STECF EWG 16-13
Length based indicators

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1 Introduction

Length based indicators based on those reported in ICES WKLIFE V (2015) were calculated for the stocks and GSAs of interest (see Table 2.1.1.4.1 in the ICES report). The indicators calculated are: $Lmean$ relative to $Lopt$ ($Lmean/Lopt$) and $Lmean$ relative to $LFeM$ ($Lmean/LFeM$).

$Lmean/LFeM$ can be used as an indicator of $FMSY$ and is recommended to be $>= 1$, i.e. a value < 1 suggests overfishing. $Lmean/Lopt$ can be used as an indicator of yield compared to MSY. It is recommended to be 1.

$Lopt$ is calculated as $Linf * 2/3$. $Lmean$ is the mean length of individuals larger than Lc. Lc is the length at first catch, calculated as the length of 50% of the mode. $LFeM$ is then calculated as $0.75Lc + 0.25Linf$.

Both of the indicators are very dependent on the value of Lc. The calculation of Lc is based on the ICES R script, *LBindicators.R*, by T. Miethe and C. Silva (ICES, 2015). LC depdends on the mode of the catch distribution at length. In the R script the mode is taken to be the count in the first length class for which the following length class has a decreased count, i.e. the first peak in the catch distribution starting from the smallest size. This may not be the largest peak in the data, but the first peak of a multimodal distribution. The length class which contains half this mode is then taken as Lc. The method of using the first peak in the data makes the calculation of Lc very sensitive to the shape and sparsity of the catch distribution.

In this document the catch distributions of the stocks, including the calculated values for Lc and $Lmean$, are plotted over time. The length based indicators are then calculated and, where possible, compared to the estimated fishing mortality (F) from the stock assessment.

Interpretation of the indicators but must be done with caution given the data requirements noted above.

To generate this report with 'R' and 'knitr' you need the DCF catch and biological data as .csv files.

2 Data

2.1 Loading catch at length data

The catch distribution data is taken from the DCF data. First this is loaded and then transformed to a more helpful shape.

```
# Load landings data
landat <- fread("../../Fisheries_data/landings.csv")
# Area column has GSA or SA. Want just numeric.
# Make a new numeric GSA column based on area
landat$gsa <- as.numeric(gsub("[^0-9]", "", landat$area))

# Just want length classes, GSAs, species, unit and years
#cols <- c(which(colnames(landat) %in% c("year", "gsa", "species", "unit")), grep("lengthclass", co
cols <- c(which(colnames(landat) %in% c("year", "gsa", "species", "unit","gear","fishery","country"
dat <- landat[, cols, with=FALSE]
# Change lengthclass columns to just the value
lccols <- grep("lengthclass", colnames(dat))
colnames(dat)[lccols] <- gsub("[^0-9]", "", colnames(dat)[lccols])
# Push into helpful shape
mdat <- melt(dat, id.vars=c("year", "gsa", "species", "unit", "country", "gear", "fishery"), variab
#mdat <- melt(dat, id.vars=c("year", "gsa", "species", "unit"), variable.name="start_length", value
mdat$start_length <- as.numeric(mdat$start_length)
# Set -ve values to NA
mdat[(mdat$value<0) & !is.na(mdat$value),"value"] <- NA
```

The units for some stocks are a mix of cm and mm across the different GSAs. To allow us to combine GSAs we transform all records in mm to cm.

```
    # Convert start lengths to cm and round down to start of LC
    mdat[unit=="mm"]$start_length <- floor(mdat[unit=="mm"]$start_length / 10)
    mdat[unit=="mm"]$unit <- "cm"
```

We need a mean length column (the length classes are 1cm wide). Finally, we sum the counts in each length class over gear and country so that the data is only disaggregated by year, GSA and species.

```
# Add mean lengths columns
mdat$mean_length <- mdat$start_length + 0.5
```

3 Tidying the data

To estimate the indicators over time requires the catch distribution to be relatively stable over time (i.e. selectivity remains constant). This is not always the case and so some additional data manipulation was necessary.

3.1 ANE

All the ANE stocks in the required GSAs are OK.

3.2 PIL

PIL in GSA 5 has no length based data and is removed from the analysis

```
all(is.na(mdat[species=="PIL" & gsa==5]$value))

## [1] TRUE
```

The data for PIL in GSA 7 has some issues. In 2012 the French PS gear starts operating (SPF fishery). The values for this gear in 2013 are approximately 1000 times larger than in 2012 and 2014 (Figure 1).

```
# Sum over the gears
temp_dat <- mdat[species=="PIL" & gsa==7,.(value=sum(value, na.rm=TRUE)),
    by=.(year, mean_length)]
ggplot(temp_dat[mean_length < 30], aes(x=mean_length, y=value)) +
    geom_bar(stat="identity") + facet_wrap(~year, ncol=2) +
    ggtitle("PIL in GSA 7") + xlab("Mean length") + ylab("Count")
```

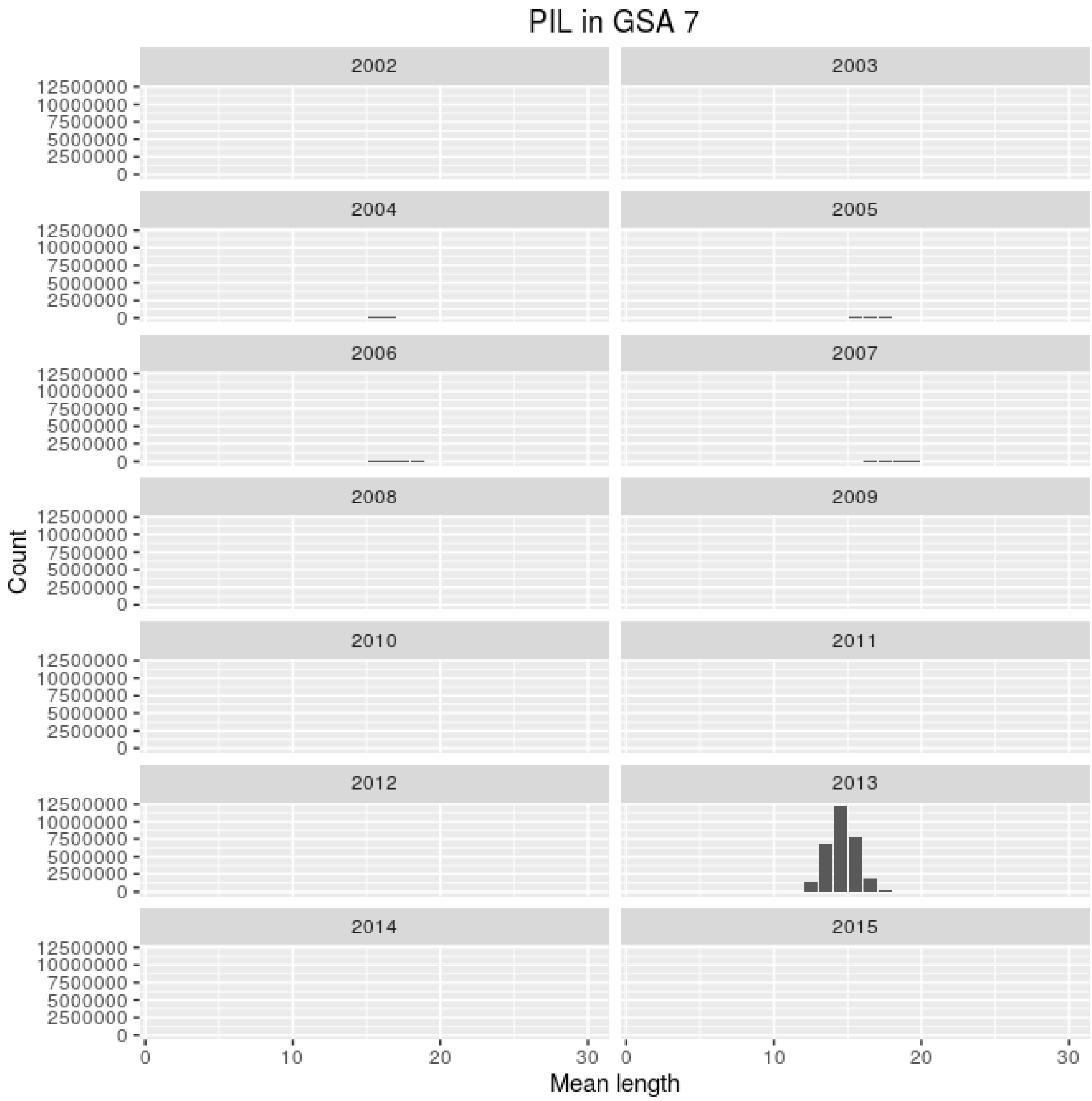

Figure 1: Catch distribution of PIL in GSA 7. Note the drop in numbers from 2010. The stock is dropped from the analysis.

Correcting the 2013 data for this gear solves this particular issues. However, the data then shows a large drop in numbers after 2009. The reason for this is not investigated.

```
# Correct the 2013 PS gear
mdat[species=="PIL" & gsa==7 & year == 2013 & country=="FRA" &
    gear=="PS" & fishery=="SPF" ]$value <-
    mdat[species=="PIL" & gsa==7 & year == 2013 & country=="FRA" &
    gear=="PS" & fishery=="SPF" ]$value / 1000
```

The data for PIL in GSA 17-18 show a large increase in catch numbers in 2013, 2014 and 2015. This is due to the presence of Croatian data in those years. This may affect the calculation of the indicators. The data is not removed.

3.3 HOM

HOM in GSAs 17 - 20 shows large spikes in the catch distribution for the the smaller fish in 2013 and 2014 (Figure 2). These are caused by the presence of Greek fisheries which are only present in 2013 and 2014.

```
temp_dat <- mdat[species=="HOM" & gsa %in% c(17:20),.(value=sum(value, na.rm=TRUE)),
    by=.(year, mean_length)]
ggplot(temp_dat[mean_length < 40], aes(x=mean_length, y=value)) +
    geom_bar(stat="identity") + facet_wrap(~year, ncol=2) +
    ggtitle("HOM in GSA 17-20") + xlab("Mean length") + ylab("Count")
```

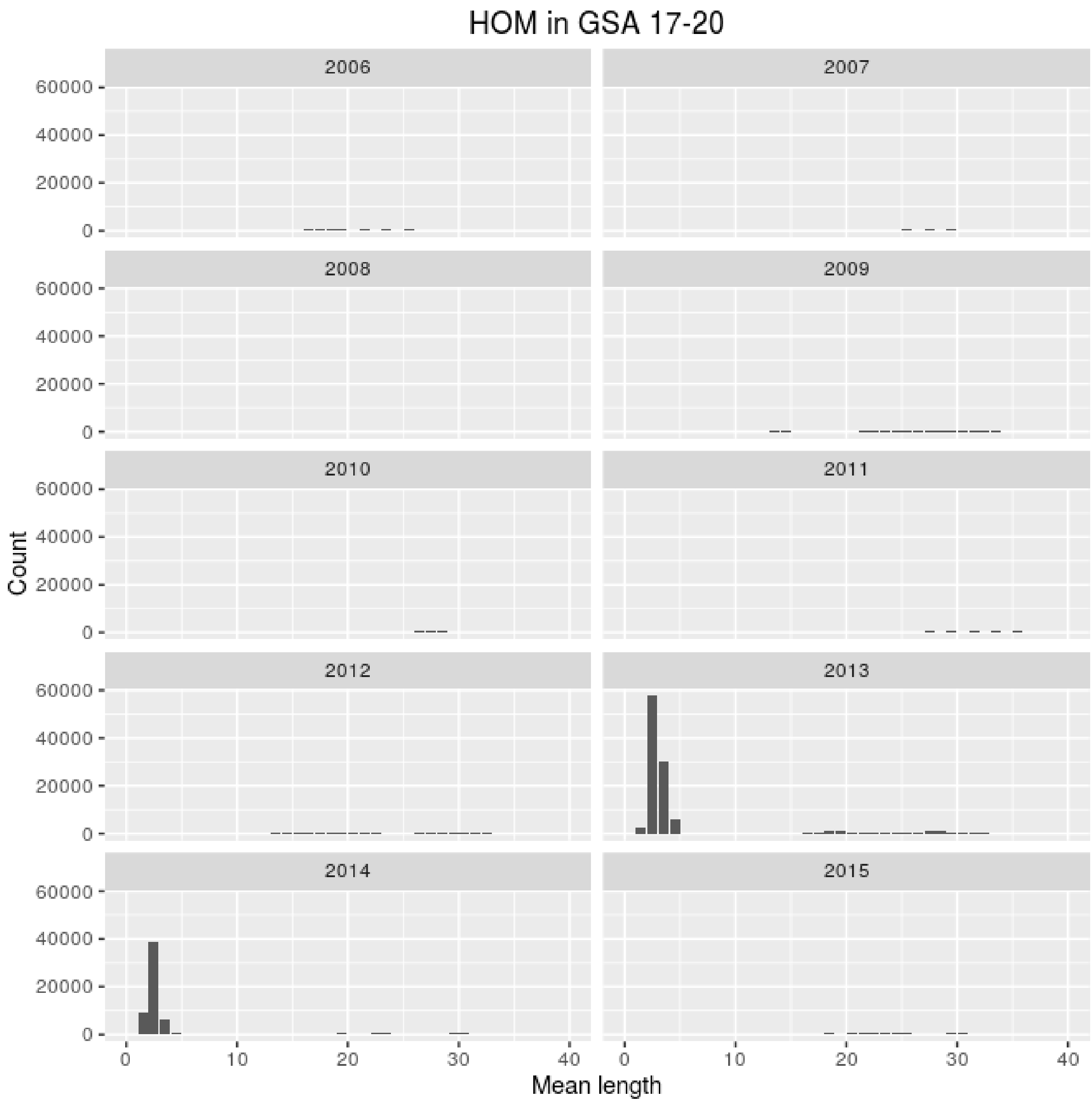

Figure 2: Catch distribution of HOM in GSAs 17-20. Note the spikes in smaller fish in 2013 and 2014 caused by the presence of Greek fisheries

Removing the Greek data makes the catch distribution more stable. The year 2008 is removed as there is no data for that year.

```
# Remove the Greek data from HOM in GSAs 17-20
mdat <- mdat[!(species=="HOM" & gsa %in% c(17:20) & country == "GRC")]
# Remove 2008 data (all 0s)
mdat <- mdat[!(species=="HOM" & gsa %in% c(17:20) & year == 2008)]
```

3.4 MAC, MAS and MAZ

The mackerel stocks are a combination of MAS, MAZ and MAC. These were all combined to MAC.

```
mdat[species=="MAS"]$species <- "MAC"
mdat[species=="MAZ"]$species <- "MAC"
```

The MAC stock shows large spikes in the catch distribution for the smaller fish in 2014 and 2015 (Figure 3). These are caused by the presence of Greek fisheries which are only present in 2014 and 2015. Removing the Greek data makes the catch distribution more stable.

```
temp_dat <- mdat[species=="MAC" & gsa %in% c(17:20),.(value=sum(value, na.rm=TRUE)),
    by=.(year, mean_length)]
ggplot(temp_dat[mean_length < 40], aes(x=mean_length, y=value)) +
    geom_bar(stat="identity") + facet_wrap(~year, ncol=2) +
    ggtitle("MAC in GSA 17-20") + xlab("Mean length") + ylab("Count")
```

