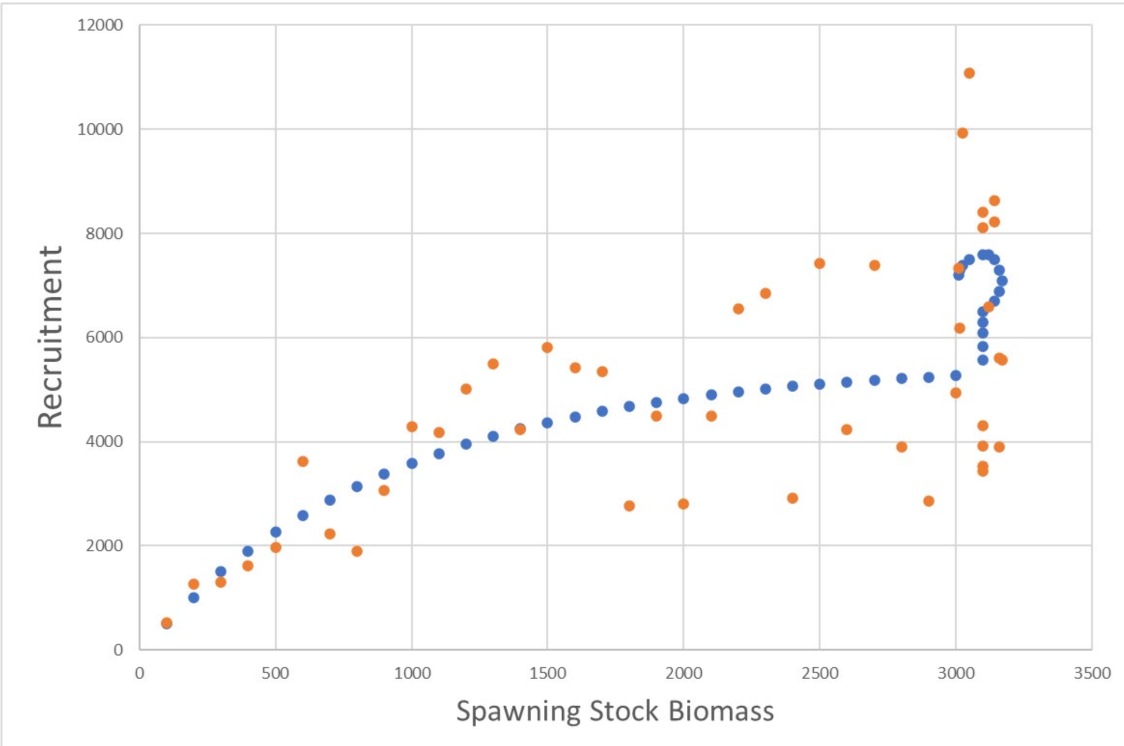
SSC Catch Level Projections Workgroup

Final Report



Provided to SSC April 2022
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Genny Nesslage, Fred Scharf, Erik Williams

The working group met on eight separate occasions: 1) Wednesday, September 1, 2021; 2) Tuesday, October 5, 2021; 3) Wednesday, November 3, 2021; 4) Monday, December 13, 2021; 5) Thursday, January 27, 2022; 6) Friday, February 25, 2022; 7) Monday, March 14, 2022; and 8) Wednesday, April 6, 2022.

Contents

Executive Summary

The Scientific and Statistical Committee (SSC) has recommended different approaches for projecting recruitment in catch level projections for South Atlantic stocks. In order to provide consistent advice, the SSC requested the formation of a working group to review the current peer reviewed literature, review past SSC decisions, and make recommendations on recruitment assumptions for projections providing catch advice. The workgroup met from Sept. 2021 to April 2022 to complete the four tasks laid out in the Scope of Work (Appendix 1).

Modeling and forecasting recruitment are fundamental to assessing the status of a stock and guiding management recommendations. There are several approaches to forecast recruitment: (1) functional stock-recruitment (SR) relationships (e.g., the Beverton-Holt and Ricker models); (2) sampling methods (i.e., drawing from past values estimated in the assessment); (3) empirical dynamic modeling; (4) time-series analysis; and (5) incorporation of environmental effects. Van Beveren et al (2021) undertook a comprehensive simulation study to evaluate the forecast skill of a wide range of recruitment forecasting methods under various circumstances. However, the authors could not identify the single best method to forecast recruitment. Thus, the workgroup used the work of Van Beveren et al (2021) and basic statistical principles to guide many of their recommendations for short-term and long-term, catch level projections.

<u>Recommendations for Short-term Forecasts for ABC Determination</u>

1. Short-term forecasts for ABC determination should be limited to 5 years (post terminal year of the assessment, including interim years before management has taken effect).
2. Short-term forecasts should use recent mean recruitment. Recent mean recruitment with autocorrelated deviates resulted in no bias in the short-term projections (Van Beveren et al 2021); however, recent mean recruitment was not defined. Thus, the working group recommends recent mean recruitment be defined for each species only for short-term, catch level projections.

The Van Beveren et al (2021) paper and recent literature also allow for using other traditional methods for short-term projections. If an assessment has a well-defined stock-recruitment curve or another method for projecting recruitment, then short-term projections are likely sufficient for management use.

<u>Recommendations for Long-term Forecasts for Determining Rebuilding and Benchmarks</u>

We recommend the following hierarchy be used for modeling long-term forecasts, with the primary purposes being benchmark determination and rebuilding schedules.

Type A: Forecast using average recruitment and historic variability.
Type B1: Forecast using stock-recruit relationship and historic variability.
Type B2: Forecast using time series properties or environmental correlates.
Type C: Forecast using S-R model, with time-series and/or environmental correlates included.

In addition to the recommendations for the catch level projections and the longer-term rebuilding and benchmark projections, the working group also recommended some additional information to be included in stock assessment reports, as well as future research recommendations. Given all the uncertainties, it is imperative that scientists provide managers with an accurate reflection of the unknowns, assumptions, and uncertainties in fish population forecasts.

Background and Introduction

The number of recruits, or young, entering fish populations each year is dependent upon a number of interacting factors. Identification of these factors has driven process-based studies in fisheries science for more than a century. Beyond the adult population biomass, factors that influence the feeding success, survival, and transport of early larval stages have been hypothesized to cause a large degree of interannual variation in recruitment. Major paradigms have included the ‘critical period’, ‘match-mismatch’, and ‘stable ocean’ hypotheses, each centered on early larval feeding success and its effects on survival. The influence of oceanographic processes, particularly through the transport and/or retention of larvae in favorable habitats, was also demonstrated and led to organized frameworks for research such as the ‘aberrant drift’ and ‘member-vagrant’ hypotheses. Still, the ability to identify causal mechanisms for recruitment variation, and importantly, the ability to forecast recruitment accurately have remained elusive.

Recruitment can be estimated directly through fishery-independent surveys of pre-recruit life stages; however, comprehensive and validated pre-recruit surveys are expensive, and as such, are rare, particularly in the US South Atlantic region. Therefore, other forms of data are often used to inform estimates of recruitment over time in fishery stock assessments. However, both the quality and quantity of those data impact the model estimates of recruitment, creating potential biases and high uncertainty.

In the US South Atlantic, many federally managed stocks have generated estimates of recruitment during the most recent decade that are well below long-term averages. Declining recruitment could be the result of several biological processes, most notably recruitment overfishing caused by a reduction in spawning stock biomass. If historic exploitation rates have reduced adult stock biomass sufficiently, the stock may no longer be capable of replenishing itself. Alternatively, changes to key environmental traits as a result of climate change (e.g., warming ocean temperatures) could be negatively impacting the recruitment process for many US South Atlantic species (Climate Vulnerability Analysis and Ecosystem Status Report). Lastly, a combination of biotic and abiotic changes could lead to a regime shift (e.g., Klaer et al 2015) that negatively impacts stock productivity and lowers annual recruitment. However, misspecification of the stock assessment model or poor quantity/quality of input data could also generate low recruitment estimates. This could be caused by poor data fitting (short or highly variable time series), changes in the data sampling frame over time, lack of a fishery-independent index of recruitment, inability to generate precise estimates of steepness through the stock-recruit curve fitting, and even spatial changes in the stock (e.g., distributional shifts).

Modeling and forecasting recruitment are fundamental to assessing the status of a stock and guiding management recommendations. However, it is challenging to estimate and predict recruitment with the degree of accuracy needed for management purposes due to its high spatial and temporal variation and lack of mechanistic understanding of the recruitment dynamics (Subbey et al 2014). There are several approaches to forecast recruitment: (1) functional stock-recruitment (SR) relationships (e.g., the Beverton-Holt and Ricker models); (2)

sampling methods (i.e., drawing from past values estimated in the assessment); (3) empirical dynamic modeling; (4) time-series analysis; and (5) incorporation of environmental effects. Each method has its own assumptions and drawbacks.

