Experimental demonstration of catch hyperstability from habitat aggregation, not effort sorting, in a recreational fishery

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3   **Authors:** Colin J. Dassow, Alexander J. Ross, Olaf P. Jensen, Greg G. Sass, Brett T. van Poorten, Christopher T. Solomon, Stuart

4   E. Jones

5   **C.J. Dassow** , cdassow@nd.edu, Department of Biological Sciences, University of Notre Dame, Notre Dame, IN, USA

6   **S.E. Jones** sjones20@nd.edu Department of Biological Sciences, University of Notre Dame, Notre Dame, IN, USA

7   **C.T. Solomon**, solomonc@caryinstitute.org, Cary Institute of Ecosystem Studies, Millbrook, NY, USA

8   **A.J. Ross,** Cary Institute of Ecosystem Studies, Millbrook, NY, USA , **Current address:** aross10@lakeheadu.ca, Natural Resources

9   Management, Lakehead University, Thunder Bay, ON, Canada

10   **O.P. Jensen**, ojensen@marine.rutgers.edu, Department of Marine and Coastal Sciences, Rutgers University, New Brunswick, NJ,

11   USA

12   **G.G. Sass**, gregory.sass@wisconsin.gov, Escanaba Lake Research Station, Wisconsin Department of Natural Resources, Boulder

13   Junction, WI, USA

14   **B.T. van Poorten**, brett.vanpoorten@gov.bc.ca, British Columbia Ministry of Environment and Climate Change Strategy,

15   Vancouver, BC, Canada

16   **Corresponding author** C.J. Dassow, 299A Galvin Life Sciences, University of Notre Dame, Notre Dame, IN, USA 46556,

17   cdassow@nd.edu, telephone: 1 574 631 5703, fax: 1 574 631 7413

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25 **Abstract:**

26 The relationship between angler catch rates and fish abundance can contribute to or hinder sustainable

27 exploitation of fisheries depending on whether catch rates are proportional to fish abundance or are

28 hyperstable. We performed a whole-ecosystem experiment where fish abundance was manipulated and

29 paired with weekly angler catch rate estimates from controlled experimental fishing. Catch rates were

30 hyperstable (β=0.47) in response to changes in fish abundance. By excluding effort sorting (i.e., catch

31 rates remaining high because less-skilled anglers leave the fishery as abundance declines), our

32 experiment isolated the influence of fish aggregation as a driver of hyperstability. Spatial analysis of

33 catch locations did not identify clustering around specific points, suggesting that loose aggregation to

34 preferred habitat at the scale of the entire littoral zone was enough to maintain stable catch rates. In

35 our study, general, non-spawning, habitat preferences created loose aggregations for anglers to target,

36 which was sufficient to generate hyperstability. Habitat preferences are common to nearly all fishes and

37 widely known to anglers, suggesting that many harvest-oriented recreational fisheries can be expected

38 to exhibit hyperstability.

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46   **Introduction:**

47   The relationship between catch per unit effort (CPUE) and fish abundance plays a critical role in

48   sustainable exploitation of fisheries. Ideally, CPUE is proportional to abundance, signaling fishers to

49   reallocate effort as a stock declines. This assumption is often explicit in population models used to

50   manage fisheries (Hilborn and Walters 1992). Often, however, CPUE remains nearly constant even as

51   abundance declines considerably (Paloheimo and Dickie 1964; Peterman and Steer 1981; Shuter et al.

52   1998; Harley et al. 2001; Mrnak et al. 2018). This phenomenon, known as hyperstability, weakens signals

53   that might feed back to reduce fisher effort and thus increases the vulnerability of fisheries to

54   overexploitation (Post et al. 2002).

55   Two mechanisms have been proposed to generate hyperstability in CPUE. First, the average skill

56   (i.e., the catchability coefficient, q) of fishers engaged in the fishery may increase concomitantly with the

57   decrease in fish abundance. This can occur through improvements in fishing technology that augment

58   fishers' skills and/or because the distribution of active fishers shifts towards those with more skill as less

59   skilled anglers are quicker to leave the fishery when abundance declines, a process known as effort

60   sorting (Walters and Martell 2004; Ward et al. 2013; van Poorten et al. 2016; Tidd et al. 2017). Second, if

61   fish aggregate to preferred habitat at some life history stage, then the density of fish in that habitat may

