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Effects of underestimating catch and effort on surplus production models

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ABSTRACT

Fisheries can be managed based on surplus production models when only catch and effort data are available. However, reported catch and effort may not equal the true values. We studied the effects of jointly underestimated catch and effort on surplus production model parameter estimates (e.g., MSY, B_{msy} and F_{msy}) as well as estimates of key ratios (e.g., F/F_{msy}). We used ASPIC to examine various scenarios of underreporting for three example fisheries, North Atlantic swordfish, northern pike in Minnesota and queen conch in the Turks and Caicos Islands. With constant underestimation of catch and effort throughout time, MSY, B_{msy} and B_{next} are all underestimated by the same percentage, while F_{last} and the ratios, F/F_{msy} and B/B_{msy}, are not affected. As a result, harvest regulations can be set based on fishing mortality and the ratios. That is, when one thinks the harvest is MSY with $F = F_{msy}$, one is achieving MSY and F_{msy} even though the catch is actually larger than it is thought to be. However, increasing or decreasing trends in underreporting of catch and effort over time lead to errors in the parameter and ratio estimates whose direction is case-specific and whose magnitude can be high or low. Each fishery model responded differently to the simulated scenarios, which may be a result of different exploitation histories or the quality of the fit of the production model to the data. The wide range of outcomes observed may be due to the fact that underestimation of catch and effort can lead to a gain or reduction in data contrast. Simulations of a variety of possible scenarios similar to the methods in this study should be conducted if catch and effort are believed to be underestimated to determine how the surplus production model responds.

1. Introduction

Surplus production models, also referred to as biomass dynamic models (Ricker, 1975; Hilborn and Walters, 1992), are some of the simplest methods of stock assessment; the only required inputs being a time series of catch and effort. In fitting production models, the following parameters can be estimated, maximum equilibrium population size (K), intrinsic rate of population growth (r), the catchability coefficient (q) and population biomass in the first year of the assessed period (B_1). From these, estimates of biomass and fishing mortality rate can be derived for each year in the time series. In addition, other important parameters, notably maximum sustainable yield (MSY), the biomass at which MSY is obtained (B_{msy}), and the fishing mortality rate that produces MSY (F_{msy}), can be derived from the fundamental parameters. These additional parameters can be used to determine reference points for harvest regulations.

More complex models have been developed such as integrated size- or age-structured models (e.g., Methot and Wetzel, 2013) and should be used when the data are available (National Research Counci, 1998). However, the advanced methods require additional data which are not available for many stocks. For example, age-composition is often difficult to obtain in tropical species, invertebrates (Punt et al., 2013), and highly migratory species (Kopf et al., 2010; Chang and Maunder, 2012). Data-poor stocks, such as those in artisanal fisheries (e.g., Jamaican reef fisheries, Koslow et al., 1994), shark fisheries, or caught as bycatch (e.g., hammerhead species, *Sphyrna* spp., Jiao et al., 2011), also require use of simple assessment methods such as production models. Although production models are known not to yield as robust or as accurate parameter estimates compared to more complex models (National

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Research Counci, 1998), they are still able to produce general trends and provide approximate parameter estimates for management advice. In particular, simulations of production models using only fishery catch-per-unit-effort (CPUE) data produced some estimates close to the true values compared to the production models that used only survey data or both CPUE and survey data (National Research Counci, 1998). Production models are still being used in assessments for several highly migratory species fisheries, such as skipjack tuna (*Katsuwonus pelamis*, ICCAT, 2014) and sailfish (*Istiophorus albicans*, ICCAT, 2010a), invertebrates, such as horseshoe crab (*Limulus polyphemus*, Davis et al., 2006) and Caribbean queen conch (*Strombus gigas*, Ehrhardt and Valle-Esquivel, 2008), and other data-poor species, such as Iberian anglerfish (*Lophius* spp., Azevedo et al., 2008), in addition to the three case fisheries presented in this analysis. MacCall (2002) also advocates using production models to estimate stock productivity and as a form of verifying results from stock-recruitment models.

One problem with catch and effort data, particularly from historical records, is that the information may not be complete, e.g., due to illegal, unreported, and unregulated (IUU) fisheries (Lodge et al., 2007). With high value species, such as eastern Atlantic bluefin tuna, there have been problems with misreported catches (Gagern et al., 2013). This could be due to problems with the validity of logbooks (Polacheck, 2012). IUU fishing increased during the late 1990′s and 2000′s for Atlantic bluefin tuna causing catch and effort to be under-reported apparently in response to management actions and mismanagement (Fromentin et al., 2014). An extreme case of unreported catch is the South African abalone (*Haliotis midae*) fishery; this species is in high demand which leads to poaching and illegal export (Hauck and Sweijd, 1999) of up to 10 times the total allowable catch in one year (Plagányi et al., 2011). Bycatch mortality can also lead to underestimation of catch and effort when the species of interest is caught incidentally in a different fishery, and neither the catch nor effort from the incidental fishery is considered in the assessment. Bycatch mortality is a particularly contentious problem for long-lived species with low reproductive rates (Hall et al., 2000). This additional mortality should always be included in the fishing mortality (Chopin et al., 1996; Hall et al., 2000). An additional source of non-recorded catch and effort is the artisanal component of mixed sector fisheries, which often lack fishery reporting regulations (Koslow et al., 1994).

