Quantifying the effect of vessel interference on catch rates: A theoretical approach

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\textbf{A B S T R A C T}

In response to a vessel buyback scheme in a major Australian Commonwealth fishery, nominal catch-per-unit-effort (CPUE) showed dramatic increases. These led to a discontinuity in the statistically standardised CPUE time series, which may also suggest a discontinuity in the relationship between catch-per-unit-effort and abundance. We hypothesise the discontinuity in CPUE is due to reduced vessel interaction effects. Vessel interactions can arise due to, for example, competition or information sharing, and as such can influence CPUE independent of the underlying fish abundance. Thus there remains a need to quantitatively understand the nature of the effect of vessel interactions on CPUE. Awareness of such interactions is common, yet it has not been described in the context of rapid changes of effort brought about by management interventions such as a vessel buyback. Here we focus on vessel interference, ecologically defined as a depression in foraging (catch) rate with increased foraging (fisher, or vessel) density. We present a mechanistic model incorporating a vessel interference term, that could explain situations where CPUE is more responsive to effort buybacks than if no vessel interference is assumed. Our hypothesis is that vessel interference makes CPUE a nonlinear function of effort. We define an interference term that interacts with stock dynamics and catchability. Under a simulated buyback, the trajectories of abundance and CPUE change in a manner dependent on the magnitude of the interference. Our simple model of the non-linear effect of vessel interference holds up well under a large range of values for biological and operational parameters. The effect of interference also appears independent of stock carrying capacity, vessel numbers, and the magnitude of relative reduction in vessel numbers. We conclude that our model provides a promising approach to the technically challenging problem of estimating relative abundance under conditions of sudden changes in fishing effort, and thereby improving sustainable fisheries management via appropriate levels of control rules set in response to such estimates.

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1. Introduction

The most common assumption made about the relationship between fishing effort $E$, the abundance of a targeted stock $N$, and catch $C$ is that catch is a linear function of both, so that $C = qN$ (where $q$ is catchability), and consequently Catch Per Unit Effort CPUE = $qN \propto N$. If this really is the case, then intuition suggests that when effort is reduced on a heavily exploited population, the population will generally increase and the CPUE would also increase (for fixed $C$ and $q$). Conversely, if effort is increased, then CPUE would be expected to decline.

The Southern and Eastern Scalefish and Shark Fishery (SESSF) in Australia (Smith and Smith, 2001; Smith et al., 2008) experienced management intervention via a vessel licence buyback scheme in 2005/2006. This resulted in a 40% reduction in the trawl fleet, and a 16% reduction in non-trawl vessels (Vieira et al., 2010). The buyback was enacted in response to a lack of profitability that had been impacting fishing practices, and quota transfers. The total allowable catch (TAC) remained unchanged during the buyback: the notion was that increased profitability would be achieved by distributing the same catch among fewer vessels.

In some cases, such as for flathead (\textit{Neoplatycephalus richardsoni}), nominal CPUE showed dramatic increases as a result of the reduction in vessel numbers (Sporcic and Haddon, 2015) increasing by 25.6% from 2005 to 2006 and by 40.8% from 2006 to 2007, and then stabilizing over the next five years. Moreover, standardised CPUE (which is used in SESSF stock

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assessments via generalised linear models to obtain a relative abundance estimate trend), did not appear to adequately account for the factors contributing to these increases (while noting that co-incident factors such as increased recruitment, or increased availability due to environmental conditions, cannot be ruled out as having been responsible): following the reduction in vessel numbers, there remained a discontinuity in the standardised CPUE time series about the time of the buyback That is, the standardised CPUE did not adequately decouple the relationship between stock abundance and confounding variables.

Vessel interaction effects have been identified and acknowledged more broadly (e.g. Gillis, 1999). Dreyfus-Leon and Gaertner (2006) considered information sharing between fishers in the context of a neural network model, and showed that performance decreased at bigger group sizes, probably due to competition and depletion effects of some fishing grounds.

