# Exploratory analysis of U.S Atlantic and Gulf of Mexico scalloped hammerhead recruitment indices

Henning Winker

SEDAR77-AW01

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27 May, 2022

## Contents



Installing JARA requires the librabry(devtools), which can be install by 'install.packages('devtools')' and a R version >= 3.5. Then simply install JARA from github with the command:

```
devtools::install_github("henning-winker/JARA")
```

# 1 Load JARA and data

Load package

```
library(JARA)
```

Load Recruitment indices compiled as `rdata`

```
load("RecruitIndex.rdata", verbose = T)
   Loading objects:
     ATL.I
     ATL.CV
     GOM.I
     GOM.CV
```

# 2 GOM index

Now set up a first JARA model for GOM the indices (see details `?build_jara`)

```
inpGOM = build_jara(I = GOM.I, se = GOM.CV, assessment = "GOM", scenario = "GOM1",
    model.type = "relative", variance.weighting = "model", silent = T)
```

and fit JARA (details `?fit_jara`)

```
fGOM = fit_jara(inpGOM, do.ppc = T, silent = T)
   module glm loaded
   Compiling model graph
      Resolving undeclared variables
      Allocating nodes
   Graph information:
      Observed stochastic nodes: 57
      Unobserved stochastic nodes: 143
      Total graph size: 858

   Initializing model
```

```
ngom = names(GOM.I)[-1]

jrpar(mfrow = c(2, 2), plot.cex = 0.8)
for (i in 1:2) {
    jrplot_fits(fGOM, add = T, single.plots = T, indices = ngom[i])
    jrplot_runstest(fGOM, add = T, single.plots = T, indices = ngom[i])
}

   ><> jrplot_fits() - fits to abudance indices <><

   ><> jrplot_runstest()   <><

   Runs Test stats:

   ><> jrplot_fits() - fits to abudance indices <><

   ><> jrplot_runstest()   <><
```

```
   Runs Test stats:
```

```
jrplot_residuals(fGOM)

   ><> jrplot_residuals() - Joint residual plot  <><
```

```
jrplot_PPC(fGOM)

   ><> jrplot_PPC() - Posterior Predictive Checks <><
```

