Standardized purse seine CPUE of skipjack in the Indian Ocean for the European fleet

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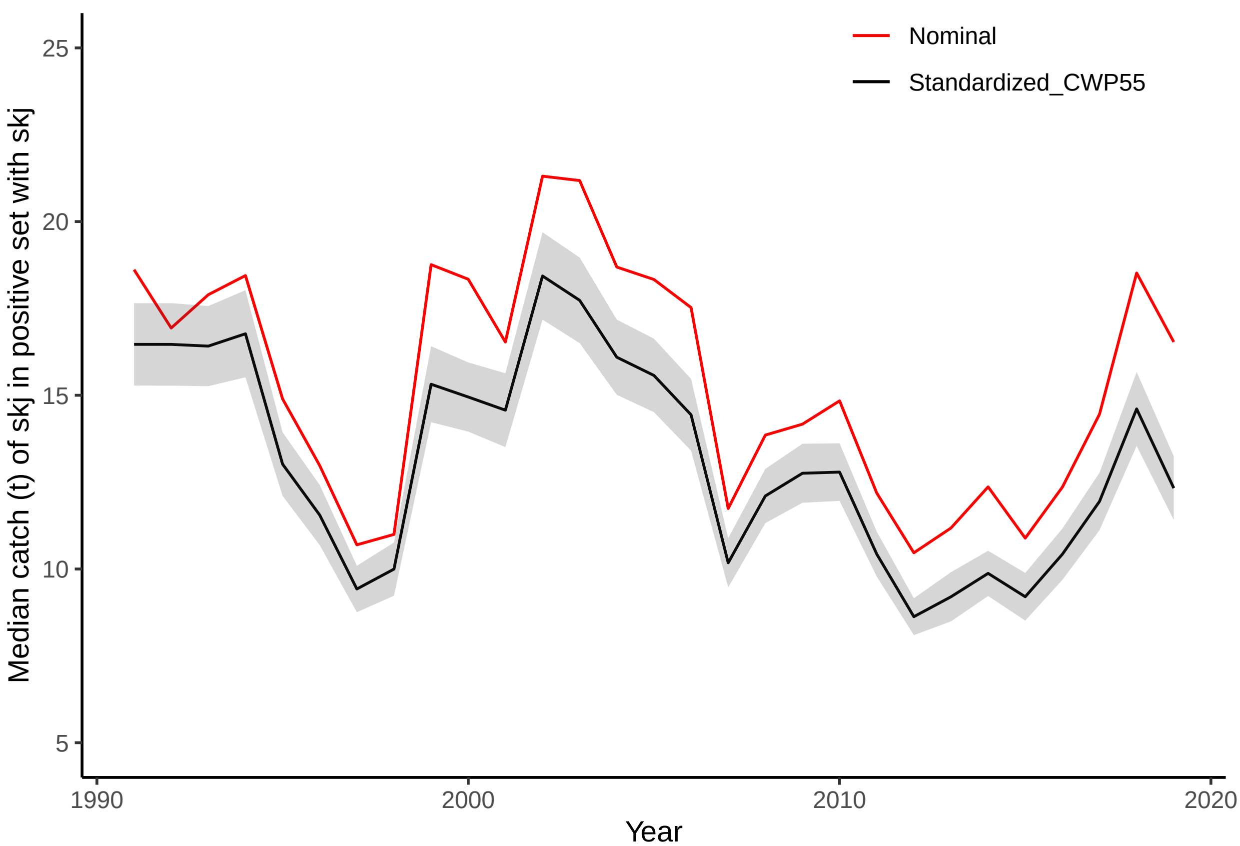
Overview

