Research Paper

The effect of hook spacing on longline catch rates: Implications for catch rate standardization

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ABSTRACT

Catch per unit effort (CPUE) is a widely used index of population abundance for informing stock assessments for the purpose of estimating population status and setting fishing policies. However, for CPUE to be an unbiased index, influences that are not related to population abundance (e.g., spatial variation in effort and temporal changes in gear efficiency) must be accounted for in analyses known as CPUE standardization. In longline fisheries, one important factor that can affect CPUE is the spacing between hooks ('spacing effect'), which influences effective effort and has largely been ignored in previous analyses. Here, we use the Pacific halibut (*Hippoglossus stenolepis*) long-line fishery as a case study to explore the spacing effect. Both commercial and experimental (fishery-independent) data with hook spacing, and a survey-based CPUE series, are available for this fishery. It thus provides a unique opportunity to explore the effect of hook spacing and its effect on CPUE trends. We quantify this effect using non-parametric and parametric relationships inside a spatially-explicit (geospatial) CPUE standardization model for commercial data, and non-linear mixed-effects model for experimental data. We found a clear non-linear spacing effect (i.e., hooks were less effective the closer they were), but accounting for space had a larger effect on CPUE trends than accounting for hook spacing. For this stock, it is likely the effect of hook spacing on CPUE was minimal due to little variation in average hook spacing over time. Regardless, historical and future trends in hook spacing can have important effects on longline CPUE standardization, highlighting the value of collecting this information. Accounting for hook spacing effects in other fisheries may improve estimates of trends in relative abundance and lead to better management.

1. Introduction

Catch per unit effort (CPUE) is a key source of information used to manage a wide range of commercially valuable species such as tunas, as well as vulnerable species like sharks (Maunder and Punt, 2004). CPUE is typically assumed to provide an index of population abundance (*N*), that is robust for detecting trends and informing stock assessments provided that catchability (*q*) and selectivity are constant through time and space (i.e., $CPUE = qN$). However, this assumption can be violated for a variety of reasons. One important case is when catchability varies in time and space, such as when fish densities interact with fishermen behavior, and thus spatial patterns of catch (Branch et al., 2006; Walters, 2003). Another important case is when the unit of effort varies, such as with changing technological (e.g., gear) and economic factors or targeting strategies (Bishop, 2006). Either case undermines the comparability of CPUE among years and areas, and can lead to effects like hyperdepletion or hyperstability (Harley et al., 2001), which complicates interpretation of CPUE trends as accurately reflecting true

stock status trends (e.g., see Myers and Worm, 2003; Polacheck, 2006). CPUE trends are therefore typically standardized to remove effects other than changes in abundance, where possible, so they more accurately reflect changes in abundance (Bishop, 2006; Maunder and Punt, 2004).

Standardizing CPUE from baited longline gear has the additional complexity that the probability of catching a fish, and thus catchability, depends on volitional (foraging) behavior that is affected by gear configuration and environmental variables (Stoner, 2004). This has been shown for important pelagic and demersal species caught by longline (Bigelow and Maunder, 2007; Stoner and Ottmar, 2004; Stoner et al., 2006; Ward, 2008). Thus, it is important to consider variation in configuration for longline gear in CPUE standardization. Longline gear is a simple, but versatile, form of gear where baited hooks are attached to a mainline fixed at regular intervals ('fixed' gear), attached dynamically as it is deployed ('snap' gear), or attached at pre-determined points and deployed via an automated machine ('autoline' gear; see Bjordal and Løkkeborg, 1996). Longline gear can be configured to

target demersal species such as Pacific halibut (*Hippoglossus stenolepis*) and sablefish (*Anoplopoma fimbria*), as well as pelagic species such as bigeye tuna (*Thunnus obesus*; see Løkkeborg et al., 2010). Appropriately accounting for gear configuration in CPUE standardization is thus key for a wide range of important fisheries.

Although ostensibly simple, interactions between longline gear and fish foraging behavior are complicated. A motivated fish must detect, locate, and then consume bait, but each of these factors can strongly depend on varying environmental conditions such as temperature, turbidity, and light level, among others (Stoner, 2004). In addition, intraspecies local density and size structure can affect fish behavior, such as when there is social facilitation with greater numbers of fish or a length hierarchy for feeding (Stoner and Ottmar, 2004; Stoner et al., 2006). Likewise, both intraspecies and interspecies competition for hooks can play an important role in catch rates, particularly when differences in aggression exist (Rodgveller et al., 2008; Skud, 1978). These interactions complicate the definition of a unit of effort for longline gear, which would ostensibly be a hook (i.e., catch per hook). However, the spacing between hooks influences the foraging behavior of fish by affecting the region baits are detected, called the capture field or active space. Ideally, hook spacing would be measured between hooks directly, but is typically only available as measured along the mainline. Successfully accounting for the effect of hook spacing on effort could thus improve CPUE standardization for longline gear.

Three hypotheses have been proposed for how the capture field changes with hook spacing, which we refer to as the 'spacing effect' (Fig. 1; Hamley and Skud, 1978). Consider a hypothetical set with h hooks with varying hook spacings (and thus set length) fished at reasonable densities (e.g., hook saturation is not an issue; Hamley and Skud, 1978) and uniformly distributed fish. In the *length* hypothesis, as spacing and set length decreases, overlapping capture fields compete with each other, and catch per hook will decrease (e.g., Eggers et al., 1982). In this case, the length of the set would be the unit of effective effort. Alternatively, in the *hook* hypothesis, overlapping capture fields increase fish response, canceling out the effect of hook competition, and catch per hook is constant (except where high density might lead to hook saturation). In this case, the unit of effort would be the number of hooks, and could occur when increased odor plumes from overlapping baits increased f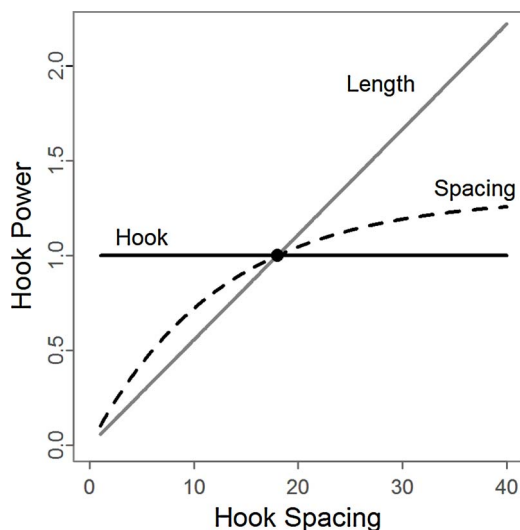ish response from a wider area (Sigler, 2000). Lastly, the *spacing* hypothesis is intermediate, such that hooks spaced widely enough are effectively independent, but hooks closer together compete, to some degree. In this case, the number of hooks are adjusted according to hook spacing, so that an "effective hook" is the unit of effort. Which of these hypotheses (hook spacing effect) is true is driven by the foraging ecology of the species of interest, not the gear itself, and is important for CPUE standardization because it defines the appropriate unit of effort for the gear.