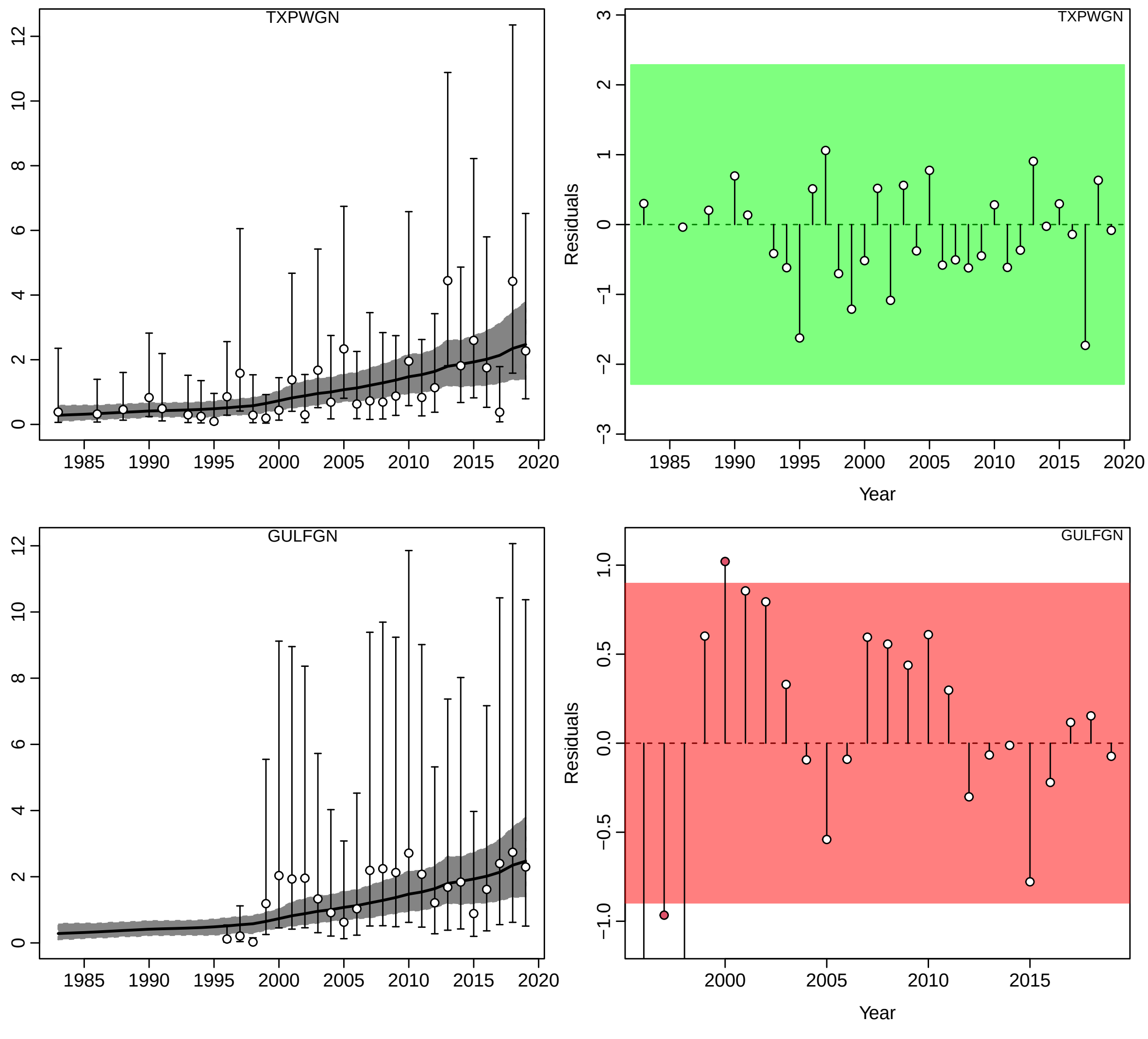


Figure 1: Fits of underlying state-space trend by index and residual runs tests for the GOM recruitment indices.

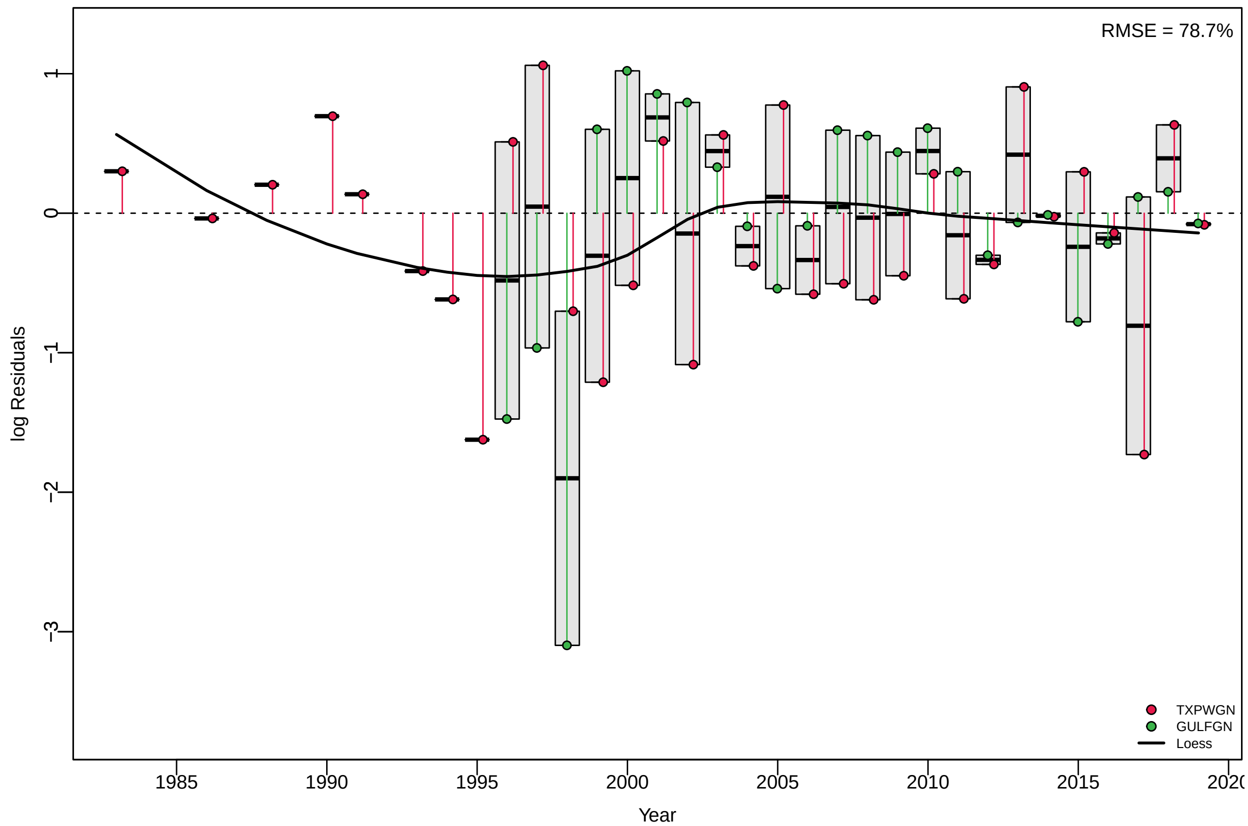


Figure 2: Joint-Residual plot for GOM fits for evaluating data conflicts in recruit indices