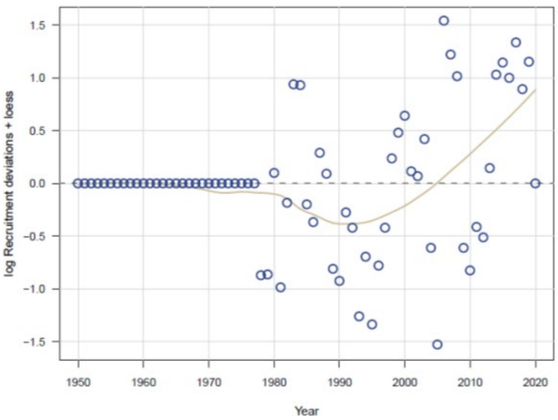
Forecasting recruitments based on the amount of spawning stock biomass (SSB) relies on a well-established SR relationship. However, the spawner-recruit data are often noisy, and the relationships are often weak, thereby limiting their predictive power. Cury et al (2014) quantified the SR relationship for 211 fish stocks worldwide and revealed that parental biomass accounted for only 5% to 15% of the total variance in recruitment. Furthermore, failure of fitting a SR relationship is not uncommon based on simulation studies (Szuwalski et al 2019, Van Beveren et al 2021). Steepness of the SR relationship is often estimated with bias and low precision (Lee et al 2012, He and Field 2019). For sampling-based methods using recent recruitment as a reference period that are independent of SSB, the bias increased as the forecasting period lengthened (Van Beveren et al 2021). Accounting for autocorrelation in recruitment can improve forecast performance (Johnson et al 2016); however, this is not always the case. For instance, time-series methods accounting for temporal autocorrelation and based on a longer-term reference period produced the least reliable forecast compared with other methods (Van Beveren et al 2021). Van Beveren et al (2021) undertook a comprehensive simulation study to evaluate the forecast skill of a wide range of recruitment forecasting methods under various circumstances. They could not identify the single best method to forecast recruitment; however, they found that time-series methods were most likely to perform poorly.

There have been an increasing number of studies attempting to further explain recruitment variability by incorporating environmental variables (Cao et al 2017; Schirripa et al 2009; Tanaka et al 2019). However, most of the attempts have used pre-existing indices of environmental variability or a few measured environmental variables (e.g., Sea Surface Temperature, Sea Surface Salinity) as an additional component of the SR function. This approach has at least two drawbacks: first, these indices are, in most cases, only the proxies to the environmental conditions that are correlated with a species' recruitment dynamics and thus are inherently noisy. Therefore, the explained variance and predictive power are typically low. Second, changes in recruitment are likely a result of several environmental factors operating simultaneously and potentially with interacting effects, and hence difficult to predict using simple models of measured environmental variables. Unless a high causal relationship between environmental variables and recruitment can be identified (e.g., California sardine), inclusion of environmental data doesn't necessarily improve recruitment estimation and forecasting (Subbey et al 2014; Crone et al 2019).

Adjustments to Acceptable Biological Catch (ABC) in order to incorporate shifts in recruitment or production varies by region within the United States, but has generally only been done for data rich species that are assessed with age-based stock assessments. Some regions have surveys that monitor recruitment and are able to predict likely changes in biomass or population sizes based on recruitment patterns. In these situations, the scientific buffer from the Overfishing Limit (OFL) is adjusted up or down based on predicted recruitment associated with environmental conditions. These stocks have stock assessments that are updated on a regular basis. The ABC is generally set for two years at a time.

Most regions have limited ability to adjust the scientific buffer between the OFL and ABC based on environmental conditions. In these cases, the ABC is based on average recruitment or on a stock recruitment relationship based on the results of a stock assessment. The Scientific and Statistical Committees (SSCs) have adjusted ABCs when recruitment deviated from historic patterns as part of the scientific uncertainty. There were no consistent methods to adjust the ABCs or the time period for the new recruitment scenario. Typically, SSCs have adjusted the ABC downward associated with decreased recruitment. The time period included in the recruitment period for ABC projections varied between 5 and 15 years. It appears few stocks have had increased recruitment like Red Snapper in the US South Atlantic.

Generally, the decisions regarding projections for recruitment in the South Atlantic have not been consistent across species, even with similar trajectories in stock status and estimated recruitment levels (Figure 1). Several species have been evaluated by the SSC including red grouper, black sea bass, red porgy, golden tilefish, gag grouper, red snapper, and snowy grouper, as summarized here. Red grouper has had lower than expected recruitment in the last decade, which has prevented making progress with respect to rebuilding of the stock. The projections for determining the ABC for red grouper used recent recruitment. Black sea bass recruitment was estimated to have a negative trend. The projections for determining the ABC for black sea bass used the recruitment time series from 1991 to the present. Red porgy recruitment has been estimated to be declining since the 1990s with the terminal year recruitment estimated to be the lowest on record. The projections for determining the ABC for red porgy used the most recent three years of recruitment. Golden tilefish stock assessment can't estimate the most recent years of recruitment, but 2003 to 2011 were estimated to be below R_{MSY}. The projections for determining the ABC for golden tilefish used the stock-recruitment curve. Gag grouper recruitment was estimated to be the lowest during the last 10 years. The projections for determining the ABC for gag grouper used the stock-recruitment curve to project future recruitments. Red snapper recruitment was estimated to be higher in the recent 10 years compared to historical values, and the estimation did not include the use of a stock-recruitment curve. The projections for determining the ABC for red snapper used an average of the recent recruitment from 2010-2019. Snowy grouper recruitment estimates have been low, thus the projections for determining the ABC for snowy grouper used an average of the recent recruitment from 2011-2017. Scamp also have recruitment values estimated to be lower than expected, but the assessment hasn't been operationalized for management use yet. What this summary demonstrates is a need for guidance on decisions to be made for projections in order to restore some consistency across species.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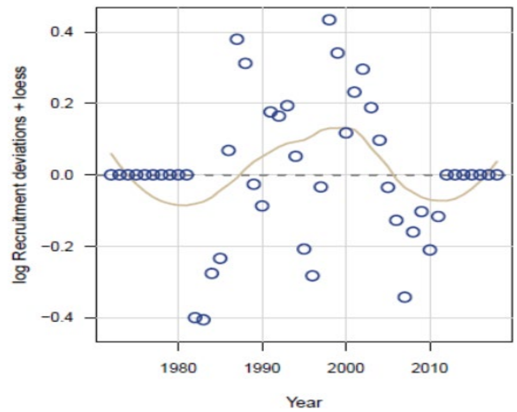
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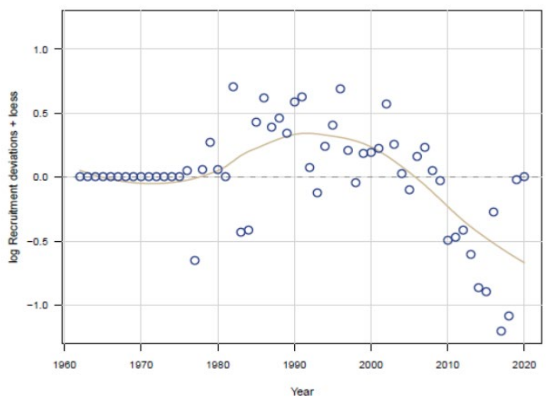
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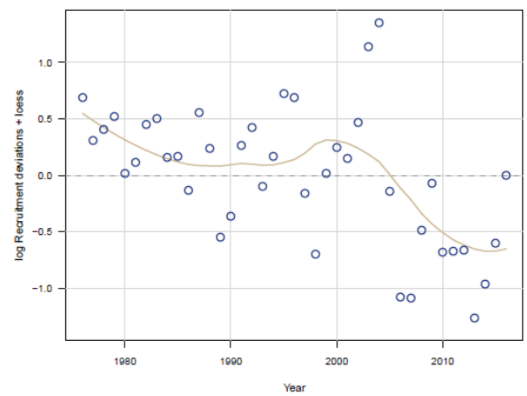
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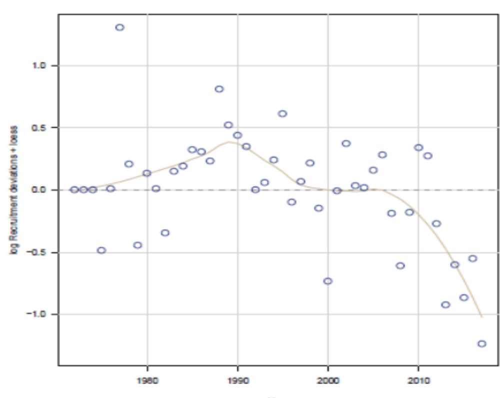
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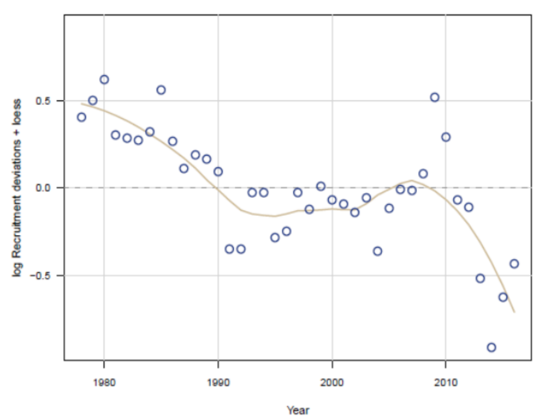
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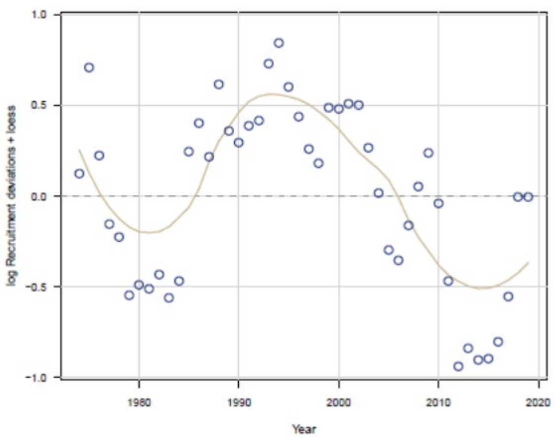

Figure 1 - Time series of recruitment estimated for each species from the respective stock assessments. Top row: Red snapper, Golden tilefish; Second row: Gag grouper, Red grouper; Third row: Red porgy, Black sea bass; Fourth row: Snowy grouper

The choice of how recruitment should be projected for projections used to set catch advice is often difficult to make with the weight of evidence for multiple choices being equal, especially given the scientific uncertainties and respective impacts. The number or weight of fish can be quite different depending on the expectation of recruitment in the future (Tables 1 and 2) and can have an impact on the socioeconomics of the fishery. Thus, consistency of choice given scientific uncertainty and knowledge is critical to providing the best guidance for management.