Studies have evaluated the effects of misreported catch in production models and proposed methods to address the issue using techniques for censored catch data assuming effort is known (Hammond and Trenkel, 2005). Soto et al. (2006) examined how uncertainty in species composition and total catch affected the parameter estimates in production models for tropical tuna. However, the effects of the joint underestimation of catch and effort have not been addressed.

The degree of underestimation of catch and effort may stay constant or may change through time. Unreported catch and effort in artisanal fisheries may increase as the local population grows. Alternatively, increased monitoring or enforcement efforts might result in reduction of unreported catch and effort. There is a tradeoff between using recent, short time series with higher quality data with less dynamic range versus utilizing a longer time series with less accurate data, but more contrast (e.g., Georges Bank yellowtail flounder, Jacobson et al., 2002). Less data contrast as well as trends in catch and effort demonstrating only an increase or decrease can lead to poor model fits (Hilborn and Walters, 1992; Magnusson and Hilborn, 2007).

It is necessary to understand the robustness of the production models used in assessments because there is an increasing demand for stock assessments for data-poor species, and catch and effort data can be inaccurate. The objective of this study was to address the reliability and robustness of the surplus production model, as formulated by Pella and Tomlinson (1969) and Prager (1994), to estimate parameters such as MSY, B_{msy} and F_{msy} and ratios, such as B/B_{msy} and F/F_{msy}, when catch and effort are both underestimated. We used three managed fisheries to represent realistic issues regarding underreported data. These stocks, North Atlantic swordfish (*Xiphias gladius*), northern pike (*Esox lucius*) and queen conch (*Strombus gigas*), were selected because they have different life histories and catch and effort are likely underestimated. We altered data inputs to simulate how underreported catch and effort influence estimated production parameters.

2. Materials and methods

2.1. Case study fisheries

The stocks selected for this study represent a range of life history characteristics and fishery types (i.e., commercial, mixed recreational-artisanal and mixed commercial-artisanal). These fisheries also vary in the length of the time series and information content (contrast) in the data, providing a spectrum of model fits (good to poor) (Fig. 1). Each of the assessments for these fisheries has used or currently incorporates surplus production models.

North Atlantic swordfish is a highly migratory, fast-growing fish with longevity of 15 years (Arocha et al., 2003; DeMartini et al., 2006). The fishery on this stock is managed by the International Commission for the Conservation of Atlantic Tunas (ICCAT) and is valuable. The target fishery has been operating since the 1950′s and pelagic longlines are the primary gear type. The tuna longline fishery, which catches swordfish opportunistically, started in 1956 (ICCAT, 2010b). A combined, standardized CPUE index from 1950 to 2011 from all country participants in the swordfish fishery was used in the 2013 stock assessment (ICCAT, 2013) as well as in this study. The North Atlantic swordfish fishery was a prime example of a fishery that depends on a multitude of factors that could result in underestimated catch and effort. For example, the calculated catch and effort may have underestimated the swordfish mortality associated with bycatch from other fisheries. Another scenario in which catch and effort were lower than the true values was underreported or illegal fishing. However, with better management practices, the reporting of catch and effort is improving, thus leading to a decrease of underestimation in the more recent years.

The northern pike is a temperate to boreal freshwater fish with a longevity of around 17 years in Mille Lacs Lake, Minnesota (R. Bruesewitz, Minnesota Department of Natural Resources, *pers. comm.*). The northern pike fishery in Mille Lacs Lake was selected because it supports a recreational and a tribal subsistence fishery. It is regulated jointly by the Great Lakes Indian Fish and Wildlife Commission and Minnesota Department of Natural Resources. The recreational fishery is based on hook and line, with catch and effort records starting in 1985. The tribal fishery targets walleye (*Sander vitreus*) using gillnets, with northern pike occurring as a bycatch species. The records for tribal catch for northern pike began in 1997 when the tribal right to fish was affirmed by a court ruling. Although the tribal catch was initially small compared to the recreational fishery, it surpassed the recreational catch from 2003 to 2012. Surplus production models are currently used to determine the status of the northern pike population. Years used for this time series are 1985–2011. Underestimation of catch and effort was thought to occur for northern pike when the tribal fishery was introduced because the pike bycatch mortality from the walleye fishery was not considered in the assessment. As a result catch and effort were thought to be a certain percentage lower each year.