62   remain high despite population-level declines in abundance, and fishers may sustain high CPUE by

63   preferentially targeting the preferred habitat (Myers et al. 1997; Hansen et al. 2005; Erisman et al. 2011;

64   Sadovy de Mitcheson and Erisman 2012; Mrnak et al. 2018).

65   In recreational fisheries, both the effort sorting and aggregation mechanisms have been

66   suggested to induce hyperstability, though the evidence is stronger for the former. Perhaps the best

67   effort to date to resolve hyperstability mechanisms in a recreational fishery is the research by Ward et

68   al. (2013) on rainbow trout (*Oncorhynchus mykiss*) in British Columbia. Ward et al. (2013) observed

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69 hyperstability across a set of open-access lakes which varied widely in trout density, and showed that

70 angler skill (as measured by the number of days spent fishing annually) was higher in the low-density

71 lakes. They also showed that there was no hyperstability in a set of experimental lakes fished by a single

72 angler. Collectively, these two data sets provided compelling evidence that differences in average angler

73 skill via effort sorting drove hyperstability in these systems. Several other studies have documented

74 hyperstability in recreational fisheries and speculated about the role of effort sorting and aggregation

75 mechanisms as drivers, but other mechanistic examinations are rare (Table 1).

76   We tested whether hyperstability occurred in a recreational fishery due to fish aggregation to

77 preferred habitat, while controlling for effort sorting. We experimentally manipulated fish abundance in

78 a natural lake, and measured CPUE of a fixed set of anglers at each level of fish abundance. Because our

79 model fish species (largemouth bass, *Micropterus salmoides*), like many fishes in freshwater and marine

80 environments, has strong habitat preferences that anglers recognize and exploit, we hypothesized that

81 the aggregation mechanism alone would be sufficient to generate hyperstability in this system. Because

82 bass potentially aggregate to habitat at multiple scales – the littoral zone within a lake, and patches of

83 cover like coarse woody habitat and macrophytes within the littoral zone (Essington and Kitchell 1999;

84 Ahrenstorff et al. 2009) - we secondarily considered which scale was most important for driving any

85 hyperstability observed. Our study provides a unique experimental test for the mechanisms driving

86 hyperstability in recreational fisheries.

87

88 **Methods:**

89 *Experimental Design and Study Site*

90   Testing for hyperstability requires estimates of CPUE across a wide range of fish abundance. We

91 measured the CPUE of a set of experimental anglers who repeatedly fished a single lake as we

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92   purposefully manipulated largemouth bass abundance. The same set of experimental anglers also

93   repeatedly fished a similar, nearby, unmanipulated reference lake, allowing us to control for potential

94   variation in CPUE due to seasonal trends, weather anomalies, and/or other factors independent of our

95   abundance manipulation.

96   Our experiment was conducted on Camp Lake (26.1 ha, 45°59'52.5" N, 89°43'59.7" W), and

97   reference experimental angling was conducted on nearby Little Rock Lake (15.8 ha, 45°59'44.7" N,

98   89°42'09.0" W). The lakes are within 3 km of one another in the Northern Highlands Lake District of

99   Wisconsin, USA. Largemouth bass are the dominant fish species in both lakes, along with bluegill

100   (*Lepomis macrochirus*) in Camp and yellow perch (*Perca flavescens*) in Little Rock (Sass et al. 2006, 2012;

101   Ahrenstorff et al. 2009). Recreational angler effort on both lakes is limited due to difficult access and

102   motor restrictions (electric motors only allowed on Camp; no motors allowed and gated access on Little

103   Rock). Camp Lake has two distinct basins, connected by a channel that is ~ 30 m long and was less than 6

104   m wide and 1 m deep during our study (Ahrenstorff et al. 2009; Sass et al. 2012). Previous work,

105   including tagging and radio telemetry studies, indicated minimal movement of bass between basins via

106   this channel (Ahrenstorff et al. 2009; Sass et al. 2012).

107   We manipulated largemouth bass abundance in the 8.5 ha northern basin of Camp Lake, using

108   the 17.6 ha southern basin as a holding area for bass that we removed from the northern basin. This

109   allowed us to add fish to, as well as remove them from, the manipulated basin and to minimize long-

110   term effects on the population. Because there is some public use of Camp Lake we were not able to

111   physically separate the two basins; instead we used open-population mark-recapture models to account

112   for limited natural movement of fish through the connecting channel and our experimental movement

113   of fish between basins.

