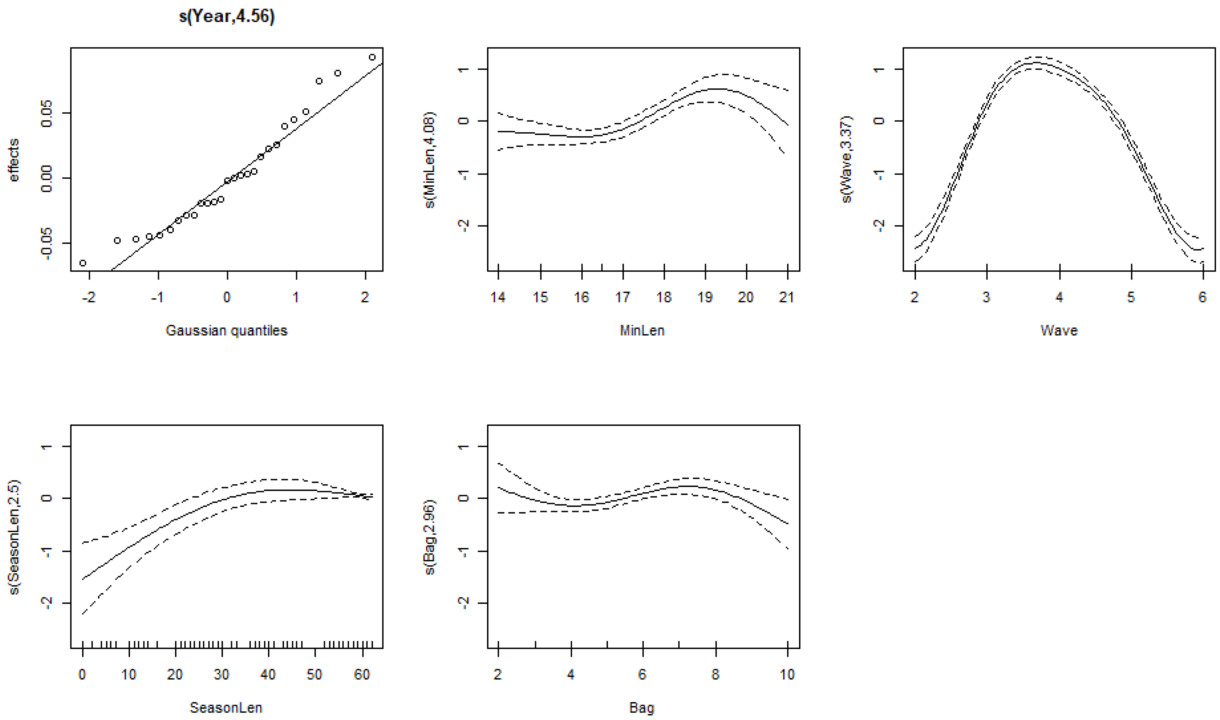

Figure 4 – Output on the covariate effects from the recreational fishery fleet dynamics GAM for the summer flounder discard model.

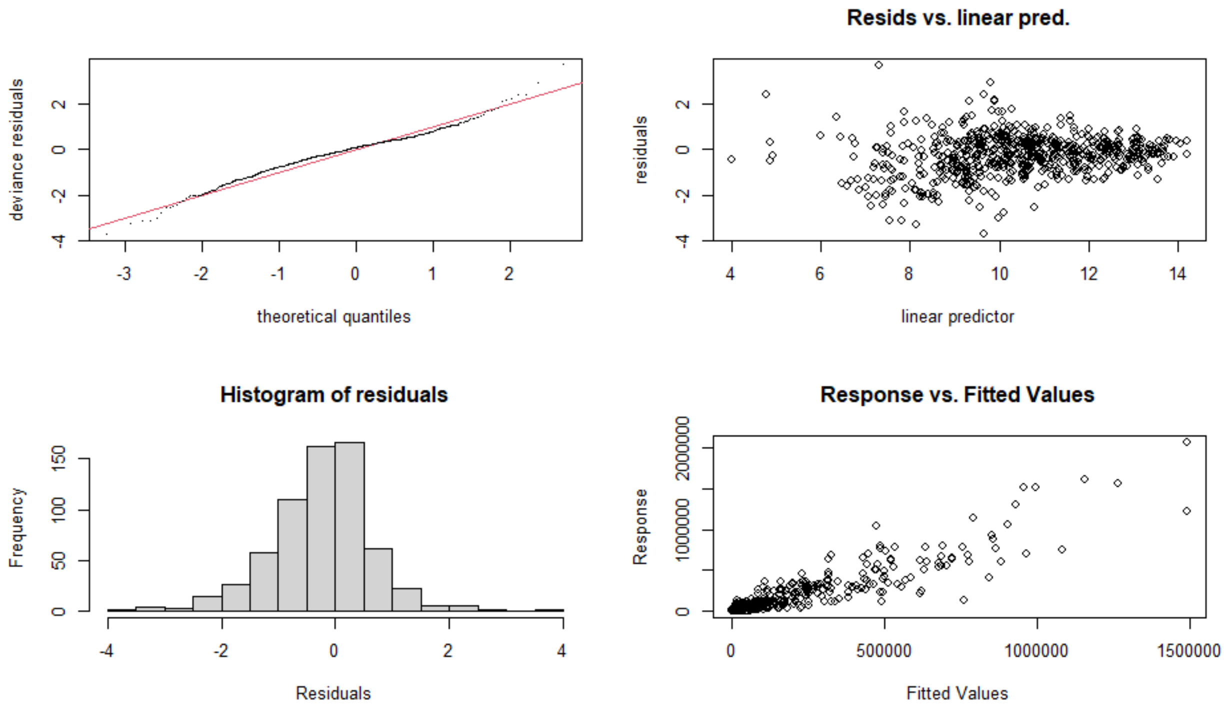

Figure 5 – Model diagnostics for the recreational fishery fleet dynamics GAM for the summer flounder discard model.