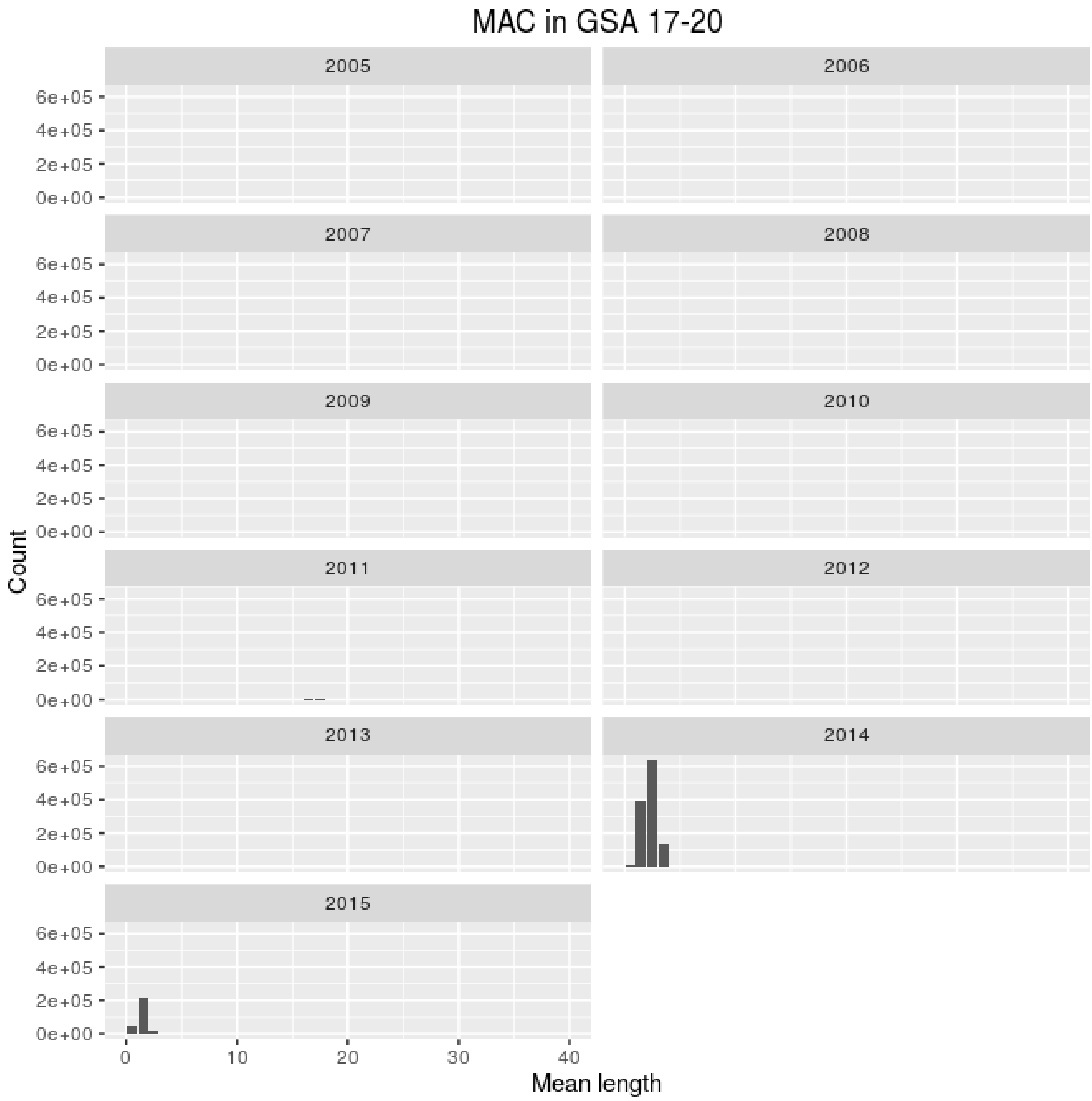

Figure 3: Catch distribution of MAC in GSAs 17-20. Note the spikes in smaller fish in 2014 and 2015 caused by the presence of Greek fisheries

```
# Remove Greek data
mdat <- mdat[!(species=="MAC" & gsa %in% c(17:20) & country == "GRC")]
```

3.5 Summing over the gears

After tidying the data for the stocks we sum over all countries, fisheries and gears.

```
# Sum over year, GSA, species and length class - combine gears, countries etc.
mdat <- mdat[,.(value=sum(value, na.rm=TRUE)), by=.(year,gsa,species, mean_length)]
```

4 Getting $Linf$ values

We need to get the $Linf$ value for each stock and GSA. We make a list of stocks and GSAs to store the information.

```
spdat <- list(
              ANE_5 = list(species = "ANE", gsa = 5),
              ANE_6 = list(species = "ANE", gsa = 6),
              ANE_7 = list(species = "ANE", gsa = 7),
              ANE_9 = list(species = "ANE", gsa = 9),
              ANE_10 = list(species = "ANE", gsa = 10),
              ANE_17_18 = list(species = "ANE", gsa = c(17,18)),

              #PIL_5 = list(species = "PIL", gsa = 5),
              PIL_6 = list(species = "PIL", gsa = 6),
              PIL_7 = list(species = "PIL", gsa = 7),
              PIL_10 = list(species = "PIL", gsa = 10),
              PIL_17_18 = list(species = "PIL", gsa = c(17,18)),

              HOM_1_5_6_7 = list(species = "HOM", gsa = c(1,5,6,7)),
              HOM_9_10_11 = list(species = "HOM", gsa = c(9,10,11)),
              HOM_17_18_19_20 = list(species = "HOM", gsa = c(17,18,19,20)),

              MAC_1_7 = list(species = "MAC", gsa = 1:7),
              MAC_9_11 = list(species = "MAC", gsa = 9:11),
              MAC_17_20 = list(species = "MAC", gsa = 17:20)
              )
```

The $Linf$ values are taken from the DCF biological data. The catch distribution is not disaggregated by sex. When the $Linf$ values are disaggregated by sex we take the mean of the values for that GSA. When there are multiple GSAs, the mean of the $Linf$s is used.

Not every stock in every GSA had reported $Linf$ values.

```
gp <- fread("../../Biological_parameters/gp.csv")
gp$gsa <- as.numeric(gsub("[^0-9]", "", gp$area))
# Need to combine MAC, MAS and MAX
gp[species=="MAS"]$species <- "MAC"
gp[species=="MAZ"]$species <- "MAC"
linf <- list()
for (i in 1:length(spdat)){
    linf[[i]] <- NA
    sp_temp <- spdat[[i]]$species
    gsa_temp <- spdat[[i]]$gsa
    linftemp <- rep(NA, length(gsa_temp))
    for (gsacount in 1:length(gsa_temp)){
        gptemp <- gp[species==sp_temp & gsa == gsa_temp[gsacount]]
        # Max year for which we have values
        gptemp <- gptemp[!is.na(gptemp$vb_linf)]
        if(nrow(gptemp) > 0){
            max_linf_year <- max(gptemp$start_year[!(is.na(gptemp$vb_linf))])
            gptemp <- gptemp[start_year == max_linf_year]

            # 999 is a null value (!)
            gptemp$vb_linf[gptemp$vb_linf >= 999] <- NA
            # If combined available, use that
            gptemp$sex <- toupper(gptemp$sex)
            if (any(gptemp$sex == "C")){
```

```
                linftemp[gsacount] <- mean(subset(gptemp, sex=="C")$vb_linf, na.rm=TRUE)
            } else {
            # Else take mean of avilable (M / F)
                linftemp[gsacount] <- mean(gptemp$vb_linf, na.rm=TRUE)
            }
        }
    }
    # Take mean of the GSAs
    linf[[i]] <- mean(linftemp, na.rm=TRUE)
    spdat[[i]][["Linf"]] <- linf[[i]]
}
```

Given the uncertainty in the reported *Linf* values, the largest observed fish was also taken as *Linfobs*.

```
linfobs <- list()
for (i in 1:length(spdat)){
    linfobs[[i]] <- NA
    sp_temp <- spdat[[i]]$species
    gsa_temp <- spdat[[i]]$gsa
    mtemp <- mdat[species==sp_temp & gsa %in% gsa_temp]
    # Some stocks have missing data - only get if not missing
    if (sum(mtemp$value, na.rm=TRUE) > 0){
        linfobs[[i]] <- max(mtemp[value >0]$mean_length)
    }
    # Hack for bad data in HOM 1,5,6,7 - Take second from last
    if (names(spdat)[i] == "HOM_1_5_6_7"){
        lc <- sort(mtemp[value >0]$mean_length)
        linfobs[[i]] <- lc[length(lc)-1]
    }
    spdat[[i]][["Linfobs"]] <- linfobs[[i]]
}
```

5 Calculating *Lc* and *Lmean*

Lmean and *Lc* (and other indicators) are calculated by calling the **get_indicators()** function. The following code also generates and stores a plot to show the distributions and indicators.

```
ind <- list()
plots <- list()
for (sp_count in 1:length(spdat)){
    sp_temp <- spdat[[sp_count]]$species
    gsa_temp <- spdat[[sp_count]]$gsa
    ind_name <- paste(sp_temp, paste(gsa_temp, collapse="_"),sep="_")
    temp_dat <- mdat[species==sp_temp & gsa %in% gsa_temp]
    # When we have multiple GSAs we need to sum lengths
    temp_dat <- temp_dat[,.(value=sum(value, na.rm=TRUE)), by=.(year, mean_length)]
    # If all 0s in a year, drop it - HOM 1,5,6,7
    temp_dat <- ddply(temp_dat, .(year), function(y){
                    if(!(sum(y$value, na.rm=TRUE) > 0)){
                        return(data.frame())
                    }
                    else {
                        return(y)
                    }
                })
```

```
    lrefs_temp <- c(Linf = spdat[[sp_count]]$Linf,
                    Linfobs = spdat[[sp_count]]$Linfobs)
    ind_temp <- ddply(temp_dat, .(year), get_indicators, Lrefs=lrefs_temp)
    ind[[ind_name]] <- ind_temp
    # Trim empty lengths and store the plot
    if (nrow(temp_dat) > 0){
        max_length <- ceiling(max(subset(temp_dat, value >0)$mean_length) * 1.2)
        temp_dat <- subset(temp_dat, mean_length < max_length)
        p <- ggplot(temp_dat, aes(x=mean_length, y=value)) + geom_bar(stat="identity") + facet_wrap(~ye
        # Add Linf, Lc and Linfobs
        refdf <- ind_temp[,c("year","Linf","Linfobs","Lc","Lmean")]
        refdf <- melt(refdf, id.vars="year")
        p <- p + geom_vline(aes(xintercept=value, colour=variable), lwd=2, data=refdf)
        plots[[ind_name]] <- p
    }
}
# Turn list of indicators into dataframe
megaind <- ldply(ind, function(x){return(x)})
```

6 Exploring the data

In this section catch distribution for each stock and GSA is ploted with indicators superimposed (Lc, $Lmean$, $Linf$, $Linfobs$).

