

1 **Beyond visualizing catch-at-age models: lessons learned**  
2 **from the r4ss package about software to support stock**  
3 **assessments**

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20

21 **Abstract**

22

23 Stock assessment analysts are exploring an increasingly diverse and complex range of models while also  
24 facing higher expectations for consistency, documentation, and transparency in reports and  
25 management advice, all within a tight timeline. Meeting these goals requires increased efficiency at all  
26 steps in the assessment process from data processing, through model development and selection, to  
27 report writing and review. Here, we describe one widely used tool that has proven successful in  
28 increasing the efficiency of the assessment process: the *r4ss* package, which supports the use of the  
29 Stock Synthesis modeling framework. What began 15 years ago as a tool to provide simple model  
30 diagnostics, including plots showing data and model results, has grown into a large collection of R  
31 functions to support many aspects of the assessment process. We provide an overview of the *r4ss*  
32 features and illustrate its utility with examples from recent applications. Finally, we discuss lessons  
33 learned from the ongoing development of *r4ss* that can be applied to similar efforts associated with the  
34 next generation of stock assessment packages.

35

36 **1. Introduction**

37

38 Assessment of fish stocks (hereafter referred to as “stocks”) is a necessary task, largely because of  
39 mandates by federal and regional governing bodies to provide information about stock status and apply  
40 harvest control rules to inform catch limits under harvest policies. While incorporating disparate data  
41 sources into a single population model (integrated analysis) to determine stock status is routine,  
42 understanding the fit to each data set and its associated influence on the model results can be  
43 challenging (Maunder and Punt, 2013; Maunder and Piner, 2015). A standardized set of visualization  
44 tools is key to providing understanding and transparency throughout this process for stock assessment

45 analysts, reviewers, stakeholders, and managers. For example, standardized tools allow analysts to  
46 quickly understand model results and explore new model configurations during the model development  
47 and peer review processes; reviewers scrutinize the analyses and investigate other alternatives with the  
48 aid of visualization tools, ultimately deciding if the assessment results are appropriate for use by  
49 management; and lastly, stakeholders and managers need to understand the model results, and hence,  
50 need intuitive visualization tools to inform the range of management options and decide on which  
51 management measures to take.

52

53 Visualization tools can aid analysts throughout the assessment process. For example, Richards et al.  
54 (1997) found while developing a stock assessment for Pacific ocean perch (*Sebastes alutus*) that  
55 visualization tools allowed them to better understand their data sets and pinpoint data features that  
56 needed to be accommodated, develop a statistical catch-at-age model well suited to the data sets, and  
57 evaluate model output more thoroughly. Stock assessments often require hundreds of model runs.

58 Tools for quickly visualizing model results allow analysts to more efficiently select among them. As an  
59 illustration of the power of automated workflows and visualization tools, calculating residuals by hand  
60 would take hours, while visualizing patterns in residuals already plotted can take just minutes.

61 Visualization tools can also relieve the feeling of being time-poor when conducting stock assessments  
62 (Bentley, 2015). Aside from efficiency, a thorough and standardized set of tools for visualizing model  
63 output can help catch errors such as misspecified models and aid in the report writing process, as most  
64 stock assessment reports require numerous figures and tables.

65

66 The peer review process for stock assessments (e.g., Brown et al., 2020), to determine if assessment  
67 results can be used by management bodies for decision making, benefits from visualization tools. For  
68 example, Regular et al. (2020) found that interactive data and model dashboards improved their ability

69 to communicate with stakeholders during the stock assessment review process for a northern cod stock  
70 in the northwest Atlantic. Producing standardized figures across assessments increases ease of  
71 understanding for readers and simplifies comparisons across assessments. Often, peer reviewers are  
72 tasked with evaluating modeling decisions and model results, ultimately deciding if the assessment  
73 results are appropriate for use by management. Requests for visualizations made during assessment  
74 review processes are often expected in subsequent reviews, especially if the same reviewers may be  
75 engaged in the future, and should be added to assessment analyst toolboxes, such that they can be  
76 better prepared for future reviews. Thus, this toolbox grows with each review and helps facilitate  
77 efficient reviews, because analysts are able to quickly produce desired output before it is asked for.

78

79 The Terms of Reference (ToR) for stock assessment reviews have also coevolved with visualization tools,  
80 increasing the value of standardization. For instance, 10 years ago the ToR for groundfish stock  
81 assessments conducted for the Pacific Fishery Management Council (PFMC 2009) had an eight-point  
82 bulleted list of general stock assessment team deliverables, while the ToR used in 2019 (PFMC 2019) had  
83 a check list of 74 elements within 18 sections with more specificity. These ToR changes have been driven  
84 in part by feedback from reviewers seeing the benefit of new visualizations and diagnostics for individual  
85 assessments as described above. The ToR changes, in turn, lead to wider adoption of the new  
86 approaches for analysts working to meet them, a shift which is easier when the analysts can use shared  
87 tools to meet the new standards.

88

89 Effectively translating complicated assessment models and results into an easily digestible form for  
90 fishery managers and stakeholders can be challenging, especially when presenting information across a  
91 large range of stocks (Dichmont et al. 2016). Presenting assessment results in a consistent manner  
92 across stocks can lessen the communication challenge, allowing for improved discussions between

93 analysts, stakeholders, and managers. The development and application of an assessment toolbox for  
94 use by analysts facilitates this process without creating additional workload.