Rijnsdorp et al. (2008) examined competition effects in the Dutch demersal fishing fleet and found that in the ten years following the introduction of the beam trawl in the 1960s, a decline in catchability, attributed to vessel competition, was observed in beam trawlers used for reference measurements. Gillis et al. (2006) suggested that increasing fleet size may have a disproportionately small impact on fishing mortality because of limitations in information exchange.

Rijnsdorp et al. (2000a) inferred that declines in catch rate over 48 h may be in part due to interference competition among vessels. Rijnsdorp et al. (2000b) found that catch rates of vessels that continued fishing during a week in which a segment of the fleet stayed in port was 10% higher than in the adjacent weeks.

There remains a need to quantitatively understand the nature of the effect of vessel interactions. In this paper, we focus on vessel interference effects, where interference is ecologically defined as a rapidly reversible depression in foraging (catch) rate (CPUE) with increasing foraging (fisher, or vessel) density (Rijnsdorp et al., 2000b). While the hypothesised effect of vessel interference is most pronounced around sudden and large reductions in effort, as per a buyback scheme, smaller-scale interference is presumably occurring in an ongoing manner. In the context of CPUE time series continuity, it is important to identify and isolate the effect of changes in the effort (i.e. number of vessels) on the CPUE. Awareness of technical interactions is common, yet it has not been described in the context of rapid changes of effort brought about by management interventions such as the structural adjustment; we attempt to provide a simple quantitative description of the processes involved.

While interference is commonly acknowledged, there are few empirical studies quantifying vessel interference. Those examples are largely centred on the assumption of an ideal free distribution (Fretwell and Lucas, 1970). Gillis et al. (1993) noted that many traditional analyses of fisheries data assume that i) there is a negligible effect of alternative fish stocks on the spatial distribution of fishing effort (the “dynamic pool assumption”), and ii) the localisation of effort does not influence catchability Such assumptions can lead to potential biases in the interpretation of CPUE statistics. Assuming an ideal free distribution, Gillis et al. (1993) found evidence for competition among vessels, but its mechanism, whether interference or exploitation competition, was unable to be determined.

Gillis and Peterman (1998) examined the relationship between catch rate and abundance incorporating a vessel interference term as an input parameter to a model based on the assumption of an ideal free distribution (see also Gillis, 2003). They used Hassel and Varley’s (1969) form of interference among foraging insects to define fishing mortality, \( F(E) \) as a function of catchability, \( q \), effort, \( E \), and a vessel interference term, \( m < 1 \):

\[
F(E) = qE^{1-m}
\]

Results indicated that even low levels of interference among fishing vessels can cause a breakdown in the correlation between CPUE and local abundance.

Gillis and van der Lee (2012) developed theoretical curves of equal catch rates, to test ideal free distribution hypotheses, and suggested that non-linear effects may arise from extreme interference competition.

Poos and Rijnsdorp (2007) estimated the strength of interference competition by considering the decline in value-per-unit-effort about a sudden increase in vessel density associated with a local area closure. They argued that because interference acts immediately, and exploitation acts gradually, interference and exploitation competition can be disentangled if a sudden change in vessel density occurs. We employ the same logic but in a theoretical context.

Structural adjustments such as vessel buybacks do not occur frequently in fisheries, but have major economic and sustainability impacts when they do (Vieira et al., 2010). In this paper, we explore the hypothesis that the dramatic observed changes in the CPUE for some species are due to vessel interactions (interference between vessels) that the current statistical CPUE standardisation does not take into account. Our theoretical approach extends the simple Schaefer model such that catch rate is an inverse function of the number of vessels, with the latter weighted by a parameter, \( \beta \), describing the magnitude of the effect of vessel numbers. We derive an equation for \( \beta \) based on two main assumptions pertaining to biomass, and investigate the extent to which our solution holds under alternative conditions. This is the first attempt to provide an independent means of directly quantifying a vessel interaction effect that is process-based rather than fitted to data.