The importance of correctly determining effective effort in a longline data set also depends on properties of the gear. Consider a case where hook spacing is consistent for all years and vessels. In this case, using the number of hooks or length of line will be equivalent up to a multiplicative factor which gets absorbed into catchability and leading to the same trend. However, ignoring effective effort when there is variation in hook spacing across either time, space, or vessel, may positively or negatively bias effort for some sets and undermine the relationship between density and CPUE. Perhaps the most important case is when an annual trend in hook spacing exists (e.g., consistent reduction in spacings over a decade), which may result in a biased effective and assumed effort (and thus CPUE), potentially creating a trend in apparent CPUE that is not related to abundance. This was the case in the Pacific halibut fishery with a notable shifts toward wider spacings from 1955 to 1970, resulting in misleading CPUE trends (Skud, 1972). Similar concerns remain because of trends over time and space in the composition of gear type, since each has a different spacing distribution (Fig. 2).

To investigate the spacing effect for Pacific halibut, Hamley and Skud (1978) initiated an experimental study (i.e., controlled fishing), but these data have insufficient samples at small spacings to adequately quantify this effect over its current applied range. In contrast, recent commercial fishery data have wide variation in hook spacings, and provide an opportunity to quantify and contrast the spacing effect to that from experimental data. In this study, we investigate the spacing effect for Pacific halibut, and its implication for standardized CPUE. First, we develop and apply a spatially-explicit (spatiotemporal) model to commercial catch data to estimate standardized CPUE trends while simultaneously estimating the hook spacing effect. Then, we reanalyze the experimental data from Hamley and Skud (1978), and compare the two relationships and test whether the same information about the spacing effect is available in commercial catch data. We conclude by discussing and demonstrating how these techniques can be used to improve CPUE standardization in longline fisheries.

2. Materials and methods

2.1. Effective hooks

We hypothesized that as the distance to its neighbors varies, so will its power and thus effective effort of a hook (Fig. 1). We thus needed a way to convert nominal hooks into effective hooks. The first step was to quantify the spacing effect with a function (f) that relates expected catch per hook with hook spacing. We explore three possible relationships below.

Next, we adopted the approach taken by Hamley and Skud (1978) and chose a reference spacing, creating what could be thought of as relative hook power. We used 18 ft (5.5 m) as a reference in this study to maintain continuity with previous studies, and due to historical relevancy in the fishery. Relative hook power is unit-less and represents the relative ratio in efficiency between hooks fished at different spacings. For instance, a hook with a relative power of 0.5 at 10 ft indicates that we expect half the catch from that hook compared to if it were fished at 18 ft, all else being equal. We then calculated the number of effective hooks in a set as:

$$h_{effective}(s) = h \cdot f(s)/f(18) \qquad (1)$$

where $h_{effective}$ is the number of effective hooks, h the nominal (reported)

Fig. 1. Stylized representations of three hypotheses for how the power of a hook changes with hook spacing, for a set with the same number of hooks but increasing total length and thus hook spacing. In the *hook* hypothesis, the hooks do not compete and thus effective effort is the nominal hooks. In the *length* hypothesis, hooks compete at all spacings such that the length of the set is the effective effort. Lastly, the *spacing* hypothesis is intermediate and hooks compete at lower spacings only. Figure recreated from Hamley and Skud (1978).
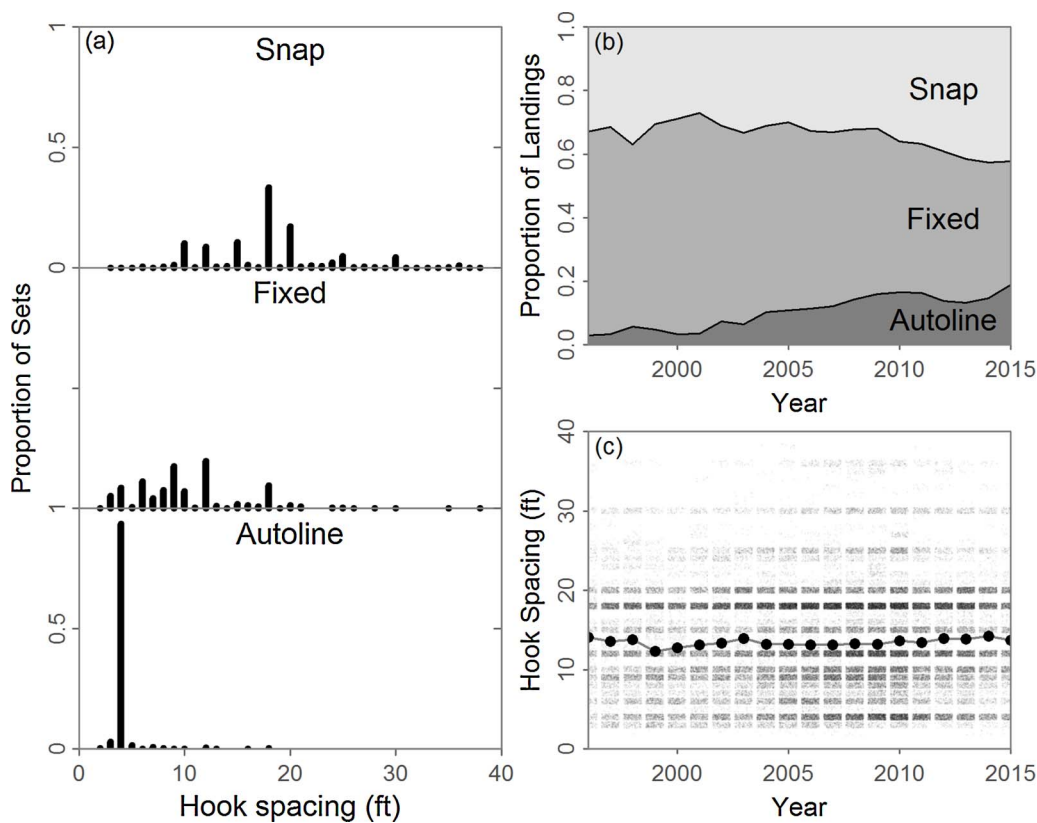
Fig. 2. Properties of the fishery-dependent data (commercial catches). (a) The distribution of hook spacing within each of the three gear types. (b) Trends in proportion of catches by gear type by weight. (c) Annual distribution of hook spacing for all gear types (small points; jittered for clarity) and means (large points).

