Spawning variation in Northeast Arctic Haddock in the years 2000-2017

Shedding light on ecology using economic data

Even Mikkelsen Bjørgesæter

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Even M Bjørgesæter

evenbm@student.ibv.uio.no

+4746642027

Supervisors

Øystein Langangen
Researcher
Oystein.langangen@ibv.uio.no

Lucie Buttay
Postdoctoral fellow
Lucie.buttay@ibv.uio.no

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Author Even M Bjørgesæter

http://www.duo.uio.no/

Trykk: Reprosentralen, Universitetet i Oslo

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Abstract

In this thesis I will investigate variations in annual mean latitude of spawning of the North-east Arctic (NEA) haddock (*Melanogrammus aeglefinus*) along the Norwegian coast. For this purpose, I have used commercial landing data from the Norwegian directorate of fisheries. The mean latitude of haddock spawning ground have been calculated from the latitude and biomass information of each individual landing, based on selected landings from the spawning grounds and within the spawning period. In addition, the variations in the mean latitude of spawning has been compared with temperature data from the KOLA section as gathered by Russian Federal Research Institute Of Fisheries and Oceanography (VNIRO), spawning stock biomass (SSB) from the 2018 International Council for the Exploration of the Sea (ICES) Arctic fisheries working group (AFWG) report, mean weight of spawners (which have been calculated based on weight at age, numbers at age and proportion mature at age from the same ICES report) and mean latitude of landings. A correlation between SSB and spawning location was found, a larger SSB resulted in a more northerly distribution. There was also a correlation between mean latitude of spawning and temperature in the Barents Sea in the moths prior to spawning with a higher temperature also correlated with a higher mean latitude of spawning. The results were tested through a linear model, a stepwise model selection, and an AICc and found to be statistically significant.

Introduction

North-east Arctic (NEA) haddock is an important species for fisheries in Norway. It is the third most caught gadoid species being fished in Norway by weight with 94,521 thousand tons caught in 2018, and comes in behind cod(373,924 thousand ton) and saithe(*Pollachius virens, 202,426* thousand tons)(https://www.ssb.no/jord-skog-jakt-og-fiskeri/faktaside/fiske) . In the period between 2000-2017 landings of haddock has generated more than16 billion NOK in total revenue(https://www.ssb.no/statbank/sq/10028096).

The spawning migration undertaken by NEA haddock is a behavioral trait that is quite common in fish species. From the European eel (*Anguila anuila*), brown trout (*Salmo trutta*) and the NEA haddocks close relative and neighbor the Northeast arctic cod (*Gadhus morhua*) and many other species. All these species travel great distances to spawn. The eel travels from freshwater rivers out into the Atlantic and onto the Sargasso Sea, Salmon (*Salmo salar*) migrates from the sea into rivers and haddock and cod that migrates from one part of the ocean to another. The reasons for these migrations are not clear, although several proposed reasons have been presented, most of whom describe it as a parent/offspring tradeoff (Dodson, 1997)where better climatic conditions(Kristiansen, Drinkwater, Lough, & Sundby, 2011), availability of food and presence of favorable currents that can transport eggs to nursing grounds offsets the initial costs of the parental generation migrating vast distances to spawn. These benefits have been suggested to improve growth in NEA cod (Farber, Durant, Vindenes, & Langangen, 2018), this growth is enough to offset the cost of migration for the adults. Given that NEA cod is closely related to NEA haddock, live in the same area and undergo a similar migration it is conceivable that similar benefits can be found for NEA haddock.

Understanding the spawning migration of NEA haddock is important for several reasons. From a conservationist point of view understanding how spawning migration is changing and why could be highly important to preserve these populations for the future. This is also important when it comes to an economic point of view, making sure that our understanding of the stock is accurate and is based on reliable data is critical if we want to predict stock sizes, distribution and understand how to best maintain a sustainable population through quotas. Understanding spawning migration is also important for fishermen to understand where and when to fish to maximize yield per unit effort.

The current spawning grounds for NEA haddock along the Norwegian coast extend for more than 1000km from off the coast of Møre to the eastern shelf edge of the Barents Sea, 72˚ north. This spawning area can be divided in to separate distinct spawning grounds, most of which are gathered around the Lofoten archipelago (see figure 1).

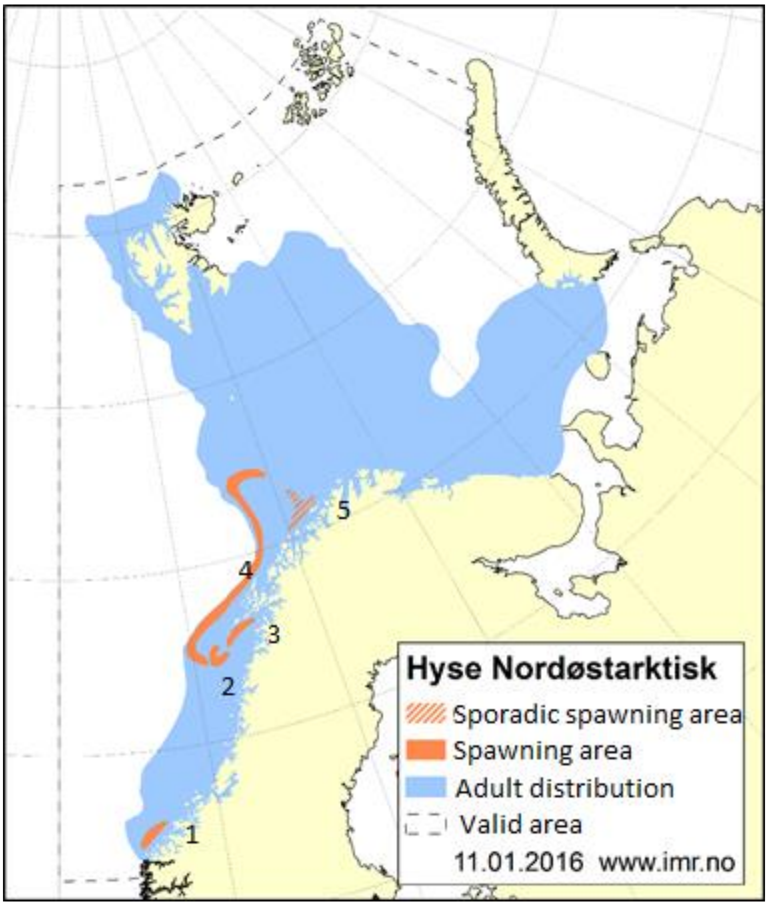

Figure 1 Map of NEA haddock spawning grounds, it illustrates the species distribution and spawning grounds. Spawning grounds are numbered for easy recognition. Spawning ground nr 1 is in the text often referred to in this text as the Møre spawning ground.
Taken from the IMR website ([https://www.imr.no/hi/temasider/arter/hyse/nordostarktisk-hyse)](https://www.imr.no/hi/temasider/arter/hyse/nordostarktisk-hyse) ,02.07.2019 *) and adapted.*

Every year, mature NEA haddock migrate from the Barents Sea to the spawning ground along the shelf edge and other spawning grounds along the coast of Norway to spawn(Jakobsen & Ozhigin, 2011, p. 272). The reasons for the NEA haddock spawning at specific locations are not well known, but we do have indications that the mean latitude of spawners vary from year to year(Ø. Langangen et al., 2018). These results were based on a large survey on NEA haddock eggs from the Soviet-Russian ichtyoplankton survey, which was conducted twice per year in spring and summer between 1959 and 1993. Based on data from this ichtyoplankton survey, changes in the spawning ground distribution were associated with the SSB of NEA haddock. The mechanism was suggested to work through expansion of the NEA haddocks feeding ground (the feeding ground is the area in the Barents Sea where the haddock population lives and feeds until it reaches maturity and only leaves for spawning) It has been shown that a higher spawning stock biomass leads to a more northeasterly distribution (Landa, Ottersen, Sundby, Dingsør, & Stiansen, 2014) as this is the only direction where expansion is possible (see figure 1,5). This could potentially increase mean latitude of spawning, assuming that the mean distance a NEA haddock would migrate remains stable while starting point varies. This could mean that the NEA haddock would have to migrate farther from their feeding grounds to reach the spawning ground along the continental shelf edge or off the Norwegian coast. Since we do not know the starting point of the migrations or the mean distance a haddock migrates this is all hypothetical at this point.

Around the year 2000 a sudden increase in biomass of haddock was observed (figure 2), this lasted until 2010 before slowly decreasing. The stock is still at a much higher biomass than before 2000. The spawning stock biomass has also seen an increase at the same time but with a time lag. At the same time climate change has led to changes in the ocean such as a rise in temperatures(Levitus, Antonov, Boyer, & Stephens, 2000). With these changes in the system it is no longer clear whether SSB is still a major driver in spawning location since these results were based on data gathered prior to these major changes (ichthyoplankton survey). Hence, it is highly relevant to investigate the processes involved in shaping the spawning ground distribution of haddock using modern data. Knowing how a populations spawning grounds varies over time is an important part of fisheries management, becoming especially relevant for spatially explicit management(Stelzenmüller, Ellis, & Rogers, 2010).

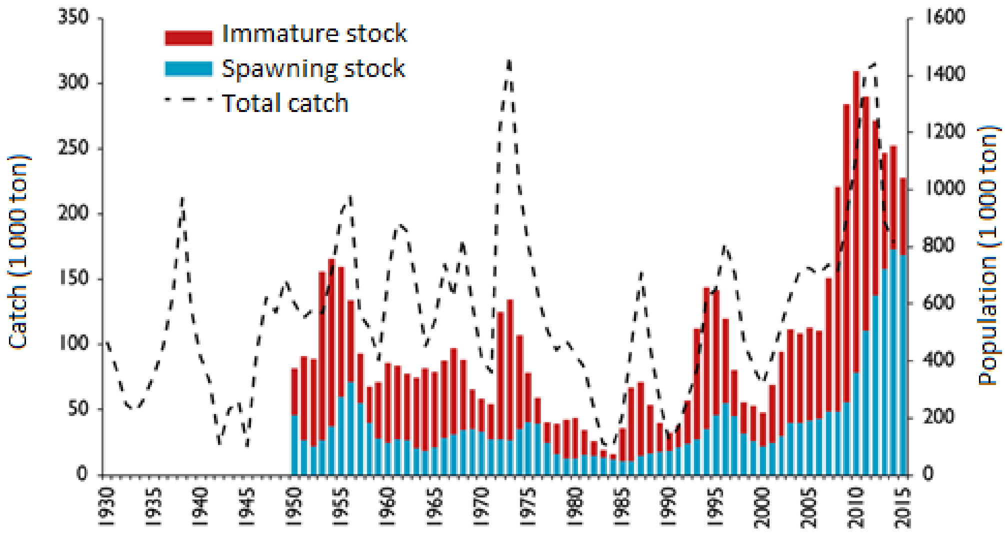

Figure 2 SSB, immature stock biomass and total catch of NEA haddock, taken from IMR https://www.hi.no/filarkiv/2016/05/hyse_noa.pdf/nb-no)

Haddock

Haddock are from the family Gadidae which contains many of Norway's most important commercially fished species, e.g. Cod. It is a boreal and demersal, meaning that it lives its adult life near the sea floor in boreal environments and lives in temperature ranges of 2-10°C. Haddock is distinguished easily from its Gadidae relatives by a dark mark above the pectoral fin(figure 3), it can reach a length of 110 cm and weigh as much as 14kg but most catches of NEA haddock average about 40-65cm and 1-3kg. The haddock matures when it reaches lengths of about 40-60cm and which corresponds to about 4-7 years(Jakobsen & Ozhigin, 2011, p. 272). NEA haddock is iteroparous and skipped spawning have been observed(Skjæraasen et al., 2015).

Figure 3 Picture of an adult haddock, the black spot above the pectoral fin that easily distinguishes this species from other gadoids. Photo by Steven G. Johnson, lincense https://creativecommons.org/licenses/by-sa/3.0/deed.en (https://no.wikipedia.org/wiki/Fil:Haddock,_Boston_Aquarium.JPG)

The mature haddock migrates in winter/spring to spawning grounds located between the Norwegian coast and the shelf edge of the coast of Norway between about 62°N and 70°N. Spawning usually takes place at a depth of 200 to 300 meters and a temperature range of 4-6°C. Male haddock are territorial and will defend a small area by patrolling and emanating a pulse sound to attract mates and scare away competitors(Casaretto, Picciulin, & Hawkins, 2015). The spawning lasts from March to June and peaks in late April/early May. The eggs and larvae of haddock are pelagic and one of the benefits associated with the migration is that it allows the fish eggs and larvae to mature faster in the warmer waters(Opdal, Vikebø, & Fiksen, 2008) while being transported by currents into the Barents Sea where they gradually develop and takes on a demersal lifestyle. Once the NEA haddock larvae reach the Barents sea, the 0-groups main prey are small zooplankton like copepods (especially *Calanus finmarchicus)*, krill (*Thysanoessa inermis),* Limancina and appendicularians(Dalpadado, Bogstad, Eriksen, & Rey, 2009). The adult NEA haddock's main prey is benthic organisms like crustaceans, mollusks, echinoderms and polychaetas(Jakobsen & Ozhigin, 2011, p. 273).

The population in the time series that I am investigating are dominated by strong year classes between 2004 and 2006(ICES, 2018) which have led to an all-time high SSB in recent years (figure 2). The SSB of NEA haddock has risen sharply (figure 2, 4) from the start of my dataset to 2013-2015 when the SSB started declining again following a record high catch of 316 tons in 2012(ICES, 2018). This was followed by a decline in catches in the period after 2013. NEA Haddock is to a large extent caught be gillnet as bycatch in cod fisheries, the quota for 2016 was on a total of 244 000 tons (https://www.hi.no/filarkiv/2016/05/hyse_noa.pdf/nb-no).