The queen conch is a high value commercial species in the Turks and Caicos Islands, British West Indies. It is collected by free diving (Medley and Ninnes, 1999) and is an example of a commercial

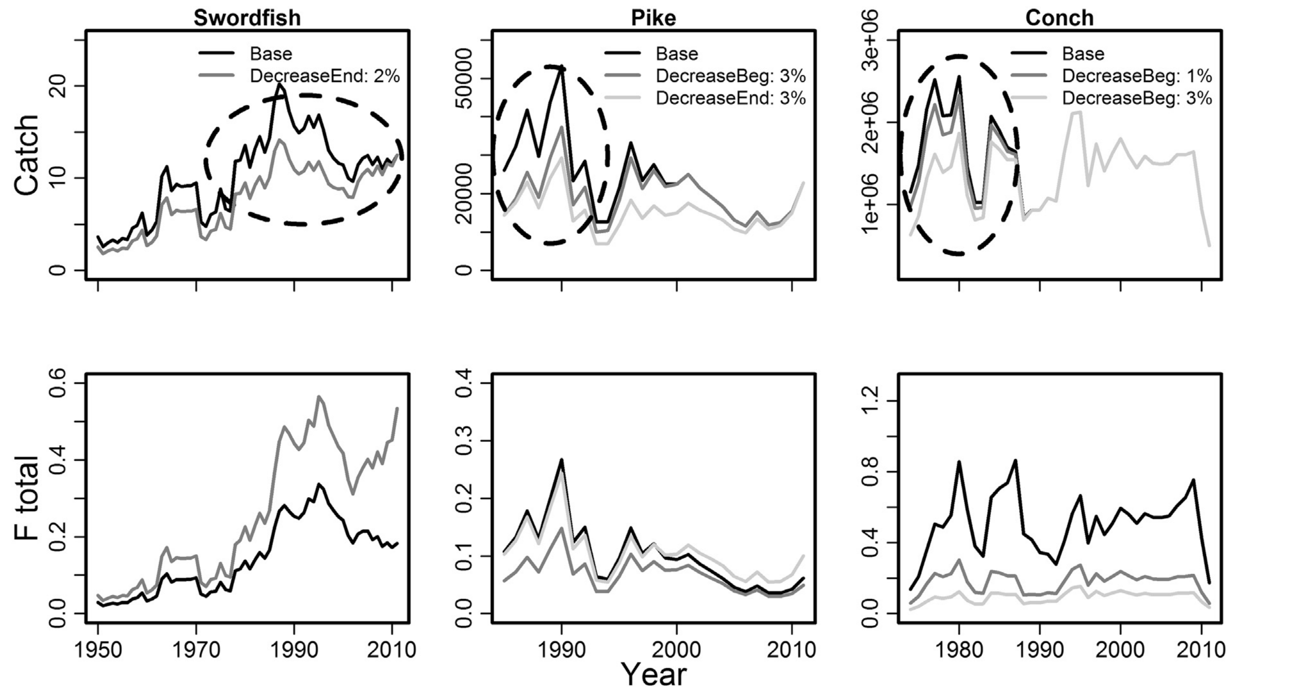

Fig. 1. Catch (top panel) and estimated fishing mortality (F total; bottom panel) time series for the original data (base case, black line) and for the decreasing underreporting scenarios that yielded the largest percent differences for North Atlantic swordfish (left column), northern pike (center column) and queen conch (right column). Dashed ovals indicate where the contrast is lowered by underreporting.

and artisanal fishery. Historically, queen conch was a staple food for the local inhabitants, with landings data recorded from 1904 with minimal export. The conch fishery went through several high and low periods of catch during the 20th century due to commercial and economic demands. It is now the second most important fishery in the Turks and Caicos Islands (Ninnes, 1994; Appeldoorn, 1996). Because there are only 5–6 processing plants (Medley and Ninnes, 1999) for commercial export for all islands, the landings and effort were recorded for all commercial landings. Recorded catch and effort used for this study span from 1974 to 2011. However, the recorded catch and effort did not account for the local consumption from both local residents and tourists. There were two scenarios that arose from this issue. The first was that local consumption was constant throughout the time series, thus assuming a constant underestimation of catch and effort. The second was the concern that underreporting of catch and effort would increase as the population and tourism continues to grow, leading to a gradual increase in underreporting.

2.2. Simulation methods

We treated the reported catch and effort as if they were recorded without error (true values). We decreased both by the same percentages throughout the time series to simulate realistic scenarios of underestimation and observed how the assessment results changed. The scenarios represented in this study were based on real concerns from the case study fisheries. For example, a constant underreporting represented not incorporating bycatch mortality in the pike fishery (since the start of the tribal fishery) or local consumption in the conch fishery (throughout the time series). If the island population and tourism increased in the Turks and Caicos Islands, then underreporting would have increased throughout the years so the alternative scenario of increasing underreporting over time was also considered. A decreasing underestimation is speculated in the swordfish fishery because of improvements in reporting rates.

The simulation scenarios encompassed eight groups (Fig. 2): 1) a constant lower percentage of catch and effort by 10%, 20%, 30%, 40% or 50% (Constant), 2) an increase in the underestimation of catch and effort gradually by 1%, 2%, or 3% of the true value each year for the first 15 years followed by continued underestimation at 15%, 30% or 45%, respectively (IncreaseBeginCont), 3) the same increase in underestimation for the first 15 years as in (2) followed by no underreporting for all subsequent years (IncreaseBeginStop), 4) no underestimation initially followed by a continual increase in underreporting for the last 15 years as in (2) (IncreaseEnd), 5) a decrease in underestimation gradually by 1%, 2% or 3% of the true value each year starting at 15%, 30% and 45% underestimation at the beginning, respectively (DecreaseBegin), 6) same as in (5) but at the end of the time series (DecreaseEnd), 7) a geometric increase (1.01^y, 1.02^y or 1.03^y, where y = year number from 1, 2, . . .15) with continued underestimation after year 15 similar to (2) (GeoIncreaseBegin) and 8) the same geometric increase as in (7), but for the last 15 years (GeoIncreaseEnd). All scenarios were created for each of the three species.