2. Methods

We work with a discrete time Schaefer model for population size \( N(t) \) at time \( t \)

\[
N(t + 1) = N(t) + rN(t) \left( 1 - \frac{N(t)}{K} \right) - C(t)
\]

where

\[
C(t) = \frac{QV}{1 + \beta V} N(t)
\]

with the usual interpretations of \( r \) as the maximum per capita reproduction, \( K \) as the carrying capacity of the population and \( Q \) as the catchability, \( V \) is the number of vessels (equating to an effort measure), and \( \beta \) is a coefficient reflecting the magnitude of the effect of vessel interference on catchability. We here treat catchability independently from the effects of interference. However, since interference, as modelled here, clearly impacts the proportion of the exploitable stock biomass taken with one unit of effort, per the classic definition of catchability, \( q \), (Haddon 2011), we replace the classic \( q \) by \( Q \), \( Q \) represents the classic catchability, \( q \), when \( \beta = 0 \). Alternatively, \( \frac{Q}{\beta} \) equates to the classic catchability \( q \) when \( V = 1 \). Thus the term \( \frac{QV}{1 + \beta V} \) is essentially the traditional catch equation (\( C = qEN \), where \( E \) equates to effort) and the term \( \frac{1}{1 + \beta V} \) captures the effect of vessel interference. We are assuming interference competition not exploitation competition (sensu Poos and Rijnsdorp (2007)), and, for simplicity, we assume that \( r, K, \) and \( Q \) are known.

Our use of an asymptotic relationship to represent interference differs from Gillis and Peterman’s (1998) power relationship. The latter has fishing mortality increasing exponentially when the vessel interference term is less than \( 0 \), where fishing mortality at zero interference is a point on the continuum. In contrast, equation (1a) imposes an asymptote about zero interference, meaning that fishing mortality is maximised in the absence of interference.
3. Background results

We illustrate how a directly proportional relationship between CPUE and N can break down under a vessel buyback with reduced interference. Fig. 1(a) shows a population starting at carrying capacity, K, and fished down to a steady state, with a simulated vessel buyback (of 75%, from 20 to 5 vessels) occurring midway through the time series. Generally, there is an assumption that the same values for CPUE pre- and post-buyback correspond to the same underlying abundance, N. However, if vessel interference occurs, the same values of CPUE may correspond to different levels of abundance pre- versus post-buyback. An example is shown in Figs. 1(a)–(c): for CPUE = 3.0 (indicated by the horizontal and vertical dashed lines), the corresponding abundance is different pre- and post-buyback (N ≈ 890, and N ≈ 780, respectively). This is further illustrated in Fig. 2a, which plots N versus CPUE for a range of assumed values of β, the interference term. Abundance is plotted as a function of CPUE, since it is the latter that is used to estimate the former. Fig. 2b shows that, under a simulated buyback, with interference, there is a breakdown in the linear relationship between CPUE and N. For a given level of interference, β, the CPUE vs N trajectory changes – and in a different manner depending on the magnitude of the interference. That is, CPUE is no longer a function of abundance, N, since there is more than one possible value of CPUE for a given value of N.

Thus, unless the level of vessel interference, β, is known, it is not possible to relate CPUE to abundance, nor to predict the magnitude of change in CPUE under a buyback. If β is known, the line in Fig. 2a describing the relationship between CPUE and abundance is also known, given the number of vessels. We now show how to determine β.

We make the following assumptions (all of which can be relaxed):

- The initial population size is N(0) = K.
- At the time of the vessel buyback, t_b, the population, N(t_b), has reached a steady state corresponding to the pre-buyback level of effort.
- All changes in CPUE in the first year after the buyback are associated solely with the change in vessel numbers. This is consistent with Poos and Rijnsdorp (2007), who emphasised that interference competition occurs instantaneously, and can therefore be disentangled from exploitation competition when a sudden change in vessel numbers occurs. Thus, we assume that N(t_b + 1) = N(t_b).