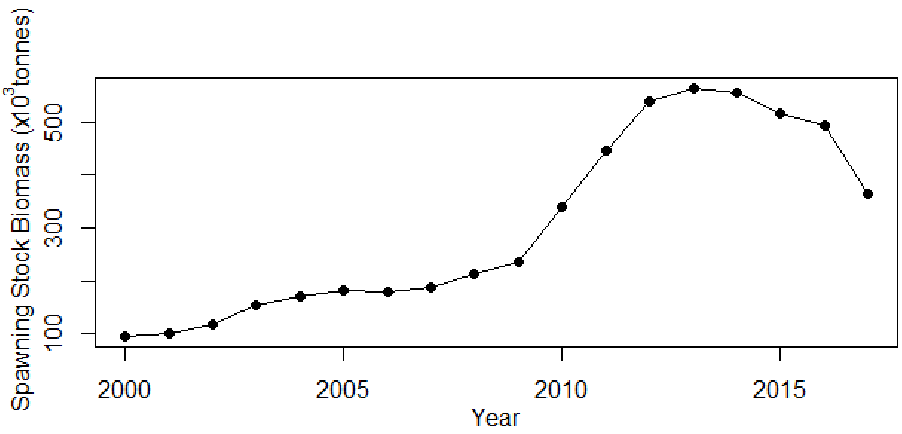

Figure 4 Spawning stock biomass of NEA haddock show an abrupt increase in 2009 increasing more than 100'000 tons in one year going from 234,729 tons to 338,146 tons. The overall increase is also significant, going from less than 100,000 tons in 2000 to more than 560,000 tons in 2013. Based on data from the ICES AFWC 2018 report.

The Barents Sea

The Barents Sea, located to the north of Norway and north western Russia, is a shallow shelf sea with an average depth of 230m. Due to its location the Barents Sea receives large amounts of water containing a lot of nutrients flowing from the deep waters of the Atlantic and is pushed up by the shelf edge that lines the eastern edge of the Barents Sea. This influx of nutrients and subsequent primary production gives the Barents Sea primary production similar to areas with upwelling and slightly higher than the mean average primary production for all seas(Jakobsen & Ozhigin, 2011, p. 82).

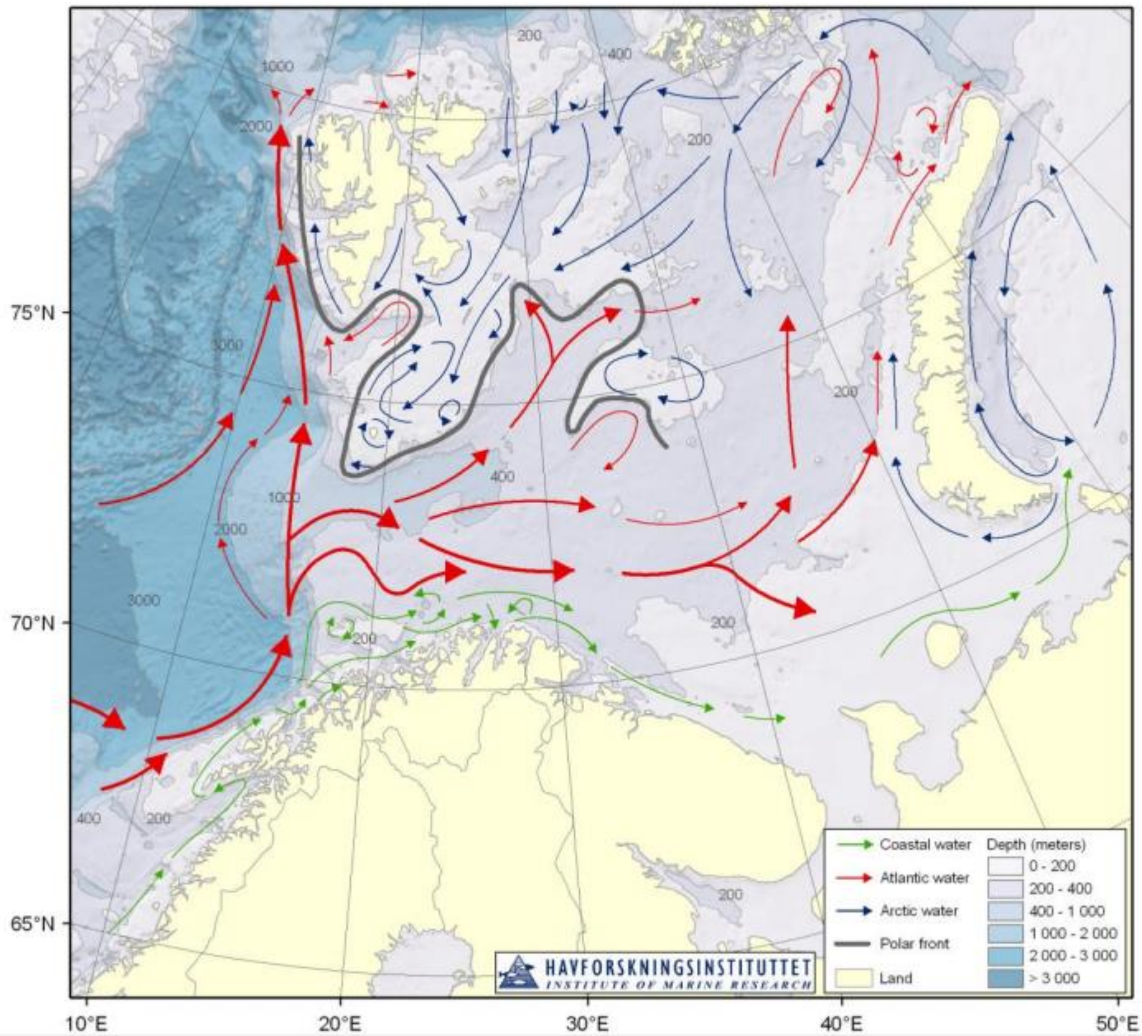

Figure 5 Currents in the Barents Sea, the red lines indicate currents from the Atlantic Ocean while the blue lines indicate currents from the arctic region. Taken from the Joint PINRO/IMR Report on the State of the Barents Sea Ecosystem 2006 with Expected Situation and Consideration for Management. (Stiansen & Filin, 2007)

Aims for my thesis

This thesis has two main aims.

- To investigate whether there has been significant interannual variation in the mean latitude of spawning NEA haddock under the new ecological parameters.

This first point is to investigate if there has been a change in mean latitude of spawners, by analyzing the data I will try to explore and quantify the potential changes. I will investigate the mean weight of spawners and the mean latitude of landings to try to determine this.

- If a significant change is found based on the first aim, then I will also investigate what factors (if any) could be responsible for the observed change.

In this thesis I will be focusing on three factors that have changed during the recent years, spawning stock biomass, mean weight of spawners and temperature. I will also add a fourth factor, mean latitude of landings to investigate if my results are driven by fish or fisher behavior

The data

The data used is taken from the directorate of fisheries in Norway (website at, https://www.fiskeridir.no/) and consists of landing tickets which are typically filled out dockside. This means that the data is gathered from commercial fishing vessels that operate along the Norwegian coast. The entire data set consists of all boats fishing cod and herring, this covers close to 100% of NEA haddock catches in the same period (personal communication, Directorate of Fisheries 2018). The original datasets consist of 8,100,038 data points of various species, 834,333of which were NEA haddock. This data set contained more than 50 columns of data on everything from size of the boats, build year, engine power of the boats to means of catch, date, location, landing site, weight, species and state of catch of the fish being landed.

The data set that I used as the main part for my study is summarized in table 1.

Table 1, A breakdown of what my dataset contained and what the names mean. The names written in cursive are columns I have added later to simplify the process.

Name	**Explanation**
Fartøyid	individual ships code
Største lengde	The length of the ships
Bruttotonnasje 1969	The tonnage of the ships
Byggeår	Year of construction for the ships
Ombyggings år	Year of which the boat was "rebuilt" or reoutfitted
Motorkraft	Engine power of the ships
Organisasjonsformkode/ Bokmål	Code for what kind of organizational structure caught the fish. (A/S, sole proprietorship etc.) and name in Bokmål
Fangstår	Year of catch
Dokumenttypekode/Bokmål	Code and name describing what kind of document was submitted for the catch. Landing or sales ticket.
Formulardato	The date the ticket was signed
Salgslagkode/bokmål	A code and name that describes which "Salgslag" sold that specific landing
Fartøytypekode/ Bokmål	Code and name for what kind of vessel that received the catch
Nasjonalitet fisker kode/ Bokmål	Code and name of the nationality of the fishermen who catch/land the fish
Fiskerkommune kode/bokmål	Code and name of the municipality of the fishermen in which they pay taxes.
Landingsnasjonskode	Code and name for the nation in which the catch was landed. (Only Denmark and Norway in my dataset.)
Landingskommunekode / Bokmål	Code for the municipality in which the catch was landed, received from locked storage, delivered to a cooling ship or picked up by "Føringsbåt"
Landingsdato	Date of the landing
Dellandingssignal	Code that tells you if there was more than one ticket delivered during one landing
Nasjonalitet mottakerkode/ Bokmål	Code and name of the nationality of the buyers.

Regmerke kvotefartøy	Registration of other ships taking part in the fishing.
Kvotetypekode/ Bokmål	Code and name for what type of quota the landing is registered as. (Regular, scientific, school etc.)
Artskode/ Bokmål	A code and name for which species the catch was a part of.
Redskapskode/ Bokmål	A code and name of what kind of fishing implement was used to make the catch
Sonekode/ Bokmål	Code and name for which economic zone the landing was taken from.
fangstfeltkode	Code for which catch area the majority of the landing was taken from.
Kysthavkode	Code describing whether or not the catch was made within 12 nautical miles of the coast. 8=inside, 12=outside
Hovedområdekode/ Bokmål	Code and name describing the main area of the catch. (vest-finmark, vestfjorden etc.)
Produkt-tilstands kode/Bokmål	Code for in what state the fish was landed (Live, whole, beheaded etc.)
Strørrelse-gruppering	Code that describes how size was measured. (induvidiuals per kg, mm, hectogram etc.)
Produktvekt	Net weight of landing.
rundvekt	Calculated weight of live fish. Made by taking weight of product and multiplying it with a set unit conversion factor.
Støttebeløp	Money received by in NOK by the fisherman in support from the state before value added-tax.
Lagsavgift	Fee paid by the fishermen to the salgslag they deliver their landings to
fangstverdi	Paid value for the fishermen, calculated as Amount to fisher+Støttebeløp+etterbetaling-Lagsavgift-Indratt fangstverdi.
sistefangstdato	The last date the fishing vessel took and a catch.
fangstdato	Date of the catch, with year, month and day in one string

Year	*Year of the catch*
Month	*Month of the catch*
Day	*Day of the catch*
Xkoord	*Longitude of the "fangstområde" where the landing was caught*
Ykoord	*Latitude of the "fangstområde" where the landing was caught*
Sground	*Which spawning ground (numbered 1-5) the landing was fished at.*

Covariates

Data was collected from the ICES 2018 AFWG report (ICES, 2018) which contained SSB, proportion mature at age, weight at age and individuals at age for the NEA haddock and allowed me to check for correlation between SSB(Ø. Langangen et al., 2018) and mean weight of spawners(Jørgensen, Dunlop, Opdal, & Fiksen, 2008) against mean latitude of spawners. This data as I described earlier in this thesis shows a steady increase in SSB from the start of the 21st century to 2010 when it starts massively increasing from 234,729 tons in 2009 over three years reaching a record high of 564,781 tons in 2013 before falling off again (figure 4).

To find the mean weight of spawners I used the information from ICES (ICES 2018, table 4.6,4.7,4.11 and 4.13) on weight at age(W), proportion of mature individuals at age(M) and abundance at age(N). I summed up W, N and M for each age (a) and divided by SSB for each year(y)

$$MW_y = \frac{\sum_a W_{ay} N_{ay} M_{ay}}{SSB_y}$$

I also use data from VNIRO (Russian Federal Research Institute Of Fisheries and Oceanography, formerly PINRO), this data contains average temperatures in the Barents sea based on values gathered from the KOLA section (Tereshchenko, 1996). This time series starts in 1951, but I only selected data from 1999 and onwards as I assumed that temperatures before this would have little impact on migrations from 2000-2017. I chose stations 3-7 and depths of 0-200(http://www.pinro.ru/labs/hid/kolsec22.php?lang=e ,01.11.2019). Data for all the months between two consecutive spawning seasons (August to February) was averaged as this is the period when I would expect the NEA haddock to be present in the Barents Sea (figure 6). A second average for entire year prior to spawning was also created (figure 7). This data was used to determine if temperature could be correlated to the mean latitude of spawners. Again to examine if there is a correlation with weighted mean latitude of spawning as shown in cod (Sundby & Nakken, 2008).