We used the non-equilibrium logistic model of Pella and Tomlinson (1969) as described in Prager (1994) rather than a more generalized model with a shape parameter because this is the model used in the actual assessments of the stocks. Additionally, the simpler model is considered better to use when the shape of the surplus production curve is unknown, particularly for swordfish-like species (Prager, 2002, 2003). The same kind of analysis can be used for any production model including state-space models (e.g., Montenegro and Branco, 2016). We ran each of the scenarios and the base datasets (the original, reported catch and effort, treated as the true values) through the ASPICv5 software (A Stock Production Model Incorporating Covariates Version 5, Prager, 1994) to obtain parameter estimates. ASPICv5 uses a lognormal observation error in fishing effort, which is found to provide the least biased and most precise parameter estimates (Polacheck et al., 1993; Prager, 2002). All parameter estimates were bootstrapped 1000 times, the maximum number allowed in ASPICv5, using residual bootstrap-

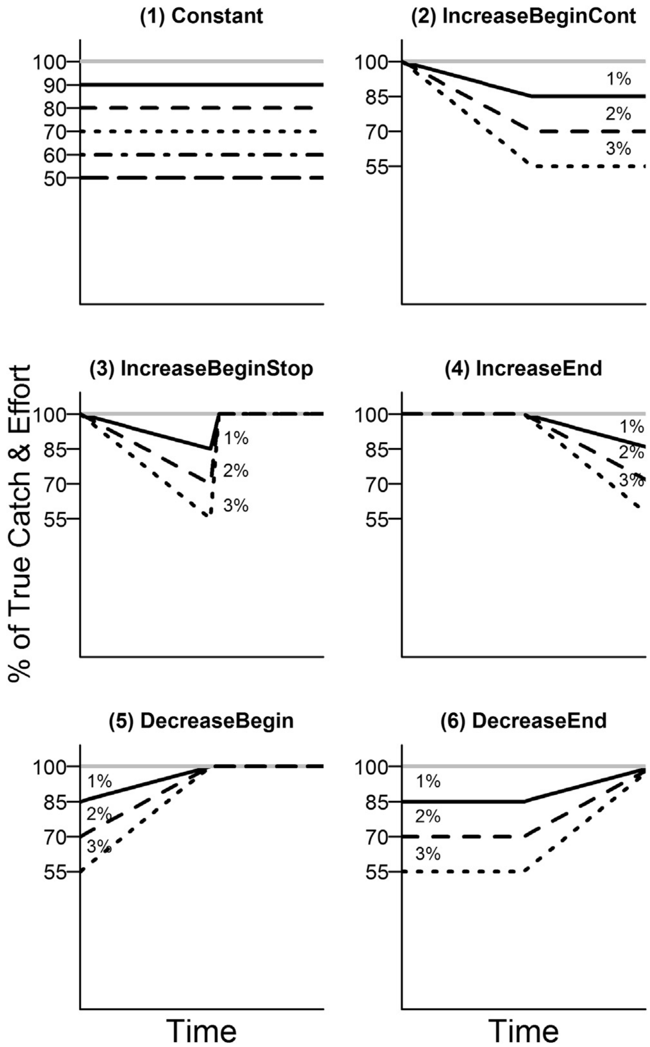

Fig. 2. The percent underestimation of catch and effort for comparison with the "true" catch and effort at 100% (grey line) for each group of scenarios. Note: The trends of (7) GeoIncreaseBegin and (8) GeoIncreaseEnd are similar to (2) IncreaseBeginCont and (4) IncreaseEnd respectively, and are not shown.