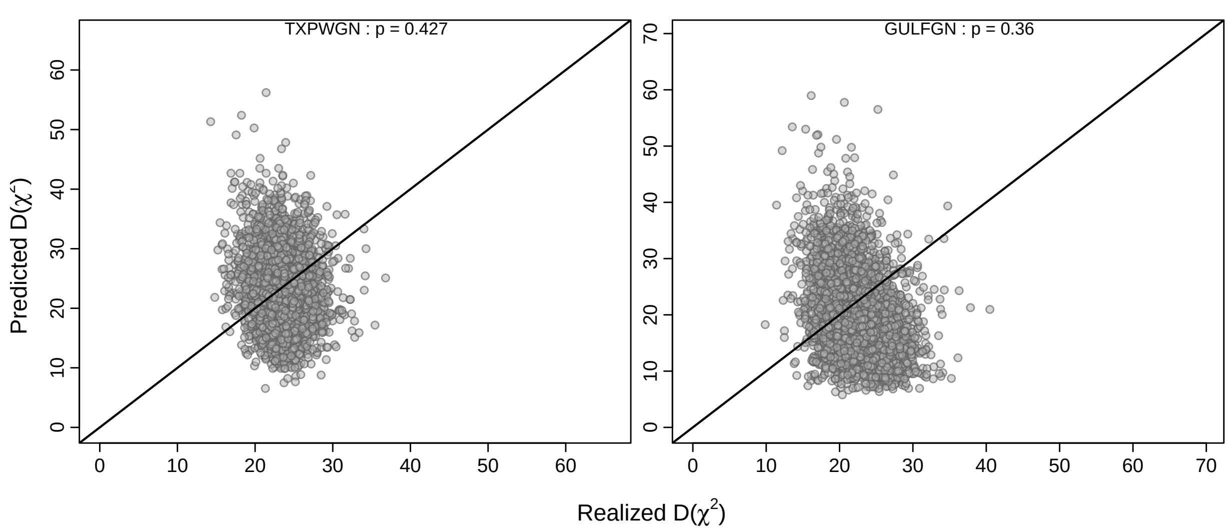


Figure 3: Posterior predictive checks for GOM by recruitment index

Posterior Predictive Checks with Bayesian p values

| | Index | Bayesian.p | nobs |
|---|---|---|---|
| 1 | TXPWGN | 0.4267619 | 32 |
| 2 | GULFGN | 0.3604762 | 24 |
| 3 | Combined | 0.3936190 | 56 |

```r
jrplot_jointindex(fGOM, plot.cex = 0.8)
```

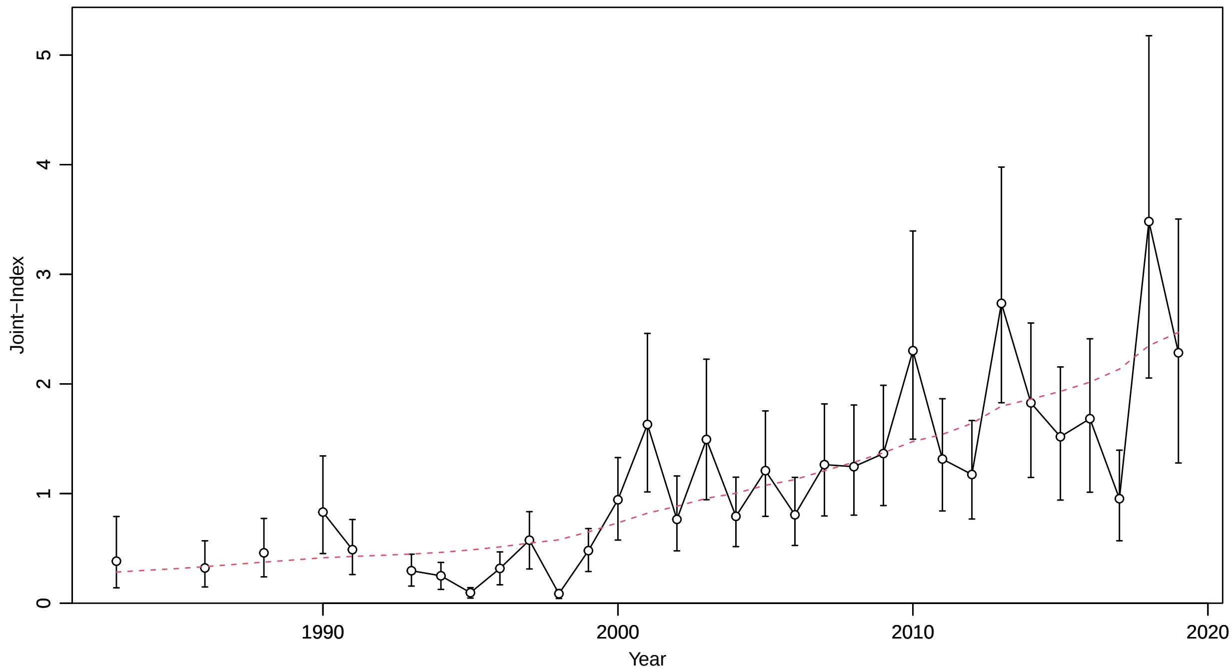


Figure 4: Estimated joint CPUE index for GOM with 95% CIs and the red dashed line indicating the underlying state-space trend

Make output table

```r
GOMtab = jointindex(fGOM)
GOMtab[-1] = round(GOMtab[-1], 3)

knitr::kable(GOMtab, align = "ccccc", escape = FALSE, row.names = FALSE, caption = "Joint CPUE recruitme
```