114   We initiated our experiment on 22 May 2018 with a four-night electrofishing mark-recapture

115   experiment to estimate initial abundance of bass in each basin of Camp Lake. One week later, and on a

116   weekly basis for each of the following 12 weeks, we first estimated angler CPUE with daytime angling in

117   the manipulated basin of Camp Lake and in Little Rock Lake, and then electrofished the manipulated

118   basin of Camp Lake that same night to estimate the current abundance and collect fish for removal to

119   the holding basin. When abundance increases for the manipulation basin were desired, we electrofished

120   the holding basin to collect fish to add to the manipulated basin. For many of the early weeks in the

121   experiment, during the initial draw-down of fish abundance, we electrofished again the subsequent

122   night to increase the magnitude of that week's manipulation.

123

124   *Angler CPUE*

125   Each week, a set of three anglers was randomly selected from a fixed pool of seven anglers to

126   fish the manipulated basin of Camp Lake and Little Rock Lake using conventional hook-and-line

127   techniques and standardized tackle (Wilde et al. 2003). Each lake was fished for two hours after sunrise

128   and two hours before sunset, alternating weekly which lake was fished first in each morning and evening

129   session. Anglers casted towards shore as they slowly boated along the shore; in each 2-hour sampling

130   period, anglers covered the entire 1.2 km shoreline of the manipulated basin of Camp Lake and about

131   one third of the 3.3 km shoreline of Little Rock Lake. The portion of Little Rock shoreline to be sampled

132   was randomly selected each week. The location of capture of each angled bass in Camp Lake was

133   recorded with a GPS unit to test for patch-scale aggregation (see below). We calculated the mean and

134   variance of angler CPUE for each lake in each week across 6 samples (3 anglers x 2 sessions). We

135   restricted our estimates of angling CPUE, as well as our abundance estimates and manipulations, to

136   "catchable" bass ≥ 200 mm total length (TL). All captured bass were checked for tags; untagged bass ≥

137   200 mm TL were marked by implanting 23 mm Oregon RFID HDX passive integrated transponder (PIT)

138   tags. All captured bass were subsequently released at the point of capture.

139

140   *Manipulating and estimating abundance*

141   We used AC boat electrofishing along the entire shoreline to estimate bass abundance and to

142   transfer bass between the two basins of Camp Lake. Abundance estimates were derived from a robust

143   design mark-recapture model implemented in the R package RMark and fit via maximum likelihood

144   (White and Burnham 1999; Laake et al. 2013; R Core Team 2018). The robust design model was well

145   suited for our study because we had a high proportion of the population tagged, a large number of

146   recapture events, and an open population with fish naturally moving or being experimentally moved

147   between the basins of Camp Lake (Pine et al. 2003). The model used individual fish capture histories to

148   estimate fish survival between closed population states, emigration/immigration, encounter probability,

149   and probability of first capture and recapture. We considered model structures in which these

150   parameters were fixed, and structures in which they varied with time or sampling session. We used

151   Akaike's information criterion, corrected for small sample size, to identify the models with the best

152   predictive ability (Cavanaugh 1997).

153

154   *Testing for hyperstability*

155   Catch per unit effort (CPUE, or C/E) can be described as a function of catchability (q), the

156   abundance of fish (N), and a parameter β which describes the degree of non-linearity in catch rate as a

157   function of abundance and therefore distinguishes between hyperstability (β <1), proportionality (β =

158   1), or hyperdepletion ($\beta > 1$):

159 $$CPUE = qN^{\beta} \tag{1}$$

160   (Harley et al. 2001). We estimated β for our paired fish abundance and angler CPUE observations, using

161   simple linear regression of the log-transformed version of Eq. 1 because the precision of our abundance

162   estimates was high (Ward et al. 2013). We included mean angler CPUE from our reference system, Little

163   Rock Lake, as a covariate in the model to account for the potential effects of weather, angler identity,

164   and seasonality on angler CPUE.

165

166   *Testing for patch-scale aggregation*

167   If fish aggregation to patch-scale habitat contributes to hyperstability, we would expect the

168   distribution of angling catches to be clustered around specific areas of the littoral zone. We tested this

169   hypothesis by expressing the capture location of each fish as a point on a line representing the shoreline

170   of the manipulation basin, and testing for clustering at a range of spatial scales using Ripley's L test

171   (Fortin and Dale 2005).

