1 # Improving the communication and accessibility of

2 # stock assessment using interactive visualization tools

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9   **Abstract**: Scientists across many fields are faced with the challenge of synthesizing and

10   communicating information from large and complex data sets. The field of stock assessment is

11   no exception as the volume and variety of the data has grown alongside the computational

12   methods used to integrate them. While this growth in data and model complexity has improved

13   many stock assessments, the process of communicating key results to colleagues and

14   stakeholders in a meaningful way has become more daunting. The traditional approach of

15   presenting information across a series of static slides often fails to convey the richness of

16   information available and, as such, important patterns and details are easily overlooked. Here we

17   contend that this problem can be mediated through the effective use of new open source tools for

18   building interactive visualizations. These tools allow a broader audience to conduct detailed

19   explorations of the results, leading to a deeper and collective understanding of both the data and

20   models used to inform stock assessments. As a consequence, the peer review process is more

21   open and accessible.

24   *The greatest value of a picture is when it forces us to notice what we never expected to see.*

25   - Tukey (1977)

26   Quantitative stock assessment plays a central role in modern fisheries management (Hilborn and

27   Walters 1992). Over time, and as new methods are developed, there is an increasing amount of

28   data available to inform stock assessments. These data might be richer information on stock

29   structure using an increasing array of markers and biomarkers, and/or the continued lengthening

30   of population status and catch time series. Concurrently, analytical methods are now able to

31   integrate many data sources into one stock assessment model (Maunder and Punt 2013). While

32   these advances have surely improved the advice provided on stock status, it has become more

33   difficult to communicate the basis of this advice in a meaningful way. Visualizations play a

34   critical role in communicating this information to stakeholders (Levontin et al. 2017). However,

35   traditional formats (e.g. slides) are often insufficient to convey the richness of information

36   available and the static and sequential nature of these formats can stifle meaningful discussions.

37   A solution to this problem is the effective use of interactive visualization tools (Keena et al.

38   2016). These are common tools we use every day on a range of web sites, but their use is no

39   longer restricted to web site developers as these tools are being integrated into software

40   commonly used by the research community (Perkel 2018). As a result, an increasing number of

41   scientists across a wide range of disciplines are starting to apply interactive visualization tools to

42   explore and communicate their results (e.g. Jones et al. 2016; Letcher et al. 2018; Yeatman et al.

43   2018).

44   Fisheries scientists are a part of this trend and, as such, there are a growing number of interactive

45   tools available that facilitate the exploration and communication of fisheries science. For

46   instance, they can be used to disseminate real-time information for dynamic ocean management

47   (Maxwell et al. 2015; Hazen et al. 2018), explore hindcasts and projections from various habitat

48   suitability models (McHenry et al. 2019), and evaluate different fisheries management

49   approaches (Goethel et al. 2019; Miller et al. 2019) (see Appendix A for more examples). Such

50   tools complement static documentation as they allow audiences to explore data and models in

51   ways not amenable to static formats and, in the process, they improve accessibility and augment

52   communication efforts. These will be helpful tools to utilize as we proceed through an age of

53   heightened scientific scrutiny (McInerny et al. 2014), and here we aim to promote their use in

54   fisheries science by demonstrating a series of interactive visualization tools built to aid in the

55   peer review of stock assessments.

56   We first demonstrate the application of interactive tools to data that are commonly presented in

57   stock assessments to show how they can simplify the detailed exploration of data from long-term

58   monitoring programs. Second, we focus on the modeling aspect of stock assessment and

59   demonstrate how interactive tools can be used to explore, diagnose, and communicate results

60   from an integrated assessment model. This structure corresponds to two important steps in the

61   stock assessment process: 1) data exploration, and 2) data modeling. In both cases interactive

62   visuals are nested inside dynamic documents called "dashboards". The concept of using a

63   dashboard was borrowed from the business community where they are frequently used to group a

64   series of interactive visuals and tables to provide at-a-glance views of key performance

65   indicators. These dashboards were constructed within the framework of the R programming

66   language (R Core Team 2017) and the RStudio IDE (RStudio Team 2015) using three or more of

67   the packages listed in Table 1. See Supplement 1 for a "getting started" tutorial that highlights

68   one approach to constructing a dashboard using R; using this as a guide, an R user can start

69   constructing basic dashboards within a day.

70   Table 1: Names and descriptions of the key packages used to build the interactive applications

71   presented in this paper. Descriptions are directly from the DESCRIPTION file of each package.

shiny	Makes it incredibly easy to build interactive web applications with R. Automatic "reactive" binding between inputs and outputs and extensive prebuilt widgets make it possible to build beautiful, responsive, and powerful applications with minimal effort (Chang et al. 2018)
shinydashboard	Create dashboards with 'Shiny'. This package provides a theme on top of 'Shiny', making it easy to create attractive dashboards (Chang and Borges Ribeiro 2018).
rmarkdown	Convert R Markdown documents into a variety of formats (Allaire et al.

	2018).
`flexdashboard`	Format for converting an R Markdown document to a grid oriented dashboard. The dashboard flexibly adapts the size of its components to the containing web page (Allaire 2017).
`plotly`	Easily translate 'ggplot2' graphs to an interactive web-based version and/or create custom web-based visualizations directly from R (Sievert 2018).
`leaflet`	Create and customize interactive maps using the 'Leaflet' JavaScript library and the 'htmlwidgets' package. These maps can be used directly from the R console, from 'RStudio', in Shiny applications and R (Cheng et al. 2018).
`crosstalk`	Provides building blocks for allowing HTML widgets to communicate with each other, with Shiny or without (i.e. static .html files) (Cheng 2016).

Data exploration

73 The data sets used in stock assessments are constantly growing due to the continuation of long-

74 term monitoring efforts, the addition of new monitoring programs, or both. As such, stock

75 assessment biologists need to manage large volumes of data from a variety of sources. Time

76 series of reported landings and catch-at-age are often analyzed in conjunction with data from

77 "fishery-independent" surveys that track changes in relative abundance and, in many cases, also

78 monitor trends in biological factors such as age composition, growth rates, sex ratios and

79 maturation stages. For some data-rich stocks, mark and recapture studies are also carried out to

80 estimate movement, migration, growth rate, natural mortality, and discard mortality. All of the

81 above-mentioned data sets are complex and, as the volume and variety of these data increases, it

82 becomes more difficult to be aware of the details of each data set and discover key patterns

83 within each. It has long been recognized that this challenge can be mediated, to a degree, by the

84 application of interactive visualization tools as they allow detailed exploration of the data behind

85 a plot (Tukey and Tukey 1985; Fisherkeller et al. 1988). For instance, the ability to zoom in on

86 features or areas of interest, turn off layers and hover over specific points to reveal more

87 information creates an interactive user-driven experience that expedites explorations of data.

88   These abilities are illustrated by two recently developed interactive tools: 1) a tool designed to

89   quickly examine fishery-independent survey data; and 2) an interactive mapping tool developed

90   for the exploration of a long-term tagging study.

91   **Survey data**

92   Fisheries and Oceans Canada (DFO) has been conducting a multi-species stratified-random

93   survey across the Newfoundland and Labrador shelf since the 1970s (Rideout and Ings 2018).

