Improving the communication and accessibility of stock assessment using interactive visualization tools

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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.

2

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

23 - Tukey (1977)

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

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

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

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

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

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

30 well-monitored stocks, the challenge has shifted from having sufficient data and information for

31 providing sound advice on stock status, to presenting large quantities of data and output from

32 increasingly complex statistical models in a meaningful way. Traditional formats (e.g. slides) for

33 presenting information at stakeholder meetings are often insufficient to convey the richness of

34 information available and the static and sequential nature of these formats can stifle meaningful

35 discussions. A solution to this problem is the effective use of interactive visualization tools

36 (Keena et al. 2016). These are common tools we use every day on a range of web sites, but their

37 use is no longer restricted to web site developers as these tools are being integrated into software

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

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

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

41 2018). This trend includes fisheries research and many of these tools, and the code used to

42 produce them, are available online (see Appendix A for examples).

43 Here we aim to demonstrate how interactive visualization tools provide an efficient and effective

44 means of exploring and communicating the ever-expanding array of data inputs and model

45   outputs. We especially highlight the use of interactive visuals inside dynamic documents called

46   "dashboards". The concept of using a dashboard was borrowed from the business community

47   where they are frequently used to group a series of interactive visuals and tables to provide at-a-

48   glance views of key performance indicators. We first demonstrate the application of these tools

49   to data that are commonly presented in stock assessments to show how they can simplify the

50   detailed exploration of data from long-term monitoring programs. Second, we focus on the

51   modeling aspect of stock assessment and demonstrate how interactive dashboards can be used to

52   explore, diagnose and communicate results from an integrated assessment model. This structure

53   corresponds to two important steps in the stock assessment process: 1) data exploration, and 2)

54   data modeling. In each case, the dashboards were constructed within the framework of the R

55   programming language (R Core Team 2017) and the RStudio IDE (RStudio Team 2015) using

56   three or more of the packages listed in Table (Table 1).

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

58   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

4

	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

59

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

5

78 **Survey data**

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

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

81 These data are analyzed using a standard stratified analysis via a locally developed R package

82 called RStrap (for details on methodology see Smith and Somerton 1981). Both the inputs and

83 outputs from RStrap analyses are very large and, depending on the species, the time-series may

84 include > 40 years and span the majority of the Newfoundland and Labrador shelf. In order for

85 people to quickly and reliably explore these data without iteratively modifying R scripts one

86 species at a time, an application (hereafter called RStrap Explorer) was built using a combination

87 of shiny, crosstalk, flexdashboard, plotly and R markdown (Table 1). RStrap Explorer started as

88 a way to visualize estimates of biomass and abundance trends of specific species by supplying

89 RStrap output to a flexdashboard file designed to organize and visualize the results. The shiny

90 package was latter applied as it allows RStrap to be run in the background and therefore allows

91 the user to dynamically explore abundance and biomass estimates from multiple species in one