number of hooks, s is the distance between hooks (in ft), and f is a mathematical function relating hook spacing and expected catch per hook (defined below). Note that by definition sets fished with 18 ft spacings will have equivalent nominal and effective hooks, but will be larger or smaller than the nominal hooks depending on the spacing.

To explore the shape of f we used three different forms. First, we fit one without any effect of hook spacing:

$$f_{constant}(s) = 1. \tag{2}$$

This constant form ignores hook spacing and would be necessary, e.g., if spacings were not reported or could not be calculated from reported skate length and number of hooks.

We also used a flexible random walk 'smoother' (i.e., non-parametric) form, from which the shape of the hook spacing relationship can be elucidated with few *a priori* assumptions. We arbitrarily fixed the initial spacing effect to be 1 at 1 ft, since it gets canceled out in calculating effective hooks in Eq. (1). Larger spacings were determined by multiplying the previous spacing effect by a lognormal deviation. The deviations were modeled as random effects with a normal distribution: $\tau \sim N(0, \sigma_d)$. Specifically, the smoother form is defined as:

$$f_{smoother}(s) = \begin{cases} 1 & \text{if s=1} \\ f(s-1) \cdot e^{\tau_s} & \text{otherwise} \end{cases}. \tag{3}$$

This form assumes spacings are discrete (i.e., whole numbers), but interpolation between discrete spacings could be used with fractional spacings. In this study, spacings were discrete and so no interpolation was done.

Lastly, we fit a generalized version of the non-linear parametric relationship used in Hamley and Skud (1978):

$$f_{parametric}(s) = \alpha [1 - (e^{-\beta_s s})^\lambda]. \tag{4}$$

As with the smoother form, the parameter α cancels out in the relative hook calculation (1) and is thus fixed arbitrarily at $\alpha = 1$. We note that this formula represents the *spacing* hypothesis directly, but can

also represent the *hook* and *length* hypotheses as special cases (as $\lambda \to \infty$ or $\beta \to 0$, respectively). For this form, it is also possible to calculate an effective hook at infinite spacing, $h_\infty = h(\infty)$, analytically, which quantifies how close to independent hooks are at 18 ft. Below we fit the smoother form to explore the shape of the spacing effect, the parametric form to calculate relative abundance trends, and the constant form to test the effect of ignoring hook spacing.

2.2. Analysis of fishery-dependent data

2.2.1. Data

These data come from International Pacific Halibut Commission (IPHC) commercial logbooks and are summarized in Monnahan and Stewart (2014). Logbooks are required to be maintained, but only logbooks representing about 73% of landings were available in the IPHC database. The basic datum is a single commercial demersal longline set made from linking together sections (skates) of gear. After soaking, gear is retrieved and total legal-sized weight for the set recorded. Information is not collected on sub-legal halibut or other species, and is thus not available for this study. Set-level information is recorded in logbooks, and later collected and collated into an IPHC database. There are approximately 700,000 recorded sets available over the time period 1991–2015, ranging from northern California to the Bering Sea. We used the raw data (sets) in our analyses, but only presented obscured locations and data summaries due to data confidentiality.

In addition to total catch, these fishery-dependent data contain various information useful for CPUE standardization, such as the type of longline gear (fixed, snap, or autoline), hook spacing, nominal hooks, and set length, and hook size. For most sets, the latitude and longitude at the beginning and end of the set were also available. Although environmental factors are known to influence catch rates (Stoner, 2004; Stoner et al., 2006), the only environmental covariate available here is depth, calculated as the average of the beginning and end of each set.

For computational convenience, we narrowed the dataset down in

several ways. First, we focused on data from the central Gulf of Alaska starting in 1996 because some previous geographic coordinates were recorded irregularly. We also filtered out sets without spatial coordinates or missing other key information. A small percentage of sets had zero catch (2.85%) and were excluded since they may represent targeting of other species and the reporting rates were likely not consistent over time. This step seemed reasonable because preliminary exploration of sets with zero catches had no apparent difference in hook spacing distributions. We also filtered out sets which were longer than 18 miles or had more than a 50 fa (91.44 m) difference in depth at the set endpoints. Initial exploration suggested a relatively minor effect on the results due to the filtering. After filtering the data there were approximately 100,000 sets.

2.2.2. Spatiotemporal model

To explicitly account for space in our standardization, we fit spatiotemporal models (Clark, 2007; Cressie and Wikle, 2015) to the commercial logbook data. These tools are used in many ecological fields, including estimating spatial densities of fish (e.g., Kai et al., 2017; Shelton et al., 2014; Thorson et al., 2015). In this modeling framework, the distribution of fish density is assumed to arise from unobserved environmental and biological factors, and to vary smoothly in space and time. Further, this distribution can be represented as a Gaussian random field, such that a finite set of points in space will have a multivariate normal distribution with spatial dependence captured by a covariance matrix.