172

173   **Results:**

174   We successfully manipulated the abundance of largemouth bass in the manipulated basin of

175   Camp Lake over the course of the study, with mark-recapture estimates indicating an order of

176   magnitude decline. Based upon individual recapture histories for 865 fish tagged in both basins of Camp

177   Lake, we fit 351 unique robust design model structures. The top four models had ΔAIC values < 4 and

178   very similar structures (Table S1); we used the parameter estimates from the top model to calculate

179   point estimates and confidence intervals for abundance in each week. The abundance of largemouth

180   bass ≥200mm TL in the manipulated basin ranged from 352 individuals at the beginning of the

181   experiment to 25 individuals by week 11 (Fig. 1a). Confidence intervals around our weekly estimates

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182   were well constrained, often an order of magnitude less than the estimate itself (Table S2). In

183   generating the population estimates, electrofishing catches accounted for 83% and 63% of the applied

184   and recaptured tags respectively, with the remainder caught by angling.

185   Dynamics of angler CPUE across our experiment were different in the manipulated basin and

186   reference lake (Fig. 1b, 1c). Angler CPUE ranged from 0.5 to 4 fish per angler hour in the manipulated

187   basin and from 3 to 12 fish per angler hour in the reference lake. Angler catch rates in the manipulated

188   basin were relatively high during the first six weeks of our experiment, then lower for a period of five

189   weeks, and then increased again in the final week of the study (Fig. 1b). Angler CPUE in the reference

190   lake remained relatively constant and high throughout the summer (Fig. 1c).

191   We identified a strong signal of hyperstability in catch rates in our manipulated basin (Fig. 2).

192   The estimated value of β (=0.47) was significantly less than 1.0 (df=11, p=0.013). Mean angler CPUE in

193   the manipulated basin ranged from about 4 fish per angler hour to 1.5 fish per angler hour across a

194   range of abundances from 350 to 75 individuals. Below about 75 individuals, mean angler CPUE ranged

195   from about 1.5 fish per angler hour to 0.5 fish per angler hour. Mean angler CPUE and fish abundance

196   were positively correlated in models with or without the reference lake CPUE as a covariate (β=0.42,

197   df=11, p=0.039; and β=0.47, df=11, p=0.013, respectively). Including the reference lake CPUE as a

198   covariate provided a significantly better fit than the base model based upon a likelihood ratio test

199   (p=0.034).

200   The distribution of largemouth bass capture locations around the shoreline of our manipulated

201   basin revealed no clustering (Fig. 3a). At all spatial scales we considered, our observed Ripley's L

202   estimates did not exceed the 95% confidence intervals from 1000 Ripley's L calculations based upon

203   random draws from a uniform distribution of possible catch locations (Fig. 3b). When comparing Ripley's

204   L estimates for catch locations at abundances above and below 75 individuals we saw no evidence of

205   clustering of catch locations at either high or low fish abundance (Fig. 3c & 3d).

206

207   **Discussion:**

208   Previous research documenting hyperstability in recreational fisheries has rarely tested for the

209   mechanisms driving hyperstable catch rates (Table 1). The few studies that inferred a mechanism have

210   linked hyperstable catch rates to differences in angler skill or spawning aggregations (Erisman et al.

211   2011; Ward et al. 2013; van Poorten et al. 2016). To our knowledge, no study has experimentally

212   manipulated the abundance of fish over which angler CPUE is estimated, but rather most existing

213   research leverages spatial patterns of fish abundance, effort, and catch rates. Our study used an

214   experimental approach, but also controlled for effort sorting to test whether fish aggregation to

215   preferred habitat was sufficient to drive hyperstability of catch rates in a recreational fishery.