94   These data are analyzed using a standard stratified analysis via a local R package called RStrap

95   (for details on methodology see Smith and Somerton 1981). Both the inputs and outputs from

96   RStrap analyses are very large and, depending on the species, may include > 40 years and span

97   the majority of the Newfoundland and Labrador shelf. In order for fisheries scientists to quickly

98   and reliably explore these data without iteratively modifying R scripts one species at a time, an

99   application (hereafter called RStrap Explorer) was built using a combination of shiny, crosstalk,

100   flexdashboard, plotly and R markdown (Table 1). RStrap Explorer started as a way to visualize

101   estimates of biomass and abundance trends of specific species by supplying RStrap output to a

102   flexdashboard file designed to organize and visualize the results. The shiny package was latter

103   applied as it allows RStrap to be run in the background and therefore allows the user to

104   dynamically explore abundance and biomass estimates from multiple species in one session.

105   Both crosstalk and plotly were incorporated to allow the user to interact with the data.

106   RStrap Explorer contains four primary tabs: 1) "Survey Indices" contains stock level estimates of

107   biomass and abundance (Figure 1), 2) "Age & Length Distributions" contains length and age

108   frequency plots (Figure 2), 3) "Recruitment" displays recruitment indices, and 4) "Help"

109   provides additional context to the survey data and analysis. The input interface for RStrap

110   Explorer is divided into two parts: basic and advanced inputs. Basic inputs are those like species,

111   season, and survey year(s). Advanced inputs allow the user to define the length or age of

112   recruitment, select whether they would like analyses conducted by length and/or age, and so on.

113   This application was built for data exploration and allow the user to obtain quick and easy

114   visualization of survey data, before the thorough data checking and analysis required for formal

115   stock assessment begins.
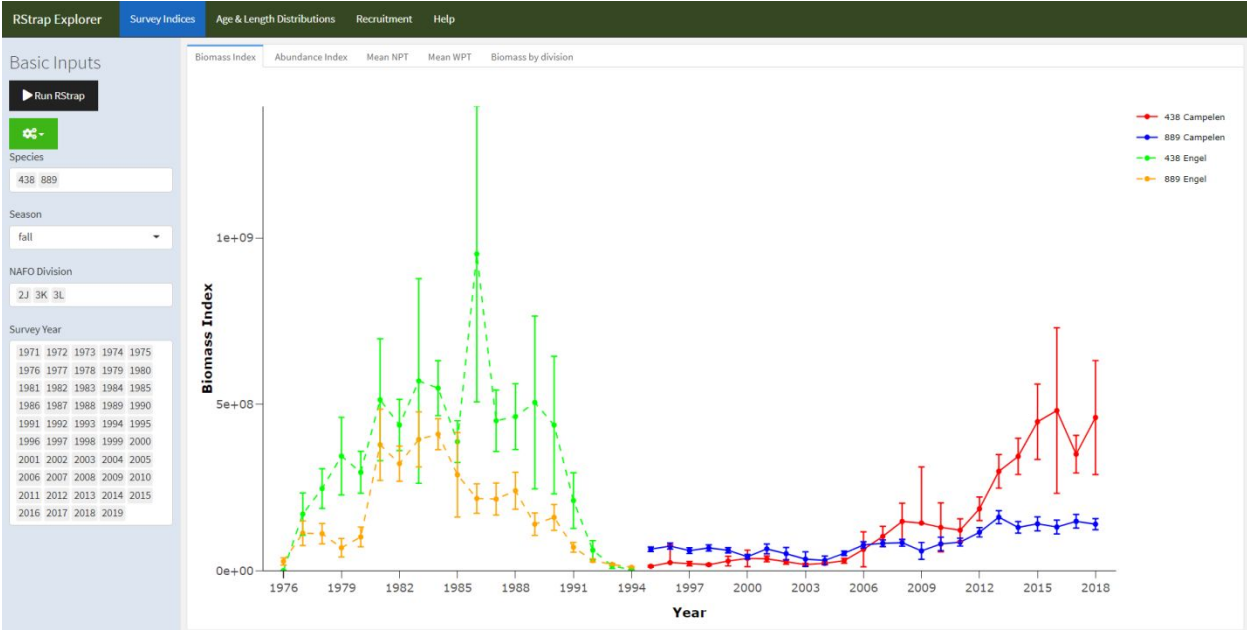

116

117   Figure 1: - Screen shot of the "Survey Indices" page of the RStrap Explorer application. The

118   "Basic Inputs" sidebar is fixed across all pages and allows the user to specify the species, NAFO

119   Divisions, season, and survey years of interest. The "Biomass Index" sub-tab is illustrated here.

120   This sub-tab shows a time-series of biomass data with 95% confidence intervals, with a break in

121   the lines when the survey gear changed from an Engle to Campelen trawl, for both cod (*Gadus*

122   *morhua*; species code 438) and American Plaice (*Hippoglossoides platessoides*; species code

123   889). All trend lines can be toggled off using plotly's dynamic user interface.
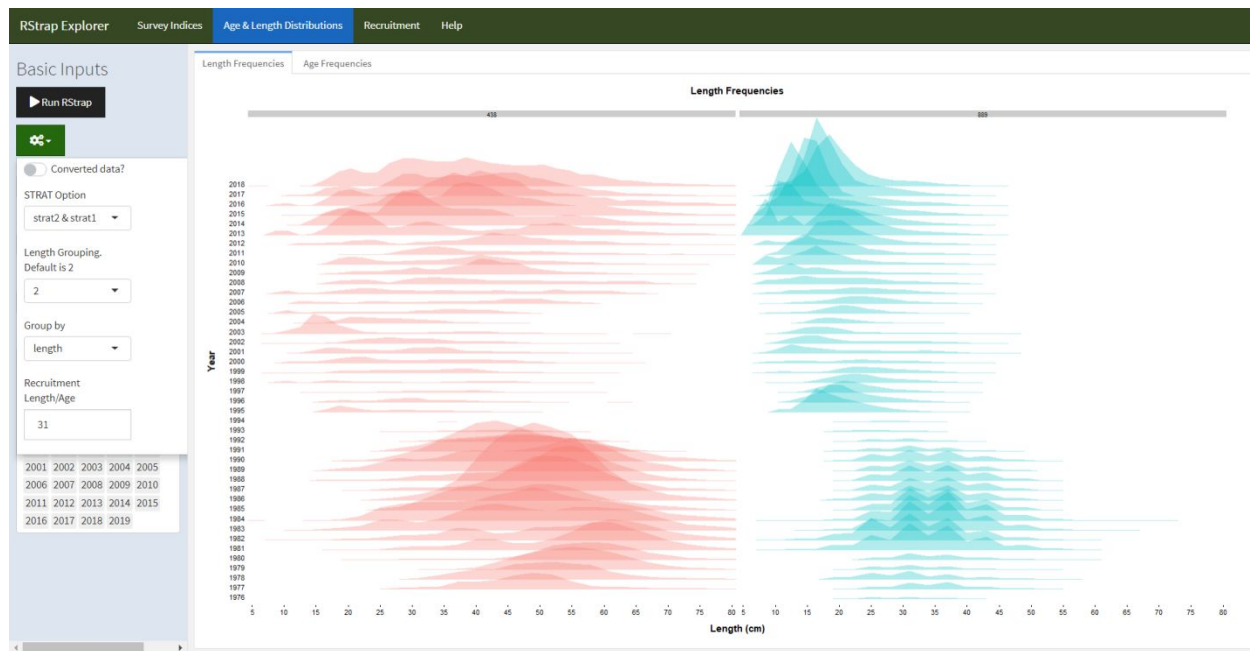
124

125 Figure 2: - "Age and Length Frequencies" tab of the RStrap Explorer tool. This tab illustrates the

126 length frequency distributions of both cod (*Gadus morhua*; species code 438) and American

127 plaice (*Hippoglossoides platessoides*; species code 889) binned into 2 cm length bins. The

128 binning is easily modified using the "Length Group" field in the "Advanced Options" drop down

129 menu (shown on left side).