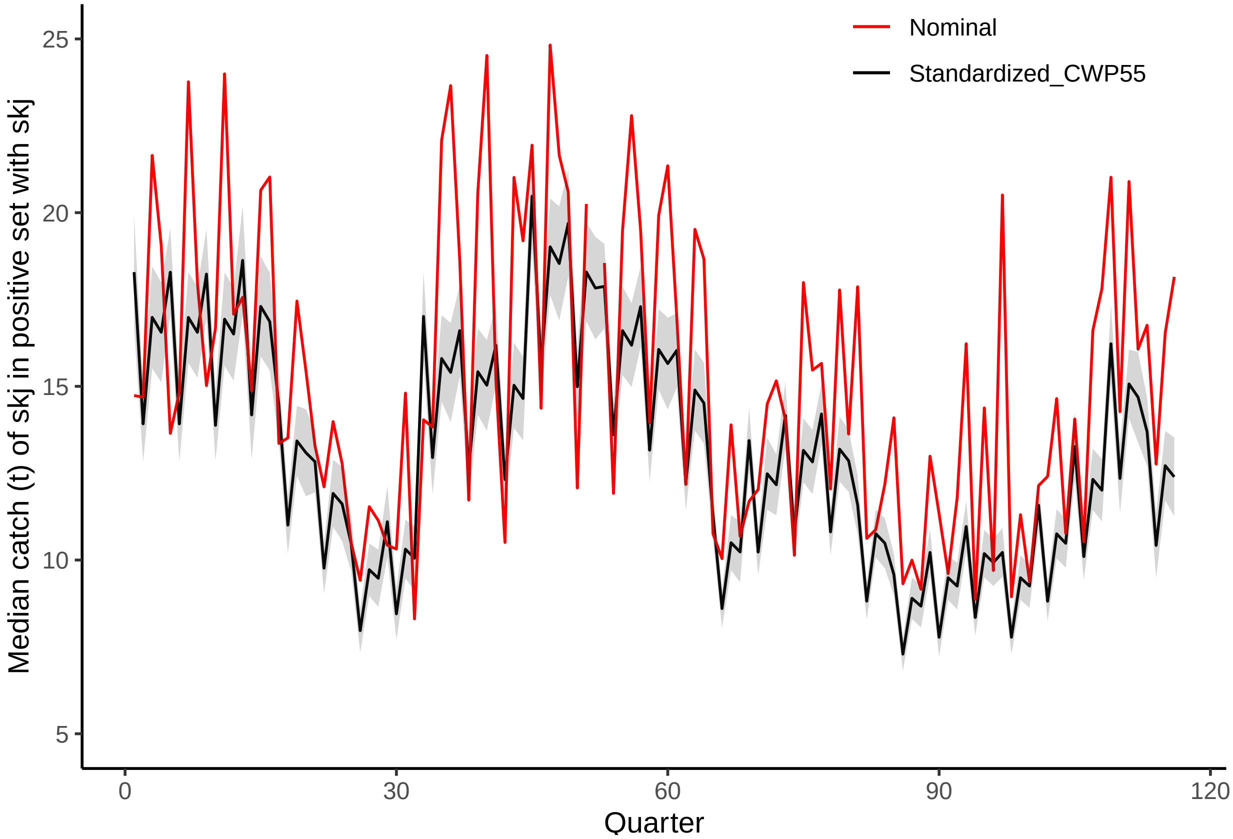
This document does the data filtering and the analyses necessary for standardized Indian Ocean European purse seine CPUE of skipjack analyses for the 1991-2019 period.

Plots

Year



Quarter



Dataframe of standardized purse seine CPUE of skipjack in the Indian Ocean for the European fleet

Year

Table 1: Median_catch_pred stands for the predicted median catch and Med_catch_nom for the nominal median catch

Year	Median_catch_pred	Median_catch_nom	SE	CI95%_min	CI95%_max	Coef_Var
1991	16.466046	18.616	0.6050754	15.280098	17.651994	1.712577
1992	16.464614	16.936	0.6061653	15.276530	17.652697	1.827140
1993	16.415707	17.896	0.5887549	15.261748	17.569667	1.795776
1994	16.771270	18.446	0.6395200	15.517810	18.024729	2.117951
1995	13.018150	14.896	0.4667633	12.103294	13.933006	2.221841
1996	11.552484	12.976	0.4419375	10.686287	12.418682	2.356630
1997	9.424400	10.696	0.3411723	8.755702	10.093098	2.363620
1998	9.997445	10.996	0.3907929	9.231492	10.763400	1.870984
1999	15.318087	18.760	0.5577474	14.224902	16.411272	2.094505
2000	14.950167	18.340	0.5078940	13.954695	15.945639	1.922073
2001	14.570868	16.533	0.5423931	13.507778	15.633958	2.041925
2002	18.434866	21.307	0.6415429	17.177442	19.692290	2.117405
2003	17.732661	21.181	0.6285961	16.500612	18.964709	1.832382