Specifically, we model the relative fish density for set i, D_i, as:

$$D_i = \exp(\beta_0 + \beta_{y_i} y_i + \beta_{d_1} d_i + \beta_{d_2} d_i^2 + \omega_{c_i} + \varepsilon_{c_i,y_i}) \quad (5)$$

for depth d and year y. The first four terms correspond to the typical component of a standardization, and the last two make up the spatial component. We adopted the spatial hierarchical statistical modelling approach (Cressie and Wikle, 2015), meaning we fit a vector of random effects to all years (baseline spatial effects), ω, and separate vectors for each year (spatiotemporal effects), $\varepsilon(y)$, with separate covariance matrices, but the same geostatistical decorrelation range (κ). These random effects determine the density of fish in a particular spatial cell (indexed by c_i – see below). The result is an approximately smooth surface representing fish density, where each cells density is affected (correlated) to all other cells based on distance between them. We estimated an independent surface in each year. Specifically, the random vectors were distributed as:

$$\omega \sim MVN(0, \Sigma_\omega)$$
$$\varepsilon(y) \sim MVN(0, \Sigma_\varepsilon) \quad (6)$$

Because densities are observed imperfectly, there is also an observation component of the model which accounts for expected catch, given density and external factors such as the number and spacing of hooks, gear type, and vessel. We define the expected catch, μ_i, as:

$$\mu_i = h_{effective}(s_i) \cdot D_i \cdot q_i, \quad (7)$$

where D is defined in Eq. (5) and $q_i = \exp(g_i + \eta_{v_i})$ is the catchability for gear type g (i.e., fixed, snap or autoline), and vessel random effect η_{v_i} for vessel v_i, and where $\eta \sim N(0, \sigma_\eta)$. The vessel effect was included because we expect different vessels to have different fishing efficiencies and thus different expected catch, all else (spatial variation in catchability due to behavior or competition with other species) being equal and assumed to be part of the error structure. If unaccounted for, this unmodeled variation would appear as observation error. We further assume observed catches, C, have a log-normal distribution with estimated observation error σ_{obs}: $\log C_i \sim N(\log \mu_i, \sigma_{obs}^2)$.

Given the number of data points and resulting sizes of covariance matrices, this model is computationally infeasible. We therefore followed the lead of Thorson et al. (2015) and simplified the model in three ways. First, we approximated the random field by binning the data points into smaller regions or cells (defined by m "knots"), which reduced the dimensionality of the covariance matrices from n to approximately m, an approach known as predictive process modeling (Banerjee et al., 2008). The placement of the knots was determined using the R function kmeans (R Core Team, 2017), which uses a clustering algorithm to partition the data such that the sum of squares from points to the assigned cluster centers is minimized. We then used the R package INLA (Lindgren and Rue, 2015) to create a mesh from the resulting cluster centers. The result is a distribution of cells within which all data points were associated with the same spatial random effect. Initial exploration suggested that 2000 knots were sufficient to achieve convergence of the approximation (i.e., further increases resulted in no substantial changes to results).

Second, we reduced the number of parameters of the covariance matrices by using a Matérn semivariogram function with smoothness $\nu = 1$ (Cressie and Wikle, 2015). The Matérn function relates the covariance between two points (or centers of cells) as a function of the distance between them, given range and variance parameters which are estimated from the data (Royle and Wikle, 2005). We further assumed isotropy and stationarity of the spatial process so that the orientation of the distance made no difference, and the spatiotemporal process, Σ_ε, was constant between years.

Lastly, we adopt the stochastic partial differential equation approach which converts the Gaussian random field into a Gaussian Markov random field (Lindgren and Rue, 2015; Lindgren et al., 2011). With this technique cells that are not directly neighbors are assumed to have zero covariance (i.e., be independent). By having non-zero covariance only for direct neighbors, the inverse covariance matrix is sparse (has more off-diagonal zeros) which reduces computation (Lindgren et al., 2011). These simplification techniques are widely used in geospatial modeling and greatly reduce the computational load, while retaining the key properties of the spatial process of interest, making an analysis of 100,000 data points feasible. We provide model code and further details of our analyses in Appendix A (Supplementary material).

Fully exploring a CPUE spatiotemporal standardization model for commercial catch data is beyond the scope of this paper. Here our focus is on accounting for enough of the biological and fishery properties to facilitate estimation of the hook spacing effect. We thus consider our spatiotemporal model a simplified analysis useful as a proof of concept, but note there are independent estimates of relative abundance trends from a scientific survey over the same time and space (Stewart and Monnahan, 2016), against which we compare and contrast our predictions.

2.2.3. Calculating CPUE trends

In contrast to other CPUE standardization models which explicitly model relative catch rates, our spatiotemporal model predicts density in each cell. From these we multiply cell density by its area (a_c), and then sum all cells to get annual total relative abundance, A_y:

