NRC Research Press

ARTICLE

Using censored regression when estimating abundance with CPUE data to account for daily catch limits

Marvin M. Mace III and Michael J. Wilberg

Abstract: In fisheries where there is a limit on total catch in a given period, catch-per-unit-effort (CPUE) data may not be proportional to abundance because catches may be censored at the limit. Commonly used depletion estimators (e.g., Leslie method) could be biased when ordinary least squares (OLS) regression is used to estimate abundance with censored CPUE data. We used simulations to examine the performance of OLS regression and a censored regression approach when estimating abundance and exploitation using censored CPUE data over a range of known exploitation rates. We also applied the censored regression approach to data from a commercial fishery for the eastern oyster (*Crassostrea virginica*). The censored regression approach always performed better than the OLS regression when estimating abundance and exploitation in our simulations. Harvest and abundance of oysters in Fishing Bay, Maryland, increased during 2009 to 2013 and then decreased through 2016, while exploitation rates had no substantial trend over time. The censored regression approach is useful for estimating abundance and exploitation when the distribution of CPUE is affected by daily catch limits.

Résumé : Dans les pêches visées par une limite des prises totales pendant une période donnée, les données sur les captures par unité d'effort (CPUE) peuvent ne pas être proportionnelles à l'abondance puisque les prises peuvent être censurées par cette limite. Les estimateurs d'appauvrissement couramment utilisés (p. ex. la méthode de Leslie) pourraient être biaisés quand la méthode des moindres carrés ordinaires (MMCO) est utilisée pour estimer l'abondance à partir de données de CPUE censurées. Nous avons utilisé des simulations pour examiner la performance de la MMCO et d'une approche de régression censurée pour estimer l'abondance et l'exploitation à partir de données de CPUE censurées pour une fourchette de taux d'exploitation connus. Nous avons également appliqué l'approche de régression censurée aux données d'une pêche commerciale à l'huître (*Crassostrea virginica*). L'approche de régression censurée donne toujours de meilleurs résultats que la MMCO pour l'estimation de l'abondance et de l'exploitation dans nos simulations. Les prises et l'abondance d'huîtres dans la baie Fishing (Maryland) ont augmenté de 2009 à 2013, puis diminué jusqu'en 2016, alors que les taux d'exploitation ne montrent pas de tendance importante dans le temps. L'approche de régression censurée est utile pour estimer l'abondance et l'exploitation quand des limites sur les prises quotidiennes ont une incidence sur la distribution des CPUE. [Traduit par la Rédaction]

Introduction

Estimating the abundance of populations using catch-per-unit-effort (CPUE) depletion data dates back over 100 years and has been widely used in fisheries research (also called catch–effort, depletion, or removal methods; Ricker 1975; Seber 1982). The basic assumption when using CPUE data to estimate abundance is that CPUE is directly proportional to the total population size. Therefore, CPUE should decline after a series of removals from the population without replacement. Several methods have been developed to estimate abundance using CPUE data, most of which estimate catchability and abundance using ordinary least squares (OLS) regression (Leslie and Davis 1939; DeLury 1947; but see Gould and Pollock 1997).

Many fisheries are regulated by limiting the amount of harvest allowed during a given period (e.g., maximum catch per day or trip), which can result in censored data. Censored data are a condition in which the value of an observation or measurement is only partially known (Hammond and Trenkel 2005). Daily or trip limit regulations can result in CPUE metrics that are censored at the catch limit and, therefore, may not change proportionally with abundance. For example, using a CPUE measured in Maryland bushels (≈46 L) of oysters per day, many CPUE observations may reach the daily limit, especially early in the season when oysters are most abundant. One solution would be to use an alternative effort metric (e.g., hours), but often those data may be unavailable or unreliable. Another solution could be to use an analysis that accounts for the effect of catch limits on CPUE observations, such as a censored regression approach (e.g., tobit regression; Tobin 1958; Henningsen 2010). The censored regression approach modifies the OLS regression assumption of normally distributed errors by modeling the errors using a distribution with a normally distributed component for the noncensored observations and a discrete component for the censored observations. The expected probability of obtaining a censored estimate is calculated from the portion of the normal distribution that exceeds the value at which the data are censored (for data with an upper bound; i.e., right censoring).

The eastern oyster (*Crassostrea virginica*) fishery in Maryland was historically one of the largest oyster fisheries in the world, but harvest and abundance have declined substantially due to a variety of causes, including fishing, disease, and habitat loss (Rothschild et al. 1994; Wilberg et al. 2011; Damiano and Wilberg 2019). Oyster abundance in Maryland has been estimated previously using CPUE data from the commercial fishery (Cabraal and Wheaton

Received 7 March 2019. Accepted 27 October 2019.