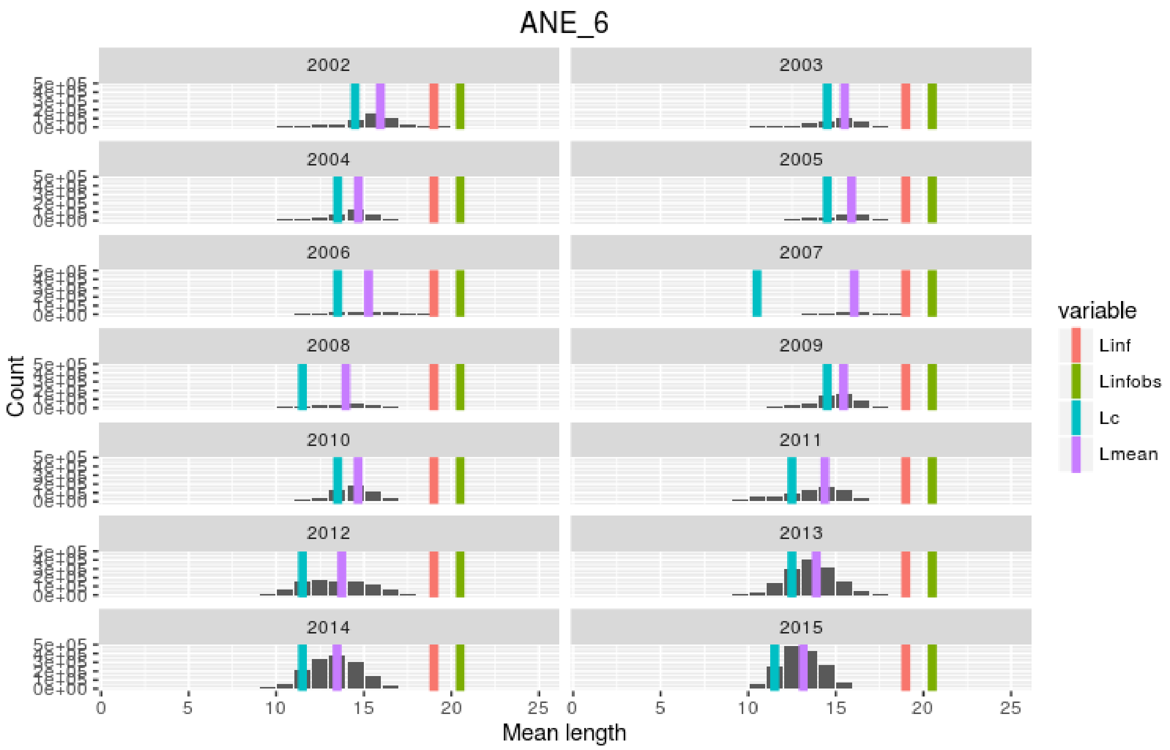

Figure 4: Exploratory catch distribution and indicators for ANE 6

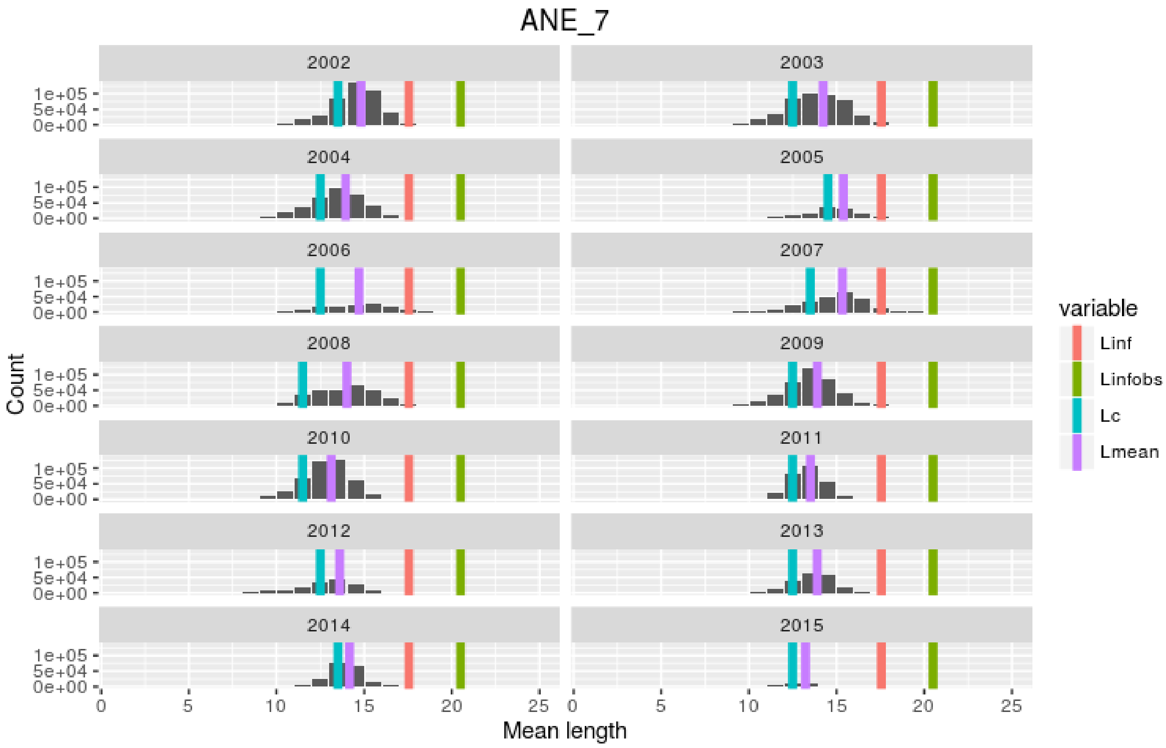

Figure 5: Exploratory catch distribution and indicators for ANE 7

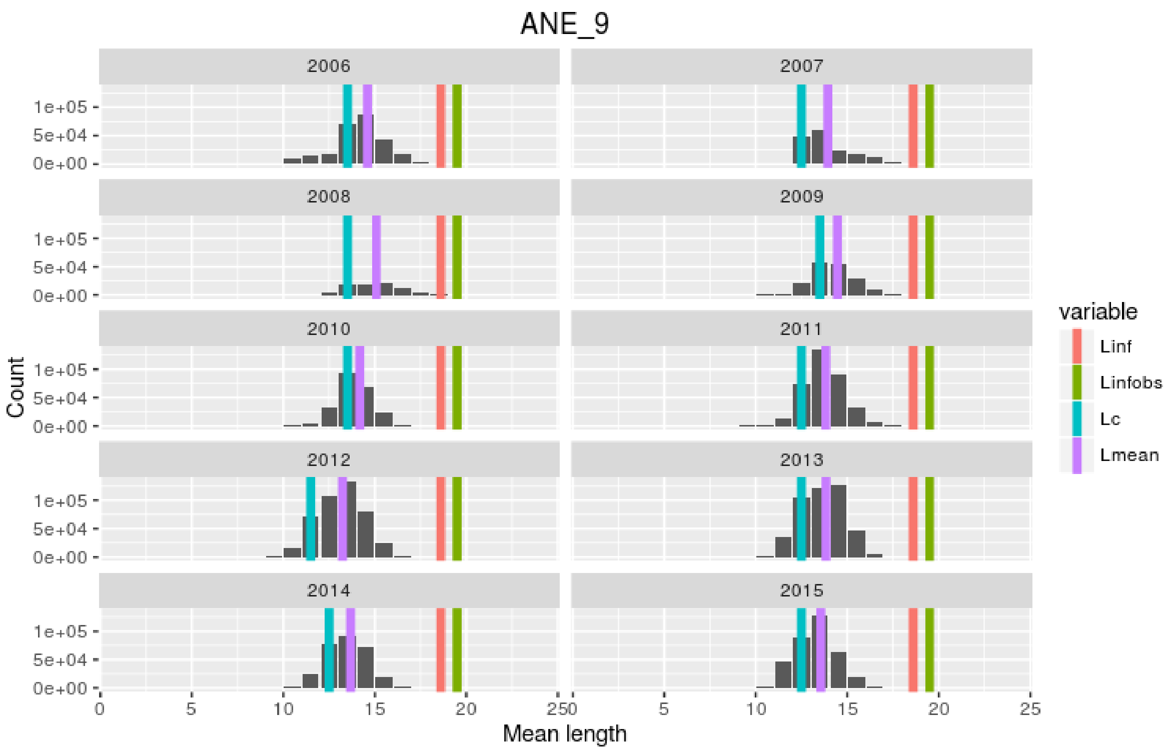

Figure 6: Exploratory catch distribution and indicators for ANE 9

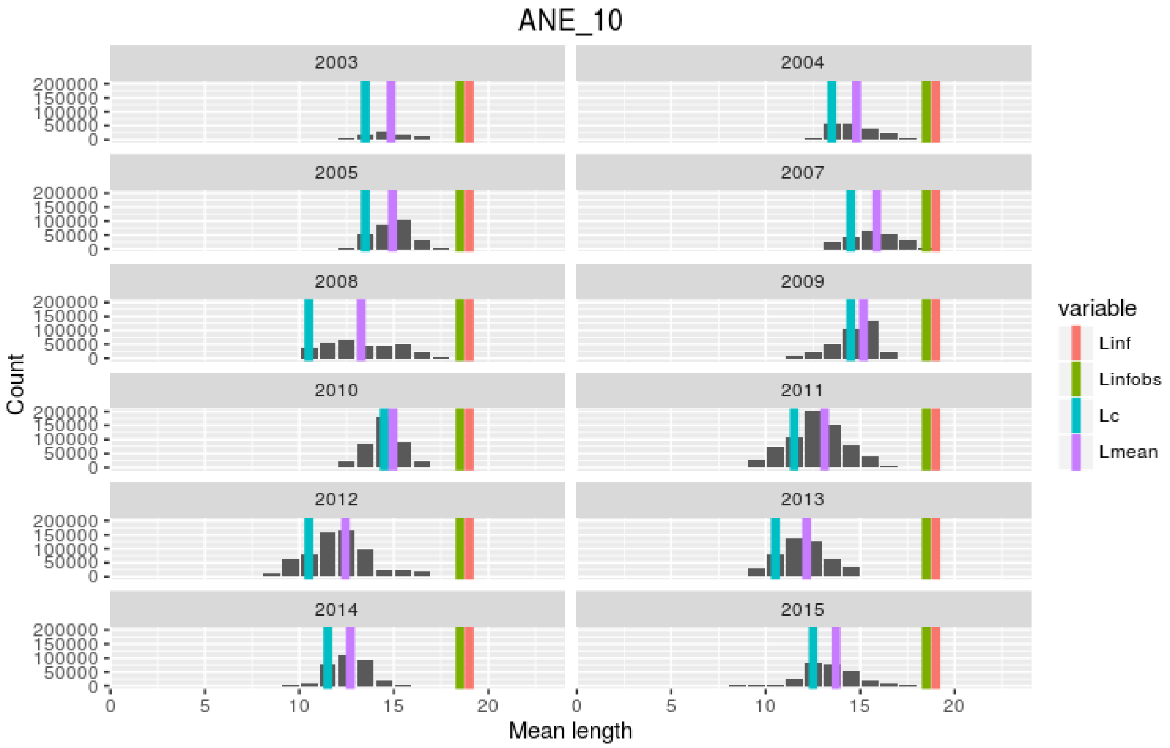

Figure 7: Exploratory catch distribution and indicators for ANE 10

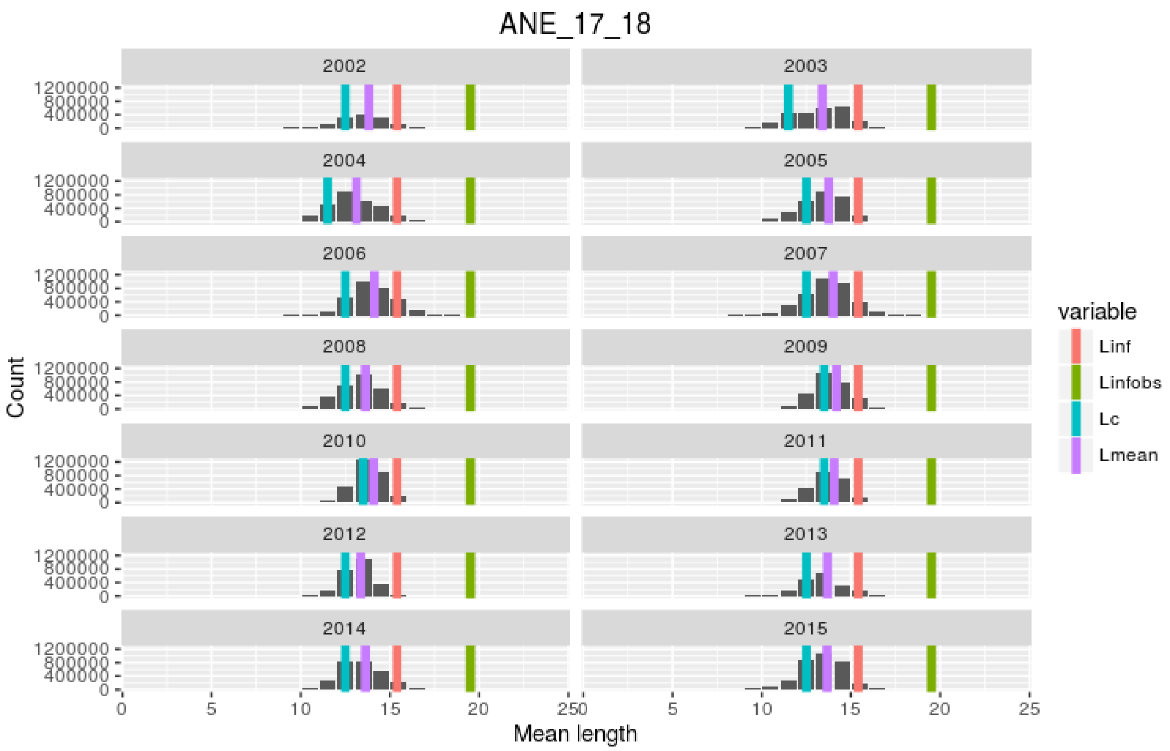

Figure 8: Exploratory catch distribution and indicators for ANE 17 18

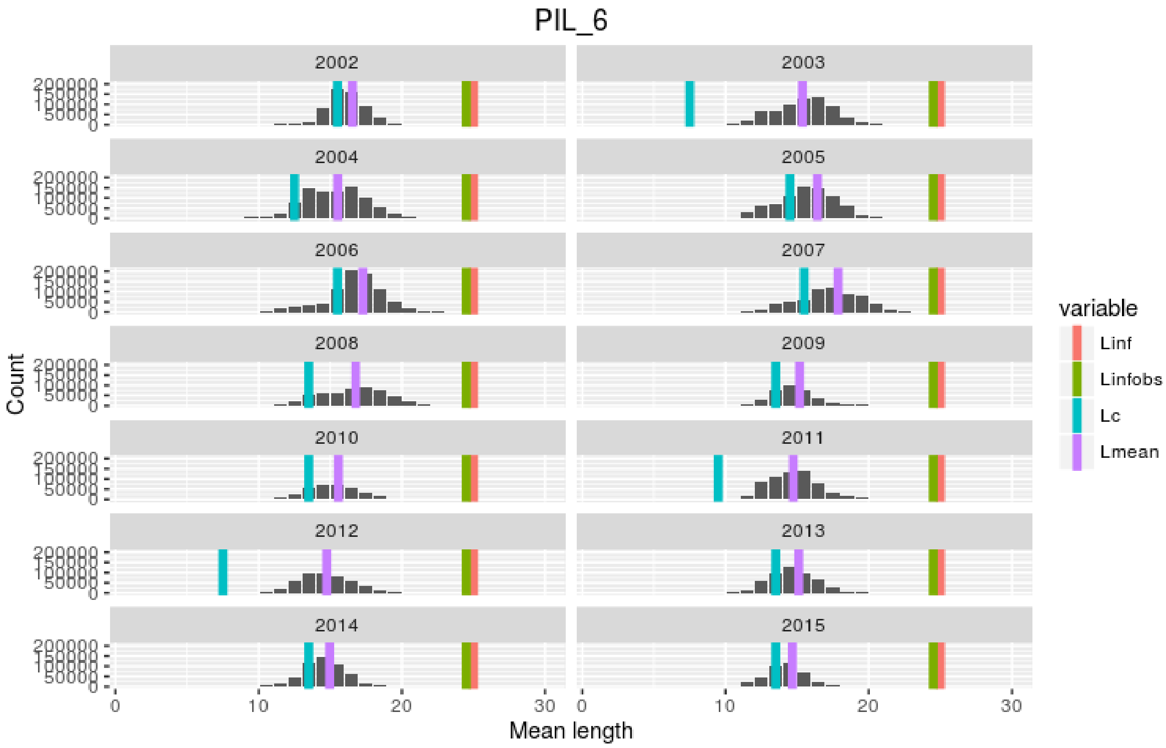

Figure 9: Exploratory catch distribution and indicators for PIL 6

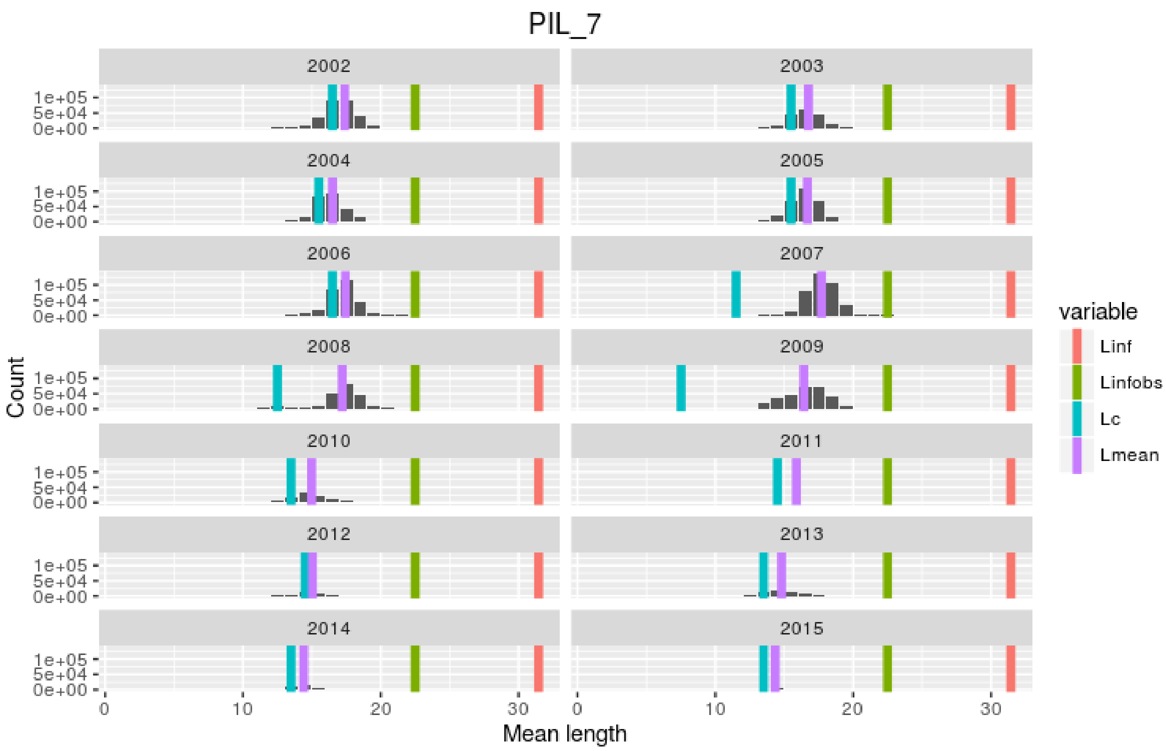

Figure 10: Exploratory catch distribution and indicators for PIL 7

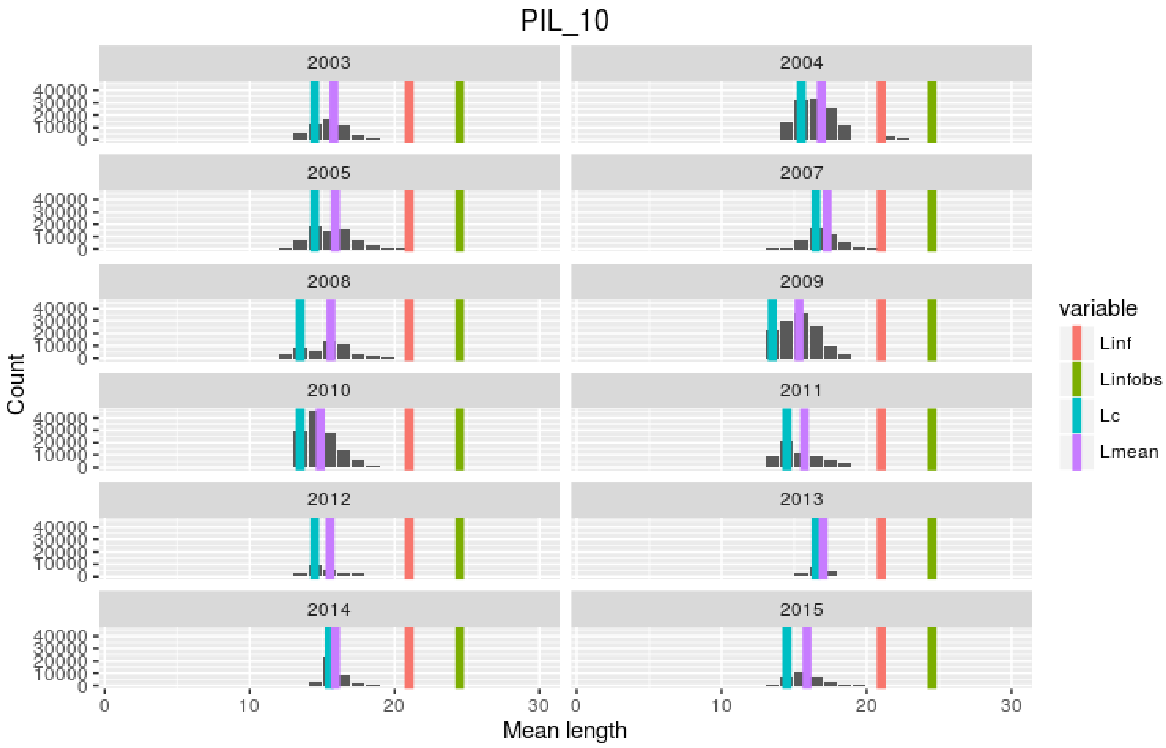

Figure 11: Exploratory catch distribution and indicators for PIL 10

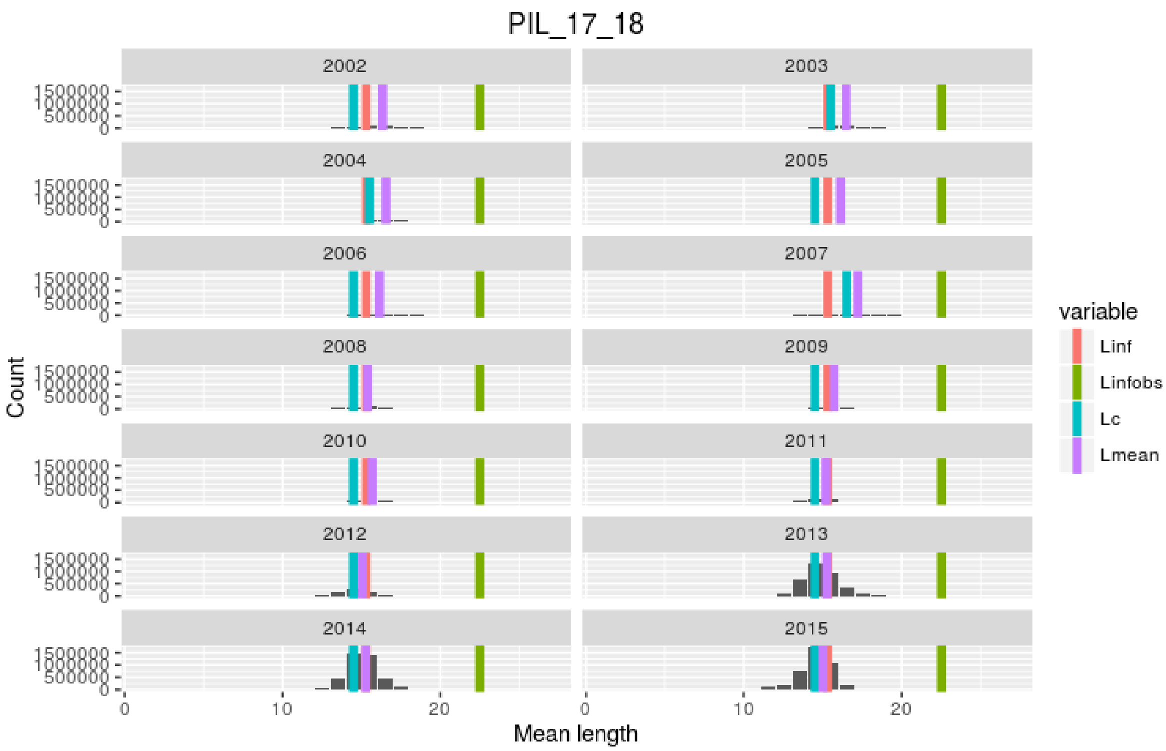

Figure 12: Exploratory catch distribution and indicators for PIL 17 18

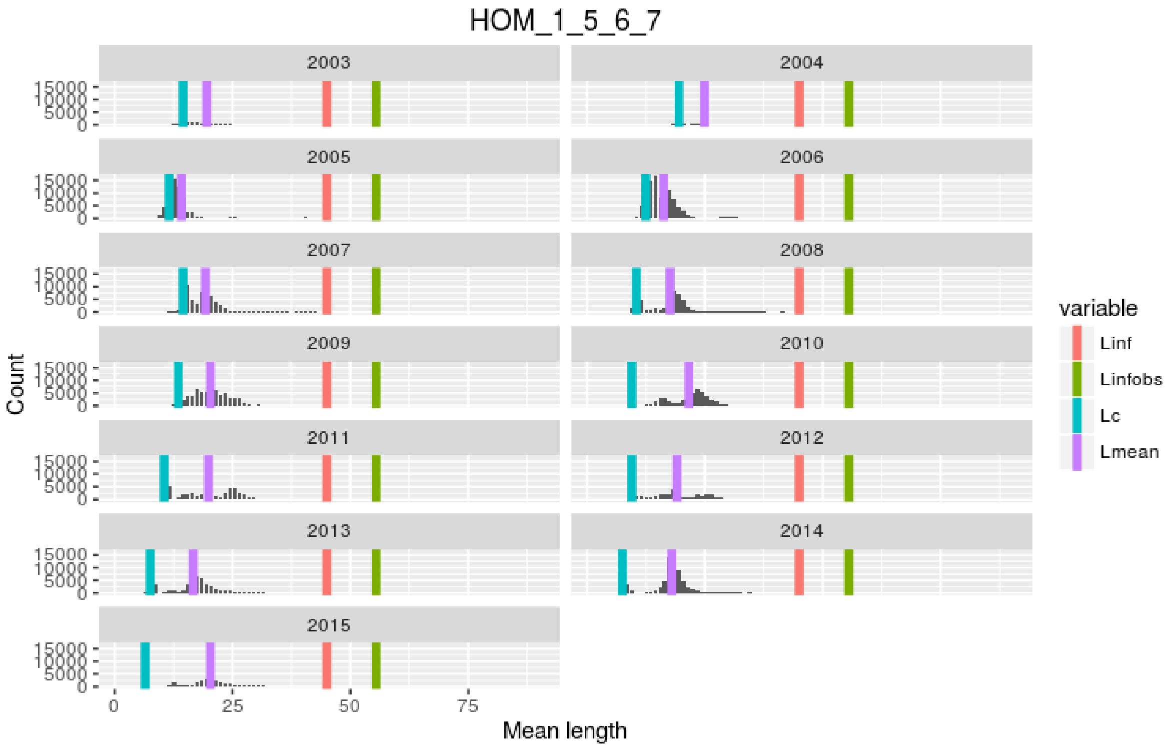

Figure 13: Exploratory catch distribution and indicators for HOM 1 5 6 7

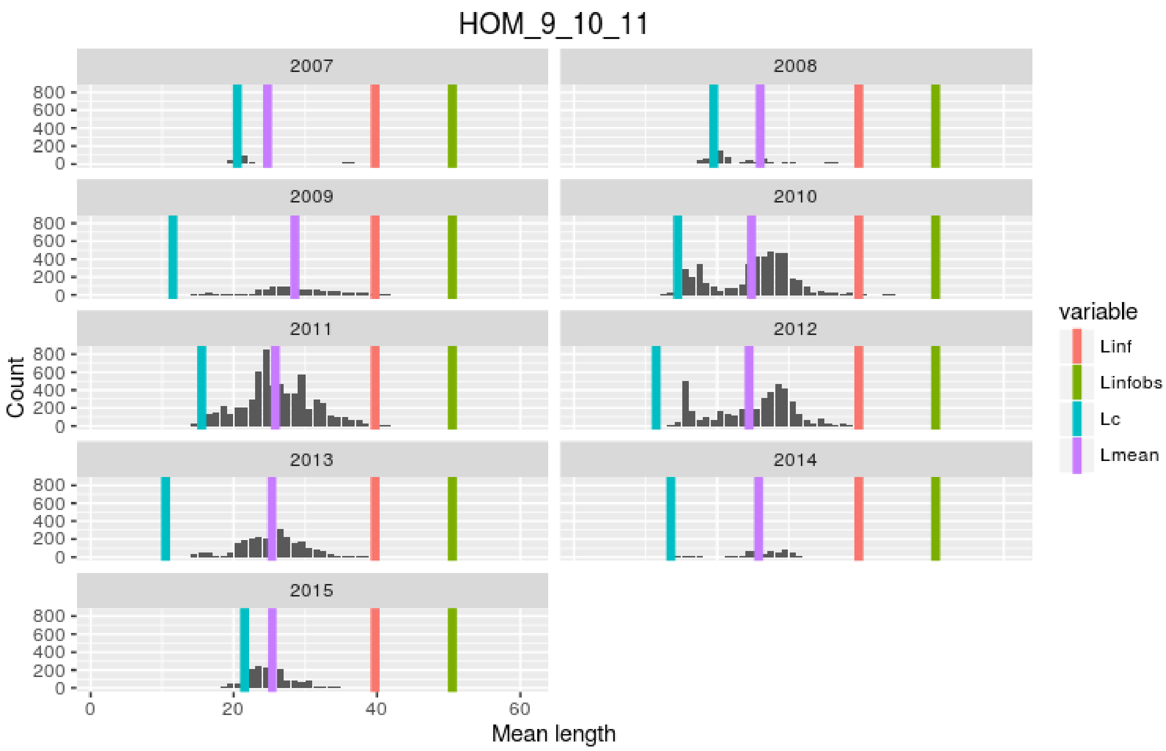