216   A review of existing studies suggests that hyperstability can occur in diverse recreational

217   fisheries, but experimental or statistical support for underlying mechanisms is limited (Table 1). Most

218   studies discuss potential mechanisms for observed hyperstability in catch rates based on what has been

219   observed in the marine literature or other recreational fisheries hyperstability papers, but few can

220   convincingly point to a specific mechanism (Erisman et al. 2011; Ward et al. 2013). Early studies

221   hypothesized that aggregation underpinned hyperstability of catch rates in recreational fisheries

222   because existing theory and well-known marine examples identified aggregation as a mechanism for

223   increased catchability with declining stock abundance (Paloheimo and Dickie 1964; Peterman and Steer

224   1981; Hutchings 1996; Erisman et al. 2011; Sadovy de Mitcheson and Erisman 2012). Although only

225   studies investigating intense aggregation during spawning have conclusively identified aggregation as a

226   mechanism for hyperstability of recreational catch rates (Erisman et al. 2011; Sadovy de Mitcheson and

227   Erisman 2012), general aggregating behaviors such as those exhibited by fish around fish aggregating

228   devices (FADs) in marine systems are also known to promote hyperstability (Hilborn and Walters 1992;

229   Girard et al. 2004; Letessier et al. 2013). Aggregation has also been proposed as one of the mechanisms

230   which kept catch rates in the commercial fishery high even as abundance collapsed in Northwest

231   Atlantic cod (*Gadus morhua*) fisheries (Rose and Kulka 1999). More recent studies in recreational

232   fisheries have identified negative relationships between average angler skill level and population

233   abundance (effort sorting) as the mechanism leading to hyperstability of catch rates (Ward et al. 2013;

234   van Poorten et al. 2016). These authors correctly raise the point that earlier studies that identified

235   hyperstability of catch rates in recreational fisheries did not identify, but could plausibly have been

236   influenced by, effort sorting.

237   Despite controlling for angler skill and conducting our experiment outside of spawning season,

238   we observed significant hyperstability in angler catch rates of largemouth bass. In our study system, bass

239   home ranges encompassed the entire basin but littoral areas are preferred (Essington and Kitchell 1999;

240   Ahrenstorff et al. 2009). Individual patches of habitat had no effect on the hyperstability observed here

241   given the lack of clustering observed in the spatial distribution of angling capture locations around the

242   entire shoreline of our manipulated basin. Instead, general preferences for littoral areas in our model

243   species were sufficient to produce aggregations that promoted hyperstability. As fish were removed

244   from their preferred littoral areas in our manipulated basin, mixing of fish between pelagic and littoral

245   habitats could have slowed the decline in density, and catch rates, in preferred littoral areas as new fish

246   filled spaces left by the removed fish. This hypothesized mechanism is supported by the combination of

247   consistent catch rates and randomly distributed catch locations along the shoreline of our experimental

248   system even as the population was experimentally reduced (Fig. 1 and 3). These dynamics are analogous

249   to classic foraging arena theory, where in this case sport fish are subject to a risk-resource tradeoff in

250   their preferred, but angler-targeted, habitat (Ahrens et al. 2012; Matthias et al. 2014).

251   Given that most fishes have preferences for certain habitat types and that only minimal skill may

252   be required for anglers to target these habitats, we would expect that most recreational, harvest-

253   oriented species exhibit hyperstable catch rates independent of heterogeneity in angler skill. However,

254   we might expect the degree of hyperstability to relate to the spatial intensity and temporal extent of

255   aggregation. In this context, spawning for many fishes can be thought of as a spatially intense, but

256   temporally short type of aggregation (Mrnak et al. 2018). In contrast, our results suggest that even

257   moderate spatial intensity of habitat use over a longer temporal extent may lead to hyperstability.

258   Although non-spawning spatial aggregation appears to be sufficient to generate hyperstable

259   catch rates in a recreational fishery, the effect of angler skill on catch rates is also clear (Ward et al.

260   2013). Anglers are known to segregate themselves based upon skill across lakes with varying densities of

261   fish, with high skill anglers generally dominating low fish density lakes (Ward et al. 2013). It is likely that

262   these two processes can have additive effects on the response of catchability to population abundance,

263   but could they interact in a non-additive manner? One possibility for non-additive interaction between

264   these two mechanisms would be if knowledge about the location, in space and time, of fish aggregations

265   was related to avidity or skill level. Although many anglers are or become aware of intense spawning

266   aggregations or general preferences for littoral habitat, knowledge of other more subtle or short-lived

267   aggregations may be more limited and linked to differences in angler skill.

268   Given that aggregation and effort sorting are individually, and likely in combination, sufficient to

269   generate hyperstable catch rates, we would expect widespread hyperstability in recreational fisheries.