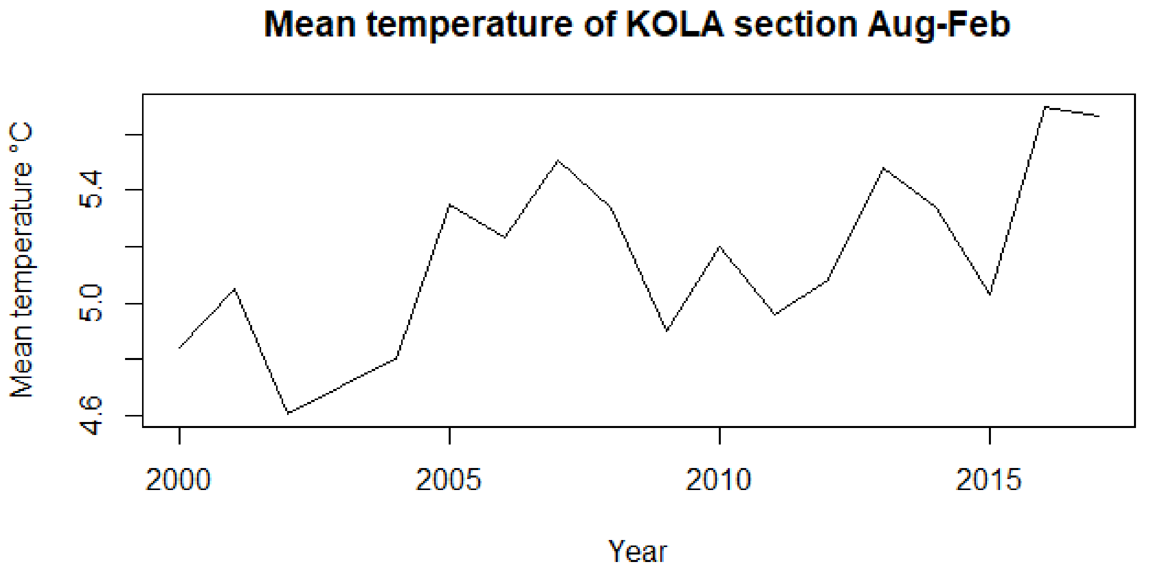

Figure 6 This figure shows the mean temperature of the KOLA section in the months between the end of the last spawning season and the start of the new spawning season.

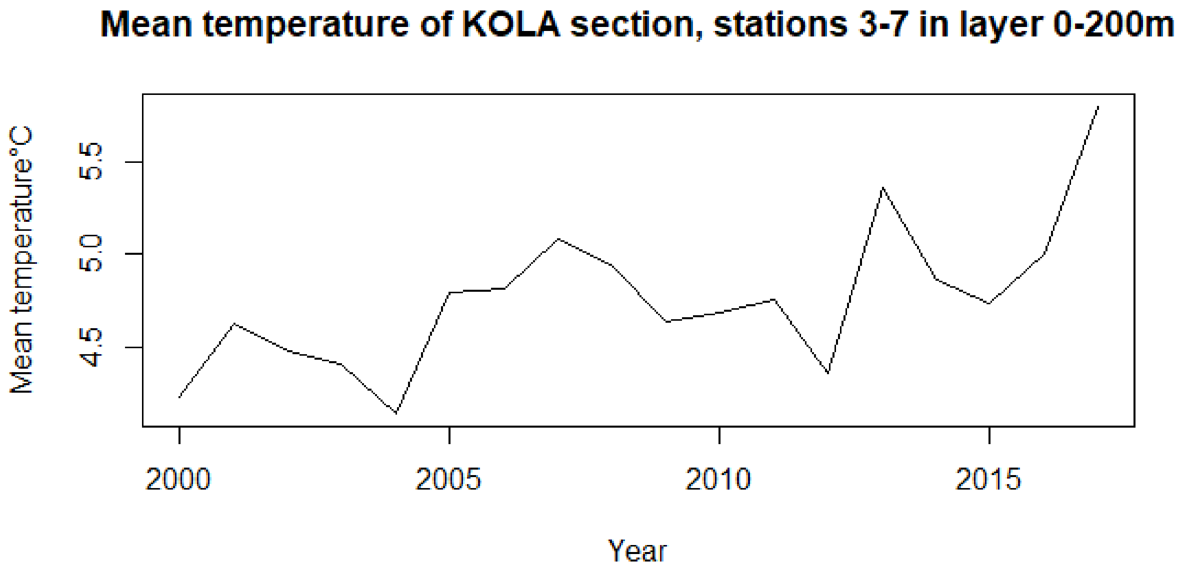

Figure 7 Average temperature from the KOLA meridian stations 3-7 0-200m in Celsius. These have been averaged out per year.

Data on the location of NEA haddock spawning grounds were also gathered from IMR and consisted of 5 spawning grounds along the Norwegian coast, with geographical extent from Møre in the south and to the shelf edge along the Barents Sea and Sørøya in the north(see figure 1). These were used to identify landings in the main data set that corresponded with the spawning grounds and allowed me to identify the landings of fish that are likely to be spawning by being present at the spawning areas at the spawning time.

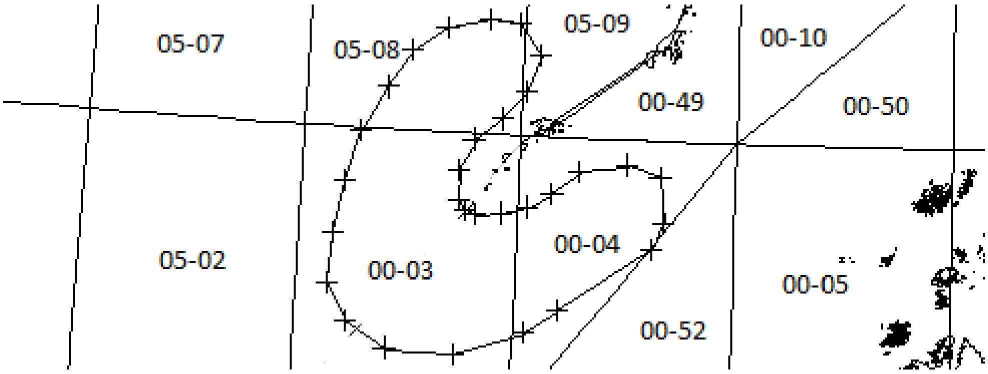

Figure 8 Spawning ground Nr 2 located of the southern tip of the Lofoten archipelago with the island of Røstlandet being in the middle of the horseshoe shaped spawning ground. The grid is the catch area grid which I used to identify which area corresponds to which code.

And finally, the last data set was taken from Directorate of fisheries map service(https://kart.fiskeridir.no/stat), and is a map showing the different "Fangstområder" or catch areas(see figure 8) and their corresponding codes. Having these two allowed me to manually match the catch data to a specific geographic location using the codes reported on the landing tickets.

Handling the data

I examined the files from the directorate of fisheries which were separated in individual years from 2000-2003 and 2014-2017 and two datafiles containing the years 2004-2008 and 2009-2013. Examining the datasets, I was able to identify species name in the form of a column named "artbokml" and the corresponding codes named "artskode". Product state codes was named "produktilstandskode" which describe in what state the landing was delivered in. Using these to quantify how many entries where associated with NEA haddock and what state they were in.

After having looked at these datasets by themselves I combined all my data into one dataset now containing 8'100'038 landings and removed all entries that were not related to NEA haddock based on the species code. This left me with 834’333 landings of NEA haddock. I made sure to check my data at every step by comparing it to the numbers from the individual datasets to make sure that no important data was lost. Using the date column in the dataset I created three new columns that had year, month and day of the month in separate columns to make it easier to handle. I further-more separated out the NEA haddock caught during the spawning season (March to June) based on information from IMR (https://www.imr.no/hi/temasider/arter/hyse/nordostarktisk-hyse) and the previously mentioned date columns. This meant I had 342’064 remaining landings. Using this procedure and eliminating data outside of the spawning period mean that I minimize the risk of analyzing non-spawning NEA haddock.

To find which area codes corresponded to which spawning grounds I drew a map of the Norwegian coast in R(R Core Team, 2018) using the map file given to me by kartverket. On top of this map I layered(Hijmans 2019,Bivand 2019) the spawning grounds from IMR and then used the map tool at the directorate of fisheries map tool (https://kart.fiskeridir.no/stat) to find the code for each of the areas. When I selected these areas, I included every area the spawning grounds touched even if they only overlapped in a relatively small area. Looking at figure 8 that would mean that I included numbers 00-03, 00-04 and 05-08 as they have a large degree of overlap with the outlined spawning ground but also included 05-09 despite the fact that the spawning ground only accounts for a small part of the total area. Using this information, I extracted only the entries that were caught at these areas. When these area codes are written down a “80” is often put in front of the code to let us know that this area is outside the 12 nautical mile economic zone, however not all the entries follow this naming convention meaning that some areas are described with just the zone one number like “404” *or* with the extra description “80404”, whenever this was the case I made sure to include both codes.

To find a latitude for the landings I reached out to fiskeridirektoratet (Directorate of fisheries) and they sent me a file with the center coordinates for all the areas which I entered in to my dataset as Xkoord and Ykoord longitude and latitude respectively.

All this made it possible to do an average latitude of spawners weighted by landed biomass or Weighted mean latitude of spawners (WLS) I did this by multiplying the round weight (W) per landing (l) with latitude(L) of landing and dividing the product by the total sum of round weight (TW) for that year(y).

$$WLS_y = \frac{\sum W_l \; x \; L_l}{\sum TW_y}$$

I now needed to make a dataset with mean latitude of landings (MLL) This was done by calculating the total number of landings per area separated by year. The total number of landings(N) per area(a) was multiplied by the latitude(L) of the area and divided by the sum of landings for that year(y).

$$MLL_y = \frac{\sum N_{ay} x L_{ay}}{\sum N_y}$$

Uncertainty

I employed a bootstrap analysis in order to estimate some of the uncertainty associated with these numbers. I resampled landings within years looking at the weighted average of spawners per year and 2,5% and 97,5% percentiles. I did this using the boot function in R(Ripley, 2019), I split the dataset down into individual subsets divided by year and created a command that would return the weighted average(based on the equation for WLS) for each of year and asked for the return of the average weighted mean as well as the 2,5% and 97,5% percentiles(figure 9, 10).

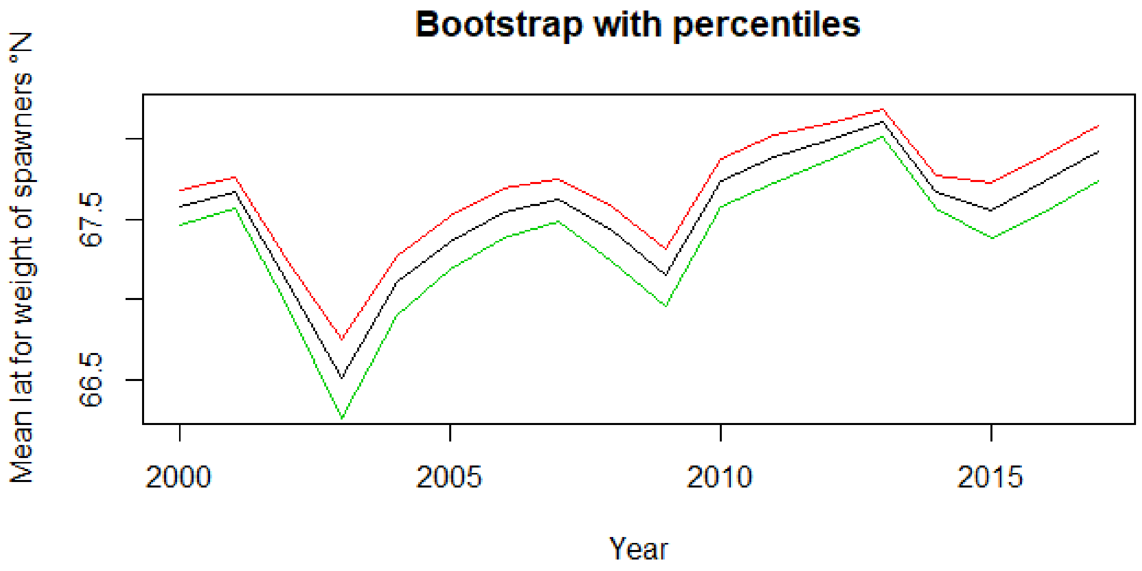

Figure 9 Bootstrap of the weighted mean biomass of spawners with the entire dataset included. This shows a weak trend towards a more northernly distribution. The red line shows the 97,5% percentile and the green line is the 2,5% percentile. The percentiles are well within the annual variation.

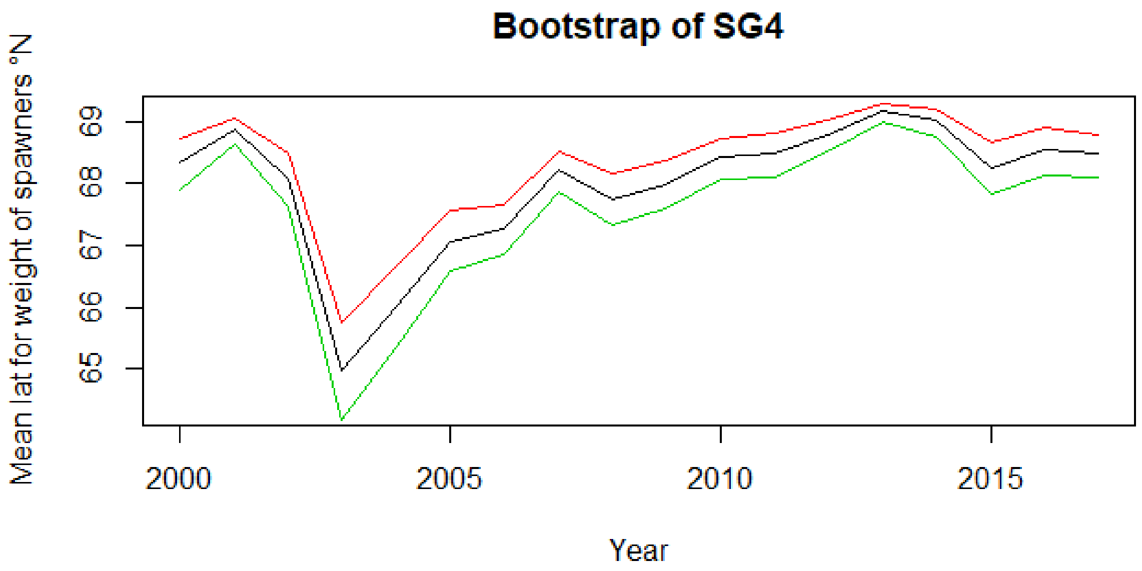

Figure 10 Bootstrap of spawning ground nr4.