Figure 14: Exploratory catch distribution and indicators for HOM 9 10 11

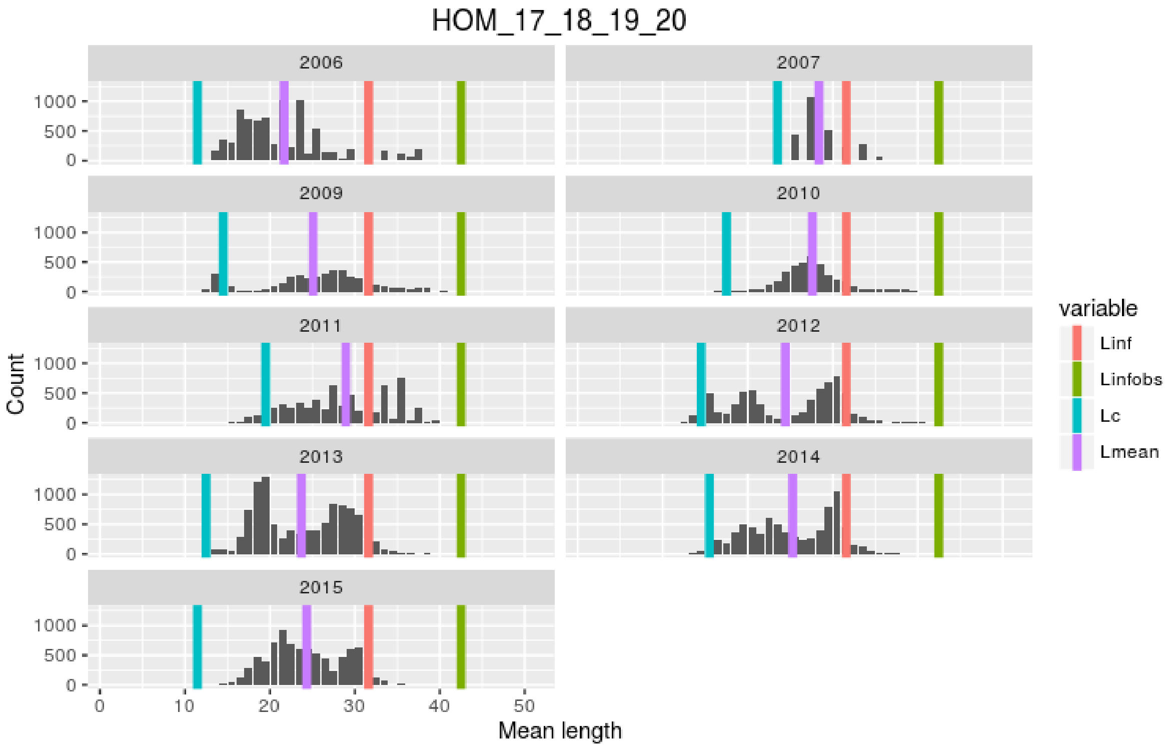

Figure 15: Exploratory catch distribution and indicators for HOM 17 18 19 20

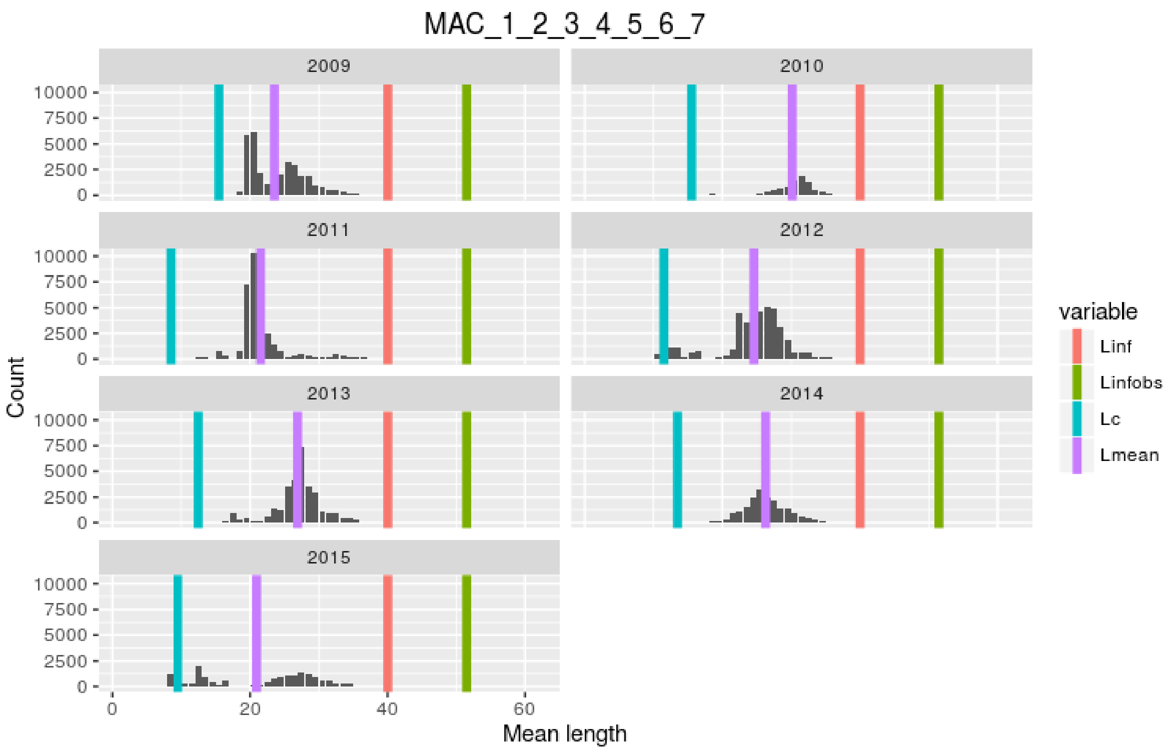

Figure 16: Exploratory catch distribution and indicators for MAC 1 2 3 4 5 6 7

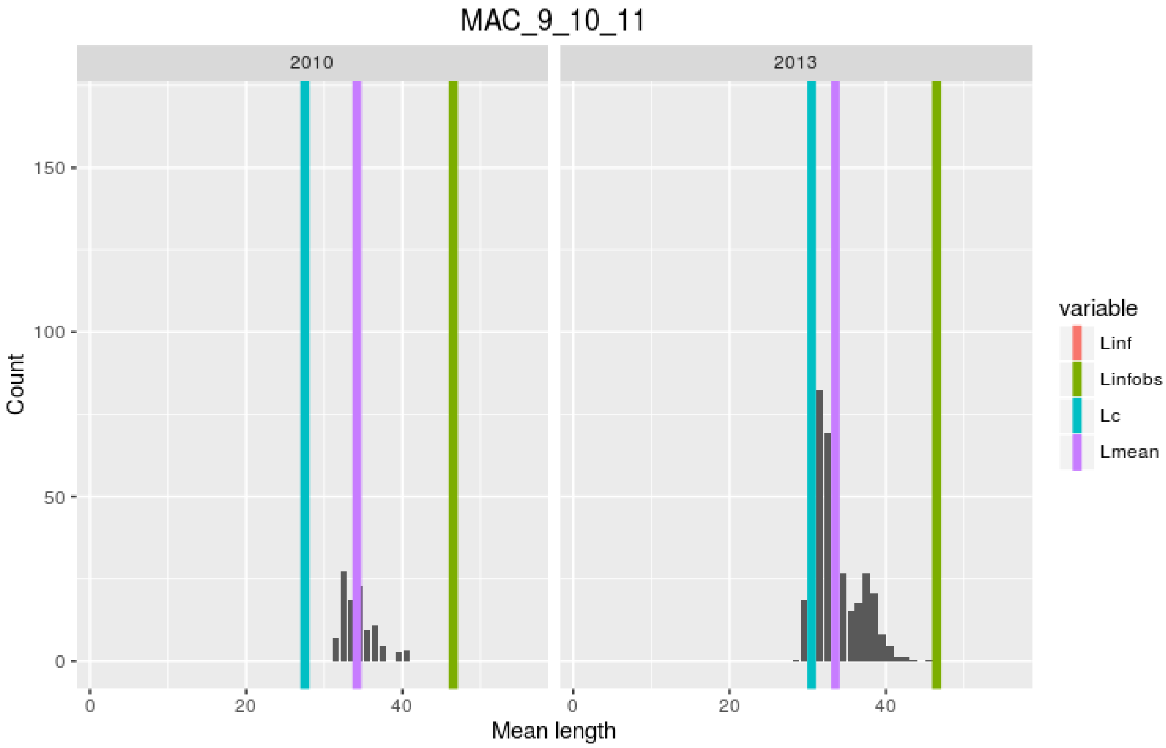

Figure 17: Exploratory catch distribution and indicators for MAC 9 10 11

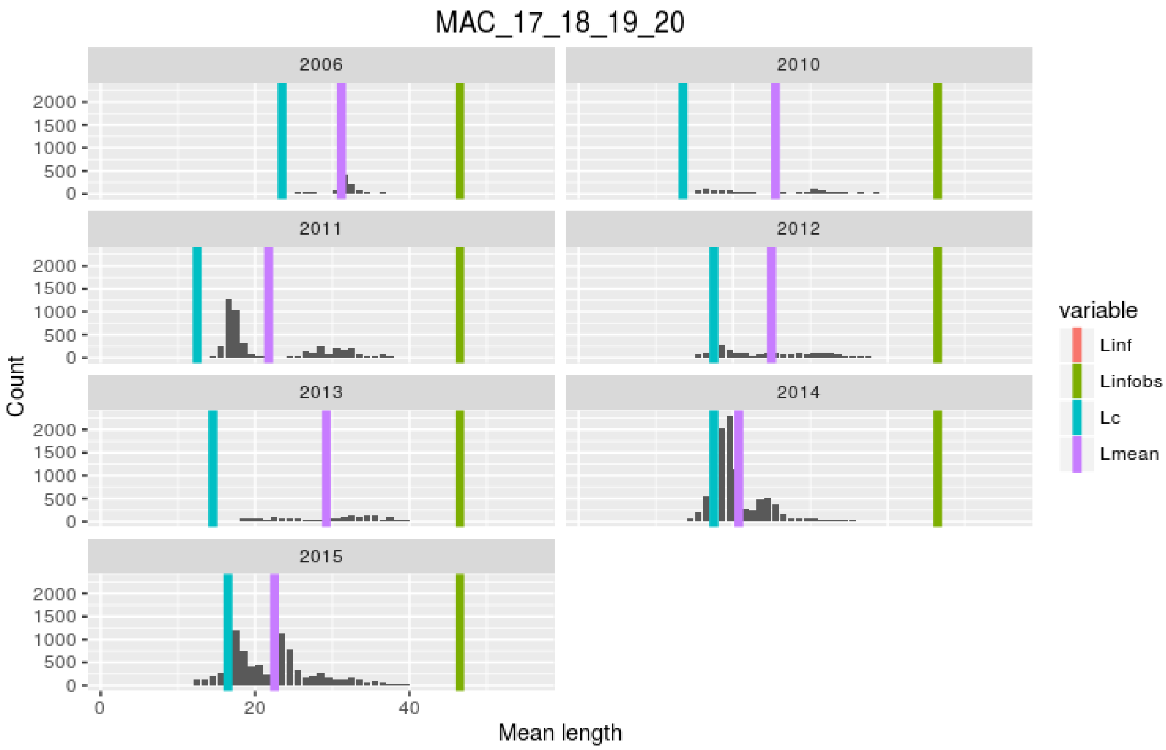

Figure 18: Exploratory catch distribution and indicators for MAC 17 18 19 20

All of the ANE stocks have relatively stable distributions. There is some instability in the catch distribution for PIL, other than in GSA 6. PIL in GSA 7 and in GSA 10 experience a fall in catches in the last years of the time series while PIL in 17-18 has an increase in catches from 2013 due to the presence of Croatian data (as mentioned above). The HOM and MAC stocks show evidence of multimodality in the catch distributions (e.g. HOM in GSAs 9, 10 and 11 in 2010). This is a result of summing the catches over all the gears, fisheries, countries and GSAs.