Tagging data

131 Northern cod (NAFO Divisions 2J3KL) has a rich history of tagging, starting as a dedicated

132 program in 1954 (Taggart et al. 1995) and continuing to this day. The tagging and recovery data

133 are captured in a standardized database, with fields typical of most tagging programs. This

134 database has over 600,000 records as of early 2019, with 2,000-10,000 tags deployed annually in

135 recent decades. The tagging and recovery data are used in the current assessment model for this

136 stock (Cadigan 2016), but tools to explore this extensive data set were limited, especially from a

137 spatial perspective. To begin to explore and understand this large data set, we built a simple

138   application using shiny and leaflet (Table 1) that allows a user to quickly and dynamically subset

139   the data (e.g. ranges of tag release and tag recovery years, specific geographic locations). As the

140   application developed, it was incorporated into shinydashboard, to take advantage of the number

141   of layout options available in shinydashboard (Table 1). Given the large number of tags released,

142   often at nearby sites, visualizing the data with static mapping was particularly challenging. The

143   markercluster (https://github.com/Leaflet/Leaflet.markercluster) function available in leaflet was

144   particularly useful as a means to dynamically scale the level of pooling of spatial points (Figure

145   3). This basic mapping tool allowed us to quickly become familiar with the data, identify outliers

146   and incorrect data entries, as well as explore options on how to spatially pool the data for

147   subsequent demographic analysis. Further tabs were added to provide basic summaries of the

148   selected data (Figure 4).
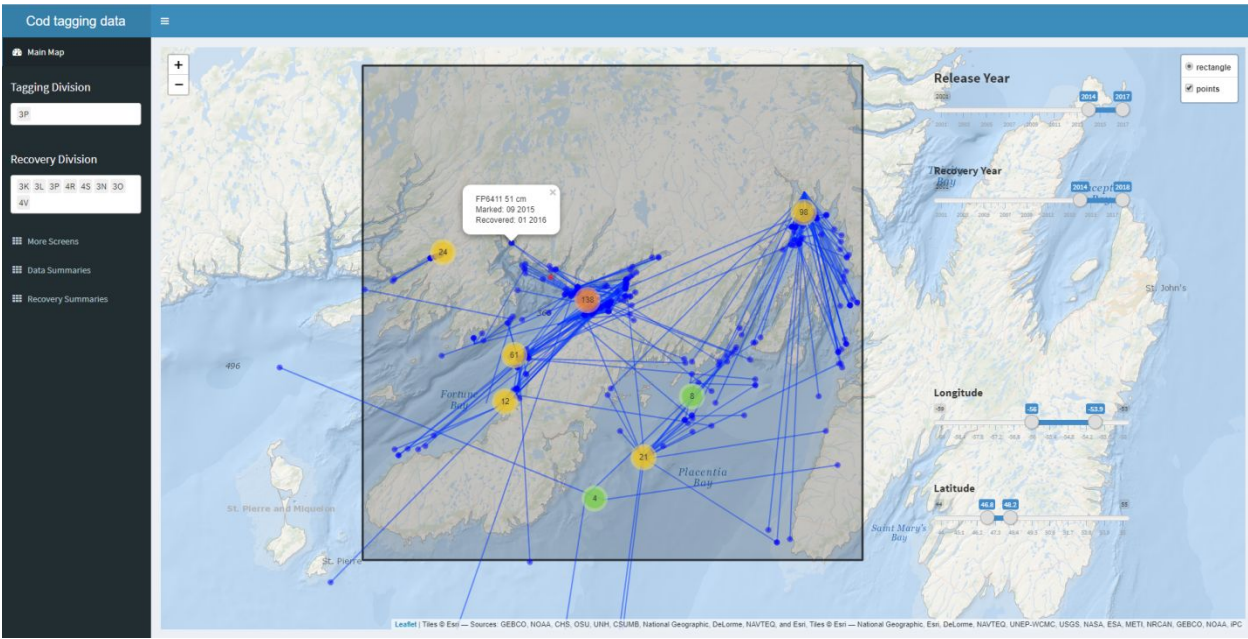
149

150   Figure 3: A screen shot of cod tag mapping tool. The markercluster function dynamically splits

151   or pools tagging locations (red, orange, green or yellow points) depending on zoom level, the

152   recovery positions (blue) are much fewer, and are left to be plotted individually at all scales.

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153   Options to include pop up labels are included, so specific information on each point can be

154   retrieved with a mouse click (in this case: tag number, fish length, date released, and date

155   recovered), which is particularly useful when error checking. Base map created with leaflet

156   (Cheng et al. 2018) using ESRI's Ocean BaseMap (Sources: Esri, GEBCO, NOAA, National