$$A_y = \Sigma_c a_c D_{c,y}. \quad (8)$$

This calculation assumes that the process of selecting sampling sites is independent of the underlying biological process (density). This is true for surveys (Thorson et al., 2016, 2015), but here it is violated because captains are likely targeting areas with higher densities of fish. This is known as preferential sampling and can lead to biased inference (Diggle et al., 2010). Here our focus is on the hook spacing effect, and note that this is an open issue and analyses used for management should further investigate the bias and potentially mitigate it in the model (Carruthers et al., 2011; Conn et al., 2017; Thorson et al., 2016; Walters, 2003). Here we calculate relative abundance trends with and without a spatial effect, and with and without a hook spacing effect to quantify the relative effects of these aspects.
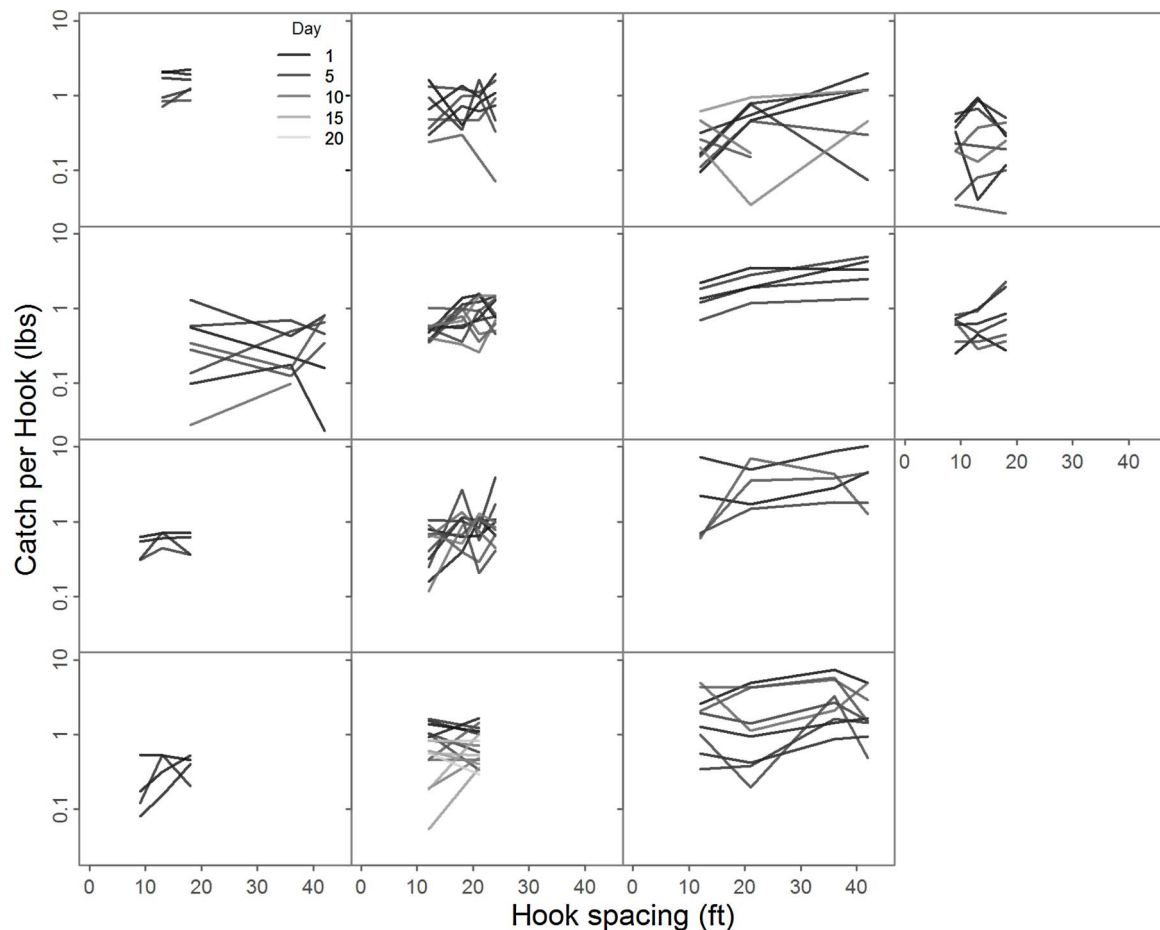
Fig. 3. The raw data from Hamley and Skud (1978). Each panel is a separate site, and each line represents a series of sets fished at different spacings on the same day. Day number is colored. Sets with zero catch are removed.

2.3. Analysis of experimental data

2.3.1. Data

The 'experimental' data come from chartered commercial vessels fishing parallel sets of fixed gear with variable hook spacing (6–40 ft), repeated every day for 3–19 days at the same location (Hamley and Skud, 1978). These trips were repeated at different locations, in different years, but not always by different vessels. Catches varied by site, reflecting the underlying spatial variability in fish density (Fig. 3). As with the fishery-dependent data, we filtered out 11 sets with zero catches (2.7%), leaving 397 sets from 14 distinct locations. There were experimental sets with few fish, suggesting sets with zero catches may be a natural part of the distribution. Despite this, we still removed these sets to more closely match the fishery-dependent data analysis, and because we do not expect them to influence estimates of hook spacing.

These data differ from the fishery-dependent data because they were collected under a controlled sampling protocol. Nevertheless, the experimental data were unbalanced with respect to hook spacing, replicates, and vessels (Fig. 3). Local depletion was also a concern given that the same area was fished repeatedly, but for a variable number of days. Perhaps more importantly, there were few experiments with hook spacings at less than 10 ft, which is currently a commonly used spacing in the fishery.

2.3.2. Parametric hook spacing model

New methods and software now exist to take into account the complexities of the data which were largely ignored in the original least squares analysis (Hamley and Skud, 1978). Specifically, we refit these data using non-linear mixed effects model that accounts for site-specific

differences and local depletion. This model structure is widely used throughout ecology and fisheries, and better accounts for the data complexities and provides approximate uncertainty estimates about the fit and derived quantities (Royle and Dorazio, 2008).

As with the spatiotemporal model (7), catch was predicted as a function of density, hook spacing, and catchability:

$$\mu_i = h_i(s_i) \cdot D_i \cdot q_i \qquad (9)$$

In contrast to the spatiotemporal model, we assumed sites are distant enough to effectively be independent. Thus, we estimated site level densities as independent random effects, and included a local depletion term γ that such that density decreases exponentially with day d: $D_i = e^{\chi_{s_i} - \gamma d_i}$, where $\chi \sim N(\mu_\eta, \sigma_\eta^2)$ is the vector of site densities. No other information on environmental or gear quantities were available.

We only used the $f_{parametric}$ (4) hook spacing form, and assumed that $\lambda = 1$ due to the lack of information at small spacings in the data. Since the data were collected in a controlled manner, we further set $q = 1$, such that the site level density effect captures catchability. Lastly, we assumed that observed catch is lognormally distributed, $\log C_i \sim N(\log \mu_i, \sigma_{s_i}^2)$, where σ_s is the site-specific observation random effect, assumed to be normally distributed: $\sigma_s \sim N(\theta, \sigma_\theta^2)$. We provide further details of the model and the data in Appendix A (Supplementary material).