Year	Median_catch_pred	Median_catch_nom	SE	CI95%_min	CI95%_max	Coef_Var
2004	16.096007	18.691	0.5521683	15.013757	17.178257	1.796661
2005	15.571322	18.333	0.5395662	14.513772	16.628872	2.088871
2006	14.438529	17.524	0.5266836	13.406229	15.470829	2.404760
2007	10.177539	11.740	0.3611033	9.469776	10.885301	2.228780
2008	12.101735	13.854	0.3983159	11.321036	12.882434	2.035615
2009	12.755960	14.169	0.4330745	11.907134	13.604786	2.148844
2010	12.788875	14.840	0.4229395	11.959914	13.617837	2.113434
2011	10.430703	12.188	0.3298822	9.784134	11.077272	2.002208
2012	8.627334	10.466	0.2709490	8.096274	9.158394	1.767401
2013	9.200744	11.180	0.3614857	8.492233	9.909256	2.548625
2014	9.874032	12.364	0.3323807	9.222566	10.525498	2.179475
2015	9.200983	10.888	0.3498994	8.515180	9.886786	2.416829
2016	10.425830	12.357	0.3769413	9.687024	11.164635	2.559069
2017	11.945057	14.456	0.4219005	11.118132	12.771982	2.382209
2018	14.608032	18.520	0.5427069	13.544326	15.671737	2.792777
2019	12.327208	16.534	0.4672655	11.411367	13.243048	2.666060

Quarter

Table 2: Median_catch_pred stands for the predicted median catch and Med_catch_nom for the nominal median catch

Year_quarter	Med_catch_pred	Med_catch_nom	SE	CI95%_min	CI95%_max	Coef_Var
1991_1	18.288055	14.7360	0.8286487	16.663904	19.912207	0.5146332
1991_2	13.919201	14.6860	0.5553723	12.830671	15.007730	0.8548231
1991_3	16.986100	21.6460	0.7501708	15.515765	18.456434	1.0654375
1991_4	16.555271	19.0510	0.7329836	15.118623	17.991919	1.4014958
1992_1	18.286464	13.6460	0.6362757	17.039364	19.533564	0.7694316
1992_2	13.917990	14.8360	0.5561112	12.828012	15.007968	1.0396315
1992_3	16.984622	23.7660	0.6655830	15.680079	18.289164	0.9080995
1992_4	16.553831	17.9760	0.6670830	15.246348	17.861314	1.1109337
1993_1	18.232146	15.0210	0.6600648	16.938419	19.525873	0.7611318
1993_2	13.876648	16.6860	0.5260137	12.845661	14.907635	0.9238591
1993_3	16.934171	23.9960	0.6856027	15.590390	18.277952	1.0194201
1993_4	16.504660	17.0760	0.6845274	15.162986	17.846333	1.1999053
1994_1	18.627052	17.5660	0.7982843	17.062415	20.191690	0.8751480
1994_2	14.177214	14.8760	0.6562357	12.890993	15.463436	1.1981366
1994_3	17.300963	20.6460	0.7336127	15.863082	18.738844	1.3368718
1994_4	16.862149	21.0260	0.7175904	15.455671	18.268626	1.3484368
1995_1	14.458641	13.3560	0.5384405	13.403297	15.513984	1.0946294
1995_2	11.004599	13.5160	0.4214856	10.178488	11.830711	1.1432663
1995_3	13.429307	17.4560	0.5150371	12.419835	14.438780	1.2480526
1995_4	13.088692	15.4410	0.6391792	11.835901	14.341483	1.5642280
1996_1	12.830796	13.2860	0.4512613	11.946323	13.715268	0.9853927
1996_2	9.765632	12.1060	0.3758800	9.028907	10.502357	1.1028601
1996_3	11.917351	13.9860	0.4925239	10.952004	12.882698	1.3140842
1996_4	11.615084	12.7710	0.5445278	10.547810	12.682359	1.6090529
1997_1	10.467233	10.4860	0.4039825	9.675427	11.259039	1.2094456
1997_2	7.966704	9.4160	0.3219977	7.335588	8.597819	1.2601064
1997_3	9.722054	11.5360	0.3849917	8.967470	10.476638	1.3187398