Regarding the $Linf$ values, for some stocks in some GSAs the reported $Linf$ is close to the $Linfobs$ (ANE in GSA 9, ANE in GSA 10, PIL in GSA 6, HOM in GSAs 17-20). However, for some stocks the $Linfobs$ was noticably larger (ANE in 6, ANE in 7, ANE in 17 and 18, PIL in 10, HOM in GSAs 1-7, HOM in GSAs 9-11 and MAC in GSAs 1-7). For HOM in GSAs 1-7, both the reported $Linf$ and observed $Linfobs$ were far outside of the observed catch distribution. For PIL in GSA 7, the reported $Linf$ much greater than $Linfobs$ and far outside range of distribution suggesting a problem with the reported value. For PIL in GSAs 17 and 18, the reported $Linf$ is in the middle of the distribution suggesting a problem with the reported value. Only MAC in GSAs 1-7 have a reported $Linf$.

As mentioned above, the indicators are strongly dependent on the calculated value of Lc (for example, $Lmean$ is the mean length of individuals larger than Lc). The value of Lc is calculated using the first peak in the data. This makes the value of Lc very sensitive to the shape and sparsity of the catch distribution, even when the catch distribution is relatively well behaved.

For example, for ANE in GSA 7 in 2005 the Lc is the same value as the mode and is in the length class adjacent to $Lmean$. Another example is ANE in GSA 7 in 2007, where the Lc is much smaller than the rest of the distribution.

The calculation of Lc is particularly sensitive when the catch distribution is narrow. This suggests that, as the catch distributions for ANE and PIL are very slim, the indicators may be unreliable.

7 Indicators

As mentioned above we calculate two indicators: $Lmean/Lopt$ and $Lmean/LFeM$, where $Lopt$ is given as $Linf * 2/3$ and $LFeM$ is calculated as $0.75Lc + 0.25Linf$. According to ICES (2015), the optimal yield indicator ($Lmean/Lopt$) should be 1 and the MSY indicator ($Lmean/LFeM$) should be $>= 1$.

In this analysis we have two values for $Linf$, the reported $Linf$ and $Linfobs$. Here we calculate the indicators for the stock and GSA combinations for both values of $Linf$ where available. The pattern of the indicators is not affected by the value of $Linf$ but the scaling is.

Many of the stock and GSA combinations have very unstable time series of the indicators. For example, $Lmean/LFeM$ for PIL 6 has spikes in 2003 and 2012 for both values of $Linf$. This is driven by the estimates of Lc being much lower in those years than in the other years.

Another example is the $Linfobs$ based indicators for MAC in GSAas 17-20 which experience a sharp drop from 2013 to 2014 driven by a drop in $Lmean$ (Lc only changes a little). The shape of the catch distributions in 2013 and 2014 are different.

```
repdat <- melt(megaind[,c(".id", "year", "Lmean_LFeM", "Lmean_Lopt")],
    id.vars=c(".id","year"))
obsdat <- melt(megaind[,c(".id", "year", "Lmean_LFeMobs", "Lmean_Loptobs")],
    id.vars=c(".id","year"))
```

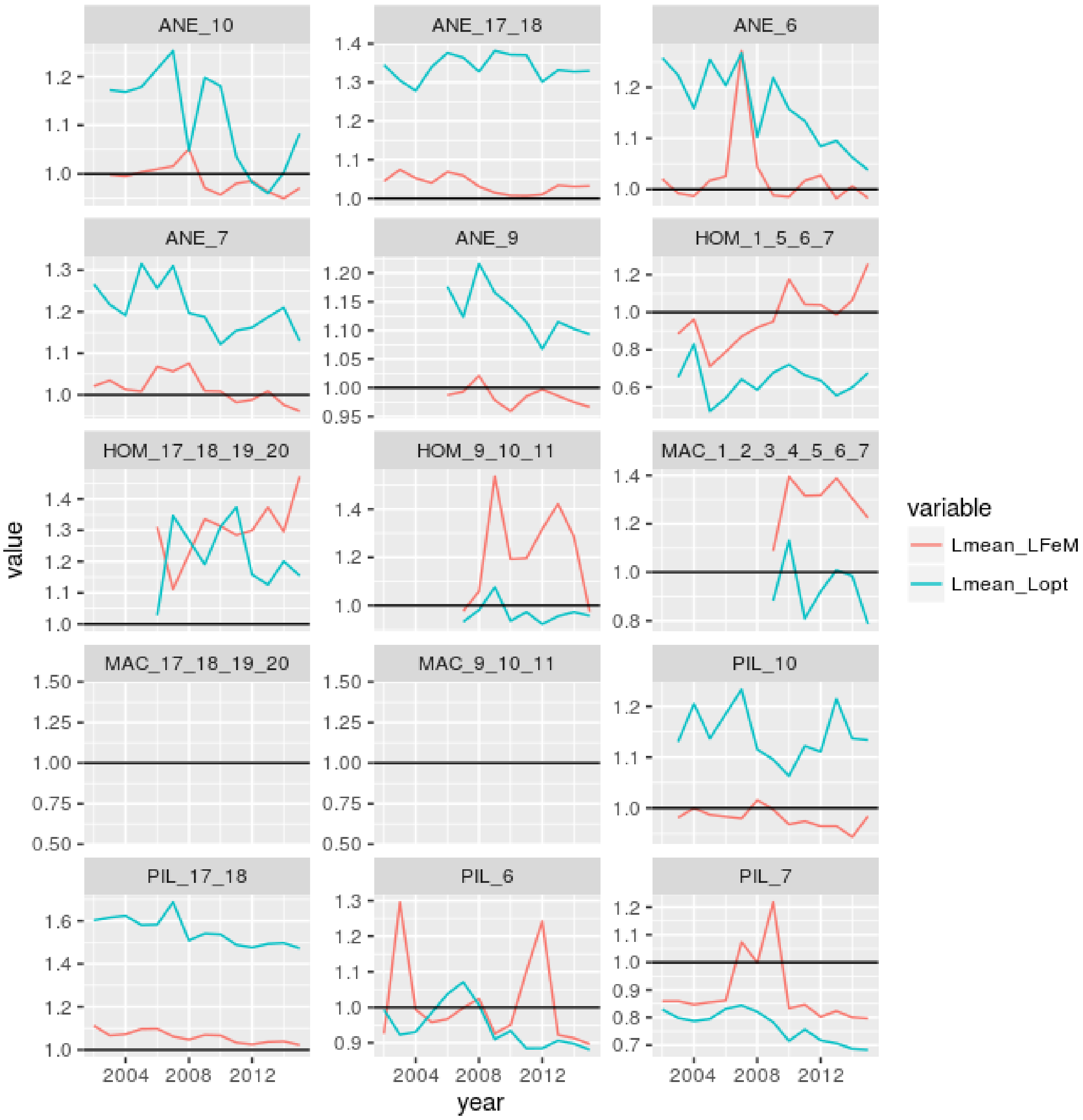

Figure 19: Indicators using reported $Linf$. Note the differing scales on the y-axis.

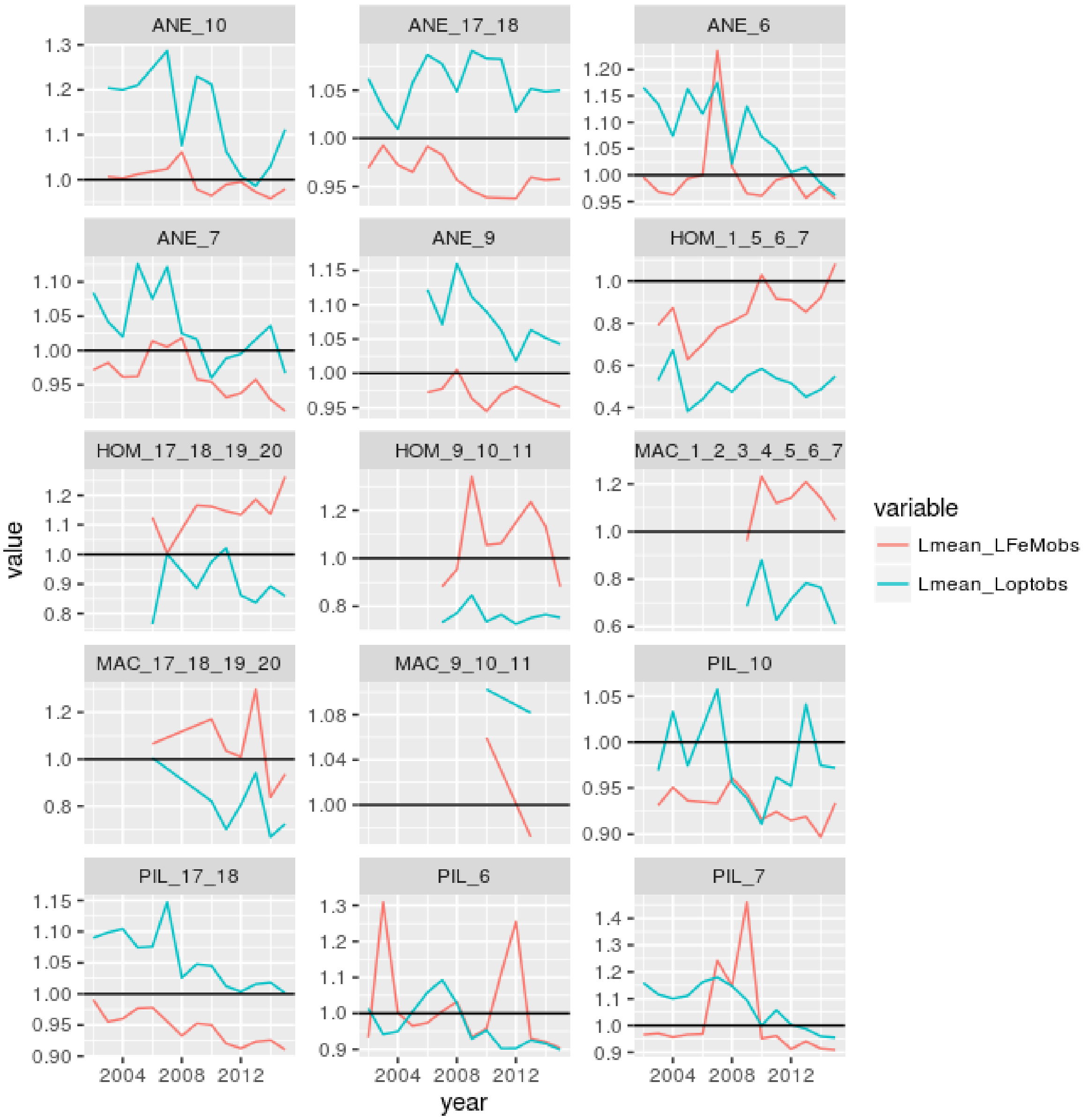

Figure 20: Indicators using observed $Linf$. Note the differing scales on the y-axis.

8 Comparing the indicators to the stock assessment results

Here we compare the estimated Fs to $Linf/LFeM$ for a range of stocks. $Linf/LFeM$ is recommended to be $>= 1$. Additionally, if the length based indicator was a useful indicator of fishing pressure, we would expect $Linf/LFeM$ and the estimated F to be inversely related. However, the calculated value strongly depends on which value of $Linf$ is used (see Figures 19 and 20)

8.1 PIL in GSAs 17 and 18

PIL in GSAs in 17 and 18 was assessed using SAM. Ideally the estimated Fs should be scaled by $FMSY$ for the comparison but for this stock there is no accepted value of $FMSY$ for this stock. However, it is still possible to investigate the relationship.

```
f <- c(0.09, 0.11, 0.13, 0.11, 0.10, 0.11, 0.22, 0.19, 0.17, 0.19, 0.18, 0.22,
    0.26, 0.28, 0.30, 0.23, 0.20, 0.14, 0.16, 0.14, 0.16, 0.23, 0.24, 0.31,
    0.33, 0.42, 0.45, 0.46, 0.38, 0.41, 0.30, 0.36, 0.33, 0.34, 0.50, 0.57,
    0.99, 1.08, 1.10, 1.88, 1.95)
pil1718F <- data.frame(year=1975:2015, AssessedF = f)
pil1718Obs <- join(data.frame(year=1975:2015, AssessedF = f), ind[["PIL_17_18"]]
    [,c("year","Lmean_LFeMobs")])
colnames(pil1718Obs)[3] <- "Lmean_LFeM"
pil1718Rep <- join(data.frame(year=1975:2015, AssessedF = f), ind[["PIL_17_18"]]
    [,c("year","Lmean_LFeM")])
colnames(pil1718Rep)[3] <- "Lmean_LFeM"
pil1718 <- rbind(cbind(Linf="Observed", pil1718Obs),
    cbind(Linf="Reported", pil1718Rep))
# Lop off years with no length indicator
pil1718 <- pil1718[!is.na(pil1718$Lmean_LFeM),]
```

Although there is some evidence to suggest an inverse relationship there is a high level of variability (Figure 21).

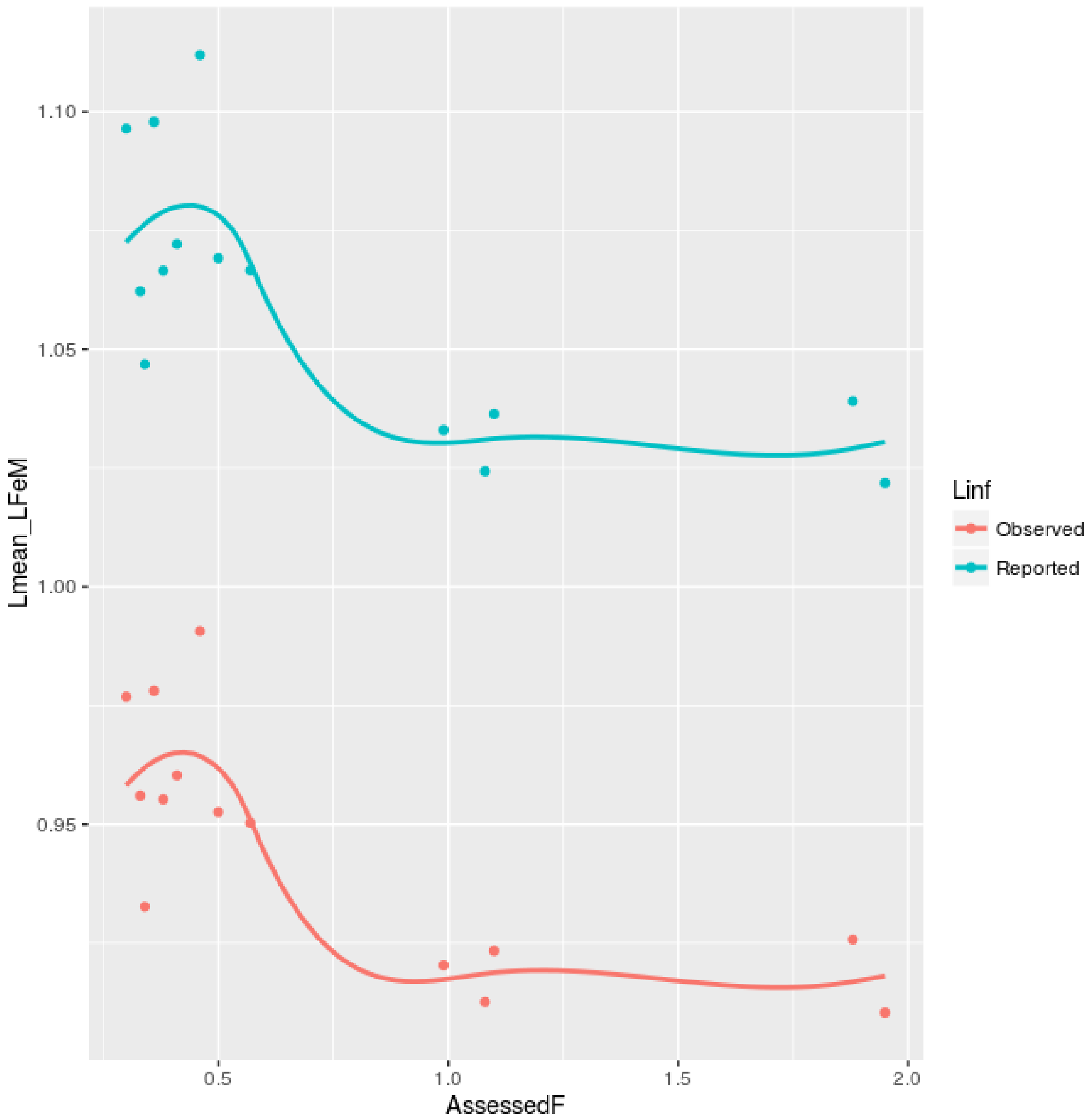

Figure 21: Estimated F against length based $Linf/LFeM$ for PIL in GSAs 17 and 18. We would expect the variables to be inversely related.