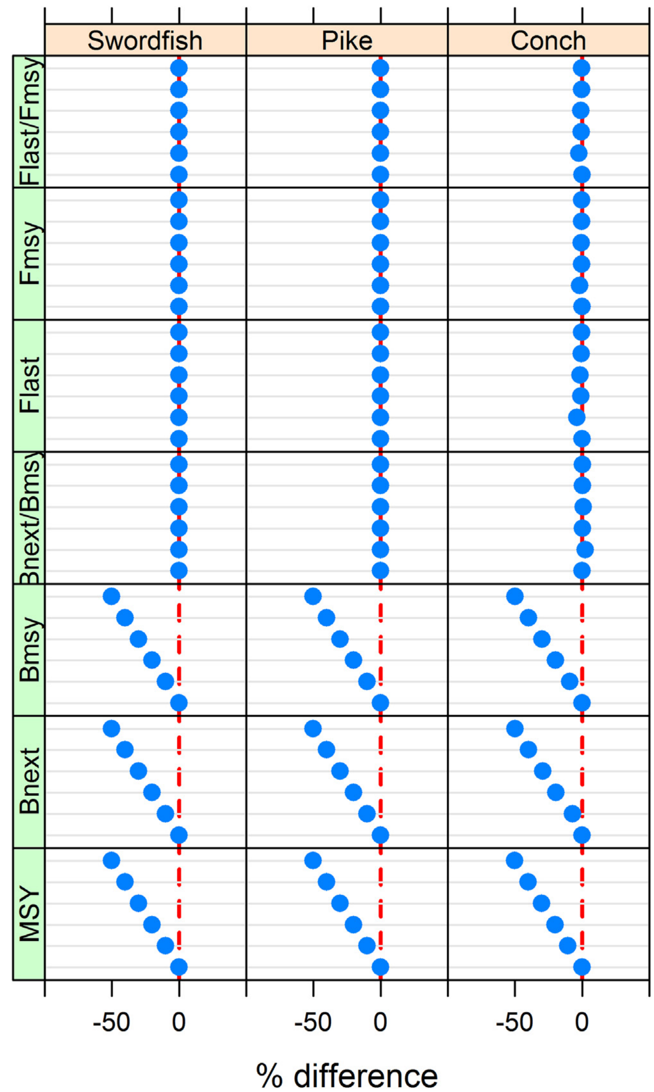

Fig. 3. Estimates from the production models of individual parameters and parameter ratios for scenarios of constant percent underestimation of catch and effort for North Atlantic swordfish, northern pike and queen conch. For each panel, the scenarios from bottom to top are: 0%, 10%, 20%, 30%, 40% and 50% underestimation of catch and effort throughout the time series.

ping (Efron and Tibshirani, 1986). We compared each of the outputs from the different scenarios to the base by calculating the percentage difference (% difference) for each parameter and ratio estimate. Using estimates of MSY as an example:

$$\%\ difference = \frac{\widehat{MSY}_{scenario} - \widehat{MSY}_{base}}{\widehat{MSY}_{base}} \times 100$$

where the "ˆ" symbol denotes an estimate.

We examined the percent difference for MSY, B_{msy}, B_{next} (the starting biomass for the next year after the last), B_{next}/B_{msy}, F_{msy}, F_{last} (fishing mortality in the last year), and F_{last}/F_{msy}.

3. Results

As expected, under a constant percentage of underestimation of catch and effort throughout a time series, the B_{next}/B_{msy} and F_{last}/F_{msy} ratio estimates correctly matched the known ratios (~0% difference), whereas the catch and effort underestimation was reflected in some, but not all individual parameter estimates (Fig. 3). If the reported catch and effort were X% lower than the true values, B_{next}, B_{msy} and MSY estimates would also show the same X% difference. Because B_{next} and B_{msy} are both underestimated by the same percentage, the ratio B_{next}/B_{msy} remains unchanged. The variables F_{last} and F_{msy} were not affected by the constant underestimation of catch and effort, thus the ratio F_{last}/F_{msy} was also unchanged (Fig. 3).

Although scenarios with a constant lower percentage of catch and effort demonstrated consistent results across species, trends in underestimation throughout the time series produced different patterns among species (Fig. 4 and 5). No major differences between an increasing linear underestimation by 1%, 2% and 3% each year (IncreaseBeginCont and IncreaseEnd) and the corresponding geometric increase (GeoIncreaseBegin and GeoIncreaseEnd, respectively) were discerned. Therefore, results from the geometric increase are not shown.

The percent differences in the swordfish production model were generally intuitive for all scenarios. For example, the increasing underestimation trend at the start of the time series (1%, 2%, or 3% increase per year), followed by a constant underestimation (at 15%, 30% or 45%, respectively, IncreaseBeginCont) resulted in about 15%, 30% or 45% difference for MSY, B_{next} and B_{msy}. The parameter estimates B_{next}/B_{msy}, F_{last}, F_{msy} and F_{last}/F_{msy} had close to no difference