Year_quarter	Med_catch_pred	Med_catch_nom	SE	CI95%_min	CI95%_max	Coef_Var
1997_4	9.475468	11.1360	0.4202001	8.651876	10.299060	1.5361941
1998_1	11.103688	10.4260	0.5183871	10.087649	12.119727	1.3433901
1998_2	8.451115	10.3160	0.3805047	7.705326	9.196904	1.0414128
1998_3	10.313199	14.8060	0.4337572	9.463035	11.163363	0.9764447
1998_4	10.051619	8.3060	0.4718332	9.126826	10.976412	0.9258215
1999_1	17.013072	14.0360	0.6668232	15.706098	18.320045	0.8860096
1999_2	12.948799	13.8260	0.5392353	11.891898	14.005701	1.1041460
1999_3	15.801884	22.0860	0.6342914	14.558673	17.045095	1.3788625
1999_4	15.401092	23.6570	0.7264840	13.977183	16.825000	1.4268722
2000_1	16.604440	18.6350	0.6731529	15.285061	17.923820	0.9182231
2000_2	12.637787	11.7250	0.4890032	11.679340	13.596233	1.1497965
2000_3	15.422344	20.5780	0.6337961	14.180103	16.664584	1.3002181
2000_4	15.031178	24.5250	0.6658168	13.726177	16.336179	1.2560003
2001_1	16.183171	15.1820	0.5848955	15.036776	17.329566	0.8121951
2001_2	12.317155	10.5055	0.4377242	11.459215	13.175094	0.9226142
2001_3	15.031065	21.0150	0.6254153	13.805251	16.256879	1.3553031
2001_4	14.649824	19.1870	0.6164611	13.441560	15.858087	1.1669075
2002_1	20.474730	21.9430	0.7698153	18.965892	21.983568	0.8245954
2002_2	15.583498	14.3700	0.4855992	14.631724	16.535272	0.8686073
2002_3	19.017101	24.8250	0.7100671	17.625370	20.408833	1.4208210
2002_4	18.534759	21.6475	0.8387658	16.890778	20.178740	1.4281816
2003_1	19.694824	20.5930	0.7857902	18.154675	21.234973	0.9707677
2003_2	14.989905	12.0740	0.5541459	13.903779	16.076031	0.6866490
2003_3	18.292718	20.2490	0.7254405	16.870855	19.714581	1.2015584
2003_4	17.828749	29.0140	0.7525738	16.353705	19.303794	1.2065330
2004_1	17.877070	18.5510	0.6211587	16.659599	19.094541	0.7984049
2004_2	13.606396	11.9180	0.4754254	12.674563	14.538230	0.6820272
2004_3	16.604373	19.4870	0.6521019	15.326253	17.882493	1.1703060
2004_4	16.183227	22.7955	0.6169289	14.974046	17.392408	1.1725073
2005_1	17.294328	19.4880	0.5941760	16.129743	18.458913	0.9115862
2005_2	13.162866	13.9530	0.4623556	12.256649	14.069083	0.9891503
2005_3	16.063117	19.9215	0.5914440	14.903887	17.222347	1.3255200
2005_4	15.655699	21.3490	0.6735238	14.335592	16.975806	1.2476090
2006_1	16.036189	16.9770	0.5457532	14.966512	17.105865	0.8602913
2006_2	12.205285	12.1760	0.3957721	11.429572	12.980998	0.7942787
2006_3	14.894547	19.5210	0.5963486	13.725704	16.063390	1.5356039
2006_4	14.516768	18.6650	0.5935369	13.353435	15.680100	1.6537485
2007_1	11.303709	10.7590	0.3630072	10.592215	12.015203	0.9145441
2007_2	8.603353	10.0390	0.2826497	8.049359	9.157346	0.9039174
2007_3	10.498980	13.8920	0.4053114	9.704570	11.293390	1.4460076
2007_4	10.232688	10.6810	0.4443044	9.361852	11.103525	1.3557924
2008_1	13.440822	11.6950	0.4777910	12.504352	14.377292	0.7197871
2008_2	10.229929	12.0315	0.3406344	9.562285	10.897572	1.0529698
2008_3	12.483949	14.4950	0.5287777	11.447544	13.520353	1.4475799
2008_4	12.167311	15.1590	0.4478148	11.289594	13.045028	1.2996820
2009_1	14.167438	14.0500	0.4869954	13.212928	15.121949	1.2221008
2009_2	10.782963	10.1380	0.3908893	10.016820	11.549106	1.0201834
2009_3	13.158836	17.9895	0.4678920	12.241768	14.075904	1.2419613
2009_4	12.825081	15.4660	0.4724303	11.899118	13.751044	0.9952658
2010_1	14.203996	15.6610	0.4440299	13.333698	15.074295	0.9816126
2010_2	10.810787	12.0450	0.3396479	10.145077	11.476497	0.9999455
2010_3	13.192791	17.7750	0.4768512	12.258163	14.127420	1.2567802

