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Methods For Accounting For The Impact Of The COVID-19 Pandemic On Adult Salmon Stock Estimates In Scotland

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Executive summary

Estimation of Scotland's Atlantic salmon stocks is a key component of national and international management and requires information on rod catches. During 2020 rod fisheries were adversely impacted by restrictions associated with the COVID-19 pandemic. Without accounting for reduced fishing effort, stock abundance may be underestimated due to lower-than-expected catch.

Two complimentary approaches to account for lower-than-expected catches on stock estimates were developed and presented to the Working Group on North Atlantic Salmon in March 2021. The first approach uses historic catches to estimate expected-catches for the affected months in 2020. This simple approach captures the within year pattern of catches and allows overall catches to vary between years. The second approach was based on estimating expected-catch by first modelling a "corrected effort" that would have been expected in the absence of restrictions and then converting this to expected-catch using a model of monthly catch per unit effort. The choice of which model to apply to each of the 173 assessment areas used for national management was made by comparing model fits for the 2019 season. There was a fairly even balance between the number of areas that were favoured by the two overall approaches.

Applying a COVID-correction to catches increases the whole-of-Scotland stock estimate by approximately 22%, although the degree of correction differed between different assessment areas depending on area-specific catch and effort data. Although it is not possible to fully account for the complexity of the pandemic and it's impact on rod fishing the methods described allow the impact of the COVID-19 pandemic to be accounted for in stock assessments.

Introduction

The COVID-19 pandemic severely impacted Atlantic salmon (*Salmo salar*) fisheries in Scotland over the 2020 season. While fishing was specifically allowed as a non-contact, outdoor activity, stay-at-home orders along with subsequent restrictions on national and international travel disrupted access to, and the business of, salmon fishing. In 2019, Marine Scotland began collecting information on fishing effort from salmon fisheries, in addition to catch statistics. These data showed a clear reduction in fishing effort in the spring/early summer season of 2020 compared to 2019 (Fig.1). This decrease in effort may ultimately have led to lower-than-expected catches and makes comparisons of catches with previous years challenging.

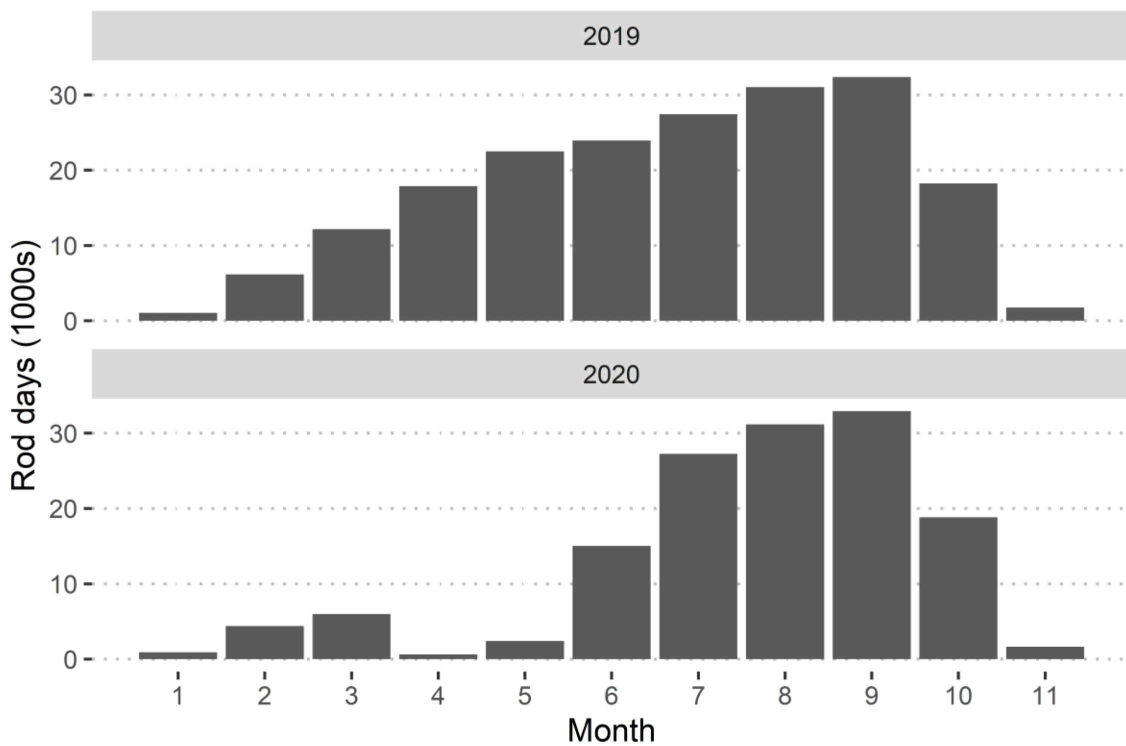

Figure 1: Wild Atlantic salmon angling effort (rod days) in Scottish rivers, 2019 and 2020. Rod days are the number of rods fished each day, regardless of the amount of time spent fishing each day.

Atlantic salmon stock abundance estimation is undertaken in Scotland to guide both national- and international-level management. At the national level, the Conservation of Salmon (Scotland) Regulations 2016 require mandatory catch and release of salmon in areas which fall below their defined conservation limit following an assessment of the stock. Assessment is undertaken at the scale of the river, or on groups of smaller neighbouring rivers where rod fishery data is not yet available by river (hereafter, ‘assessment areas’). In international assessments, pre-fishery abundance of salmon stocks are estimated using information on in-river abundance aggregated to a regional level (East and West Scotland). These estimates are compared with nationally-derived conservation limits in the provision of catch options and advice for two high seas fisheries in the North Atlantic (ICES, 2021). Both assessments rely on the estimation of in-river abundance.