Even though there is no agreed value for $FMSY$ it is accepted that the stock is overexploited. When $Linf/LFeM$ is based on the observed $Linf$ the values are all less than 1 suggesting overexploitation (Figure 22). However, when the reported $Linf$ is used the values are greater than or equal to 1 suggesting sustainable exploitation. In both cases, there is a downward trend suggesting a deterioriating situation, following the increasing trend in the estimated Fs. The absolute level of the indicator might be uncertain, depending on what value of $Linf$ is used, but the trend seems to be a reasonable guide to the trend of the exploitation.

```
pil17182 <- rbind(data.frame(year=1975:2015, value = f, variable="F"),
    melt(ind[["PIL_17_18"]][,c("year","Lmean_LFeMobs","Lmean_LFeM")], id.vars="year"))
pil17182 <- pil17182[pil17182$year >= 2002,]
```

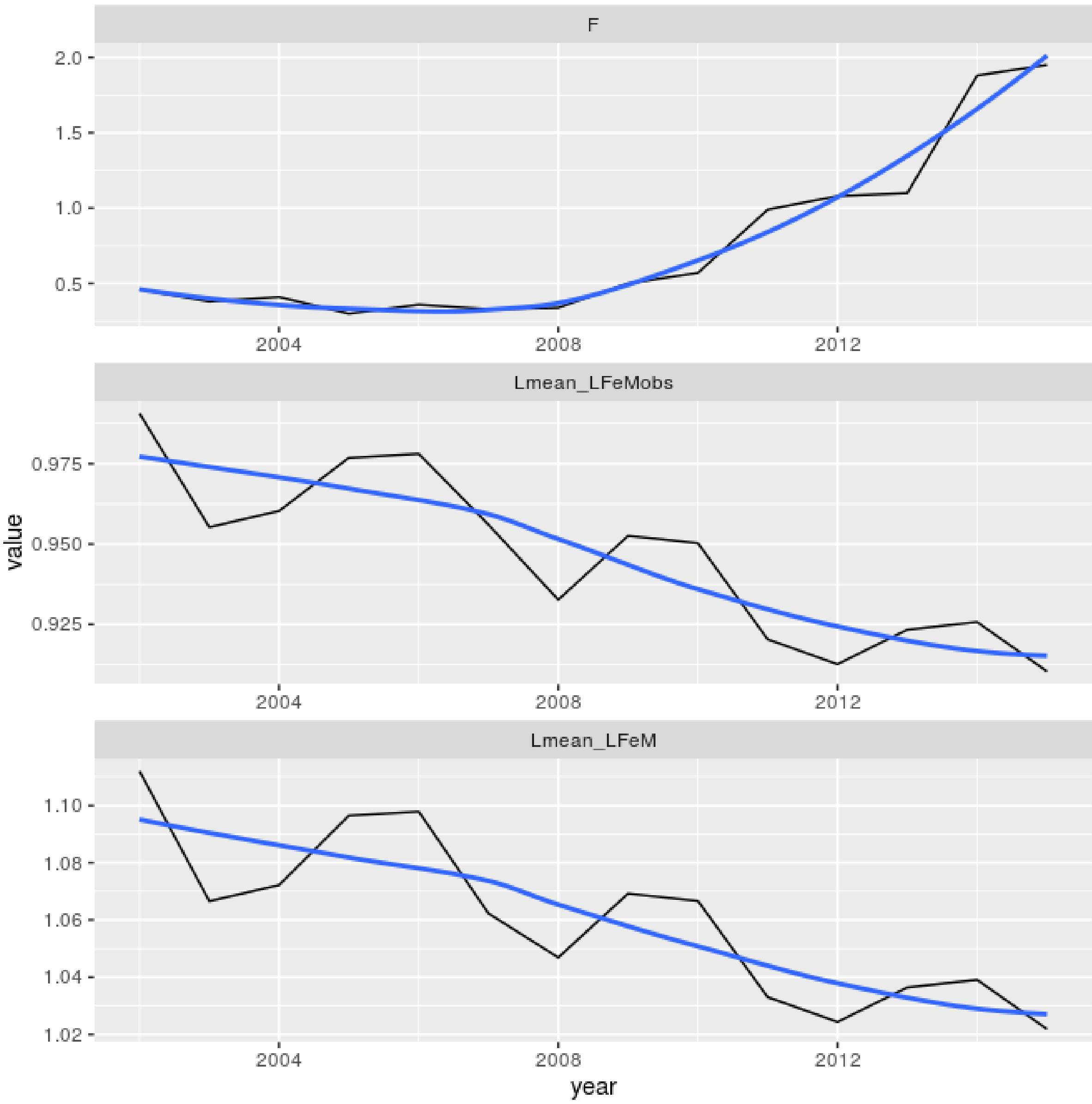

Figure 22: Trends in the indicators agree with the estimated F from the assessment (there is an inverse relationship) for PIL in GSAs 17 and 18. A smoother has been added.

8.2 ANE in GSAs 17 and 18

```
f <- c(0.18, 0.17, 0.17, 0.19, 0.19, 0.21, 0.21, 0.22, 0.23, 0.27, 0.35, 0.32,
    0.28, 0.32, 0.34, 0.35, 0.38, 0.38, 0.38, 0.39, 0.45, 0.48, 0.53, 0.56,
    0.54, 0.66, 0.79, 0.85, 0.73, 0.68, 0.58, 0.57, 0.70, 0.93, 1.02, 1.24,
    1.54, 1.32, 1.23, 1.25, 1.33)
ane1718F <- data.frame(year=1975:2015, AssessedF = f)
ane1718Obs <- join(data.frame(year=1975:2015, AssessedF = f), ind[["ANE_17_18"]]
    [,c("year","Lmean_LFeMobs")])
colnames(ane1718Obs)[3] <- "Lmean_LFeM"
ane1718Rep <- join(data.frame(year=1975:2015, AssessedF = f), ind[["ANE_17_18"]]
    [,c("year","Lmean_LFeM")])
colnames(ane1718Rep)[3] <- "Lmean_LFeM"
ane1718 <- rbind(cbind(Linf="Observed", ane1718Obs),
```

```
    cbind(Linf="Reported", ane1718Rep))
  # Lop off years with no length indicator
  ane1718 <- ane1718[!is.na(ane1718$Lmean_LFeM),]
```

There is evidence to suggest an inverse relationship between the indicator and estimated F (Figure 23).

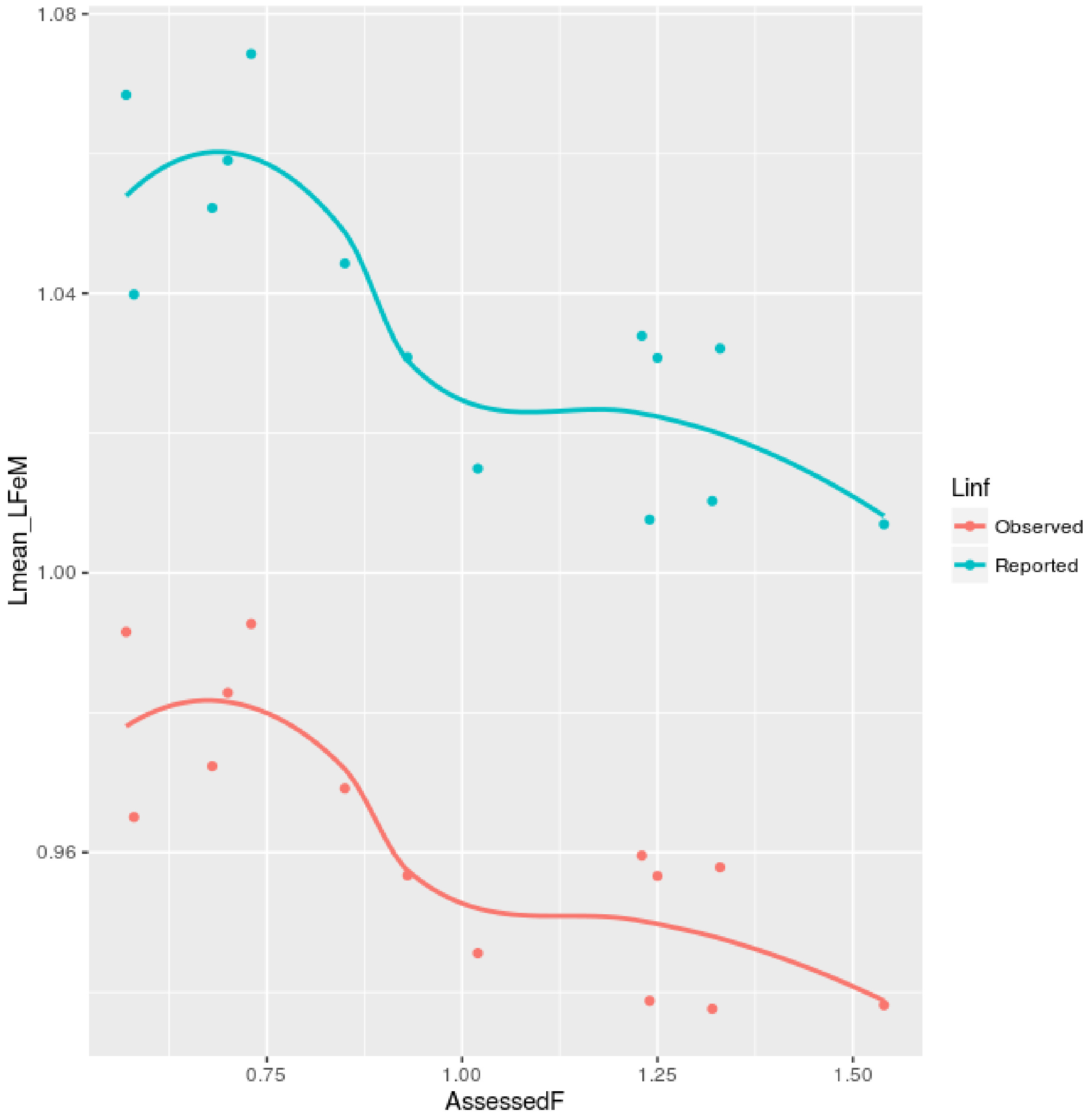

Figure 23: Estimated F against length based $Linf/LFeM$ for ANE in GSAs 17 and 18. We would expect the variables to be inversely related.

Even though there is no agreed value for $FMSY$ it is accepted that the stock is overexploited. When $Linf/LFeM$ is based on the observed $Linf$ the values are all less than 1 suggesting overexploitation (Figure 24). However, when the reported $Linf$ is used the values are greater than or equal to 1 suggesting sustainable exploitation. The absolute level of the indicator might be uncertain, depending on what value of $Linf$ is used, but the trend seems to be a reasonable guide to the trend of the exploitation. For example, the period of increasing F (2006 to 2011) corresponds with the period of decreasing indicator value suggesting that when trends do exist the indicators could be useful in identifying changes in the estimated value of F.

```
ane17182 <- rbind(data.frame(year=1975:2015, value = f, variable="F"),
    melt(ind[["ANE_17_18"]][,c("year","Lmean_LFeMobs","Lmean_LFeM")], id.vars="year"))
ane17182 <- ane17182[ane17182$year >= 2002,]
```

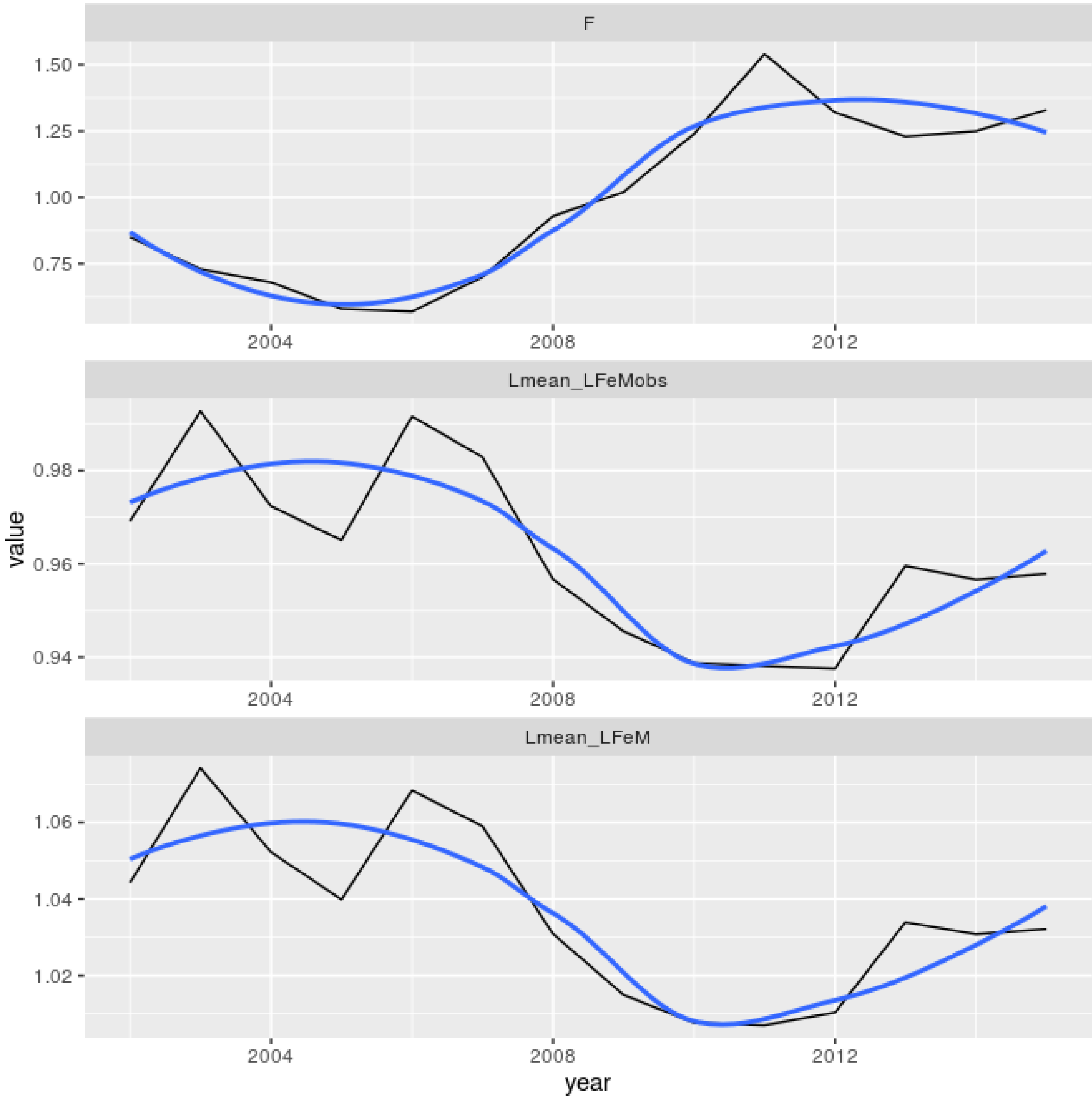

Figure 24: Indicators and estimated F for ANE in GSAs 17 and 18. A smoother has been added.

8.3 PIL in GSA 6

```
    f <- c(0.50, 0.40, 0.29, 0.60, 0.86, 1.90, 1.62, 1.26, 1.56, 0.64, 1.39, 2.92,
        1.77)
    pil6F <- data.frame(year=2003:2015, AssessedF = f)
    pil6Obs <- join(data.frame(year=2003:2015, AssessedF = f), ind[["PIL_6"]]
        [,c("year","Lmean_LFeMobs")])
    colnames(pil6Obs)[3] <- "Lmean_LFeM"
    pil6Rep <- join(data.frame(year=2003:2015, AssessedF = f), ind[["PIL_6"]]
        [,c("year","Lmean_LFeM")])
```

```
colnames(pil6Rep)[3] <- "Lmean_LFeM"
pil6 <- rbind(cbind(Linf="Observed", pil6Obs),
    cbind(Linf="Reported", pil6Rep))
# Lop off years with no length indicator
pil6 <- pil6[!is.na(pil6$Lmean_LFeM),]
```

The indicators from using the reported and the observed $Linf$s are very similar. There is some evidence to suggest an inverse relationship between the indicator and estimated F however there is a great deal of variability (Figure 25).