2.4. Model fitting

Both the spatiotemporal model and the parametric hook spacing model are non-linear hierarchical (mixed effects) models, containing both fixed and random effects. The most complex spatiotemporal model

(using $f_{smoother}$) has 30 fixed effects and 59,254 total random effects (1116 for vessel effects, 2765 for spatial, 55,300 for spatiotemporal, and 43 for smoother deviations). To fit these large, complex mixed effects models we used Template Model Builder (Kristensen, 2017; Kristensen et al., 2016), which is a freely available tool that uses automatic differentiation to fit models using maximum marginal likelihood and random effect integration via the Laplace approximation (Skaug and Fournier, 2006). Uncertainties in fixed effects were estimated using standard frequentist asymptotic assumptions, and derived quantities (such as hook power and relative abundance) via the Delta method, both of which are computed automatically by TMB.

INLA is a popular software tool for spatial models, and here we used it to generate inputs for the stochastic partial differential equation approach for our spatiotemporal model (Lindgren and Rue, 2015). This model could have been fit with INLA (Rue et al., 2009), but by using TMB we had the convenience of a consistent software platform for inference of all models.

3. Results

The spatiotemporal fishery-dependent analysis using the smoother hook spacing form showed a clear trend toward decreasing power of hooks with smaller spacings, albeit with much uncertainty at spacings wider than 30 ft (Fig. 4a). The parametric form estimated a maximum relative hook power, $h_\infty = 1.771$ (SE of 0.057; Table 1). That is, a hypothetical set fished at spacings wide enough that hooks were independent would catch 1.771 times as much as at 18 ft. This value for
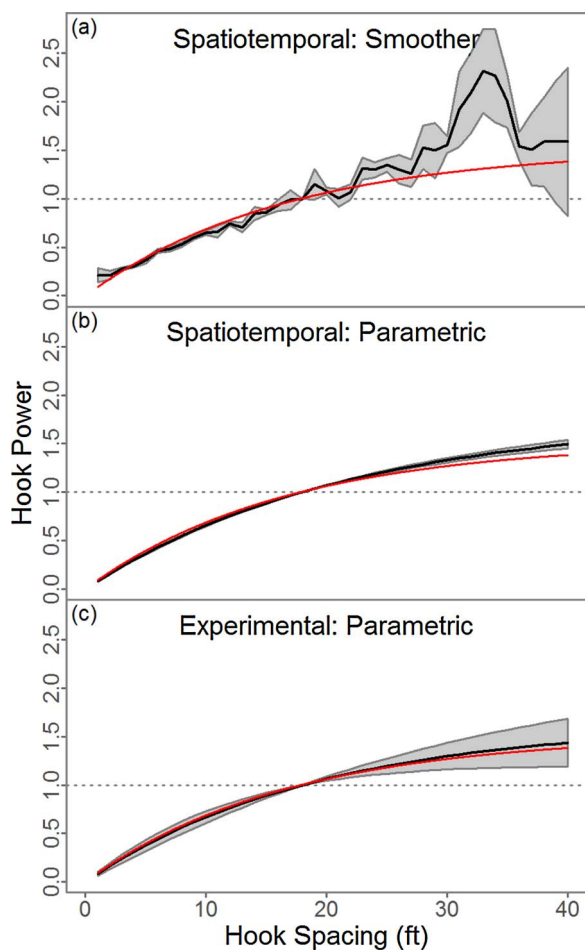

Fig. 4. Estimated hook spacing effects for the smoother (a) and parametric forms from the spatiotemporal (b) and experimental model (c). Lines and shaded region show estimates and approximate 95% confidence interval, and red line shows historical parametric fit to experimental data from (Hamley and Skud, 1978).

the parametric form of the experimental data ($h_\infty = 1.64$ (0.28); Table 2) was similar to that of the fishery-dependent. These estimates suggest the hook spacing relationship asymptotes slower, and have lower hook power at smaller spacings than previously estimated (Fig. 4b). For the experimental model, the effect of local depletion (day of fishing) was positive and significant: $\gamma = 0.05$ (0.01). Overall, this model had much more uncertainty in the hook spacing effect, despite assuming $\lambda = 1$. In general, the parametric form from Eq. (4) matches the fits well, suggesting this form is reasonable for halibut.

The spatiotemporal model estimates for the geostatistical properties were relatively insensitive to the form of hook spacing used (Table 1). For instance, the variance of the spatiotemporal component (σ_ε) was 0.360, 0.342, and 0.345 for hook spacing effect of constant, smoother, and parametric forms, respectively. This pattern was not true for the observation error, σ_{obs}, where the models with the parametric form without space had a substantially larger estimate (0.772) than the spatiotemporal model (0.654). This 15% reduction in variance is expected as the spatiotemporal component explains variation in catch due to sets being proximate in time and space. The spatiotemporal residuals showed no clear spatial pattern (not shown – confidential), suggesting the model adequately captured those processes.

When using the fishery-dependent data to estimate trends in relative abundance the overall pattern was consistent, but there were some important differences (Figs. 5, S1). All models predicted a relatively stable period from 1996 to 2004, a decline from 2005 to 2014, and a significant uptick in 2015. However, the uncertainty estimates for the spatiotemporal model were larger, particularly compared to the model without space or a hook spacing effect. There were some smaller annual differences when the hook spacing was not estimated, such as in 2007. However, in general the spatial effect had a much larger effect on predicted abundance trends than the effect of hook spacing. Compared to a trend estimated using fishery-independent survey data (with constant hook spacing) over the same period of time and general area (Webster, 2017), our estimates had generally the same trend, but tended to have smaller year-to-year changes and less uncertainty (Fig. 6).

4. Discussion

We found clear evidence for reduction in hook fishing power (or effectiveness) at smaller spacings, supporting the hypothesis that nearby hooks compete for Pacific halibut. This implies that for CPUE analyses, the relevant unit of effort is an effective hook. We also found that the parametric form (Eq. (4)) was a reasonable approximation for this relationship. Further, the parametric model fits to both the fishery-dependent and experimental data sets were fairly consistent, demonstrating this relationship can be estimated directly from commercial data, without the need for a controlled experiment. Estimating effective hooks in the CPUE standardization has the added benefit that the uncertainty in the spacing effect is propagated into the trends of relative abundance. Lastly, despite a clear hook spacing effect, we found limited effects on standardized CPUE trends. This was likely because although there has been a temporal shift to different gear types, on average the hook spacing has changed slightly over the time period examined. Comparisons among other regulatory areas with systematic differences in gear usage may be much more important to the interpretation of Pacific halibut trends. Further, in other stocks managed with longline CPUE with significant temporal trends, ignoring hook spacing may mischaracterize abundance trends and lead to poor management decisions.