M.M. Mace III and M.J. Wilberg.* Chesapeake Biological Laboratory, University of Maryland Center for Environmental Science, P.O. Box 38, Solomons, MD 20688, USA.

Corresponding author: Marvin M. Mace III (email: marvin.mace.iii@gmail.com).

*Michael J. Wilberg currently serves as an Associate Editor; peer review and editorial decisions regarding this manuscript were handled by Marten Koops.

1981). However, commercial eastern oyster harvesters in Maryland are restricted in the number of bushels they can harvest per day dependent on the gear type. This censoring of commercial CPUE likely causes problems in applying traditional CPUE depletion approaches for abundance estimation.

Our objective was to evaluate the performance of CPUE depletion methods using OLS regression and censored regression for estimating abundance and exploitation rates when CPUE observations are censored. Specifically, we compared the bias and precision of these two estimators over a range of exploitation rates using simulated data. We then applied the censored regression approach to estimate abundance and exploitation rates for the eastern oyster in a tributary of the Chesapeake Bay.

Materials and methods

To evaluate the performance of OLS regression and censored regression, we created 1000 replicate CPUE data sets from several scenarios that differed in the total fraction of the population harvested (i.e., exploitation rate). Each replicate data set was then used to estimate the abundance and exploitation rate with OLS and censored regression. The estimated values were compared with the true values to determine the performance of these two methods.

Abundance estimators

To estimate abundance, we used OLS and censored regression versions of the method developed by Leslie and Davis (1939). The Leslie and Davis (1939) approach describes CPUE at time i as a linear function of the starting abundance (N_0), cumulative harvest to time i (K_i), and the catchability (q):

$$\text{(1)} \qquad \text{CPUE}_i = qN_0 - qK_i$$

CPUE should decline linearly (with slope q) with increasing cumulative catch (Ricker 1975). In the traditional application of the Leslie and Davis (1939) approach, the parameters are estimated using OLS regression. The value of cumulative catch when CPUE is zero (i.e., the x intercept) is the initial population size (N_0).

The censored regression model assumes that there is an unobservable variable (CPUE*) that is linearly related to K_i through the following equation:

$$\text{(2)} \qquad \text{CPUE}_i^* = a + qK_i + \epsilon$$

The observed CPUE_i is defined as

$$\text{(3)} \qquad \text{CPUE}_i = \begin{cases} \text{CPUE}_i^*, & \text{if CPUE}_i < \text{CPUE}_U \\ \text{CPUE}_U, & \text{if CPUE}_i^* \geq \text{CPUE}_U \end{cases}$$

where CPUE_U is the upper limit on CPUE.

Maximum likelihood can be used to estimate parameters of the censored regression model. First, an indicator function is defined as

$$\text{(4)} \qquad I(\text{CPUE}_i) = \begin{cases} 0, & \text{if CPUE}_i \geq \text{CPUE}_U \\ 1, & \text{if CPUE}_i < \text{CPUE}_U \end{cases}$$

and the log-likelihood is

$$\text{(5)} \qquad \ell(\boldsymbol{\beta}, \sigma | \text{CPUE}, \boldsymbol{K}) = \sum_{i=1}^{n} I(\text{CPUE}_i)\log\left[\frac{1}{\sigma}\varphi\left(\frac{\boldsymbol{K\beta} - \text{CPUE}_i}{\sigma}\right)\right] + [1 - I(\text{CPUE}_i)]\log\left[1 - \phi\left(\frac{\text{CPUE}_U - \boldsymbol{K\beta}}{\sigma}\right)\right]$$

Table 1. Values of the slope (q) and initial population size (N_0) used in different exploitation rate (u) scenarios to examine the performance of ordinary least squares regression and censored regression when estimating abundance with CPUE data.

u	N_0	q
0.10	627 712	0.0000265
0.30	209 237	0.0000796
0.50	125 542	0.0001327
0.70	89 673	0.0001857
0.90	69 746	0.0002388

where φ is the standard normal probability density function, ϕ is the standard normal cumulative distribution function, $\boldsymbol{\beta}$ is a vector of parameters (e.g., slope and y intercept in the present model) that determine the relationship between CPUE* and K_i, and $\boldsymbol{K}$ is a vector with 1 as the first element and K_i as the second element. The R package VGAM (Yee 2017) was used to conduct censored regression analyses.