157   Geographic, DeLorme, HERE, Geonames.org, and other contributors).
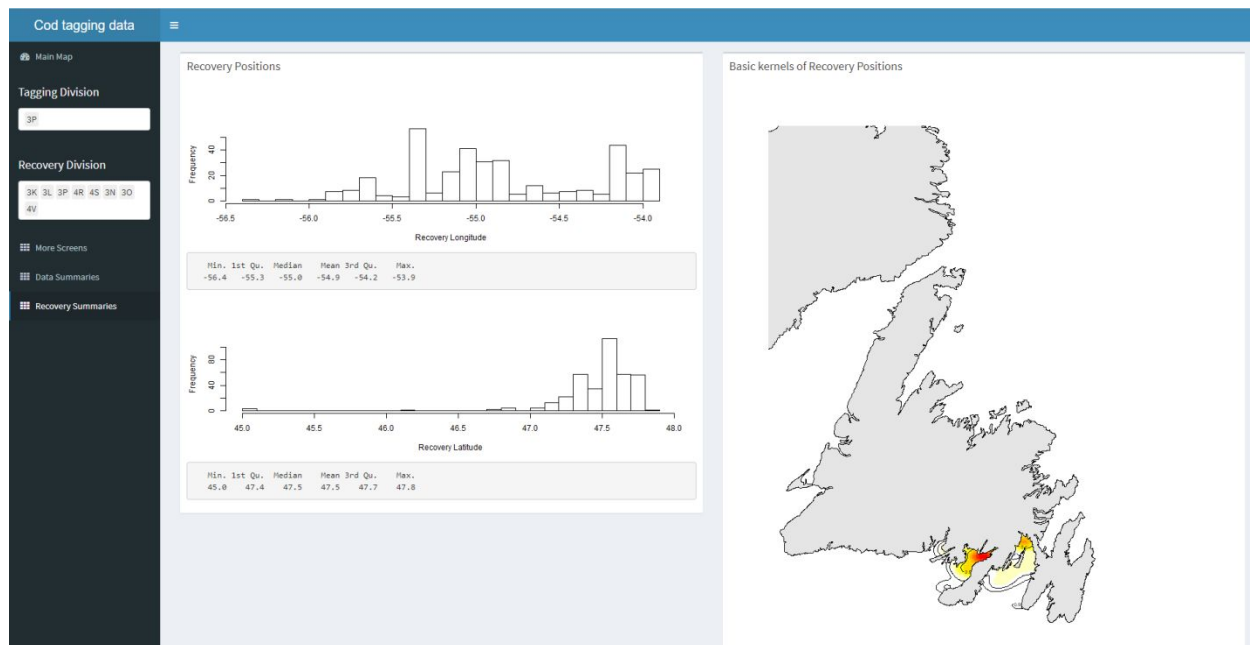
158

159   Figure 4: Basic summaries of the recovery data from the tags selected within the cod tag

160   mapping tool. In this case, histograms and summary statistics of the recovery positions are

161   returned, along with a simple map of kernels showing the spatial distribution of the selected tag

162   recoveries. Base map created in R with package maps (Becker et al. 2018b) and mapdata (Becker

163   et al. 2018a).

Data modeling

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165   Synthesizing data from multiple sources presents a key challenge to stock assessment. Analyses

166   of different data sources were traditionally carried out independently and the summaries or

167   parameters from these analyses were used in the assessment model. This approach, however, is

168   less than ideal because information may be lost and uncertainty may be unaccounted for when

169   we "do statistics on the statistics" (Link 1999; Maunder and Punt 2013).). Such issues have

170   largely been curtailed in contemporary stock assessments as advances in statistical computing

171   have enabled integrated analyses of data from multiple monitoring programs (Maunder and Punt

172   2013). Specifically, statistical modeling tools such as JAGS (Plummer 2003), AD Model Builder

173   (Fournier et al. 2012), and Template Model Builder (TMB; Kristensen et al. 2016) allow the

174   construction of a joint likelihood for an array of observations to, in theory, extract as much

175   information as possible about the biological and fishery processes. From a computational

176   perspective, analyses of a variety of large data sets has never been easier. However, from a

177   human perspective, contemporary stock assessment biologists are faced with the challenge of

178   understanding and integrating data from multiple sources into a single model and communicating

179   the methods and results to stakeholders and fisheries managers. This challenge was palpable for

180   the data-rich case of Northern cod.

181   The Northern cod stock off southern Labrador and eastern Newfoundland is one of the most well

182   studied stocks in eastern Canada. As such, there are multiple monitoring programs that help

183   inform the status of the stock and data from most of these programs have been integrated into a

184   state-space stock assessment model, called NCAM (Cadigan 2016). The model includes

185   information from research vessel autumn trawl surveys (1983-present), Sentinel fishery surveys

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186   (1995-present), inshore acoustic surveys (1995-2009), fishery catch-at-age compositions, and

187   reported fishery landings (1983-present), and tagging (1983-present). Using a series of

188   observation equations, this TMB based model simplifies thousands of data points into quantities

189   such as annual recruitment, spawning stock biomass, fishing mortality, and natural mortality.

190   Once the model is fit to the data, the next step is to produce visual representations of the data and

191   model output. The traditional approach would involve producing static presentations and

192   documents with a series of figures and tables. However, with numerous model inputs and

193   outputs, this approach quickly becomes overwhelming for both the analyst and the stakeholders

194   involved for at least two reasons. First, it is no longer feasible for the analyst to include and

195   describe every figure and table produced in a single document. Second, it is difficult for

196   stakeholders to efficiently digest the information that has been compressed into a series of static

197   slides or pages. Interactive documents provide a potential solution to this problem as they allow

198   much more information to be contained and accessible on a single screen.

199   In the pursuit of an easier and more efficient way to communicate results from NCAM, an

200   interactive "dashboard", called NCAM explorer, was developed for the 2018 assessment of

201   Northern cod (Dwyer et al. 2019). We used R-based packages (Table 1) to construct a tool for

202   exploring the input and output of NCAM, specifically the flexdashboard package to group

203   interactive plotly-based visuals into a dynamic document. We also used the crosstalk package to

204   link the data displayed across multiple plots. Via R Markdown, the dashboard is rendered into a

205   self-contained html file that is reproducible, interactive, and easy to update following

206   modifications to the model or the addition of new data. The intent of this tool was not to replace

207   detailed documentation on the model (i.e. Cadigan 2016; Dwyer et al. 2019), however, it was

208   built to serve as an interactive alternative to a standard presentation for communicating the latest

209   results to an audience with a working knowledge of the stock and assessment model.

210   Explanatory text and detail were therefore kept to a minimum, allowing the audience to explore

211   the figures and data unencumbered by verbose descriptions.

212   The NCAM dashboard (Supplement 2) contains a series of pages, the first of which provides

213   terse point-form background on the model (page named "Background"). Subsequent pages

214   provide a series of diagnostic plots for assessing model fits to catch ("Landings"; accessed from

215   the "Fishery" drop-down menu), survey ("RV survey", "SN survey" and "SS survey"; accessed

216   from the "Surveys" drop-down menu), and tagging ("Tagging") data. For instance, the "RV

217   survey" page includes plots of observed and predicted values of mean numbers per tow captured

218   in the research vessel survey (Figure 5). The dashboard also includes pages focused on model

219   estimates such as selectivity ("Selectivity"; accessed from the "Fishery" drop-down menu) and

220   catchability ("Catchability"; accessed from the "Surveys" drop-down menu). Pages for viewing

221   trends in various population parameters are included under the "Trends" drop-down menu, where

222   the "Retrospective analysis" page displays results from a retrospective analysis, the "Model

223   comparison" page displays population trends from different model runs, the "Status and rates"

224   page displays trends in stock size and vital rates (Figure 6), and the "Productivity" page focuses

225   on trends in Spawning Stock Biomass (SSB) and recruitment. Finally, details on the projections

226   are accessed from the "Projections" drop-down menu ("Assumptions", "Past projections", "Retro

227   projections", and "Results" pages), and key inputs and outputs are accessed from "Tables" drop-

228   down menu ("Inputs", "Settings", "Outputs" pages). The plots and tables included in the

229   dashboard are similar to those typically presented at assessment meetings and in research

230   documents. However, there are two key benefits of this approach over the *modus operandi* of

231   producing static documents and slides. First, interactive plots nested in a dashboard permit

232   relatively easy and efficient access to the details as it replaces scrolling through tens, if not

233   hundreds, of pages or slides with mouse-clicks across a smaller number of dynamic pages

234   holding data-rich illustrations (i.e. both broader patterns and finer details in the data are

235   accessible via zooming and tooltips). Second, the automated nature of the dashboard circumvents

236   the monotonous, time-consuming and error-prone task of copying and pasting figures, tables, and

237   values into documents and slides, although, we note that this issue can be addressed through

238   other approaches (e.g. slide shows can easily be made using R markdown). Both benefits

239   expedite the process of exploring a range of model configurations as the automated output

240   facilitate quick views of standard diagnostics and the interactive plots facilitate detailed

241   explorations and comparisons of models with different configurations. For instance, explorations

242   of the residual plots in the dashboard allowed the authors to quickly identify conflicts between

243   two surveys used in the model. Potential solutions to this problem were then explored by

244   modifying the configuration of the model and these changes were quickly evaluated using a

245   dashboard that is produced in seconds.