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

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

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

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

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

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

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

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

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

6

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

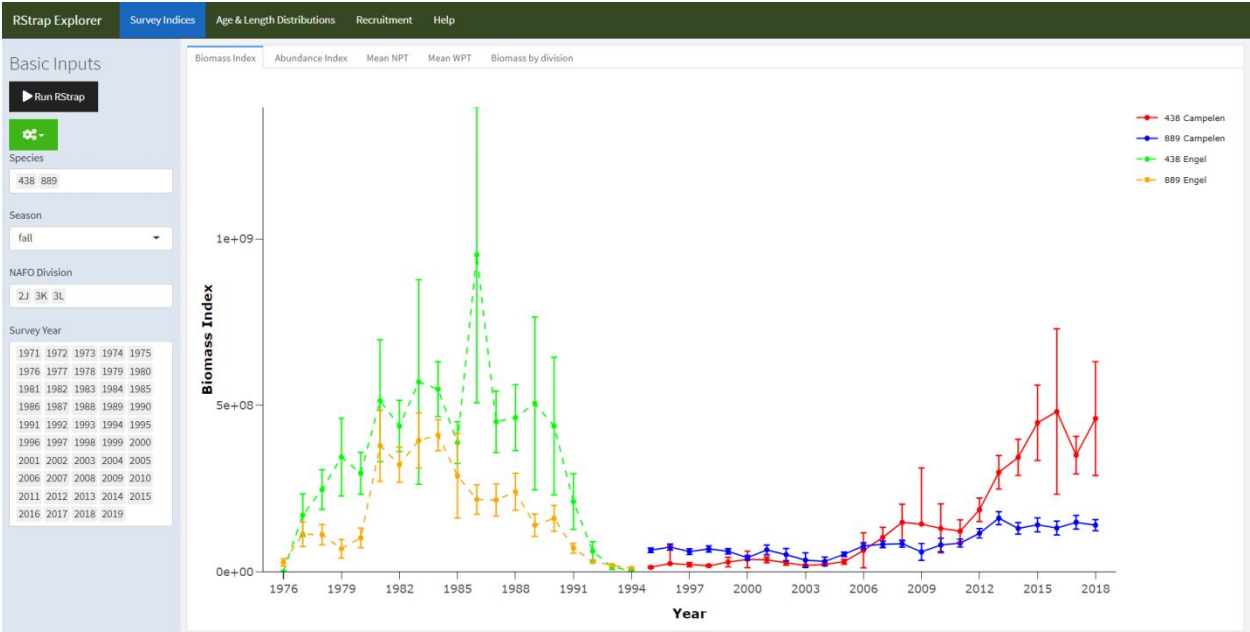102　formal stock assessment begins.

103

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

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

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

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

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

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

110　889). All trend lines can be toggled off using plotly's dynamic user interface. The user also has

111　the ability to hover over the points to compare estimates and export the figure as a png file.

112

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

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

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

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

117 menu (shown on left side).

118 **Tagging data**

119 Northern cod (NAFO Divisions 2J3KL) has a rich history of tagging, starting in in 1954 (Taggart

120 et al. 1995) and continuing to this day. The tagging and recovery data are captured in a

121 standardized database, with fields typical of most tagging programs. This data base has over

122 600,000 records as of early 2019, with 2,000-10,000 tags deployed annually in recent decades.

123 The tagging and capture data are used in the current assessment model for this stock (Cadigan

124 2016), but tools to explore this extensive data set were limited, especially from a spatial

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

8

126   using shiny and leaflet (Table 1) that allows a user to quickly and dynamically subset the data

127   (e.g. ranges of release and capture years, specific geographic locations). As the application

128   developed, it was incorporated into shinydashboard, to take advantage of the number of layout

129   options available in shinydashboard (Table 1). Given the large number of tags released, often at

130   nearby sites, visualizing the data with static mapping was particularly challenging. The

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

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

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

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

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

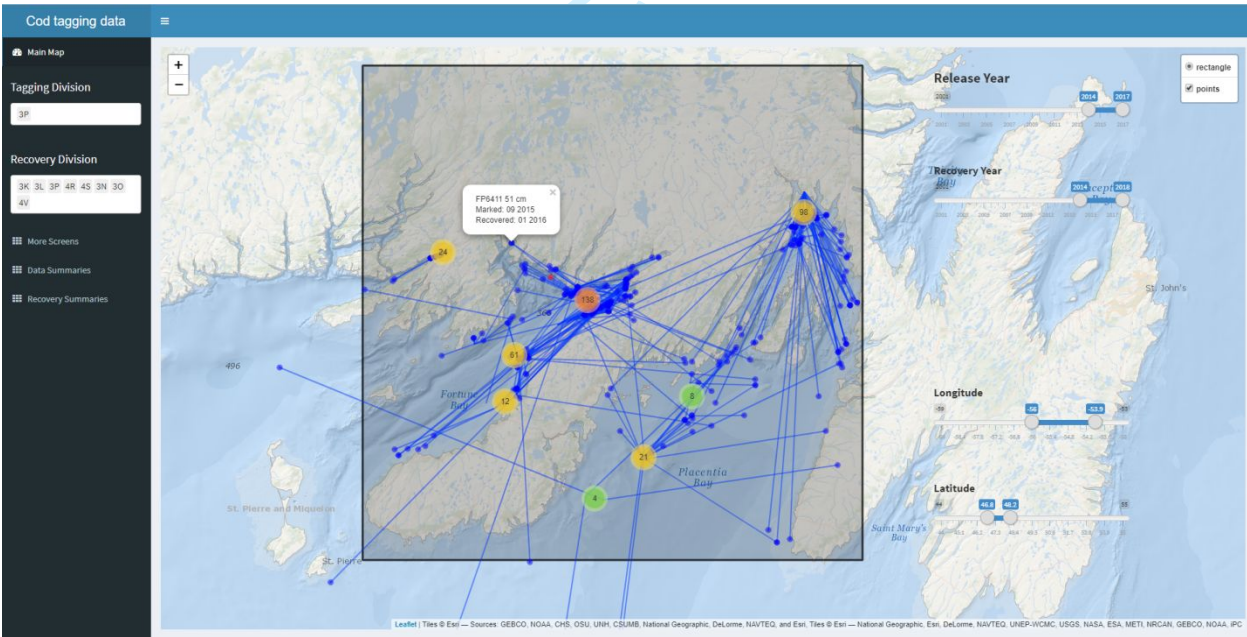136   selected data (Figure 4).