In-river abundance estimates for Scotland are mainly derived from monthly reported rod catches, which are scaled up using information from fish counters on a selection of catchments. The process also accounts for changes in river flow which may impact on angling conditions and ability to catch salmon (Anon., 2019). The reduction in fishing effort as a result of the COVID-19 pandemic, and subsequent potential reduction in reported rod catch, therefore presented a particular challenge to stock estimation for the 2020 season. Without accounting for reduced fishing effort, stock abundance may be underestimated due to lower-than-expected catch.

In a ‘normal year’, fishery-independent information on the abundance of salmon such as counts of fish passing over counters in selected catchments could be used to account for reduced fishing effort. However, due to unforeseen circumstances, accurate counter data was not available for the majority of those catchments normally included in the assessment process in 2020. It was therefore necessary to estimate an ‘expected-catch’ value as the catch of salmon expected in the absence of COVID-19 restrictions. Expected-catch estimates (with associated uncertainty) then provide input to the abundance modelling process.

Restrictions impacting fishing effort were not consistent across the salmon angling season. Stay-at-home orders were issued in March; travel (for leisure or exercise) was restricted to local travel only (5 miles from place of residence) from late May until July. In November, Scotland entered another period of emergency measures, with domestic travel restrictions dependent on the development of the COVID-19 pandemic in local areas. The months for which it was necessary to estimate an expected-catch value were therefore March, April, May, June and November.

Two approaches were developed for estimating expected-catch in 2020. These were presented to the Working Group on North Atlantic Salmon in March 2021 in respect of international assessments (ICES, 2021) and further refined in April-May 2021 in respect of national assessments. The first approach considered that in areas where there is a large amount of historic data on salmon catches and where the seasonal pattern of catch is consistent (Fig. 2A), this information could be used to estimated expected-catches for the affected months in 2020. This simple approach captures the within year pattern of catches and allows overall catches to vary between years.

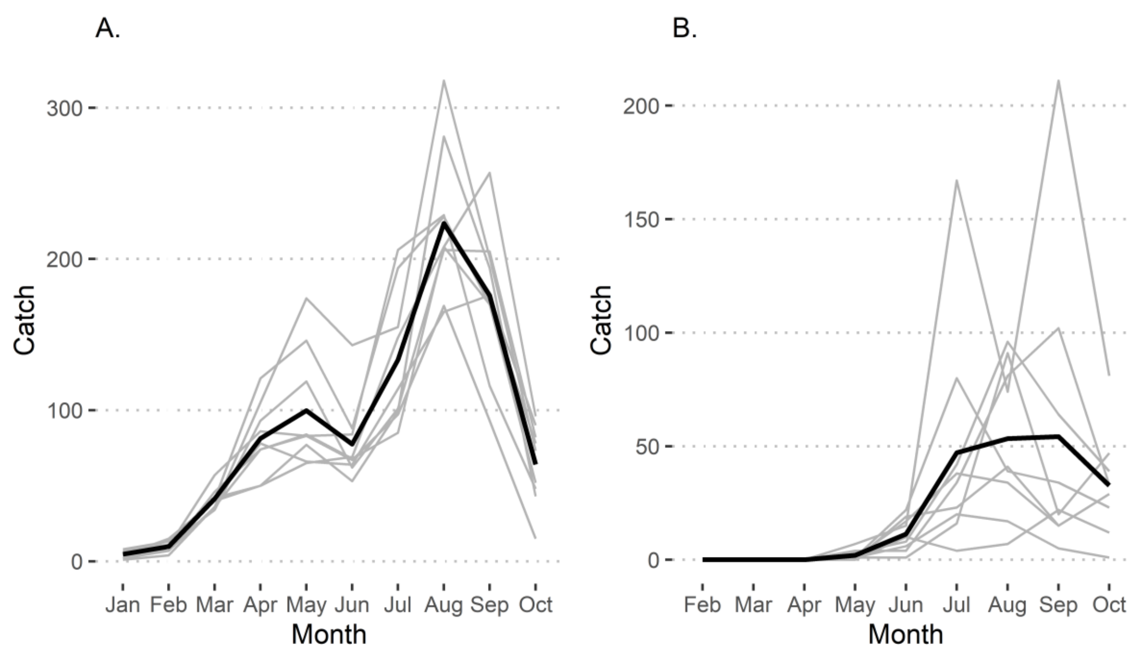

Figure 2: Examples of monthly catches from the period 2011-2019 from assessment areas with (A.) a consistent seasonal pattern and (B.) an inconsistent seasonal pattern of catches over multiple years. Grey lines show annual data, with the black line highlighting the mean monthly catch over this time period.

In many assessment areas in Scotland, salmon catch data is sparse and/or less consistent (Fig. 2B). However, catch is necessarily related to the amount of angling effort and as a result effort data can be used as an alternative means to model expected-catch. A second approach was developed which exploited patterns in catch per unit effort (CPUE). This method was based on estimating expected-catch by first modelling an ‘expected-effort’ value that would have been observed in the absence of restrictions and then converting this to expected-catch using a model of monthly catch per unit effort (CPUE).

The aim of the present analysis was to identify an appropriate method for estimating expected-catch for the 2020 salmon angling season within individual assessment areas in Scotland. The ultimate aim was to produce more accurate stock estimates which form the basis of conservation assessments and management of salmon stocks.

Methods

Data

The number of rod-caught salmon in Scotland have been collected since 1952 using a survey of fisheries, with approximately 2000 forms sent out in recent years. Each fishery is obliged to return monthly catches of salmon and since 2019 fisheries have also been asked to provide the number of rod days fished per month as a measure of effort. Traditionally catches were collected at the fishery district level, where a district could contain multiple rivers. Data collected since 2011 are also available at a finer geographic scale which comprises the assessment areas as defined in the Conservation of Salmon (Scotland) Regulations 2016.