270   The apparent cosmopolitan nature of these mechanisms means traditional management strategies may

271   struggle to address complications of management driven by hyperstability of catch rates leaving

272   fisheries vulnerable to overexploitation (Carpenter et al. 2017). Many authors highlight additional

273   control of effort, rather than harvest, as a potentially important management strategy (Camp et al.

274   2015, 2016; Lynch et al. 2017). Many management agencies impose seasonal closures of fisheries during

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275   known spawning aggregations, in part to limit harvest (as was the case for largemouth bass in northern

276   Wisconsin until recently), but additional spatial or temporal limits on effort, as have been employed in

277   the case of marine protection areas, may be beneficial in attempting to address the effects of

278   aggregation on hyperstability of catch rates (Russ 2002; Roberts et al. 2005). Spatial or temporal

279   closures, though likely to be unpopular with anglers, are being recognized and used by fisheries

280   managers, however the sustainability of a fishery may still be compromised when fish aggregate

281   throughout the season. These non-spawning aggregations in conjunction with effort sorting may require

282   additional measures to be taken by managers.

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405   **Table Caption**

406   Table 1. Review of key research exploring hyperstability in recreational fisheries. Two different methods

407   for identifying hyperstability have been used in these studies. The value of the parameter β can be used

408   to identify instances of hyperstabiliy when β <1. Alternatively, whether or not catchabilty (q) is inversely

409   related to fish density is another method by which researchers can identify hyperstable catch rates.

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Figure Captions

Figure 1. a) Population estimate for largemouth bass (*Micropterus salmoides*) >200mm TL in the manipulated basin of Camp Lake, Vilas County, Wisconsin over the course of the 12-week hyperstability study in 2018. Error bars are 95% CI. b) Manipulated basin, mean angler largemouth bass catch-per-unit effort (CPUE) over the course of the experiment. Error bars denote 1 standard deviation about the mean. c) Little Rock Lake, Vilas County, Wisconsin (reference system) mean largemouth bass angler CPUE over the course of the experiment. Error bars denote 1 standard deviation about the mean.

Figure 2. Mean angler largemouth bass (*Micropterus salmoides*) CPUE (fish angler^{-1} hour^{-1}) accounting for potential variation due to seasonal CPUE trends, weather anomalies, and/or other factors independent of abundance manipulations as a function of fish abundance on the manipulated basin of Camp Lake, Vilas County, Wisconsin during 2018.

Figure 3. a) Locations of angling captures of largemouth bass (Micropterus salmoides) >200mm TL in two-dimensional space (grey polygon) and one-dimensional space (line segment) on the manipulated basin of Camp Lake, Vilas County, Wisconsin during 2018. Plots of Ripley's L as a function of the number of neighbors within a given distance in meters on either side of a catch location (solid line) for b) all catches during the experiment, c) catches during periods where fish abundance was >75 individuals, and d) catches during periods where fish abundance was <75 fish. Dotted lines represent 95 % CI around Ripley's L for randomly distributed data (dashed line).

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Table 1. Review of key research exploring hyperstability in recreational fisheries. Two different methods for identifying hyperstability have been used in these studies. The value of the parameter β can be used to identify instances of hyperstabiliy when β <1. Alternatively, whether or not catchabilty (q) is inversely related to fish density is another method by which researchers can identify hyperstable catch rates.

Authors	Recreational Fishery	Method	Hyperstability	Mechanism	Beta	q
Peterman & Steer 1981	British Columbia and Oregon Chinook Salmon (*Oncorhynchus tshawytscha*)	Estimate catchability from a time series of catch and fish abundance data.	Yes	No mechanism explored. Suggest fish aggregation to easily targeted habitats drives hyperstability.		Negative correlation between q and abundance
Shuter et al. 1998	Ontario Lake Trout (*Salvelinus namaycush*)	Describe relationship between estimate of catchability and fish abundance for two lakes through time and 17 lakes spanning a gradient of fish densities.	Yes	No mechanism explored. Suggest the non-random distribution of fish is exploited by anglers who can find these aggregations.		Negative correlation between q and abundance
Hansen et al. 2000	Northern Wisconsin Walleye (*Sander vitreus*)	Non-linear models fit to estimates of walleye density and angler/spearfishing catch rates for 118 WI lakes	Spearing -Yes; Angling -No	None explored	Spearing fishery = 0.65	
Hansen et al. 2005	Northern Wisconsin Walleye (*Sander vitreus*)	Analysis of data presented in Hansen et al. (2000), this time accounting for measurement error in catch rates and abundance estimates.	Both-Yes	None explored	Spearing = 0.65; Angling = 0.825	