137

138   Figure 3: Screen shot of cod tag mapping tool using shinydashboard and leaflet. The

139   markercluster function dynamically splits or pools tagging locations (red, orange, green or

140   yellow points) depending on zoom level, the recoveries positions (blue) are much fewer, and are

9

141 left to be plotted individually at all scales. Options to include pop up labels are included, so

142 specific information on each point can be retrieved with a mouse click (in this case: tag number,

143 fish length, date released, and date captured), which is particularly useful when error checking.
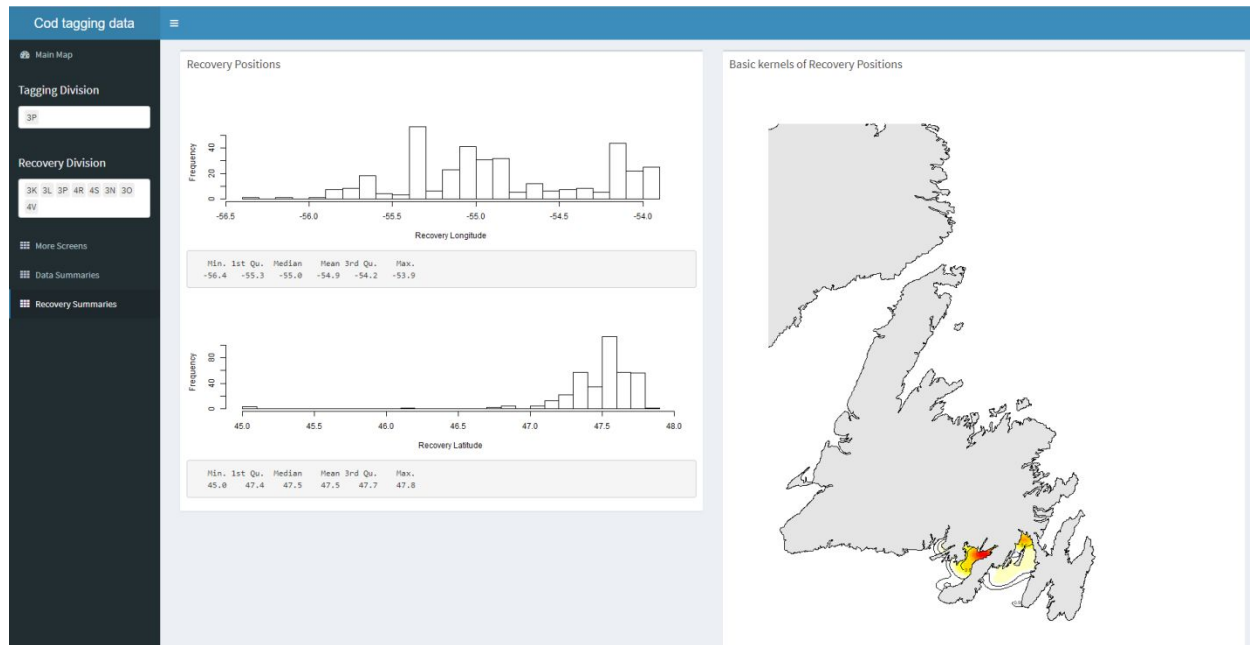

144

145 Figure 4: Basic summaries of the recovery data from the tags selected within the shiny dashboard

146 cod tag mapping tool. In this case, histograms and summary statistics of the recovery positions

147 are returned, along with a simple map of kernels showing the 2D spatial distribution of the

148 selected tag recoveries.