246   The dashboard also makes it easy to share the results with colleagues and stakeholders as it is

247   rendered into a self-contained html file. This allows others to independently scrutinize details of

248   both data and the model that are typically only accessible to the analyst. Such access improves

249   the transparency of the stock assessment model which, in turn, leads to richer discussion and

250   scrutiny of the biological and statistical rigor of the model. For instance, visualizations depicting

251   the model assumptions, process errors and confidence intervals around the projections raised

252   important questions on the impact of the assumptions on the projections from the model. These

253   questions were raised during the first assessment meeting in which this tool was used and the

254   ensuing discussions left us with the impression that this tool helped the assessment biologists,

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255   academics, resource managers, and fisheries representatives in the room gain a deeper

256   understanding of the uncertainties and the patterns in the risk tables. Feedback and personal

257   testimony from multiple stakeholders who have used the dashboard reaffirmed our impression

258   that the tool is helpful as there was general agreement that access to the details eases

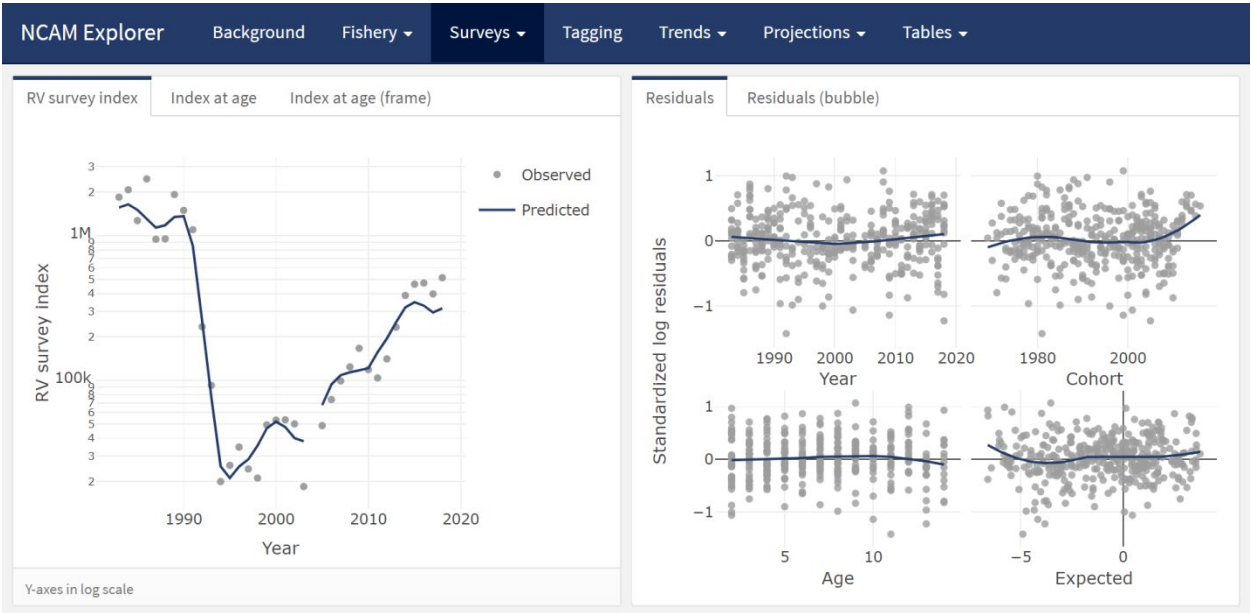259   communication and relieves any potential concerns that something is hidden.

260

261   Figure 5: Screenshot of the "RV survey" tab from the NCAM dashboard where total observed

262   (dots) and NCAM model predicted values (lines) for the DFO RV survey index are shown in the

263   left panel and standardized log residuals by year, cohort, age, and expected value (dots), with

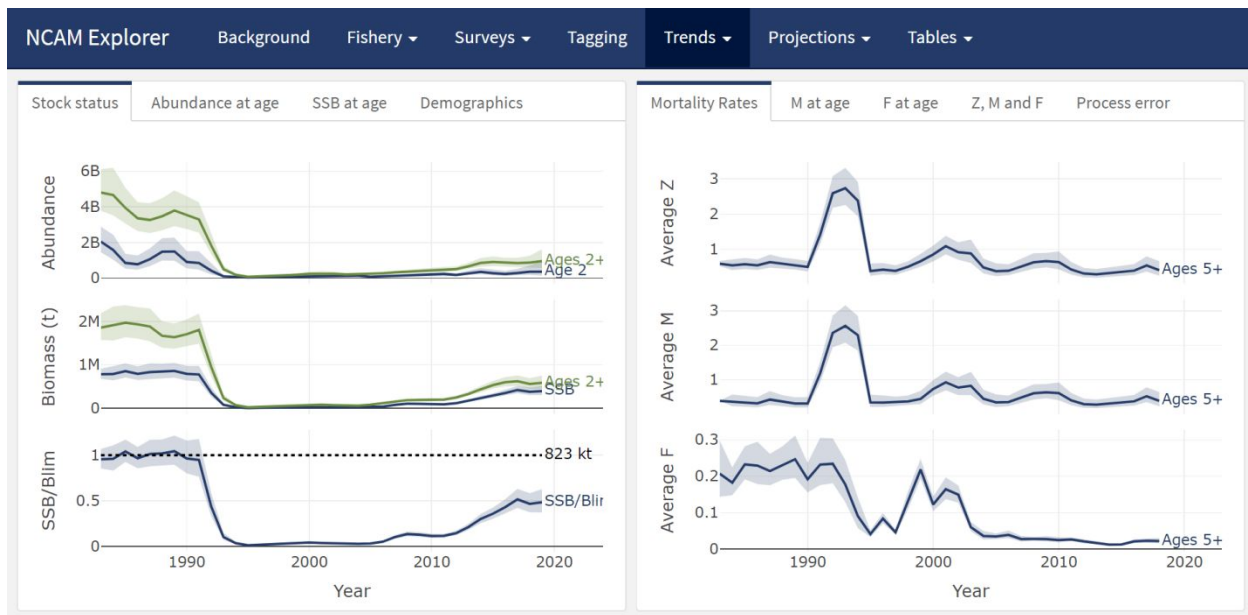264   lowess curves (lines), are shown in the right panel.

Figure 6: Screenshot of the "Trends" tab which displays stock status estimates (abundance, biomass, and biomass relative to B_{lim} [average biomass through the 1980s]) on the left panel, and mortality rates (average F, M, and Z) on the right panel.