Sensitivity

Having done all calculations on the entire data set I tried limiting the data to see if any trends would become more apparent on a selected subset of the data. In the second analysis I looked only at the major spawning ground, nr4. This is the largest spawning ground in area, the spawning ground with the largest north-south range and the spawning ground with the most weight landed with 1,255,672 tons landed between 2000 and 2017. An ongoing genetic analysis on haddock sampled from the spawning grounds indicates that NEA haddock migrating to spawn only migrate to spawning ground nr 4 and that the other spawning grounds are used by other populations (Paul Berg, October 2019, Pers. com).

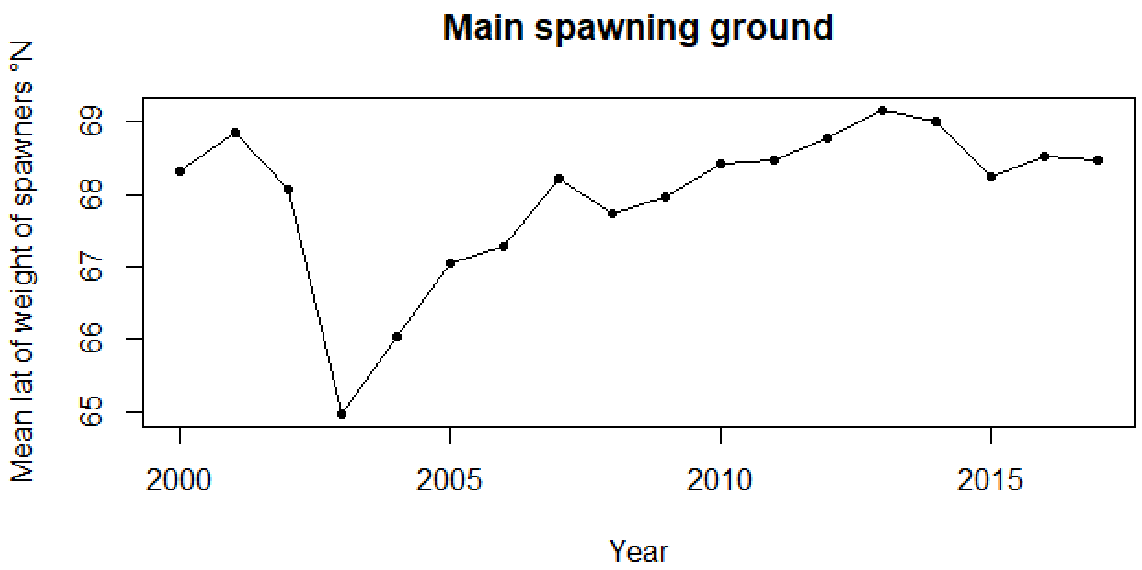

Figure 11 Mean weight of spawners for spawning ground nr4/main spawning ground

Results

The results of the bootstrap analysis indicated in both the complete dataset and the subset that the uncertainty was less than the interannual variation (See figure 9, 10). This indicates that the noise in the data set is not impacting the results significantly.

I used the lm function in R to create linear models for my parameters. I made several of these models for single explanatory valuables and multiple explanatory valuables in one model (see table 2). A stepwise model selection selected SSB and landings when TY was included but SSB and TS when TS was the temperature given.

My results show that there has been a northwards trend for mean latitude of spawners during the observed period for both data sets (figure 12,11). Varying between ~66.5º north to about ~68,2º north. In addition, I find some evidence for an association between SSB, temperature and more northernly mean latitude of spawning. As SSB increases the mean latitude of spawning is seen to increase (the correlation coefficient is 0,62, and 39,6% off the variation in weighted mean latitude of spawners can be explained by an increase in SSB, figure 13).

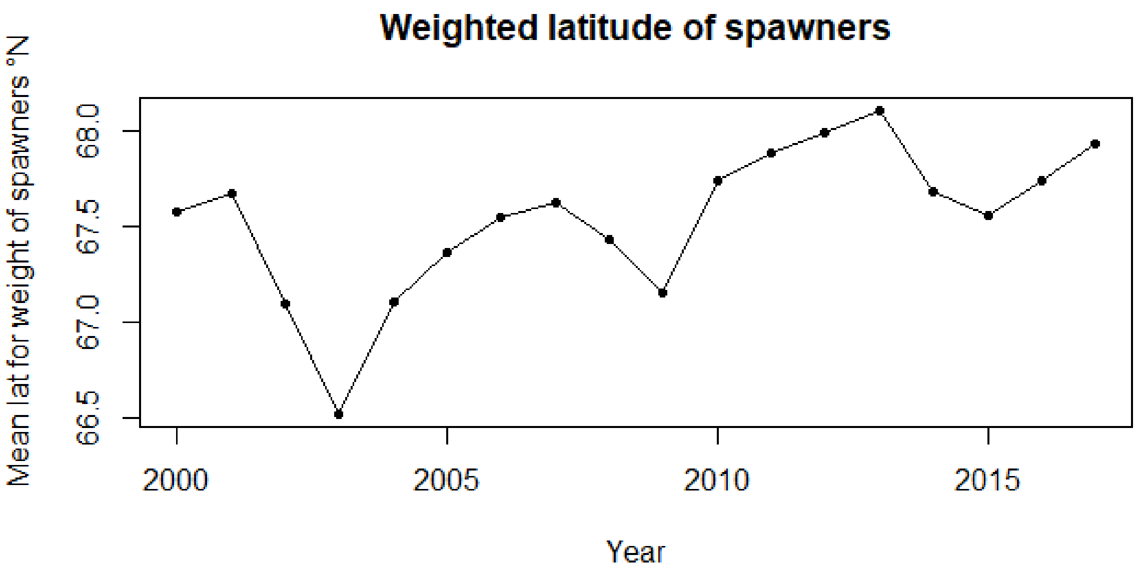

Figure 12 The weighted mean latitude of spawning from 2000 to 2017 for the whole population.

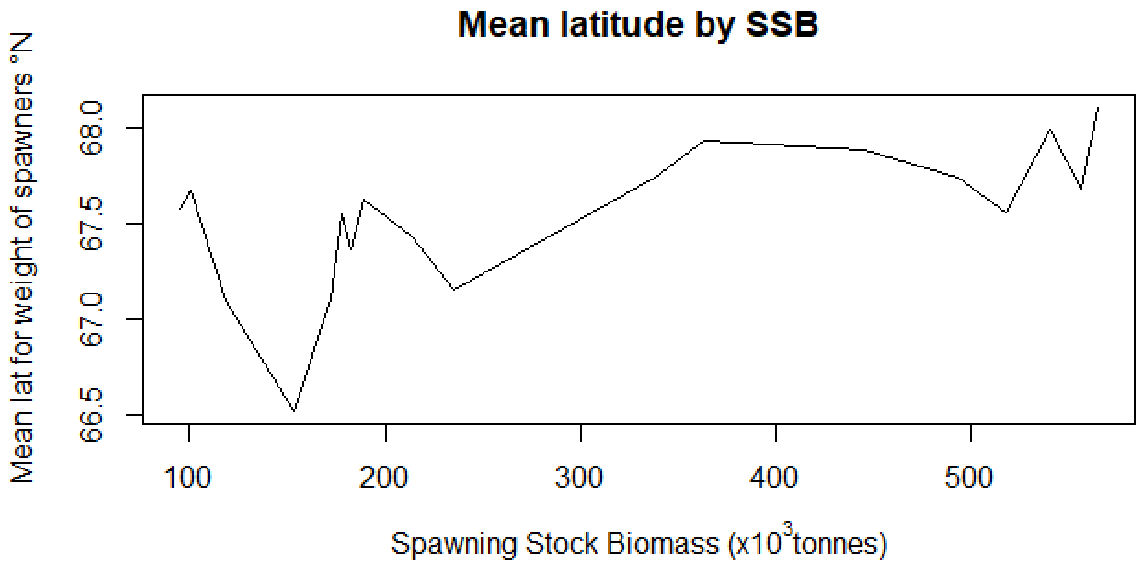

Figure 13 Graph showing the weighted latitude plotted against SSB. A general trend can be seen with increasing SSB correlating well with increased latitude of spawning.

I did the same calculations with the mean temperatures for whole years (TY) from VNIRO and found a weaker degree of correlation, 27% of the variation is explainable by the temperatures from the previous year. However, when I checked for correlation with the seasonal temperature (TS) I found that it was much higher at 39,7% of the variation explained by TS (figure 14).

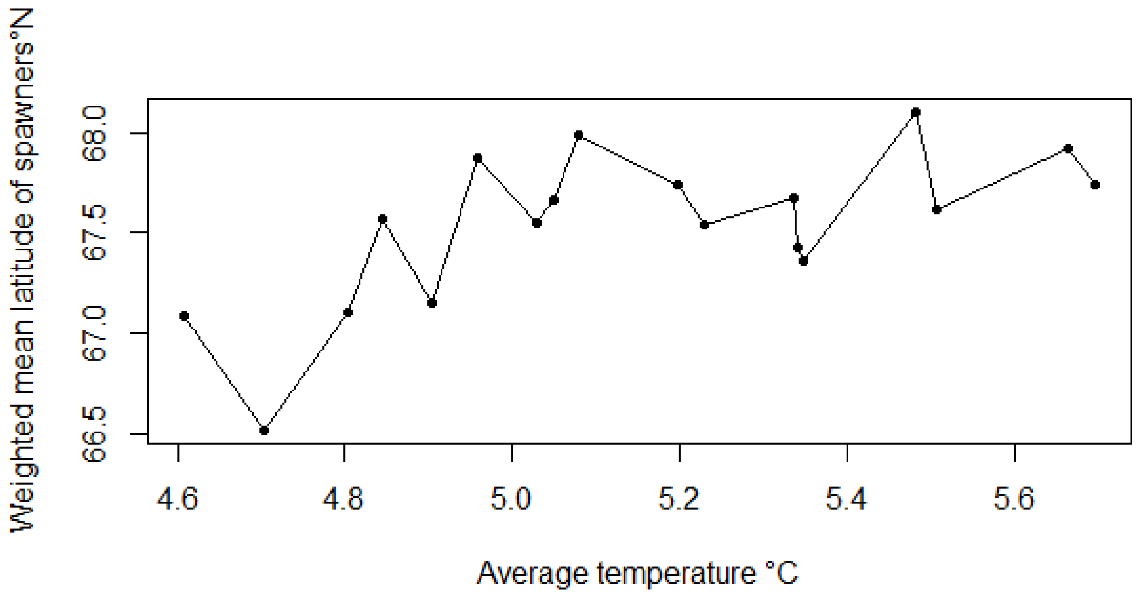

Figure 14 Weighted mean latitude of spawners by TS

Analysis of the main data set

I started the analysis with the complete data set, containing all the available data from all the spawning grounds. I performed several linear model tests on my explanatory values: SSB, mean weight of spawners (MWS) and the two temperature sets (TS, TY). I will call these parameters biological values because they impact the biology. In addition to these I added the fourth value, mean latitude of landings (MLL), which I have called a non-biological value to examine whether or not the variation observed was due to change in behavior of the fishermen rather than in behavior of the fish. When only the biological values and mean temperature=TY were included in a stepwise model selection, SSB was the only parameter considered to be significant with a Pr(>|t|) value of 0,0423 and p=0,02139. When mean latitude of landings (MLL) was introduced this became the best explanatory with a Pr(>|t|) value of 0,0455 however SSB was still selected but with a new Pr(>|t|) value of 0,0527 and p=0,002876(see table 2). When temperature=TY was swapped out for temperature=TS in a stepwise model selection analysis with all explanatory values the model returned only SSB and TS as statistically significant with Pr(>|t|) values of 0,0406 and 0,0397 respectively and p=0,002555. An AICc was run (Mazerolle 2019) (see fig 2) this was chosen because of the short time series. It also showed that the linear model with SSB and TS as explanatory variables was the model that fit the data best getting a better score than SSB, TS and MLL, but the difference was less than 2 and not statistically significant (table 2).

Table 2 AIC, describing the fit of my explanatory variables to the mean latitude of spawners for the entire R squared is given as Adjusted R squared to account for the different amounts of explanatory variables in the different models. TY=temperature averaged by year, TS=temperature averaged from summer to winter, MWS=mean weight of spawners, MLL=mean latitude of landings.

Entire data set	df	AICc	R^2
SSB+TY+MWS+MLL	6	20.64	0.43
SSB+TY+MWS	5	18.18	0.40
SSB+TS+MWS+MLL	6	19.60	0.46
SSB	**3**	**14.49**	**0.36**
TS	**3**	**14.44**	**0.36**
MWS	3	22.99	0
MLL	**3**	**14.18**	**0.37**
TY	3	17.81	0.03
SSB+TS	**4**	**12.61**	**0.49**
SSB+TS+MLL	5	15.04	0,5

Analysis for the datset containting only spawning ground 4

The analysis where preformed a second time, this time on only the largest spawning ground(“Nr.4”). A stepwise model selection on all explanatory variables did include TS and MLL but both well above the significance value and SSB remained the only significant explanatory value. An AICc test showed SSB alone to be the variable that best fit the data with no other variable having an AICc value within 2 points (see table 3).