Data modeling

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

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

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

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

10

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

155   been curtailed in contemporary stock assessments thanks to advances in statistical computing

156   that have facilitated the analysis of all available data, in as raw a form as appropriate, in a single

157   integrated analysis (Maunder and Punt 2013). Specifically, statistical modeling tools such as

158   JAGS (Plummer 2003), AD Model Builder (Fournier et al. 2012) and Template Model Builder

159   (Kristensen et al. 2016) allow the construction of a joint likelihood for an array of observations

160   to, in theory, extract as much information as possible about the biological and fishery processes.

161   From a computational perspective, analyses of a variety of large data sets has never been easier.

162   However, from a human perspective, contemporary stock assessment biologists are faced with

163   the challenge of understanding and integrating data from multiple sources into a single model

164   and communicating the methods and results to stakeholders and fisheries managers. This

165   challenge was palpable for the data-rich case of Northern cod.

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

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

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

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

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

171   (1995-present), inshore acoustic surveys (1995-2009), fishery catch-at-age compositions and

172   partial fishery landings (1983-present), and tagging (1983-present). Using a series of observation

173   equations, this TMB based model simplifies thousands of historical data points into quantities

174   such as recruitment, spawning stock biomass, fishing mortality and natural mortality. Once the

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

176   output. The traditional approach would involve producing static presentations and documents

177   with a series of figures and tables. However, with large amounts of model inputs and outputs,

178   this approach quickly becomes overwhelming for both the analyst and the stakeholders involved

179   for at least two reasons. First, it is no longer feasible for the analyst to include and describe every

180   figure and table produced in a single document. Second, it is difficult for stakeholders to

181   efficiently digest the information that has been compressed into a series of static slides or pages.

182   Interactive documents provide a potential solution to this problem as they allow much more

183   information to be contained and accessible on a single screen.

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

185   interactive and self-contained "dashboard", called NCAM explorer, was developed for the 2018

186   assessment of Northern cod (Dwyer et al. 2019). We used R-based packages (Table 1) to

187   construct a tool for exploring the input and output of NCAM, specifically the flexdashboard

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

189   crosstalk package to link the data displayed across multiple plots. Via R Markdown, the

190   dashboard is rendered into a self-contained html file that is reproducible, interactive, and easy to

191   update following modifications to the model or the addition of new data.

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

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

194   provide a series of diagnostic plots for assessing model fits to catch ("Catch"), survey ("RV

195   survey", "SN survey" and "SS survey"; accessed from the "Surveys" drop-down menu), and

196   tagging ("Tagging") data. For instance, the "RV survey" page includes plots of observed and

197   predicted values of mean numbers per tow captured in the research vessel survey (Figure 5). The

198   dashboard also includes pages focused on model estimates such as catchability and selectivity

199   ("Catchability"), stock size and vital rates ("Trends"; Figure 6), and stock productivity

12

200 ("Productivity"). Finally, some results from a retrospective analyses are included under the

201 "Retro" page, trends from different models are compared under the "Comps" page, details on the

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

203 projections", "Retro projections", and "Results" pages), and key inputs and outputs are accessed

204 from "Tables" drop-down menu ("Inputs", "Settings", "Outputs" pages). The plots and tables

205 included in the dashboard are similar to those typically presented at assessment meetings and in

206 research documents. However, there are two key benefits of this approach over the modus

207 operandi of producing static documents and slides. First, interactive plots nested in a dashboard

208 permit relatively easy and efficient access to the details as it replaces scrolling through tens, if

209 not hundreds, of pages or slides with mouse-clicks across pages holding data-rich illustrations

210 (i.e. both broader patterns and finer details in the data are accessible via zooming and tooltips).