95

96 Communication methods for stock assessment results are not a frequent topic in fisheries science  
97 journals, but it is an area where new ideas are rapidly developing and which deserves greater  
98 prominence in the literature. The widespread adoption of the generalized integrated analysis platform  
99 Stock Synthesis (SS, Methot and Wetzel, 2013) provided an opportunity to develop a standardized set of  
100 visualization and automation tools, given a larger pool of potential applications, users, and contributors  
101 (Punt and Maunder, 2013). Here, we discuss how *r4ss*, an R package containing tools for working with SS  
102 models, has improved the stock assessment development and review processes for individual analysts,  
103 reviewers, and managers over its 15 years of active development. We also highlight lessons learned  
104 from developing and using *r4ss* that could be applied when developing new visualization tools for a new  
105 stock assessment modeling platform.

106

## 107 **1.1 History**

108

109 The *r4ss* package grew organically from a single code script written by a single author in 2005 for use in  
110 the R statistical programming language (R Core Team, 2020) to a large open-source R package with  
111 many contributors. Before *r4ss* was developed, the typical workflow for SS users was examining the  
112 output text files directly or importing them into Excel where figures were generated using Visual Basic  
113 scripts or created manually for each model. The figures were time-consuming to create, had limited  
114 reproducibility, and did not provide reviewers and managers with a consistent product with which they  
115 could become familiar as modifications for an individual model were rarely generalized for the benefit of  
116 other models. The original *r4ss* R script became widely used by the stock assessment team at the

117 National Oceanic and Atmospheric Administration (NOAA) Northwest Fisheries Science Center (NWFSC)  
118 and grew in complexity as members of the assessment team provided suggestions for additions. The  
119 increase in use also increased the burden associated with maintaining the code, and in 2008 the lead  
120 developer role was shifted to a postdoctoral researcher which allowed for more directed development,  
121 facilitating the growth and use of the code to function across SS-assessed stocks. Shortly thereafter, the  
122 code was put under version control and released as open source to facilitate distribution and  
123 development, to increase transparency, and to reduce the burden of maintenance on any individual  
124 developer.

125

126 Although, in the early years of its development, most of the code was written by just two people,  
127 feedback from users was essential to improving the package. In particular, conversations with  
128 participants at the annual Inter-American Tropical Tuna Commission (IATTC) Stock Assessment  
129 Workshop series (since succeeded by the Center for the Advancement of Population Assessment  
130 Methodology workshops) led to significant steps forward in the project. The initial public release of *r4ss*  
131 took place during the 2008 IATTC workshop (Maunder, 2008); discussions at the 2009 workshop inspired  
132 the conversion of the script into a formal R package available on the Comprehensive R Archive Network  
133 (CRAN); and a demonstration of the Javascript viewer for Multifan-CL (SPC, 2010) associated with the  
134 2011 workshop led to the development of an HTML viewer for *r4ss* plots. Formatting the *r4ss* script as  
135 an R package brought the benefits of structured documentation for each function; making the *r4ss*  
136 package available on CRAN made it easier to find and install (as CRAN is the first source most users will  
137 look to for R packages). The number of authors, all of whom have made substantial code contributions,  
138 has also grown from 5 in 2009 to 29 in 2020. The methods used to incorporate code into the *r4ss*  
139 codebase have also evolved from contributors emailing files to the lead developer, to GitHub pull  
140 requests that get automatically checked and manually reviewed before merging. Although the

141 development workflow has grown more sophisticated, the organic evolution of *r4ss* leaves many legacy  
142 aspects of the code and package structure, which are typical of research software (Ram et al. 2019), but  
143 would be designed differently if starting from scratch today.

144

145 **1.2 Overview of the package**

146

147 The *r4ss* package ([github.com/r4ss/r4ss](https://github.com/r4ss/r4ss)) includes functions designed to work with SS input and output  
148 files (Supplement 1). The main types of functions in the package are: 1) functions to read and plot  
149 information from SS output files to visualize model results; 2) functions to automate tasks associated  
150 with SS models that are routinely performed; and 3) functions to read, create or modify SS input files.  
151 In the examples, we will focus on functions to visualize model results and automate routine tasks.

152

153 **2. Examples**

154 **2.1 Multimodel management (Pacific halibut)**

155 The Pacific halibut (*Hippoglossus stenolepis*) stock assessment comprises four individual models which  
156 are used to create an ensemble for management use by the International Pacific Halibut Commission  
157 (IPHC; Stewart and Martell, 2015; Stewart and Hicks, 2018). Each of the models represent a different  
158 hypothesis regarding the best approach for modelling the stock dynamics. The four models vary in the  
159 length of the modelled period, the level of data aggregation, and data-weighting, among other factors  
160 (Stewart and Hicks, 2020). Use of special features (e.g., environmental covariates, time-varying  
161 catchability) in a subset of the models is automatically detected by *r4ss* functions and appropriate  
162 reporting is included in subsequent output. With four models to diagnose, it is efficient to run the same  
163 function calls and retrieve a complete set of output without having to adjust the code for each individual

164 model. When suitable models have been identified and refined, the output can be easily summarized  
165 (Figure 1).

166 This application also highlights the benefit of standardized output for review purposes. For the 2019  
167 stock assessment, the IPHC conducted a two-stage review, utilizing its standing Scientific Review Board,  
168 as well as a contracted external reviewer (IPHC 2020). Model input files and directories containing the  
169 *r4ss* HTML and individual output files from the *SS\_output* function were provided electronically to all  
170 reviewers. This approach allowed for standardized reporting (reviewers were all familiar with *r4ss*  
171 output) and comprehensive diagnostics for all four models in a more detailed summary than could have  
172 been provided only in a standard written document. Reviewers were not required to re-run the *r4ss*  
173 code to explore the detailed results, but the HTML-approach re-created a user-friendly summary on  
174 demand.