Table 1. Projections for gag grouper under two different recruitment scenarios: 1) conditioned on the stock-recruitment curve (upper panel) and 2) conditioned on average recent recruitment (lower panel).

Year	R.base (1000)	R.med (1000)	F.base	F.med	S.base (mt)	S.med (mt)	L.base (1000)	L.med (1000)	L.base (1000 lb gutted)	L.med (1000 lb gutted)	D.base (1000)	D.med (1000)	D.base (1000 lb gutted)	D.med (1000 lb gutted)	pr.recover
2020	301.18	263.776	1.01	0.98	225.39	224.39	49.313	49.156	539.102	538.9	25.234	21.922	103.89	91.036	0
2021	296.442	256.188	0.95	0.96	211.9	209.63	55.544	54.863	539.102	538.9	24.425	22.628	103.915	96.657	0
2022	287.234	242.554	0.75	0.79	241.1	229.66	55.62	55.611	539.102	538.855	19.07	18.417	82.344	80.024	0
2023	306.491	247.035	0.16	0.16	346.3	318.03	16.925	15.765	175.632	163.358	4.505	3.885	19.45	16.991	0.001
2024	359.64	277.292	0.16	0.16	545.55	501.69	23.158	21.688	261.171	244.306	5.179	4.308	22.202	18.787	0.014
2025	420.701	328.196	0.16	0.16	765.23	707.54	29.077	27.192	348.352	326.123	6.042	5.003	25.826	21.681	0.069
2026	459.641	360.882	0.16	0.16	984.01	913.66	34.954	32.588	435.081	406.069	6.763	5.638	29.176	24.554	0.168
2027	484.396	386.694	0.16	0.16	1203.36	1115.8	41.129	38.369	524.625	490.171	7.258	6.087	31.627	26.777	0.273
2028	501.62	407.898	0.16	0.16	1432.4	1332.63	47.415	44.367	617.778	578.332	7.596	6.438	33.333	28.5	0.373
2029	514.749	419.62	0.16	0.16	1670.67	1559.54	53.422	50.002	711.419	667.376	7.841	6.728	34.557	29.86	0.465
2030	525.047	435.112	0.16	0.16	1904.94	1779.41	58.772	55.083	800.088	752.284	8.027	6.93	35.475	30.851	0.551
2031	532.929	449.995	0.16	0.16	2122.35	1993.02	63.304	59.391	879.758	829.754	8.17	7.169	36.177	31.953	0.631
2032	538.838	458.191	0.16	0.16	2316.29	2180.5	67.043	62.972	948.911	897.005	8.278	7.324	36.71	32.745	0.704

Year	R.base (1000)	R.med (1000)	F.base	F.med	S.base (mt)	S.med (mt)	L.base (1000)	L.med (1000)	L.base (1000 lb gutted)	L.med (1000 lb gutted)	D.base (1000)	D.med (1000)	D.base (1000 lb gutted)	D.med (1000 lb gutted)	pr.recover
2020	301.18	177.174	1.01	0.98	225.39	217.75	49.313	48.986	539.102	538.756	25.234	17.447	103.89	76.131	0
2021	196.725	177.549	0.95	1	206.15	191.73	55.36	53.736	539.102	538.754	19.296	16.554	87.093	72.184	0
2022	196.725	177.218	0.77	0.97	224.9	189.17	54.674	53.442	539.102	538.644	13.677	15.917	60.582	69.128	0
2023	196.725	177.982	0	0	320.78	245.14	0.157	0.121	1.707	1.29	0.031	0.028	0.136	0.124	0
2024	196.725	177.752	0	0	534.16	406.14	0.216	0.176	2.608	2.048	0.032	0.03	0.141	0.132	0.003
2025	196.725	178.128	0	0	762.13	605.27	0.269	0.231	3.52	2.9	0.032	0.03	0.143	0.135	0.013
2026	196.725	177.395	0	0	990.59	827.74	0.314	0.283	4.384	3.789	0.032	0.03	0.143	0.136	0.049
2027	196.725	177.015	0	0	1214.91	1059.97	0.352	0.327	5.184	4.653	0.032	0.03	0.143	0.137	0.133
2028	196.725	176.889	0	0	1426.55	1284.09	0.383	0.363	5.901	5.435	0.032	0.03	0.143	0.136	0.26
2029	196.725	178.065	0	0	1620.78	1491.28	0.408	0.392	6.535	6.139	0.032	0.03	0.144	0.137	0.394
2030	196.725	177.006	0	0	1795.92	1679.85	0.428	0.416	7.092	6.755	0.032	0.03	0.144	0.137	0.516
2031	196.725	177.838	0	0	1951.74	1850.2	0.446	0.436	7.578	7.287	0.032	0.03	0.144	0.137	0.62
2032	196.725	178.425	0	0	2088.94	2000.02	0.46	0.453	8.002	7.762	0.032	0.03	0.144	0.137	0.701

Table 2. Projections for red snapper under two different recruitment scenarios: 1) conditioned on the recent average recruitment (10 years; upper panel) and 2) conditioned on the long-term average recruitment (lower panel).

year	R.b	R.m	F.b	F.m	S.b	S.m	L.b(n)	L.m(n)	L.b(w)	L.m(w)	D.b(n)	D.m(n)	D.b(w)	D.m(w)	pr.reb
2020	718	628	0.39	0.34	307585	325212	40	39	416	409	443	407	2019	1910	0.053
2021	718	629	0.35	0.31	347034	372325	39	38	420	413	332	288	1626	1473	0.117
2022	718	629	0.21	0.21	401322	430186	25	28	284	319	195	189	983	996	0.206
2023	718	629	0.21	0.21	465178	491225	28	31	327	363	202	191	1036	1016	0.307
2024	718	629	0.21	0.21	529917	551037	31	33	368	403	207	194	1076	1034	0.415
2025	718	630	0.21	0.21	593360	608291	33	35	408	441	210	196	1104	1050	0.526
2026	718	623	0.21	0.21	653509	662653	35	36	446	475	211	196	1122	1062	0.637
2027	718	630	0.21	0.21	710246	712268	36	38	480	506	212	197	1133	1067	0.733
2028	718	629	0.21	0.21	762093	757711	38	39	511	533	212	197	1138	1072	0.81
2029	718	630	0.21	0.21	809274	799286	39	40	538	559	212	197	1143	1076	0.871
2030	718	624	0.21	0.21	851779	835646	40	41	562	581	212	198	1146	1080	0.915
2031	718	625	0.21	0.21	889553	868429	41	42	584	602	212	198	1148	1083	0.946
2032	718	628	0.21	0.21	923163	896936	42	43	603	619	213	198	1151	1086	0.968
2033	718	627	0.21	0.21	952682	921751	42	44	620	635	213	198	1153	1092	0.98
2034	718	631	0.21	0.21	978473	944097	43	44	634	649	213	199	1154	1093	0.988
2035	718	629	0.21	0.21	1001094	963960	44	45	647	662	213	199	1156	1096	0.993
2036	718	626	0.21	0.21	1020799	981064	44	45	658	673	213	199	1157	1097	0.996
2037	718	630	0.21	0.21	1037826	995602	44	45	668	683	213	199	1158	1099	0.998
2038	718	629	0.21	0.21	1052612	1008953	45	46	676	692	213	199	1159	1103	0.999
2039	718	629	0.21	0.21	1065380	1019871	45	46	683	698	213	199	1160	1103	0.999
2040	718	630	0.21	0.21	1076422	1030010	45	46	689	704	213	198	1161	1102	1
2041	718	634	0.21	0.21	1085957	1038653	45	47	695	710	213	199	1161	1105	1
2042	718	627	0.21	0.21	1094186	1046759	46	47	699	715	213	199	1162	1102	1
2043	718	631	0.21	0.21	1101288	1053572	46	47	703	719	213	199	1162	1103	1
2044	718	627	0.21	0.21	1107417	1059173	46	47	707	722	213	199	1163	1104	1