For each assessment area monthly catch data was available for the period 2011-2020, with effort data being available for 2019 and 2020. Effort data was provided on 84% of forms in 2019 and 83% of forms in 2020. In order to estimate effort across a whole assessment area, it was necessary in some assessment areas to scale effort up to account for those fisheries which did not return information. This was done by assuming that the relationship between catch and effort was the same for all fisheries within the assessment area:

$$E_{total} = E_{reported} \times \frac{C_{total}}{C_{effort}}$$

Where E_{total} is total effort in rod days across the whole assessment area, $E_{reported}$ is effort in rod days reported for a portion of the assessment area, C_{total}

is total catch reported across the whole assessment area and C_{effort} is catch reported across those fisheries that also reported effort within the assessment area.

In total there was effort data from 165 areas, including 8 areas where there were not enough years of catch data to allow a full conservation assessment to be undertaken (non-assessment areas). These non-assessment areas were included in the modelling. Catch data was available for all 173 assessment areas, with the catch modelling being undertaken on these rivers.

Information on historic catches was used as a predictor when modelling catch and effort, on the assumption that past catch levels would be a good predictor of the catches in a given year/month/area combination. Historic catch was defined as the mean of monthly catches over the 5 preceding years for each assessment area. This was available for all 173 assessment areas using monthly data from 2016 to 2020 (2016 being the first year of data that had the required 5 preceding years to produce the historic catch metric used).

Wetted area available to salmon was used as a predictor when modelling CPUE. The reported salmon distribution was used to determine appropriate wetted areas for each assessment area (Gardiner and Egglishaw, 1986 and subsequent updates). This provided information on areas where salmon were present, absent and unknown. Wetted areas were calculated from OS MasterMap using ESRI ArcGIS software. For each assessment area wetted area was restricted to fluvial habitat and was assumed to be the salmon present area plus half of the unknown habitat.

Modelling Process

The method for estimating expected-catch is comprised of two different approaches; one based on historic catch and one based on CPUE (Fig. 3). The approach based on historic catch information requires a single statistical model, hereafter M_{HC}. The approach based on CPUE requires two statistical models; a model of CPUE, hereafter M_{CPUE} and a model of expected-effort, hereafter M_E.

For both approaches predictions of expected-catch in 2019 and 2020 were generated. The predictions for 2019 were used to select between the approaches on an assessment area basis. The criteria for selecting one approach over another was based on the agreement of the predictions with the observed catches for a given assessment area during the COVID-19 impacted months in 2019 (i.e. March, April, May, June and November). The 2020 predictions from the selected approach for each assessment area were ultimately used in the stock estimate.

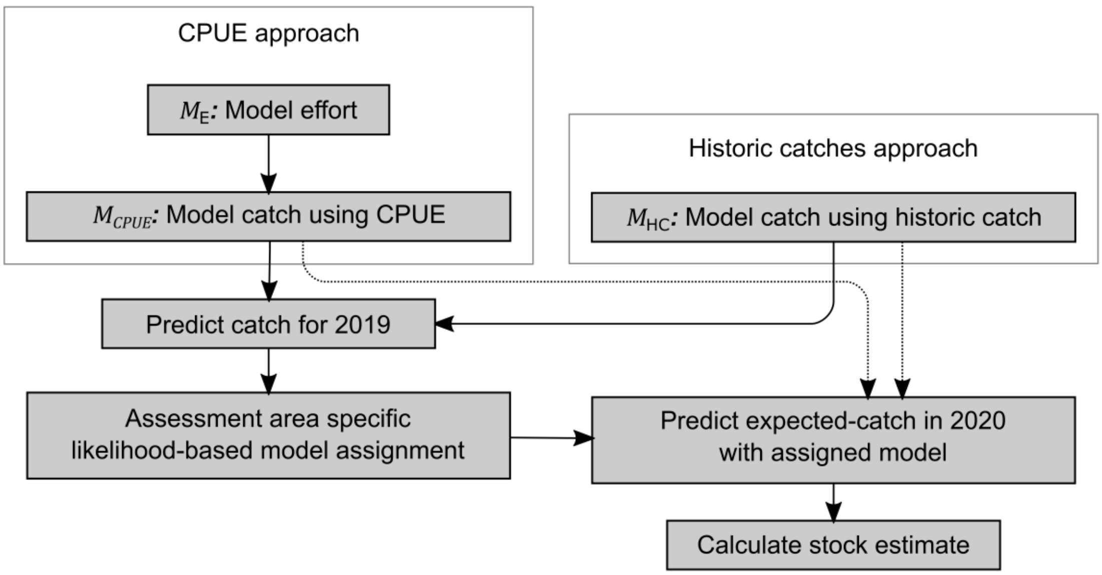

Figure 3: Flow diagram of the modelling process used to derive a COVID-19 adjusted stock estimate. Dotted lines indicate where a selected model was used to generate predicted expected-catch values.

Statistical model structure

In order to properly propagate uncertainty through the modelling process and into the stock estimation M_{HC}, M_{CPUE} and M_E were modelled within a Bayesian framework. All assessment areas for which data were available were considered simultaneously in each model in a hierarchical structure, facilitating the pooling of information across assessment areas when estimating parameters to aid in prediction.

The distributions of monthly catches and monthly effort across all assessment areas are highly skewed and zero inflated (Fig. 4). To account for this M_{HC}, M_{CPUE} and M_E were hurdle log-normal regression models.