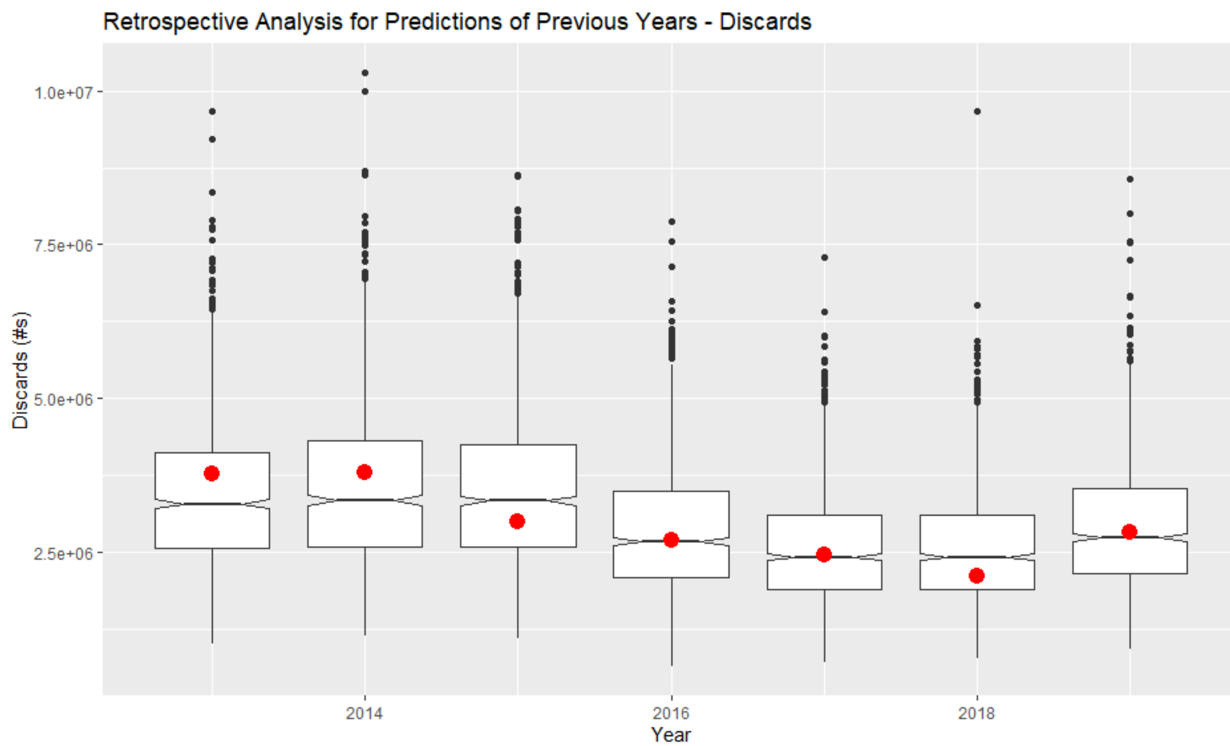

Figure 6 – Retrospective analysis using simulated data from the summer flounder SCAM and comparing it to MRIP summer flounder discard estimate for years 2014 - 2019. The box and whisker plot is the model estimate with uncertainty and the red dot is the “observed” MRIP estimate.

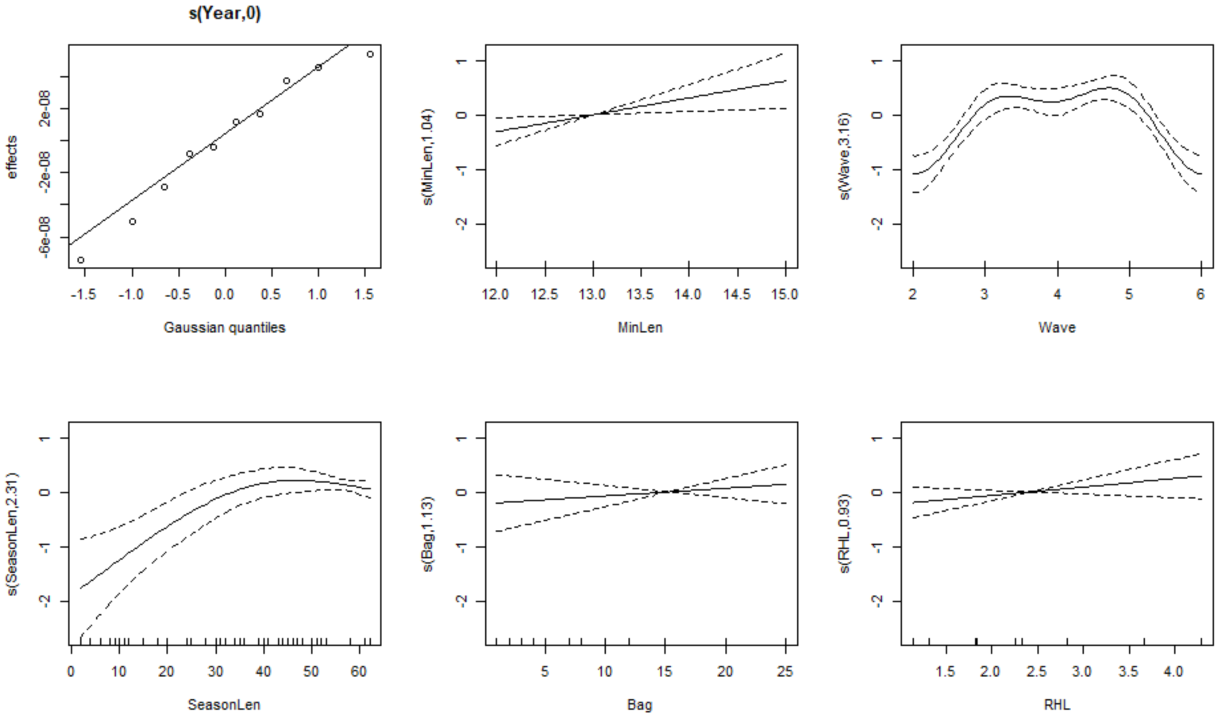

Figure 7 – Output on the covariate effects from the recreational fishery fleet dynamics GAM for the black sea bass harvest model.

