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1	Comparisons of mean length-based mortality estimators and age-structured models for six
2	southeastern United States stocks
3	
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11	
12	Keywords: data-limited, data-poor, fisheries management, overfishing, biological reference
13	points

14 Abstract

15 Length-based mortality estimators have been developed as alternative assessment methods for 16 data-limited stocks. We compared mortality estimates from three methodologically-related 17 mean length-based methods to those from an age-structured model. We estimated fishing 18 mortality and determined overfishing status, i.e., if $F/F_{MSY} > 1$, for six stocks which support 19 important recreational and commercial fisheries in the southeastern United States. The 20 similarities in historical fishing mortality between the length-based methods and the most 21 recent assessments varied among the case studies, but the classification of overfishing status in 22 the terminal year did not differ based upon the choice of models for all six stocks. There was 23 also high agreement in the number of overfishing years within different historical periods. 24 Applications of length-based methods can be consistent with the results that might be obtained 25 from an age-structured model. In one case, diagnostics were used to identify the problems with 26 the length-based estimators. The potential for determining overfishing status from these 27 methods can encourage data collection programs for unassessed stocks.

28 Introduction

29 Simpler, alternative stock assessment methods for exploited stocks are generally 30 desirable when a more complex age-structured stock assessment model may not be viable or 31 practical from a management perspective (Chrysafi and Kuparinen, 2016). Simple methods are 32 largely used in "data-limited" situations, where the data available for an assessment may be 33 restrictive, for example, due to lack of sampling resources (Bentley, 2015). In these cases, 34 tractable assessment methods typically make necessary simplifying assumptions regarding the 35 population. On the other hand, a more comprehensive stock assessment model, such as an age-36 structured model (ASM), is typically used in "data-rich" scenarios where ageing information and 37 multiple sources of data exist (Dichmont et al., 2016). In both data-limited and data-rich 38 scenarios, analytical methods are used to estimate historical trends in fishing mortality (F), 39 biomass (B), or both. Model output, including forecasts and reference points, from such 40 methods can be used to provide short-term management advice. 41 In data-limited situations, length-based assessment methods are appealing because 42 they are easy to use and length information is easily collected for many fisheries. In conjunction 43 with growth parameters, simple methods typically estimate mortality from a single size 44 composition or mean length, often with equilibrium assumptions (Hordyk et al., 2015; Hordyk 45 et al., 2016; Kokkalis et al., 2015; Beverton and Holt, 1956). 46 Recently, four related mean length-based methods have been developed to analyze 47 time series of mean length. These methods expanded the estimator of Beverton and Holt 48 (1956), which estimates total mortality (Z) from a single observation of mean length. 49 Development of these methods were motivated by the ability to relax the equilibrium

50 assumptions of the Beverton-Holt method. Gedamke and Hoenig (2006) developed a non-51 equilibrium method for estimating total mortality. Changes in mortality over time are 52 characterized by stepwise changes, and the non-equilibrium method accounts for the gradual 53 change in mean length that arises following such a change. From a time series of mean length, a 54 historical series of mortality rates and the timing of the changes in mortality are estimated. This 55 method has also been used with proxy reference points for maximum sustainable yield (MSY) 56 to determine overfishing status, i.e., if $F/F_{MSY} > 1$ (Huynh, 2016). 57 Subsequent extensions of Gedamke and Hoenig (2006) model incorporate additional 58 data types with mean lengths to relax additional assumptions and evaluate goodness of fit. The approach can be expanded to incorporate recruitment indices and effort to relax the constant 59 60 recruitment assumption and provide year-specific mortality estimates, respectively (Gedamke 61 et al., 2008; ICES, 2016; Then et al., 2018). Indices of abundance also contain information on 62 mortality and can be used with mean lengths to estimate mortality (Huynh et al., 2017). 63 To evaluate how simpler, data-limited methods may perform relative to age-structured 64 models, the former can be applied to data sets from stocks for which there are age-structured 65 assessments (for example, Dick and MacCall, 2011; Kokkalis et al., 2016). Synchrony in the 66 results among models, i.e. whether or not the historical stock trends are in agreement, can be a 67 form of endorsement for the data-limited methods. While there is no guarantee that the age-68 structured model is correct nor that it produces precise and accurate estimates, benchmark assessments undergo a thorough peer-review process and the results of the age-structured 69 70 models usually represent our best knowledge of the stock (Dichmont et al., 2016). If similar 71 results are obtained among models, then the use of simpler models is inconsequential for

72 classifying overfishing status. Use of the simpler models could also be advantageous for 73 management agencies to allocate resources to stocks that have not been previously assessed. 74 In this study, we use three multi-year, mean length-based methods to estimate 75 historical fishing mortality for six stocks in the southeastern United States. These stocks are of 76 interest because they have been assessed using age-structured models. The stocks are Gulf of 77 Mexico (GOM) greater amberjack Seriola dumerili, GOM Spanish mackerel Scomberomorus 78 maculatus, GOM cobia Rachycentron canadum, Atlantic (ATL) cobia, GOM king mackerel S. 79 cavalla, and ATL king mackerel. The Beaufort Assessment Model (BAM; Williams and Shertzer, 80 2015) was used for ATL cobia, while Stock Synthesis (SS; Methot and Wetzel, 2013) was used for all others. 81

82 For these stocks, length composition data were used in the age-structured assessments 83 which were accepted as the basis for management advice by NOAA (National Oceanic and 84 Atmospheric Administration) Fisheries. The length data from these assessments were then 85 obtained for analysis with the mean length-based methods. In an ASM, length data potentially 86 contain information on recruitment strength, mortality, and selectivity. While these data 87 primarily inform mortality with fixed assumptions regarding recruitment and selectivity in the 88 mean length-based models, a common subset of data allows for comparison of historical 89 mortality rates between these two types of models. We compared the trends in historical 90 fishing mortality and the classification of overfishing status using F/F_{MSY} estimates between the 91 mean-length based models and the age-structured assessments. We also used model 92 diagnostics, i.e., residuals, for the mean-length based models to explain whether the methods 93 were suitable for the particular stocks.