Table 1: Joint CPUE recruitment index for GOM, summarizing the underying state-space trends, estimated mean CPUE, stadard error on log(CPUE), and lower and upper 95% CI's

| year | trend | index | log.se | lci | uci |
|---|---|---|---|---|---|
| 1983 | 0.284 | 0.383 | 0.401 | 0.140 | 0.791 |
| 1984 | 0.300 | NA | NA | NA | NA |
| 1985 | 0.315 | NA | NA | NA | NA |
| 1986 | 0.333 | 0.321 | 0.320 | 0.148 | 0.569 |
| 1987 | 0.354 | NA | NA | NA | NA |
| 1988 | 0.374 | 0.459 | 0.288 | 0.240 | 0.773 |
| 1989 | 0.394 | NA | NA | NA | NA |
| 1990 | 0.414 | 0.831 | 0.267 | 0.453 | 1.343 |
| 1991 | 0.426 | 0.488 | 0.256 | 0.261 | 0.763 |
| 1992 | 0.437 | NA | NA | NA | NA |
| 1993 | 0.448 | 0.296 | 0.257 | 0.156 | 0.447 |
| 1994 | 0.463 | 0.250 | 0.265 | 0.126 | 0.372 |
| 1995 | 0.485 | 0.096 | 0.269 | 0.047 | 0.142 |
| 1996 | 0.513 | 0.317 | 0.253 | 0.168 | 0.467 |
| 1997 | 0.548 | 0.575 | 0.244 | 0.312 | 0.835 |
| 1998 | 0.578 | 0.086 | 0.257 | 0.043 | 0.124 |
| 1999 | 0.650 | 0.479 | 0.214 | 0.289 | 0.681 |
| 2000 | 0.733 | 0.943 | 0.200 | 0.576 | 1.328 |
| 2001 | 0.821 | 1.630 | 0.213 | 1.015 | 2.461 |
| 2002 | 0.884 | 0.764 | 0.213 | 0.477 | 1.160 |
| 2003 | 0.956 | 1.493 | 0.205 | 0.944 | 2.226 |
| 2004 | 1.003 | 0.792 | 0.196 | 0.516 | 1.149 |
| 2005 | 1.075 | 1.209 | 0.196 | 0.792 | 1.754 |
| 2006 | 1.128 | 0.806 | 0.193 | 0.526 | 1.148 |
| 2007 | 1.208 | 1.264 | 0.199 | 0.796 | 1.818 |
| 2008 | 1.286 | 1.245 | 0.201 | 0.803 | 1.808 |
| 2009 | 1.372 | 1.365 | 0.198 | 0.890 | 1.988 |
| 2010 | 1.475 | 2.303 | 0.199 | 1.496 | 3.395 |
| 2011 | 1.540 | 1.315 | 0.196 | 0.841 | 1.865 |
| 2012 | 1.639 | 1.174 | 0.191 | 0.768 | 1.666 |
| 2013 | 1.797 | 2.735 | 0.196 | 1.828 | 3.978 |
| 2014 | 1.861 | 1.827 | 0.194 | 1.147 | 2.556 |
| 2015 | 1.932 | 1.518 | 0.203 | 0.941 | 2.155 |
| 2016 | 2.016 | 1.683 | 0.212 | 1.012 | 2.412 |
| 2017 | 2.136 | 0.953 | 0.222 | 0.569 | 1.396 |
| 2018 | 2.349 | 3.481 | 0.228 | 2.054 | 5.176 |
| 2019 | 2.470 | 2.284 | 0.249 | 1.279 | 3.504 |

# 3 ATL index

```
inpATL = build_jara(I = ATL.I, se = ATL.CV, assessment = "GOM", scenario = "GOM1",
    model.type = "relative", variance.weighting = "model", silent = T)
```

```
fATL = fit_jara(inpATL, do.ppc = T, silent = T)
   Compiling model graph
      Resolving undeclared variables
      Allocating nodes
   Graph information:
      Observed stochastic nodes: 44
      Unobserved stochastic nodes: 108
      Total graph size: 605

   Initializing model
```

```
natl = names(ATL.I)[-1]

jrpar(mfrow = c(3, 2), plot.cex = 0.8)
for (i in 1:3) {
    jrplot_fits(fATL, add = T, single.plots = T, indices = natl[i])
    jrplot_runstest(fATL, add = T, single.plots = T, indices = natl[i])
}

   ><> jrplot_fits() - fits to abudance indices <><

   ><> jrplot_runstest()   <><

   Runs Test stats:

   ><> jrplot_fits() - fits to abudance indices <><

   ><> jrplot_runstest()   <><

   Runs Test stats:

   ><> jrplot_fits() - fits to abudance indices <><

   ><> jrplot_runstest()   <><
```

```
   Runs Test stats:
```

```
jrplot_residuals(fATL)

   ><> jrplot_residuals() - Joint residual plot  <><
```