Year_quarter	Med_catch_pred	Med_catch_nom	SE	CI95%_min	CI95%_max	Coef_Var
2010_4	12.858175	13.6255	0.4563122	11.963803	13.752547	1.0503518
2011_1	11.584887	17.8670	0.4317789	10.738600	12.431173	1.0600928
2011_2	8.817360	10.6220	0.2710956	8.286012	9.348707	0.8717902
2011_3	10.760140	10.8750	0.3510814	10.072021	11.448260	1.1131825
2011_4	10.487225	12.1840	0.3675398	9.766847	11.207603	1.2296254
2012_1	9.581970	14.0960	0.3046252	8.984905	10.179035	0.9658548
2012_2	7.292922	9.3160	0.2468920	6.809014	7.776831	0.8243901
2012_3	8.899814	9.9990	0.3026645	8.306592	9.493037	1.0298293
2012_4	8.674083	9.1565	0.3128878	8.060823	9.287343	0.9772666
2013_1	10.218830	12.9895	0.3393664	9.553672	10.883988	1.0428123
2013_2	7.777642	11.3255	0.2834766	7.222028	8.333256	0.9629351
2013_3	9.491335	9.6080	0.3264055	8.851580	10.131090	1.2056080
2013_4	9.250601	11.8000	0.3429707	8.578378	9.922823	1.3342031
2014_1	10.966618	16.2285	0.3765392	10.228601	11.704635	1.1273190
2014_2	8.346790	8.8680	0.2690640	7.819425	8.874155	0.8306538
2014_3	10.185887	14.3800	0.3486110	9.502610	10.869165	1.2344710
2014_4	9.927537	9.6990	0.3446248	9.252072	10.603001	1.1766980
2015_1	10.219095	20.5080	0.3594903	9.514494	10.923696	0.9818461
2015_2	7.777844	8.9400	0.2510421	7.285801	8.269886	0.8903887
2015_3	9.491581	11.3070	0.3280899	8.848525	10.134638	1.1333357
2015_4	9.250841	9.3770	0.3185389	8.626504	9.875177	1.2993804
2016_1	11.579474	12.1410	0.3773247	10.839917	12.319030	1.1381680
2016_2	8.813240	12.4090	0.2900705	8.244701	9.381778	0.9724677
2016_3	10.755112	14.6480	0.3618150	10.045955	11.464270	1.2902621
2016_4	10.482324	10.7720	0.3584545	9.779753	11.184895	1.3003511
2017_1	13.266807	14.0610	0.4963998	12.293864	14.239751	1.3798588
2017_2	10.097485	10.5220	0.3439138	9.423414	10.771556	1.0447953
2017_3	12.322322	16.6080	0.4516068	11.437173	13.207472	1.3540485
2017_4	12.009784	17.8090	0.4565447	11.114956	12.904612	1.1296099
2018_1	16.224447	21.0200	0.5686257	15.109940	17.338953	1.4740781
2018_2	12.348570	14.2700	0.5142758	11.340589	13.356551	1.3730748
2018_3	15.069403	20.8960	0.5034762	14.082589	16.056216	1.3000076
2018_4	14.687189	16.0680	0.6655665	13.382678	15.991699	1.6219123
2019_1	13.691244	16.7590	0.5026790	12.705993	14.676495	1.3212429
2019_2	10.420527	12.7600	0.4749236	9.489677	11.351377	1.2663179
2019_3	12.716543	16.5360	0.5119783	11.713065	13.720020	1.4437865
2019_4	12.394006	18.1520	0.5767283	11.263618	13.524393	1.8578203