94	
95	Methods
96	Stocks of interest and their assessments
97	Greater amberjack is managed under the Reef Fish Fishery Management Plan, and
98	Spanish mackerel, cobia, and king mackerel are managed under the Coastal Migratory Pelagic
99	Fishery Management Plan of the Gulf of Mexico Fishery Management Council and South
100	Atlantic Fishery Management Council. Each of the four species are considered to be separate
101	Gulf of Mexico (GOM) and Atlantic (ATL) stocks for management purposes.
102	Over time, these stocks have been managed with seasonal closures, bag limits,
103	minimum size limits, and catch limits, i.e., quotas. Size limits, i.e. minimum retention sizes, have
104	generally increased over time for the recreational sector (Table 1). The recreational sector
105	includes the charterboat/private fleet and the headboat fleet. The charterboat/private fleet
106	consists of boats rented by day (or half day) for a small group of recreational anglers, whereas
107	headboats charge on a per-person, per-trip basis and typically have more anglers than
108	charterboats per fishing trip.
109	Benchmark assessments for these stocks were conducted in 2013 - 2014 (SEDAR, 2013a,
110	2013b, 2013c, 2014a, 2014b, 2014c). Data inputs for these ASM included landings, discards,
111	standardized indices of abundance, length composition, and length-at-age observations from
112	commercial and recreational sectors. Fishery-dependent indices were derived from fishery
113	catch-per-unit-effort (CPUE). Fishery-independent indices and length compositions from
114	surveys were also included in the assessments, although the time series are shorter than for
115	fishery-dependent data. For some assessments, the charterboat/private and headboat fleets

were combined into a single recreational fleet if both are thought to behave similarly intargeting the stock (Table 2).

In addition to fishing mortality, ASM assessments estimated selectivity (specified to be 118 119 either logistic or dome-shaped), annual recruitment, and growth parameters. The number of 120 growth parameters varied among assessments. For example, K was estimated with L_{∞} fixed for 121 GOM greater amberjack, whereas both were fixed for ATL cobia and all growth parameters 122 were estimated for GOM cobia, GOM king mackerel, and ATL king mackerel. For all stocks, 123 estimates from growth studies were available prior to the assessment (Table 3). Natural 124 mortality (M) varied by age in the assessment, using the parameterization from Lorenzen 125 (1996) and subsequently re-scaled such that the mean value was equal to that obtained from 126 Hoenig (1983) using maximum observed age.

127

128 Mean length mortality estimators

129 Three mean length-based methods were used to estimate mortality: (1) the non-130 equilibrium mean length (ML) estimator of Gedamke and Hoenig (2006); (2) the mean length-131 catch rate (MLCR) estimator of Huynh *et al.* (2017); and (3) the mean length-effort (MLeffort) 132 estimator of Then *et al.* (2018). A technical description of the three methods is provided in 133 Supplementary Materials A.

The analyses were based on the data from the recreational sector. This sector was chosen because it is believed that this sector has been most informative for inference on stock trends in the benchmark assessments (Sagarese *et al.*, 2016). In the southeastern U.S., the largest targeted fishing effort has historically come from the recreational sector (Siegfried *et al.*,

138 2016). The indices from the recreational sector also have generally had the lowest root mean 139 square error (RMSE) in the age-structured assessments (Sagarese et al., 2016). In cases where 140 the two recreational fleets are distinct units in the assessment, data from the larger 141 charterboat/private fleet were used for the length-based methods. The length compositions, 142 standardized indices of abundance, and the landings corresponding to the index were obtained 143 directly from the assessments (Table 2). 144 In contrast to the ASM which accommodates and estimates the parameters of various 145 selectivity functions, all mean length-based methods assume knife-edge selectivity and require 146 an estimate of the length at full selection (L_c) to be determined prior to the analysis. The mode 147 of the length composition compiled for all years was chosen to be the L_c, which was larger than 148 the minimum retention size for all stocks (Figure 1). There was generally no trend in the modal 149 length over most years for the six stocks. The annual mean length of animals larger than L_c was calculated, and von Bertalanffy asymptotic length (L_{∞}) and growth coefficient (K) were 150 151 obtained from growth studies presented during the benchmark assessment (Table 3). 152 First, ML estimator was used to estimate mortality. From annual observations of mean 153 length, the time series is partitioned into stanzas of constant mortality. The total mortality rates 154 and the duration of each stanza are then estimated. Total mortality is modeled as a step-wise 155 change from one stanza to another, and the predicted mean length changes gradually 156 depending on previous mortality rates and elapsed time since mortality changed. 157 Second, the index of abundance was used in conjunction with the mean length time

series with MLCR. In this model, both the mean length and the index are predicted to decrease
gradually after a step-wise increase in mortality and, similarly, to increase after a decrease in

160 mortality. This allows for an evaluation of the consistency between the length and index data161 for mortality estimation.

The ML and MLCR models were systematically fitted by varying the number of stanzas and Akaike Information Criterion (AIC) was used to select the best fitting model, i.e., the model with the lowest AIC score. To avoid overfitting, models with more parameters were accepted only if the reduction in AIC was greater than two (Burnham and Anderson, 2002). Models were fitted assuming zero, one, or two change points in mortality (additional analyses with more than two change points were not supported by AIC).

While ML and MLCR estimate *Z*, we assume, as many age-structured models do, that *M* is constant over time. Thus, changes in *Z* examined here are assumed to arise solely from changes in *F*. From total mortality estimates, fishing mortality *F* was obtained by subtracting the value of *M* assumed in the benchmark assessments (Table 3). Since the mean length models also assume constant mortality across all selected ages, the age-invariant *M* obtained from the Hoenig (1983) method was used.

174 Third, year-specific mortality rates were estimated from mean lengths and estimates of effort, the latter is modeled as an index of mortality using the mean length-effort model 175 176 (MLeffort; Then *et al.*, 2018). In this method, fishing mortality F is proportional to fishing effort f 177 via the estimated catchability coefficient q. Total mortality Z in year y of the model is $Z_y = qf_y + M$, where f_y is the effort and M was fixed in the model (to the same value used in 178 ML and MCLR). This formulation precludes the need to estimate mortality in time stanzas. The 179 180 effort time series was obtained by taking the ratio of the landings (thousands of fish) and index 181 of abundance (catch-per-unit-effort, number of fish per angler hour). Since the model requires

a full time series of effort, the first year of the model was set to the first year with available

182

183 indices of abundance. The equilibrium effort prior to the first year of the model was set equal to the effort in the first year. 184 185 All three models were fit using maximum likelihood. Visual analysis of standardized 186 residuals, calculated by subtracting the predicted value from the observed and then dividing by 187 the estimated standard deviation, was used to indicate the quality of fit in the respective 188 model. Residuals in mean lengths were calculated for all methods, with additional residuals in 189 the indices of abundance also calculated for the MLCR model. 190 Comparison among models 191 192 Two sets quantities were used to facilitate comparison among the ASM, ML, MLCR, and 193 MLeffort. First, the absolute magnitude of the F estimates from the all four models was used. 194 Annual estimates of F from the ASM were obtained from assessment reports (SEDAR, 2013a, 195 2013b, 2013c, 2014a, 2014b, 2014c). Only estimates since the first year of length composition 196 data were considered here (Table 2). 197 Second, the annual F estimates were divided by F_{MSY} (relative F). The F/F_{MSY} ratio is often 198 relevant to management for classification of historical and current overfishing status. Proxy 199 reference points are often used instead of directly estimating F_{MSY} . In the benchmark 200 assessments, $F_{30\%}$, the fishing mortality rate that reduces the spawning potential ratio (SPR) to 201 0.3, was generally used as the proxy for F_{MSY} . The exception was in the case of ATL Cobia, where 202 F_{MSY} was reported for the ASM instead of a proxy (SEDAR, 2013c).