175 **2.2 Adoption of new modeling approaches and diagnostics (Big skate)**

176

177 The 2019 assessment of big skate (*Beringraja binoculata*) off the U.S. west coast (Taylor et al., 2019)  
178 illustrates the efficiency gained by using tools like *r4ss*. Specifically, *r4ss* facilitated the use of conditional  
179 age-at-length (CAAL) data, exploration of numerous model configurations, timely model development  
180 during the review process, and an efficient development and revision of the assessment report.

181

182 The stock assessment of big skate used CAAL data (Figure 2), which has become a standard treatment of  
183 age- and length-composition data collected from the same samples used in integrated assessments to  
184 reduce biases associated with length-based selection and better inform parameters related to variability  
185 in length-at-age (Hoyle and Maunder, 2006; Stewart, 2005; Piner et al., 2016). However, adopting this  
186 approach to modeling compositional data was initially hampered by lack of associated model diagnostics

187 and appropriate data weighting methods. In response to this concern new diagnostics were developed,  
188 including the calculation of the implied fit to the marginal age composition (called “ghost” age  
189 compositions within *r4ss*) and a new diagnostic figure to evaluate the fit of the model expectation to the  
190 mean and variability around the mean age at length (Figure 3). Data weighting approaches for CAAL data  
191 have likewise been the subject of ongoing research and new diagnostics. Francis (2011) proposed a new  
192 approach to tuning input sample sizes for marginal composition data. Two authors independently  
193 developed R code for applying the Francis (2011) algorithm and their functions were combined and  
194 contributed to *r4ss* in 2014. This facilitated more frequent use of this method and the discovery that an  
195 extension was needed for CAAL data (Punt 2017) which was subsequently incorporated into *r4ss*. The  
196 assessment of big skate used the Francis-Punt tuning method but also considered the sensitivity of the  
197 model results to the Dirichlet-Multinomial (Thorson et al., 2017) and McAllister-Ianelli (McAllister and  
198 Ianelli, 1997) methods of data weighting as alternatives. These sensitivity analyses were trivial to  
199 implement and easy to compare thanks to the support for all three approaches in SS and *r4ss*. Choosing  
200 among the methods unfortunately remains somewhat subjective, but the opportunity to quickly develop  
201 all three models and examine the associated fits to the CAAL data and other data types is essential for  
202 understanding the impact of data weighting choices on the perception of stock status and the structural  
203 uncertainty associated with assessment results.

204

205 The assessment of big skate also benefited from previous work to understand sex ratios in models fit to  
206 data for Pacific halibut. These explorations led to the inclusion of a new diagnostic figure within *r4ss*  
207 showing the sex ratio derived from the observed and expected age- or length-composition data (Figure  
208 4). For big skate, the figure revealed unbalanced sex ratios at sizes where there was little evidence of  
209 dimorphic growth, suggesting that sex-specific differences in selectivity should be included in the model.  
210 The availability of a diagnostic previously developed for a different stock was vital to the model

211 development during a period where the time available to explore new ways to understand patterns in  
212 the data was limited. After applying the diagnostic to big skate, discussions facilitated by the use of the  
213 GitHub issue tracker led to further refinement of the diagnostic. This collaborative effort highlights how  
214 open source code can increase efficiency, promote collective understanding, and allow for incremental  
215 progress.

216

## 217 **2.3 Efficient exploration of alternative models (Big skate)**

218

219 In the process of developing the big skate assessment, over 800 different model configurations were run  
220 during 2 months, almost 200 of which were run during the 5-day review meeting. These included seven  
221 new candidate “base” models, 108 models that were part of likelihood profiles, 72 sensitivity analyses,  
222 and three alternative forecast scenarios. Functions in *r4ss* were used to run the likelihood profiles and  
223 create the associated plots as well as automatically repeat sensitivity analyses for new candidate  
224 models. This volume of model examination, comparison, and selection has become a typical part of the  
225 assessment process in many regions, but thorough examination of this many models is only possible  
226 with tools to quickly compare and aggregate results.

227

228 In total, approximately 40,000 standard *r4ss* diagnostic figures were created during the 2-month model  
229 development period (~200 figures from each of ~200 models). The option to look at a suite of  
230 diagnostics for any given model allowed the authors to quickly determine whether the data were  
231 entered into the model input files correctly, look for outliers, and, as the models developed, evaluate  
232 whether alternative modeling approaches merited further consideration. The full collection of diagnostic  
233 figures and tables and the associated HTML viewer files (e.g., [r4ss.github.io/r4ss/BigSkate](https://r4ss.github.io/r4ss/BigSkate)) for models

234 that were discussed in the review were shared with the review panel to allow them to further explore  
235 these models beyond the limited information that could be provided in a brief presentation.