Data formatting code

```r
# Import Data
ECD_Ind <- readRDS("data/ecd_ind_eu_xinfo.2020-07-29.RDS")
ECD_Ind$cwp11 <- as.character(ECD_Ind$cwp11)
ECD_Ind$cwp55 <- as.character(ECD_Ind$cwp55)

# Define options
code_PS <- c(5,6)
bad_c_opera = c(2,4,7,8,9,11,12,13,14,15,19,20,33)
modif_date = c("20200803")
```

```r
# Add a category for Areas Beyond National Jurisdiction (ABNJ)
ECD_Ind$eez_iso_3digit <- as.character(ECD_Ind$eez_iso_3digit)
ECD_Ind$eez_iso_3digit[is.na(ECD_Ind$eez_iso_3digit)] <- 'ABNJ'
ECD_Ind$eez_iso_3digit <- as.factor(ECD_Ind$eez_iso_3digit)

# Creation of vessels' age
ECD_Ind$an_serv <- as.numeric(ECD_Ind$an_serv)
ECD_Ind$age <- ECD_Ind$annee_de_peche - ECD_Ind$an_serv
View(ECD_Ind[is.na(ECD_Ind$age),c("pays","numbat","age","annee_de_peche","an_serv")])
# After verification in TURBOBAT, an_serv and cap_m3 of numbat = 1227 & 1223 was not in the file for 20
# corrections for 1227 (1223 is a supply and will be filtered)

ECD_Ind$an_serv[ECD_Ind$numbat == 1227] <- 2019
ECD_Ind$cap_m3[ECD_Ind$numbat == 1227] <- 1900
ECD_Ind$age[ECD_Ind$numbat == 1227] <- ECD_Ind$annee_de_peche[ECD_Ind$numbat == 1227] - ECD_Ind$an_serv

# Subset of purse senners in IO
ECD_Ind_cut <- ECD_Ind[ECD_Ind$pays %in% c(1,4) # FR + SP
                       & ECD_Ind$type_bat %in% code_PS # purse senners
                       & ECD_Ind$d_act >= '1991-01-01'
                       & ECD_Ind$d_act <= '2019-12-31',]

# Add capture per day/boat for Gulland calculation
ECD_Ind_cut$day_boat <- paste(ECD_Ind_cut$d_act,ECD_Ind_cut$numbat, sep="_")

capture_skj_dayboat <- tapply(ECD_Ind_cut$capture_skj_corrigee,ECD_Ind_cut$day_boat,sum)
capture_skj_dayboat <- as.data.frame(cbind(day_boat = names(capture_skj_dayboat),
                                           capture_skj_dayboat))

ECD_Ind_cut <- merge(ECD_Ind_cut,capture_skj_dayboat,by="day_boat")
ECD_Ind_cut$capture_skj_dayboat <- as.numeric(as.character(ECD_Ind_cut$capture_skj_dayboat))

# Remove boat with weak experience (5% left hand)
lim_left <- 0.05
x <- as.data.frame(tapply(ECD_Ind_cut$d_act, ECD_Ind_cut$quille, function(x)length(unique(x))))
x <- cbind(rownames(x), x)
colnames(x) <- c("quille", "num_day")
x <- x[order(x$num_day),]
x$cum <- cumsum(x$num_day)
lim_cum <- lim_left*max(x$cum)
list_badboat <- as.numeric(as.character(x$quille[x$cum <= lim_cum]))

I <- ECD_Ind_cut$quille %in% list_badboat
ECD_Ind_cut <- ECD_Ind_cut[!I,]

# Remove bad num_sets_tot
tmp <- ECD_Ind_cut[,c("numbat","d_act","nombre_de_calees")]
tmp2 <- aggregate(tmp$nombre_de_calees,list(as.factor(tmp$numbat),as.factor(as.character(tmp$d_act))),su
tmp3 <- tmp2[tmp2$x > 5,]
colnames(tmp3) <- c("numbat","d_act","num_sets_tot")

bad_str <- paste(tmp3$numbat, tmp3$d_act)
```

```r
x = paste(ECD_Ind_cut$numbat,ECD_Ind_cut$d_act)
I = x %in% bad_str
ECD_Ind_cut = ECD_Ind_cut[!I,]

# Remove bad operations
bad_days = ECD_Ind_cut[ECD_Ind_cut$c_opera %in% bad_c_opera | # Normal bad operations