211 Second, the automated nature of the dashboard circumvents the monotonous, time-consuming

212 and error-prone task of copying and pasting figures, tables and values into documents and slides,

213 although, we note that this point is not exclusive to the proposed approach (e.g. slide shows can

214 easily be made using R markdown). Both benefits expedite the process of exploring a range of

215 model configurations as the automated output facilitate quick views of standard diagnostics and

216 the interactive plots facilitate detailed explorations and comparisons of models with different

217 configurations. The dashboard also makes it easy to share the results with colleagues and

218 stakeholders as it is rendered into a self-contained html file. This allows others to independently

219 scrutinize details of both data and the model that are typically only accessible to the analyst.

220 Such access improves the transparency of the stock assessment model which, in turn, leads to

221 richer discussion and scrutiny of the biological and statistical rigor of the model. For instance,

222 visualizations depicting the model assumptions, process errors and confidence intervals around

13

223   the projections raised important questions on the impact of the assumptions on the projections

224   from the model. These questions were raised during the first assessment meeting in which this

225   tool was used and the ensuing discussions left us with the impression that this tool helped the

226   assessment biologists, academics, resource managers and fisheries representatives in the room

227   gain a deeper understanding of the uncertainties and the patterns in the risk tables. Feedback and

228   personal testimony from multiple stakeholders who have used the dashboard reaffirmed our

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

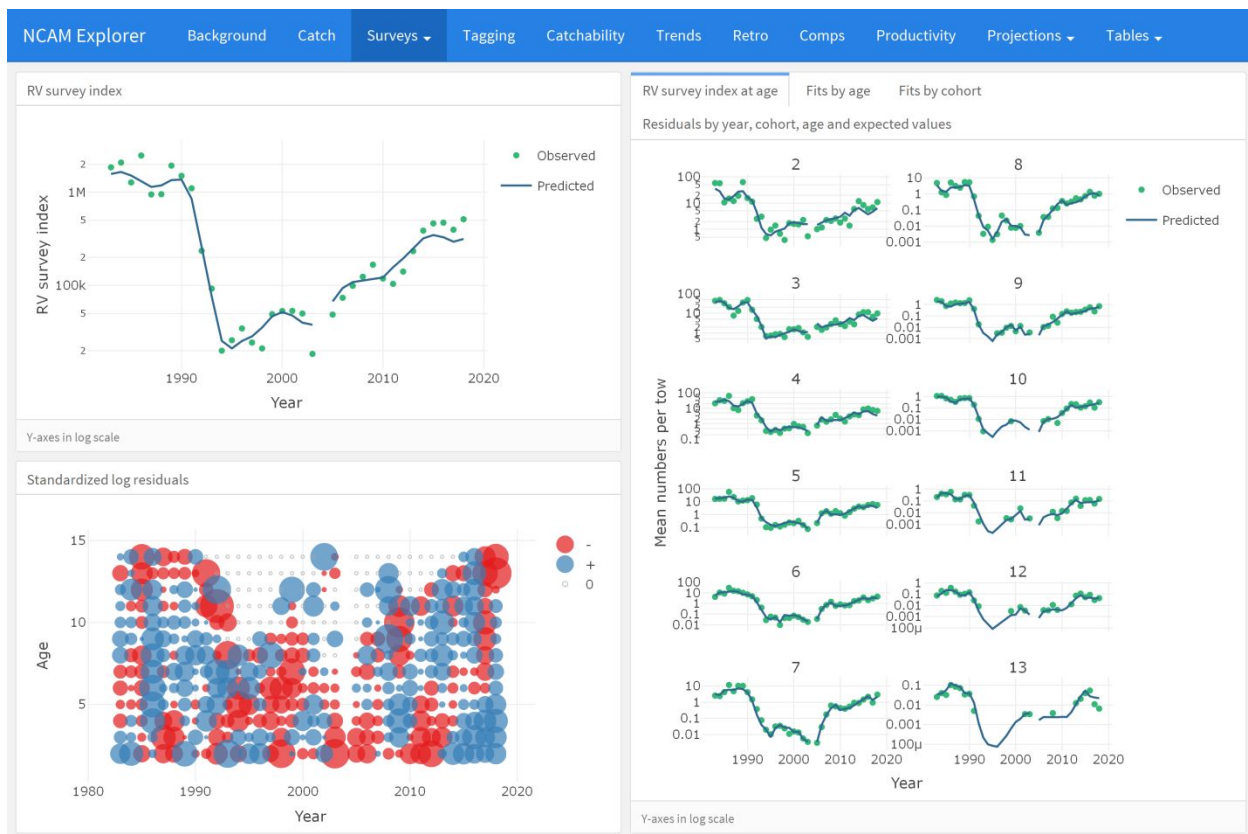230   communication and relieve concerns that something is hidden.