From bespoke to general tools

The interactive tools highlighted here were custom built to solve data visualization challenges that are common to many fisheries management organizations but the solutions presented are specific to the Northwest Atlantic Fisheries Centre. The concept is therefore broadly applicable, however, the underlying code will require modifications to accommodate region and stock specific data management and modelling approaches. Even within our own region, different approaches and needs meant that the code behind NCAM explorer (Supplement 2) required modifications when applied to a model developed for another cod stock. Nevertheless, considerable chunks of code were recycled and, in the process, new features were added to allow the visualization of multiple model configurations within the one dashboard. Additionally, a

279   French colleague is currently modifying the tool to visualize output from SAM, a state-space

280   stock assessment model widely used to assess ICES stocks (Nielsen and Berg 2014). Likewise,

281   the concept behind RStrap Explorer and the tagging tool could be applied to other regions and

282   the most efficient approach may be to build upon existing general frameworks (e.g. StoX

283   software; Johnsen et al. 2019). These are, of course, early days in the development and

284   application of interactive tools to stock assessment. Because the tools we highlight are

285   themselves general, flexible, and accessible, we suspect that bespoke applications will continue

286   to be developed in parallel with more general stock assessment dashboards depending on user

287   needs and preferences. Regardless of the approach, a common goal is to make the workflow

288   more efficient, reproducible, and transparent.

289   ## Towards open stock assessment

290   The amount of data available to scientists has grown by orders of magnitude in recent decades as

291   has the complexities of data management, exploratory data analysis, formal analyses and

292   associated diagnostics (Lewis et al. 2018). The majority of this sequence of events, sometimes

293   called "the data pipeline" (Leek and Peng 2015a), have not traditionally been part of the peer-

294   review process which sees only the end products of an analysis. However, decisions made along

295   the data pipeline increasingly influence the outcome of the study. Gelman and Loken (2014)

296   coined the term "garden of forking paths" to illustrate that different conclusions can be arrived at

297   depending on what decisions are made during different stages of the analysis. Due to a number

298   of limitations, such as available pages in journals, much of the data pipeline is not transparent

299   nor is it reproducible. A number of authors have recently advocated for a culture of open science

300   and reproducible research, i.e., a change in the transparency and reproducibility of science

301 (Hampton et al. 2013, 2015; Leek and Peng 2015a, 2015b). Proponents of open science and

302 reproducible research highlight a number of benefits including a more productive and

303 responsible scientific culture, an ability to address larger and more complex questions, as well as

304 a more efficient workflow and ability to reproduce one's own work (Fomel and Claerbout 2009;

305 Lowndes et al. 2017).

306 A culture of openness is actively evolving in the field of stock assessment and, at this point, it is

307 not hard to picture a future where it is commonplace for the full data pipeline to be open and

308 accessible. Open resources are actively being developed and used to improve accessibility to all

309 the data, methods and results that feed into stock assessments (e.g. the Transparent Assessment

310 Framework, https://taf.ices.dk/app/about; Magnusson and Millar 2020). Likewise, tools are being

311 developed to facilitate the creation of reproducible advisory documents (e.g. ICES 2018;

312 Anderson et al. 2020; Regular et al. 2020), and these documents can be interactive, as is the case

313 for the VISA tool (ICES 2018), or they can be supplemented by interactive tools. There is plenty

314 of opportunity for synergies between these initiatives, as most are being developed using R, and

315 all details and decisions can be traceable and accessible using an online repository such as

316 GitHub. We therefore foresee a future where stock assessments become increasingly open and

317 reproducible.

318 Providing open access to code and data, however, does not necessarily make a stock assessment

319 more accessible. We believe that interactive tools, such as those presented here and in Appendix

320 A, represent an important step forward in terms of open science as they make the peer review

321 process more efficient. Although these tools do not reveal the entire data pipeline, a wide range

322 of stakeholders and scientists can easily access and review details of an analysis without running

323 a line of code. For most participants of a stock assessment, even if the entire pipeline was

324 completely open, the details would remain inaccessible simply because most participants are

325 already overcommitted (Banks 2011) and do not have the time to fully review and recreate a

326 particular analysis in its entirety. Further, in the case of NCAM, considerable statistical

327 experience and expertise is required simply to run the model. However, the dashboard approach

328 removes many of these obstacles. The html file contains all model inputs, outputs and

329 diagnostics in an open, and easy to use, interactive document that can be distributed prior to

330 meetings. As such, participants can assess the results and diagnostics at their leisure. Specific

331 experience with the tools used to generate the results are not required to constructively and

332 critically review the results presented in the dashboard.

333 **Conclusions**

334 Visualizations play an important role in communicating fisheries science to a wide range of

335 stakeholders (Levontin et al. 2017) and here we posit that interactive tools extend the utility of

336 data visualizations by providing a richer approach to communicating scientific information.

337 However, we must acknowledge there are costs to adopting the use of interactive tools. The first

338 and obvious one being that staff are required to have both the time and training to effectively

339 develop these tools. Ideally, professional programmers and graphic designers would be hired to

340 construct dashboards and other interactive info-graphics (McInerny et al. 2014), but fisheries

341 management organizations rarely have the resources to fund such initiatives. Consequently, the

342 process of communicating fisheries science tends to be the responsibility of fisheries scientists

343 who lack formal training in these fields. In our three examples, the developers (first, second and

344 third authors) were relatively proficient with R and have natural aptitudes for programming and

345 graphic design, but all had their formal training in field-based population ecology. While some

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346 learning time was needed, the learning curve was relatively minor because there was no need to

347 learn a new programming language (e.g. JavaScript, CSS, etc.). We can confirm that an R user

348 can construct a basic dashboard within a day, using Supplement 1 as a guide, and a more custom

349 dashboard in a matter of weeks. Moreover, a growing user base means that most programming

350 issues can be readily addressed through simple internet searches. There are also a growing

351 number of exemplars (Appendix A), beyond what we show here, to inspire the development of

352 new interactive tools. Once over the initial learning curve, the time investment may not be much

353 greater than one would invest into a standard presentation. We expect the accessibility and

354 quality of these tools to continue to improve as more people in the fisheries community develop

355 and use interactive documents. It is our experience that the upfront time investment has been

356 worthwhile considering the improved efficiency of delivering products for subsequent stock

357 assessments, and in the quality of the data exploration and understanding.

Appendix A

367 Partial list of applications developed to explore and communicate marine and fisheries science:

368 • Marine Aggregates Application (https://openscience.cefas.co.uk/ma_tool/); a benthic-
369 focused tool to assist with marine license application and compliance monitoring.
370 • Species Dashboard (https://shiny.marine.ie/speciesdash/); a tool for exploring biological
371 fisheries data collected in Irish waters
372 • The Stock Book (https://shiny.marine.ie/stockbook/); a tool for accessing up-to-date
373 information on the status of fish stocks in Irish waters.
374 • Data-Limited Fisheries Toolkit demo (https://www.datalimitedtoolkit.org/demo); an
375 application for demonstrating the key features of the management strategy evaluation
376 toolkit.
377 • Toy Tuna MSE application (https://puntapps.shinyapps.io/tunamse/); a toy MSE example
378 built to allow users to enter various management procedures and assess their performance.
379 • Exploring Groundfish in an Ecosystem Context
380 (https://incorporatingecosystemapproach.shinyapps.io/indiapp/); a tool accessing results
381 from an analysis exploring links between stock indices and ecosystem trends.
382 • EcoCast Explorer (https://coastwatch.pfeg.noaa.gov/ecocast/explorer.html); an application
383 for displaying results from a dynamic ocean management tool focused on bycatch
384 avoidance (see Hazen et al. 2018 for more detail).
385 • B-VBGM! Bayesian Von Bertalanffy Growth Model tool
386 (https://fishecology.shinyapps.io/B-VBGM/); a supplement Catalán et al. (2018) that
387 facilitates the exploration of the model described in the paper.
388 • Beyond Temperature tool (https://heatherwelch.shinyapps.io/beyond_temperature/); a
389 supplement to McHenry et al. (2019) that allows the exploration of habitat suitability
390 hindcasts and projections by species and model type.
391 • BRSApp (https://catalinagomez.shinyapps.io/BRSApp/); a supplement to Gomez et
392 al. (2016) that allows the exploration of behavioural response severity scores of marine
393 mammals to noise.
394 • VISA tool (e.g. https://ices-tools-dev.github.io/VISA_tool/hke.27.3a46-
395 8abd.html#ices_advice_2018); an alternative to pdf files for displaying and exploring up-to-
396 date ICES advice (developed to meet an "EU request on dissemination of ICES advice
397 beyond pdf files"; ICES 2018).