Our results support the hypothesis that hooks compete with each other, at least under the densities observed, and conditioned on the specific foraging behavior of Pacific halibut. However, the commercial data used here only contained information on retained legal halibut and set-level characteristics, and did not include key factors that certainly affect catch rates. For example, we were not able to account for the

Table 1
Select model estimates and standard errors (parentheses) for models with and without space, and the parametric and smoother form for hook spacing. Depending on the model structure some parameters are not estimated, represented by ($-$), or the first level of a factor set to zero and thus there is no standard error. See Appendix A Supplementary material for further results.

		No Space	No Space	Spatiotemporal	Spatiotemporal
Symbol	Description	Smoother	Parametric	Smoother	Parametric
β_0	Global intercept	0.334 (0.037)	0.368 (0.035)	0.551 (0.060)	0.572 (0.058)
β_{d_1}	Linear effect of depth	3.66E-3 (1.89E-4)	3.65E-3 (1.89E-4)	8.54E-4 (2.72E-4)	1.03E-3 (2.74E-4)
β_{d_2}	Quadratic effect of depth	-7.46E-6 (8.23E-7)	-7.15E-6 (8.23E-7)	-3.99E-6 (9.95E-7)	-4.43E-6 (9.97E-7)
κ	Geostatistical range	–	–	0.399 (1.07E-2)	0.400 (1.07E-2)
σ_ε	Spatiotemporal variation	–	–	0.342 (5.68E-3)	0.345 (5.70E-3)
σ_ω	Spatial variation	–	–	0.370 (1.04E-2)	0.358 (1.00E-2)
g_1	Gear type: autoline	0 ($-$)	0 ($-$)	0 ($-$)	0 ($-$)
g_2	Gear type: fixed	0.341 (0.022)	0.348 (0.020)	0.249 (0.022)	0.269 (0.020)
g_3	Gear type: snap	0.093 (0.028)	0.080 (0.026)	0.083 (0.027)	0.099 (0.025)
σ_{obs}	Observation variance	0.770 (0.002)	0.772 (0.002)	0.653 (0.002)	0.654 (0.002)
σ_η	Vessel variance	0.514 (0.013)	0.515 (0.013)	0.360 (0.010)	0.361 (0.010)
β_s	Parametric hook spacing	–	0.099 (0.515)	–	0.024 (0.040)
λ	Parametric hook spacing	–	0.567 (2.948)	–	1.925 (3.211)
σ_d	Smoother variation	0.142 (0.024)	–	0.140 (0.023)	–
h_∞	Hook power at infinite spacing	–	1.570 (0.042)	–	1.771 (0.057)

Table 2
Model estimates and standard error (parentheses) for the parametric model fit to the experimental data.

Parameter	Estimate (SE)
β_s	0.052 (0.015)
γ	0.048 (0.011)
λ	1.0 ($-$)
h_∞	1.636 (0.280)
θ	0.668 (0.062)
σ_θ	0.211 (0.050)
ϕ	-0.133 (0.199)
σ_η	0.711 (0.142)

effects of environmental factors nor halibut size structure and density. Neither we were able to account for multispecies competition, which also has important influences on longline catch rates (Rodgveller et al., 2008). Thus, we caution against a biological interpretation of our results, and against applying our estimates to other species or situations, as foraging behavior may vary widely and lead to fundamentally different relationships (Fig. 1). For instance, initial captures of sablefish do not affect subsequent captures leading to a random distribution of occupied hooks, while Pacific halibut tend to cluster (Sigler, 2000). Future lab experiments on Pacific halibut or other species, while controlling for environmental and other key factors, would provide valuable corroboration and further insights in the relationship between individual foraging behavior, hook competition, and the resulting population-level hook spacing effects.

The assessment of Pacific halibut uses CPUE that excludes snap and autoline gear due to concerns over confounding between gear type, hook spacing, and changes in density (Stewart et al., 2016). Our analysis provides a method for including all gear types in future analyses and improving the information on which management is based. Although our analysis is specific to Pacific halibut, similar analyses for other stocks assessed, at least in part, with standardized longline CPUE could use a similar approach. For instance, hook spacing for sablefish is known to be important from experiments, but is not consistently reported for commercial catches and thus cannot be directly used in the CPUE standardization (Sigler and Lunsford, 2001). Likewise, CPUE analyses for bigeye tuna account for hooks between floats and hooks per set, but the length of sets are unreported and thus the effect of hook spacing is unknown (e.g., Hoyle and Okamoto, 2011). Our results demonstrate the potential value in collecting hook spacing for commercial longline catch data, and suggest incorporating this information in the future, especially for stocks with temporal or spatial trends hook spacing over time.

Efforts to estimate fish stock status from longline CPUE trends while ignoring spatial effort have been widely criticized (e.g., see debates in Hampton et al., 2005; Myers and Worm, 2003; Walters, 2003). As a consequence, incorporating spatial strata into standardizations is commonplace (Maunder and Punt, 2004). However, these improved methods still typically ignore spatial correlation among cells, and can be sensitive to cell resolution (Ichinokawa and Brodziak, 2010; Tian et al., 2010). One promising new method for accounting for space in standardizations is hierarchical spatiotemporal models (Thorson et al., 2015). Hierarchical models have become increasingly popular tools across a wide range of applications in fisheries science (Thorson and Minto, 2014), and their application for spatiotemporal models provides a natural approach for dealing with spatial complexities when estimating fish densities. In contrast to data collected using a random design (e.g., surveys), the preferential sampling of commercial data (i.e., high density areas are targeted; see Conn et al., 2017; Diggle et al., 2010) remains an open issue when using these methods. We did not attempt to address this issue in our simplified model, here used as a proof of concept and to investigate hook spacing effects, but note we were encouraged that our estimates closely matched a survey CPUE trend (Fig. 6). However, before using these methods for management, we suggest future studies more closely investigate the effects of preferential sampling, in addition to other factors ignored here (e.g., zero catches and anisotropy), which may have an important influence on some stocks. We expect development of these models to continue being an active area of research, and will eventually be applied widely to analyze complex spatial fisheries data.