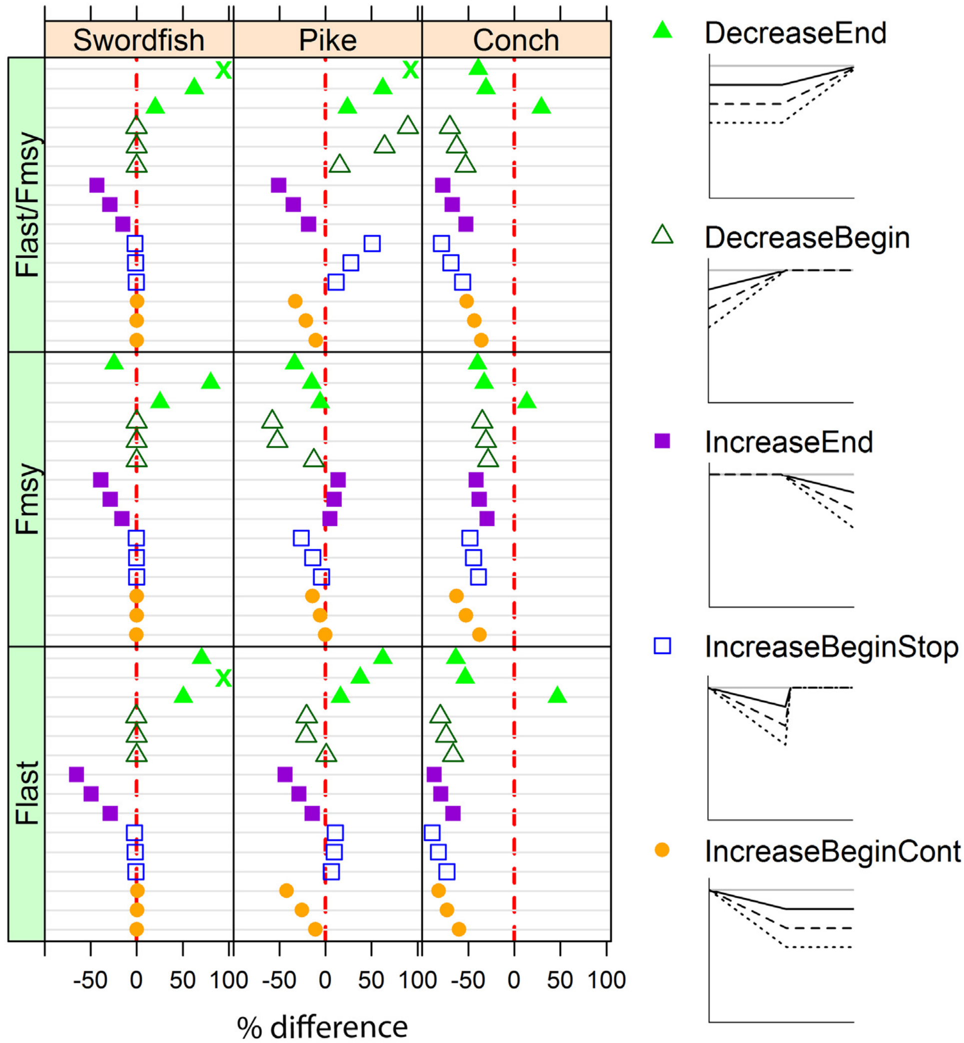

Fig. 4. Production model estimates for Flast, Fmsy and Flast/Fmsy for five sets of scenarios indicated at the right. Within a scenario set, percent changes in reporting of 1%, 2% and 3% are arranged from bottom to top. The X's mark % differences greater than 100% differences.

from the base (−0.65 to 0.88% difference) under the IncreaseBeginCont scenario (Figs. 4 and 5). This was the same pattern as seen for the constant percentage of underestimation (Constant, Fig. 3). In addition, the decreasing underestimation trend at the start of the time series (DecreaseBegin) did not appear to affect the parameter and ratio estimates for swordfish (close to 0% difference).

Both the pike and conch production models did not have intuitively obvious differences for the parameter and ratio estimates for increasing and decreasing trends in underestimation (Figs. 4 and 5). The trends in the errors were case- and scenario-specific. For example, with an increasing underestimation of catch and effort at the start of the time series followed by no underestimation for the remaining years (IncreaseBeginStop), the F_{last}/F_{msy} estimates for the swordfish models had no differences, whereas pike models had negative differences and conch models yielded positive differences (Fig. 4). In addition, the F_{msy} estimates for swordfish for the three DecreaseEnd scenario cases (1–3% increase over the true value each year) produced increasingly positive differences for the 1% and 2% increase and a negative difference for the 3% (Fig. 4). The B_{next} estimates appeared to be only slightly affected by underestimation in the pike models; in contrast, almost all B_{next} estimates in the conch models yielded percent differences greater than 100% (Fig. 5). In the conch models under all scenarios, almost all the fishing mortality estimates, F_{last}, F_{msy} and F_{last}/F_{msy}, had negative differences (Fig. 4), whereas the biomass estimates, B_{next}, B_{msy} and B_{next}/B_{msy}, had positive differences (Fig. 5). The pike and swordfish models did not follow this generality.

The conch dataset led to the majority of the extreme percent differences, representing ten of the largest fifteen differences overall (Table 1). The largest percent difference for conch was 701%. All of the percent differences that were greater than 100% were associated with biomass parameter estimates, B_{next} and B_{msy}, and these arose with both increasing and decreasing trends in underestimation of catch and effort. Small changes in catch and effort in the conch models yielded large differences in model results. The pike dataset had the second most number of extreme differences (4 of 15) and also returned the top two largest differences observed. For swordfish and pike, decreasing underestimation (improved reporting rates) at the start or end of the time series appeared to generate the largest differences (Table 1). Estimated parameters in the pike production models associated with biomass, e.g., B_{msy} and MSY, appeared to yield more extreme differences compared to the fishing mortality parameters. In general, it appeared that small changes in catch and effort in the pike models led to small % differences except with the decreasing trends. For swordfish, decreasing trends in underestimation tended to have a greater effect and generate more variability on the estimated fishing mortality parameters, e.g., F_{last}, compared to the biomass parameters. Yet, for all cases the %