203	The calculation of the value of the proxy reference point should be consistent with the
204	assumptions of the method used to estimate F. As a result, two separate calculations of
205	spawning potential ratio (SPR) were used. For the ASM, the value of $F_{30\%}$ was obtained from the
206	assessment documents, while for the mean length-based methods, a separate value was
207	calculated for $F_{30\%}$ assuming knife-edge selectivity and constant <u>M</u> with age (Supplementary
208	Materials B). Values of $F_{30\%}$ were identical for ML, MLCR, and MLeffort because the selectivity
209	and <i>M</i> assumptions among them were identical.
210	To evaluate the synchrony of relative <i>F</i> among models, the proportion of years in which
211	overfishing is estimated to occur was calculated for four time periods: (1) pre-1995
212	(approximately the first half of the time series for the six stocks), (2) post-1995 (approximately
213	the second half of the time series), (3) the last five years, and (4) the terminal year of the time
214	series.
215	All analyses were performed in the R statistical environment using the MLZ package,
216	which is publicly available on the CRAN repository (R Core Team, 2017; Huynh, 2018).
217	
218	Results
219	For most stocks analyzed here, all methods generally indicated high mortality in the
220	1980-1990s followed by a reduction in mortality since then (Figure 2). For all six stocks, the four
221	models agreed in the overfishing status in the terminal year of the time series, i.e., $F/F_{MSY} > 1$
222	for GOM greater amberjack and $F/F_{MSY} < 1$ for the other five stocks (Figures 3-4).
223	

224 GOM greater amberjack

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225	There was strong agreement in the mortality estimates over time both in terms of trend
226	and magnitude (Figure 2a). Both the ASM and MLeffort models showed an increase in F from
227	1981 – 1993 followed by a gradual decrease from 1993 – 2012, with higher inter-annual
228	variability in <i>F</i> from MLeffort. Both models suggested very similar declines in mortality. The ML
229	and MLCR models showed two changes in mortality, an initial increase to an extended plateau
230	in mortality during the 1990s, corresponding to the time period surrounding the peak in the
231	ASM and MLeffort models, followed by a reduction in the 2000s. The <i>F</i> from ML and MLCR
232	during the 1990s were higher compared to estimates from the ASM.
233	Further, all models showed that overfishing was occurring in 2012, the terminal year of
234	the time series (Figure 3a). The magnitudes of relative F, i.e., F/F_{MSY} , over time were very similar
235	among the four models, with a very large relative <i>F</i> in the late 1980s and 1990s coinciding with
236	large observed catches (SEDAR, 2014a). Although a reduction in relative F followed, overfishing
237	was still occurring in 2012. Additionally, the four models generally agreed on the extent of
238	overfishing within the four time periods (Figure 4). While a lower proportion of overfishing
239	years was inferred in the most recent 5 years for the MLeffort model compared to the other
240	three models, this appeared to be a result of the high inter-annual variability in relative <i>F</i> .
241	
242	GOM Spanish mackerel
243	The ASM, ML, and MLCR models all showed a general reduction in mortality over time,

although the trends and timing differ (Figure 2b). The MLeffort model did not converge. The
ASM showed relatively high *F* in the 1980s and early 1990s followed by a gradual reduction in *F*afterwards. The reduction started in the late-1990s coincident with the gillnet ban in Florida,

247	although mortality from all sectors (commercial, recreational, and bycatch) has since reduced
248	(SEDAR, 2013b). The trend from the ML model is markedly different compared to the ASM and
249	MLCR. Two changes in mortality were indicated, with a decrease in mortality to a very low level
250	during the early 1990s from the initial mortality rate. This was caused by the large increase in
251	mean length from 1990-1995 (Figure 5b). Afterwards, a modest increase to an intermediate
252	mortality rate until the present time was estimated. The trends in the index, however, did not
253	support two changes in mortality (Figure 5b). Thus, only one change in mortality, a modest
254	decrease over the time series, was inferred in the MLCR model (Figure 2b).
255	Compared to the ML and MLCR models, the ASM showed more contrast in relative F,
256	with overfishing occurring in eight out of 14 years (57%) in the pre-1995 period (Figure 4). The
257	ML and MLCR models showed that overfishing has not occurred (Figure 3b). All three models
258	agreed that overfishing has not occurred post-1995.
259	
260	GOM cobia

All four models indicated a reduction in mortality since the 1990s (Figure 2c). The ASM showed an initial upward ramp in mortality followed by a gradual decrease after 1990. The MLeffort model showed a large decrease prior to 1986-1990 (effort data were not available prior to 1986), but after 1990, the mortality trend closely mimicked that inferred in the ASM in magnitude over time. The ML and MLCR models both estimated two changes in mortality, with a temporary decrease in the late-1990s followed by a modest increase to a mortality rate that is less than the initial estimated mortality rate. This pattern was inferred from the synchronous

268	increase and decrease in the mean length and index in the late-1990s (Figure 5c). The ML and
269	MLCR models estimate much higher <i>F</i> than the other two models (Figure 2c).
270	The relative <i>F</i> in MLeffort was lower over time than in the other three models. Pre-1995,
271	an increase and decrease in relative <i>F</i> corresponded to overfishing in one out of nine years
272	(11%) in the MLeffort model, but seven out of 16 years (44%) in the ASM (Figure 4). During the
273	same time period, the ML and MLCR estimated a plateau in mortality which indicated
274	overfishing in all included years. Post-1995, overfishing has not occurred based on all four
275	models (Figure 3c).
276	
277	ATL cobia
278	Differing trends in mortality were inferred among the four models (Figure 2d). While
279	there were trends in the mean length over time, the ML model indicated zero changes in
280	mortality based on AIC. On the other hand, the MLCR model indicated a decrease in mortality,
281	largely based on the increase in the index after 1995 (Figure 5d). The MLeffort model showed a
282	gradual decrease in mortality over time. The mean length-based models estimate lower F than
283	the ASM in recent years, although there is high inter-annual variability in <i>F</i> estimates in the
284	latter without a clear trend over time. Based on the relative F from all four models, overfishing
285	has not occurred (Figures 3d and 4).
286	
287	GOM king mackerel
288	Differing trends in mortality were estimated among the models (Figure 2e). The stability
289	in mean lengths over time resulted in estimates of constant F over the entire time series from

