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Predicting changes in the catchability coefficient through effort sorting as less skilled fishers exit the fishery during stock declines

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ABSTRACT

Effort sorting is a process in fisheries where fishers of various skill levels sort according to fish density so that the mean catchability of remaining fishers increases as stock size declines. The resulting hyperstability in catch rates masks declining density, sometimes until fish populations have effectively collapsed. Effort sorting as a potential mechanism leading to hyperstability has been known for a while, but the ability to detect it using existing fisheries data has been limited. We present a way to detect effort sorting in fisheries and evaluate it using published recreational fisheries data. Specifically, we propose that catchability among anglers is log-normally distributed, but the anglers remaining fishing on any particular lake will have catchabilities high enough to exceed a minimum acceptable catch rate given available stock size. It is then possible to discern between hypotheses about causes of hyperstability, namely effort sorting or range contraction. However, the fitted model cannot reliably be used to predict fish density from catch-per-unit effort (CPUE) data, reiterating the importance of fishery-independent data, and serving as a warning against using CPUE as an index of density in management.

1. Introduction

Catchability is a measure of the fishing efficiency per fish density or the fishing mortality rate per unit of fishing effort (Arreguin-Sanchez, 1996). Catchability is a function both of fish behavior (e.g., activity, aggregation, naiveté; Arreguin-Sanchez, 1996; Askey et al., 2006; Kuparinen et al., 2010; Alos et al., 2012) and fisher behavior (e.g., skill in finding and capturing fish; Jones et al., 1995; Gaertner et al., 1999; Ruttan, 2003; Salas and Gaertner, 2004). It is commonly assumed that catchability is constant across a wide range of fish densities, implying that catch-per-unit effort (CPUE) is directly proportional to density. Assuming constant catchability is important because in the absence of fishery-independent data CPUE is commonly used as an index of density (Hilborn and Walters, 1992; Quinn and Deriso, 1999). However, catchability in many (particularly recreational) fisheries is density-dependent and most often hyperstable (Erisman et al., 2011; Shuter et al., 1998; Ward et al., 2013a), meaning catchability increases as density declines. Density dependent catchability is problematic for managers monitoring catch rates because density declines more quickly than catch rates, masking potential fishery collapses (Hilborn and Walters, 1992; Post et al., 2002). Understanding the range of conditions under which catchability may vary is important for fisheries management and conservation (Fenichel et al., 2013; Hunt et al., 2011), especially in situations where fisheries-independent data are sparse or absent.

It is typical for the skill of recreational anglers to vary considerably (Abrahams and Healey, 1990; Baccante, 1995; Ruttan, 2003; Ward et al., 2013b), often seen as catch inequality across individuals. If there is a minimum success rate that anglers are willing to tolerate, then less skilled anglers will exit the fishery (or seek other recreational opportunities) before more skilled individuals during periods of stock decline (Post, 2013; Walters and Martell, 2004). This "effort sorting" process (Walters and Martell, 2004) will lead in turn to increases in the average catchability coefficient of the subset of anglers still actively participating. Such a perceived increase in average catchability coefficient can cause fishing morality rate to remain high despite effort decreases and cause CPUE to exhibit hyperstability even when other mechanisms that typically cause hyperstability (handling time, range contraction) are absent. Obviously, this process will also depend on the dynamics of other fishing opportunities, making direct observation difficult. The notion of effort sorting is not new, but the ability to detect it as a mechanism has been limited. The effort sorting mechanism is not specific to recreational fisheries. For example, commercial fisheries experi-

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ence effort sorting near the end of a fishing season as less efficient boats leave early to balance revenue against costs. Vessel buyback programs are also more likely to attract less efficient skippers and owners. While the relative influence of effort sorting in different fisheries has not been evaluated, it seems likely that this mechanism is particularly strong in recreational fisheries, where skill and experience vary widely (Walters and Martell, 2004).

We propose a framework for predicting how the average catchability coefficient, i.e., the fishing mortality rate if effort is known, will change under the assumption that anglers have similar constraints that result in similar catch rates at which they cease fishing. Within this framework, we explore alternative hypotheses for variation in catchability. Namely, we suggest that effort sorting may occur due to one or more of the following mechanisms: 1) the basic effort sorting mechanism outlined above; 2) effort sorting exacerbated by tolerance for low catch rates being related to catchability, so skilled anglers will also accept lower catch rates than less skilled anglers due to factors such as increases in maximum fish size; or 3) effort sorting exacerbated by hyperstability in catchability due to spatial contraction of fish at low densities. We evaluate these models against catch rate data presented in Ward et al. (2013a) on freshwater recreational fisheries in British Columbia.

2. Characterizing change in catchability as less-skilled anglers leave the fishery

Anglers will only continue to fish if they believe there is a positive benefit. Suppose that catching fish is the primary motivation for fishing, and the catch rate at which anglers exit the fishery is c_o. An angler i, who has catchability coefficient q_i, will seek other options (either fishing elsewhere or not at all) when stock density N is low enough so that catch rate q_iN is less than c_0, or equivalently when that individual's q_i satisfies:

$$q_i < {}^{c_0}\!/\!N. \tag{1}$$

Next, suppose that the distribution of q_i's over the population of anglers is approximately log-normal (or the distribution of $q_i{}^* = \log_e(q_i)$ is normally distributed), with mean μ_q and standard deviation σ_q. That is, suppose that 50% of anglers will exit the fishery, so that effort drops below half its maximum value, when$q_i{}^* = \log_e(c_0) - \log_e(N) < \mu_q$. Highly heterogeneous angler populations are represented by high σ_q (Walters and Martell, 2004), potentially resulting in a few very skilled anglers. For the constant-catchability case (Eq. (1)), a normal distribution of $q_i{}^*$'s over anglers implies that the effort response (number of anglers fishing) to increasing N will have a sigmoidal shape, i.e., will be a cumulative log-normal distribution with cumulative probability 0.5 at the density for which catch rate is equal to c_0.