231

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

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

234   upper left panel and scaled matrix plot of age-disaggregated standardized log residuals are shown

14

235   in the lower left panel (blue = positive, red = negative, symbols scaled by size; grey = index

236   values of zero). Age-disaggregated observed (dots) and predicted (lines) values from the DFO

237   RV survey are shown in the right panel.
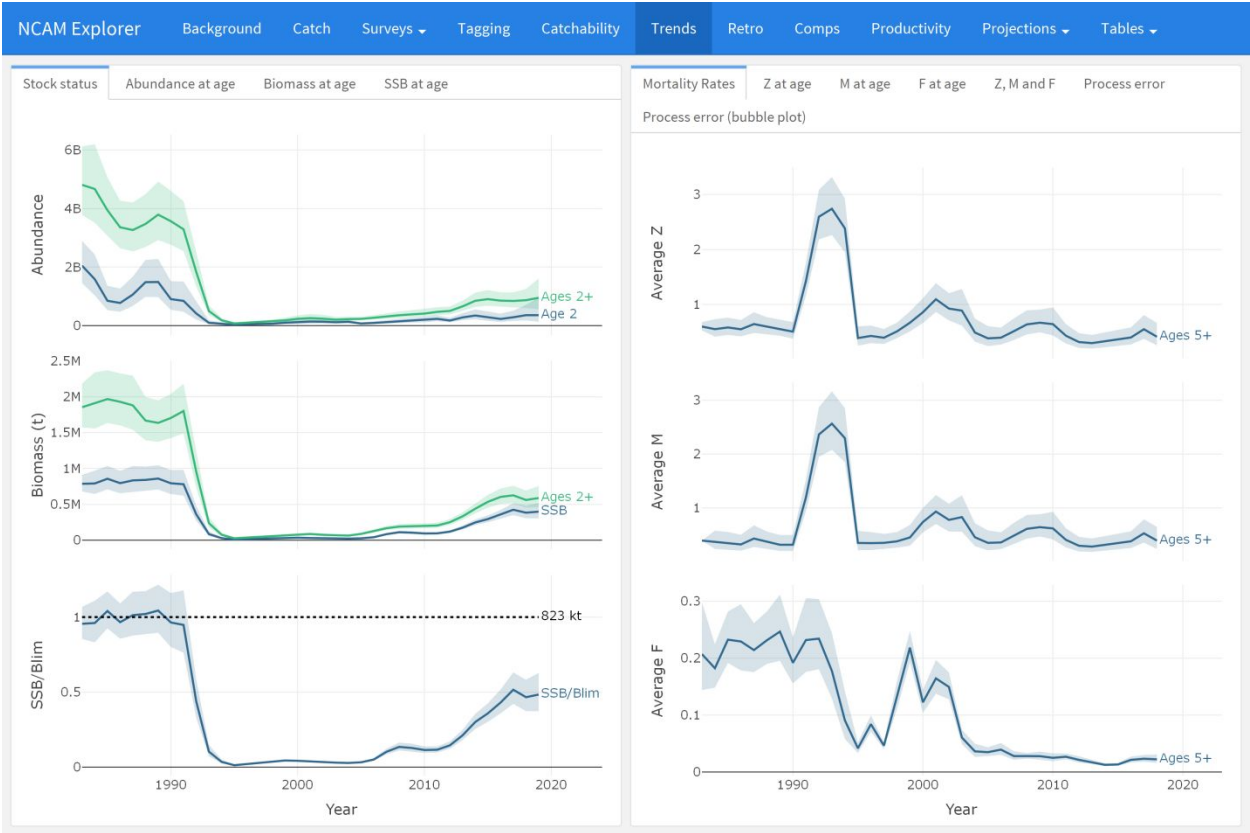

238

239   Figure 6: Screenshot of the "Trends" tab which displays estimates of recruitment, stock size, and

240   stock size relative to B_{lim} (left panels) and mortality rates (F, M, Z, right panels).