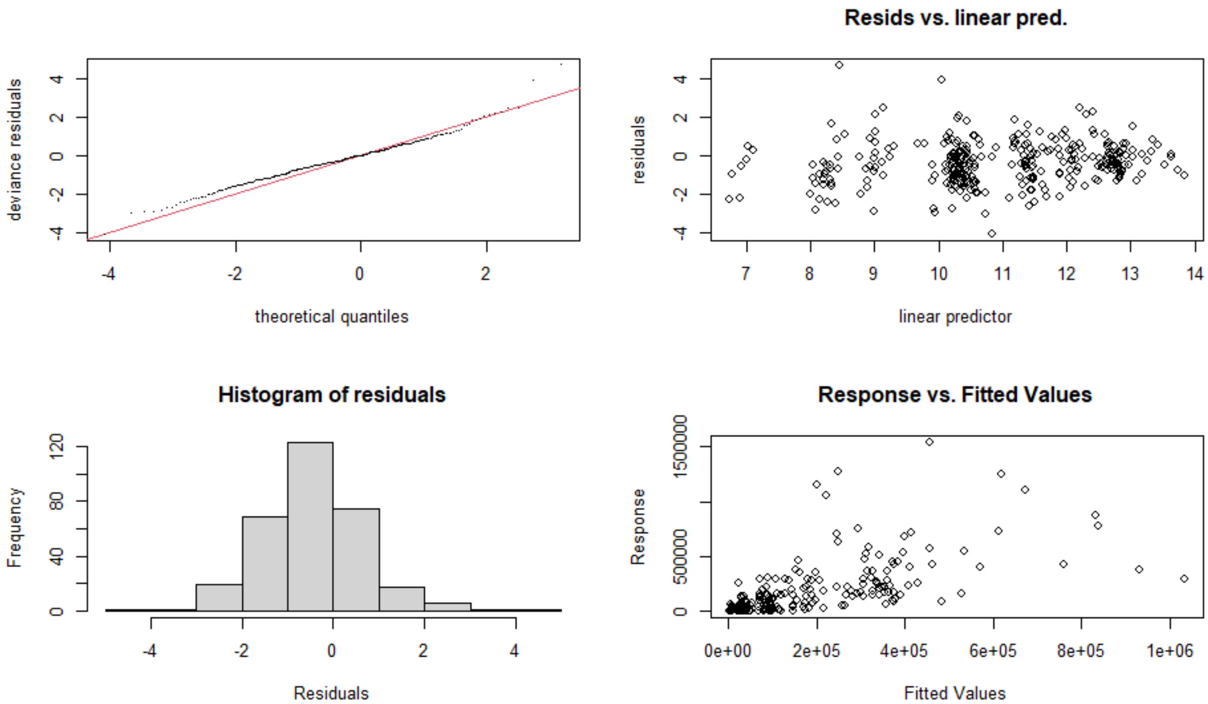

Figure 8 – Model diagnostics for the recreational fishery fleet dynamics GAM for black sea bass harvest model.

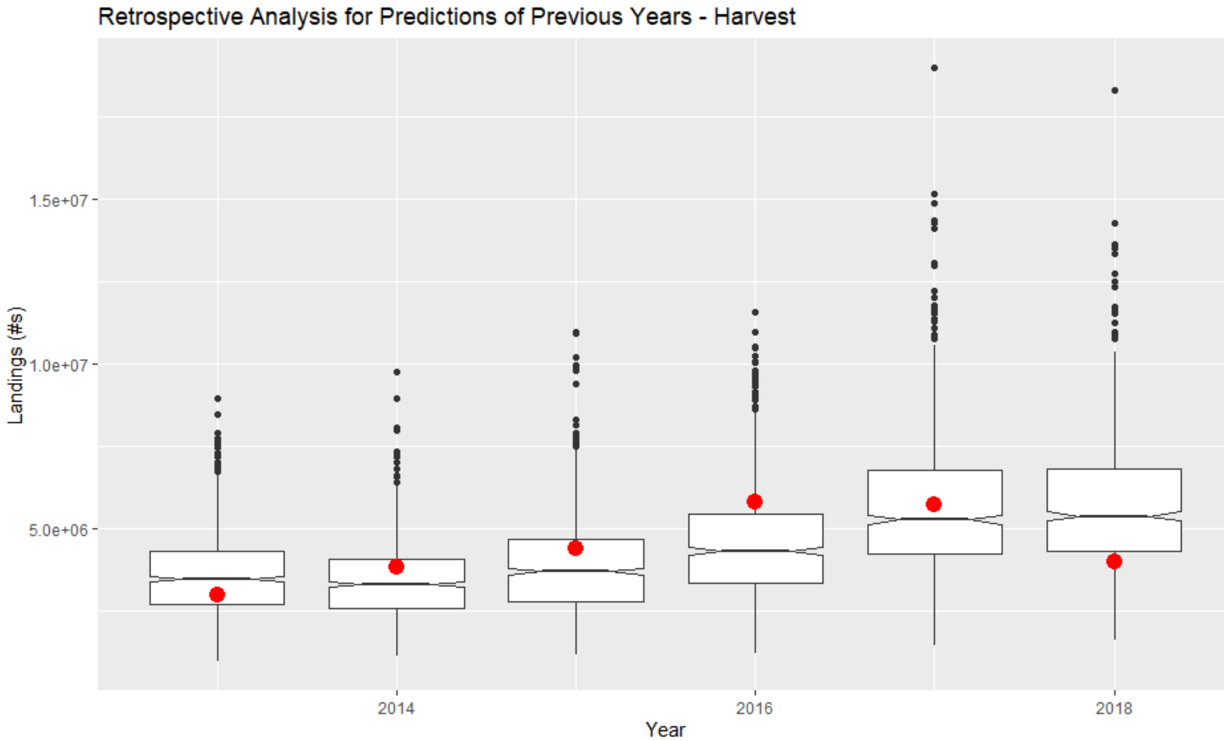

Figure 9 – Retrospective analysis using simulated data from the black sea bass SCAM and comparing it to MRIP black sea bass harvest estimate for years 2014 - 2018. The box and whisker plot is the model estimate with uncertainty and the red dot is the “observed” MRIP estimate.