Given a density N, we can then predict the mean catchability coefficient of the anglers that will continue to fish at that density as the back-transformed mean of the truncated normal distribution with lower truncation limit q_{min} given by Eq. (1). That mean is given by (Greene, 2003)

$$q_e = \exp\left(\mu_q + \sigma_q \frac{n(d)}{1 - N(d)}\right) \tag{2}$$

where q_e is the mean of the remaining anglers with individual q_i's, $n(d)$ is the standard normal density function (mean 0, standard deviation 1.0) evaluated at the deviate

$$d = \frac{\left(\log_e(q_{min}) - \mu_q\right)}{\sigma_q} \tag{3}$$

using q_{min} equal to the q_i from Eq. (1) and $N(d)$ is the cumulative standard normal distribution function evaluated at standard deviate d.

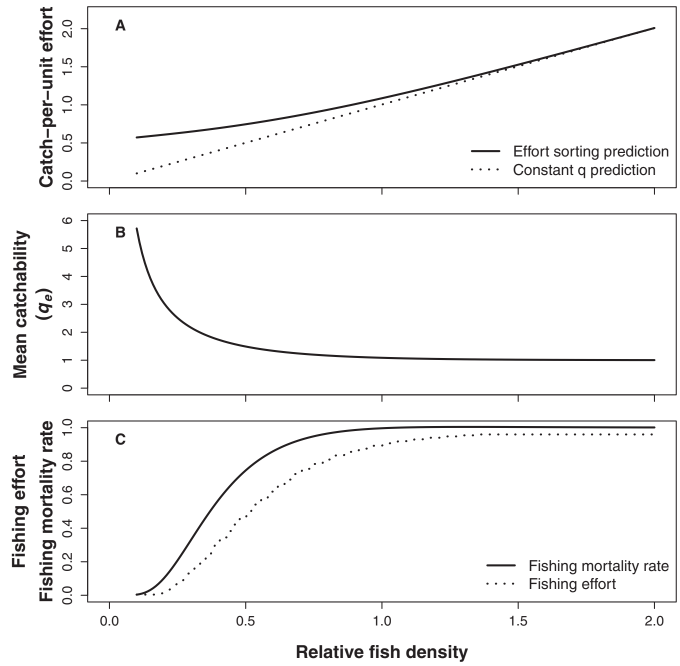

Fig. 1. (A) Hyperstability in CPUE caused by increases in mean q_i at low stock size due to effort sorting even assuming CPUE = qN, where q is catchability and N is fish density; (B) change in catchability as density declines due to effort sorting; (C) change in fishing mortality rate and fishing effort as fish density declines.

For illustrative purposes, when N changes from 0.0 to 2.0, $\mu_q = 0$, $\sigma_q = 0.25$ and $c_0 = 0.5$, effort sorting leads to differences in CPUE at low stock sizes (Fig. 1A) and increases in q_e at low stock sizes (Fig. 1B). However, fishing mortality, calculated as $F = q_e \times$ effort, does not increase at low stock sizes due to decreases in fishing effort (Fig. 1C). Note that the outcome of this process is that CPUE for this example would display dangerous hyperstability for stock sizes below 0.75.

It should not be difficult to obtain reasonable estimates of c_0 from observations of catch rates at which anglers exit the fishery and from economic analysis of the costs of fishing relative to catch per effort (Cinner et al., 2008; Daw et al., 2012). The catchability distribution parameters μ_q and σ_q are much more difficult to estimate. One possibility is to examine how observed CPUE changes with density estimates from various assessment methods (e.g. Fig. 1). Another possibility is to conduct experimental fishing with standardized q and to compare a standardized q to changes in mean q measured over the heterogeneous angler population as Ward et al. (2013a) did for recreational trout fishing in British Columbia.

Note that the q distribution cannot be estimated just by examining short term variation in catch rates among anglers; many factors contribute to that variation, especially chance variation in encounter rates (Ruttan, 2003). For example, in recreational fisheries we typically see Poisson or negative binomial distributions of catch rates across anglers over short sample periods (Seekell, 2011). This variation does not mean that catchability varies among anglers, or that the distribution of catchability among anglers is Poisson or negative binomial; rather, it means only that luck varies for every angler and "real" or persistent variation in catchability among anglers can only be seen by comparing average catch rates across anglers over long time periods (fishing seasons, years; Deriso and Parma, 1987). Over longer periods, we expect q_i for any given angler to increase with experience (Ward et al., 2013a,b) and accumulated information about best fishing sites and practices, then decrease with angler age for those old enough to have difficulty handling the physical rigors of fishing. An obvious statistical approach is to use a hierarchical modeling approach such as is com-