With these assumptions, it is possible to derive simple analytical results of great generality. In particular, we will derive and solve a deterministic linear equation for the vessel interference term, β. Since the catch at time t, C(t) is

\[ C(t) = Q \frac{V}{T + \beta V} N(t) \]  

(1a)
it follows that the fishing mortality,
\[
    F(V) = Q \frac{V}{1 + \beta V}
\]

is an increasing but asymptotic function of vessel numbers.
Assuming the number of vessels is an approximation of effort
(which is predicated on the assumption that each vessel has equiva-
lent fishing power, and that each expends the same amount of
nominal effort), then catch-per-unit-effort, \(CPUE(t)\) is:
\[
    CPUE(t) = Q \frac{1}{1 + \beta V} \, N(t)
\]

which reduces to the traditional form, \(CPUE(t) = QN(t)\), when
\(\beta = 0\).
If \(V_1\) is the pre-buyback number of vessels, the steady state
population size \(\tilde{N}(V_1,\beta)\) at the time of the buyback is
\[
    \tilde{N}(V_1,\beta) = K \left( 1 - \frac{Q\,V_1}{1 + \beta V_1} \right)
\]

Since \(N(0) = K\),
\[
    CPUE(0) = Q \frac{K}{1 + \beta V_1}
\]

which allows us to determine \(Q\):
\[
    Q = \frac{CPUE(0)}{K} \left( 1 + \beta V_1 \right)
\]

If the number of vessels after the buyback is \(V_2\), then the change
in \(CPUE\) at the time of the buyback is
\[
    \Delta CPUE = \tilde{N}(V_1,\beta) \left[ \frac{Q}{1 + \beta V_2} - \frac{Q}{1 + \beta V_1} \right]
\]

Using Eqs. (3)–(5) we obtain
\[
    \Delta CPUE = CPUE(0) \beta \Delta V \frac{1}{1 + \beta V_1} \left[ \frac{1}{1 + \beta V_2} \right]
\]

where \(\Delta V = V_1 - V_2\).
Since \(Q\) is known, we can rearrange and simplify Eq. (6) to solve
for \(\beta\).
\[
    \beta = \frac{\Delta CPUE(CPUE(0)\Delta V)}{\left( \frac{1}{1 + \beta V_1} \Delta CPUE(CPUE(0)) \right) \Delta CPUE(CPUE(0)) V_2}
\]

That is, the strength of vessel interference can be calculated as a
function of the change in catch-per-unit-effort at the time of vessel
Table 1
Simulation parameters.

<table>
<thead>
<tr>
<th>Quantity</th>
<th>Definition</th>
<th>Value(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta ) (specified)</td>
<td>Vessel interference term</td>
<td>(0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0)</td>
</tr>
<tr>
<td>( r )</td>
<td>Maximum rate of change of the population</td>
<td>(0.05, 0.1, 0.2, 0.25, 0.3, 0.35, 0.4, 0.45, 0.5, 0.6)</td>
</tr>
<tr>
<td>( K )</td>
<td>Carrying capacity</td>
<td>1000</td>
</tr>
<tr>
<td>( Q )</td>
<td>Catchability</td>
<td>(0.001, 0.01, 0.05, 0.07, 0.1, 0.15)</td>
</tr>
<tr>
<td>( t_b )</td>
<td>Time of vessel reduction/buyback</td>
<td>100</td>
</tr>
<tr>
<td>( T )</td>
<td>Season length</td>
<td>200</td>
</tr>
<tr>
<td>( V_1 )</td>
<td>Number of vessels prior to buyback</td>
<td>20</td>
</tr>
<tr>
<td>( V_2 )</td>
<td>Number of vessels following buyback</td>
<td>5</td>
</tr>
</tbody>
</table>

Table 2
Values of \( Q, \beta \) and \( r \) (across the ranges examined) for which \( \frac{\Delta Q}{Q} \) is not equal to zero, i.e. the \( \beta \) calculation does not hold.