In a hurdle log-normal regression model, the data generation process is assumed to comprise of two components. First, a zero outcome may occur with some probability as a result of a process captured by a set of covariates. This component is modelled as a logistic regression. Second, if a zero outcome did not occur in the first step (the hurdle is passed) then a non-zero outcome is realised resulting from a separate process captured by an additional set of covariates. This second component is modelled as a log-normal regression.

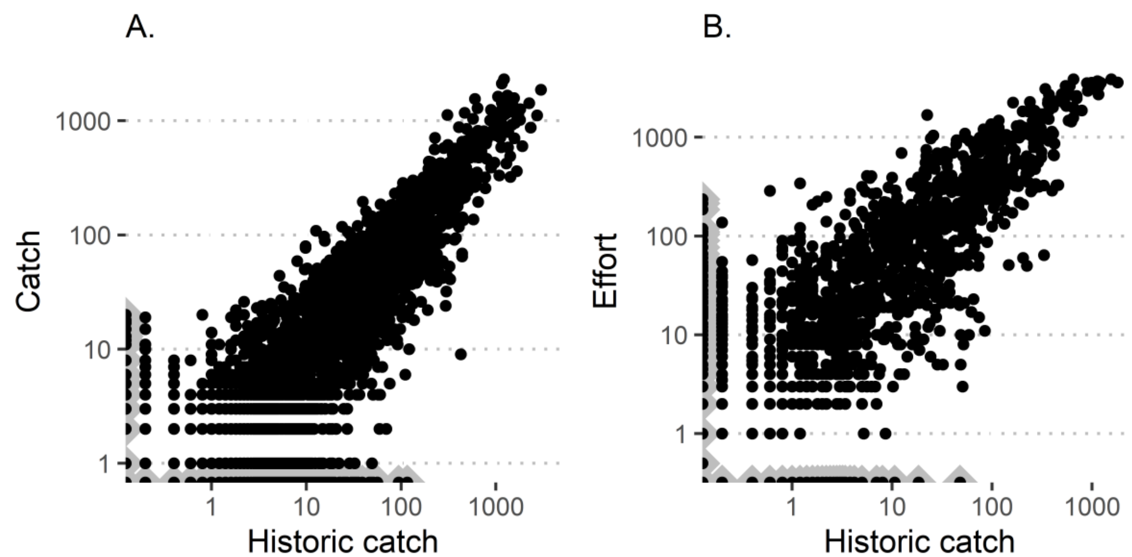

Figure 4: Plot showing the relationship between the historic catch and A. catch and B. effort. Note that axes are log transformed. Points on the y axis surrounded by a grey diamond indicate where historic catches were 0. Those on the x axis highlight where catches/effort were 0.

In addition, due to heteroscedasticity in the relationships between catch and historic catch, and effort and historic catch (Fig. 4), the error term in the non-zero components of each model were allowed to vary.

All three models, M_{HC}, M_{CPUE} and M_E had the same underlying model structure differing only in the choice of covariates and, in the case of M_E, the response variable. Specifically, M_{HC} and M_{CPUE} were modelled as follows:

$$\begin{aligned}
P(Y = y_{i,j}) &= \begin{cases} \pi_{i,j}, & y_{i,j} = 0 \\ (1-\pi_{i,j})\phi_{i,j}, & y_{i,j} > 0 \end{cases} \\
\text{logit}(\pi_{i,j}) &= \alpha W_{i,j} + \eta_j \\
\phi_{i,j} &= e^{\beta X_{i,j} + \gamma_j + \epsilon_{i,j}} \\
\gamma_j &\sim N(0, \sigma_\gamma) \\
\eta_j &\sim N(0, \sigma_\eta) \\
\epsilon_{i,j} &\sim N(0, \sigma Z_{i,j} + \delta_j) \\
\delta_j &\sim N(0, \sigma_\delta)
\end{aligned} \qquad \text{(Equations 1)}$$

where $P(Y = y_{i,j})$ is the probability of monthly catch i from assessment area j, $X_{i,j}$ and $W_{i,j}$ are the covariates for the non-zero and zero catch components respectively with associated coefficient vectors β and α. Parameters γ_j and η_j are assessment area-specific terms with a normally-distributed group structure with associated standard deviations σ_γ and σ_η. Finally, $Z_{i,j}$ is are the covariates for the variance in the non-zero catch component with corresponding coefficient vector σ and assessment area-specific parameters δ_j with a normally-distributed hierarchical structure with associated standard deviation σ_δ.

Model M_E was identical to Equations (1) with the exception that the response variable $y_{i,j}$ is the probability of monthly effort i from assessment area j.
To mitigate against over-fitting through the non-constant error term $\epsilon_{i,j}$, variants of M_{HC} and M_{CPUE} (M_{HC^*} and M_{CPUE^*}) with fixed variance were included in the model assignment process. For both models, $\epsilon_{i,j}$ was replaced with $\epsilon^*_{i,j}$ defined as:

$$\epsilon^*_{i,j} \sim N(0, \sigma^*)$$

Modelling expected catch using historical catch information

Catches of salmon vary among months, years and assessment areas, with monthly catches ranging from 0 to 4530 during 2011-2019. However, they do not vary randomly and there are underlying within year patterns shown by different assessment areas (e.g. Fig. 2A).

To reflect this, in M_{HC} and M_{HC^*} the non-zero catch covariates and associated coefficients, $\beta X_{i,j}$, included (log) historic catch, month and year, whilst the zero catch covariates and associated coefficients, $\alpha W_{i,j}$, included an intercept and (log) historical catches. The covariates and associated coefficients for the variance, $\sigma Z_{i,j}$ in M_{HC}, included an intercept and (log) historic catches.