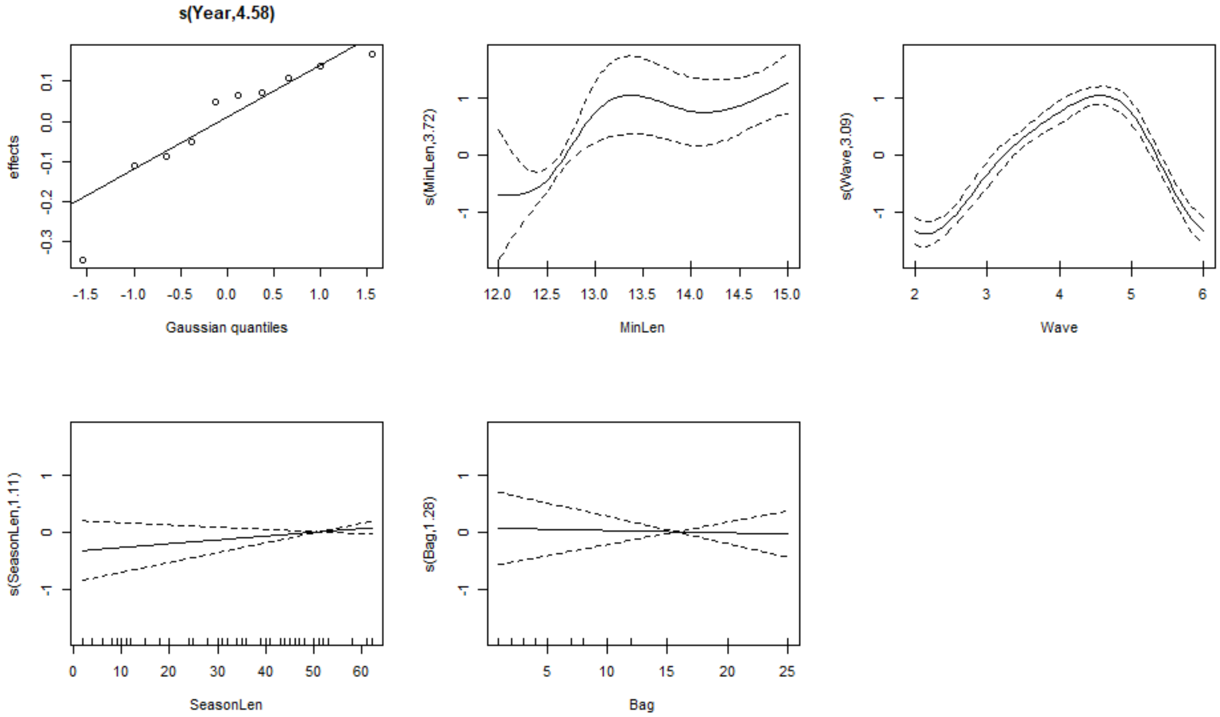

Figure 10 – Output on the covariate effects from the recreational fishery fleet dynamics GAM for the black sea bass discard model.

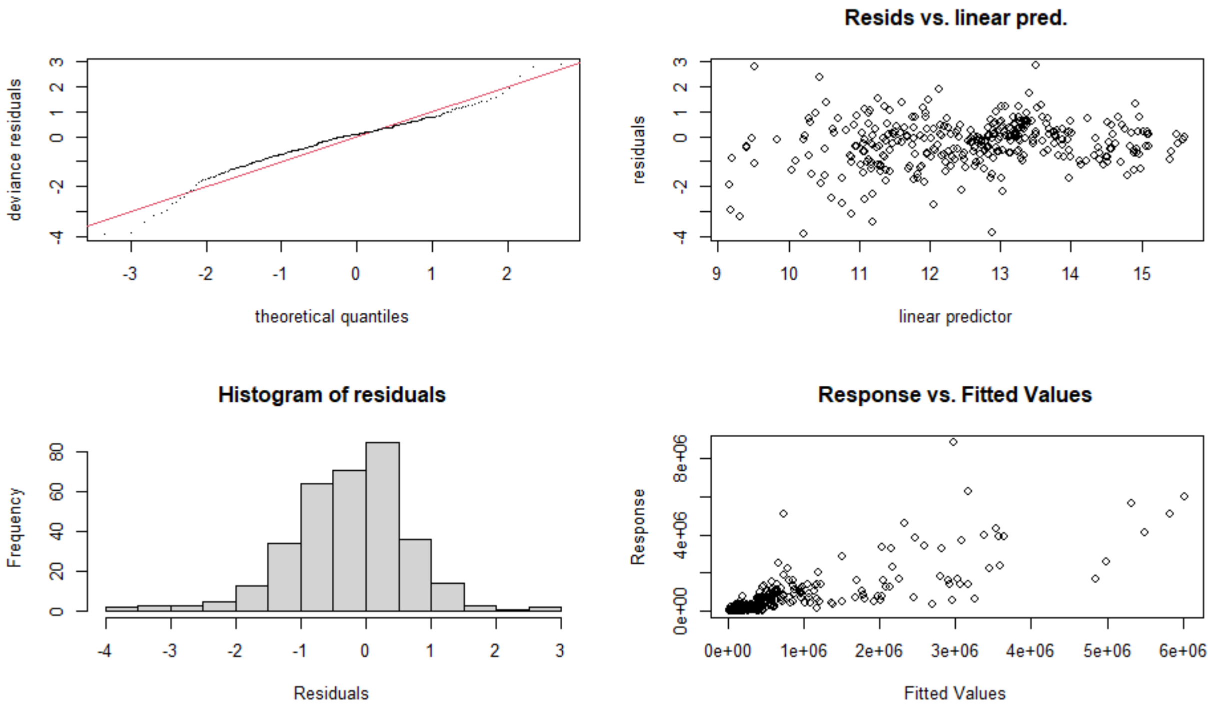

Figure 11 – Model diagnostics for the recreational fishery fleet dynamics GAM for black sea bass discard model.