After obtaining y intercept and slope estimates, initial population size (N_0), which is the cumulative catch K when CPUE = 0, was estimated by setting CPUE = 0 and solving for K in

$$\text{(6)} \qquad \text{CPUE} = a + qK$$

which results in an estimate of initial population size (N_0)

$$\text{(7)} \qquad N_0 = -\frac{a}{q}$$

The exploitation rate was estimated by dividing the total harvest by the estimate of initial abundance (Ricker 1975).

Simulation methods

We simulated 1000 data sets for five exploitation rate scenarios (Table 1) to compare the OLS and censored regression estimators. To create the simulated data sets, we used the following equation:

$$\text{(8)} \qquad \text{CPUE}_{i,j} = a + qK_i + \epsilon_{i,j}$$

where

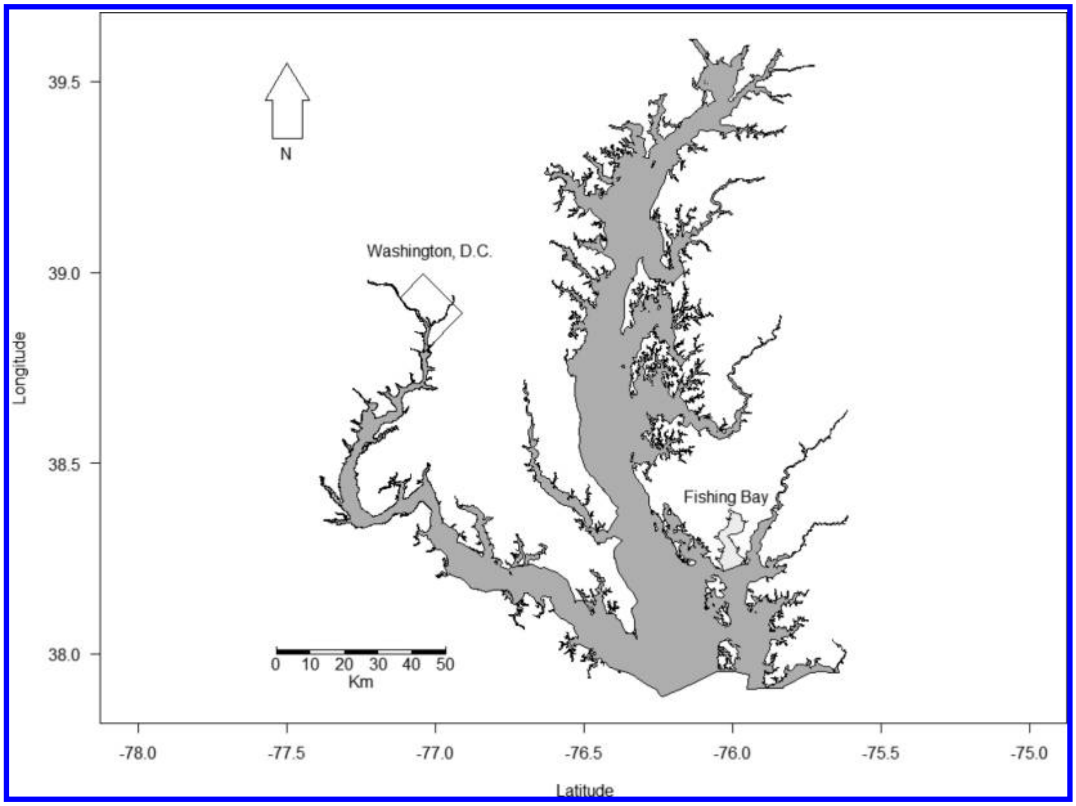
$$\text{(9)} \qquad a = qN_0$$

and $\text{CPUE}_{i,j}$ is the jth CPUE observation on day i, and ϵ is a normally distributed random variable with a mean of 0. To create censored data sets, we set all CPUE observations >12 equal to 12, which resulted in a censored CPUE data set that was used in subsequent analyses. We chose a value of 12 to match the daily harvest limit per license for power dredging of oysters in Maryland (see Application to oyster data section below).