<table>
<thead>
<tr>
<th>( \beta )</th>
<th>0.1</th>
<th>0.2</th>
<th>0.3</th>
<th>0.4</th>
<th>0.5</th>
<th>0.6</th>
<th>0.7</th>
<th>0.8</th>
<th>0.9</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r )</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.05</td>
<td>( Q \geq 0.001 )</td>
<td>( Q \geq 0.001 )</td>
<td>( Q \geq 0.001 )</td>
<td>( Q \geq 0.001 )</td>
<td>( Q \geq 0.001 )</td>
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<td>( Q \geq 0.001 )</td>
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<tr>
<td>0.1</td>
<td>( Q \geq 0.001 )</td>
<td>( Q \geq 0.001 )</td>
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<td>( Q \geq 0.001 )</td>
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<tr>
<td>0.2</td>
<td>( Q \geq 0.001 )</td>
<td>( Q \geq 0.001 )</td>
<td>( Q \geq 0.001 )</td>
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<tr>
<td>0.25</td>
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<tr>
<td>0.3</td>
<td>( Q \geq 0.001 )</td>
<td>( Q \geq 0.001 )</td>
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<tr>
<td>0.35</td>
<td>( Q \geq 0.001 )</td>
<td>( Q \geq 0.001 )</td>
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<tr>
<td>0.4</td>
<td>( Q \geq 0.001 )</td>
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<td>0.45</td>
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<tr>
<td>0.5</td>
<td>( Q \geq 0.001 )</td>
<td>( Q \geq 0.001 )</td>
<td>( Q \geq 0.001 )</td>
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</tr>
<tr>
<td>0.6</td>
<td>( Q \geq 0.001 )</td>
<td>( Q \geq 0.001 )</td>
<td>( Q \geq 0.001 )</td>
<td>( Q \geq 0.001 )</td>
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</table>

Reduction, the number of vessels before and after the reduction (assuming this is not equal: \( \Delta V = 0 \) results in a zero denominator in Eq. (7)), the initial catch-per-unit-effort, the maximum rate of change of the population, \( r \), and the carrying capacity, \( K \).

Having derived this equation for \( \beta \), we undertook an investigation of its performance in a deterministic context. We coded the numerical solution of Eq. (1)–(7) with inputs as per Table 1. We projected the population under an assumed value for \( \beta \) according to Eq. (1), and the corresponding catch rate time series was calculated using Eq. (2). After the time of the vessel reduction (buyback), we calculated \( \beta \) according to Eq. (7), with change in simulated CPUE, \( \Delta \text{CPUE}_{\text{sim}} \), calculated as

\[
\Delta \text{CPUE}_{\text{sim}} = \text{CPUE}(t_b + 1)_{\text{sim}} - \text{CPUE}(t_b)_{\text{sim}}
\]

(8)

We examined a range of 10 values for \( \beta \), 10 for \( r \), and 6 for \( Q \) (Table 1), to determine the accuracy of our estimate of \( \beta \) in Eqn 7, which we denoted by \( \beta_{\text{calc}} \), relative to the true (specified) value, given the assumptions used in deriving Eqn 7. We also consid-
ered the performance of the $\beta_{\text{calc}}$ given the extent to which the key assumptions hold.

We further conducted a small suite of sensitivity analyses to assess the performance of Eq. (7) under alternative assumed values for carrying capacity, $K$, and the relative reduction in vessel numbers.

We measured performance in terms of the relative error ($RE$) in $\beta$ predicted by Eq. (7):

$$RE = \frac{\beta - \beta_{\text{calc}}}{\beta}$$  \hspace{1cm} (9)

4. Results

The estimate of $\beta_{\text{calc}}$ generally holds for higher values of $r$ and true $\beta$, and lower values of catchability, $Q$ (Fig. 3). Generally, the $\beta_{\text{calc}} \approx \beta$ when $r > 0.3$ and $\beta > 0.4$, and the $\beta_{\text{calc}}$ is close to zero when $r < 0.2$ (Table 2). For lower values of true $\beta$, $\beta_{\text{calc}}$ is zero for an increasing range of $r$ values. Occasionally, $\beta_{\text{calc}} > \beta$ by up to twice its value (Fig. 3).

The accuracy of $\beta_{\text{calc}}$ also strongly depends on the assumed value for catchability, with increasingly good performance across the considered range of $r$ and $\beta$ as catchability is reduced. Values of $Q < 0.01$ commonly resulted in $\beta_{\text{calc}} \approx \beta$, and $\beta_{\text{calc}}$ more closely approximated $\beta$ across a greater range of catchabilities at higher values of $r$ and $\beta$ (Table 2).