The data used in fitting M_{HC} and M_{HC^*} covered 2016 to 2020, though importantly the months in 2020 in which restrictions were in place were omitted. The historic catches covariate was specific to the year, for example spanning 2014 - 2018 for 2019 catches, 2015 - 2019 for 2020 catches and so on. This allows the information on recent changes in catches in a specific assessment area to inform the fit. The inclusion of a year term also allows the model to capture any national-level difference in catches between 2019 and 2020 based on observed catches in 2020 when restrictions were not in place.

With this combination of covariates and data, a fitted model facilitates a straight forward prediction of out-of-sample expected-catches for the omitted months in 2020. Within sample predictions for 2019 were similarly generated for the model selection process.

Modelling total effort

To model effort, M_E was constructed with the same covariates and data structure as M_{HC}. The fitted model was used to generate samples of the posterior predicted effort for both 2019 and 2020, which were used as new input values when predicting expected-catch from M_{CPUE} and M^*_{CPUE}.

Modelling expected catch using CPUE

In order to model expected catch using CPUE, $X_{i,j}$ for M_{CPUE} and M_{CPUE^*} included (log) effort with the corresponding β fixed to 1. Using this formulation $\phi_{i,j}$ can be rewritten for M_{CPUE} as:

$$\phi_{i,j} = E_{i,j} e^{\beta X_{i,j} + \gamma_j + \epsilon_{i,j}}$$

where $E_{i,j}$ is the effort for month i of assessment area j. A similar adjustment can be made for M_{CPUE^*}. In this form, all parameter estimates for the non-zero catch component are effectively fit against catch directly scaled by effort.

CPUE is often assumed to to be an indicator of abundance and so is likely to vary with the size of the assessment area and over the course of the adult salmon run. CPUE is also likely to be non-linear; catch efficiency will decline as the population is exploited, even with substantial catch and release.

Consequently, for M_{CPUE} and M_{CPUE^*}, the non-zero and zero catch covariates and associated coefficients, $\beta X_{i,j}$ and $\alpha W_{i,j}$, included an intercept term, month, (log) wetted area and (log) effort. For M_{CPUE} the structure on variance, $\sigma Z_{i,j}$ included an intercept term and (log) effort.

The data used to fit M_{CPUE} and M_{CPUE^*} encompassed all months in 2019 and 2020 for which data was available, including the months in which restrictions were in place. Implicit in this is the assumption that CPUE itself was not affected by restrictions, rather simply that effort was reduced; though the inclusion of (log) effort as a covariate allows the model to capture the way in which CPUE scales with effort itself. As a consequence, a predicted increase in effort in 2020 does not necessitate a corresponding linear increase in catch. In contrast to the historic catch approach, the CPUE model is thus able to incorporate information from catches in 2020 when restrictions were in place.

When predicting catch for 2019 and 2020, a Monte Carlo process was used, with each sample of the posterior prediction of expected-catch using a different sample from the posterior predictions of effort from M_E, thus incorporating the uncertainty in M_E. In the scenario that the sampled predicted effort was lower than the reported effort, the reported effort value was used.

Priors

With the exceptions detailed below, default priors as specified in the R package brms (Bürkner 2017, 2018) were used for all parameters for all models. These priors are relative to a design matrix centered around the mean. The priors on the intercept parameters in the non-zero catch / effort components were Student-t distributions with three degrees of freedom, a location of 1.6, and scale 3.1. The priors on the intercept parameters of the zero catch/effort components were logistic distributions with mean 0 and scale 1. The priors for all variance parameters, including the assessment area group level standard deviations were half Student-t distributions with 3 degrees of freedom, location 0 and scale 3.1.

Individual assessment area parameters were standard normal priors. All other priors were unconstrained.

For M_{CPUE} and M_{CPUE^*}, it was necessary to introduce a standard normal prior on the coefficients of month in the zero catch component, as the relatively low number of data points for November lead to difficulties when fitting. The added constraint of the normal prior resolved this issue.

MCMC sampling

All models were fit using brms package version 2.14 (Bürkner 2017, 2018) in R version 3.6 (R Core Team 2020). All models were run for at least 2000 warm up iterations and at least 4000 post warm up iterations across at least 4 chains, resulting in at least 10 000 posterior samples.

Trace plots were examined to ensure convergence, and for all models Rhat < 1.01, and the bulk and tail effective sample size > 1000 for all parameters.

Model selection

It was expected that the different modelling approaches would be more applicable for some assessment areas than others. In order to select the most appropriate model when generating predictions of expected-catch in 2020, for each assessment area a model was selected based on the performance of the model when predicting catch in 2019 for that area.

The predictive performance of each model for assessment area j was quantified using the log pointwise predictive density, $lppd$ (Gelman et al. 2014), given the observed catches for that area in 2019, $y_{i,j}$. Given S samples of the posterior distribution, θ, of each model, $lppd_j$ is calculated as:

$$lppd_j = \sum_{i \in N} \log\left(\frac{1}{S}\sum_{s=1}^{S} p\left(y_{i,j} | \theta^s\right)\right)$$

where N is the set of data points in 2019 corresponding to the months in which restrictions were in place in 2020. This ensures that the models are assessed based on their predictive performance in the months that are required for the prediction of expected-catch.

The model with the highest $lppd_j$ was used when predicting expected-catch in 2020.

Impact on stock estimates

Stock assessments were run in order to determine the impact of correcting for the disruption caused by the COVID-19 pandemic. The normal stock assessment process (Anon 2019) was run using the reported catches and the expected-catches produced using the model with the highest $lppd_j$. The stock model takes a Monte Carlo approach, where 10 000 draws are taken to account for uncertainly in the correction factor used to convert catches to stock. This process was expanded to account for uncertainly in the expected catches during the COVID-19 impacted months (drawing both catch and expected-catch from a distribution rather than just the correction factor). Comparisons were then made between the estimated stock using the reported and expected-catch inputs.