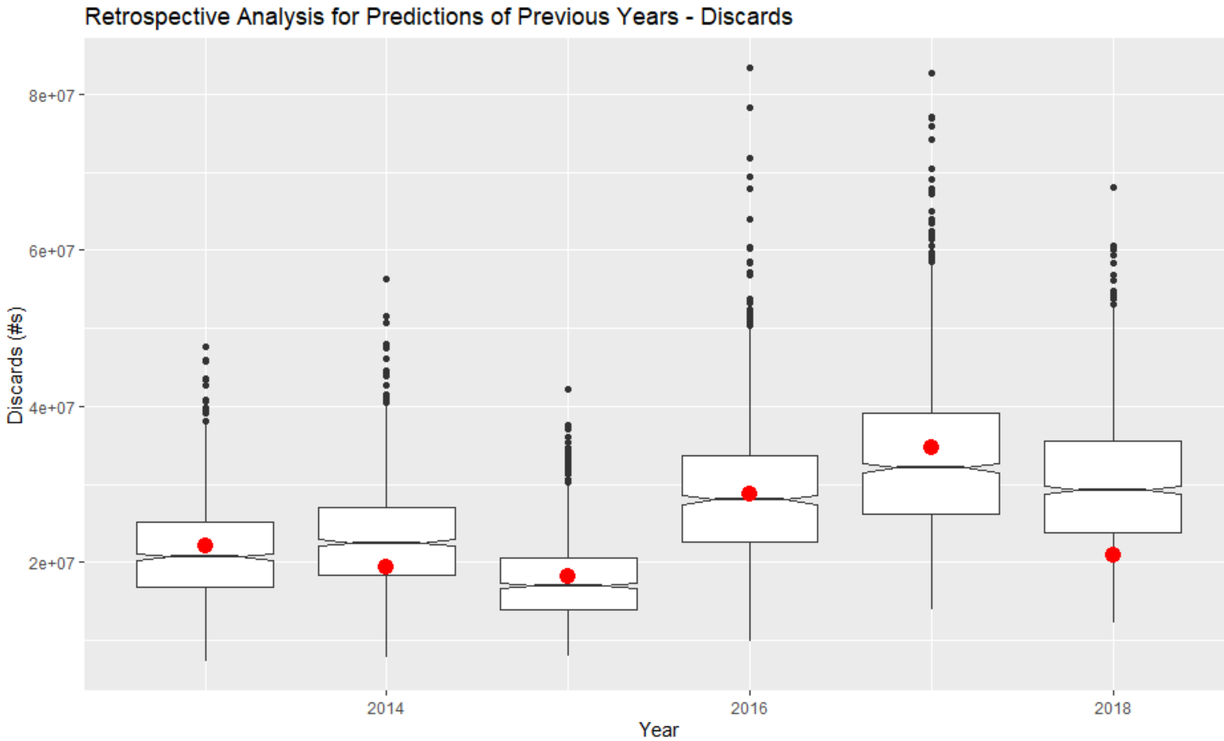

Figure 12 – Retrospective analysis using simulated data from the black sea bass SCAM and comparing it to MRIP black sea bass discard estimate for years 2014 - 2018. The box and whisker plot is the model estimate with uncertainty and the red dot is the “observed” MRIP estimate.

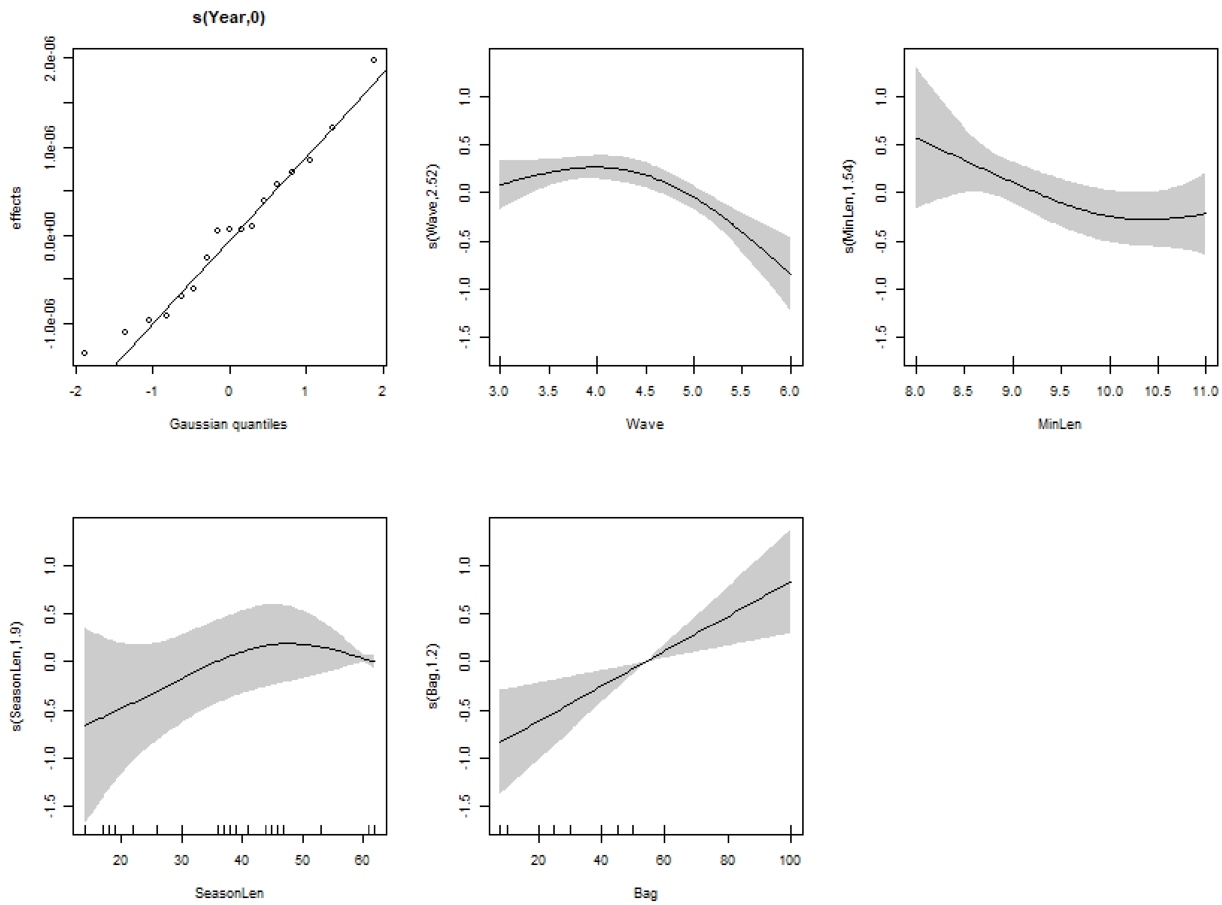

Figure 13 - Output on the covariate effects from the SCAM for scup harvest.