Table 3, AIC table for the data set limited to spawning ground nr 4.

SPG4	df	AICc	R^2
SSB+TY+MWS+MLL	6	62,65	0,22
SSB+TY+MWS	5	59,96	0,16
SSB+TS+MWS+MLL	6	62,30	0,24
SSB	**3**	**54,07**	**0,24**
TS	3	56,24	0,14
tMWS	3	60,07	0
MLL	3	59,65	0
TY	3	56,71	0,12
SSB+TS	4	56,13	0,24

Discussion

An important part of the analysis is to understand how the results generated translates into impacts on the biology. The interannual variation of 1,5° of latitude translates into a distance of 167km. A 42cm long(the length at which many NEA haddock reach maturation, (Jakobsen & Ozhigin, 2011, p. 272) haddock has a maximum sustainable swim speed of ~5km/h (Breen, Dyson, O'Neill, Jones, & Haigh, 2004) that would mean that a NEA haddock would need to swim continuously in a straight line with no stops for ~33 hours to make up the distance. More southernly spawning has been associated with better growth of eggs and larvae(Martell, Kieffer, & Trippel, 2005; Opdal et al., 2008; G Ottersen & Loeng, 2000) meaning that a more northernly and subsequently colder waters might lead to smaller larva arriving at the feeding grounds (Opdal, Vikebø, & Fiksen, 2011). This could in turn have consequences for the future population as these smaller year classes might have higher mortality rates than year classes born on more southernly spawning grounds (Opdal et al., 2011).

The data set examined in this thesis may potentially be associated with uncertainties and problematic issues. One of the greatest challenges is that my data is mostly gathered from cod fisheries and haddock was to a large extent bycatch. One of the ways this might have had an impact is on the weighted mean latitude of spawners. When I put the weighted mean latitude of haddock landings and compare them with the same graph on cod (O. Langangen et al.,

2019) they show a high degree of similarity. This could suggest that the haddock landing data are strongly affected by the fishermen trying to target cod.

The landings are a result of fisherman effort, NEA haddock abundance and distribution. These factors are not wholly accounted for, thus there is some uncertainty associated with the results. By examining models with and without MLL and comparing them we can however say that it does not invalidate the findings presented in this thesis, as the signal from MLL is less than from the other explanatory values. The landing tickets themselves carry a lot of uncertainty, it is difficult to say what errors may have occurred upon writing them out at delivery or when they are typed in to the digital storage, mislabeling and other similar errors may also be prevalent. The data sets for each year are not equal according to the documentation of the landing ticket data, for instance landing tickets from Norges Råfisklag where not included before the end of 2002 and is not complete for the first years. From 2007 landings from Sunnmøre og Romsdals Fiskesalslag were included and some reports from 2005 and 2006 where included as well. Vest-Norges Fiskesalslag and Norges Sildesalgslag where entered into the dataset in 2011 with some documents from 2010 included. This could lead to bias for some years. However, when I examine the data set I cannot find this discrepancy and Norges råfisklag, which according to the document from IMR was not supposed to be present before 2002 is in fact present from 2000.

It is an open question whether the separate spawning grounds corresponds to the same population. The presence of different spawning grounds could suggest that there is not one population spawning in all of the spawning ground as suggested by IMR (see figure 1) but that we might see several sub populations that spawn close to each other without overlap in spawning grounds. This would suggest that working on the total dataset would not give an accurate representation of the trends of the Barents Sea population and it is for this reason that I chose to rerun some of the tests with limited spawning grounds to see if this would have a significant impact on the results. I did this by excluding all but one spawning ground. I wanted to choose one with a lot of catches, with a large north-south extent and that was close to the Barents Sea to make sure that my new analysis would be relevant for NEA haddock. This made the choice of spawning ground to focus on simple because only one fulfilled all the criteria. Spawning ground nr 4. This was as mentioned also potentially the only spawning ground with individuals from the Barents Sea (Paul Berg, October 2019, Pers. com). Therefore, I repeated my analysis with only this spawning ground to see if the results held up.

Previously mentioned sources of error are important and cannot be ignored. However, the data still has high value and can be used to say something about the subject at hand because of its massive size and the law of large numbers(Etemadi, 1981). Over 8 million datapoints in total, over eight hundred thousand landings of haddock and one hundred and forty-four thousand landings of just NEA haddock on spawning grounds in the spawning period. A coarse estimate of number of individuals of NEA haddock on the spawning ground in the spawning season that were caught and recorded in my data set based on total catch weight divided by mean weight of spawners indicate that these 140’000 landings contain over 580 million individuals! Being such a large dataset means that small variabilities should even each other out and making general trends distinguishable despite the noise.

A percentile analysis was also performed. Due to the limited spatial resolution in the dataset (most areas being 56km north to south) this did not yield useful information.

SSB was chosen as an explanatory variable because this has been shown to be correlated with feeding and spawning ground variation in haddock before(Ø. Langangen et al., 2018). The proposed mechanism for why an increase in SSB would lead to a more northernly spawning distribution(Marshall & Frank, 1995) is that a larger population would through competition (Geir Ottersen, Michalsen, & Nakken, 1998) force younger cod to areas with colder temperatures. This would force the NEA haddock population further north and east at the feeding grounds, as the southern border of the Barents Sea is surrounded by land and the western border is on the edge of the continental shelf. The above mentioned more northeasterly distribution would take individuals further away from the spawning grounds, meaning that if the population of spawning NEA haddock migrates around the same mean distance the more northeasterly individuals would end their migration at a more northernly location compared to their more southwesterly counterparts. This would potentially separate the spawning grounds by a distance equal to the distance between the two places of origin.

The reason I chose temperature as an explanatory variable is twofold. Firstly, much like with SSB, temperature could lead to a more northeasterly distribution in the Barents Sea. This could happen for at least two reasons. The first is that warmer waters would melt more of the sea ice that lines the north of the Barents sea opening up more of the ocean to primary production(Engelsen, Hegseth, Hop, Hansen, & Falk-Petersen, 2002) and make more prey available to the haddock in areas where prey abundance had previously been unfavorable. The second mechanism would be through growth. Warmer waters would promote more growth in

not just the NEA haddock but in its prey species as well(Helle & Pennington, 1999; Loeng & Drinkwater, 2007; Mueter et al., 2009). In Northwest arctic haddock, temperature has also been suggested as an important trigger for egg release(Page & Frank, 1989). This could mean that temperature could lead to a more northernly mean latitude of spawning. I selected two temperature means to examine. The first one was a mean of the entire calendar year before the spawning migration. This was to see if there was an overall trend with temperature, it could possibly have more effect on the ice extent and because it was the easiest way of getting a dataset to work with.
I also introduced a second data set which now contained only the temperatures in the months the NEA haddock would be present in the Barents Sea and not on the spawning grounds, this was divided into seasons i.e. summer and fall of 2002 combined with early winter of 2003. This was chosen because it would have the most direct impact on the NEA haddock as it is present in the Barents Sea and would therefore potentially be more biologically significant for the NEA haddock population. It should also be mentioned that there has been some evidence to suggest that there is a correlation between temperature and SSB in NEA haddock(Dalpadado et al., 2009).

Mean weight of spawners was chosen as an explanatory variable under the assumption that larger individuals would migrate further than smaller individuals, meaning a population consisting of larger individuals would migrate farther. The explanation for this difference in behavior is that larger NEA haddock potentially migrates due to its size, as a larger individual would be able to store more energy and therefore be able to swim farther as has been found in Cod(Jørgensen et al., 2008). It is also the closest variable to the demography variable that several other studies have found to be the best explanatory variable for mean latitude of spawning in NEA cod(Opdal, 2009; Opdal & Jørgensen, 2015).

Mean latitude of landings was chosen as an explanatory variable because it would indicate whether or not my data showed real trends and correlations caused by changing migratory behavior in NEA haddock or if it was caused by a change in the behavior of fishermen. The impact here would be seen as fishers alter their behavior to catch more fish(Pinsky & Fogarty, 2012)(specifically NEA cod), as this population also saw a variation in mean spawners latitude in the observed period(O. Langangen et al., 2019). If the observed change in latitude is closely correlated with landings, then it is more likely that the observed change is due to fisherman behavior and not changes in the actual mean latitude of spawners. On the other hand, if mean latitude of spawners is not closely correlated with mean landings then the probability that the observed changes are due to real changes in mean latitude of spawners increase as in this thesis.

Unfortunately, haddock is still an understudied species and papers on the species are rare compared with other more popular and economically important gadoid species like Cod. This means that there are a lot of unanswered questions when it comes to haddock. However, as cod and haddock are a part of the same family (Gadidae) they are potentially similar enough that findings on cod may be in some form applicable to Haddock. In NEA haddock and NEA cod they also share similar distributions, migration and spawning grounds. Considering this I have included many references to papers done on Cod with the assumption that some of these findings in these papers are also applicable to haddock.

Conclusion

The data set clearly indicates that there has been a shift in weighted mean latitude of spawners of northeast arctic haddock. Between 2000-2017 this northward shift resulted in a variation of 1,5 degrees or over 150 km between mean and max latitude of spawning. This has a biological significance and represents a change in distribution for NEA haddock that should be further investigated.

I have also found sufficient evidence to attribute parts of this shift in latitude to spawning stock biomass of NEA haddock implying that changes in population will have an effect on mean latitude of spawning. Temperature was also shown to have an effect on mean latitude of spawners and in a period in which temperature is predicted to rise understanding the effects of this on spawning migration will be crucial for population management. The results reported in this thesis is also supported by previously published studies(Ø. Langangen et al., 2018) giving another strong indication that the results presented in this thesis are a good representation of the NEA haddock population and the forces driving its spawning distribution.

Subjects for future study

This dataset has a lot of potential, there a vast amount of information that I have not had the time to examine. One of these are size of spawners vs latitude which could indicate if larger individuals migrate longer distances than smaller individuals. Using the data to examine temporal variation in spawning between years could also be very interesting, using temperature and mean weight of spawners one could determine if other aspects of the spawning migrations has changed.

Many of my parameters are indicators of other more direct effects, studies looking at production of prey in the Barents sea, population distribution and other effects of changing ecological states in the Barents Sea could give more definitive answers on what actually drives mean latitude of spawners in NEA haddock, but this would be time and resource consuming projects especially compared to the ease of access to the data in this thesis.

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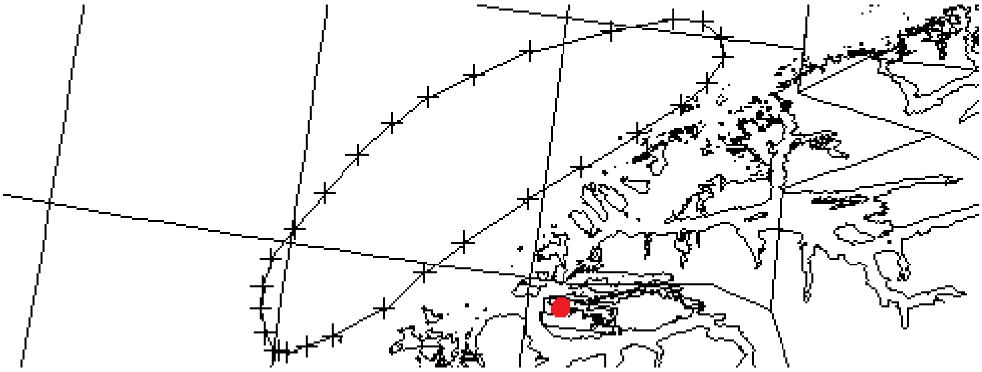
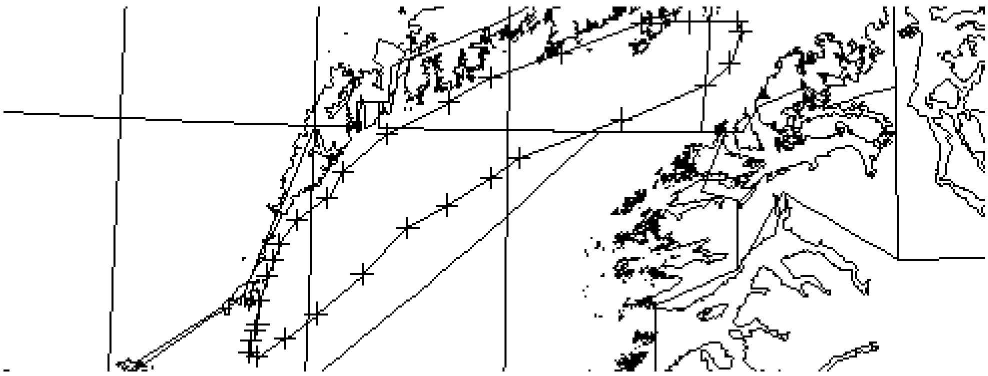
Appendix

Additional graphs and figures.