Results

Model assignment

Each of the four different models were found to have the best predictive performance for some of the assessment areas (Table 1). Examples of these are shown in Figure 5. These graphs illustrate that, in general, the predictions for the different models were often very similar, particularly for M_{CPUE} / M_{CPUE^*} and M_{HC} / M_{HC^*}. There were occasions where models M_{CPUE} and M_{CPUE^*} produced better fits than models M_{HC} and M_{HC^*} (e.g. River Oykel SAC in April) and vice versa (e.g. Wick River in June). There were also months when all models performed relatively well (e.g. River Oykel SAC in June) and occasions where they were all relatively poor (e.g. River Oykel SAC in May).

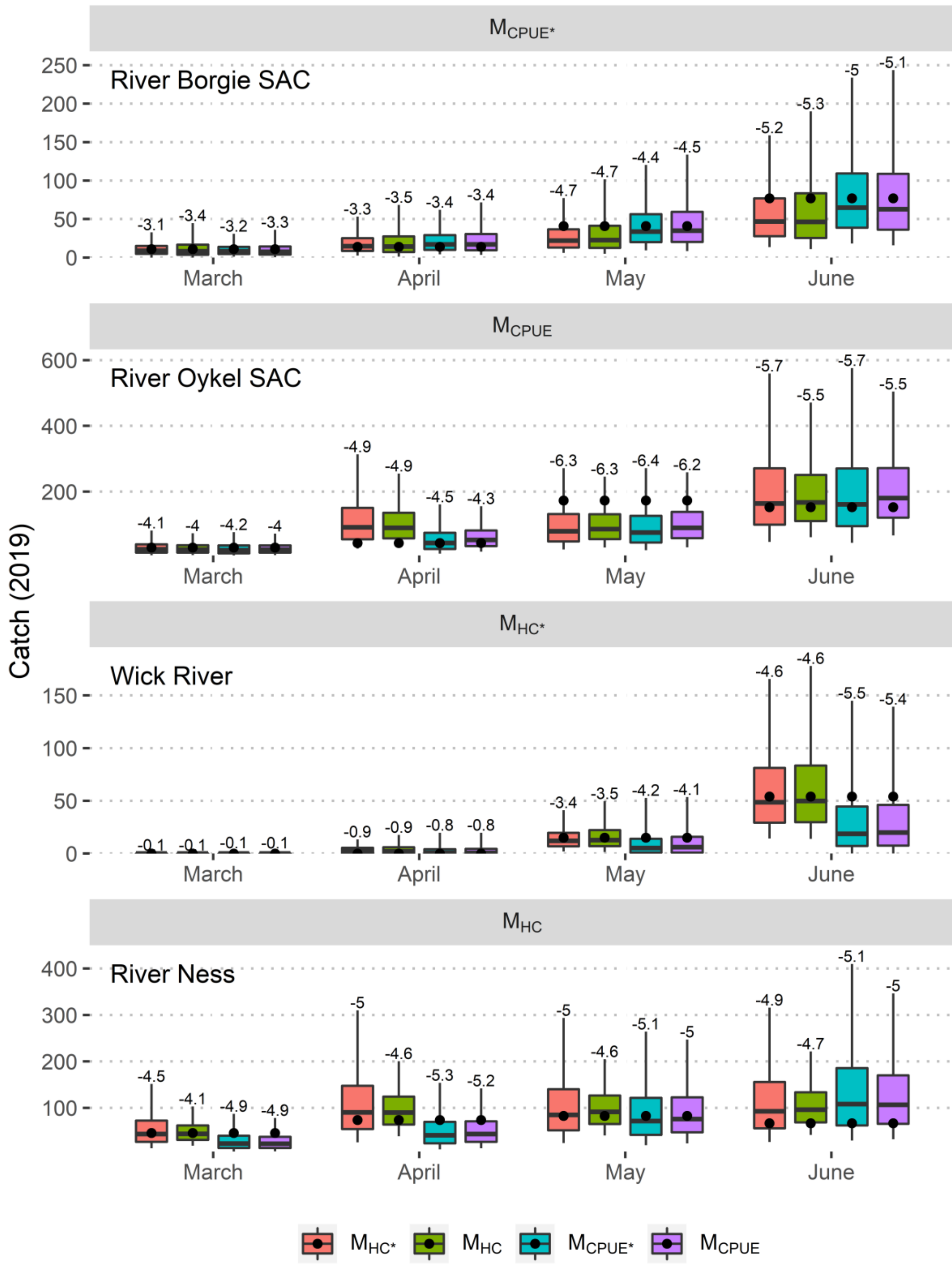

Figure 5: Comparisons of posterior predictions of the catch in 2019 from the four models in four assessment areas. The title of each panel indicates the assigned model for that assessment area. Points give true catch, boxplots show median prediction and 50% and 90% CIs and numeric values indicate the log predictive density for that data point. Note that there is no November fishing in any of the four areas.

Table 1: Number of assessment areas assigned to each model, based on log pointwise predictive density of catch in relevant months of 2019.

Assigned Model	Number of Assessment Areas
M_{HC^*}	47
M_{HC}	52
M_{CPUE^*}	51
M_{CPUE}	39

The assignment of assessment areas to the four different models was relatively even, with no single model providing the best predictive performance (Table 1). In general, larger areas were best predicted by models M_{HC} and M_{HC^*}, whilst smaller areas were best predicted by models M_{CPUE} and M_{CPUE^*} (Fig. 6). Additionally, models which allowed for a non-constant residual variation M_{CPUE} and M_{HC}, generally had better predictive performance for larger areas. This was a result of the fixed variance models M_{CPUE^*} and M_{HC^*} overestimating the uncertainty for large catches (e.g. catches in June for River Oykel SAC and River Ness in Figure 5).