To focus on the effect of different exploitation rates, we varied the slope (q; Table 1) and kept the values of the y intercept (a) and the standard deviation of the random errors (ϵ) constant when creating simulated data sets. For data and parameters other than the slope (q), we used CPUE data from Fishing Bay, a tributary of the Chesapeake Bay, for the 2013 commercial fishing season (1 October 2013 – 31 March 2014). Because we used the same amount of total harvest (K) for each simulated data set, the initial population (N_0) was different for each exploitation rate and was calculated as

$$\text{(10)} \qquad N_0 = \frac{K}{u}$$

Fig. 1. Map of Upper Chesapeake Bay showing the location of Fishing Bay. Map data: Esri, HERE, NPS, MD iMAP, DNR MGS, NOAA, and Maryland Coastal Zone Management Program Bay.



where K is total cumulative harvest over the 2013 season for Fishing Bay, and u is the exploitation rate. After obtaining the initial population sizes for each exploitation rate, the slope necessary to obtain the given exploitation rate was calculated as

$$q = \frac{a}{N_0} \tag{11}$$

For each simulated data set, we used the same number of CPUE records (j) and cumulative harvest (K_i) for each day during the season as reported for Fishing Bay during the 2013 season. For the y intercept (a) and standard deviation (SD) of the random errors (ϵ), we used estimates obtained from a censored regression ($a = 16.65$; SD = 1.387), using an upper limit on CPUE of 12 bushels per day, of CPUE on cumulative harvest for Fishing Bay during the 2013 season.

Bias and accuracy of both estimators were evaluated using percent relative error and percent root mean square error (%RMSE). Percent relative error was calculated as

$$\text{Percent relative error} = \left(\frac{\text{Estimated} - \text{Known}}{\text{Known}}\right) \times 100 \tag{12}$$

where Estimated was the value from the regression, and Known was the true value. Percent relative error was calculated for each simulated data set and both estimators under each of the exploitation rate scenarios. %RMSE was calculated as

$$\%\text{RMSE} = \frac{\sqrt{\dfrac{\sum (\text{Estimated} - \text{Known})^2}{n}}}{\text{Known}} \times 100 \tag{13}$$

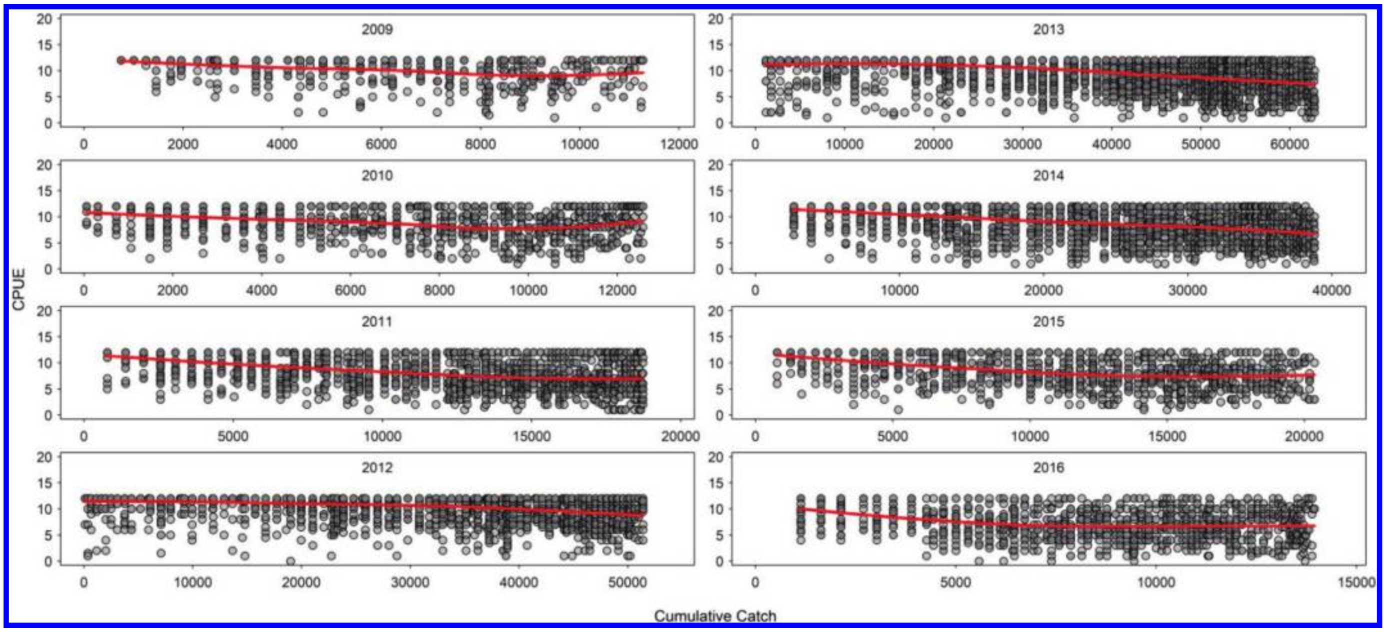
where n is the number of simulations per scenario.