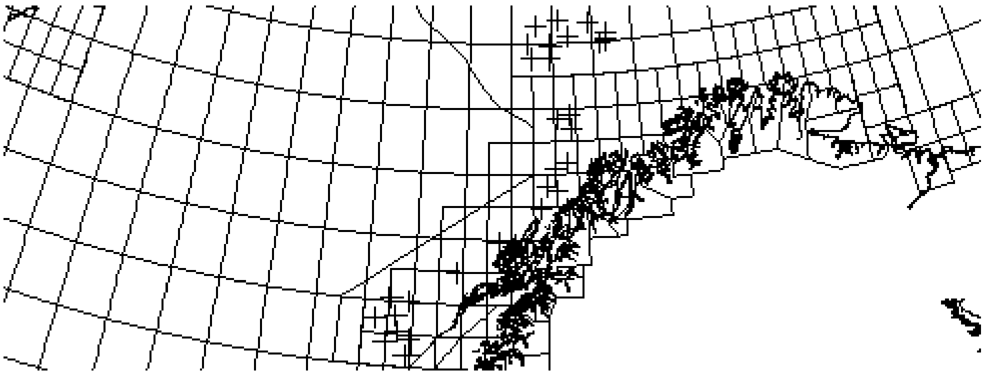
Maps of the remaining spawning grounds and the economic areas.



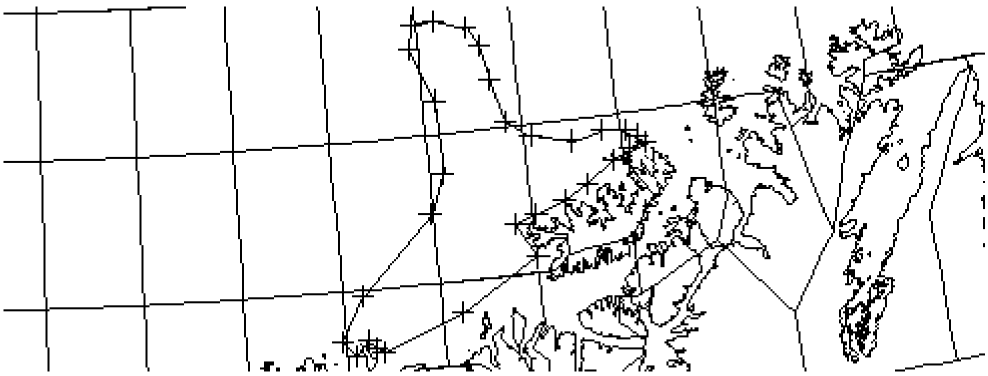
Spawning ground Nr1, located off the coast of Møre(Ålesund marked by a red dot), this is the southernmost spawning ground and is quite a long way away(around 440 km) from the rest. Due to this I have chosen to do some of the calculations without this spawning ground. The grid is the catch area grid.



Spawning ground nr 3, located to the south and east of Lofoten, sheltered by the archipelago. The grid is the catch area grid.



Spawning ground nr 4, by far the biggest spawning ground. it stretches along the shelf edge from the south of Lofoten all the way up to the edge of the Barents Sea. The grid is the catch area grid.



Spawning ground nr 5 and the most easterly of them all, may not be a permanent spawning ground. The grid is the catch area grid.