year	R.b	R.m	F.b	F.m	S.b	S.m	L.b(n)	L.m(n)	L.b(w)	L.m(w)	D.b(n)	D.m(n)	D.b(w)	D.m(w)	pr.reb
2020	437	380	0.39	0.34	306993	324501	40	39	416	409	408	378	1980	1874	0.052
2021	437	380	0.35	0.31	342360	367864	38	37	420	413	272	240	1499	1369	0.107
2022	437	381	0.21	0.21	383368	411610	23	26	272	306	139	138	802	828	0.172
2023	437	380	0.21	0.21	425543	451782	24	26	297	332	133	127	753	754	0.228
2024	437	381	0.21	0.21	463111	485158	24	26	316	349	130	123	718	698	0.278
2025	437	381	0.21	0.21	496234	514040	24	26	333	364	129	120	703	672	0.326
2026	437	377	0.21	0.21	524777	537790	25	27	348	376	129	120	699	660	0.367
2027	437	382	0.21	0.21	549973	558120	25	27	362	387	129	120	699	658	0.407
2028	437	381	0.21	0.21	571053	574740	26	27	373	396	129	120	700	656	0.442
2029	437	380	0.21	0.21	589145	588635	26	27	383	403	129	120	701	659	0.475
2030	437	378	0.21	0.21	604572	600270	26	27	391	409	129	120	703	660	0.505
2031	437	378	0.21	0.21	617621	609684	27	28	399	415	129	120	703	663	0.532
2032	437	380	0.21	0.21	629021	616987	27	28	405	420	129	120	704	663	0.555
2033	437	380	0.21	0.21	638622	623669	27	28	410	424	129	120	705	664	0.579
2034	437	381	0.21	0.21	646751	628410	27	28	415	428	129	120	705	665	0.602
2035	437	380	0.21	0.21	653879	633676	27	28	419	431	129	120	706	666	0.619
2036	437	379	0.21	0.21	659968	637613	28	28	422	434	129	120	706	666	0.636
2037	437	380	0.21	0.21	665049	641425	28	28	425	437	129	120	706	667	0.649
2038	437	381	0.21	0.21	669434	644985	28	29	427	439	130	121	707	669	0.664
2039	437	379	0.21	0.21	673167	647829	28	29	430	441	130	121	707	671	0.678
2040	437	381	0.21	0.21	676404	650366	28	29	431	442	130	120	707	670	0.69
2041	437	385	0.21	0.21	679200	653062	28	29	433	443	130	121	707	669	0.702
2042	437	381	0.21	0.21	681614	654532	28	29	434	445	130	120	707	670	0.71
2043	437	382	0.21	0.21	683697	656977	28	29	435	446	130	121	708	669	0.721
2044	437	380	0.21	0.21	685495	657844	28	29	436	447	130	121	708	670	0.729

To better understand stock assessment projection analyses we need some basic understanding of historical patterns in recruitment from stock assessments. This would aid in understanding statistical properties that might be exploited to improve forecasting future recruitment. Some of the basic exploratory data analysis (EDA) of recruitment time series in the South Atlantic has not been completed. These important time series analyses include cross correlation (across and within datasets), autocorrelation (at various lags), and spatial patterns. A thorough analysis of recruitment patterns can tell us if there are shared region wide patterns in recruitment that might be exploited, or if there are inherent time-series properties that could improve forecasts.

Much of the scientific literature generally supports the notion that fish populations will follow a stock-recruit relationship to some degree. Region wide analysis of the effectiveness of stock-recruit relationships for South Atlantic species might provide guidance on best practices to use in forecast models.

Whether we use time series properties and/or a stock recruit curve, we have yet to quantify the performance of these forecasting methods. An important analysis would be to analyze the overall regional performance of various forecast models. For example, an analysis of past projection predictions from stock assessment used for management would be helpful, as well as a method called hindcasting (Kell et al 2016).

Stock assessment modeling, like other types of statistical modeling, should also follow some basic premises established by science. Models should be supported by adequate data. At the heart of most statistical models is the assumption that collected data can be used to predict future outcomes. One of the more influential parameters we have to predict in stock assessment forecasts is recruitment.

Hypothetically, if all we had was a time series of recruitment estimates, we might start by forecasting future recruitment using a simple mean. The mean should be the default when no other information is available. The complication with recruitment data is that it is almost always from a time series, which has inherent properties that likely go beyond the mean. The problem is gathering the information and data that supports deviations from the mean assumption (e.g. hypothesis testing). We know that the natural environment has many types of cyclical properties that have the potential to aid in improving recruitment forecasts. We also know that recruitment in fishes has to be limited by egg production at some point. Barring parthenogenesis, a single fish cannot produce any recruits. In many situations we lack the information to truly understand the factors that affect survival of fish eggs to larvae, larvae to juveniles, and juveniles to age at recruitment (or maturity). Whole books have been written on the subject. Thus, let’s not lose sight of the immense challenge that lies before us in attempting to forecast fish populations, and let’s recognize what we do know and more importantly what we do *not* know.

Observations and Recommendations for Forecasting

Our current assumption about fish population dynamics are based around the idea that fish populations experience short term fluctuations (e.g., recruitment, die-offs, fishing) and long-term shifts (e.g., regime shifts, climate change). Within these short-term fluctuations and long-term shifts is a tendency for ecosystem stability (or equilibrium), suggesting an attraction point for the populations in the ecosystem. The attraction point is usually the basis for benchmarks and management targets. The attraction point itself may change, but is most likely affected by the longer-term shifts, rather than any recent fluctuations. For this reason, it is imperative that fisheries scientists and managers recognize the ability to control short-term fishing dynamics, while accounting for long-term goals.

- For stocks that display high proportional variability (Van Beveren et al 2021) throughout the full recruitment time series, the uncertainty in projections will reflect that variability. Low autocorrelation in recent recruitment reflects low ecosystem stability and will generate additional uncertainty when projecting recruitment forward. Lastly, stocks that demonstrate life history traits (e.g., early age at maturity) that contribute to greater variability in recruitment are likely to present the greatest challenges for projections. In these cases, the projections of future recruitment should clearly recognize this uncertainty and be interpreted cautiously.

- We have seen situations in our stocks where short term (or recent) population dynamics differ from longer term dynamics. When it comes to immediate future ABC determination, the more recent dynamics are likely the most relevant. But that does not mean the longer-term dynamics should not be considered. In a changing (possibly cyclical) environment one would expect immediate conditions to dictate near-term future forecasts, while the longer term is best forecast using the complete history of changes. Should directional shifts in the ecosystem be occurring (e.g. regime shift or climate change), then the longer term could be adjusted or even forecast into the future. Under this situation the premise of short-term conditions still applies, that immediate conditions are more likely to be accurate in short term forecasts.

- Long-term dynamics in fish populations tend to cycle around a central tendency. We have seen cases of fish stocks reaching very low levels and then recovering, suggesting there is a pull towards a long-term mean condition. That mean condition may be surrounded by broad fluctuations, with the stock rarely settling into the specific central condition, but nonetheless this mean condition seems to exist in the sense of an attracting point to which the fluctuations return. Because of this likely condition in ecosystems, long-term forecasts should always consider the complete history of the stock as we know it.

- A random walk should not be used to project recruitment, nor time series methods (as defined in Van Beveren et al 2021 paper).

As such, we make the following recommendations based on basic statistical principles and the guidance provided in Van Beveren et al (2021) for short-term, catch level projections:

Short-term Forecasts for ABC Determination

1. Short-term forecasts for ABC determination should be limited to 5 years (post terminal year of the assessment, including interim years before management has taken effect).

- Stock assessments should be done more frequently;

- Van Beveren stated that the projections weren't sensitive to the forecasting approach when forecast was for a shorter period;
- If an analysis is done that finds projections are accurate and performing well for a given species, then lengthening the projection time frame can be considered; and
- Adjustment of P* should occur when projections go beyond the recommended years. If uncertainties haven't been fully accounted for or new uncertainties would arise after the forecast time period, then consider an additional buffer via P*, if the projections surpass the recommended length of years for catch level projections.

2. Short-term Forecasts should use recent mean recruitment.

We recommend the default method for short-term forecasts should use recent mean recruitment. Recognizing that using recent mean recruitment is a type autocorrelated time-series assumption, Van Beveren et al (2021) showed applying autocorrelation in forecasts resulted in no bias in short-term (3-5 years) projections.

A. Van Beveren et al (2021) does not define recent recruitment, thus the working group recommends recent mean recruitment be defined for each species on a case by case basis (only for short-term catch level projections, not for reference point determination);

B. "The reference period typically comprises only more recent years to avoid forecasting historical recruitment that are unlikely to reoccur in the near future" (Van Beveren et al 2021).

- 3, 5, and 10 years were explored in the Van Beveren et al (2021) paper.
- Analysts can recommend a time period based on analyses of the species' data.

Pending the research recommendations below, the Van Beveren et al (2021) paper and recent literature allows for using methods as they have been used assuming you are doing short-term projections. Essentially, if projections are being done using a well-defined stock-recruitment curve or another method, then short-term projections are likely sufficient for management use. Recommendations could and likely will change in the future.

Long-term Forecasts for Determining Rebuilding and Benchmarks

As we note above, recent conditions likely reflect near-term dynamics. This then implies that longer term conditions are best for forecasting long-term forecasts. Long-term forecasts in this context are those 10 years and beyond. Further study on the whole ecosystem might get us closer to understanding what the rate of change in the system really is, but intuitively it seems 10 years is long enough that the ecosystem can shift away from current conditions. This suggests that when forecasting for the long-term that the whole time series should be used.