                         (!is.na(ECD_Ind_cut$dist_port_km) & ECD_Ind_cut$dist_port_km<10), # Spanish 20
                       c("numbat","d_act")]
bad_days_str = paste(bad_days$numbat, bad_days$d_act)

x = paste(ECD_Ind_cut$numbat,ECD_Ind_cut$d_act)
I = x %in% bad_days_str
ECD_Ind_cut_good_ops = ECD_Ind_cut[!I,]

# Colnames
I <- which(colnames(ECD_Ind_cut_good_ops) %in% c("annee_de_peche"))
colnames(ECD_Ind_cut_good_ops)[I] <- c("yr")
I <- which(colnames(ECD_Ind_cut_good_ops) %in% c("trimestre"))
colnames(ECD_Ind_cut_good_ops)[I] <- c("quarter")
I <- which(colnames(ECD_Ind_cut_good_ops) %in% c("mois_de_peche"))
colnames(ECD_Ind_cut_good_ops)[I] <- c("mon")

#### Piracy ####
cwp11_long_lat <- unique(ECD_Ind[,c("cwp11","lon","lat")])

data("World")
wrld_simpl <- World
class(wrld_simpl)

st_crs(cwp11_long_lat) <- st_crs(wrld_simpl)

tm_shape(World) +
  tm_borders()

P1_x <- c(40,63,67,69,69.5,69.5,69,68,67,60,55,51,47,43,41,39,40)
P1_y <- c(23,23,18,14,10,7,5,3,1,-4,-8,-11,-12,-11,-10,-6,23)
xym <- cbind(P1_x, P1_y)
sp_2010 <- st_sfc(st_polygon(list(as.matrix(xym))),
                  crs = st_crs(wrld_simpl))
pi_2010 <- st_difference(sp_2010,st_union(wrld_simpl))
year <- 2010
pi_2010 <- st_sf(year,pi_2010)
plot(st_geometry(sp_2010), axes=T); plot(st_geometry(wrld_simpl), add=T); plot(st_geometry(pi_2010), ad

P1_x <- c(41,58,60,62,63,63,61,59,53,50,49,44,42,39,41)
P1_y <- c(17,17,16,14,13,7,2,-1,-7,-9,-10,-9,-8,-4,17)
xym <- cbind(P1_x, P1_y)
sp_2009 <- st_sfc(st_polygon(list(as.matrix(xym))),
                  crs = st_crs(wrld_simpl))
pi_2009 <- st_difference(sp_2009,st_union(wrld_simpl))
year <- 2009
pi_2009 <- st_sf(year,pi_2009)
plot(pi_2009, add=T, col='blue')
```

```r
P1_x <- c(42,57.5,59.5,60.5,61.0,61.0,60.5,59.5,58.5,56.0,53.0,48.0,42.0,41.0,42)
P1_y <- c(13,16.5,15.5,13.5,11.5,8.0,6.0,4.0,2,-1,-3,-5,-4,-2,13)
xym <- cbind(P1_x, P1_y)
sp_2008 <- st_sfc(st_polygon(list(as.matrix(xym))),
                  crs = st_crs(wrld_simpl))
pi_2008 <- st_difference(sp_2008,st_union(wrld_simpl))
year <- 2008
pi_2008 <- st_sf(year,pi_2008)
plot(pi_2008, add=T, col='grey')

cwp11_piracy_2008 <- sf::st_intersection(cwp11_long_lat,pi_2008)
cwp11_piracy_2009 <- sf::st_intersection(cwp11_long_lat,pi_2009)
cwp11_piracy_2010 <- sf::st_intersection(cwp11_long_lat,pi_2010)

# Add Piracy
ECD_Ind_cut_good_ops$Piracy <- 0

I = ECD_Ind_cut_good_ops$cwp11 %in% cwp11_piracy_2008$cwp11 &
  ECD_Ind_cut_good_ops$yr == as.numeric(unique(cwp11_piracy_2008$X2008))
ECD_Ind_cut_good_ops$Piracy[I] <- 1

I = ECD_Ind_cut_good_ops$cwp11 %in% cwp11_piracy_2009$cwp11 &
  ECD_Ind_cut_good_ops$yr == as.numeric(unique(cwp11_piracy_2009$X2009))
ECD_Ind_cut_good_ops$Piracy[I] <- 1

I = ECD_Ind_cut_good_ops$cwp11 %in% cwp11_piracy_2010$cwp11 &
  ECD_Ind_cut_good_ops$yr == as.numeric(unique(cwp11_piracy_2010$X2010))
ECD_Ind_cut_good_ops$Piracy[I] <- 1

table(ECD_Ind_cut_good_ops$Piracy,ECD_Ind_cut_good_ops$yr)