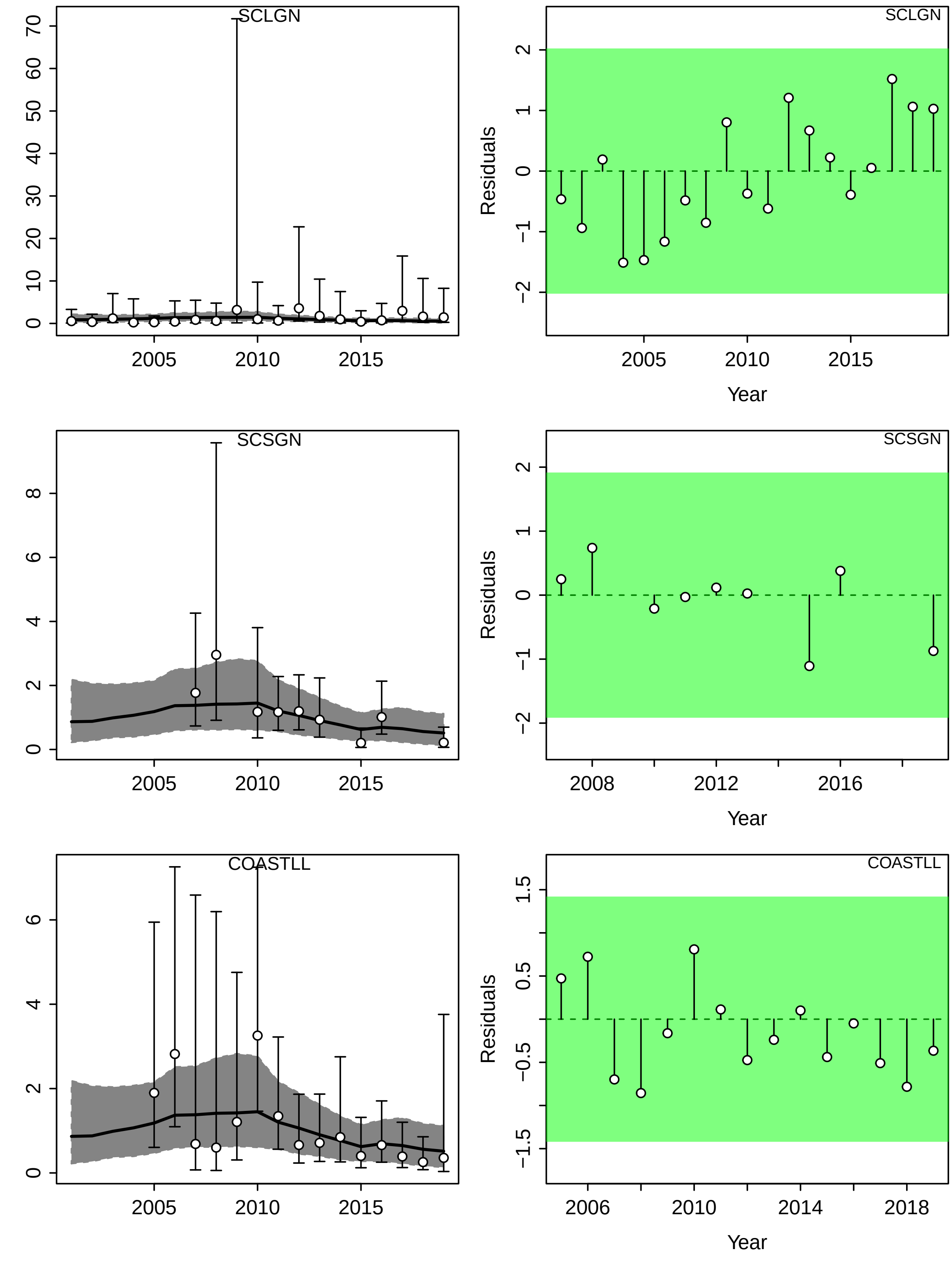


Figure 5: Fits of underlying state-space trend by index and residual runs tests for the ATL recruitment indices.