R script

Following is my script and a brief explanation on what it contains.

```
rm(list=ls())
## Reading all the data sets into R
## The datasets are devided into induvidual years with the exeptions being
##D04 containing 04-08 and D09 containing 09-13
setwd("~/Master/Oppgave/Original data")
D00<-read.table("Fangst_torsk_2000.csv", header=TRUE, sep=';')
D01<-read.table("Fangst_torsk_2001.csv", header=TRUE, sep=';')
D02<-read.table("Fangst_torsk_2002.csv", header=TRUE, sep=';')
D03<-read.table("Fangst_torsk_2003.csv", header=TRUE, sep=';')
D04<-read.table("Torsk2004-08-test.csv", header=TRUE, sep='\t')
D09<-read.table("Torsk2009-13-test.csv", header=TRUE, sep='\t')
D14<-read.table("Fangst_torsk_2014.csv", header=TRUE, sep=';')
D15<-read.table("Fangst_torsk_2015.csv", header=TRUE, sep=';')
D16<-read.table("Fangst_torsk_2016.csv", header=TRUE, sep=';')
D17<-read.table("Fangst_torsk_2017.csv", header=TRUE, sep=';')

##Combining some of the data sets
D0001 <- rbind(D00, D01)
D0203 <- rbind(D02, D03)
D1415 <- rbind(D14, D15)
```

```
##Removing rows that not present in all data sets
D17$omrdeiceskode <- NULL
D17$omrdeicesbokml <- NULL
D1415$omrdeiceskode <- NULL
D1415$omrdeicesbokml <- NULL
D16$omrdeiceskode <- NULL
D16$omrdeicesbokml <- NULL

##Combining my newly combine data sets, to get all singe year data sets in
##one data set
D0003 <- rbind(D0001, D0203)
D0003$omrdeiceskode <- NULL
D0003$omrdeicesbokml <- NULL
D1416 <- rbind(D1415, D16)
D1417 <- rbind(D1416, D17)
data.singleyears <- rbind(D0003, D1417)
## I now have one dataset containing each of the singe year datasets.

##Now i do the same for my larger data sets
D04$omrdeiceskode <- NULL
D04$omrdeicesbokml <- NULL
data.flerårig <- rbind(D04, D09)
data.flerårig$flerenvgmakrell <- NULL
data.flerårig$fleretorsk <- NULL
data.flerårig$anonFID <- NULL
##Increase the data limit to allwo me to make the entire data set
memory.size(15000)
data.tot <- rbind(data.singleyears, data.flerårig)
## Write it into a new csv file.
write.csv(data.tot, "TotalCatchAY.csv")
rm(list=ls())
setwd("C:/Users/Even/OneDrive/Data")
TotCatch <- read.table("TotalCatchAY.csv", header = TRUE, sep = ",")
##Total 8'100'038 rows
##Now i want to limit this data to include only north east arctic haddock
##Do this i need to examine how much was caught in artbokml and find the matching artkode
table(TotCatch$artbokml)
table(TotCatch$artkode)
##Using these two tables i find that the species codes that match potential
##nea haddock are 1027,102701 and 102703
OnlyHaddockL <- which(TotCatch$artkode==1027|TotCatch$artkode==102701|TotCatch$artkode==102703)
OnlyHaddock <- TotCatch[OnlyHaddockL,]
write.csv(OnlyHaddock, "TotalCatchHaddock.csv")

##Loading in the new dataset
TotHaddock <- read.table("TotalCatchHaddock.csv", header = TRUE, sep = ",")
##Removing collumns added by the "Write.csv" function
TotHaddock$X.1 <- NULL
TotHaddock$X <- NULL
##Transform the date into a format R recognises
TotHaddock$fangstdato=as.Date(TotHaddock$landingsdato,"%d.%m.%Y")
TotHaddock$fangstdato=as.Date(TotHaddock$landingsdato,"%d.%m.%Y")
##Create three new colums with day, month and year.
TotHaddock$year = format(TotHaddock$fangstdato,"%Y")
TotHaddock$month = as.numeric(format(TotHaddock$fangstdato, format = "%m"))
TotHaddock$day = as.numeric(format(TotHaddock$fangstdato, format = "%d"))
##I then used the day and moth columns do limit the data to the spawning months
months<- which(TotHaddock$month==3|TotHaddock$month==4|TotHaddock$month==5|TotHaddock$month==6|TotHaddock$month==7)
HaddockSpawnPer<-TotHaddock[months,]
##And write a new dataset.
write.csv(HaddockSpawnPer, "HaddockSpawnPer.csv")
rm(list=ls())

##Loading this new datset inn to limmit the data to the spawning grounds.
HaddockSpawnPer<-read.table("HaddockSpawnPer.csv", header = TRUE, sep = ",")
install.packages("maptools")
library("maptools")
library("raster")

##readShapePoly is no longer being uppdated and as of my last test of this
##data is unfunctional
##This dataset contains the map for the fishing areas
AreaGrid <- readShapePoly("layer_565.shp")
##This contains a map of the Norwegian coast
NorwegianCoast <- readShapePoly("norskekysten.shp", delete_null_obj=TRUE)
##spg= Spawning Grounds.
```

```
spg1=read.table("spg_1.txt")
spg2=read.table("spg_2.txt")
spg3=read.table('spg_3.txt')
spg4=read.table("spg_4.txt")
spg5=read.table("spg_5.txt")
## These datasets are in another format than my other maps so i have to convert them into UTM
hsp1 = SpatialPoints(cbind(spg1$V1, spg1$V2), proj4string=CRS("+proj=longlat"))
hsp1.UTM <- spTransform(hsp1, CRS("+init=epsg:32633"))
#2
hsp2 = SpatialPoints(cbind(spg2$V1, spg2$V2), proj4string=CRS("+proj=longlat"))
hsp2.UTM <- spTransform(hsp2, CRS("+init=epsg:32633"))
#3
hsp3 = SpatialPoints(cbind(spg3$V1, spg3$V2), proj4string=CRS("+proj=longlat"))
hsp3.UTM <- spTransform(hsp3, CRS("+init=epsg:32633"))
#4
hsp4 = SpatialPoints(cbind(spg4$V1, spg4$V2), proj4string=CRS("+proj=longlat"))
hsp4.UTM <- spTransform(hsp4, CRS("+init=epsg:32633"))
#5
hsp5 = SpatialPoints(cbind(spg5$V1, spg5$V2), proj4string=CRS("+proj=longlat"))
hsp5.UTM <- spTransform(hsp5, CRS("+init=epsg:32633"))

##Now i plot the into a the map of the norwegian coast for refrence and
##and project the area grid on top.
plot(hsp1.UTM)
lines(AreaGrid)
lines(NorwegianCoast)
##I then compare this map with the directory of fisheries map of are codes and find the area
##Areacodes that overlap my spawning grounds. And these where the codes i found
##07-31,07-06,07-33,07-05,07-19
##Repeat for all 5 spawning grounds
##Spawning ground nr 2
plot(hsp2.UTM)
lines(AreaGrid)
lines(NorwegianCoast)
##05-08,00-03,00-04,05-09
##Spawning ground nr 3
plot(hsp3.UTM)
lines(AreaGrid)
lines(NorwegianCoast)
##00-44,00-46,00-48,00-10,00-47,00-49
#Spawning ground nr 4
plot(hsp4.UTM)
lines(AreaGrid)
lines(NorwegianCoast)
#05-02,05-01,05-07,05-06,05-12,05-13,05-14,05-18,05-19,05-20,05-22,
#05-23,05-24,05-25,05-28,05-29,05-30,05-34,05-35,04-06,04-07,04-17,
#04-18,12-01,12-03,12-07,12-08,12-09
#Spawning ground nr 5
plot(hsp5.UTM)
lines(AreaGrid)
lines(NorwegianCoast)
##04-03,04-04,04-10,04-11,04-12,04-13,04-22

## I then compile this into one list(spawning ground 4 is divided into three)
HOSG <-
which(HaddockSpawnPer$fangstfeltkode==80731|HaddockSpawnPer$fangstfeltkode==731|HaddockSpawnPer$fangstfeltkode==80706|Had
dockSpawnPer$fangstfeltkode==706|HaddockSpawnPer$fangstfeltkode==80733|HaddockSpawnPer$fangstfeltkode==80705|HaddockSpaw
nPer$fangstfeltkode==705|HaddockSpawnPer$fangstfeltkode==80719|HaddockSpawnPer$fangstfeltkode==719|

HaddockSpawnPer$fangstfeltkode==80508|HaddockSpawnPer$fangstfeltkode==508|HaddockSpawnPer$fangstfeltkode==80003|HaddockS
pawnPer$fangstfeltkode==3|HaddockSpawnPer$fangstfeltkode==80004|HaddockSpawnPer$fangstfeltkode==80509|HaddockSpawnPer$fan
gstfeltkode==509|

HaddockSpawnPer$fangstfeltkode==80044|HaddockSpawnPer$fangstfeltkode==80046|HaddockSpawnPer$fangstfeltkode==80048|Haddoc
kSpawnPer$fangstfeltkode==80010|HaddockSpawnPer$fangstfeltkode==80047|HaddockSpawnPer$fangstfeltkode==80049|

HaddockSpawnPer$fangstfeltkode==502|HaddockSpawnPer$fangstfeltkode==501|HaddockSpawnPer$fangstfeltkode==507|HaddockSpawn
Per$fangstfeltkode==506|HaddockSpawnPer$fangstfeltkode==512|HaddockSpawnPer$fangstfeltkode==513|HaddockSpawnPer$fangstfeltk
ode==80514|HaddockSpawnPer$fangstfeltkode==514|HaddockSpawnPer$fangstfeltkode==518|HaddockSpawnPer$fangstfeltkode==80519|
HaddockSpawnPer$fangstfeltkode==519|HaddockSpawnPer$fangstfeltkode==80520|HaddockSpawnPer$fangstfeltkode==520|

HaddockSpawnPer$fangstfeltkode==522|HaddockSpawnPer$fangstfeltkode==80523|HaddockSpawnPer$fangstfeltkode==523|HaddockSpa
wnPer$fangstfeltkode==80524|HaddockSpawnPer$fangstfeltkode==524|HaddockSpawnPer$fangstfeltkode==80525|HaddockSpawnPer$fan
gstfeltkode==528|HaddockSpawnPer$fangstfeltkode==80528|HaddockSpawnPer$fangstfeltkode==80529|HaddockSpawnPer$fangstfeltkode
==529|HaddockSpawnPer$fangstfeltkode==80530|HaddockSpawnPer$fangstfeltkode==530|HaddockSpawnPer$fangstfeltkode==534|Haddo
ckSpawnPer$fangstfeltkode==80535|HaddockSpawnPer$fangstfeltkode==535|
```

```
HaddockSpawnPer$fangstfeltkode==406|HaddockSpawnPer$fangstfeltkode==407|HaddockSpawnPer$fangstfeltkode==417|HaddockSpawnPer$fangstfeltkode==418|HaddockSpawnPer$fangstfeltkode==1201|HaddockSpawnPer$fangstfeltkode==1203|HaddockSpawnPer$fangstfeltkode==1207|HaddockSpawnPer$fangstfeltkode==1208|HaddockSpawnPer$fangstfeltkode==1209|

HaddockSpawnPer$fangstfeltkode==80403|HaddockSpawnPer$fangstfeltkode==80404|HaddockSpawnPer$fangstfeltkode==80410|HaddockSpawnPer$fangstfeltkode==410|HaddockSpawnPer$fangstfeltkode==80411|HaddockSpawnPer$fangstfeltkode==411|HaddockSpawnPer$fangstfeltkode==80412|HaddockSpawnPer$fangstfeltkode==412|HaddockSpawnPer$fangstfeltkode==80413|HaddockSpawnPer$fangstfeltkode==422
)
HaddockOnSG <- HaddockSpawnPer[HOSG,]
write.csv(HaddockOnSG, "HaddockOnSG.csv")
rm(list=ls())

HaddockOnSG <- read.table("HaddockOnSG.csv", header = TRUE, sep = ",")
HaddockOnSG$X.1<-NULL
HaddockOnSG$X<-NULL
#I now create two new colums in wich i will fill inn the coordinates of the area grid
HaddockOnSG$ykoord<-NA
HaddockOnSG$xkoord<-NA

## Readig in the dataset containting the area coordinates
AreaCodes <- read.table("statistikk_lokasjoner_midtpunkt.csv", header = TRUE, sep = ",")
##Ordering the dataset to more easily find the areas i am looking for
AreaCodes[order(AreaCodes$lokref),]
## That lets me find these coordinates
##Again i divide by spawning grounds to more easily detect errors
##Spawning ground nr 1
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80705),]$xkoord<-"4.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80705),]$ykoord<-"62.25000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==705),]$xkoord<-"4.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==705),]$ykoord<-"62.25000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80706),]$xkoord<-"5.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80706),]$ykoord<-"62.75000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==706),]$xkoord<-"5.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==706),]$ykoord<-"62.75000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80719),]$xkoord<-"6.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80719),]$ykoord<-"63.25000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==719),]$xkoord<-"6.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==719),]$ykoord<-"63.25000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80731),]$xkoord<-"6.562397"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80731),]$ykoord<-"62.76533"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==731),]$xkoord<-"6.562397"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==731),]$ykoord<-"62.76533"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80733),]$xkoord<-"5.597522"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80733),]$ykoord<-"62.21811"

##Spawning ground nr 2
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80003),]$xkoord<-"11.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80003),]$ykoord<-"67.25000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==3),]$xkoord<-"11.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==3),]$ykoord<-"67.25000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80004),]$xkoord<-"12.333333"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80004),]$ykoord<-"67.33333"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80508),]$xkoord<-"11.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80508),]$ykoord<-"67.75000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==508),]$xkoord<-"11.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==508),]$ykoord<-"67.75000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80509),]$xkoord<-"12.386054"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80509),]$ykoord<-"67.80045"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==509),]$xkoord<-"12.386054"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==509),]$ykoord<-"67.80045"

##Spawning ground nr 3
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80010),]$xkoord<-"13.414230"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80010),]$ykoord<-"67.82298"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80044),]$xkoord<-"15.611450"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80044),]$ykoord<-"68.27428"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80046),]$xkoord<-"14.565795"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80046),]$ykoord<-"68.15924"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80047),]$xkoord<-"14.155556"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80047),]$ykoord<-"67.94444"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80048),]$xkoord<-"13.713852"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80048),]$ykoord<-"68.08439"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80049),]$xkoord<-"12.742754"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80049),]$ykoord<-"67.64251"
```

```
##Spawning gorund 4 is divided into 3 parts as it is the biggest
##The three parts are s,m and n for south, middle and north
##Spawning ground nr 4s
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==501),]$xkoord<-"9.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==501),]$ykoord<-"67.25000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==502),]$xkoord<-"10.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==502),]$ykoord<-"67.25000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==506),]$xkoord<-"9.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==506),]$ykoord<-"67.75000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==507),]$xkoord<-"10.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==507),]$ykoord<-"67.75000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==512),]$xkoord<-"10.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==512),]$ykoord<-"68.25000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==513),]$xkoord<-"11.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==513),]$ykoord<-"68.25000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80514),]$xkoord<-"12.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80514),]$ykoord<-"68.25000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==514),]$xkoord<-"12.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==514),]$ykoord<-"68.25000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==518),]$xkoord<-"12.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==518),]$ykoord<-"68.75000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80519),]$xkoord<-"13.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80519),]$ykoord<-"68.75000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==519),]$xkoord<-"13.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==519),]$ykoord<-"68.75000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80520),]$xkoord<-"14.564010"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80520),]$ykoord<-"68.75918"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==520),]$xkoord<-"14.564010"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==520),]$ykoord<-"68.75918"
##Spawning ground nr 4m
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==522),]$xkoord<-"13.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==522),]$ykoord<-"69.25000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80523),]$xkoord<-"14.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80523),]$ykoord<-"69.25000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==523),]$xkoord<-"14.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==523),]$ykoord<-"69.25000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80524),]$xkoord<-"15.473741"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80524),]$ykoord<-"69.26583"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==524),]$xkoord<-"15.473741"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==524),]$ykoord<-"69.26583"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80525),]$xkoord<-"16.616342"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80525),]$ykoord<-"69.26902"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80528),]$xkoord<-"15.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80528),]$ykoord<-"69.75000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==528),]$xkoord<-"15.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==528),]$ykoord<-"69.75000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80529),]$xkoord<-"16.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80529),]$ykoord<-"69.75000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==529),]$xkoord<-"16.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==529),]$ykoord<-"69.75000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80530),]$xkoord<-"17.491000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80530),]$ykoord<-"69.74206"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==530),]$xkoord<-"17.491000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==530),]$ykoord<-"69.74206"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==534),]$xkoord<-"16.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==534),]$ykoord<-"70.25000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80535),]$xkoord<-"17.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80535),]$ykoord<-"70.25000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==535),]$xkoord<-"17.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==535),]$ykoord<-"70.25000"