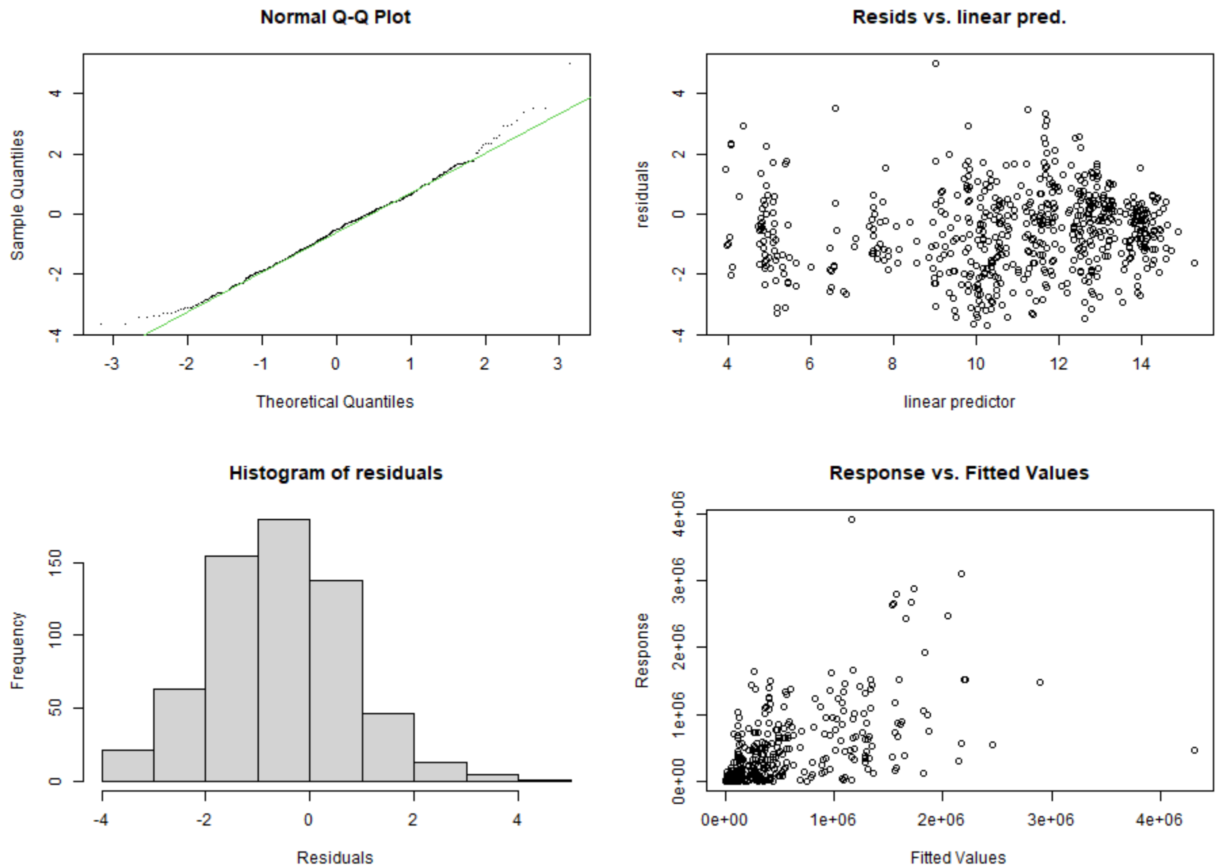

Figure 14 – Model diagnostics for the recreational fishery fleet dynamics GAM for the scup harvest model.