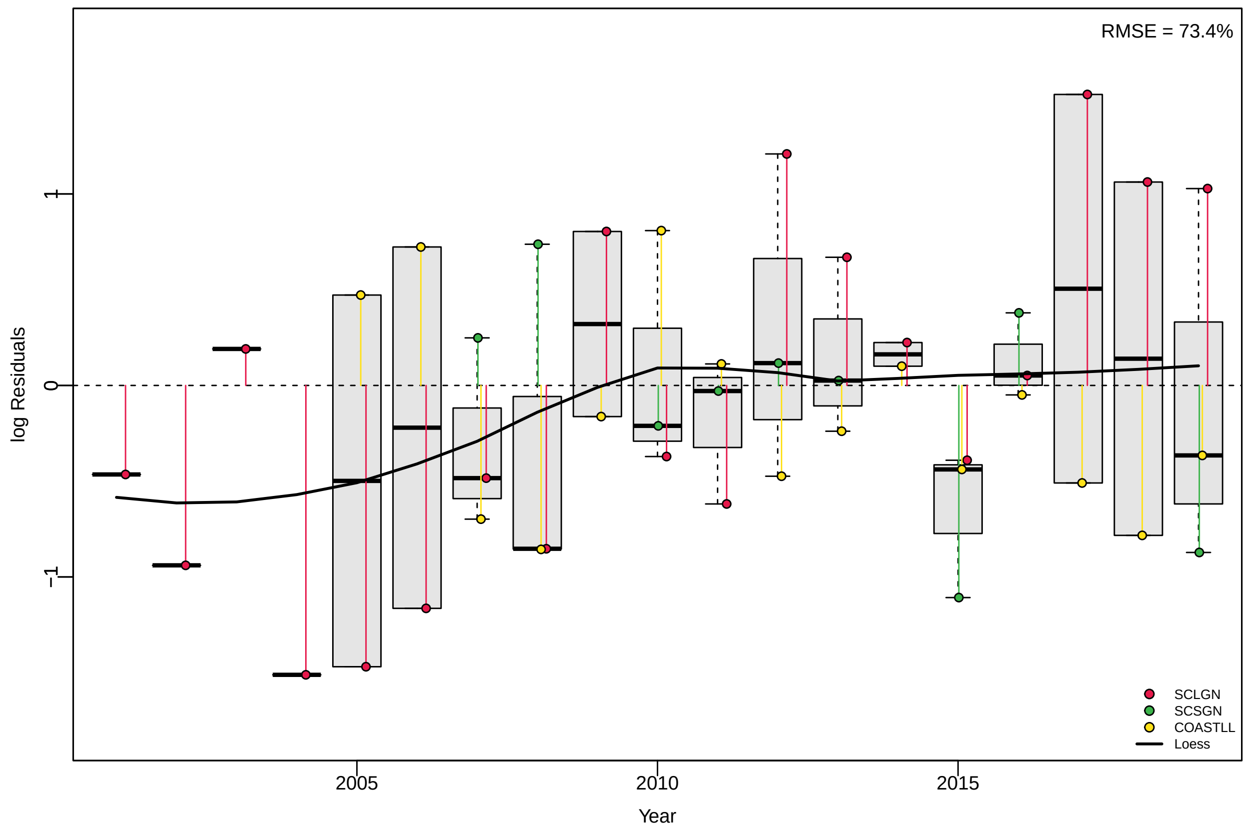


Figure 6: Joint-Residual plot for ATL fits for evaluating data conflicts in recruitment indices

```
jrplot_PPC(fATL)

   ><> jrplot_PPC() - Posterior Predictive Checks <><

    Posterior Predictive Checks with Bayesian p values
        Index Bayesian.p nobs
   1     SCLGN  0.5892381   19
   2     SCSGN  0.4459048    9
   3   COASTLL  0.7474286   15
   4 Combined  0.5941905   43
```

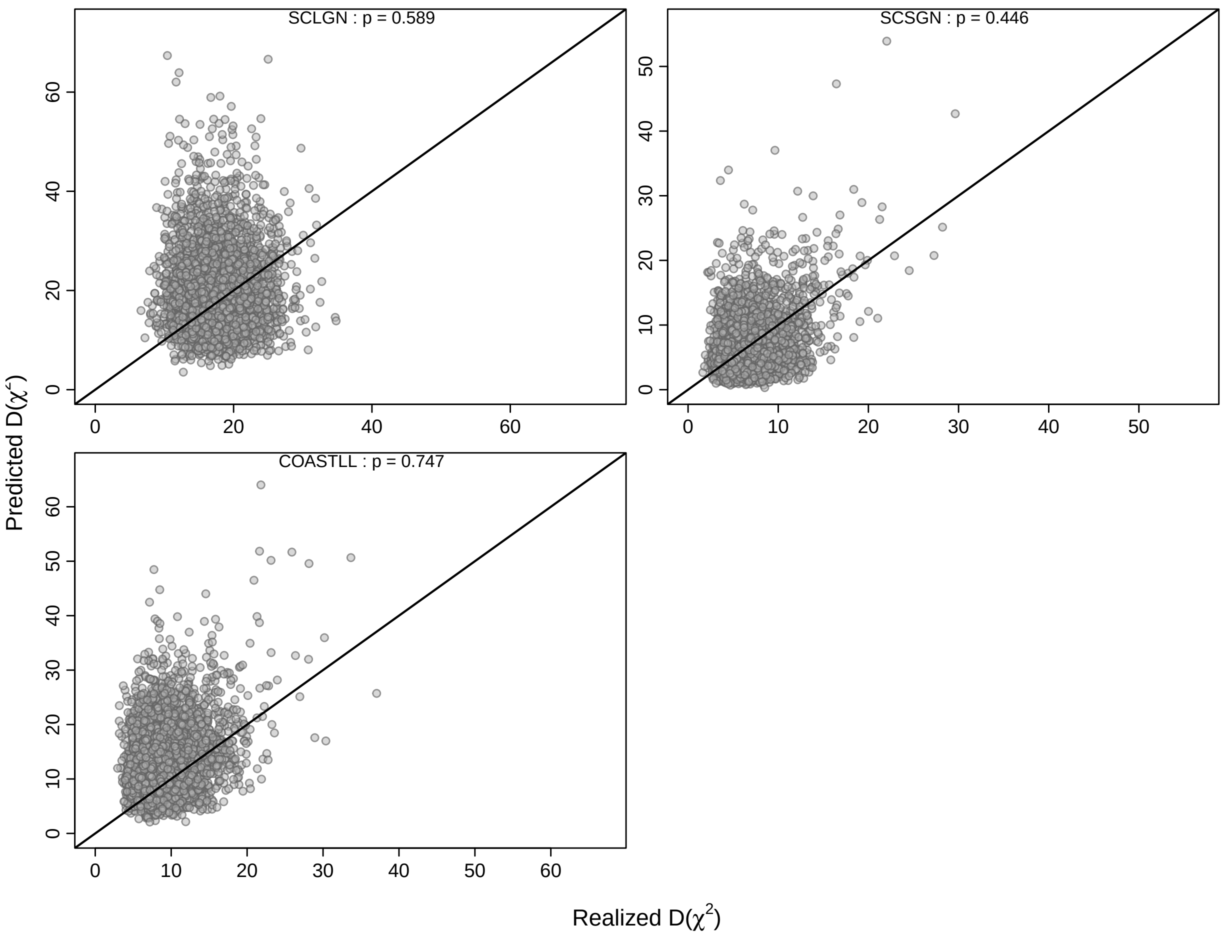


Figure 7: Posterior predictive checks for ATL by recruitment index

```
jrplot_jointindex(fATL, plot.cex = 0.8)
```