Erisman et al. 2011	Southern California coastal stocks of Barred Sand Bass (*Paralabrax nebulifer*) and Kelp Bass (*Paralabrax clathratus*)	Fit a non-linear model to catch rate and fish abundance data	Yes	Overfishing of spawning aggregations	0.44-0.59
Ward et al. 2013	British Columbia Rainbow Trout (*Oncorhynchus mykiss*)	Describe relationship between angler catch rate and fish density in a closed fishery with constant angler skill and an open fishery where angler skill varies.	Yes	Open access fishery exhibited hyperstable catch rates while the closed access fishery did not. Angler skill was strongly predicted by fish density in the open access fishery with high skill anglers targeting low fish density lakes and low skill angler targeting low fish density lakes.	0.42
vanPoorten et al. 2016	British Columbia Rainbow Trout (*Oncorhynchus mykiss*)	Competing models fit to angler CPUE and fish abundance data presented in Ward et al. (2013).	Yes	Best fitting model described hyperstability as purely a function of angler effort sorting. Low skill anglers leave fishery as catch rates decline while high skill anglers remain creating hyperstable average catch rates as high skill anglers continue to catch fish as abundance declines.	Negative correlation between q and abundance

| Mrnak et al. 2018 | Northern Wisconsin Walleye (*Sander vitreus*) | Describe relationship between catch rate and fish abundance from 1990-2015 using the same method as Hansen et al. (2005). | Both-Yes | No mechanism explored. Suggest hyperstable catch rates in spearfishery are due to spawning aggregations while hyperstability in angling fishery is due to effort sorting. | Spearing = 0.41; Angling = 0.53 |