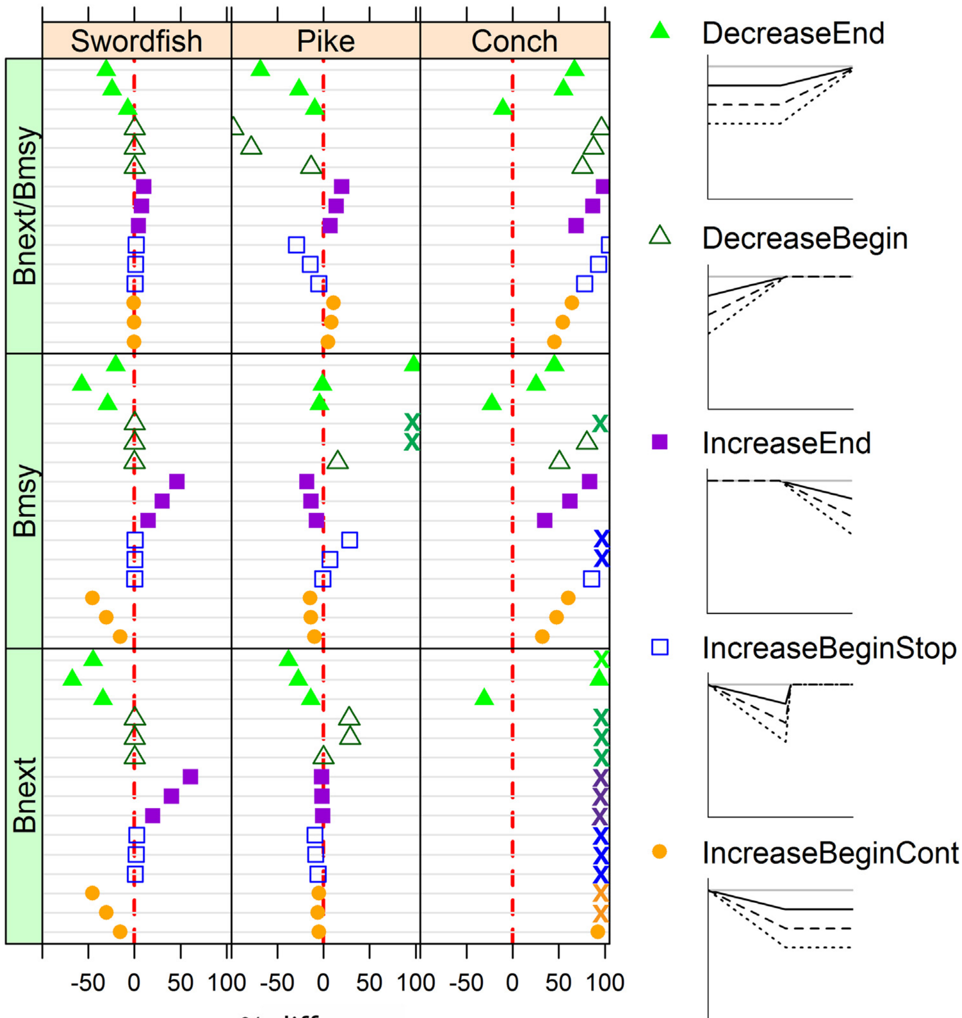

Fig. 5. Production model estimates for Bnext, Bmsy and Bnext/FBmsy for five sets of scenarios indicated at the right. Within a scenario set, percent changes in reporting of 1%, 2% and 3% are arranged from bottom to top. The X's mark % differences greater than 100% differences.

Table 1
Top 15 largest % differences (100*(scenario-true)/true) for all estimated parameters and ratios from swordfish, pike and conch production models with the corresponding scenario and the percent of increase or decrease of the true value each year (% Inc or Dec). Note that all of the calculated largest differences were positive.

	Scenario	% Inc or Dec	Species Model	% difference
1	DecreaseBegin	3%	Pike	5732
2	DecreaseBegin	3%	Pike	2348
3	IncreaseBeginStop	3%	Conch	701
4	DecreaseBegin	2%	Pike	505
5	IncreaseBeginStop	2%	Conch	400
6	DecreaseBegin	3%	Conch	347
7	IncreaseBeginStop	3%	Conch	291
8	IncreaseEnd	3%	Conch	264
9	DecreaseBegin	2%	Conch	239
10	IncreaseBeginStop	1%	Conch	230
11	IncreaseEnd	1%	Conch	203
12	DecreaseEnd	2%	Swordfish	193
13	DecreaseBegin	2%	Pike	189
14	DecreaseBegin	1%	Conch	165
15	IncreaseBegCont	3%	Conch	164

differences generally tended to be small and damped with small problems in catch and effort for the swordfish models.

Underestimation of catch and effort caused changes in the contrast of the data. In particular, the different affected sections of the time series could increase or decrease contrast depending on the particular history of the stock in the affected period (Fig. 1).