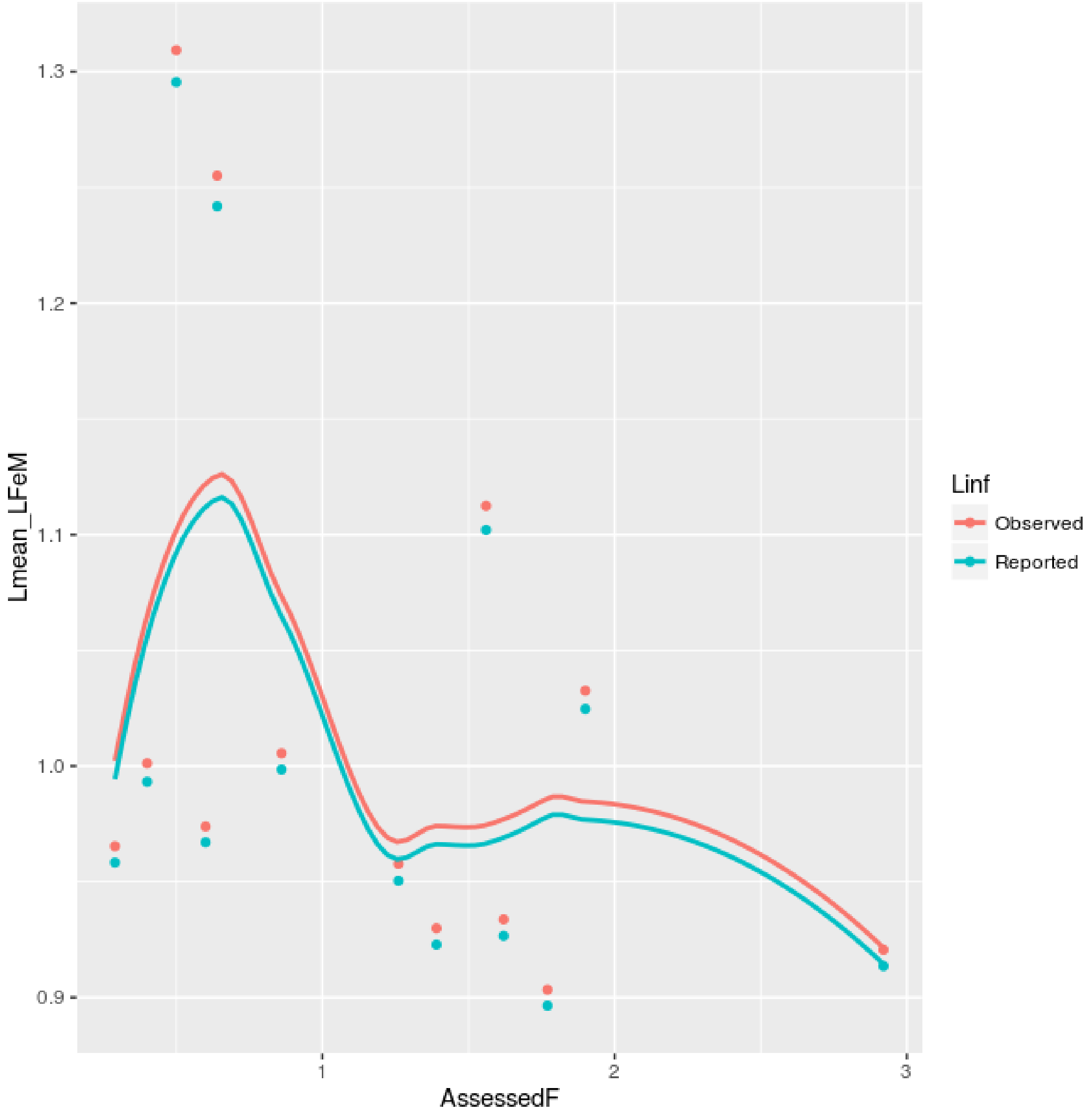

Figure 25: Estimated F against length based $Linf/LFeM$ for PIL in GSA 6. We would expect the variables to be inversely related.

The values of $Linf/LFeM$ when based on the observed and reported $Linf$ are very similar. There is no strong trend in the indicator timeseries even though there appears to be an upward trend in the estimated F (Figure 26). There is a spike in the indicator in 2012 which coincides with a drop in F. However, the increase in the indicator is far greater than the decrease in F in relation to the rest of the time series. The spike in the indicator is driven by a drop in Lc in that year (see above). The instability in the indicator suggests that it is not an appropriate guide to F.

```
pil62 <- rbind(data.frame(year=2003:2015, value = f, variable="F"),
    melt(ind[["PIL_6"]][,c("year","Lmean_LFeMobs","Lmean_LFeM")], id.vars="year"))
pil62 <- pil62[pil62$year >= 2003,]
```

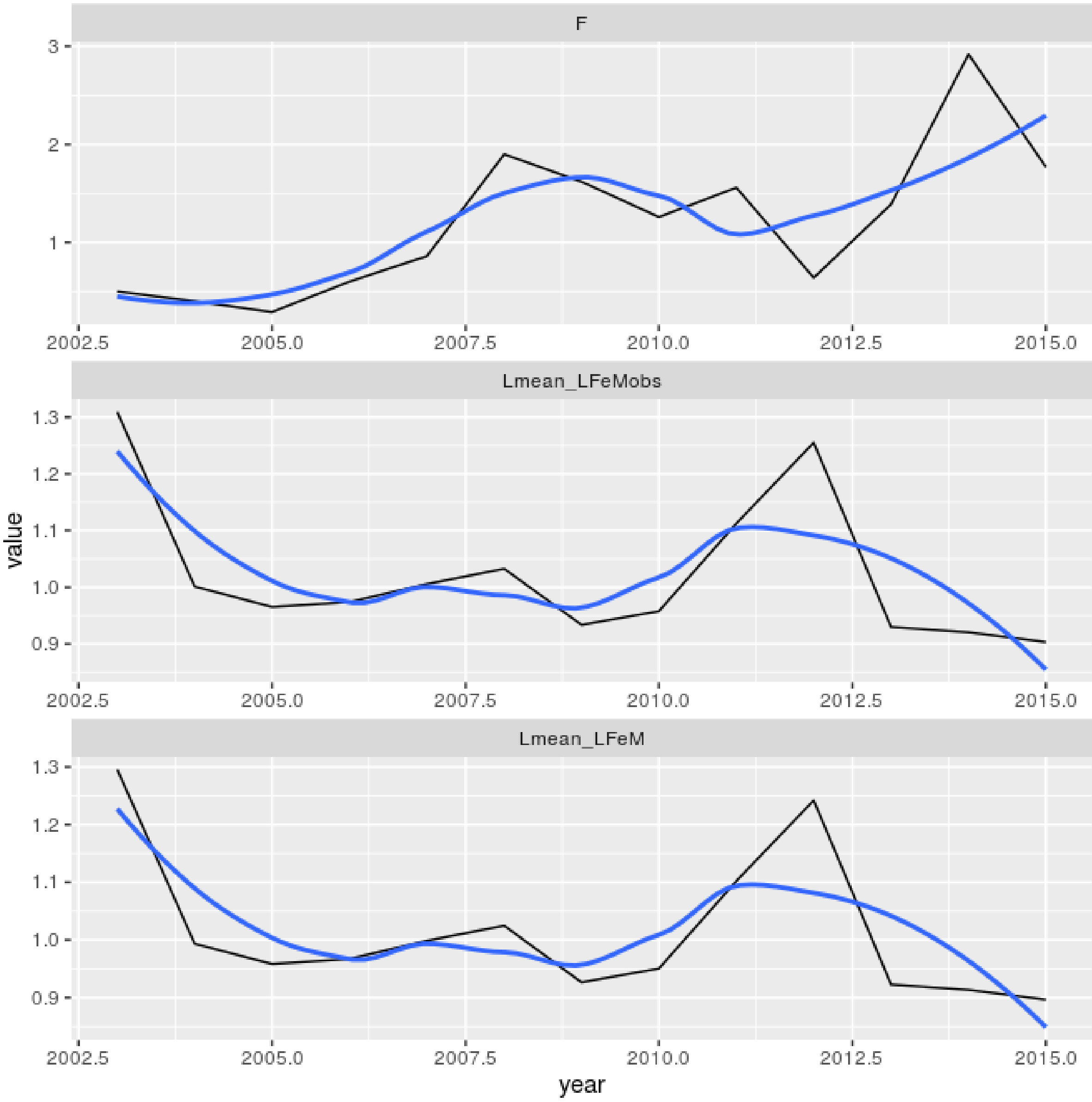

Figure 26: Indicators and estimated F for PIL in GSA 6. A smoother has been added.

8.4 ANE in GSA 9

```
f <- c(0.706, 0.564, 0.596, 1.448, 1.211, 1.811, 1.266, 1.631, 1.347, 1.139)
ane9F <- data.frame(year=2006:2015, AssessedF = f)
ane9Obs <- join(data.frame(year=2006:2015, AssessedF = f), ind[["ANE_9"]]
    [,c("year","Lmean_LFeMobs")])
colnames(ane9Obs)[3] <- "Lmean_LFeM"
ane9Rep <- join(data.frame(year=2006:2015, AssessedF = f), ind[["ANE_9"]]
    [,c("year","Lmean_LFeM")])
colnames(ane9Rep)[3] <- "Lmean_LFeM"
```

```
ane9 <- rbind(cbind(Linf="Observed", ane9Obs),
    cbind(Linf="Reported", ane9Rep))
# Lop off years with no length indicator
ane9 <- ane9[!is.na(ane9$Lmean_LFeM),]
```

The indicators from using the reported and the observed $Linf$s are very similar. There is no evidence to suggest an inverse relationship between the indicator and estimated F (Figure 27).

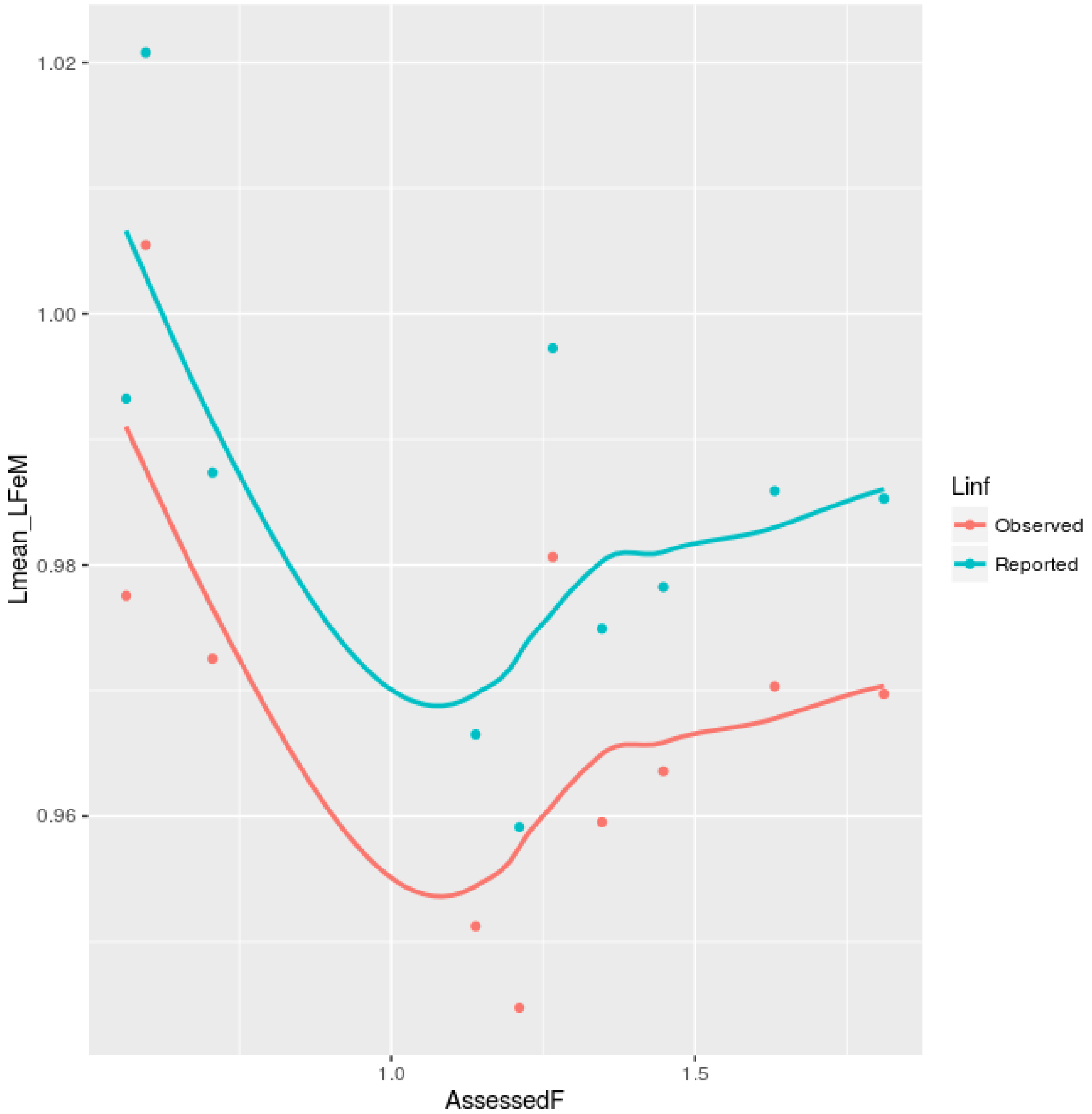

Figure 27: Estimated F against length based $Linf/LFeM$ for ANE in GSA 9. We would expect the variables to be inversely related.

When $Linf/LFeM$ is based on the observed $Linf$ the values are all slightly less than when it is based on the reported $Linf$ (Figure 28). The indicators do not appear to be a good guide to the estimated F. Their variability over the time series is low, whereas the estimated F experiences a strong increase.

```
ane92 <- rbind(data.frame(year=2006:2015, value = f, variable="F"),
    melt(ind[["ANE_9"]][,c("year","Lmean_LFeMobs","Lmean_LFeM")], id.vars="year"))
ane92 <- ane92[ane92$year >= 2006,]
```

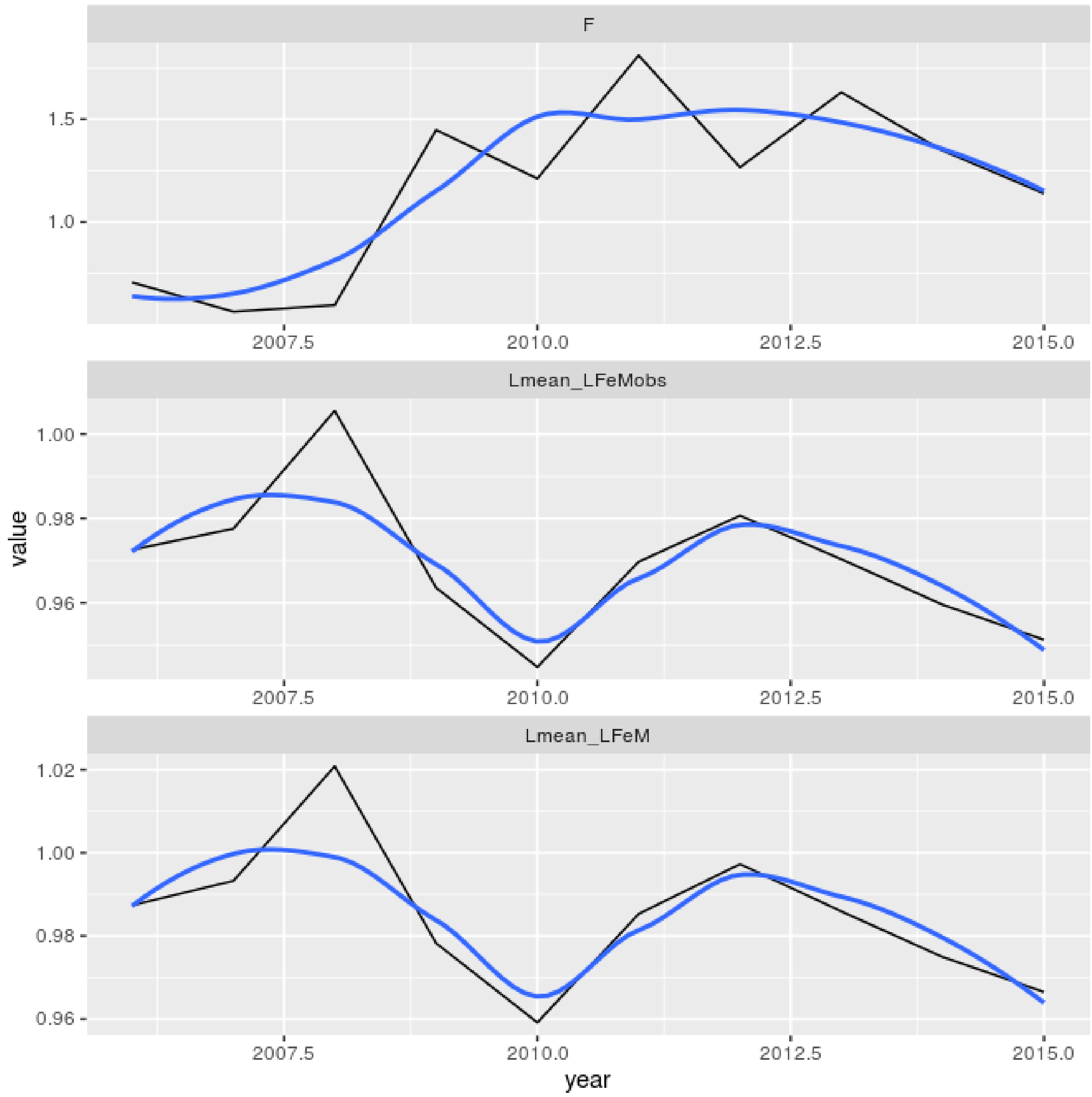

Figure 28: Indicators and estimated F for ANE in GSA 9. A smoother has been added.