290	the ML and MLCR models. The trend in <i>F</i> in the MLeffort model was relatively flat as well.
291	Fishing mortality was much higher in the ASM than in the mean length models from the 1980s
292	to the mid-2000s, although the difference decreased with a pronounced drop in <i>F</i> in the ASM
293	the late 2000s.
294	The ASM showed that overfishing was occurring over much of the pre-1995 period,
295	contrary to the other three models which showed no overfishing in the same time period
296	(Figure 3e). In the early part of the post-1995 period, the ASM showed that overfishing was
297	occurring (20-40% of years post-1995) until mortality was reduced shortly after 2000. The
298	mean length models indicated no historical overfishing.
299	
300	ATL king mackerel
301	The <i>F</i> trend in the ASM is relatively flat with a slight decrease in the recent years (Figure
302	2f). The ML and MLeffort models produce relatively stable <i>F</i> over time as well, although the
303	magnitude is higher in these models than in the ASM. The MLCR model produces a pronounced
304	step-wise increase in F in the mid-1990s due to the pronounced decrease in the index at this
305	time (Figure 5f).
306	The ASM models indicated that overfishing occurred in 29% (five out of 17 years) of pre-
307	1995 years (Figure 4). The mean length models here also did not indicate overfishing in the
308	stock history (Figure 3f).

310 Residual analysis

311	For each of the mean length-based models, residuals were analyzed visually to examine
312	goodness of fit (Supplementary Materials C). The model selection procedure with the ML model
313	generally selected the model which minimized residual trends except in the case of ATL cobia
314	(Figure C.1). In the MLCR model, an extensive trend of positive and negative residuals of the
315	mean lengths and index, respectively, was observed over time for GOM Spanish mackerel
316	(Figure C.2). Similarly, negatively correlated residuals were also present for ATL king mackerel in
317	the most recent years of the analysis. In the MLeffort model, there were trends in residuals
318	over the course of the entire time series for both GOM and ATL king mackerel (Figure C.3).
319	
320	Discussion
321	The historical mortality pattern observed here, high mortality in the 1980-1990s
322	followed by a reduction, is common for southeastern U.S. stocks that were targeted by fisheries
323	that were unregulated during these decades (Siegfried <i>et al.</i> , 2016). Although differences in the
324	magnitude of F/F_{MSY} varied for the terminal year of the analyses, which potentially affect the
325	management advice, there was agreement in the stock perception, i.e., overfishing versus not
326	overfishing, among the mean length-based models and the age-structured models for the six
327	case studies.
328	For data-limited situations, there is potential to use mean length-based to explore
329	historical changes in mortality over time, with results likely to be consistent with what might be
330	obtained from an age-structured model, despite using only a subset of the data in the former.
331	The ML and MLCR models provide a series of historical mortality rates, although it is recognized

that the changes in mortality over time will be coarser than in models with year-specific

333	mortality rates. This is due to the stepwise, time stanza structure of the ML and MLCR models.
334	The MLeffort model can provide year-specific mortality rates, and <i>F</i> estimates could be
335	smoothed post-hoc to describe the trend over time if there is high inter-annual variability.
336	
337	Trends in recruitment to the recreational sector
338	The assumption of constant recruitment to length L_c was likely violated for GOM Spanish
339	mackerel due to the changes in the dynamics of the shrimp fleet over time which affected
340	bycatch of smaller animals. In the ASM assessment, the shrimp fleet was the highest source of
341	fishing mortality (with 100% discard mortality assumed) until the late-1990s, when effort
342	subsequently decreased (SEDAR 2014b; Figure 6). This reduction increased survival and
343	recruitment to size L_c (39 cm in this study), which could have caused the decrease in the
344	observed mean length from the recreational fleet (Figure 5b).
345	For the MLeffort model, non-convergence for GOM Spanish mackerel was caused by the
	, , , ,
346	data conflict where the recreational effort was estimated to have decreased (Figure 6), while
346 347	data conflict where the recreational effort was estimated to have decreased (Figure 6), while the mean length also decreased. An increase would have been expected based on the observed
346 347 348	data conflict where the recreational effort was estimated to have decreased (Figure 6), while the mean length also decreased. An increase would have been expected based on the observed effort trend alone. Concurrently, the gradual increase in the index of abundance with the
346 347 348 349	data conflict where the recreational effort was estimated to have decreased (Figure 6), while the mean length also decreased. An increase would have been expected based on the observed effort trend alone. Concurrently, the gradual increase in the index of abundance with the decrease in mean length since mid-1990s would support the hypothesis of increased
346 347 348 349 350	data conflict where the recreational effort was estimated to have decreased (Figure 6), while the mean length also decreased. An increase would have been expected based on the observed effort trend alone. Concurrently, the gradual increase in the index of abundance with the decrease in mean length since mid-1990s would support the hypothesis of increased recruitment to the recreational fishery (Huynh <i>et al.</i> , 2017). Fewer change points was inferred
346 347 348 349 350 351	data conflict where the recreational effort was estimated to have decreased (Figure 6), while the mean length also decreased. An increase would have been expected based on the observed effort trend alone. Concurrently, the gradual increase in the index of abundance with the decrease in mean length since mid-1990s would support the hypothesis of increased recruitment to the recreational fishery (Huynh <i>et al.</i> , 2017). Fewer change points was inferred with the MLCR model compared to the ML model to avoid overfitting spurious trends in the
 346 347 348 349 350 351 352 	data conflict where the recreational effort was estimated to have decreased (Figure 6), while the mean length also decreased. An increase would have been expected based on the observed effort trend alone. Concurrently, the gradual increase in the index of abundance with the decrease in mean length since mid-1990s would support the hypothesis of increased recruitment to the recreational fishery (Huynh <i>et al.</i> , 2017). Fewer change points was inferred with the MLCR model compared to the ML model to avoid overfitting spurious trends in the mean length due to hypothesized changes in recruitment. The observed trends in the paired
 346 347 348 349 350 351 352 353 	data conflict where the recreational effort was estimated to have decreased (Figure 6), while the mean length also decreased. An increase would have been expected based on the observed effort trend alone. Concurrently, the gradual increase in the index of abundance with the decrease in mean length since mid-1990s would support the hypothesis of increased recruitment to the recreational fishery (Huynh <i>et al.</i> , 2017). Fewer change points was inferred with the MLCR model compared to the ML model to avoid overfitting spurious trends in the mean length due to hypothesized changes in recruitment. The observed trends in the paired residuals of mean length and the abundance index in the MLCR model were also consistent

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hypothesis since it estimated an increase in abundance of animals recruiting to the 39-cmlength class during the same time period (Figure 6b).