236

237 **2.4 Bayesian applications (Pacific hake)**

238 The use of Bayesian methods for integrated assessment models have well-documented benefits (e.g.  
239 use of prior information and better characterization of posterior distribution) and challenges (slow run  
240 times and shifting focus from uncertainty in model structure) (Maunder 2003, Stewart et al. 2013;  
241 Monnahan et al. 2019). Analysts using Bayesian approaches are best served by having efficient  
242 approaches for comparing posterior distributions to maximum posterior density (MPD) estimates and  
243 associated asymptotic uncertainty (Fournier et al. 2012; Stewart et al. 2013). Examining the relationship  
244 between these posterior estimates and prior distributions is also vital to understanding the influence of  
245 the choice of prior. The annual stock assessment for Pacific hake (Grandin et al. 2020) has used Markov  
246 Chain Monte Carlo (MCMC) sampling to characterize posterior density distributions for nearly two  
247 decades. The *r4ss* package can be used to plot the prior and posterior distribution of all estimated  
248 parameters (Figure 5) as well as time series plots comparing quantiles from the posterior samples of  
249 derived quantities to the associated MPD estimates and their asymptotic uncertainty intervals. This  
250 functionality was initially developed for Pacific hake in 2011 but generalized to work for any SS model; it  
251 has allowed the assessment team for Pacific hake to demonstrate the qualitative similarities between  
252 the two estimation methods and use more computationally intensive MCMC sampling for a subset of  
253 the models explored while showing only the more rapidly available MPD results for numerous sensitivity  
254 analyses. However, many of the plots included in the Pacific hake assessment report require custom  
255 code (available at [github.com/pacific-hake/hake-assessment](https://github.com/pacific-hake/hake-assessment)) as the *r4ss* package does not contain the  
256 necessary tools to plot a variety of valuable diagnostics for Bayesian models, such as the fit of posterior  
257 distribution of expected values to observed data. Adoption of the no-U-turn sampler for SS and other

258 models using ADMB and TMB (Monnahan and Kristensen, 2018), which decreases model runtime  
259 compared to the default Metropolis-Hasting algorithm used for MCMC in ADMB, may increase the use  
260 of posterior sampling in integrated models and inspire generalization of the custom Pacific hake code for  
261 more widespread use by users of *r4ss* or other generalized packages.

262 **3. Collective experience of the authors**

263 In addition to the examples above, *r4ss* has facilitated the formalization of many assessment authors'  
264 "tips and tricks" for efficiently building, diagnosing, and reporting stock assessment models. Sharing of  
265 collective experience reduces the learning curve for new assessment authors and also provides structure  
266 to remind experienced authors of perennial pitfalls. This section reports a series of problems that we the  
267 authors have collectively encountered across a large number of individual stock assessments that  
268 standardized and generalized tools like *r4ss* can solve (Table 1).

269

270 **4. Discussion**

271 Software packages are often described as black boxes (Dichmont et al., 2016) and fitting models to data  
272 has previously been described as an art rather than a science because of numerous non-trivial choices in  
273 the model development process (e.g., how to specify the model, how to weight the data). Fortunately,  
274 stock assessment scientists are formally trained in at least either model development or model fitting,  
275 helping to ensure that results fulfill mandates to provide best available science. Where stock assessment  
276 scientists typically lack formal training is in data visualization and how to effectively communicate  
277 science to stakeholders and fishery managers. Punt and Hilborn (1997) summed up the problem  
278 suggesting that "the art of stock assessment involves determining what to present to managers and the  
279 best way to summarize information." The importance of creating effective visualizations and effectively  
280 communicating science has also been noted in Management Strategy Evaluation processes (Miller et al.

281 2019). Because it is difficult to predict what decision makers know versus what they need to know  
282 (Fischhoff, 2013), leaning towards archiving vast amounts of easily accessible information is a typical  
283 practice among stock assessment scientists and their associated organizations. Key to this approach has  
284 been the development of open source tools such as *r4ss* that reduce the time needed to manipulate  
285 model-input files and run sensitivity analyses, summarize model output in a standardized way to  
286 minimize the time needed to interpret output, and openly document assumptions and protocols used  
287 along the way.

288

#### 289 **4.1 Successes**

290 We attribute some of the success of *r4ss* to increases in the use and usability of open source tools for  
291 science (e.g., Stewart Lowndes et al., 2017; Boettiger et al., 2015; Huber et al., 2015). Software  
292 development tools like version control and automated testing have facilitated the continuous  
293 development process and increased the reliability of the code base. As more scientific disciplines model  
294 themselves after the geospatial community, a leader when it comes to open source and free software  
295 development (Bocher and Neteler, 2012), code sharing has become the norm. We recognize that  
296 exposing one's work in this way may be uncomfortable at first, but the benefits to the community far  
297 outweigh the costs. For example, the routine use of *r4ss* by different users with models fit to a diverse  
298 array of datasets leads to the discovery of bugs (whereas bugs may go unnoticed with personal code)  
299 that can be reported (to [github.com/r4ss/r4ss/issues](https://github.com/r4ss/r4ss/issues)) and fixed. Many of the users also suggested fixes  
300 and improvements. Thus, the *r4ss* functions become more reliable and more useful than code used for  
301 one-off manipulations.

302

303 The *r4ss* project has been successful for the stock assessment process as a whole. For individual stock  
304 assessment analysts, using *r4ss* allows for a more automated workflow in which it is easier to pinpoint

305 issues during the base model development process, run sensitivity analyses, and generate figures for  
306 reports. The package can also be used by analysts who lack the time or training to develop their own  
307 personal diagnostics code, thus empowering many to conduct higher-quality stock assessments. The  
308 availability of *r4ss* as a platform for distributing new diagnostics and tuning methods has contributed to  
309 collaboration among researchers and facilitated timely adoption of the new approaches within the stock  
310 assessment community. For reviewers, managers, and stakeholders, the standardized and extensive set  
311 of plots created by *r4ss* has made the stock assessment process and its results more transparent and  
312 easier to interpret. One unintentional consequence of the availability of automated visualization tools is  
313 that reviewers and managers often expect more output, which reduces some of the time-savings that  
314 the tools provide for individual analysts. However, movement toward more standardized model  
315 diagnostics for integrated fisheries models (Carvalho et al., this issue) mitigates this challenge.