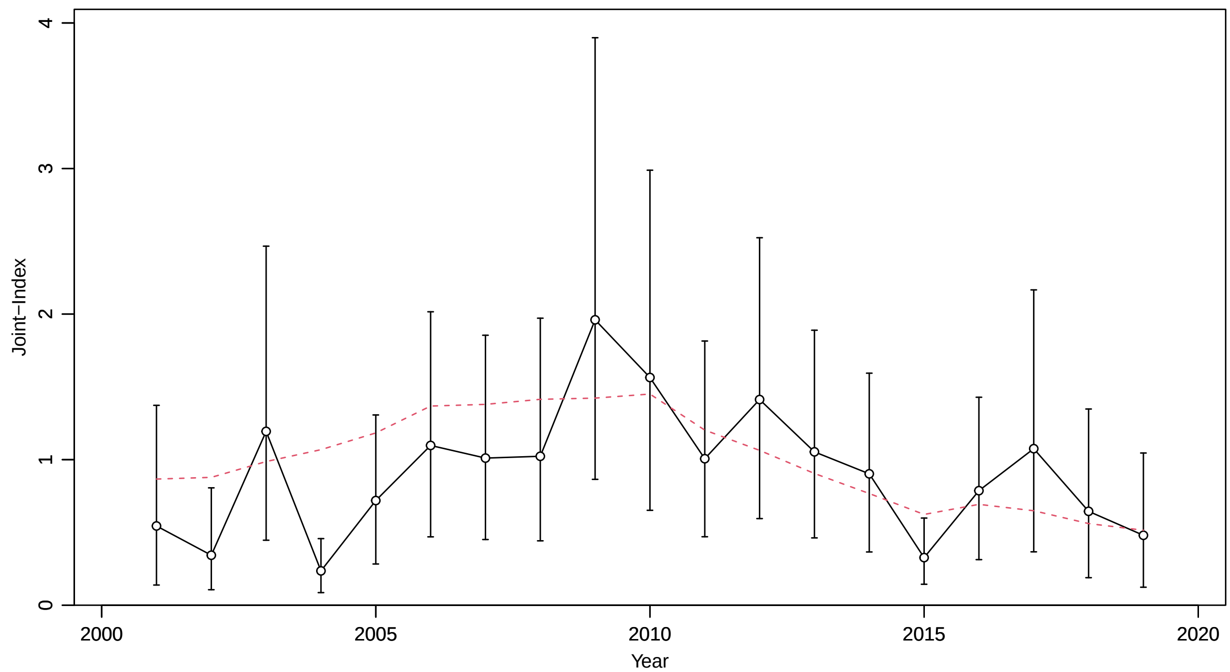


Figure 8: Estimated joint CPUE index for ATL with 95% CIs and the red dashed line indicating the underlying state-space trend

Make output table

```
ATLtab = jointindex(fATL)
ATLtab[-1] = round(ATLtab[-1], 3)

knitr::kable(ATLtab, align = "ccccc", escape = FALSE, row.names = FALSE, caption = "Combined CPUE index
```

Table 2: Combined CPUE index for ATL, summarizing the underying state-space trends, estimated mean CPUE, stadard error on log(CPUE), and lower and upper 95% CI's

| year | trend | index | log.se | lci | uci |
|---|---|---|---|---|---|
| 2001 | 0.867 | 0.544 | 0.530 | 0.139 | 1.373 |
| 2002 | 0.878 | 0.343 | 0.475 | 0.106 | 0.806 |
| 2003 | 0.987 | 1.194 | 0.413 | 0.446 | 2.467 |
| 2004 | 1.069 | 0.236 | 0.392 | 0.086 | 0.458 |
| 2005 | 1.184 | 0.719 | 0.355 | 0.283 | 1.307 |
| 2006 | 1.368 | 1.098 | 0.352 | 0.470 | 2.016 |
| 2007 | 1.380 | 1.011 | 0.341 | 0.451 | 1.855 |
| 2008 | 1.414 | 1.023 | 0.362 | 0.442 | 1.972 |
| 2009 | 1.423 | 1.961 | 0.373 | 0.865 | 3.899 |
| 2010 | 1.451 | 1.564 | 0.371 | 0.652 | 2.988 |
| 2011 | 1.203 | 1.006 | 0.336 | 0.470 | 1.815 |
| 2012 | 1.064 | 1.413 | 0.346 | 0.595 | 2.524 |
| 2013 | 0.905 | 1.054 | 0.345 | 0.462 | 1.889 |
| 2014 | 0.767 | 0.903 | 0.354 | 0.366 | 1.594 |

| year | trend | index | log.se | lci | uci |
|---|---|---|---|---|---|
| 2015 | 0.624 | 0.327 | 0.356 | 0.144 | 0.599 |
| 2016 | 0.693 | 0.787 | 0.365 | 0.313 | 1.429 |
| 2017 | 0.649 | 1.075 | 0.425 | 0.367 | 2.166 |
| 2018 | 0.561 | 0.645 | 0.450 | 0.189 | 1.348 |
| 2019 | 0.515 | 0.480 | 0.488 | 0.124 | 1.046 |