Application to oyster data

We applied the censored regression approach to CPUE data for the commercial oyster fishery in Fishing Bay, Maryland (Fig. 1), for each year from 2009 to 2016 (years denote the start of the fishing season). The distribution of CPUE during each year from 2009 to 2016 was affected by the daily bushel limit, which caused censoring at a CPUE value of 12 bushels per license per day (Fig. 2). Most harvest (79%) during the past 30 years in Fishing Bay occurred during 2009 to 2016, and power dredging has been the primary gear type used for harvest during this recent time period. Power dredging uses a chain-mesh bag attached to a frame that is lowered to the bottom using a winch and pulled along the bottom using a motorized vessel to collect oysters. The only other gear used to harvest oysters in Fishing Bay, as reported in catch statistics, are hand tongs. Hand tongs are typically constructed of two wooden shafts ranging from 16 to 30 feet long (1 foot = 0.3048 m) and attached to each other with a pin, similar to scissors, with rakes at the ends to harvest oysters (Maryland Department of Natural Resources 2016). Hand tong harvest represented only 5% of the reported harvest in Fishing Bay during 2009–2016.

We used the censored regression approach to estimate abundance and exploitation rates using catch statistics collected by the Maryland Department of Natural Resources. From these records we calculated a CPUE of bushels per license per day and the cumulative daily catch for use in the censored regression. We used data from power dredge and hand tong gears to calculate cumulative catch, but only CPUE data from the power dredge records. We only used power dredge CPUE data for model fitting because power dredging and hand tonging have different daily harvest limits, and hand tonging is expected to have a lower catchability than power dredging. We used a value of 12 bushels per license per day as the upper limit in the censored regression because this is the legal daily harvest limit per license for power dredge. Records for power dredge harvest above this limit were considered mis-

Fig. 2. Commercial catch-per-unit-effort (CPUE; Maryland bushels (~46 L) per license per day) for the eastern oyster (*Crassostrea virginica*) as a function of cumulative catch (Maryland bushels) in Fishing Bay, Maryland, during 2009 to 2016. Lines in each panel are loess (locally estimated scatterplot smoothing) curves fit to the CPUE data. [Colour online.]



takes and not included in the analyses. Harvest is reported in Maryland bushels (≈46 L), and so our abundance estimates are also in terms of bushels; however, we were also interested in abundance in terms of individuals. We used an estimate of 228 individuals per bushel to convert our abundance estimates in bushels to individuals (Maryland Department of Natural Resources 2018).

Precision of the initial abundance and exploitation rate estimates was estimated using a parametric bootstrap (Efron and Tibshirani 1993). Bootstrap replicates were created by drawing random numbers from a bivariate normal distribution with mean parameter estimates and variance–covariance matrix from the censored regression. After drawing these two random numbers, initial population size was estimated using eq. 7 and exploitation rate was estimated as total harvest divided by initial population size. This process was repeated 10 000 times, and 95% confidence intervals were estimated by taking the 0.025 and 0.975 percentiles of the initial abundance and exploitation rate distributions. This process was done separately for each year.

Results

The OLS regression approach performed worse than censored regression when estimating initial abundance and exploitation rates, and the difference in performance was especially large at low exploitation rates (Fig. 3). For initial abundance, mean percent relative error of the OLS regression was always positive, but decreased from the lowest exploitation rate (343%) to the highest exploitation rate (17%). The censored regression estimator was approximately unbiased for initial abundance (mean percent relative error < 1%) at all exploitation rates, except at the lowest exploitation rate when mean percent relative error was 4%. The censored regression estimator also performed better than the OLS regression when estimating exploitation rates (Fig. 3). Mean percent relative error of the OLS regression was always negative and was greatest (–76%) at the lowest exploitation rate. The mean percent relative error of the OLS regression approach decreased with increasing exploitation rate and was –14% at the highest exploitation rate. The censored regression estimator was approximately unbiased (mean percent relative error < 1%) under all exploitation rate scenarios. %RMSE of initial abundance and exploitation rate was lower for the censored regression compared with the OLS regression at all exploitation rates and decreased with increasing exploitation rate for both estimators.