316

317 Outside of the stock assessment workflow, *r4ss* can also be used as a dependency for other tools for  
318 working with SS models. For example, instead of maintaining similar functionality, the *ss3sim* R package  
319 (Anderson et al., 2014) imports *r4ss* as a dependency. This allows *ss3sim* to benefit from improvements  
320 and fixes added to *r4ss*. As the use of SS has grown, so has the ecosystem of tools that interact with it  
321 for conducting simulation analyses, MSEs, data-limited models and other tasks specific to a particular  
322 region or stock (Cope and Wetzel, this issue). We foresee a similar proliferation of tools associated with  
323 any widely used next generation assessment platform, where the basic functions of interpreting output  
324 files and interacting with input files can be contained within a single package on which others depend.

325

## 326 **4.2 Challenges**

327 The *r4ss* project also reveals the challenges of a standardized tool. It was created without foresight into  
328 what it would become, leading to a variety of problems. For example, a mismatch between the names

329 used in *r4ss* and SS as well as non-standardized naming and output in SS are common issues that are  
330 difficult to remedy without a significant impact on the large set of additional R packages and individual  
331 scripts that depend on *r4ss*. Keeping up with the development of SS while maintaining backward  
332 compatibility with older versions of SS that are still in use is a challenge for the *r4ss* developers. While  
333 *r4ss* saves time for users, it creates more work for developers and maintainers.

334

335 Another challenge is the increasing scope of *r4ss* over time, as more functions and options have been  
336 added to the package. Generally, the scope of *r4ss* is “tools in R to work with Stock Synthesis”, but  
337 initially the scope of *r4ss* was “visualization tools in R to work with Stock Synthesis”. This creates  
338 challenges in balancing flexibility for advanced users with understandability for newer users, while  
339 maintaining interoperability with various dependent projects like *ss3sim* and automated assessment  
340 document writing approaches. “Scope creep” is a common problem in software projects, including R  
341 packages. For example, the R package *devtools*, which is widely used by R package developers  
342 (Wickham, 2015) was split into multiple smaller R packages as a solution to *devtools* becoming large and  
343 thus harder to develop and for other packages to depend on (Hester, 2018). A similar approach could be  
344 applied to *r4ss* to manage this balance.

345

346 In addition to the increase in scope associated with new functions added to *r4ss*, the range of uses for  
347 the figures created by the original *r4ss* code has grown over time. The original intent was to produce  
348 quick diagnostics for use by assessment analysts, but those figures (many of which are effectively  
349 unchanged in appearance since 2005), are now frequently used in assessment reports and  
350 presentations, contexts which would benefit from additional adjustments and refinements.

351

352 Finally, creating a collaborative community is challenging. While *r4ss* has successfully facilitated  
353 collaborations among stock assessment scientists working around the world, it is difficult to encourage  
354 contributions to a collaborative tool over individual development. This is especially challenging because  
355 most stock assessment scientists (like many scientists working in other disciplines) have little to no  
356 formal software development training and thus the hurdle of learning collaborative software  
357 development tools like version control is high. In cases where formally trained software developers (as  
358 opposed to scientists) are the ones writing code, these developers are often working alone, unlike in  
359 typical software engineering environments (Killcoyne and Boyle, 2009), so collaboration is not as  
360 common. The *r4ss* developers have encouraged collaboration by allowing contributions in multiple  
361 ways, from formal pull requests via a version control system to emailing code to *r4ss* maintainers. We  
362 also recognize that contributing code is not the only way to contribute to a tool; for example, bug  
363 reports and discussions taking place through the *r4ss* issue tracker also allow people who may never  
364 touch the *r4ss* codebase to contribute. Like the Ocean Health Index project (Stewart Lowndes et al.,  
365 2017) and many other open source projects, the *r4ss* community attempts to meet collaborators where  
366 they are in terms of understanding and using software development tools, while encouraging and  
367 empowering them to learn new approaches and practices.

368

### 369 **4.3 Recommendations**

370 The 15-year history of *r4ss* development provides insight for the future development of tools to work  
371 with stock assessment models. First, automating the creation of model diagnostics and plots is a  
372 fundamental aspect of developing a generalized model package, as it is too time consuming for analysts  
373 and reviewers to evaluate the validity of models using ad hoc approaches. The challenge of developing  
374 *r4ss* after SS highlights the difficulties in retrofitting tools to work with existing models. Retrofitting *r4ss*  
375 to SS has led to model inputs and outputs that change over time and are not standardized with other

376 modeling platforms, thus creating an increase in development time for *r4ss*. Thus, we believe that  
377 development of future tools for stock assessment modeling workflows should be developed in tandem  
378 with any new stock assessment modeling framework and some standardization is needed between the  
379 stock assessment model framework (or frameworks) and tools for efficient workflow and model  
380 diagnostics. However, the stock assessment modeling framework and associated tools should be kept  
381 somewhat independent, as the software requirements and development processes for assessment  
382 modeling frameworks, which depend on computational efficiency and reliability, are different from  
383 those that best suit associated tools like *r4ss*. While long-term planning is helpful, it will not be possible  
384 to perfectly plan the tools because future needs are unpredictable. Adopting a flexible approach will be  
385 necessary in a future tool.

386

387 We recommend using R as the basis for similar tools associated with the next generation of integrated  
388 models. While there are other languages that could be faster or better-suited to some of the tasks, R is  
389 widely used in fisheries science (Schnute et al., 2007, Anderson et al. 2020) and thus there is a larger  
390 pool of potential users and developers. We argue that having a large group of users and developers is  
391 more important than computational efficiency for this aspect of the stock assessment process.