Towards open stock-assessment

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

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

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

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

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

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

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

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

250 number of limitations, such as available pages in journals, much of the data pipeline is not

251 transparent nor is it reproducible. A number of authors have recently advocated for a culture of

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

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

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

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

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

257 Lowndes et al. 2017).

258 The tools presented here are additions to the growing number of interactive stock assessment

259 tools being developed and applied across the globe (see Appendix A). We believe that such tools

260 represent an important a step forward in terms of open science and reproducible research in

261 addition to being a major step forward in how stock assessments are presented and critiqued.

262 Although these tools do not reveal the entire data pipeline, in conjunction with posting code and

263 data on-line, they represent a significant advance over more traditional methods. Similarly, these

264 tools do not fully alleviate pragmatic issues associated with reproducible research. For example,

265 it is unlikely that an individual has the time to fully review and recreate a particular analysis in

266 its entirety when most participants are already overcommitted (Banks 2011). Further, in the case

267 of NCAM, considerable statistical experience and expertise is required simply to run the model.

268 However, the dashboard approach removes many of these obstacles. The html file contains all

16

269   model inputs, outputs and diagnostics in an open, and easy to use, interactive document that can

270   be distributed prior to meetings. As such, participants can assess the results and diagnostics at

271   their leisure. Specific experience with the tools used to generate the results are not required to

272   constructively and critically review of the results presented in the dashboard.

273   ## Conclusions

274   We must acknowledge there are costs to adopting the use of interactive tools. The first and

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

276   these tools. In our three examples, the developers (first, second and third authors) were relatively

277   proficient with R and have natural aptitudes for programming, but all had their formal training in

278   field-based population ecology. While some learning time was needed (a few weeks), the

279   learning curve was relatively minor because there was no need to learn a new programming

280   language (e.g. JavaScript, CSS, etc.). Moreover, a growing user base means that most

281   programming issues were readily addressed through simple internet searches. There are also a

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

283   development of new interactive tools. We expect the accessibility and quality of these tools to

284   continue to improve as more people in the fisheries community develop and use interactive

285   documents. It is our experience that the upfront investment in time has already paid dividends in

286   terms of efficiencies of delivering products for subsequent stock assessments, and in the quality

287   of the data exploration and understanding.

17

Acknowledgements

288

289   We thank the numerous colleagues and participants of various stakeholder and stock assessment

290   meetings who encouraged us to further develop these interactive visualization tools, and

291   especially those who took the time to make suggestions on how to make them more accessible

292   and useful. We are also grateful for the constructive feedback from Gary Carvalho, Kelli

293   Johnson, Colin Millar and four anonymous reviewers.

Appendix A

294

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

296   •   Marine Aggregates Application (https://openscience.cefas.co.uk/ma_tool/) from Cefas
297   •   Benthic Non Native Species Tool (https://openscience.cefas.co.uk/invasive_species/) from
298   Cefas
299   •   Species Dashboard (https://shiny.marine.ie/speciesdash/) from The Marine Institute
300   •   The Stock Book (https://shiny.marine.ie/stockbook/) from The Marine Institute
301   •   Data-Limited Fisheries Toolkit demo (https://www.datalimitedtoolkit.org/demo) from the
302   Fisheries Center, University of British Columbia
303   •   Exploring Groundfish in an Ecosystem Context
304   (https://incorporatingecosystemapproach.shinyapps.io/indiapp/) from Fisheries and Oceans
305   Canada, Maritimes Region
306   •   Catchy Data (https://eu.oceana.org/en/catchy-data) from Oceana
307   •   VISA tool (e.g. https://ices-tools-dev.github.io/VISA_tool/hke.27.3a46-
308   8abd.html#ices_advice_2018) from ICES, which was developed to meet an "EU request on
309   dissemination of ICES advice beyond pdf files"

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