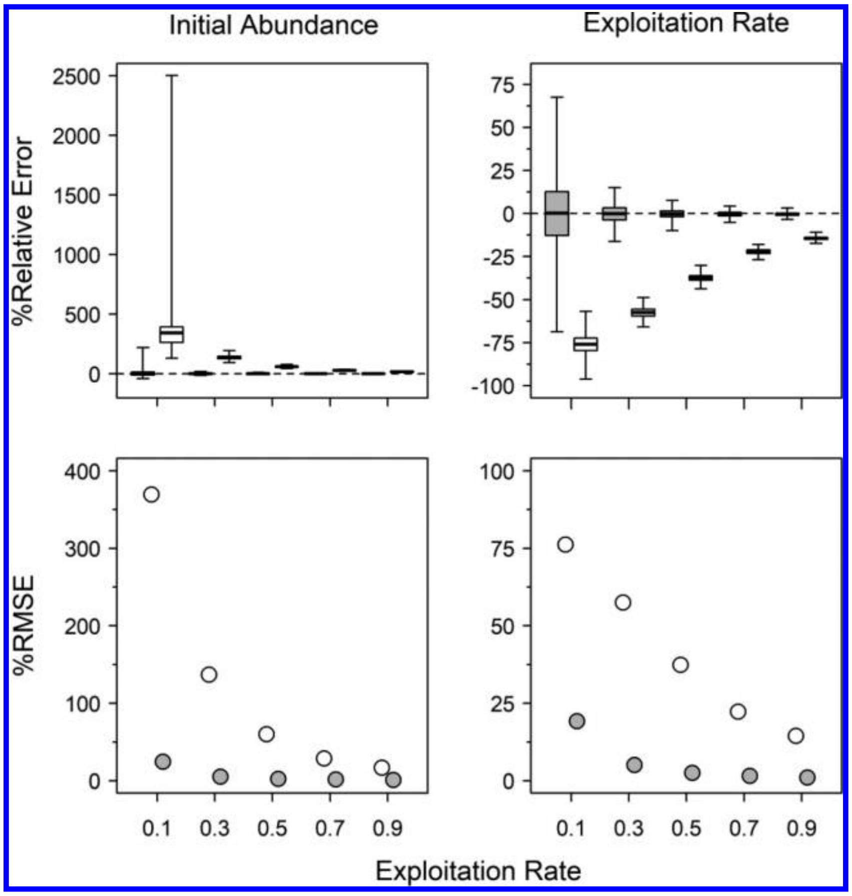
Total harvest of oysters in Fishing Bay during 2009–2016 increased from 11 311 bushels in 2009 to a maximum of 62 812 bushels in 2013 and then decreased to 13 961 in 2016 (Fig. 4). Initial abundance estimates ranged from 25 336 bushels to 123 246 bushels and followed a similar pattern over time as harvest. Converted from bushels to number of individuals, initial abundance estimates ranged from 5 776 758 to 28 100 175 individuals. Exploitation rate estimates ranged from 0.34 per season to 0.55 per season and showed no strong patterns over time.

Discussion

The censored regression approach outperformed the OLS regression approach in our simulation study. The censored regression approach produced nearly unbiased estimates in all the scenarios we examined, whereas the OLS approach tended to overestimate abundance and underestimate the exploitation rate. The poor performance of the OLS approach was caused by the censoring of the CPUE observations, which resulted in a negative bias in the estimated intercepts and positive bias in the estimated slopes. The bias in the OLS estimates occurred because our simulations produced CPUE data that had a pattern of most censored values of CPUE occurring at the beginning of the season, and by the end of the season most CPUE values were below the maximum. Therefore, when the CPUE data are censored, CPUE does not decrease as fast as abundance, on average, which causes the bias in estimates of the OLS approach.

Both estimators we evaluated performed best under high exploitation rate scenarios. Gould and Pollock (1997) also found that the estimators they evaluated, including the Leslie estimator, became less precise as the catchability coefficient decreased. In general, CPUE depletion estimators perform better at high exploitation rates because these methods assume that fishing has a measurable effect on the population abundance, and as the fraction of individuals removed (i.e., exploitation rate) increases, abundance estimates will be more precise and less biased. Put another way, the number of individuals removed is a minimum estimate of population size, and as a larger and larger fraction of the stock is

Fig. 3. Percent relative error and percent root mean square error (%RMSE) for the censored regression (grey boxes and circles) and ordinary least squares (OLS) regression (white boxes and circles) estimators of abundance and exploitation at known exploitation rates from 0.1 to 0.9. For the boxplots, the line in the middle of the box indicates the mean, the boxes indicate the interquartile range, and the whiskers extend to the minimum and maximum.