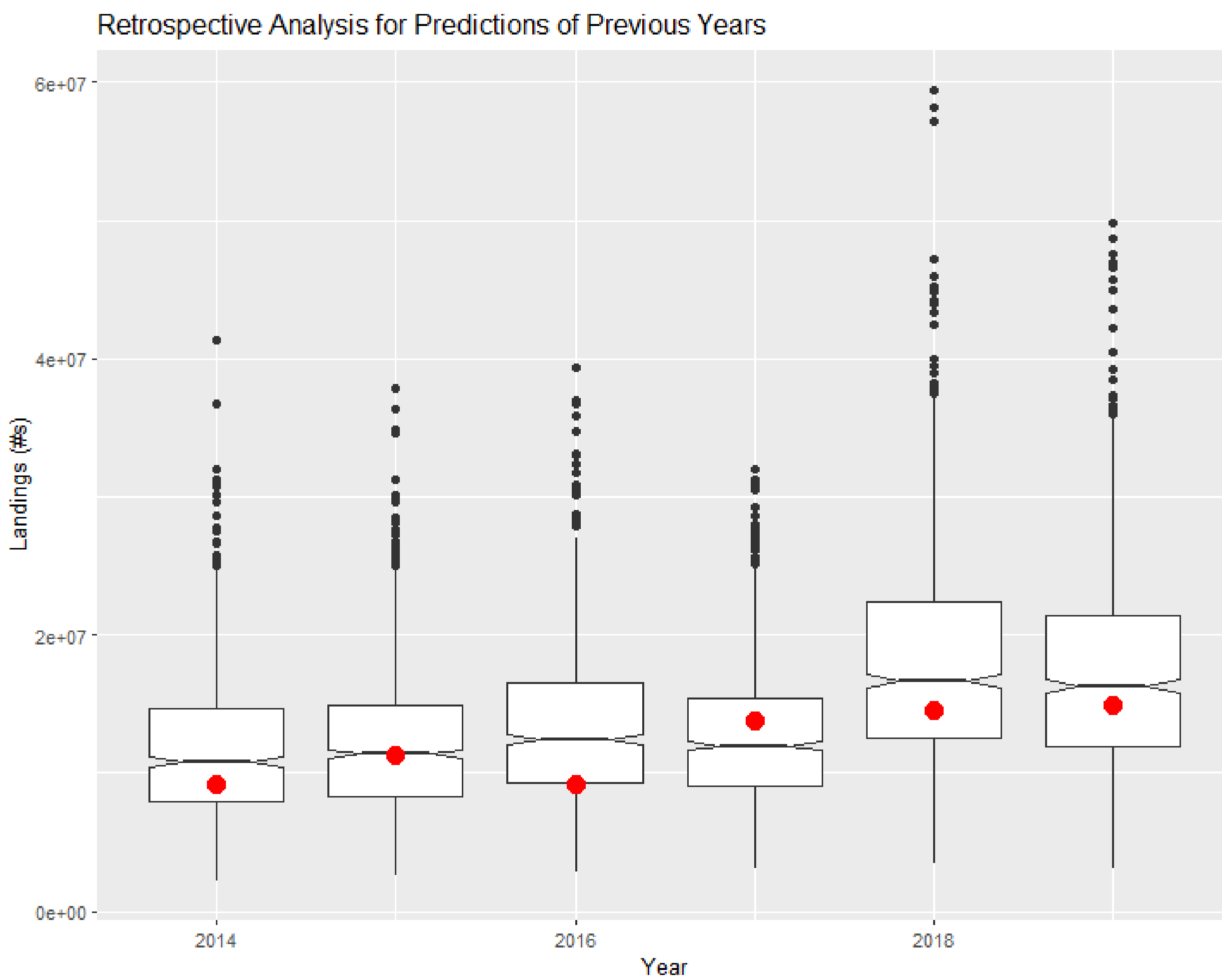

Figure 15 – Retrospective analysis using simulated data from the scup harvest SCAM and comparing it to MRIP scup harvest estimates for years 2014 - 2019. The box and whisker plot is the model estimate with uncertainty and the red dot is the “observed” MRIP estimate.

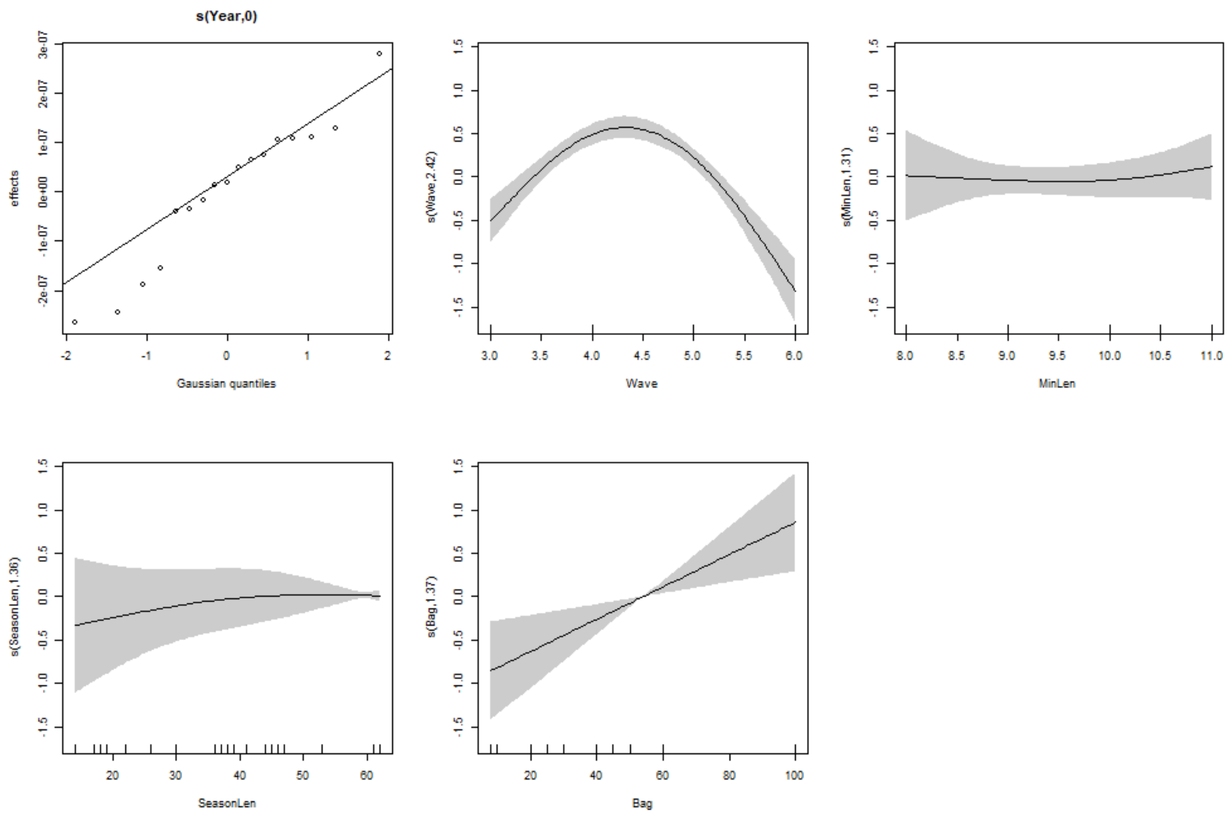

Figure 16 - Output on the covariate effects from the SCAM for scup discards.