A central tenet of fisheries science is the concept of a stock-recruit curve and maximum sustainable yield (MSY). These are the foundations of population dynamics not only for fishes, but for many natural populations. In fisheries science we have built many management benchmarks based on the concept of MSY, including F_{MSY}, SSB_{MSY}, MSY, MSST, MFMT, etc. By definition these concepts are meant to represent a long-term population condition, with the premise that the population may fluctuate about that condition, but will in the long-term tend to that condition. One can debate whether populations do fluctuate about a long-term central tendency, but the MSY concept, which is more or less codified into the Magnuson Act, is based on this notion of a long-term average condition. If fish stocks do not follow this, then policies need to be changed and this falls outside the realm of this report.

However, should there be evidence for a shift in the population dynamics for a stock or an ecosystem, then that certainly should be accounted for. Regime shifts or unidirectional climate change are likely long-term processes that will take time and data collection to detect, but once done, should be accounted for in our stock assessment models. Klaer et al (2015) discusses when it is appropriate to incorporate regime shift changes into stock assessments and forecasts.

As has been exhaustively covered in the above text is the importance of recruitment to fish population dynamics. The high variability we see in fish recruitment is often enough to swamp out other ecosystem effects (e.g., predator-prey). Thus, forecasting recruitment accurately is critical to providing accurate management advice.

We recommend the following hierarchy be used for modeling long-term forecasts, with the primary purposes being benchmark determination and rebuilding schedules.

Type A: Forecast using average recruitment and historic variability.

- The whole time series should be used as the default condition.
- If evidence of regime shift (or other semi-permanent ecosystem change), then apply the average from the years under this condition. Rely on Klaer et al (2015) for guidance on how to define or detect regime shifts.

Type B1: Forecast using stock-recruit relationship and historic variability.

- Provided a significant stock-recruit curve is detected.
    - Analysts and review bodies will determine the level of significance required.
- The S-R curve can be fitted internally or externally to the assessment model.

Type B2: Forecast using time series properties or environmental correlates.

- Provided significant time series of correlates that affect longer term processes are detected.
    - Analysts and review bodies will determine the level of significance required.
- As stated in the introduction above, literature and past experiences suggest these relationships often break down.

Type C: Forecast using S-R model, with time-series or environmental correlates that affect longer term processes included.

- Provided significant time series of correlates are detected.
    - Analysts and review bodies will determine the level of significance required.
- It is a rarity for stocks to follow this type of predictive model. Caution as above applies in that correlates with recruitment often break down or become invalid.

The hierarchy of forecast methods described above seems easy enough to apply, but what is not declared is the significance level that should be used to determine sufficiency of adopting a predictive model type. Acceptable model diagnostics and significance levels are generally adopted by the scientific community as a whole. What comes with this notion is also an inherent shift in tolerances for accepting/rejecting levels of fit. We recommend that determination of an acceptable model be left to the analysts, stock assessment process, and review bodies. Over time this should work itself into a general understanding and default condition to assume.

Issues with short-term and long-term forecasts

It is likely to be more common than not that short-term and long-term forecasts do not agree. Much like the natural system, short-term dynamics are not reflective of long-term shifts, changes, or equilibrium tendencies. In an example case, we might see long-term (rebuilding) forecasts indicating the need for much lower ABC values compared to the short-term projections. This can happen when the rebuilding time frame, which is dictated by policy rather than biology, is very short and recent recruitment remains high. Vice versa, we might also see a case where the short-term forecasts extended out beyond the recommended 5-year limit might not successfully rebuild in time. These situations do not mean that either the rebuilding or short-term forecast is wrong, rather they are both correct but express different types of risks (e.g., short-term and long-term risks). Managers need to be aware of these risks and how their decisions affect the short-term and long-term goals for the fishery, the fish stock, and the ecosystem.

Uncertainty Assumptions in Forecast Models

Given all the uncertainties described above it seems imperative that science provide managers with an accurate reflection of the unknowns, assumptions, and uncertainties in fish population forecasts. Major sources of uncertainty in stock assessment models include recruitment, natural mortality, and the S-R relationship (e.g., steepness). Other sources of uncertainty may be significant depending on the data collection and fishery characteristics. Information sources like discards, abundance indices, and ageing accuracy have the potential to increase uncertainty significantly. In some areas of the world just getting an accurate accounting of total removals can be a large uncertainty hurdle.

In the South Atlantic, the primary stock assessment modeling package (BAM) incorporates a cutting edge type of uncertainty modeling (MCBE). This method allows for a more full accounting of total uncertainty in stock assessment models, to the point that a couple reviewers have suggested there is a slight chance the method is overestimating total uncertainty. This modeling advantage should be embraced in our region and incorporated into projection analyses.

Stock assessment report recommendations

Some additional information would be useful to the SSC to make decisions regarding projections; thus, the work group requested the following information be included in stock assessment reports provided to the SSC:

- A full description of the recruitment variance assumptions within the model
    i. Inclusion of analyses of autocorrelation in recruitment
    ii. Provide a graph of the distribution of recruitment
- A full description of the data informing the estimation of recruitment deviations over time including information on the quality of those data. Include any information regarding changes in the data over time that could be important such as changes in sampling frame (e.g., sampling frame of an index) or species compositions (e.g., mixed fisheries or not identifying to the species level until a given year)
- Inclusion of a sensitivity run removing the S-R curve (Maunder and Thorson 2019)
- Inclusion of a sensitivity run including ageing error
- A graph of the MCBE recruitment time series envelope of uncertainty with the base run recruitment overlaid
- A graph of the MCBE recruitment deviations time series envelope of uncertainty with the base run deviations overlaid
- Inclusion of hindcasting as described in Kell et al. (2016) in order to assess and improve the forecasting ability of assessments
- For research track assessments, provide an age structured production model - help with recruitment and index diagnosis

Prioritized Research Recommendations

Much work needs to be done in order to move forward with recommendations supported by a broader base of science regarding projecting recruitment, as well as a broader base of science specific to the South Atlantic and the species managed in the region. Below is a prioritized list of recommendations to advance the science and management of South Atlantic species:

- Explore autocorrelation, proportional variability, and correlation in age at 50% maturity across species in the South Atlantic. This recommended research is meant to specifically look at the factors from Van Beveren et al (2021) for the South Atlantic species in order to help determine the best methods of projection based on the species' characteristics.

    i. With this research, scientists should be able to provide examples of the benefits and payoffs to things like increased or decreased catches, responsive management, and management tailored to species' characteristics.

- (*Work has started on this recommendation*) Analysis of recruitment patterns across multiple species in the South Atlantic. Include time series analyses, trend analyses, correlation between the recruitment time series of two or more species (looking at the strength of the connections among various species in the EwE model might also provide some leads to pursue), etc. This would help to answer questions such as: Is more recent recruitment a better predictor of short-term future recruitment? Is there a systemic pattern in recruitment and can it be used to aid in prediction? Do the recruitment time series of two or more species move together, so that looking at them jointly might help predict each individually? Are systemic recruitment patterns driven by environmental factors?
    i. In situations where correlations exist between the recruitment time series of two different species, or between the recruitment of a species and an environmental factor, methods of conditioning and conditional forecasting might be used to decrease the variance of recruitment forecasts (NASEM 2021, Appendix B).
    ii. In situations where the recruitment of one species (such as a particular species of grouper) is part of the recruitment of a larger aggregation of species (such as all grouper), and the covariance between recruitment of the single species and aggregate recruitment is relatively large, control variate methods (NASEM 2021, Appendix B) might help to reduce the variance of recruitment forecasts.
    iii. In situations where the time series of recruitment deviations for two or more species are contemporaneously correlated, then analyzing the recruitment time series of both species together can reduce the error envelope around predictions of recruitment (e.g., NASEM 2021, Appendix C – SUR-type regression).
    iv. Comparison of median recruitment for various lag periods (and other simple, robust/non-parametric measures of central tendency) to recent mean recruitment for the same number of lag periods, for the purpose of predicting recruitment.
- Analysis of the performance of projections in current assessment models. We have nearly 20 years of stock assessments in the South Atlantic that have produced forecast predictions. How well have they performed? What are the biggest sources of error?
- Implementation of collection surveys for independent sources of data to help provide independent estimates of recruitment.
- Analyze the value of investing in pre-recruit surveys such as ECOMON and MARMAP data.

- Analysis of best leading indicators of recruitment to use after the stock assessment terminal year for forecasting R. Update interim analysis to reflect this.
- Analysis of possible environmental correlates with recruitment for specific species.

References

(Literature reviewed, but not necessarily cited; See Appendix 2 for full annotated bibliography):

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Appendix 1. Scope of work

Defined for the SSC's Catch Level Projections Workgroup.

Catch Level Projections Workgroup

Scope of Work

Analysis Type: Development of Recommendations for Recruitment Assumptions Used in Catch Level Projections

Justification: The SSC has recently recommended different approaches to making recruitment assumptions in catch level projections for different stocks. To date, these recommendations have been made on a case-by-case basis in response to trends or new patterns in recruitment relative to the historical productivity of the stock. The SSC requested an opportunity to comprehensively review recent SSC decisions and available literature on the topic, and to develop recommendations for how recruitment assumptions be made in projections used to provide catch level recommendations. Ideally, recommendations should be informed by the SEFSC's working group on this topic.