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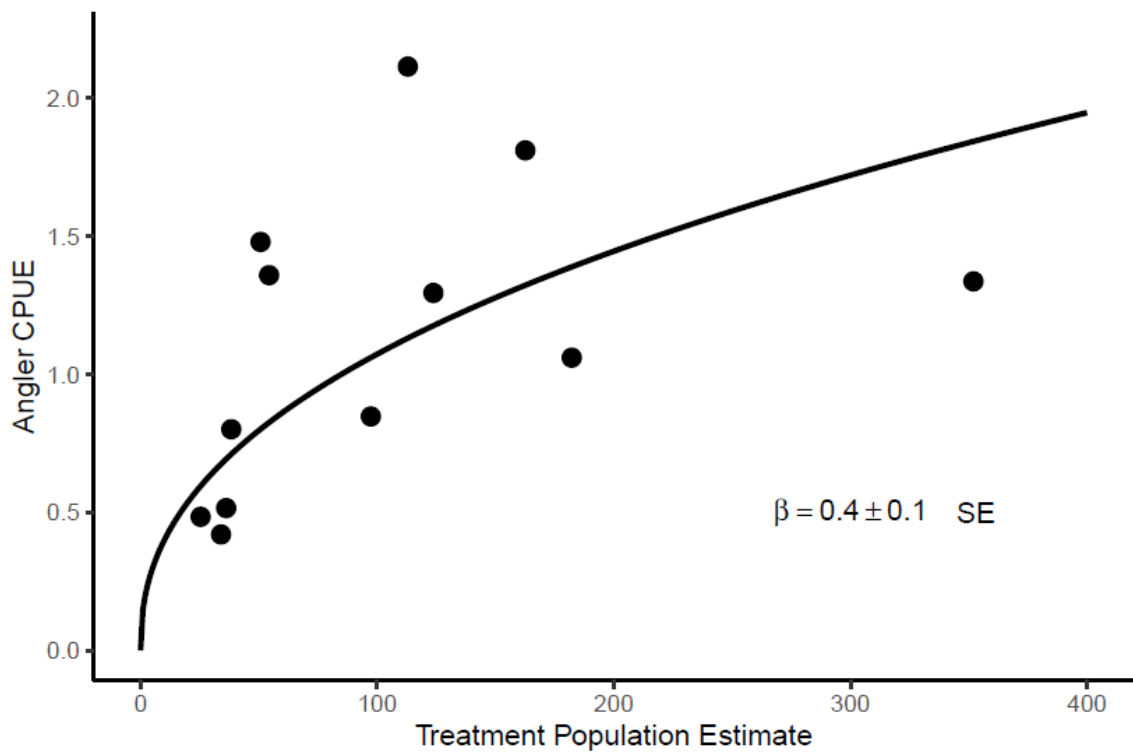
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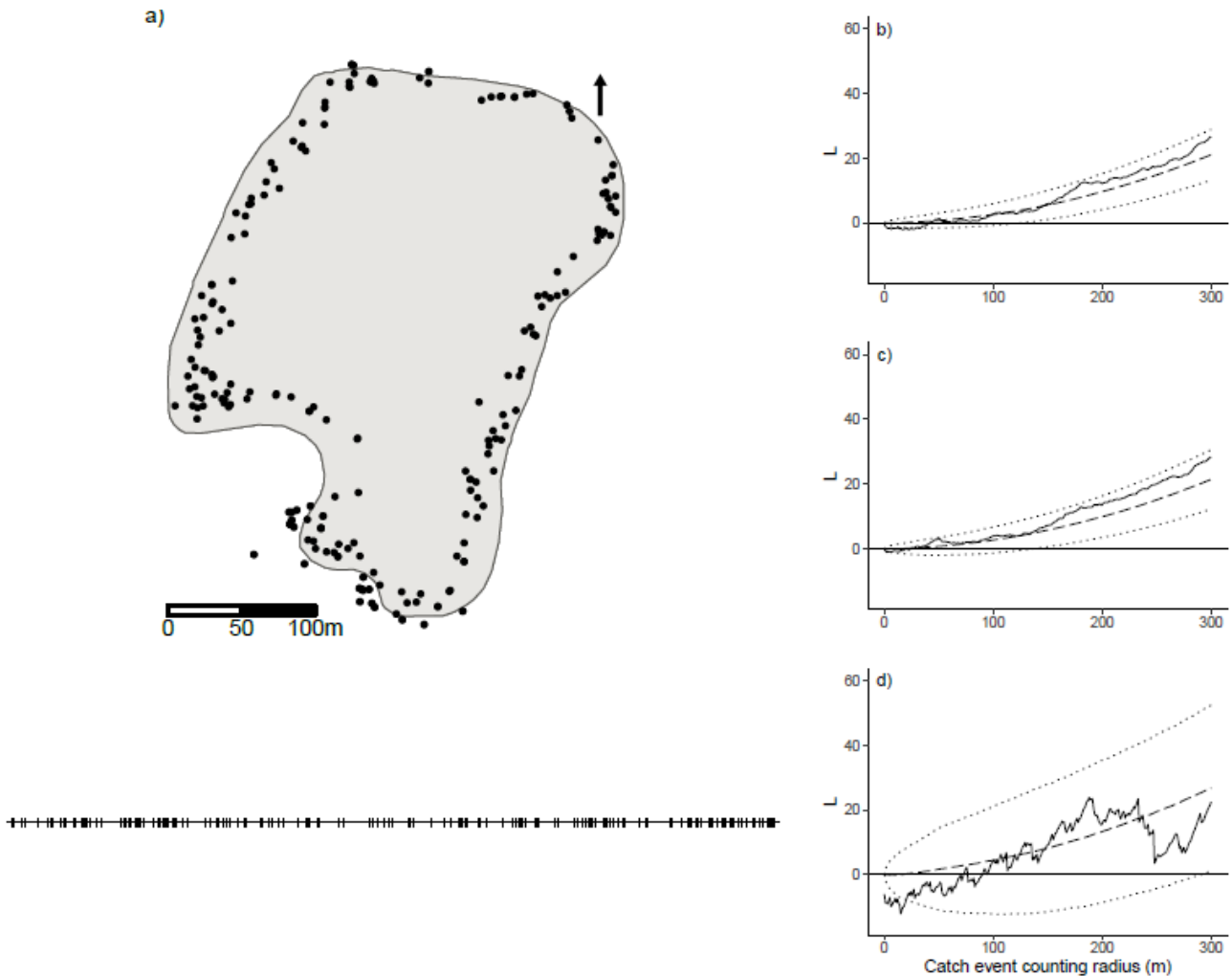
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