392

393 We also think that the open source development model and creating an environment in which users'  
394 contributions are encouraged is key to the success of a future diagnostic tool. Once the core elements  
395 are in place for a tool, users can contribute functions like new plots without having to understand much  
396 about the package. Open source leads to more bugs being caught and fixed quickly while also facilitating  
397 the growth of the tool to fit the ever changing needs of stock assessment science. While open source  
398 software may be "free", it still has maintenance costs, typically in the form of maintainers' time. In the  
399 case of *r4ss*, there is a primary maintainer who typically spends about 8 hours a week working on the

400 package. Maintenance is necessary for the long-term sustainability of software (Ram et al. 2019). Who  
401 (organizations or individuals) will maintain the software and how much time they can devote to  
402 maintenance should be carefully considered during the planning stages of a new stock assessment  
403 modeling framework and its associated diagnostic tool.

404

405 Standard software development tools and practices are key for creating scientific software that works  
406 well (Wilson et al., 2014; Wilson et al., 2017) and will be important to use in tools designed to work with  
407 the next generation of integrated models. At a bare minimum, the software should be under version  
408 control, hosted in a public repository and provide standard workflows for collaborative coding. Other  
409 tools that are essential to maintaining code that works are a testing framework for running unit and  
410 integration tests (and writing tests as code is added) and a continuous integration tool to automatically  
411 build the software and run the testing framework often.

412

413 One limitation of *r4ss* is it is designed to only work with a single stock assessment platform, SS. Non-  
414 standardized inputs and outputs among assessment model frameworks create challenges for comparing  
415 modeling approaches. A generalized package not specific to any assessment model framework would  
416 eliminate this problem while also allowing analysts to consider other potential model configurations not  
417 available in a single framework and more easily compare models developed in different frameworks.  
418 However, to our knowledge, no package which has sought to provide this type of generality has been  
419 widely used for more than one assessment platform. There are multiple challenges with creating a  
420 generalized package for model diagnostics. First, the differences in input and output formats used in  
421 different stock assessment platforms (such as those listed in Punt et al., this issue) would add overhead  
422 associated with translating into a common framework. Second, development of a generalized tool  
423 would require expertise in multiple assessment platforms (e.g., an attempt to create a function within

424 *r4ss* to convert SS output into the format required by another diagnostic package was unsuccessful  
425 because no one was adequately familiar with both platforms). Rather than focus on development of a  
426 more generalized version of a tool like *r4ss*, we believe that the effort would be better invested in the  
427 design and use of more standard formats in the next generation of stock assessment platforms and their  
428 associated tools for input and output process and model diagnostics. However, tools to translate input  
429 files between assessment packages have been successfully developed largely as one-off projects when  
430 the comparison of results across platforms is desired. For example, tools to compile results across  
431 assessment platforms were developed while conducting a project to formally compare some stock  
432 assessment platforms used in the U.S. (Li, 2020). These tools have the potential to become more  
433 generalized for future projects. Unfortunately, it is normally faster to get code to work only for what is  
434 directly needed rather than creating generalized code. As ensemble modelling in stock assessment  
435 (Stewart and Martell, 2015) becomes more popular, efforts to translate inputs and output between  
436 assessment platforms may become increasingly worthwhile.

437

438 Tools similar to *r4ss* which are developed in the future should also consider the divergent needs for  
439 interactive exploration of model results and production of written reports. Regular et al. (2020) argue  
440 that interactive visualizations support deeper understanding of models, but we have found that the  
441 consistent set of figures as stand-alone image files (and associated captions) created by *r4ss* has been  
442 valuable for automating the compiling of assessment reports. It is difficult to create a tool that works  
443 well for all purposes, so whether interactive or static visualizations (or both) are needed given the  
444 purpose of the tool should be carefully considered.

445

446 Development of a consistent format for assessment reports across regions and agencies could further  
447 simplify the report-writing process by providing all the benefits of shared code discussed above as well

448 as improve understanding of the reports for the many reviewers and researchers who work with stock  
449 assessments from multiple regions. For example, standardized static visualizations of patterns in data  
450 across 113 rockfish species developed by Anderson et al. (2020) have made these data more accessible  
451 to more people through two page reports that can be quickly explored. However, standardizing reports  
452 would require a significant effort as the processes for changing the Terms of Reference for stock  
453 assessment reports and reviews, the stock assessment modeling platforms, and the tools like *r4ss* that  
454 provide the bridge between them, differ among regions and agencies.

455  
456 Finally, although the *r4ss* code is open source and available for use in any future project, we recommend  
457 that any successor to the *r4ss* package should be developed from the ground up, learning from the  
458 successes and challenges of *r4ss*, and copying the useful features of *r4ss*, but not utilizing the existing  
459 code. This type of restart occurred when Stock Synthesis was converted from FORTRAN to ADMB during  
460 Hurricane Isabel in 2003, providing the basis for a long period of utility for a large community of stock  
461 assessment scientists. Replacing *r4ss* will take a huge effort, but we have found that the value of *r4ss*  
462 has not just come from the tool itself, but the understanding and experience gained and community  
463 built by all those who have contributed to this effort.

464  
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628

629 **Tables**

630 **Table 1.** Issues related to the stock assessment modeling process and potential solutions to alleviate or  
631 minimize the issues.

Issue	Solution
Placeholder values for data not available at the start of the assessment process inadvertently retained in the final model.	Frequently make and view plots of data included in input files.
Parameters on bounds in the final model.	The <i>r4ss</i> HTML viewer includes a table that highlights parameters on bounds in red so they are easily identified and a plot of the estimated parameter values and associated uncertainty relative to the parameter bounds and prior distribution; consider reconfiguring the model.
Incorrect parameterization of processes because it is difficult to see the resulting form from model input files, e.g., selectivity curve.	Plots of processes resulting from input parameters such as selectivity are automatically available in the <i>r4ss</i> HTML viewer; change input parameters until the desired shape is found.
Confounded parameters.	A correlation check is included in the <i>r4ss</i> HTML viewer; consider reconfiguring the model.
Small model changes can have cascading effects on the model results that go unnoticed.	The <i>r4ss</i> HTML viewer allows examination of the holistic model results and comparison functions

allow for easy visualization of how results change with each change to input files.