Goal: Develop a set of recommendations for SSC consideration when making projection requests used to set catch levels.

Analyst: Assistance of an SEFSC analyst may be required. Council staff will be needed to assist in gathering information for the workgroup.

Members: SSC – Amy Schueller (chair), Fred Scharf, Jie Cao, Scott Crosson, Chris Dumas, Other – Representative from SEFSC's working group on incorporating recruitment in projections (Erik Williams, SEFSC Beaufort)

Tasks:

1. Review recent literature on recruitment assumptions and summarize key findings for the SSC
2. Summarize recent SSC decisions regarding recruitment assumptions in projections used to set catch level recommendations. Case studies should include, but not be limited to, red grouper, red snapper, red porgy, golden tilefish, gag grouper, black sea bass, and snowy grouper
3. With the assistance of the SEFSC, explore the performance alternative recruitment assumptions and summarize the impact on catch level advice for key example stocks.
4. Draft recommendations for SSC consideration.

Appendix 2. Annotated bibliography

The literature reviewed by the Catch Level Projections Workgroup.

Chambers, RG, and IE Strand. 1986. Estimating parameters of a renewable resource model without population data. Marine Resource Economics 2: 263-274.

- Provides method for estimating recruitment using only gear/fleet-specific catch and effort and an M assumption
- Uses lagged landings and effort data
- Can build in autocorrelated recruitment assumptions
- Environmental variables can be incorporated
- Pros: Simple approach independent of stock size estimates, uses empirical data (not tied to SR form) to predict R and yield
- Cons: Do we have effort data to inform this? Instead, can we use the form with F estimates from assessment instead?

Clark, CW, and GR Munro. 2017. Capital theory and the economics of fisheries: implications for policy. Marine Resource Economics 32: 123-142.

- career retrospective, they posed models on optimal fisheries in early 80s and capital investment
- now see intrinsic growth rate and better definition of social discounting
- lots of stuff about BC groundfish experience which is game theoretic and interesting but probably not relevant to us

Conn, PB, EH Williams, and KW Shertzer. 2010. When can we reliably estimate the productivity of fish stocks? Canadian Journal of Fisheries and Aquatic Sciences 67: 511-523.

- Steepness, a main measure of productivity, can be tricky to estimate. Best estimated when true steepness is high, M is slightly higher, more years of data, and exploitation history that covers broad range of stock status.
- Variability in R did not affect ability to estimate steepness.
- <u>Pros:</u> Good study indicating optimal conditions for estimating S-R curve
- <u>Cons:</u> South Atlantic does not have the optimal conditions for most stock assessment datasets

Crone, PR, MN Maunder, H Lee, and KR Piner. 2019. Good practices for including environmental data to inform spawner-recruit dynamics in integrated stock assessments: small pelagic species case study. Fisheries Research 217: 122-132.

- Evaluated 2 methods for including environmental information into assessments using Pacific sardine as a case study - 1) including an environmental covariate in S-R curve and 2) using the environmental covariate as an index of recruitment
- Both methods were unbiased under certain specifications, so both can perform well. Both implementations had bias corrections and one had a penalty term
- Pros: Able to produced unbiased estimates of 'true' values in the OM with the EM; can include environmental data in multiple ways while also estimating unbiased results

- Cons: Inclusion of environmental data did not necessarily improve performance because the age composition data provided enough information on recruitment estimation

Cury, PM, JM Fromentin, S Figuet, and S Bonhommeau. 2014. Resolving Hjort's Dilemma: how is recruitment related to spawning stock biomass in marine fish? Oceanography 27: 42-47.

- Meta-analysis that quantified the SR relationship for 211 fish stocks worldwide using GAMs among 3 groups: demersal fishes, small pelagics, and large pelagics.
- Pros: Global patterns showed typical asymptotic shape of increasing recruitment reaching an upper limit at around ½ to ⅔ stock biomass, corroborating standard theoretical and modeling results.
- Cons: Parental biomass accounted for only 5% to 15% of the total variance in predictive models of recruitment and was just a slightly better predictor than random chance (25/29% to 20%)

Deyle, E, AM Schueller, H Ye, GM Pao, and G Sugihara. 2018. Ecosystem-based forecasts of recruitment in two menhaden species. Fish and Fisheries: 1-13.

- Explores empirical dynamic modeling (EDM) for Atlantic and Gulf menhaden recruitment time series and landings per unit effort
- Pros: Doesn't require a specified mathematical formulation; test forecast skill using cross-validation; increasing amount of data improves predictions
- Cons: Long time series is needed
- NOTE - EDM is being used to predict recruitment for Atlantic menhaden forecasts

Haltuch, MA, EN Brooks, J Brodziak, JA Devine, KF Johnson, N Klibansky, RDM Nash, NM Payne, KW Shertzer, S Subbey, and BK Wells. 2019. Unraveling the recruitment problem: a review of environmentally-informed forecasting and management strategy evaluation. Fisheries Research 217: 198-216.

- The inclusion of environmental drivers into assessments and forecasting is most likely to be successful for species with short pre-recruit survival windows (squids, sardines).
- The effects of environment may be more complicated and variable for species with a longer pre-recruit survival window, reducing the ability to quantify environment-recruitment relationships.
- Provides several research recommendations that should be pursued in future recruitment forecasting and MSE work (section 7.1-7.3)

Hannesson, R. 1988. Fixed or variable catch quotas? The importance of population dynamics and stock dependent costs. Marine Resource Economics 5: 415-432.

- Are constant catch quotas or constant fishing mortality preferable? Economics assumes the first due to fixed costs etc.
- Tests three models--purely stochastic w no pop dynamics, stochastic plus survivors, and year class model.
- Concludes that the answer depends on costs of fishing capital, variable costs, and risk aversion.

- stocks with high survival rate of biomass (growth plus surviving individuals) increases attractiveness of stable quotas

He, X, and JC Field. 2019. Effects of recruitment variability and fishing history on estimation of stock-recruitment relationships: two case studies from the U.S. West Coast fisheries. Fisheries Research 217: 21-34.

- Study to evaluate the effects of recruitment variability on the estimation of the stock-recruitment curve parameters given fishing mortality and priors on the S-R parameters
- Steepness was more likely to hit an upper bound when variability in recruitment was higher; correct priors on steepness did not negate this
- Incorrect priors on steepness led to bias, which was worse when the prior was higher than the actual value
- Pros: Well designed OM and EM simulations
- Cons: Steepness estimation was troublesome when recruitment variability was high, even with highly informative data

Holland, DS, and GE Herrera. 2009. Uncertainty in the management of fisheries: contradictory implications for a new approach. Marine Resource Economics 24: 289-299.

- Multiple and conflicting management objectives seem to be the norm.
- Approaches to dealing with uncertainty have been largely based on meeting some probability for mortality or biomass.
- Paper is basically selling the idea of incorporating economic models into MSEs.
- <u>Pros:</u> Good idea for dealing with uncertainty
- <u>Cons:</u> Does not help with projections, possible use in ABC control rule and/or characterizing uncertainty for Council

Johnson, KF, E Councill, JT Thorson, E Brooks, RD Methot, and AE Punt. 2016. Can autocorrelated recruitment be estimated using integrated assessment models and how does it affect population forecasts? Fisheries Research 183: 222-232.

- Autocorrelation in R can be important.
- When fit outside SCA models it does well. Preferably need n>40 years of data to do a good job.
- When autocorrelation is high (>0.5) then forecasts are poor for first 10 years.
- <u>Pros:</u> When present autocorrelation can and should be estimated outside SCA models
- <u>Cons:</u> Need long time series, does not necessarily improve projections

Kiaer, C, S Neuenfeldt, and MR Payne. 2021. A framework for assessing the skill and value of operational recruitment forecasts. ICES Journal of Marine Science: 1-11.

- Provides a generic approach to assessing skill and value of short-term R forecasts. (Modernized version of Chambers & Strand?)
- Assesses skill in forecasting (aka predictive ability) relative to baseline using retrospective forecasting approach that includes metrics (e.g., RMSE, MSE) and measures of uncertainty. Can include enviro factors and can utilize a range of model forms (GAMs, SR, etc.) and ensemble approach

- Assesses value using economic cost-loss decision model that estimates cost of precaution and lost value due to inaction
- Pros: utilizes concept familiar to SSC (retros) to build model that estimates future short-term recruitment and uncertainty in those estimates
- Cons: a) predictor variables must be available without large delay, b) would require more work on part of lead analyst

Kimoto, A, T Mouri, and T. Matsuishi. 2007. Modelling stock-recruitment relationships to examine stock management policies. ICES Journal of Marine Science 64: 870-877.

- A new forecasting algorithm to predict recruitment for short- or medium-term stochastic projections, using a stock–recruitment relationship
- The relative prediction error of seven existing algorithms was compared with that of the new model using leave-one out cross-validation for 61 data sets
- Pros: avoids overestimation in situations where the spawning stock is lower than the observed minimum SSB and where the recruitment was higher than generally observed
- Cons: requires laborious procedures to find the optimal set of thresholds for the stock and recruitment intervals, programming?