4. Discussion

Constant underestimation of catch and effort throughout the time series is manageable because estimates of the harvest rate and the relative biomass level are unaffected by the underreporting. The biomass estimates and MSY are incorrect, but the production models return the correct biomass ratio. When catch and effort are both underestimated by the same percentage, the differences in B_{next} and B_{msy} estimates are also lower by that same percentage. This results in the ratio B_{next}/B_{msy} being identical to the correct ratio. Consequently, management efforts can be based on the fishing mortality parameter estimates or ratios, B_{next}/B_{msy} and F_{last}/F_{msy}, from the production models if catch and effort are constantly lower (or higher) by an unknown percentage. Management can proceed without knowing the level of underreporting. However, this scenario of constant underestimation of catch and effort may not be common because fisheries change over time.

Trends in underestimation of catch and effort over time seem more probable than constant underestimation. However, these scenarios resulted in a wide range of positive and negative differences in the parameter estimates, making it difficult to determine how the production model will respond in a particular case. Soto et al. (2006) also found that the relationship between error in catch and uncertainty in the model was complex; specifically, the two smaller increases in catch led to little change, but the largest increase led to dramatic change in the parameter estimates of a production model. Also, not all parameter estimates were affected equally by underreporting in this study, similar to the results from Zhang (2013). Zhang (2013) showed that the accuracy of one parameter estimate is not necessarily reflected in another estimate from the same logistic production model when process and observation errors were considered.

Overall, each production model responded differently to underestimation of catch and effort. The swordfish production models performed in a manner that seemed intuitive, whereas the pike model sometimes displayed the opposite signs in the differences for the same corresponding scenarios. Small problems in underestimation in the swordfish models generally appeared to lead to smaller, damped differences in the parameter and ratio estimates, particularly for increasing trends of underreporting. The swordfish models appeared to be more robust to changes in catch and effort compared to the pike and conch models. Small changes in catch and effort in the pike models often translated into small differences for increasing trends in underreporting. Conch models appeared to have the greatest range of differences and the least distinct patterns in parameter and ratio estimates, particularly for biomass parameter estimates. Small problems of underestimation in the conch data tended to be magnified into large differences in most production model estimates. Additionally, small changes in catch and effort for the decreasing trends for all species were often magnified into large differences in these case studies. A decreasing trend may become more common over time because underreporting can be reduced (reporting improved) as a response to improvement in regulations of fisheries. It is disconcerting that improvements in data collection can lead to increased error in assessment.

Two explanations for the different responses under the various trend scenarios could be the length of the time series and differences in exploitation history of each fishery. In addition, it appeared that underestimation of catch and effort during different periods within the time series can change the perceived dynamics of the fishery. North Atlantic swordfish had the longest time series of 62 years, which started prior to the heavy exploitation of this species (ICCAT, 2010b). As a result, the relatively long time series began close to the carrying capacity and went through periods of high and low catch and effort. These are conditions favorable for the use of a production model. Northern pike in Mille Lacs Lake had a shorter time series of 27 years, and exploitation began prior to the start of the monitoring of the fishery so catch rates at the start of exploitation were not observed. The production models for the conch fishery were based on more years of data than the pike fishery, but the conch models did not fit very well. The results for swordfish suggested that the long term time series had more contrast throughout the history of the fishery compared to the shorter conch and pike fisheries. Therefore, an increasing trend or decreasing trend of underreporting at the start or end of the time series did not appear to eliminate all of the contrast in the swordfish data. However, in general, decreasing trends at the start of the time series may have removed much of the contrast in the apparent catch and effort trends for the conch and pike fisheries (Fig. 1). A decrease in contrast could have caused the production model to have difficulty converging and estimating parameters. This apparently was true for many of the largest percent difference cases. In many conch models, it appeared that the trends in underestimation of catch and effort led to the estimated annual fishing mortality to be lower and flattened compared to the base conch model (Fig. 1). In contrast, the change in catch and effort in the swordfish model under a DecreaseEnd scenario led to the estimated annual fishing mortality to be much higher and more variable than the base model estimates (Fig. 1). Production model results become unstable and the direction and magnitude of bias in parameter estimates is case-specific when underrepresentation of catch leads to an apparent change in contrast in the data series.

In summary, the best fitting model with high contrast in the time series (i.e., swordfish) is more robust to changes in catch and effort compared to the poorest fitting model (i.e., queen conch), with northern pike being between the two extremes in terms of contrast and robustness to underreporting. The results also suggest that the stability of the production models also depended on when the underestimation of catch and effort occurred in relation to when there was contrast in the data. Underreporting could potentially falsely enhance or eliminate the contrast within the time series. This could result in the production model becoming unstable or inaccurately modeling the dynamics of the fishery and associated parameter estimates.

We recommend conducting simulations of a variety of possible scenarios when catch and effort are believed to be underestimated. Similar simulations can be performed for any production model (e.g., Pella-Tomlinson and state-space). These simulations can provide insight into how specific parameter and ratio estimates may be affected by misreporting, and which estimates are robust to underestimation of catch and effort. Thus, changes in the parameter and ratio estimates from the simulations can potentially be used to develop precautionary benchmarks for the management of a specific stock.

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