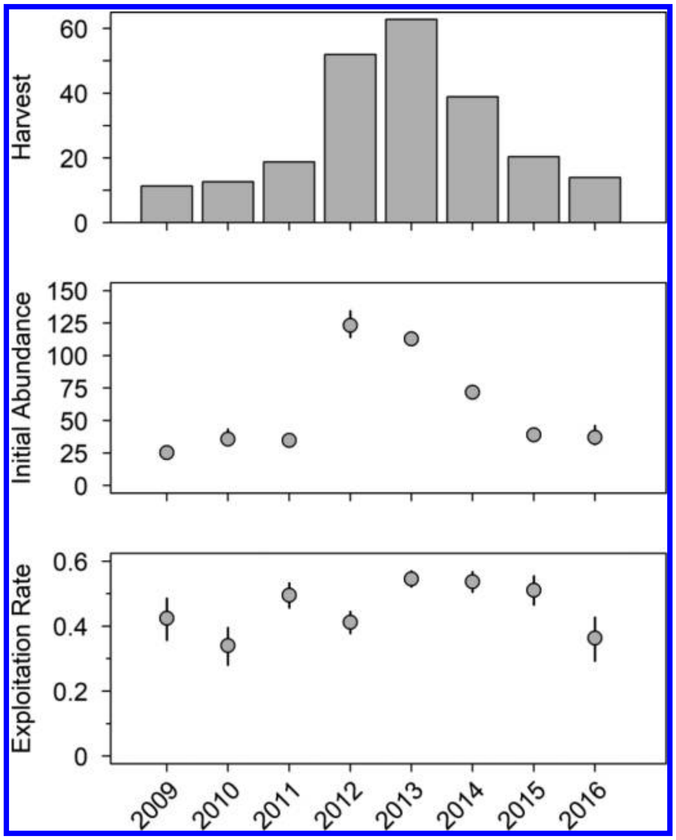
caught, the more accurate the estimates of abundance and exploitation rates will be.

We used a modification of the Leslie and Davis (1939) method to estimate parameters of the censored regression depletion model, although other approaches are available to estimate the parameters. Gould and Pollock (1997) recommended using a maximum likelihood approach instead of regression approaches for abundance estimation using CPUE depletion. We chose to use a modification of the Leslie and Davis (1939) method because censored regression approaches are commonly available in modern statistics packages (e.g., R). In addition, implementing a maximum likelihood version of CPUE depletion analysis as recommended by Gould and Pollock (1997) would require programming a custom model, and the benefits would likely be small. For example, the Leslie method often had similar performance to a maximum likelihood method (percent bias within 5%; Gould and Pollock 1997).

The censored regression approach relies on the CPUE to decrease over time (e.g., during the oyster season) such that not all CPUE values are at their limit, and if this is not the case then this method may not be appropriate. We generated scenarios that caused an observed decrease in CPUE during the fishing season. However, our approach should not work on data sets where a decrease in CPUE is not observed with increasing harvest. CPUE may not decrease with increasing harvest if catchability increases during the fishing season (Wilberg et al. 2009) or if the population is not closed to immigration and recruitment.

Estimates of abundance for eastern oysters in Fishing Bay fluctuated approximately fivefold during 2009–2016, and precision of these estimates was high (mean coefficient of variation = 0.08, range = 0.03 to 0.1). The accuracy of these estimates depends on how well the assumptions of the CPUE depletion analysis are met. Assumptions for estimating abundance with CPUE data include (*i*) a closed population (i.e., no net immigration, emigration, nonharvest mortality, or recruitment), (*ii*) removals large enough to cause a decrease in abundance and CPUE, (*iii*) cumulative harvest is known without error, (*iv*) the removals represent random samples from the population, and (*v*) catchability is constant within a season (Ricker 1975; Cabraal and Wheaton 1981). The closed population assumption is likely met because eastern oysters are sessile, and most natural mortality, growth, and recruitment occur outside the harvest season in Maryland (Albright et al. 2007; Liddel 2008; Vølstad et al. 2008). There was an observed decrease in CPUE during the fishing season in Fishing Bay; therefore, removals by the fishery were likely large enough to cause a decrease in abundance. The cumulative harvest data are thought to be an accurate representation of harvest patterns over time. The harvest data may be biased low because of underreporting (Wilberg et al. 2011; Maryland Department of Natural Resources 2018; Damiano and Wilberg 2019), which would cause the abundance estimates to be biased low by the same proportional amount. Using the unreported harvest fraction (0.1) used by Maryland Department of Natural Resources (2018), abundance would be underestimated by about 10% in our analysis, assuming that underreporting is constant throughout the season. Although we have no reason to believe that the reporting rate changes during the harvest season, a time-varying reporting rate could cause biased estimates. When reporting rates vary over time, it may be possible to estimate catch using a censored data approach that would allow variation in

Fig. 4. Harvest (thousands of Maryland bushels; ~46 L), initial abundance estimates (thousands of Maryland bushels), and exploitation rate (proportion harvested during the fishing season) estimates for the eastern oyster (*Crassostrea virginica*) in Fishing Bay, Maryland, from 1999 to 2016. The error bars represent 95% confidence intervals as estimated from parametric bootstrapping.



reporting rate over time (Hammond and Trenkel 2005; Cadigan 2016; Van Beveren et al. 2017); however, our model would have to be modified to allow error in the observed cumulative catch (*K*) to potentially use this method.