Klaer, NL, RN O'Boyle, JJ Deroba, SE Wayte, LR Little, LA Alade, and PJ Rago. 2015. How much evidence is required for acceptance of productivity regime shifts in fisheries stock assessments: are we letting managers off the hook? Fisheries Research 168: 49-55.

- Uses a weight-of-evidence approach to assist with regime shift determinations
- Developed 4 criteria - 1) Observed change in a productivity indicator; 2) Understanding of assessment model input data; 3) Understanding of assessment model structural assumptions; and 4) Explanatory hypothesis
- Table with descriptions of criteria and scoring can be found in the paper
- Additionally, the authors suggest the need to take into account management risks
- Pros: Table provided; Helps to highlight where research should be directed to address questions of these type
- Cons: Semi-quantitative ranking system; overall assessment of recommended process done across a handful of species

Kolody, DS, JP Eveson, AL Preece, CR Davies, and RM Hillary. 2019. Recruitment in tuna RFMO stock assessment and management: a review of current approaches and challenges. Fisheries Research 217: 217-234.

- Developing harvest strategies robust to recruitment uncertainty is high priority
- Recommends autocorrelation in recruitment deviations, rather than in recruitment itself to remain precautionary
- Recommends a fishery-independent indicator of recruitment such as a survey index
- σ_R should be explored with sensitivity analyses, if fixed
- Pros: Reviews several, well studied species of tunas
- Cons: Because it is a review, the paper doesn't offer additional quantitative findings

LaRiviere, J, D Kling, JN Sanchirico, C Sims, and M Springborn. 2018. The treatment of uncertainty and learning in the economics of natural resource and environmental management. Review of Environmental Economics and Policy 12: 92-112.

- Reviews what is known about the impact of learning relative to different types of uncertainty in resource management
- Covers all forms of uncertainty, non-adaptive and adaptive management, active and passive learning, etc.
- SSC has suggested some form of adaptive-learning-type ABCs, but have lacked fully thought out proposal for how way to incorporate them. This paper doesn't provide that, but got me thinking…
- Cool: they demonstrate form of uncertainty (parameter, state, stochasticity) matters in whether "greater levels of uncertainty" lead to more precautionary management. Depends on whether or not decisions irreversible.

Lee, H-H, MN Maunder, KR Piner, and RD Methot. 2012. Can steepness of the stock-recruitment relationship be estimated in fishery stock assessment models? Fisheries Research 125-126: 254-261.

- Evaluated ability to estimate steepness of the Beverton–Holt stock–recruitment relationship using simulation analyses for 12 Pacific stocks
- A high proportion of h estimates from the simulated data and the original data occurred at the bounds and that prop decreased as true h decreased
- Steepness estimated with moderate to low precision and moderate to high bias. Often there is little information in the data about h.
- Reliable estimation is attainable (good contrast of spawning stock biomass for relatively unproductive stocks when the model is correctly specified)
- Pros: some of our stocks might fit the "reliable estimation" category (gag like sablefish?)
- Cons: Most don't. SSC has been assuming models with h estimates are more reliable = bad assumption? Are we overconfident in our projections that use estimated h?

Mangel, M, AD MacCall, J Brodziak, EJ Dick, RE Forrest, R Pourzand, and S Ralston. 2013. A perspective on steepness, reference points, and stock assessment. Canadian Journal of Fisheries and Aquatic Sciences 70: 930-940.

- There are deep connections between RPs and steepness
- We have shown that fixing steepness and life history parameters (natural mortality in a PM or natural mortality and growth in an ASM) fixes many important RPs.
- Do not fix steepness and natural mortality rate (constrained likelihood or Bayesian estimation approaches)
- Replace the BH-SRR by a SRR to avoid the difficulty

Maunder, MN, and JT Thorson. 2019. Modeling temporal variation in recruitment in fisheries stock assessment: a review of theory and practice. Fisheries Research 217: 71-86.

- Basic patterns in recruitment - 1) independent and identically distributed; 2) density dependence; 3) trend over time; 4) autocorrelation; 5) regime shift; and 6) sporadic
- Descriptions of how recruitment has been estimated in assessments

- Management advice should account for R variability - 1) in benchmark calculations; 2) when reconstructing and forecasting future abundance; and 3) when defining HCRs
- Recommend running assessments with no S-R curve (supports a recommendation that we have already suggested)
- Pros: Review of methods in recruitment estimation and projections
- Cons: Because it is a review, no quantitative analysis with additional suggestions

McGough, B, AJ Plantinga, and C Costello. 2009. Optimally managing a stochastic renewable resource under general economic conditions. The B.E. Journal of Economic Analysis & Policy 9: 1-30.

- economically optimal management rules is very difficult w fisheries
- they use macroeconomic models on stochastic fisheries
- result is a reduced-form, linear approximation of the optimal escapement rule, shown to be a function of the current stock, past environmental shocks, and model parameters (demand elasticity, marginal costs, risk preferences)
- under production shocks and linear profits, optimal escapement is constant.

Munch, SB, A Giron-Nava, and G Sugihara. 2018. Nonlinear dynamics and noise in fisheries recruitment: a global meta-analysis. Fish and Fisheries 19: 964-973.

- Applied empirical dynamic modeling (EDM) to 185 fish stocks to determine if variation in recruitment is predictable and/or related to stock size
- 107 of the 185 stocks had a causal coupling between stock size and recruits
- Will be of greatest use for relatively short-lived species
- Pros: Doesn't require a specified mathematical formulation; test forecast skill using cross-validation; increasing amount of data improves predictions
- Cons: Requires a time series of data that may not always be available

Parma, AM. 1990. Optimal harvesting of fish populations with non-stationary stock-recruitment relationships. Natural Resource Modeling 4: 39-76.

- Older paper using delay-difference models.
- Knowledge of enviro conditions (e.g., good and bad years) can enhance management decisions, but only to a point. In some cases, a constant harvest policy works well.
- Anticipating good and bad years can lead to boom-and-bust scenarios in fishery for risk neutral policies, while risk averse harvest policies will tend to stabilize catches and follow the good and bad years.
- <u>Pros:</u> Including environmental data leads to better management in some cases.
- <u>Cons:</u> Can lead to unstable (boom and bust) catch scenarios.

Plaganyi, EE, MDE Haywood, RJ Gorton, MC Siple, and RA Deng. 2019. Management implications of modelling fisheries recruitment. Fisheries Research 217: 169-184.

- Paper cautions about use of enviro data for improving recruitment forecasts; must be careful in parameterization chosen.
- Environment effects not only recruitment but growth and natural mortality as well.
- Their example and analysis uses a pre-recruit survey and good environmental data.
- <u>Pros:</u> Notable cautions about use of enviro data.

- Cons: Study has little application to our region because of good pre-recruit survey and enviro data.

Punt, AE, and M Dorn. 2014. Comparisons of meta-analytic methods for deriving a probability distribution for the steepness of the stock-recruitment relationship. Fisheries Research 149: 43-54.

- The NLME method has the advantage that it does not require a hyper-prior distribution. However, the performance of the NLME method is very sensitive to the value for steepness selected when conducting assessments
- The Bayesian hierarchical method can provide a probability distribution for steepness, but is also sensitive to the value assumed for steepness when conducting assessments
- the profile method appears to be the best of the meta-analysis methods investigated

Reed, WJ. 1978. The steady state of a stochastic harvesting model. Mathematical Biosciences 41: 273-307.

- Stochastic, discrete-time Markov stock-recruitment model.
- Considers environmental uncertainty effect on SR model (random, independent, multiplicative shocks to SR function), effects of intrinsic growth rate on survival/extinction, compares long-run average yield of various harvest policies with steady-state yield from deterministic model
- Finds: max sustainable harvest rate, max harvest rate decreases with degree of enviro uncertainty and is always < deterministic sustainable max harvest rate
- Finds: stochastic generalization of critical depensation model, sufficient conditions for long-run pop survival/extinction based intrinsic growth rate and variance of environmental shocks
- Finds: a harvest rate predicted to be sustainable in deterministic analysis (such as MSY) may not be sustainable with environmental fluctuation; for species with low average annual growth rates, small environmental fluctuations may cause deterministic MSY to be unsustainable
- Pros: Provides methodology for probabilistic determination of max sustainable harvest rate, extinction prob, etc. under enviro uncertainly
- Cons: Does not consider age/size classes

Reed, WJ. 1979. Optimal escapement levels in stochastic and deterministic harvesting models. Journal of Environmental Economics and Management 6: 350-363.