Trends in CPUE may not accurately reflect true trends in abundance due to a wide variety of confounding factors. Accounting for all such confounding factors is thus critical for successful fisheries management, but is a difficult proposition and will be a source of continued research. For longline gear, in particular, the spacing between hooks clearly effects the effective effort leading to observed catches. This highlights the value in collecting hook spacing data on longline sets, particularly if there is the potential for an annual trend in hook spacing as gear configuration evolves in a fishery. Fortunately, the effective effort implied by hook spacing can be estimated within a spatially-explicit CPUE standardization model fit to commercial catch data. Including this effective hook relationship will likely lead to improved trends in relative abundance, and hence better management for other species caught by longline.
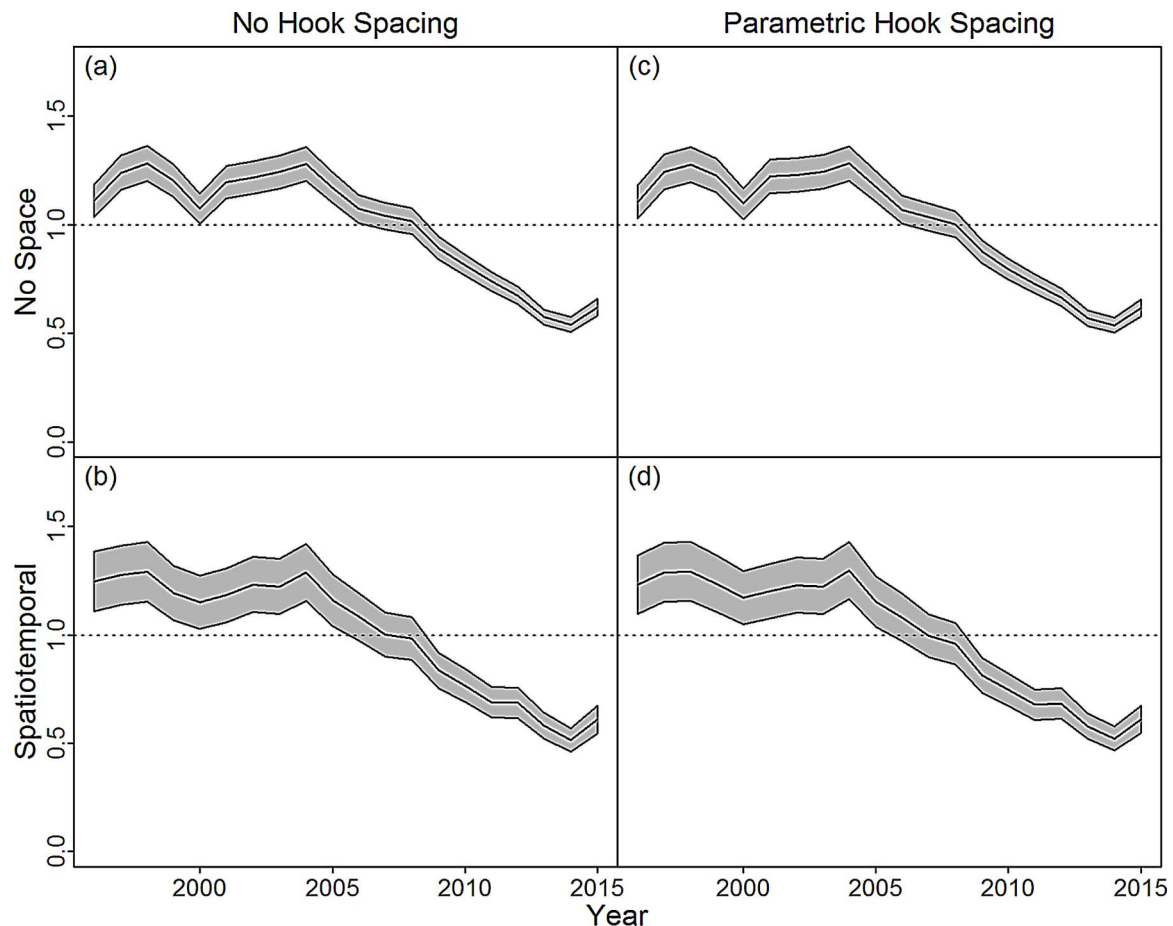
No Hook Spacing   Parametric Hook Spacing

Fig. 5. Effect of spatial component (rows) and hook spacing form (columns) on trends in relative abundance. Each panel is normalized by dividing by its mean. Lines and shaded region show estimates and approximate 95% confidence interval.
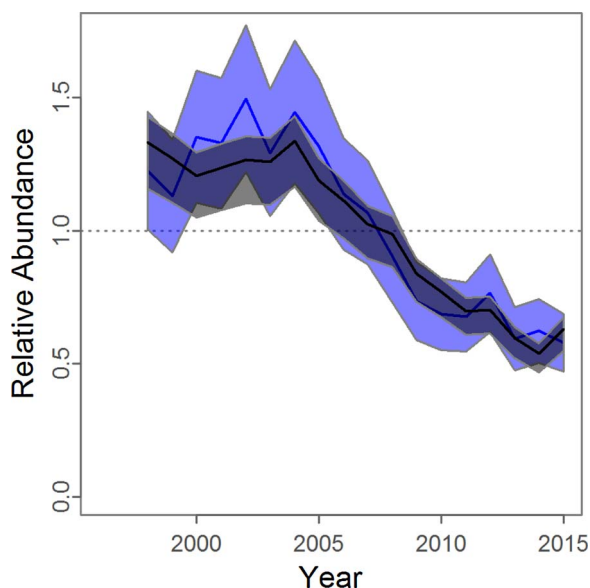

Fig. 6. The relative abundance trend from the fishery-independent survey (blue) conducted under a controlled design (constant gear on a uniform grid, see Webster, 2017), compared to the parametric fit in the spatiotemporal model. Both are normalized to have mean of one. 1996 and 1997 were unavailable for the survey series and thus left off for the spatiotemporal results. Lines and shaded region show estimates and approximate 95% confidence interval. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.fishres.2017.10.004.

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