The constant catchability assumption of our CPUE depletion analysis for eastern oyster in Fishing Bay is the most difficult to ascertain if it has been met. Powell et al. (2002) suggested that catchability increases with increased dredging effort, as they found lower catchability of oysters in Delaware Bay on oyster beds that had less historical fishing pressure than beds that were exposed to greater fishing effort. They hypothesized that fishing activities caused the oyster reef to be broken up, which caused the dredges to become more efficient. If oyster fishing increases catchability, estimates of exploitation rates could be biased low and initial abundance could be biased high. However, it is unclear how much fishing effort needs to occur before catchability stabilizes. Morson et al. (2018) found density-dependent catchability, where catchability increases as abundance declines, for a dredge survey in Delaware Bay. This kind of density-dependent catchability would cause our estimates of abundance to be biased high and the exploitation rates to be biased low. In addition, catchability could change due to changing behavior of the fishers (e.g., fishers seeking areas of highest CPUE before moving to areas where CPUE is lower; Walters 2003; Wilberg et al. 2011; Cadigan et al. 2017). Some areas within Fishing Bay likely receive more harvest pressure than others, so removals may not be random samples from the population, which may affect the relationship between CPUE and abundance. Other fisher behaviors, such as less efficient fishers ceasing fishing before more efficient fishers, could also cause changes in catchability. Any effect that causes a change in catchability during the fishing season could lead to biased estimates from our approach. However, we do not believe time-varying catchability was a substantial issue in our study because there was not a consistent departure from a linear decline in CPUE with increasing cumulative catch among years (Fig. 2). In addition, we examined whether the fishing locations changed systematically during the fishing season and did not find any consistent patterns.

Our censored regression approach includes one more assumption above those in other CPUE depletion estimators (Leslie and Davis 1939; DeLury 1947; Gould and Pollock 1997); specifically, it assumes that CPUE will be normally distributed about the regression line. This assumption is important because the estimated proportion of CPUE observations that are censored is based on a normal distribution. This seems to be a reasonable assumption for our Fishing Bay example, as CPUE appeared normally distributed near the end of most fishing seasons when the daily CPUE limit was rarely achieved.

Our approach used available software (i.e., an R package) for censored regression, but alternative versions of the model where catch is the dependent variable (instead of CPUE) could also be developed. If effort data are available at a time scale shorter than the management limit and thought to be reliable, then they could be included in a model where catch is the dependent variable, although currently available software (e.g., an R package) may not exist to fit such a model. For example, we used catch per license per day as our CPUE metric, partially because daily trip limits are used to manage the fishery. If hours of effort were available for each trip and thought to be reliable, we could have developed a model in which catch was the dependent variable and effort was an additional offset variable. We also chose not to use a model where catch was the dependent variable because effort data (e.g., hours fished, persons on the boat) were not available for many records and may not be reliable for records that did include effort data (Maryland Department of Natural Resources 2018).

Limits on the amount of catch that can be taken during a specific period (i.e., trip or bag limits) are commonly used in the management of fish and invertebrate fisheries throughout the world. The primary purpose of these types of regulations is to more evenly distribute catch among harvesters during a fishing season. However, as we have shown, these types of regulations may affect common assessment approaches and thus preclude their usage. Therefore, techniques that are designed for data from fisheries that use trip or bag limits are necessary to obtain unbiased estimates of abundance and exploitation rates. Our censored regression depletion method could be an option for data-poor fisheries because they can provide estimates of abundance and exploitation rates with only one season of fishery data. In our simulations, the censored regression approach provided unbiased estimates of initial abundance and exploitation rate using the Leslie depletion method when CPUE observations were censored and the proportion of censored observations decreased during the fishing season. For fisheries where daily harvest limits affect the distribution of CPUE values, the censored regression approach we presented may be a better method to estimate abundance than the traditional CPUE depletion approaches and may allow the use of relatively simple depletion approaches in cases where they were not previously appropriate.

Acknowledgements

We thank the Associate Editor and two anonymous reviewers for comments that helped improve this manuscript. We thank the Maryland Department of Natural Resources (MD DNR) for providing funding for this project and commercial fishery data for oysters in Fishing Bay. We acknowledge the MD DNR Oyster Stock Assessment Team for helpful comments and suggestions.

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