# Select cwp11 with FAD sets and skj (from ECD file) for at least 5 different years spread over
# at least 15 years
SKJ_FSC_1991_2019 <- ECD_Ind_cut[ECD_Ind_cut$code_assoc_groupe == 1,]
SKJ_FSC_1991_2019 <- SKJ_FSC_1991_2019[SKJ_FSC_1991_2019$capture_skj_corrigee != 0,]

A <- as.data.frame(tapply(SKJ_FSC_1991_2019$annee_de_peche,SKJ_FSC_1991_2019$cwp11,
                          function(X)max(X)-min(X)))
B <- as.data.frame(rownames(A))
C <- as.data.frame(tapply(SKJ_FSC_1991_2019$annee_de_peche,SKJ_FSC_1991_2019$cwp11,
                          function(X)length(unique(X))))
D <- as.data.frame(cbind(B, A, C))
colnames(D) <- c("Cwp11","duree","nombre")
Cwp11_SKJ_FSC_1991_2019 <- D[D$duree >= 15 & D$nombre >= 5,] #656 obs

I = ECD_Ind_cut_good_ops$cwp11 %in% Cwp11_SKJ_FSC_1991_2019$Cwp11
ECD_Ind_cut_good_ops_good_cell  <- ECD_Ind_cut_good_ops[I,]

####  Creation data file for 3rd component CPUE : Lognormal ####

# Subset for positive set
ECD_Ind_cut_good_ops_good_cell_pos <- ECD_Ind_cut_good_ops_good_cell[ECD_Ind_cut_good_ops_good_cell$noml
```

```
# Subset for FAD set
ECD_Ind_cut_good_ops_good_cell_pos <- ECD_Ind_cut_good_ops_good_cell_pos %>% filter(code_assoc_groupe ==

# Subset for capture SKJ pos
ECD_Ind_cut_good_ops_good_cell_pos$skj_pos <- ECD_Ind_cut_good_ops_good_cell_pos$capture_skj_corrigee >
ECD_Ind_cut_good_ops_good_cell_pos_catchpos <- ECD_Ind_cut_good_ops_good_cell_pos[ECD_Ind_cut_good_ops_g

## Response variable (log transformation)
min_cat <- min(ECD_Ind_cut_good_ops_good_cell_pos_catchpos$capture_skj_corrigee[ECD_Ind_cut_good_ops_goo

ECD_Ind_cut_good_ops_good_cell_pos_catchpos$captureskj_augm <- ECD_Ind_cut_good_ops_good_cell_pos_catchp
ECD_Ind_cut_good_ops_good_cell_pos_catchpos$log_capture <- log(ECD_Ind_cut_good_ops_good_cell_pos_catchp
summary(ECD_Ind_cut_good_ops_good_cell_pos_catchpos$log_capture)

# Save RDS data
Nvar <- c("cap_m3","age","nombre_de_calees_pos")
Fvar <- c("pays","yr","quarter","cwp55","numbat")
OI_CPUE_comp3_SKJ_199101_201912 <- as.data.frame(ECD_Ind_cut_good_ops_good_cell_pos_catchpos)
for (i in Nvar) OI_CPUE_comp3_SKJ_199101_201912[,i] <- as.numeric(OI_CPUE_comp3_SKJ_199101_201912[,i])
for (i in Fvar) OI_CPUE_comp3_SKJ_199101_201912[,i] <- as.factor(OI_CPUE_comp3_SKJ_199101_201912[,i])

saveRDS(OI_CPUE_comp3_SKJ_199101_201912, paste("OI_FAD_CPUE_comp3_SKJ_199101_201912_", modif_date,".RDS

# Scale all numeric explanatory variables
Nvar <- c("cap_m3","age")
Fvar <- c("pays","yr","quarter","cwp55","numbat")
OI_CPUE_comp3_SKJ_199101_201912_scale <- OI_CPUE_comp3_SKJ_199101_201912
for (i in Nvar) OI_CPUE_comp3_SKJ_199101_201912_scale[,i] <- as.numeric(scale(OI_CPUE_comp3_SKJ_199101_2
for (i in Fvar) OI_CPUE_comp3_SKJ_199101_201912_scale[,i] <- as.factor(OI_CPUE_comp3_SKJ_199101_201912_s

# Save scaled data
saveRDS(OI_CPUE_comp3_SKJ_199101_201912_scale, paste("OI_FAD_CPUE_comp3_SKJ_199101_201912_scale_", modif
```

Analyses code

On demand