357 While trends in mortality are affected by factors external to the recreational sector, the 358 analysis of residuals in the MLCR model and non-convergence of the MLeffort model allowed us 359 to diagnose issues in the application of the mean length-based models for GOM Spanish 360 mackerel without external information. With the ASM, we can corroborate that bycatch 361 mortality may have been the primary driver of the historical stock dynamics. In isolation, the 362 length composition from the recreational fleet may not provide sufficient information on the 363 stock history, i.e., reductions in F. This is evident in the contrasting trends in mortality in the ML 364 model and ASM since the mid-1990s (Figure 2b). Overall, the general presence of large animals 365 in the length composition relative to L_{∞} would indicate that the GOM Spanish mackerel stock is 366 in generally good shape (Figure 1b).

367 The impact of bycatch mortality from the shrimp fleet would not be as noticeable in the 368 length-based analysis for GOM and ATL king mackerel, since shrimp bycatch is a minor source 369 of mortality relative to the recreational fleet. Nevertheless, for ATL king mackerel, large 370 residuals in the mean lengths and index were observed in the most recent years of the MLCR 371 models (Figure C.2). The increasing mean length and decreasing index since 2007 would be 372 consistent with decreased recruitment (animals of length L_c). The ASM for ATL king mackerel 373 estimated a decreasing trend in recruitment of age-0 animals since 2003. The qualitative 374 information about recruitment trends from the MLCR model are further supported by the 375 reduced recruitment estimates from the ASM after accounting for the time lag from age 0 to 376 the age of full selection to the recreational fishery (SEDAR, 2014c).

Management actions may need to be more precautious when presented with information about recent reduced recruitment. Overall, the GOM Spanish mackerel and ATL king mackerel case studies highlight the benefit of indices of recruitment in a length-based analysis. Such information can be incorporated into the analysis to account for variable recruitment (Gedamke *et al.*, 2008).

382 These two case studies highlight the fact that age-structured models should not be 383 replaced by simpler methods without cautious considerations. Age-structured models provide 384 more modeling options to accommodate multiple drivers of fishing mortality and productivity, 385 as well as more diagnostic tools to evaluate the quality of the assessment. Nevertheless, in 386 data-rich scenarios, the mean length-based methods can be used as a diagnostic to evaluate 387 and explain how the mean length has changed over time (through fishing mortality or other 388 causes) (e.g., SEDAR, 2013c). When there are conflicting results, diagnostic procedures can 389 provide additional insight on the causes of model or data conflict. Models which incorporate 390 multiple data types are advantageous, because the agreement (or lack of) between data types 391 can be evaluated to determine whether the chosen model is appropriate for the stock of 392 interest.

393

394 Life history parameters

The mean length-based models and their corresponding reference point proxies require simpler life history assumptions than the ASM. With age-structured models, growth incorporates variability in size at age and parameters may be estimable within the model (Francis, 2016). In contrast, growth is fixed and assumed to be deterministic with age in the

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399	mean-length based models, although simulations have suggested robustness of the mean
400	length-based models to this assumption (Then <i>et al.,</i> 2015; Huynh <i>et al.,</i> 2018).
401	In many ASMs, including those presented here, natural mortality was parameterized to
402	asymptotically decline with age. Age-varying <i>M</i> would violate the assumption of age-constant <i>Z</i> ,
403	especially for the youngest age classes which may experience much higher <i>M</i> than older ones
404	(Lorenzen, 1996). If selectivity were restricted to the oldest age classes, then the violation of
405	this assumption could be minimal as <i>M</i> is more similar for these ages. Simulation studies can be
406	used to evaluate the bias, if any, in mortality estimates from the mean length methods arising
407	from age-varying <i>M</i> .
408	Errors in growth and natural mortality have similar effects on mortality estimates in
409	both length-based methods and age-structured models. An overestimate of asymptotic length
410	leads to the perception of an overly truncated size composition and smaller mean length,
411	resulting in an overestimate of fishing mortality. Since length data contain information on total
412	mortality, an overestimate of natural mortality would result in an underestimate of fishing
413	mortality. Simulation studies and sensitivity analyses have largely confirmed these trends (Clark
414	1999; Hordyk <i>et al</i> ., 2015; Huynh <i>et al.,</i> 2017). However, further work is needed to evaluate
415	whether mortality estimates from a length-based methods are more sensitive to errors than
416	those from age-structured models.
417	In data-limited situations, uncertainty in mortality estimates can be evaluated in several
418	ways. While confidence intervals can be obtained from the Hessian matrix of maximum
419	likelihood models, the intervals are conditional on the assumptions of the model, including that
420	life history parameters are known correctly. Alternatively, Monte Carlo sampling of life history

421 parameters from parametric distributions (Nadon, 2017; Huynh et al., 2017) and sensitivity 422 analyses of alternative parameter values (Gedamke and Hoenig, 2006) have been employed to 423 characterize uncertainty of mortality estimates. Bayesian methods that employ life history 424 priors can also be used to make probabilistic statements regarding the mortality estimate and 425 overfishing status (Harford *et al.*, 2015). Such methods can be employed in the mean length 426 models here to calculate confidence intervals or posterior intervals in F and F/F_{MSY} . 427 Notably, confidence intervals and posterior intervals are conditional on the assumptions 428 of the model. The length-based methods used here assume constant recruitment, but only the 429 MLCR model allows for evaluation of this assumption (Huynh et al., 2017). Even for the MLCR 430 model, confidence intervals for mortality estimates would not include the effect of failure of 431 this assumption when in fact there is a trend in recruitment over time.

432

433 Selectivity and retention behavior

Complex fishing behavior can be modeled in age-structured models, albeit at the cost of 434 435 estimating many, sometimes confounding, selectivity parameters. Multiple fishing fleets with 436 disparate selectivity patterns and fishing behaviors are typically modeled separately, and there 437 may be enough information to model logistic and dome-shaped selectivity functions. Length 438 composition of discarded and retained catch allow for estimation of the vulnerability and 439 retention functions, the product of which would be the effective selectivity of the gear for 440 retained catch. Finally, changes in size regulations can be modeled with time-varying features 441 of the ASM (Methot and Wetzel, 2013). For the mean length models, knife-edge selectivity is

442	assumed at length L_c . Thus, the analysis uses a subset of the length composition data so that
443	only animals assumed to be fully selected are included in the calculation of the mean length.
444	Application of the data-limited models should consider if changes in mean length
445	occurred due a change in retention behavior as opposed to a change in mortality. We chose
446	values of L_c that were larger than any implemented minimum retention size for the stocks in
447	this study. In this way, all lengths larger than L_c would have the same presumed selectivity to
448	minimize the effect of the management regulations. On the other hand, to the extent that
449	there has been variable fishing over time on fish smaller than L_c , the assumption of constant
450	recruitment is violated by being confounded with fishing mortality. Changes in bag limits could
451	alter discard and retention behavior; for example, the implementation of a bag limit may
452	increase discarding of smaller animals in favor of larger ones. To account for this, one would
453	need to evaluate whether there were significant changes in the length distribution of retained
454	catch once those regulations were implemented.
455	The age-structured assessments estimated dome-shaped selectivity for the recreational
456	fleet for three of the six stocks, these being GOM greater amberjack and both GOM and ATL
457	stocks of king mackerel. This contrasts with the knife-edge selectivity assumption made with
458	the mean length-based models. If the selectivity of the fleets were dome-shaped, then it is
459	presumed that mortality would be overestimated by the length-based models. However, there
460	was no consistent discrepancy for these three stocks in this study. Mortality estimates for GOM
461	greater amberjack did not substantially differ between those in the ASM and from mean-length
462	models. On the other hand, mortality estimates from mean length models were higher than
463	those in the ASM for ATL king mackerel but lower for GOM king mackerel. Certainly the degree