References

399 Allaire, J. 2017. Flexdashboard: R markdown format for flexible dashboards. Available from

400 https://CRAN.R-project.org/package=flexdashboard.

21

401   Allaire, J., Horner, J., Xie, Y., Marti, V., and Porte, N. 2018. Markdown: 'Markdown' rendering

402   for r. Available from https://CRAN.R-project.org/package=markdown.

403   Anderson, S.C., Grandin, C., Edwards, A.M., Grinnell, M.H., Ricard, D., and Haigh, R. 2020.

404   csasdown: Reproducible CSAS reports with bookdown. Available from

405   https://github.com/pbs-assess/csasdown.

406   Banks, D. 2011. Reproducible research: A range of response. Statistics, Politics, and Policy **2**(1):

407   4. bepress.

408   Becker, R.A., Wilks, A.R., and Brownrigg, R. 2018a. Mapdata: Extra map databases. Available

409   from https://CRAN.R-project.org/package=mapdata.

410   Becker, R.A., Wilks, A.R., Brownrigg, R., Minka, T.P., and Deckmyn, A. 2018b. Maps: Draw

411   geographical maps. Available from https://CRAN.R-project.org/package=maps.

412   Cadigan, N.G. 2016. A state-space stock assessment model for northern cod, including under-

413   reported catches and variable natural mortality rates. Canadian Journal of Fisheries and

414   Aquatic Sciences **73**(2): 296–308. NRC Research Press.

415   Catalán, I.A., Alós, J., Díaz-Gil, C., Pérez-Mayol, S., Basterretxea, G., Morales-Nin, B., and

416   Palmer, M. 2018. Potential fishing-related effects on fish life history revealed by otolith

417   microchemistry. Fisheries Research **199**: 186–195. Elsevier.

418   Chang, W., and Borges Ribeiro, B. 2018. Shinydashboard: Create dashboards with 'shiny'.

419   Available from https://CRAN.R-project.org/package=shinydashboard.

420   Chang, W., Cheng, J., Allaire, J., Xie, Y., and McPherson, J. 2018. Shiny: Web application

421   framework for r. Available from https://CRAN.R-project.org/package=shiny.

422   Cheng, J. 2016. Crosstalk: Inter-widget interactivity for html widgets. Available from

423   https://CRAN.R-project.org/package=crosstalk.

424   Cheng, J., Karambelkar, B., and Xie, Y. 2018. Leaflet: Create interactive web maps with the

425   javascript 'leaflet' library. Available from https://CRAN.R-project.org/package=leaflet.

426   Dwyer, K., Brattey, J., Cadigan, N., Healey, B., Ings, D., Lee, E., Maddock Parsons, D., Morgan,

427   M., Regular, P., and Rideout, R. 2019. Assessment of the northern cod (*Gadus morhua*)

428   stock in nafo divisions 2J3KL in 2018. DFO Can. Sci. Advis. Sec. Res. Doc. **2019/nnn**: v

429   + 126p.

430   Fisherkeller, M.A., Friedman, J.H., and Tukey, J.W. 1988. PRIM-9: An interactive

431   multidimensional data display and analysis system. Dynamic Graphics for Statistics: 91–

432   109. Wadsworth & Brooks/Cole.

433   Fomel, S., and Claerbout, J.F. 2009. Reproducible research. Computing in Science &

434   Engineering **11**(1): 5. IEEE Computer Society.

435   Fournier, D.A., Skaug, H.J., Ancheta, J., Ianelli, J., Magnusson, A., Maunder, M.N., Nielsen, A.,

436   and Sibert, J. 2012. AD model builder: Using automatic differentiation for statistical

437   inference of highly parameterized complex nonlinear models. Optimization Methods and

438   Software **27**(2): 233–249. Taylor & Francis.

439   Gelman, A., and Loken, E. 2014. The statistical crisis in science. American Scientist **102**: 460.

440   doi:10.1511/2014.111.460.

441   Goethel, D.R., Lucey, S.M., Berger, A.M., Gaichas, S.K., Karp, M.A., Lynch, P.D., Walter III,

442   J.F., Deroba, J.J., Miller, S., and Wilberg, M.J. 2019. Closing the feedback loop: On

443   stakeholder participation in management strategy evaluation. Canadian Journal of

444   Fisheries and Aquatic Sciences **76**(10): 1895–1913. NRC Research Press.

445   Gomez, C., Lawson, J., Wright, A.J., Buren, A., Tollit, D., and Lesage, V. 2016. A systematic

446   review on the behavioural responses of wild marine mammals to noise: The disparity

447   between science and policy. Canadian Journal of Zoology **94**(12): 801–819. NRC

448   Research Press.

449   Hampton, S.E., Anderson, S.S., Bagby, S.C., Gries, C., Han, X., Hart, E.M., Jones, M.B.,

450   Lenhardt, W.C., MacDonald, A., Michener, W.K., Mudge, J., Pourmokhtarian, A.,

451   Schildhauer, M.P., Woo, K.H., and Zimmerman, N. 2015. The tao of open science for

452   ecology. Ecosphere **6**(7): 1–13.

453   Hampton, S.E., Strasser, C.A., Tewksbury, J.J., Gram, W.K., Budden, A.E., Batcheller, A.L.,

454   Duke, C.S., and Porter, J.H. 2013. Big data and the future of ecology. Frontiers in

455   Ecology and the Environment **11**(3): 156–162. Wiley Online Library.

456   Hazen, E.L., Scales, K.L., Maxwell, S.M., Briscoe, D.K., Welch, H., Bograd, S.J., Bailey, H.,

457   Benson, S.R., Eguchi, T., Dewar, H., and others. 2018. A dynamic ocean management

458   tool to reduce bycatch and support sustainable fisheries. Science advances **4**(5):

459   eaar3001. American Association for the Advancement of Science.

460   Hilborn, R., and Walters, C.J. 1992. Quantitative fisheries stock assessment: Choice, dynamics

461   and uncertainty. Chapman; Hall.

462   ICES. 2018. EU request on dissemination of ICES advice beyond pdf files. **DOI:**

463   **10.17895/ices.pub.4657**.