Using custom plotting code not under version control edited by multiple analysts independently can lead to confusion and makes splitting up work difficult.

Sensitivities requested during a review process can be difficult to set up and implement quickly without errors.

Use generalized and standardized tools to modify the model files increases the robustness of results and decreases the likelihood of errors.

Need to quickly update figures and tables when models change.

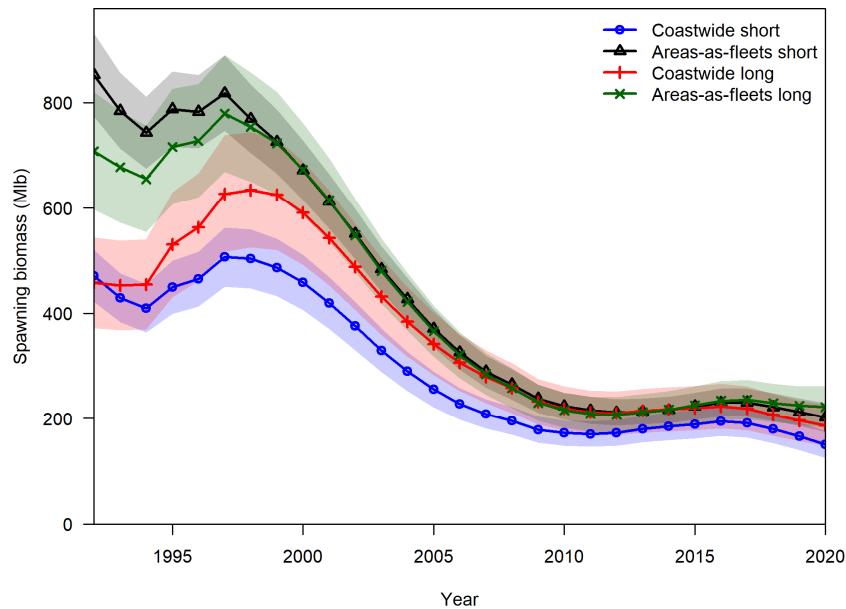
Use code (e.g., R Markdown or LaTeX) with a standardized plotting tool to generate reports.

---

632

633

634 **Figures**

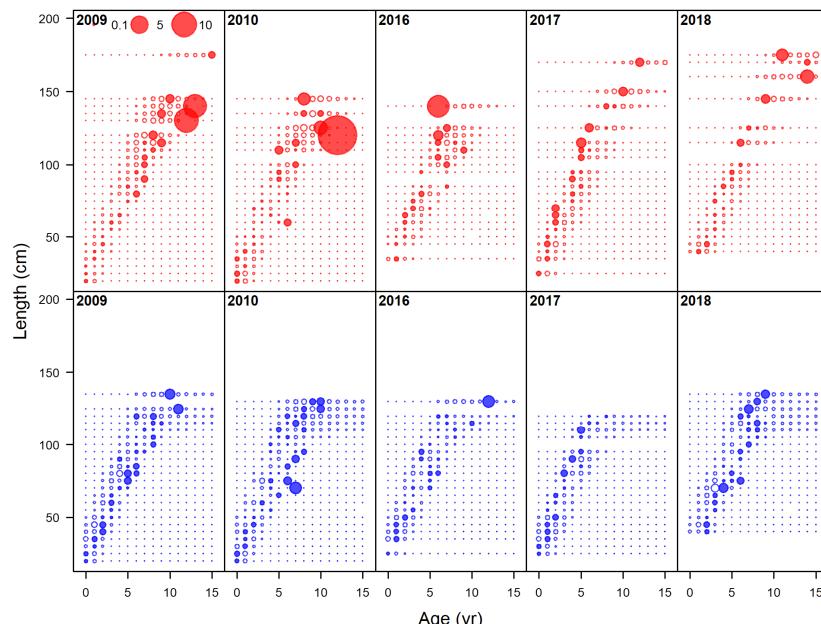


635

636 Figure 1. Recent time-series of individual model estimates for female spawning biomass for Pacific halibut created using the  
637 *SSplotComparisons* function in *r4ss*. The shaded polygons represent the approximate 95% confidence intervals derived from  
638 asymptotic uncertainty estimates from the models.