# 4 Comparison

```
jrpar(mfrow = c(2, 1))
jrplot_jointindex(fGOM, plot.cex = 0.8, add = T, xlim = c(1983.5, 2020.5))
mtext("GOM")
jrplot_jointindex(fATL, plot.cex = 0.8, add = T, xlim = c(1983.5, 2020.5))
mtext("ATL")
```

```
write.csv(jointindex(fATL), "JARA_ATL.csv")
write.csv(jointindex(fGOM), "JARA_GOM.csv")
```

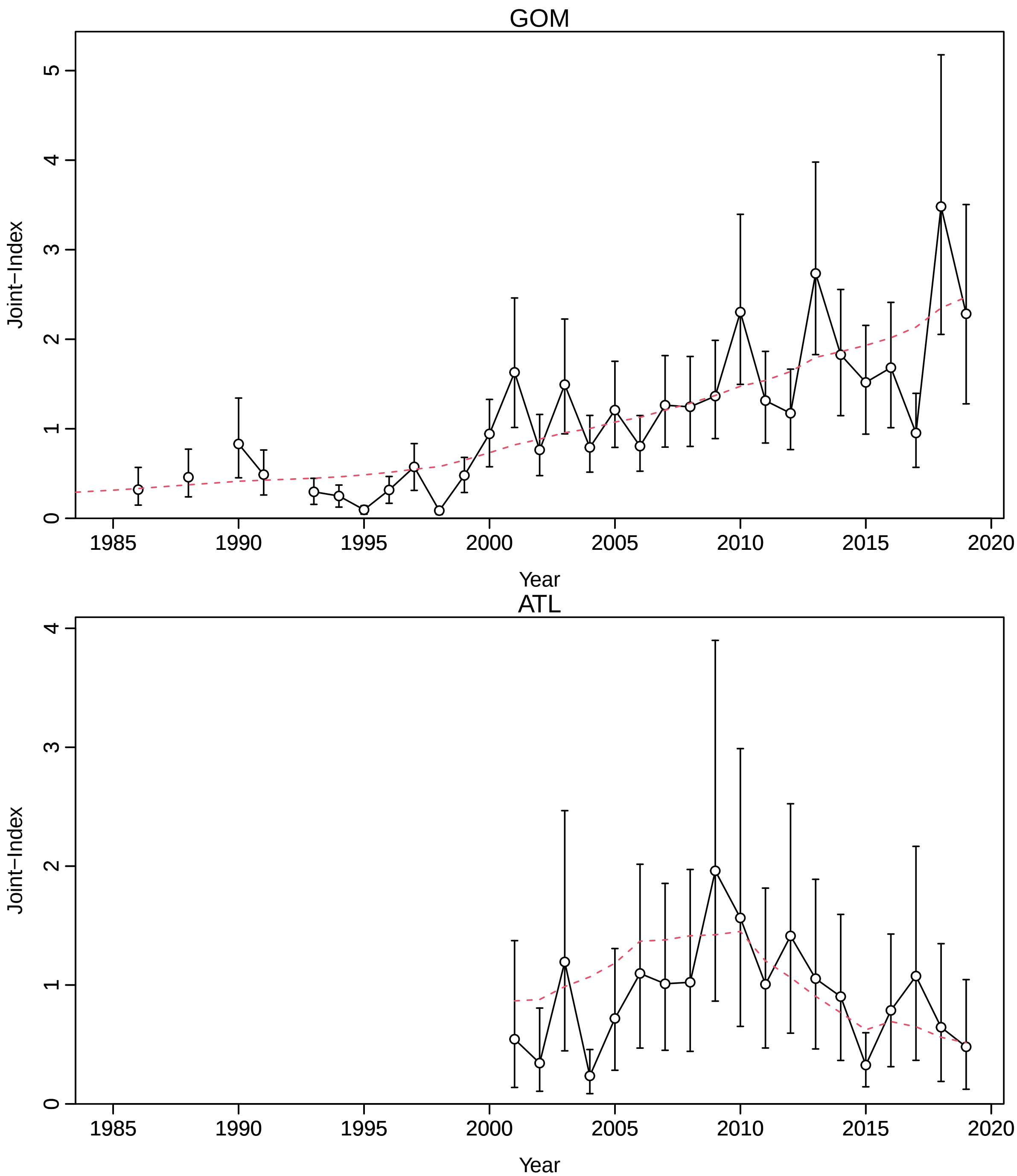


Figure 9: Comparison of estimated joint CPUE indices for GOM and ATL with 95% CIs and the red dashed line indicating the underlying state-space trend