464 Johnsen, E., Totland, A., Skålevik, Å., Holmin, A.J., Dingsør, G.E., Fuglebakk, E., and

465   Handegard, N.O. 2019. StoX: An open source software for marine survey analyses.

466   Methods in Ecology and Evolution **10**(9): 1523–1528. Wiley Online Library.

467 Jones, A.S., Horsburgh, J.S., Jackson-Smith, D., Ramírez, M., Flint, C.G., and Caraballo, J.

468   2016. A web-based, interactive visualization tool for social environmental survey data.

469   Environmental modelling & software **84**: 412–426. Elsevier.

470 Keena, N., Etman, M.A., Draper, J., Pinheiro, P., and Dyson, A. 2016. Interactive visualization

471   for interdisciplinary research. Electronic Imaging **2016**(1): 1–7. Society for Imaging

472   Science; Technology.

473 Kristensen, K., Nielsen, A., Berg, C., Skaug, H., and Bell, B. 2016. TMB: Automatic

474   differentiation and laplace approximation. Journal of Statistical Software **70**(5): 1–21.

475   doi:10.18637/jss.v070.i05.

476 Leek, J.T., and Peng, R.D. 2015a. Statistics: P values are just the tip of the iceberg. Nature News

477   **520**(7549): 612.

478 Leek, J.T., and Peng, R.D. 2015b. Reproducible research can still be wrong: Adopting a

479   prevention approach. Proceedings of the National Academy of Sciences **112**(6): 1645–

480   1646. National Acad Sciences.

481 Letcher, B.H., Walker, J.D., O'Donnell, M.J., Whiteley, A.R., Nislow, K.H., and Coombs, J.A.

482   2018. Three visualization approaches for communicating and exploring passive

483   integrated transponder tag data. Fisheries **43**(5): 241–248. Wiley Online Library.

484   Levontin, P., Baranowski, P., Leach, A.W., Bailey, A., Mumford, J.D., Quetglas, A., and Kell,

485   L.T. 2017. On the role of visualisation in fisheries management. Marine Policy **78**: 114–

486   121. Elsevier.

487   Lewis, K.P., Vander Wal, E., and Fifield, D.A. 2018. Wildlife biology, big data, and

488   reproducible research. Wildlife Society Bulletin **42**(1): 172–179. Wiley Online Library.

489   Link, W.A. 1999. Modeling pattern in collections of parameters. The Journal of Wildlife

490   Management **63**(3): 1017–1027. [Wiley, Wildlife Society].

491   Lowndes, J.S.S., Best, B.D., Scarborough, C., Afflerbach, J.C., Frazier, M.R., O'Hara, C.C.,

492   Jiang, N., and Halpern, B.S. 2017. Our path to better science in less time using open data

493   science tools. Nature ecology & evolution **1**(6): 0160. Nature Publishing Group.

494   Magnusson, A., and Millar, C. 2020. IcesTAF: Functions to support the ices transparent

495   assessment framework. Available from https://CRAN.R-project.org/package=icesTAF.

496   Maunder, M.N., and Punt, A.E. 2013. A review of integrated analysis in fisheries stock

497   assessment. Fisheries Research **142**: 61–74. Elsevier.

498   Maxwell, S.M., Hazen, E.L., Lewison, R.L., Dunn, D.C., Bailey, H., Bograd, S.J., Briscoe, D.K.,

499   Fossette, S., Hobday, A.J., Bennett, M., and others. 2015. Dynamic ocean management:

500   Defining and conceptualizing real-time management of the ocean. Marine Policy **58**: 42–

501   50. Elsevier.

502   McHenry, J., Welch, H., Lester, S.E., and Saba, V. 2019. Projecting marine species range shifts

503   from only temperature can mask climate vulnerability. Global change biology **25**(12):

504   4208–4221. Wiley Online Library.

505   McInerny, G.J., Chen, M., Freeman, R., Gavaghan, D., Meyer, M., Rowland, F., Spiegelhalter,

506   D.J., Stefaner, M., Tessarolo, G., and Hortal, J. 2014. Information visualisation for

507   science and policy: Engaging users and avoiding bias. Trends in ecology & evolution

508   **29**(3): 148–157. Elsevier.

509   Miller, S.K., Anganuzzi, A., Butterworth, D.S., Davies, C.R., Donovan, G.P., Nickson, A.,

510   Rademeyer, R.A., and Restrepo, V. 2019. Improving communication: The key to more

511   effective mse processes. Canadian Journal of Fisheries and Aquatic Sciences **76**(4): 643–

512   656. NRC Research Press.

513   Nielsen, A., and Berg, C.W. 2014. Estimation of time-varying selectivity in stock assessments

514   using state-space models. Fisheries Research **158**: 96–101. Elsevier.

515   Perkel, J.M. 2018. Data visualization tools drive interactivity and reproducibility in online

516   publishing. Nature **554**(7690): 133–134.

517   Plummer, M. 2003. JAGS: A program for analysis of bayesian graphical models using gibbs

518   sampling. *In* Proceedings of the 3rd international workshop on distributed statistical

519   computing. Vienna, Austria.

520   R Core Team. 2017. R: A language and environment for statistical computing. R Foundation for

521   Statistical Computing, Vienna, Austria. Available from https://www.R-project.org/.

522   Regular, P., Rodgers, B., Wheeland, L., Anderson, S., Grandin, C., Ismay, C., and Solomon, N.

523   2020. NAFOdown: An R markdown template for producing NAFO scientific council

524   documents. Available from https://github.com/nafc-assess/NAFOdown.

525   Rideout, R., and Ings, D. 2018. Research Vessel Bottom Trawl Survey Report (NL Region): A

526   stock-by-stock summary of survey information up to and including the 2017 spring and

527   autumn surveys. Canadian Technical Report of Fisheries; Aquatic Sciences No. 3267.

528   RStudio Team. 2015. RStudio: Integrated development environment for r. RStudio, Inc., Boston,

529   MA. Available from http://www.rstudio.com/.

530   Sievert, C. 2018. Plotly for R. Available from https://plotly-book.cpsievert.me.

531   Smith, S., and Somerton, G. 1981. STRAP: A User-Oriented Computer Analysis System for

532   Groundfish Research Trawl Survey Data. Canadian Technical Report of Fisheries;

533   Aquatic Sciences No. 1030.

534   Taggart, C., Penney, P., Barrowman, N., and George, C. 1995. The 1954-1993 Newfoundland

535   cod tagging database: Statistical summaries and spatial-temporal dynamics. Canadian

536   Technical Report of Fisheries and Aquatic Sciences **2042**.

537   Tukey, J. 1977. Exploratory data analysis. Addison-Wesley Publishing Company. Available

538   from https://books.google.ca/books?id=UT9dAAAAIAAJ.

539   Tukey, J.W., and Tukey, P.A. 1985. Computer graphics and exploratory data analysis: An

540   introduction. *In* Proceedings of the sixth annual conference and exposition: Computer

541   graphics'85. National Computer Graphics Association, Fairfax, VA. pp. 773–785.

542   Yeatman, J.D., Richie-Halford, A., Smith, J.K., Keshavan, A., and Rokem, A. 2018. A browser-

543   based tool for visualization and analysis of diffusion mri data. Nature communications

544   **9**(1): 940. Nature Publishing Group.