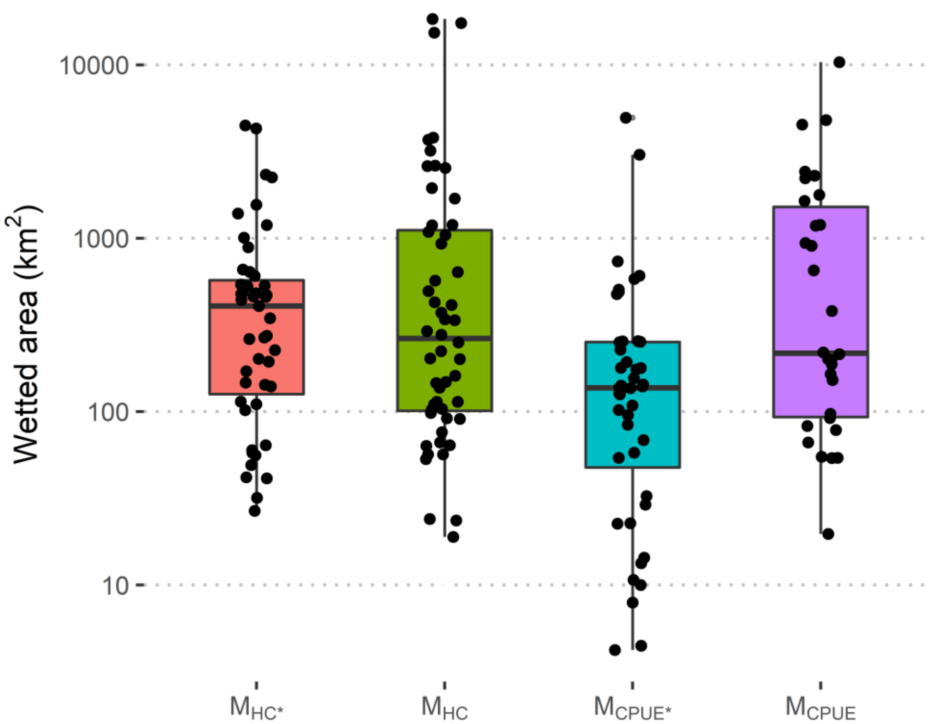

Figure 6: Distribution of wetted area for assessment areas assigned to each model, based on log pointwise predictive density of catch in relevant months in 2019.

Impact on stock estimates

At an overall Scotland level the estimated annual stock increased by a median value of 22% (Fig. 7). The uncertainly around the estimated increase is a reflection of the uncertainty around the expected catch values (e.g. Fig. 5).

The impact of the correction varied by both month and assessment area (Fig. 8). Although there is variation among assessment areas, it is clear that the correction has a bigger impact during April and May than in other months, particularly June and November. This mirrors the overall picture provided by the effort data (Fig. 1) and is driven by the timing and severity of the lockdown restrictions. Figure 8 also highlights that using the corrections presented here allows stock estimates to be produced even in the absence of fishing.

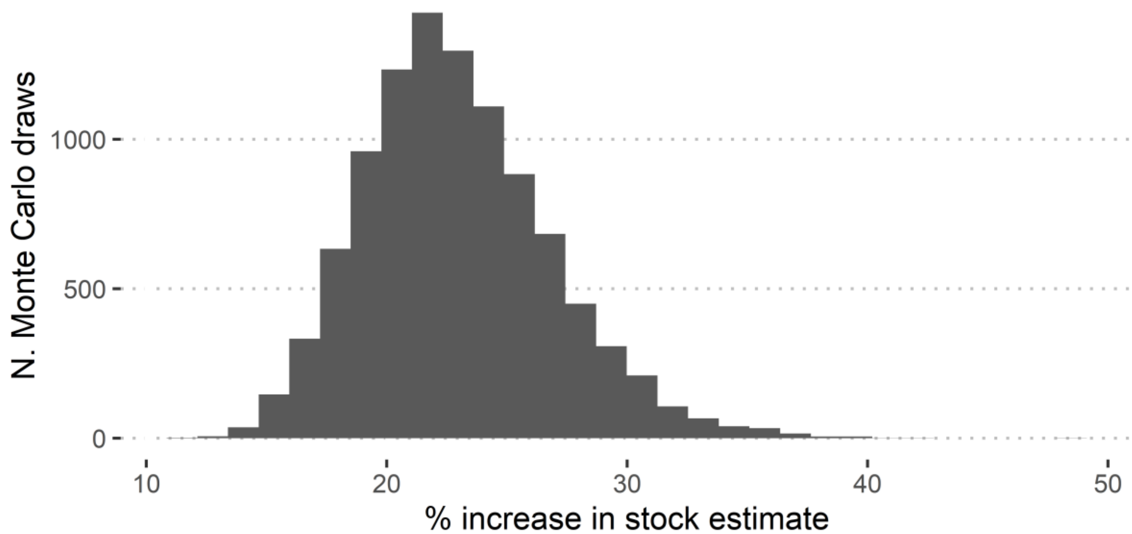

Figure 7: Histogram showing the percentage increase in the all-Scotland salmon stock level due to using the expected rather than reported catch, over 10 000 Monte Carlo samples.