Overall, our estimate of $\beta_{\text{calc}}$ is best under low catchability, and high values for maximum rate of change of the population and the vessel interference term. This combination of parameters yields population responses that result in the key assumptions of $\beta_{\text{calc}}$ being met (i.e. steady state population at the time of the vessel buyback, and all changes in CPUE in the first year after the buyback being associated solely with the change in vessel numbers).

Increasing carrying capacity, a lower relative decrease in vessel numbers (50% as opposed to 75%), or increasing the absolute numbers of vessels by 2.5, had minimal effect on the accuracy of $\beta_{\text{calc}}$ (results not shown).

There was strong dependence on the steady state assumption; $\beta_{\text{calc}} \approx \beta$ only when the steady state assumption, $N(t_0) = \bar{N}(V, \beta)$, held, which occurred more frequently for higher values of $r$ and $\beta$. Exploratory plotting (Fig. 4) indicated a positive linear relation-
ship between the overestimation of $\beta$ and the difference between $N(t_B)$ and $\bar{N}(V, \beta)$. The steady state assumption was violated when $N(t_B)$ was greater than $\bar{N}(V, \beta)$ (i.e. the population had yet to reach steady state when being fished down from above $\bar{N}(V, \beta)$). When $N(t_B)$ was less than 50% larger than $\bar{N}(V, \beta)$, $\beta_{\text{calc}}$ was increasingly (somewhat linearly) greater than $\beta$ (up to twice its magnitude), but when $N(t_B)$ was greater than 50% larger than $\bar{N}(V, \beta)$, $\beta_{\text{calc}}$ was smaller than $\beta$, and negative in value.

The relationship between $\beta_{\text{calc}}$ and $\beta$ depends less on the assumption that $N(t_B + 1) = N(t_B)$. When the population did not recover, and $N(t_B + 1) < N(t_B)$, $\beta_{\text{calc}}$ was zero. When $N(t_B + 1) > N(t_B)$ (i.e. the population recovered), $\beta_{\text{calc}}$ could equal, over- or underestimate the true $\beta$ (Fig. 4).

When $\beta < 0.4$, the $N(t_B) = \bar{N}(V, \beta)$ assumption breaks down more often, and by greater relative magnitude than the assumption that $N(t_B + 1) = N(t_B)$. There are some instances, however, where the $N(t_B) = \bar{N}(V, \beta)$ assumption almost holds, yet $\beta_{\text{calc}}$ is very different from $\beta$. When $N(t_B)$ is very different from $\bar{N}(V, \beta)$, $\beta_{\text{calc}} \neq 0$ (Fig. 3), this is usually as a result of the stock having collapsed, and/or the value for $\bar{N}(V, \beta)$ being less than zero. This results in near-zero values for $\Delta\text{CPUE}$ (i.e. there is almost no change in catch rate between the time of the vessel reduction/buyback and that in the immediately subsequent time step). The greatest differences between $N(t_B)$ and $\bar{N}(V, \beta)$ are at the lowest values of $\delta$ and higher values of $Q$, because when the maximum rate of change of the population is lower, and catchability is higher, the population is more prone to collapse (Fig. 1(b)-(d) shows an example at low $Q$ for a moderate value of $\delta (0.3)$).

When the $\beta_{\text{calc}} \neq \beta$ and $\beta_{\text{calc}} \neq 0$, this typically equates to a breakdown for the key assumption of steady state abundance at the time of the buyback. Two examples are (Fig. 3):

i) $\beta = 0.5$, $r = 0.3$, $Q = 0.15$: $\beta_{\text{calc}} = 0.61$ Here, $N(t_B) = 96$, when $\bar{N}(V, \beta) = 90$ (NB $N(t_B + 1) = 95.8$, approximately equal to $N(t_B)$).

ii) $\beta = 0.5$, $r = 0.1$, $Q = 0.05$: $\beta_{\text{calc}} = -2.11$. Here, $N(t_B) = 141$, when $\bar{N}(V, \beta) = 90.9$ (NB $N(t_B + 1) = 140.9$, approximately equal to $N(t_B)$).