8.5 HOM in GSAs 9-11

```
f <- c(0.34, 0.74, 0.73, 0.47, 0.34, 0.03, 0.77)
hom911F <- data.frame(year=2009:2015, AssessedF = f)
hom911Obs <- join(data.frame(year=2009:2015, AssessedF = f), ind[["HOM_9_10_11"]]
    [,c("year","Lmean_LFeMobs")])
colnames(hom911Obs)[3] <- "Lmean_LFeM"
hom911Rep <- join(data.frame(year=2009:2015, AssessedF = f), ind[["HOM_9_10_11"]]
    [,c("year","Lmean_LFeM")])
colnames(hom911Rep)[3] <- "Lmean_LFeM"
hom911 <- rbind(cbind(Linf="Observed", hom911Obs),
    cbind(Linf="Reported", hom911Rep))
# Lop off years with no length indicator
hom911 <- hom911[!is.na(hom911$Lmean_LFeM),]
```

The indicators from using the reported and the observed $Linf$s are very similar. There is no evidence to suggest an inverse relationship between the indicator and estimated F (Figure 29).

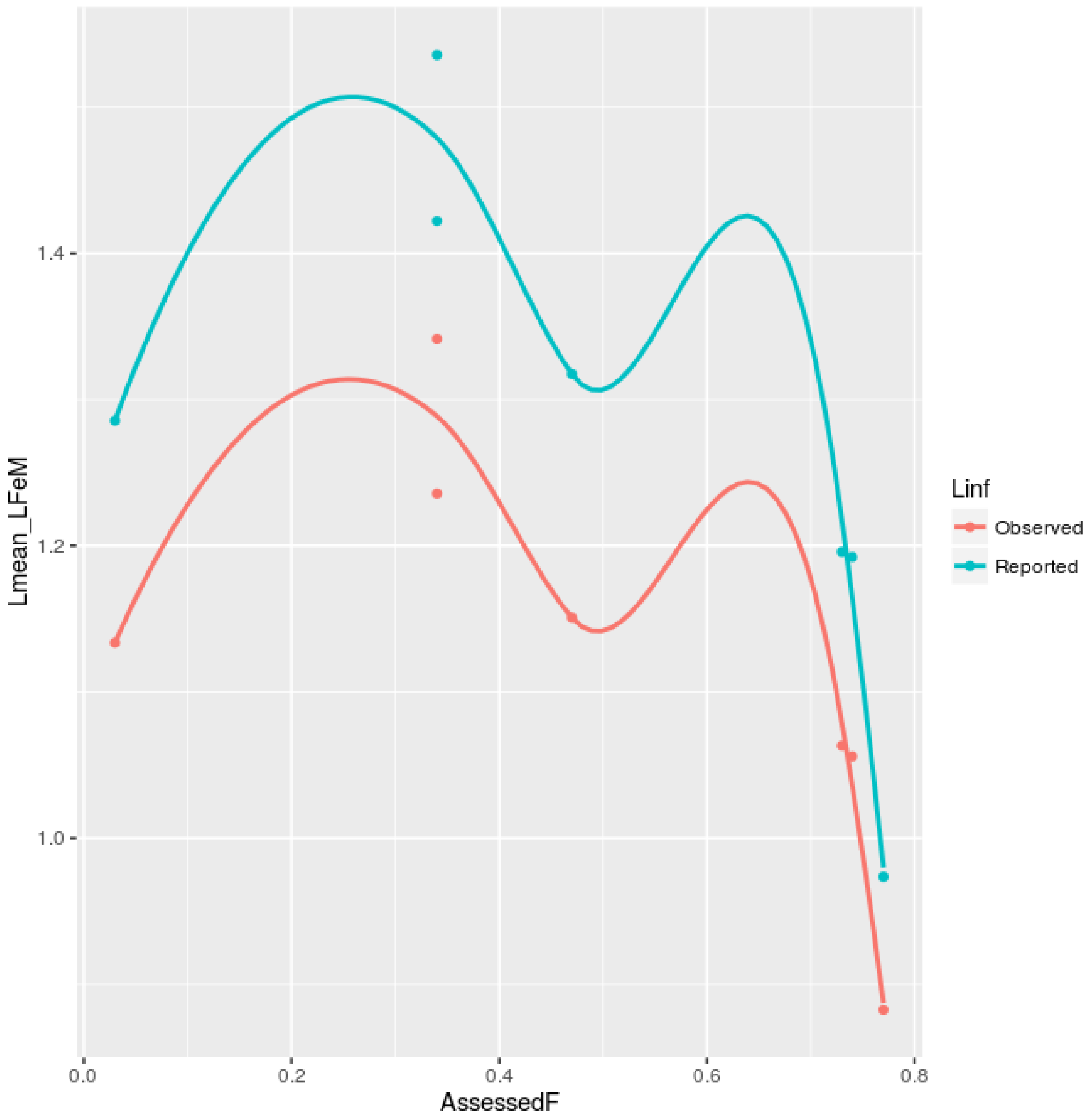

Figure 29: Estimated F against length based $Linf/LFeM$ for HOM in GSA 9-11. We would expect the variables to be inversely related.

When $Linf/LFeM$ is based on the observed $Linf$ the values are all slightly less than when it is based on the reported $Linf$ (Figure 30). The indicators are above or equal to 1 suggesting that the stock is not overexploited. The time series is short so it is not possible to to draw any firm conclusions about how well the indicators perform as guides to the level of exploitation. The trend in the indicators appear to be a reasonable guide to the trend of the estimated F. However, the very low estimated F in 2014 is not present in the indicators.

```
hom9112 <- rbind(data.frame(year=2009:2015, value = f, variable="F"),
    melt(ind[["HOM_9_10_11"]][,c("year","Lmean_LFeMobs","Lmean_LFeM")], id.vars="year"))
hom9112 <- hom9112[hom9112$year >= 2009,]
```

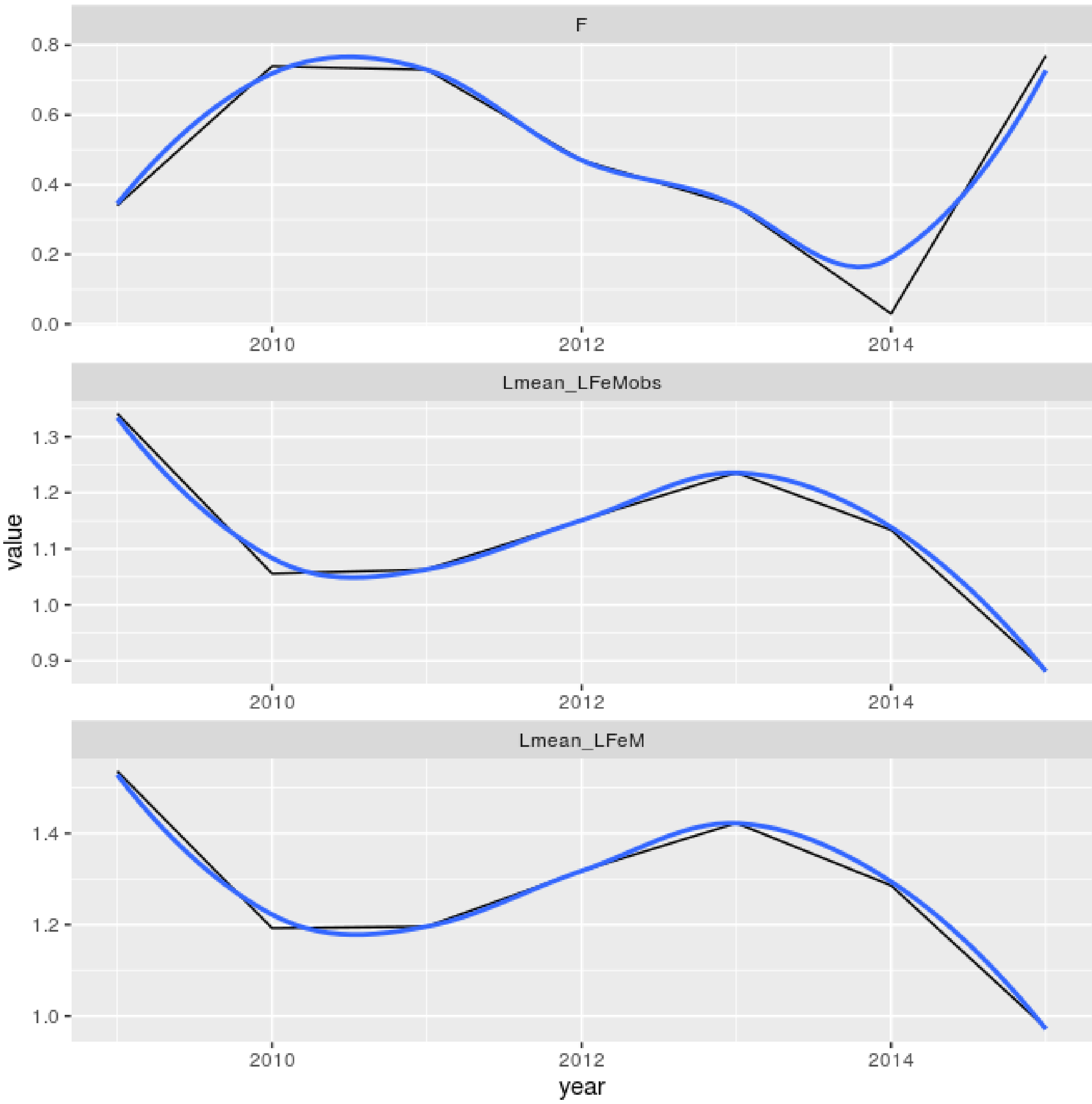

Figure 30: Indicators and estimated F for HOM in GSA 9-11. A smoother has been added.

9 MAC in GSAs 1-7

Given what we have seen in the preceeding section, can we use the indicators to say something about the possible state of exploitation of MAC in GSAs 1-7?.

```
mac17f <- ind[["MAC_1_2_3_4_5_6_7"]][,c("year","Lmean_LFeM","Lmean_LFeMobs")]
colnames(mac17f) <- c("year","Rep","Obs")
mac17y <- ind[["MAC_1_2_3_4_5_6_7"]][,c("year","Lmean_Lopt","Lmean_Loptobs")]
colnames(mac17y) <- c("year","Rep","Obs")
mac17f <- melt(mac17f, id.vars = "year")
mac17y <- melt(mac17y, id.vars = "year")
mac17 <- rbind(cbind(mac17f,measure="Lmean_LFeM"), cbind(mac17y, measure="Lmean_Lopt"))
```

If the length based indicators are a reasonable guide to the stock status then it appears that the exploitation rate has been relatively constant over the time series (apart from the first year) (Figure 31).

Using the reported or observed $Linf$ shows the $Lmean_Lopt$ indicator is greater than 1 suggesting that the stock is not overexploited. The yield indicator, $Lmean_Lopt$, is more variable. Ideally this indicator should be at 1. Using the reported or observed $Linf$ gives an indicator value of less than 1.

```
ggplot(mac17, aes(x=year, y=value, colour=variable)) + geom_line() +
    geom_smooth(se=FALSE) + facet_wrap(~measure, scales="free", ncol=1)
```

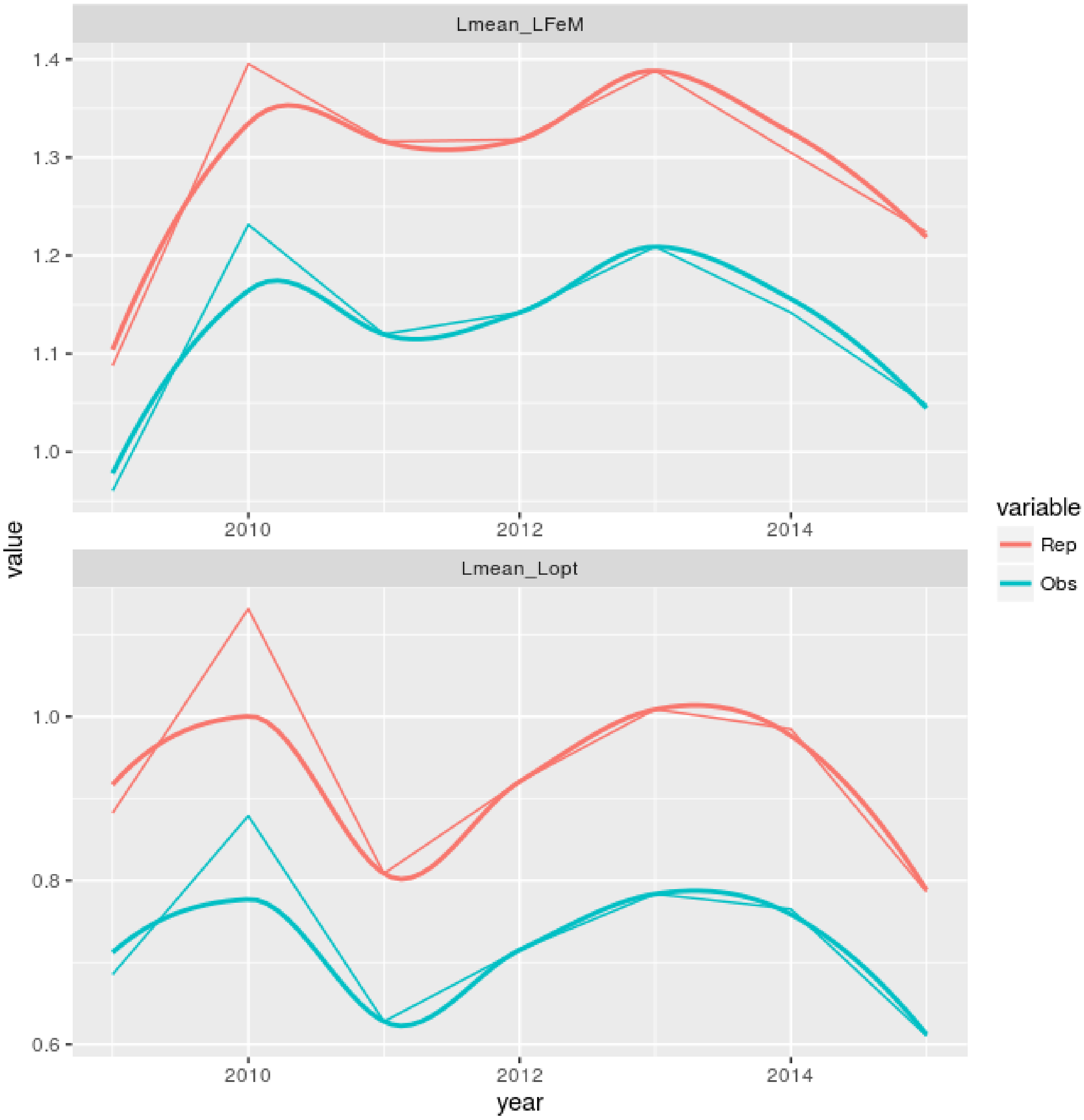

Figure 31: $Lmean/LFeM$ and $Lmean/Lopt$ indicators calculated using both reported and observed $Linf$ for MAC in GSAs 1-7.

10 Conclusion

The values of the indicators are very sensitive to the stability of the distributions, the presence of peaks in the lower tail of the catch distribution and the value of $Linf$. For example, the indicator $Linf/LFeM$ is recommended to be $>= 1$. However, the indicator can be greater or less than 1 depending on which $Linf$ is used. Stocks with narrow catch distributions, such as the PIL and ANE stocks, are more sensitive to these factors.

Comparing the indicator to the estimated F from stock assessments suggests that $Linf/LFeM$ is not a reliable guide to the stock exploitation status. The trends of $Linf/LFeM$ correspond reasonably well with estimated F (given the expected inverse relationship between them) for ANE and PIL in GSAs 17 and 18 and and HOM in GSAs 9-11. However, the absolute values depend on the value of $Linf$ making it difficult to draw conclusions about whether they are overexploited or not. For ANE in GSA 9 and PIL in GSA 6 neither the value or the trend in the indicator was not a good guide to the value or trend of F.

There is no assessment for MAC in GSAs 1-7. However, if we believe the indicators then it appears that the exploitation has been reasonably constant over time and that the stock is not overexploited.

Although the length based indicators show some promise in getting a picture of the stock status, more work needs to be done before any firm conclusions can be drawn. In particular, given the sensitivity of the indicators to Lc a more robust method for calculating Lc needs to be developed.

11 References

ICES. 2015. Report of the Fifth Workshop on the Development of Quantitative As- sessment Methodologies based on Life-history Traits, Exploitation Characteristics and other Relevant Parameters for Data-limited Stocks (WKLIFE V), 5–9 October 2015, Lisbon, Portugal. ICES CM 2015/ACOM:56. 157 pp.