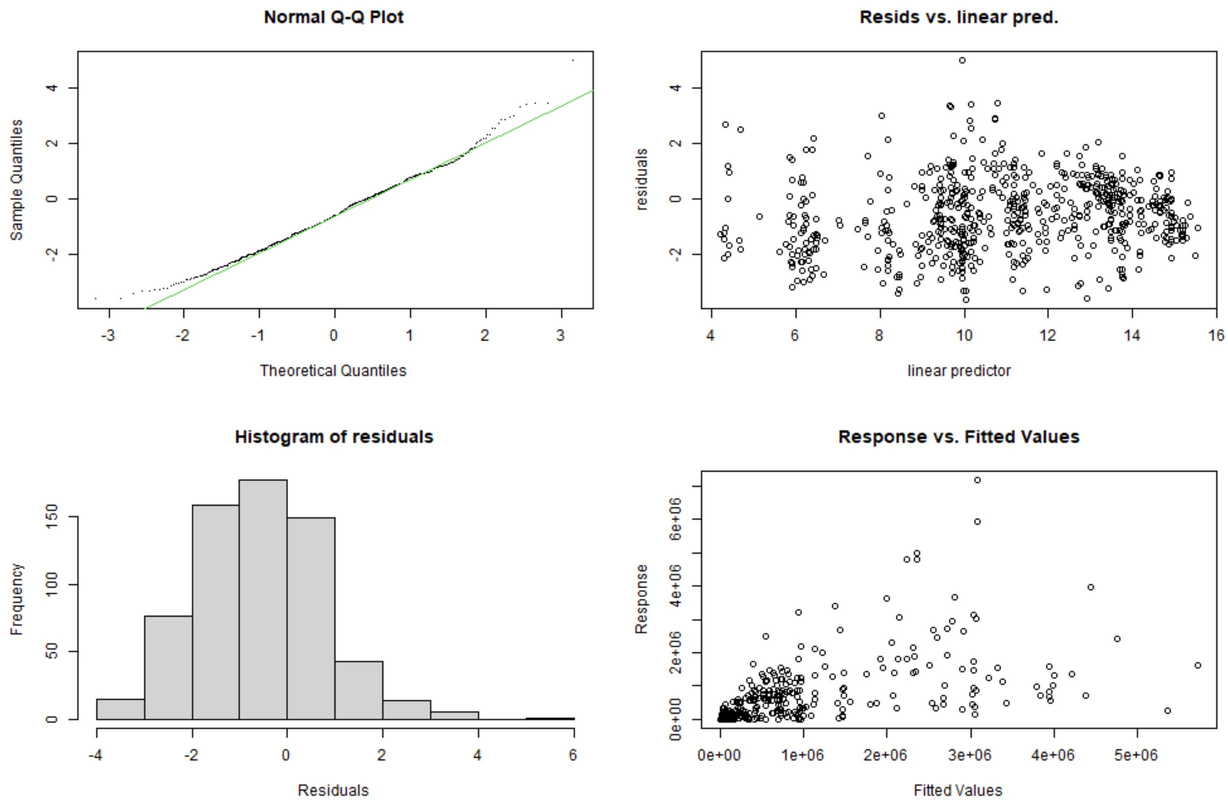

Figure 17 – Model diagnostics for the recreational fishery fleet dynamics GAM for the scup discard model.

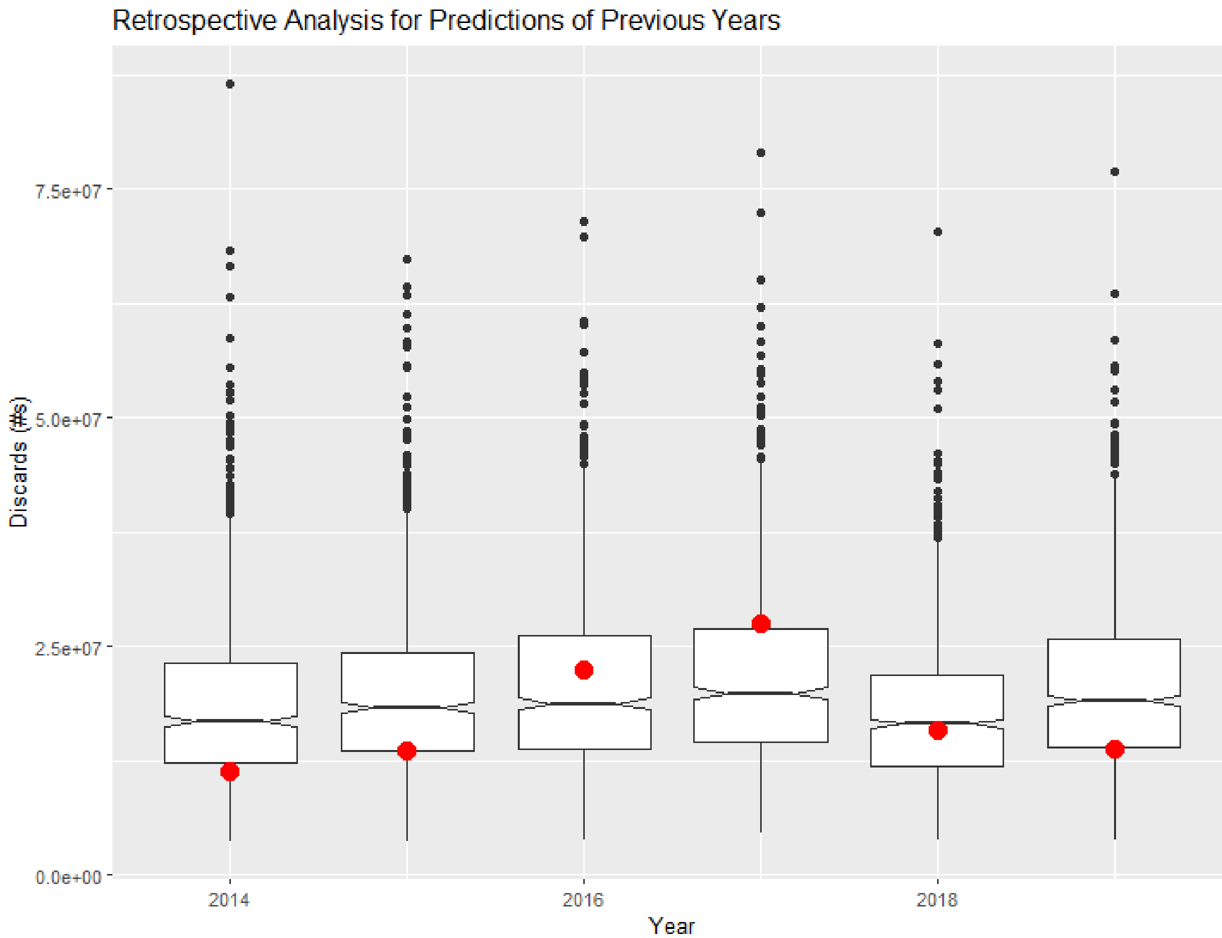

Figure 18 – Retrospective analysis using simulated data from the scup discard SCAM and comparing it to MRIP scup harvest estimates for years 2014 - 2019. The box and whisker plot is the model estimate with uncertainty and the red dot is the “observed” MRIP estimate.