464	of doming could affect the magnitude of the discrepancy. High <i>F</i> , such as those seen in GOM
465	greater amberjack, would decrease the influence of dome selectivity in the bias of mortality
466	estimates, since fewer animals would survive to the larger size classes affected by the dome
467	selectivity.
468	
469	Uncertainty in catch and effort
470	In any assessment, the quality of the data and their representativeness to the
471	underlying population dynamics should be evaluated. For example, since discard estimates had
472	generally large coefficients of variation (Siegfried et al., 2016). In data-limited situations, discard
473	data may not be available. However, in a management context, it is important to consider the
474	magnitude of discard mortality and whether it can be reduced. As another example, expert
475	judgment is needed to decide if the catch per unit effort (CPUE) can serve as index of
476	abundance. Spanish mackerel and cobia are reported to be opportunistically caught by the
477	recreational fleet, resulting in high percentages of zero catch (Bryan and Saul, 2012). This may
478	degrade the quality of the CPUE as an index of abundance. Such uncertainties can be addressed
479	through improved data collection programs. In this case study, continued investment in fishery-
480	independent surveys will produce a long time series sufficient for inferring changes in mortality
481	over time.
482	One must obtain length compositions from multiple years for application of the mean
483	length models used in this study. In this study, the recreational sector data were obtained from
484	MRFSS (Marine Recreational Fisheries Statistics Survey) and its successor MRIP (Marine
485	Recreational Information Program), which are design-based sampling programs for the charter

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and private boat fleet, and from SRHS (Southeast Region Headboat Survey), which strives to be

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487 a census of all headboats in the region. We followed the decision of the assessment team in 488 regards to combining or separating the data from these two programs. 489 Data from multiple fleets or sectors could be combined if the fleets are believed to 490 operate similarly temporally and spatially. Otherwise, mortality estimates can be confounded 491 by the contrasting fishing effort and selectivity of the different fleets. For example, a 492 multimodal length composition that arises from using two very different gears would not be 493 easily accommodated by the assumptions of the mean length models. Uncertainty in the 494 composition data could be evaluated by comparing the length data from the different gear 495 sectors separately. Differences in mortality estimates would be attributable to, among other 496 factors, disparate selectivity patterns and sampling among gears. In these cases, mortality 497 estimates are likely to have low precision (Pons et al., 2019). 498 The MLeffort model provides year-specific mortality rates, but the fit to the mean 499 lengths varies from good in the case of GOM greater amberjack to poor, as in the case of GOM 500 king mackerel (Figure 3). For multispecies fisheries, nominal effort such as days fished may not be an indicator of targeted effort due to switches in targeting. As effort in the recreational 501 502 fisheries examined here is not allocated on a species-specific basis, methods such as the so-503 called "guild" approach, where a subset of fishing trips that are believed to have targeted the 504 stock of interest are identified based on catch of associated species, are used to develop indices 505 for these fleets (e.g., SEDAR 2011, Smith et al., 2015). Poor estimates of recreational effort 506 could have contributed to poor performance of the MLeffort model for GOM and ATL king

507 mackerel. Formal statistical tests of model residuals, e.g., tests of normality or runs test, could
508 be used to accept or reject a model.

509

510 Conclusion

511 The goal of this paper was to evaluate whether length-based methods could perform 512 reasonably well and indicate when there are problems in the analysis. We did not intend to 513 evaluate whether length-based methods could replace age-structured models. Overall, mean 514 length-based methods can provide similar results, i.e., mortality trends and classifying 515 overfishing status, as those of age-structured assessments. Such case studies have important ramifications for fishery managers who manage many stocks. Simple methods can be used to 516 517 determine the overfishing status for stocks that are being assessed for the first time. If 518 managers desire to use length-based methods, then such analyses can prompt allocation of 519 more resources for data collection to improve mortality estimates. As a large majority of stocks 520 worldwide do not and will not likely have fully age-structured assessments in the near future, 521 fishery managers can use studies such as this in elucidating likely results from mean length-522 based mortality estimators.

523

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- 531 References
- Bentley, N. 2015. Data and time poverty in fisheries estimation: potential approaches and
 solutions. ICES Journal of Marine Science, 72: 186-193.
- Beverton, R. J. H., and Holt, S. J. 1956. A review of methods for estimating mortality rates in fish
 populations, with special reference to sources of bias in catch sampling. Rapports et Procès verbaux des Reunions, Conséil International Pour L'Exploration de la Mer, 140: 67-83.
- Bryan, M., and Saul, S. 2012. Recreational indices for cobia and Spanish mackerel in the Gulf of
 Mexico. SEDAR28-DW-22. SEDAR, North Charleston, South Carolina. 44 pages.
- Burnham, K. P., and Anderson, D. R. 2002. Model selection and multimodel inference: a
 practical information-theoretic approach, 2nd edition. Springer-Verlag, New York.
- 541 Clark, W. G. 1999. Effects of an erroneous natural mortality rate on a simple age-structured
 542 stock assessment. Canadian Journal of Fisheries and Aquatic Science, 56: 1721-1731.
- 543 Chrysafi, A., and Kuparinen, A. 2016. Assessing abundance of populations with limited data:
 544 Lessons learned from data-poor fisheries stock assessment. Environmental Reviews, 24: 25545 38.
- 546 Dichmont, C. M., Deng, R. A., Punt, A. E., Brodziak, J., Chang, Y.-J., Cope, J. M., Ianelli, J. N., *et al.*547 2016. A review of stock assessment packages in the United States. Fisheries Research, 183:
 548 447-460.
- 549 Dick, E. J., and MacCall, A. D. 2011. Depletion-Based Stock Reduction Analysis: A catch-based
 550 method for determining sustainable yields for data-poor fish stocks. Fisheries Research,
 551 110: 331-341.
- Francis, R. I. C. C. 2016. Growth in age-structured stock assessment models. Fisheries Research,
 180: 77-86.
- Gedamke, T., and Hoenig, J. M. 2006. Estimating mortality from mean length data in
 nonequilibrium situations, with application to the assessment of Goosefish. Transactions of
 the American Fisheries Society, 135: 476–487.
- Gedamke, T., Hoenig, J. M., DuPaul, W., and Music, J. A. 2008. Total Mortality Rates of the
 Barndoor Skate, *Dipturus laevis*, from the Gulf of Maine and Georges Bank, United States,
 1963-2005. Fisheries Research, 89: 17-25.