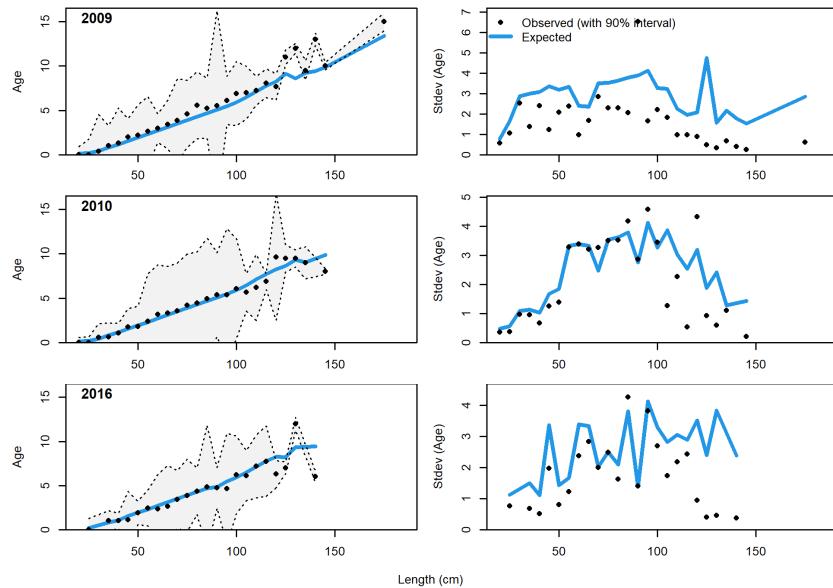
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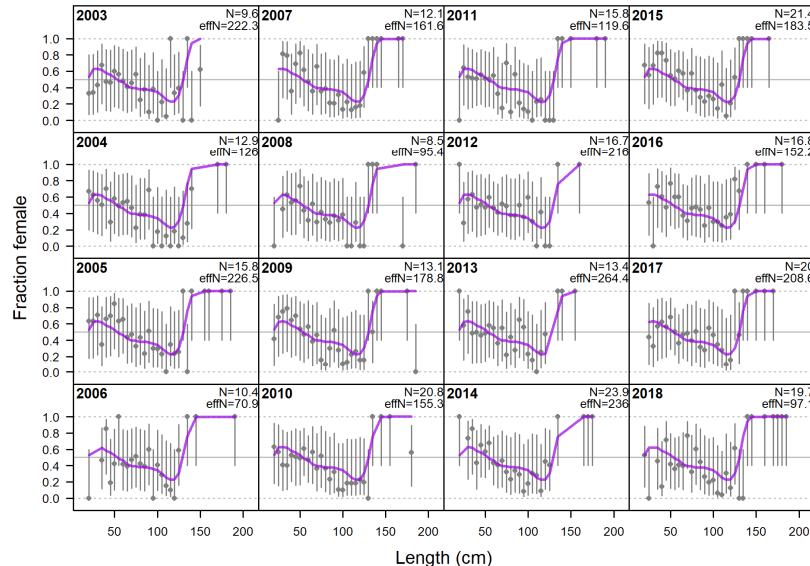
642 Figure 2. Pearson residuals showing fit of big skate model to conditional age-at-length data. Upper panels are females (red  
643 circles) and lower panels males (blue circles). Filled circles represent observations greater than the expectation, while unfilled  
644 circles represent observations less than the expectation. Size of the circles (key at top of upper left panel) represent the  
645 magnitude of the residual. The year in which the conditional age-at-length data were collected is shown in the upper left corner  
646 of each panel.



647

648 Figure 3. Application of the conditional-age-at-length diagnostic plot for three years of big skate age and length data. The left  
 649 panels are mean observed age at length by length bin (points) with 90% confidence intervals (shading) calculated from the  
 650 asymptotic standard errors (SE) compared to the expected mean age at length (solid line) for each year (upper left corner of  
 651 each left panel). The right panels show the corresponding mean age at length SE values (points) compared to the expected  
 652 standard deviation (line).

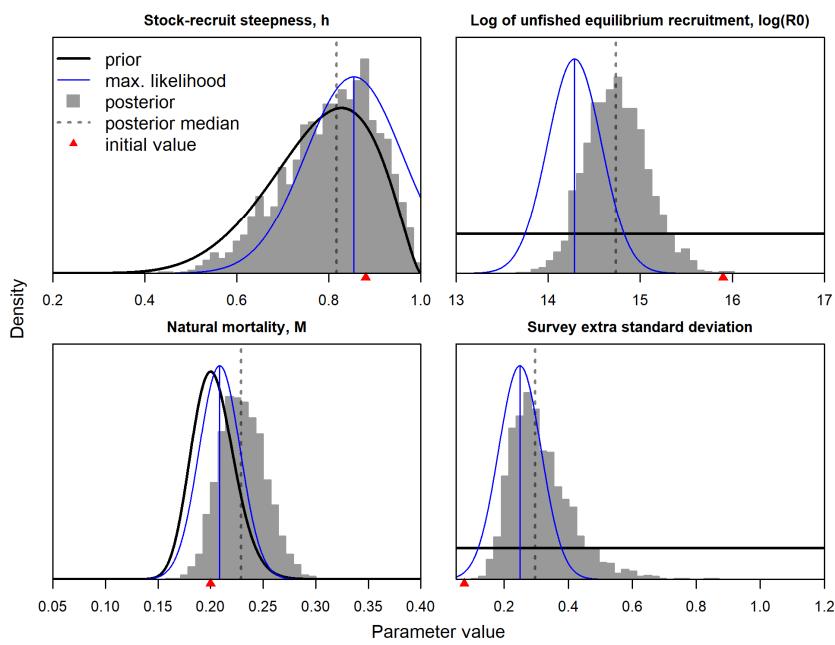
653



654

655 Figure 4. Sex ratios calculated from the bottom trawl survey length composition samples of big skate. Observed sex ratios  
 656 (points) with 75% intervals (vertical lines) calculated as a Jeffreys interval (Brown et al., 2001). The model expectation is shown  
 657 in the purple line. The year in which the length composition samples were collected is shown in the upper left corner of each  
 658 panel. The adjusted input sample size (N) and effective sample size associated with the McAllister-lanelli tuning (effN) are  
 659 shown in the upper right corner of each panel.

660



661

662 Figure 5. Prior and posterior density estimates for four parameters in the Pacific hake stock assessment. The gray polygons  
 663 show the distribution of values from 2000 MCMC samples while the blue lines show the maximum posterior density estimate  
 664 and the normal approximation to the posterior based on the asymptotic approximation of the parameter variance. The black  
 665 lines show the prior distributions (a beta distribution for steepness, a lognormal distribution for natural mortality, and uniform  
 666 distributions for the other two parameters). Starting values for the MPD estimation are shown in the red triangles.

667