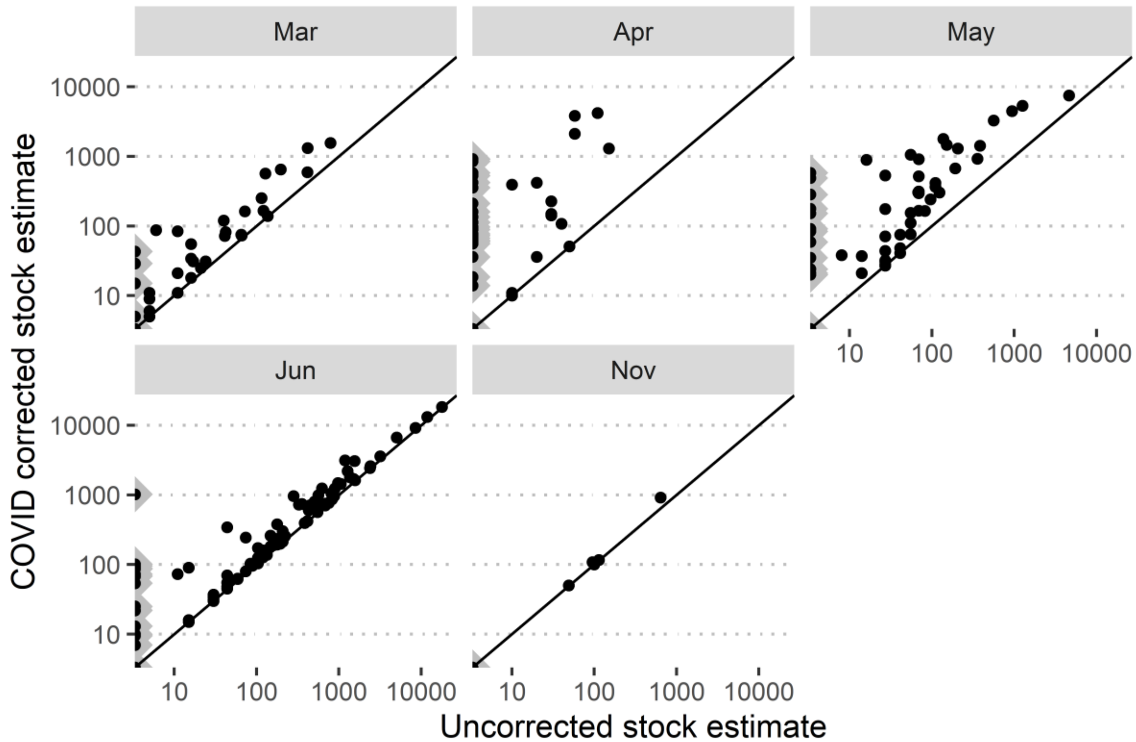

Figure 8: Plot showing the monthly median estimates of corrected and uncorrected stock estimates for the assessment areas (log transformed). The diagonal line indicates the 1:1 line where the two estimates are the same. Points on the y axis surrounded by a grey diamond indicate where uncorrected estimates are 0.

Alternate model assignments using WAIC

The $lppd$ is an overestimate of the expected $lppd$ for unobserved, out-of-sample data (Gelman et al. 2014). Predictive information criteria which include some form of penalisation term on the flexibility of the model (e.g. an estimate of the effective number of parameters) such as the WAIC (Watanabe 2010) are frequently used to address this issue. To test the potential impact of over fitting when using the $lppd$ to assign models to assessment areas, expected-catch predictions were reassigned with the inclusion of the WAIC penalisation term (following Gelman et al. 2014);

$$p_{WAIC,j} = \sum_{i \in N} V_{s=1}^{S} \left(\log(p(y_{i,j}|\theta^{s})\right)$$

where $V_{s=1}^{S}$ is the sample variance defined as:

$$V_{s=1}^{S}(a_s) = \frac{1}{S-1}\sum_{s=1}^{S}(a_s - \overline{a})^2.$$

The resulting measure of expected predictive performance for assessment area j for each model was then given by:

$$\widehat{elppd}_{WAIC,j} = lppd_j - p_{WAIC,j}$$

The result of the inclusion of this intercept term ultimately lead to some assessment areas being assigned a different model. However, in these cases the predicted catches were very similar across the models and the resultant impact on the stock estimate was negligible.

Discussion

The results of the modelling presented here highlights that failing to correct for the impact of the COVID pandemic will underestimate the total Scottish salmon stock by approximately 22%. Therefore, not accounting for the unusual 2020 angling season has the potential to impact management actions based on artificially low stock assessments.

The impact of the pandemic was shown to vary among assessment areas. Some areas do not report catches until later in the year, coinciding with their returns of salmon, and they may have been relatively unaffected by a lockdown centred in April and May. In addition, the degree of impact among areas is likely to differ depending on how badly fishing in each area was impacted by a reduction in travel. This will depend on a number of factors including the balance between local and visiting anglers. By design, the models are flexible enough to allow the estimated impact of COVID-19 to differ among assessments areas. Such differences are based on the reported data from each assessment area and account for among area differences in recent catch trends and differences in the seasonality of catch and effort.

The comparison of different modelling approaches presented here highlights the variability in the consistency of catches from year to year across assessment areas in Scotland. For many areas, information on historic catches was a reliable predictor of future catches, whilst for other areas a more nuanced model, taking into account the relationship between catch and effort, was required. The effort approach has a number of theoretical advantages over the use of historic catch data. Two key advantages being: firstly it is effort that is directly impacted by lockdown measures. Secondally, unlike using historic catches, the models contain data from COVID-19 impacted months, with CPUE relating directly to the stock in those months. However, effort data is only available for two years, compared to the five used for the historic catch model, and only for ~83% of fisheries where catches were reported. It is likely that the utility of effort data will increase as coverage increases and more years of data become available.

Despite the flexibilities built into the modelling approach it is not possible to account for the full geographic and temporal complexity of the pandemic on fisheries. With a fully working fish counter network it would be possible to investigate how the relationship between catches and stocks deviated from the usual patterns and use this information to directly estimate stock levels. However, until such a network is available such corrections will have to rely on the available data, namely catches and effort. Despite their limitations the methods described enable the impact of the COVID-19 pandemic to be accounted for in stock assessments

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