560 Harford, W., Bryan, M, and Babcock, E.A. 2015. Probabilistic assessment of fishery status using 561 data-limited methods. SEDAR46-DW-03. SEDAR, North Charleston, SC. 5 pp. 562 Hoenig, J. M. 1983. Empirical use of longevity data to estimate mortality rates. Fishery Bulletin, 563 82:898-903. 564 Hordyk, A., Ono, K., Valencia, S., Loneragan, N., and Prince, J. 2015. A novel length-based 565 empirical estimation method of spawning potential ratio (SPR), and tests of its performance, 566 for small-scale, data-poor fisheries. ICES Journal of Marine Science, 72: 217-231. 567 Hordyk, A. R., Ono, K., Prince, J. D., and Walters, C. J. 2016. A simple length-structured model 568 based on life history ratios and incorporating size-dependent selectivity: application to 569 spawning potential ratios for data-poor stocks. Canadian Journal of Fisheries and Aquatic 570 Science, 73: 1787-1799. 571 Huynh, Q.C. 2016. Estimating total mortality rates and calculating overfishing limits from length 572 observations for six U.S. Caribbean stocks. SEDAR46-RW-01. SEDAR, North Charleston, SC. 573 19 pp. 574 Huynh, Q. C. 2018. MLZ: Mean Length-based Estimators of Mortality. R package version 0.1.0. 575 Huynh, Q. C., Beckensteiner, J., Carleton, L. M., Marcek, B. J., Nepal KC, V., Peterson, C. P., 576 Wood, M. A., & Hoenig, J. M. 2018. Comparative performance of three length-based 577 mortality estimators. Marine and Coastal Fisheries 10:298-313. 578 Huynh, Q. C., Gedamke, T., Porch, C. E., Hoenig, J. M., Walter, J. F., Bryan, M., and Brodziak, J. 579 2017. Estimating total mortality rates of mutton snapper from mean lengths and aggregate 580 catch rates in a non-equilibrium situation. Transactions of the American Fisheries Society, 581 146: 803-815. 582 ICES. 2017. Report of the Benchmark Workshop on North Sea Stocks (WKNSEA), 14–18 March 583 2016, Copenhagen, Denmark. ICES CM 2016/ACOM:37. 698 pp. 584 Kokkalis, A., Thygesen, U. H., Nielsen, A., and Andersen, K. H. 2015. Limits to the reliability of 585 size-based fishing status estimation for data-poor stocks. Fisheries Research, 171: 4-11. 586 Kokkalis, A., Eikeset, A. M., Thygesen, U. H., Steingrund, P., and Andersen, K. H. 2016. 587 Estimating uncertainty of data limited stock assessments. ICES Journal of Marine Science, 588 74: 69-77. 589 Linton, B. 2012. Methods for estimating shrimp bycatch of Gulf of Mexico Spanish mackerel and 590 cobia. SEDAR28-DW-06. SEDAR, North Charleston, South Carolina. 14 pages. 591 Lombardi, L. 2014. Growth models for king mackerel from the south Atlantic and Gulf of 592 Mexico. SEDAR38-AW-01. 62 pages.

Lorenzen, K. 1996. The relationship between body weight and natural mortality in juvenile and
adult fish: a comparison of natural ecosystems and aquaculture. Journal of Fish Biology, 49:
627-642.

596 Methot, Jr., R. D., and Wetzel, C. R. 2013. Stock synthesis: A biological and statistical framework 597 for fish stock assessment and fishery management. Fisheries Research, 142: 86-99.

Murie, D. J., and Parkyn, D. C. 2008. Age, Growth and Sex Maturity of Greater Amberjack
(*Seriola dumerili*) in the Gulf of Mexico. SEDAR33-RD-13. SEDAR, North Charleston, South
Carolina. 41 pages.

Nadon, M.O. 2017. Stock assessment of the coral reef fishes of Hawaii, 2016. U.S. Department
 719 of Commerce, NOAA Technical Memorandum, NOAA-TM-NMFS-PIFSC-60: 212.

Pons, M., Kell, L., Rudd, M.B., Cope, J.M., and Fredou, F.L. 2019. Performance of length-based
data-limited methods in a multi-fleet context: application to small tunas, mackerels, and
bonitos in the Atlantic Ocean. ICES Journal of Marine Science, 76: 960-973.

R Core Team. 2017. R: A Language and Environment for Statistical Computing. R Foundation for
 Statistical Computing, Vienna, Austria.

Sagarese, S. R., Walter III, J. F., Bryan, M. D, and Carruthers, T. R. 2016. Evaluating Methods for
Setting Catch Limits for Gag Grouper: Data-Rich versus Data-Limited. In: T. J. Quinn II, J. L.
Armstrong, M. R. Baker, J. D. Heifetz, and D. Witherell (eds.), Assessing and Managing DataLimited Fish Stocks. Alaska Sea Grant, University of Alaska Fairbanks.

SEDAR. 2011. SEDAR 9: Stock Assessment Update Report, Gulf of Mexico Greater Amberjack.
 SEDAR, North Charleston, South Carolina.

SEDAR. 2013a. SEDAR 28: Gulf of Mexico Cobia stock assessment report. SEDAR, North
 Charleston, South Carolina.

616 SEDAR. 2013b. SEDAR 28: Gulf of Mexico Spanish Mackerel stock assessment report. SEDAR,
 617 North Charleston, South Carolina.

618 SEDAR. 2013c. SEDAR 28: South Atlantic Cobia stock assessment report. SEDAR, North
619 Charleston, South Carolina.

SEDAR. 2014a. SEDAR 33: Gulf of Mexico Greater Amberjack stock assessment report. SEDAR,
 North Charleston, South Carolina.

SEDAR. 2014b. SEDAR 38: Gulf of Mexico King Mackerel stock assessment report. SEDAR, North
 Charleston, South Carolina.

SEDAR. 2014c. SEDAR 38: South Atlantic King Mackerel stock assessment report. SEDAR, North
 Charleston, South Carolina.

Siegfried, K. I., Williams, E. H., Shertzer, K. W., and Coggins, L. G. 2016. Improving stock
assessments through data prioritization. Canadian Journal of Fisheries and Aquatic Science,
73: 1703-1711.

Smith, M. W., Goethel, D., Rios, A., and Isley, J. 2015. Standardized Catch Rate Indices for Gulf
 of Mexico Gray Triggerfish (*Balistes capriscus*) landed during 1986-2013 by the Headboat
 Fishery. SEDAR43-WP-06. SEDAR, North Charleston, SC. 18 pp.