- Stochastic, discrete-time Markov stock-recruitment model.
- Considers environmental uncertainty effect on SR model (random, independent, multiplicative shocks to SR function), effects of intrinsic growth rate on survival/extinction, compares long-run average yield of various harvest policies with steady-state yield from deterministic model
- Finds: constant-escapement feedback policy is optimal in maximizing expected discounted value for pop with stochastic SR model under more general harvest cost model compared to Reed 1978
- Finds: relationship between unit harvest costs and stock size can be important in determine optimal escapement

- Finds: in most cases, optimal stochastic escapement is higher than optimal deterministic escapement

Reed, WJ. 1983. Recruitment variability and age structure in harvested animal populations. Mathematical Biosciences 65: 239-268.
- Adds age-structure to Reed's model
- Considers [not finished reviewing]
- Finds: effect of harvesting is to increase variance of recruitment and yield
- Pros: Adds age-structure
- Cons: density dependence and stochasticity confined to first year of life cycle

Roughgarden, J, and F Smith. 1996. Why fisheries collapse and what to do about it. Proceedings of the National Academies of Science USA 93: 5078-5083.
- An ecologically stable target stock may be attained either with annually variable quotas following current practice or, preferably, through a market mechanism whereby fish are taxed at dockside if caught when the stock was below target and are untaxed otherwise.
- Poses fishing with a significant buffer of 25% under MSY to prevent natural fluctuations, foregone profits are made up by increase stability of catch and less risk of collapse (they call it "insurance") and model the benefits of that example is Newfoundland Cod

Sethi, G, C Costello, A Fisher, M Hanemann, and L Karp. 2005. Fishery management under multiple uncertainty. Journal of Environmental Economics and Management 50: 300-318.
- Extends biological model of Roughgarden and Smith (which considered three sources of [uniform, stationary] uncertainty in fish management: stock growth (logistic) rate error, stock measurement error, harvest quota implementation error) by wrapping it in formal stochastic dynamic programming optimization.
- Finds: Growth and implementation uncertainties have only a small effect on optimal policy, profits, and extinction risk—even when uncertainties are high. Uncertainty in stock measurement has greatest effect on policy. When stock uncertainty high, "constant-escapement" policy is not optimal; instead, optimal escapement is increasing in measured stock size. the optimal escapement level under uncertainty: (1) is lower than the optimal deterministic escapement level when measured stock is small and (2) exceeds the optimal deterministic escapement level when measured stocks are large. An increase in stock measurement *error* causes the optimal escapement level to fall.
- Finds: the optimal policy leads to 42% higher commercial profits and 56% lower extinction risk than the constant escapement policy
- Pros: Shows how different sources of uncertainty affect optimal policy. The general model and method is appropriate for setting up and solving any stochastic dynamic programming problem with Markovian transitions—provides the economic optimization machinery to wrap around the biology model.
- Cons: Assumes managers know density function of each source of uncertainty. Does not consider covariance between sources of uncertainty.

Sharma, R, CE Porch, EA Babcock, MN Maunder, and AE Punt. 2019. Recruitment: theory, estimation, and application in fishery stock assessment models. Fisheries Research 217: 1-4.

- Opening article of a recruitment uncertainty special issue
- 3 approaches - 1) model annual recruitment deviations from a stationary functional S-R relationship; 2) link recruitment variation to environmental drivers; 3) MSE across a range of plausible recruitment scenarios
- Pros: Summarizes the articles in the special issue
- Cons: Summarizes the articles in the special issue. No specific, unique recommendations on projecting recruitment

Sissenwine, MP. 1984. The uncertain environment of fishery scientists and managers. Marine Resource Economics 1: 1-30.

- The central problem facing fishery scientists and fishery managers is to understand and deal with recruitment variability
- In some cases, it may be possible to explain recruitment variability based on empirical relationship with an environmental variable
- For some species, recruitment variability may be dealt with by monitoring prerecruit abundance and predicting recruitment in advance (Georges Bank haddock).
- Fisheries managers must apply regulatory methods which are more robust with respect to current population size estimates.

Springborn, MR, and A Faig. 2019. Moving forward: a simulation-based approach for solving dynamic resource management problems. Marine Resrouce Economics 34: 199-224.

- Approximate dynamic programming (ADP) - addresses high-dimension problems with complex uncertainty
- 2 steps - 1) Monte Carlo simulation and 2) simulations used to update estimates of a value function
- Extension of work done by Reed; also uses work done by Sethi
- Pros: Considered 2 sources of biological and 2 sources of economic uncertainty simultaneously; nonparametric shape allows for greater flexibility
- Cons: Computing requirements; if I understand correctly, no fitting of data, using simulations; carrying capacity and growth were the 2 biological parameters considered

Steinshamn, SI. 1998. Implications of harvesting strategies on population and profitability in fisheries. Marine Resource Economics 13: 23-36.

- Three strategies--constant catch, constant effort, constant escapement
- Stability of fishing income and fish populations are a normal tension
- uses a surplus production model and Monte Carlo simulations
- At lowest level of stochasticity, hardly any differences in outcomes. as it rises, constant escapement becomes most profitable and least variation. Constant catch should only be for longer lived species

Subbey, S, JA Devine, U Schaarschmidt, and RDM Nash. 2014. Modelling and forecasting stock-recruitment: current and future perspectives. ICES Journal of Marine Science 71: 2307-2322.

- Paper reviews the apparent inability of models to accurately forecast recruitment even when environmental covariates are included as explanatory variables.

- The review shows that despite the incremental success in the past hundred years, substantial challenges remain if the process of modelling and forecasting stock–recruitment is to become relevant to fisheries science and management in the next 100 years.
- Need more data!
- Pros: Good review paper.
- Cons: Much work (and data) remains to truly improve recruitment forecasting.

Tahvonen, O. 2009. Optimal harvesting of age-structured fish populations. Marine Resource Economics 24: 147-169.
- The adventures of an economist looking into age structured fishery models.
- Reveals some ignorance of stock assessment models, but demonstrates cyclical and other response patterns known for these models.
- Emphasizes need to incorporate age-structured population models into economic studies. Standing age-structure of the population is important in determining optimal harvest.
- Pros: Important message about age-structure in setting optimal harvest.
- Cons: Nothing earth shattering here.

Tahvonen, O, MF Quaas, and R Voss. 2018. Harvesting selectivity and stochastic recruitment in economic models of age-structured fisheries. Journal of Environmental Economics and Management 92: 659-676.
- Looks at age-structured models in harvest policies.
- Optimal harvesting selectivity tends to target strong year classes, but is impractical to fishery.
- Managing for MSY leads to deviations from economic optimality.
- Examines Baltic Cod that has early recruitment detection.
- Pros: Interesting conclusions about optimal harvest based on MSY and economics. Possibly points to value of early recruitment survey data.
- Cons: Little relevance to our fisheries because of reliance on survey that provides early recruitment detection.

Van Beveren, E, HP Benoit, and DE Duplisea. 2021. Forecasting fish recruitment in age-structured population models. Fish and Fisheries: 1-14.
- Evaluated forecast skill in estimating SSB for 3-, 5-and 10-year forecasts of 16 recruitment forecasting methods, different scenarios, and 31 operating models
- No overall, best-performing approach arose from the mix
- Time-series methods were most likely to perform poorly, esp as #yrs inc
- Skill ~ age at mat and R autocorr (3-yr), long-term R variability (10-yr)
- Fig. 3 – don’t project >5 years and forecasts for directional trended stocks with little interannual var did well at 3 years regardless of method?!
- Favorite quote: “it is especially important to determine an appropriate recruitment reference period from which to sample. When sampling is independent of SSB, this reference period typically comprises only more recent years to avoid forecasting historical recruitments that are unlikely to reoccur in the near future.”

- Applied 16 commonly employed or recent recruitment forecasting methods on an empirical-based testing set of population dynamics for 31 finfish stocks representing a range of stock characteristics that exist worldwide
- The 16 recruitment forecasting methods fall into the following four general classes: (a) sampling methods, (b) empirical dynamic modelling, (c) time-series analysis and (d) classical methods
- Evaluating and comparing the forecast error and bias in spawning stock biomass (SSB) at the end of different forecast periods for each recruitment forecasting method and stock
- Pros: We're not crazy. This is a tough nut to crack. The simple procedure of forecasting recent mean recruitment with autocorrelated deviates resulted in no apparent bias, even after 10 years, and forecast error was comparable to most other methods.
- Cons: no clear answer beyond "don't project out too far and perhaps avoid time-series methods for forecasts 5+ years". Inability to identify best recruitment forecasting method.

Walters, C, and AM Parma. 1996. Fixed exploitation rate strategies for coping with effects of climate change. Canadian Journal of Fisheries and Aquatic Sciences 53: 148-158.

- Analyzed constant harvest policy in changing enviro. This can produce long-term harvests that are very close (within 15%) to the theoretical optimum that could be achieved if all future climatic variations were known in advance.
- Finding implies that it may be more cost effective to invest in research on how to implement fixed harvest rate strategies than to invest in research on explaining and predicting climatic effects.
- Successful implementation may require a combination of improved stock size assessments, and stringent regulatory measures to substantially restrict the proportion of fish at risk to fishing each year.
- Pros: Interesting conclusion from Uncle Carl and Aunt Ana.
- Cons: Stringent regulations that are required may not be functionally possible.

Ye, H, RJ Beamish, SM Glaser, SCH Grant, C-H Hsieh, LJ Richards, JT Schnute, and G Sugihara. 2015. Equation-free mechanistic ecosystem forecasting using empirical dynamic modeling. PNAS: E1569-E1576.

- Uses empirical dynamic modeling (EDM) to include environmental factors in fisheries forecasting models for sockeye salmon in the Fraser River
- Pros: Doesn't require a specified mathematical formulation; test forecast skill using cross-validation; increasing amount of data improves predictions
- Cons: Requires a time series of data that may not always be available