Generally (Fig. 5), $\beta_{\text{calc}} \equiv \beta$, corresponds to two distinct, linear relationships between catch rate and abundance, which have a knife-edged delineation about the time of the buyback. (i.e. the catch rate changes immediately at the time of the buyback, without an immediate change in underlying abundance). Fig. 5 illustrates how our method is operationalised: i) measure CPUE at time $t = 0$, and $\Delta\text{CPUE}$, the change in CPUE about the buyback), ii) for a known catchability $Q$, solve Eq. (7) to calculate the interference term, $\beta$, iii) once $\beta$ is known, the abundance, $N$, can be determined at any time relative to the time of the buyback.

5. Discussion

We have explored a mechanistic model that could explain situations where CPUE is more responsive to effort buybacks than expected if no vessel interference is assumed. Our hypothesis is that vessel interference makes CPUE a nonlinear function of effort. The interference term, $\beta$ interacts with stock dynamics and catchabil-
ity, \( Q \), so that it is not possible to anticipate its effect without some form of analysis. Given a technical description of vessel competition interference, we are able to estimate \( \beta \), and hence the absolute abundance, \( N \), from \( CPUE \) and assuming a known catchability, \( Q \), maximum rate of change of the population, \( r \), and carrying capacity, \( K \) (Eq. (7)).

We have described the interference process in a quantitative manner, and have shown that a simple description of the non-linear effect of vessel interference holds up well under a large range of values for biological and operational parameters. This also appears to be generally independent of the carrying capacity, actual vessel numbers, and the magnitude of relative reduction in vessel numbers. This formulation, which mimics what is effectively a classic Lotka-Volterra predator-prey competition equation (Hilborn and Walters, 1992) is clear, simple, and generally robust.

The process of statistical standardisation of \( CPUE \) focuses on accounting for processes that influence catchability, \( Q \), that decouple the linear relationship between \( CPUE \) and abundance. The effect of vessel interference, here captured via the \( \beta \) term, is rather a process change that causes temporal discontinuities, and that should be considered separately to catchability. Statistical standardisation should — at least, theoretically — therefore be able to account for catchability and interference as separate entities, resulting in a standardised \( CPUE \) that is solely a function of time and area, and hence, presumably, abundance.

We acknowledge that there is confounding between the catchability, \( Q \), and the vessel interference parameter, \( \beta \), and that this raises the question as to whether the assumption that \( Q \) is known and constant is too strong. A standardisation can be considered to be a dis-articulation of the factors that combine to constitute the catchability term, and this might be expected to change after a buy-back. Provided the factors in the standardisation are categorical, then there will be a delay before the qualitative changes following a buy-back will alter the catchability parameters for each level in such factors, while the vessel interference term captures the effect immediately. As such, the “catchability” term in our model may be considered as the component of catchability excluding that affected by vessel interference. Moreover, it is possible to measure \( Q \) in the field (for example, via a single vessel experiment). Estimating the vessel interference quantity, \( \beta \), is much harder to do empirically. In order to obtain the simple analytical results, we used steady state assumptions that surely do not always hold and we have not confronted our method with a particular data set. Those are both next steps for this promising approach to the thorny problem of estimating relative abundance under conditions of sudden changes in fishing effort. That stated, our method is unlikely to work for irregular or spasmodic fisheries (per Hilborn and Walters 1992). It may be applicable to stable/unstable/cyclic fisheries, assuming there is some underlying steady (or average, in the case of cyclic fisheries) state. This would require an alternative derivation of Eq. (7) for models other than a Schaefner model.

Despite attempts to fit four kinds of simple surplus production models (including Schaefner and Fox models) to the SESSF flathead catch and \( CPUE \) data, and thus obtain estimates of \( r \) and \( K \) that would enable an estimation of \( \beta \) via Eq. (7), flathead themselves require more complex assessment models to appropriately model the relatively complex multi-gear, multi-area fishery. However, worked examples using species that are more amenable to surplus production modelling will be featured in future work based on the theoretical foundation discussed in the present work.

Ultimately, more reliable estimates of abundance lead to improve sustainable fisheries management and reduced risk to stocks, via appropriate levels of control rules set in response to such abundance estimates.

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