Then, A. Y., Hoenig, J. M., Gedamke, T., and Ault, J. S. 2015. Comparison of Two Length-Based
Estimators of Total Mortality: a Simulation Approach. Transactions of the American
Fisheries Society, 144: 1206-1219.

Then, A. Y., Hoenig, J. M., and Huynh, Q. C. 2018. Estimating fishing and natural mortality rates,
and catchability coefficient, from a series of observations on mean length and fishing effort.
ICES Journal of Marine Science, 75: 610:620.

638 Williams, E. H., and Shertzer, K. W. 2015. Technical documentation of the Beaufort Assessment

639 Model (BAM). NOAA Technical Memorandum NMFS-SEFSC-671, U.S. Department of640 Commerce. 43 pages.

641 Tables

- 642 Table 1. Summary of size regulations from the recreational fishery (in terms of fork length).
- 643 Only years preceding the year of the assessment are considered. Size regulations were obtained
- 644 from the assessment documents, with citations in Table 2. Size regulations are published in
- 645 inches.

Stock	Minimum Legal	Years	
	Size Limit		
GOM greater amberjack	28 in (71.1 cm)	1990-2007	
	30 in (76.2 cm)	2008-2012	
GOM Spanish mackerel	12 in (30.5 cm)	1993-2011	
GOM & ATL cobia	33 in (83.8 cm)	1985-2011	
GOM & ATL king mackerel	12 in (30.5 cm)	1990-1991	
	20 in (50.8 cm)	1992-1999	
	24 in (61.0 cm)	2000-2012	

646

Table 2. Summary of assessment models and the length composition and index of abundance for the length-based mortality estimators. The Recreational fleet combines the data from both the Charter/Private and the Headboat fleets.

Stock	Assessment Model	Fleet for length	Length	Index time	Reference
		analyses	time series	series	
Gulf of Mexico greater amberjack	Stock Synthesis	Charter/Private	1981-2012	1986-2012	SEDAR (2014a)
Gulf of Mexico Spanish mackerel	Stock Synthesis	Recreational	1981-2011	1981-2011	SEDAR (2013b)
Gulf of Mexico cobia	Stock Synthesis	Recreational	1979-2011	1986-2011	SEDAR (2013a)
Atlantic cobia	Beaufort Assessment Model	Recreational	1982-2011	1985-2011	SEDAR (2013c)
Gulf of Mexico king mackerel	Stock Synthesis	Charter/Private	1985-2012	1986-2012	SEDAR (2014b)
Atlantic king mackerel	Stock Synthesis	Charter/Private	1978-2012	1980-2012	SEDAR (2014c)

Table 3. Life history parameters used in the analyses for the length-based mortality estimators. Parameters are defined in Table B.1 of the Supplementary Material.

Stock	\mathbf{L}_{∞}	K	t ₀	L _c	L _{mat}	α	b	t _{max}	Μ	Sources
	(cm)	(yr-1)	(yr)	(cm)	(cm)			(yr)	(yr-1)	
Gulf of Mexico greater	143.6	0.18	-0.95	77.5	90	7.0e-5	2.63	15	0.28	SEDAR (2014a);
amberjack										Murie and Parkyn (2008)
Gulf of Mexico Spanish	56.0	0.61	-0.50	39	31	1.5e-5	2.86	11	0.38	SEDAR (2013b)
mackerel										
Gulf of Mexico cobia	128.1	0.42	-0.53	88	70	9.6e-6	3.03	11	0.38	SEDAR (2013a)
Atlantic cobia	132.4	0.27	-0.47	95	70	2.0e-9	3.28	16	0.26	SEDAR (2013b)
Gulf of Mexico king	128.9	0.12	-4.08	80	58	7.3e-6	3.01	24	0.17	SEDAR (2014b);
mackerel										Lombardi (2014)
Atlantic king mackerel	121.1	0.15	-3.73	80	58	7.3e-6	3.01	26	0.16	SEDAR (2014c);
										Lombardi (2014)

Figure Captions

Figure 1. Summary length compositions summed across all available years of data for the six stocks for the mean length mortality estimators. Solid vertical line indicates L_c and dashed vertical line indicates L_{∞} .

Figure 2. Annual estimates of *F* from the four models (ASM = age-structured model, ML = mean length, MLCR = mean length with catch rate, MLeffort = mean length with effort). The MLeffort model did not converge for GOM Spanish mackerel. The ASM was the Beaufort Assessment Model for ATL Cobia and Stock Synthesis for all other stocks.

Figure 3. Annual estimates of F/F_{MSY} (relative F) from the four models. F_{MSY} was reported from the ASM for ATL Cobia while for all other methods, the F_{MSY} proxy is $F_{30\%}$. Separate calculations of $F_{30\%}$ were used for the ASM and mean length methods.

Figure 4. The proportion of years with overfishing as estimated with the four models within the respective time periods for the 6 stocks. The MLeffort model did not converge for GOM Spanish mackerel. For Pre-1995 and Post-1995, numbers indicate the number of years in the assessment for the respective time period.

Figure 5. Observed (connected points) and predicted mean lengths (colored lines) from the three length-based mortality estimators, and observed and predicted index for the MLCR model.

Figure 6. Upper: Estimates of relative effort for GOM Spanish mackerel from the recreational fleet, obtained as the ratio of the recreational catch and index of abundance, and the shrimp bycatch fleet, estimated as described in Linton (2012). Estimates are scaled so that the time series mean is one. Lower: Relative abundance at the 38 cm length bin (relative to the time series mean) estimated from the ASM. This length bin corresponds to the presumed length of recruitment (39 cm) to the recreational fleet in the mean length-based models. Increased recruitment to the recreational fleet from decreased shrimp bycatch mortality is hypothesized to decrease the mean length despite the decrease in recreational effort.



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Annual estimates of F from the four models (ASM = age-structured model, ML = mean length, MLCR = mean length with catch rate, MLeffort = mean length with effort). The MLeffort model did not converge for GOM Spanish mackerel. The ASM was the Beaufort Assessment Model for ATL Cobia and Stock Synthesis for all other stocks.



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Year

Figure 6. Upper: Estimates of relative effort for GOM Spanish mackerel from the recreational fleet, obtained as the ratio of the recreational catch and index of abundance, and the shrimp bycatch fleet, estimated as described in Linton (2012). Estimates are scaled so that the time series mean is one. Lower: Relative abundance at the 38 cm length bin (relative to the time series mean) estimated from the ASM. This length bin corresponds to the presumed length of recruitment (39 cm) to the recreational fleet in the mean length-based models. Increased recruitment to the recreational fleet from decreased shrimp bycatch mortality is hypothesized to decrease the mean length despite the decrease in recreational effort.