##Spawning ground nr 4n
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==406),]$xkoord<-"16.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==406),]$ykoord<-"70.75000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==407),]$xkoord<-"17.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==407),]$ykoord<-"70.75000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==417),]$xkoord<-"16.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==417),]$ykoord<-"71.25000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==418),]$xkoord<-"17.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==418),]$ykoord<-"71.25000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==1201),]$xkoord<-"16.000000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==1201),]$ykoord<-"71.75000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==1203),]$xkoord<-"20.000000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==1203),]$ykoord<-"71.75000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==1207),]$xkoord<-"16.000000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==1207),]$ykoord<-"72.50000"
```

```
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==1208),]$xkoord<-"16.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==1208),]$ykoord<-"72.50000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==1209),]$xkoord<-"17.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==1209),]$ykoord<-"72.50000"
##Spawning ground nr 5
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80403),]$xkoord<-"20.451301"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80403),]$ykoord<-"70.26784"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80404),]$xkoord<-"21.524619"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80404),]$ykoord<-"70.33232"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80410),]$xkoord<-"20.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80410),]$ykoord<-"70.75000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==410),]$xkoord<-"20.500000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==410),]$ykoord<-"70.75000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80411),]$xkoord<-"21.548272"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80411),]$ykoord<-"70.73675"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==411),]$xkoord<-"21.548272"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==411),]$ykoord<-"70.73675"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80412),]$xkoord<-"22.558333"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80412),]$ykoord<-"70.78740"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==412),]$xkoord<-"22.558333"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==412),]$ykoord<-"70.78740"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80413),]$xkoord<-"23.489812"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==80413),]$ykoord<-"70.73790"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==422),]$xkoord<-"16.000000"
HaddockOnSG[which(HaddockOnSG$fangstfeltkode==422),]$ykoord<-"72.50000"

##Write a new data set, to include coordinates
write.csv(HaddockOnSG, "MainDataSet.csv")
rm(list=ls())
setwd("C:/Users/Even/OneDrive/Data")
##Now i will add spawning grounds to my data set, once again spg 4 is divided into 3 parts.
MainDataSet<-read.table("MainDataSet.csv", header = TRUE, sep = ",")
MainDataSet$Sground<-NA
MainDataSet[which(MainDataSet$fangstfeltkode==80731|MainDataSet$fangstfeltkode==731|MainDataSet$fangstfeltkode==80706|MainDataSet$fangstfeltkode==706|MainDataSet$fangstfeltkode==80733|MainDataSet$fangstfeltkode==80705|MainDataSet$fangstfeltkode==705|MainDataSet$fangstfeltkode==80719|MainDataSet$fangstfeltkode==719),]$Sground<-"1"
#Gytegrunn nr2
MainDataSet[which(MainDataSet$fangstfeltkode==80508|MainDataSet$fangstfeltkode==508|MainDataSet$fangstfeltkode==80003|MainDataSet$fangstfeltkode==3|MainDataSet$fangstfeltkode==80004|MainDataSet$fangstfeltkode==80509|MainDataSet$fangstfeltkode==509),]$Sground<-"2"
##Gytegrunn nr3
MainDataSet[which(MainDataSet$fangstfeltkode==80044|MainDataSet$fangstfeltkode==80046|MainDataSet$fangstfeltkode==80048|MainDataSet$fangstfeltkode==80010|MainDataSet$fangstfeltkode==80047|MainDataSet$fangstfeltkode==80049),]$Sground<-"3"
##Gytegrunn nr4s
MainDataSet[which(MainDataSet$fangstfeltkode==502|MainDataSet$fangstfeltkode==501|MainDataSet$fangstfeltkode==507|MainDataSet$fangstfeltkode==506|MainDataSet$fangstfeltkode==512|MainDataSet$fangstfeltkode==513|MainDataSet$fangstfeltkode==80514|MainDataSet$fangstfeltkode==514|MainDataSet$fangstfeltkode==518|MainDataSet$fangstfeltkode==80519|MainDataSet$fangstfeltkode==519|MainDataSet$fangstfeltkode==80520|MainDataSet$fangstfeltkode==520),]$Sground<-"4"
##Gytegrunn nr4m
MainDataSet[which(MainDataSet$fangstfeltkode==522|MainDataSet$fangstfeltkode==80523|MainDataSet$fangstfeltkode==523|MainDataSet$fangstfeltkode==80524|MainDataSet$fangstfeltkode==524|MainDataSet$fangstfeltkode==80525|MainDataSet$fangstfeltkode==528|MainDataSet$fangstfeltkode==80528|MainDataSet$fangstfeltkode==80529|MainDataSet$fangstfeltkode==529|MainDataSet$fangstfeltkode==80530|MainDataSet$fangstfeltkode==530|MainDataSet$fangstfeltkode==534|MainDataSet$fangstfeltkode==80535|MainDataSet$fangstfeltkode==535),]$Sground<-"4"
##Gytegrunn nr4n
MainDataSet[which(MainDataSet$fangstfeltkode==406|MainDataSet$fangstfeltkode==407|MainDataSet$fangstfeltkode==417|MainDataSet$fangstfeltkode==418|MainDataSet$fangstfeltkode==1201|MainDataSet$fangstfeltkode==1203|MainDataSet$fangstfeltkode==1207|MainDataSet$fangstfeltkode==1208|MainDataSet$fangstfeltkode==1209),]$Sground<-"4"
##Gytegrunn nr5
MainDataSet[which(MainDataSet$fangstfeltkode==80403|MainDataSet$fangstfeltkode==80404|MainDataSet$fangstfeltkode==80410|MainDataSet$fangstfeltkode==410|MainDataSet$fangstfeltkode==80411|MainDataSet$fangstfeltkode==411|MainDataSet$fangstfeltkode==80412|MainDataSet$fangstfeltkode==412|MainDataSet$fangstfeltkode==80413|MainDataSet$fangstfeltkode==422),]$Sground<-"5"

##And now i write the main data set.
write.csv(MainDataSet, "MainDataSet.csv")
rm(list=ls())
setwd("C:/Users/Even/OneDrive/Data")
##Read inn the new dataset and remove unnessesary columns
MainDataSet<-read.table("MainDataSet.csv", header = TRUE, sep = ",", dec = ".")
MainDataSet$X <- NULL
MainDataSet$X.1<- NULL
##Converting rundvekt to a numeric
##Make a new column containing wheight times latitude
MainDataSet$rundvekt<-as.numeric(MainDataSet$rundvekt)
MainDataSet$WL <- MainDataSet$rundvekt * MainDataSet$ykoord
```

```
## I now make a value for the wheight times latitude and the
##Dividing that by the wheight
##2000
vektlat2000<-sum(MainDataSet[MainDataSet$year==2000,]$WL,na.rm=TRUE)
vektet2000<-vektlat2000/sum(MainDataSet[MainDataSet$year==2000,]$rundvekt,na.rm=TRUE)
##2001
vektlat2001<-sum(MainDataSet[MainDataSet$year==2001,]$WL,na.rm=TRUE)
vektet2001<-vektlat2001/sum(MainDataSet[MainDataSet$year==2001,]$rundvekt,na.rm=TRUE)
##2002
vektlat2002<-sum(MainDataSet[MainDataSet$year==2002,]$WL,na.rm=TRUE)
vektet2002<-vektlat2002/sum(MainDataSet[MainDataSet$year==2002,]$rundvekt,na.rm=TRUE)
##2003
vektlat2003<-sum(MainDataSet[MainDataSet$year==2003,]$WL,na.rm=TRUE)
vektet2003<-vektlat2003/sum(MainDataSet[MainDataSet$year==2003,]$rundvekt,na.rm=TRUE)
##2004
vektlat2004<-sum(MainDataSet[MainDataSet$year==2004,]$WL,na.rm=TRUE)
vektet2004<-vektlat2004/sum(MainDataSet[MainDataSet$year==2004,]$rundvekt,na.rm=TRUE)
##2005
vektlat2005<-sum(MainDataSet[MainDataSet$year==2005,]$WL,na.rm=TRUE)
vektet2005<-vektlat2005/sum(MainDataSet[MainDataSet$year==2005,]$rundvekt,na.rm=TRUE)
##2006
vektlat2006<-sum(MainDataSet[MainDataSet$year==2006,]$WL,na.rm=TRUE)
vektet2006<-vektlat2006/sum(MainDataSet[MainDataSet$year==2006,]$rundvekt,na.rm=TRUE)
##2007
vektlat2007<-sum(MainDataSet[MainDataSet$year==2007,]$WL,na.rm=TRUE)
vektet2007<-vektlat2007/sum(MainDataSet[MainDataSet$year==2007,]$rundvekt,na.rm=TRUE)
##2008
vektlat2008<-sum(MainDataSet[MainDataSet$year==2008,]$WL,na.rm=TRUE)
vektet2008<-vektlat2008/sum(MainDataSet[MainDataSet$year==2008,]$rundvekt,na.rm=TRUE)
##2009
vektlat2009<-sum(MainDataSet[MainDataSet$year==2009,]$WL,na.rm=TRUE)
vektet2009<-vektlat2009/sum(MainDataSet[MainDataSet$year==2009,]$rundvekt,na.rm=TRUE)
##2010
vektlat2010<-sum(MainDataSet[MainDataSet$year==2010,]$WL,na.rm=TRUE)
vektet2010<-vektlat2010/sum(MainDataSet[MainDataSet$year==2010,]$rundvekt,na.rm=TRUE)
#2011
vektlat2011<-sum(MainDataSet[MainDataSet$year==2011,]$WL,na.rm=TRUE)
vektet2011<-vektlat2011/sum(MainDataSet[MainDataSet$year==2011,]$rundvekt,na.rm=TRUE)
##2012
vektlat2012<-sum(MainDataSet[MainDataSet$year==2012,]$WL,na.rm=TRUE)
vektet2012<-vektlat2012/sum(MainDataSet[MainDataSet$year==2012,]$rundvekt,na.rm=TRUE)
##2013
vektlat2013<-sum(MainDataSet[MainDataSet$year==2013,]$WL,na.rm=TRUE)
vektet2013<-vektlat2013/sum(MainDataSet[MainDataSet$year==2013,]$rundvekt,na.rm=TRUE)
##2014
vektlat2014<-sum(MainDataSet[MainDataSet$year==2014,]$WL,na.rm=TRUE)
vektet2014<-vektlat2014/sum(MainDataSet[MainDataSet$year==2014,]$rundvekt,na.rm=TRUE)
#2015
vektlat2015<-sum(MainDataSet[MainDataSet$year==2015,]$WL,na.rm=TRUE)
vektet2015<-vektlat2015/sum(MainDataSet[MainDataSet$year==2015,]$rundvekt,na.rm=TRUE)
##2016
vektlat2016<-sum(MainDataSet[MainDataSet$year==2016,]$WL,na.rm=TRUE)
vektet2016<-vektlat2016/sum(MainDataSet[MainDataSet$year==2016,]$rundvekt,na.rm=TRUE)
##2017
vektlat2017<-sum(MainDataSet[MainDataSet$year==2017,]$WL,na.rm=TRUE)
vektet2017<-vektlat2017/sum(MainDataSet[MainDataSet$year==2017,]$rundvekt,na.rm=TRUE)
##I gather the mean latitude of spawners into one dataset
##Create a data set for year and merge the two
lat <-
c(vektet2000,vektet2001,vektet2002,vektet2003,vektet2004,vektet2005,vektet2006,vektet2007,vektet2008,vektet2009,vektet2010,vektet201
1,vektet2012,vektet2013,vektet2014,vektet2015,vektet2016,vektet2017)
Year <- c(2000,2001,2002,2003,2004,2005,2006,2007,2008,2009,2010,2011,2012,2013,2014,2015,2016,2017)
vd<- data.frame(lat, Year)
write.csv(vd, "WheightedLatYear.csv")
WheigtedLat <- read.table("WheightedLatYear.csv", header = TRUE, sep = ",", dec = ".")
plot(WheigtedLat$Year,WheigtedLat$lat, type = "o", xlab = "Year", ylab = "Weighted Latitude °N", main = "Weighted latitude of
spawners", pch = 20)

##Now that i have a wheighted mean latitude for 2000-2017 i can check it agains
##Temperature at PINRO and SSB
WheigtedLat <- read.table("WheightedLatYear.csv", header = TRUE, sep = ",", dec = ".")

##First i calculate the mean for the entire year before spawning
pinro<-read.table("Pinro.csv", header = TRUE, fill = TRUE)
pinro$Year <- NULL
##Remove earlier years
```

```
pinro<-pinro[-c(19), ]
##Calculate the means for each year
pinroMean<-rowMeans(pinro, na.rm = TRUE)
##Plot it to get a viusal
plot(Year, pinroMean, type = "l", xlab = "Year", ylab ="Mean temperature°C", main = "Mean temperature of KOLA section, stations 3-7 in
layer 0-200m")
##Checking the correlation
cor(pinroMean,WheigtedLat$lat)
#The correlation value is 0.523214 meaning that 27% of  the variatio can be descrbed by the temp
orderPINRO<-order(pinroMean)
plot(pinroMean[orderPINRO],WheigtedLat$lat[orderPINRO], type = "l",main = "Mean latitude by temperature", xlab="Mean temperature
°C", ylab = "Weighted Latitude")

## I then calculate the mean of the periods when NEA haddock is in
##the Barents Sea
PinroS<-read.table("PinroSesong.csv",header = TRUE)
PinroS$Sesong=NULL
PinroSMean<-rowMeans(PinroS)
plot(Year, PinroSMean, type = "l", xlab = "Year", ylab = "Mean temperature °C", main = "Mean temperature of KOLA section Aug-Feb")
WheigtedLat <- read.table("WheightedLatYear.csv", header = TRUE, sep = ",", dec = ".")
cor(PinroSMean,WheigtedLat$lat)
##0.6306916 = 39%
ordPSM<-order(PinroSMean)
plot(PinroSMean[ordPSM],WheigtedLat$lat[ordPSM],type = "o",pch = 20, xlab="Average temperature °C", ylab ="Mean weight of
spawners" )

##Now i check with the SSB
ICEST<-read.table("ICESdata.csv", header = TRUE)
ICES<-ICEST[-c(1, 2, 3, 4, 5, 6, 7, 8, 9, 10), ]
plot(Year,(ICES$SSB)*10^-3,type = "o", pch = 19, ylab =expression(paste("Spawning Stock Biomass (x", 10^3,"tonnes)")),mgp=c(2,1,0))
OrdSSB = order(ICES$SSB)
plot(ICES$SSB[OrdSSB]*10^-3, WheigtedLat$lat[OrdSSB], type="l", xlab = expression(paste("Spawning Stock Biomass (x",
10^3,"tonnes)")), ylab = "Latitude °N", main = "Mean latitude by SSB")
cor(ICES$SSB, WheigtedLat$lat)
##The corelation value is 0.6294994 meaning that 39,6% is explained by SSB
##############################################################################
library(boot)
MainDataSet$rundvekt<-as.numeric(MainDataSet$rundvekt)

##Make a dataset with landings from just one year
y200<-which(MainDataSet$year==2000)
y00 <- MainDataSet[y200,]
##Make a boot function that will return the wheighted average for that year
meanfun.data00 <- function(y00, indices){
  y00 <- y00[indices,]
  kr00<-sum(y00$ykoord*y00$rundvekt, na.rm = TRUE)
  sr00<-sum(y00$rundvekt, na.rm=TRUE)
  mm00=kr00/sr00
  return(mm00)
}
## Run the bootstrap
boot_fit00<-boot(y00, meanfun.data00, R = 1000)
##And get the 0,25%,50% and 97,5% percentile
bq00<-quantile(boot_fit00$t,probs = c(0.025,0.5,0.975), na.rm = TRUE)
##And then i repeat this for each year
y201<-which(MainDataSet$year==2001)
y01 <- MainDataSet[y201,]
##
kr01<-y01$ykoord*y01$rundvekt
sr01<-sum(y01$rundvekt, na.rm=TRUE)
##
meanfun.data01 <- function(y01, indices){
  y01 <- y01[indices,]
  kr01<-sum(y01$ykoord*y01$rundvekt,na.rm=TRUE)
  sr01<-sum(y01$rundvekt, na.rm=TRUE)
  mm01=kr01/sr01
  return(mm01)
}

##
boot_fit01<-boot(y01, meanfun.data01, R = 1000)
boot_fit01$t

bq01<-quantile(boot_fit01$t,probs = c(0.025,0.5,0.975))
plot(boot_fit01$t)
######
```

```
y202<-which(MainDataSet$year==2002)
y02 <- MainDataSet[y202,]
##
kr02<-y02$ykoord*y02$rundvekt
sr02<-sum(y02$rundvekt, na.rm=TRUE)
##
meanfun.data02 <- function(y02, indices){
  y02 <- y02[indices,]
  kr02<-sum(y02$ykoord*y02$rundvekt,na.rm=TRUE)
  sr02<-sum(y02$rundvekt, na.rm=TRUE)
  mm02=kr02/sr02
  return(mm02)
}

##
boot_fit02<-boot(y02, meanfun.data02, R = 1000)


bq02<-quantile(boot_fit02$t,probs = c(0.025,0.5,0.975))

#####
y203<-which(MainDataSet$year==2003)
y03 <- MainDataSet[y203,]
##
kr03<-y03$ykoord*y03$rundvekt
sr03<-sum(y03$rundvekt, na.rm=TRUE)
##
meanfun.data03 <- function(y03, indices){
  y03 <- y03[indices,]
  kr03<-sum(y03$ykoord*y03$rundvekt,na.rm=TRUE)
  sr03<-sum(y03$rundvekt, na.rm=TRUE)
  mm03=kr03/sr03
  return(mm03)
}

##
boot_fit03<-boot(y03, meanfun.data03, R = 1000)

bq03<-quantile(boot_fit03$t,probs = c(0.025,0.5,0.975))
#####
y204<-which(MainDataSet$year==2004)
y04 <- MainDataSet[y204,]
##
kr04<-y04$ykoord*y04$rundvekt
sr04<-sum(y04$rundvekt, na.rm=TRUE)
##
meanfun.data04 <- function(y04, indices){
  y04 <- y04[indices,]
  kr04<-sum(y04$ykoord*y04$rundvekt,na.rm=TRUE)
  sr04<-sum(y04$rundvekt, na.rm=TRUE)
  mm04=kr04/sr04
  return(mm04)
}

##
boot_fit04<-boot(y04, meanfun.data04, R = 1000)

bq04<-quantile(boot_fit04$t,probs = c(0.025,0.5,0.975))
#####
y205<-which(MainDataSet$year==2005)
y05 <- MainDataSet[y205,]
##
kr05<-y05$ykoord*y05$rundvekt
sr05<-sum(y05$rundvekt, na.rm=TRUE)
##
meanfun.data05 <- function(y05, indices){
  y05 <- y05[indices,]
  kr05<-sum(y05$ykoord*y05$rundvekt,na.rm=TRUE)
  sr05<-sum(y05$rundvekt, na.rm=TRUE)
  mm05=kr05/sr05
  return(mm05)
}

##
boot_fit05<-boot(y05, meanfun.data05, R = 1000)
```

```
bq05<-quantile(boot_fit05$t,probs = c(0.025,0.5,0.975))
####
y206<-which(MainDataSet$year==2006)
y06 <- MainDataSet[y206,]
##
kr06<-y06$ykoord*y06$rundvekt
sr06<-sum(y06$rundvekt, na.rm=TRUE)
##
meanfun.data06 <- function(y06, indices){
  y06 <- y06[indices,]
  kr06<-sum(y06$ykoord*y06$rundvekt,na.rm=TRUE)
  sr06<-sum(y06$rundvekt, na.rm=TRUE)
  mm06=kr06/sr06
  return(mm06)
}

##
boot_fit06<-boot(y06, meanfun.data06, R = 1000)

bq06<-quantile(boot_fit06$t,probs = c(0.025,0.5,0.975))
####
y207<-which(MainDataSet$year==2007)
y07 <- MainDataSet[y207,]
##
kr07<-y07$ykoord*y07$rundvekt
sr07<-sum(y07$rundvekt, na.rm=TRUE)
##
meanfun.data07 <- function(y07, indices){
  y07 <- y07[indices,]
  kr07<-sum(y07$ykoord*y07$rundvekt,na.rm=TRUE)
  sr07<-sum(y07$rundvekt, na.rm=TRUE)
  mm07=kr07/sr07
  return(mm07)
}

##
boot_fit07<-boot(y07, meanfun.data07, R = 1000)

bq07<-quantile(boot_fit07$t,probs = c(0.025,0.5,0.975))
####
y208<-which(MainDataSet$year==2008)
y08 <- MainDataSet[y208,]
##
kr08<-y08$ykoord*y08$rundvekt
sr08<-sum(y08$rundvekt, na.rm=TRUE)
##
meanfun.data08 <- function(y08, indices){
  y08 <- y08[indices,]
  kr08<-sum(y08$ykoord*y08$rundvekt,na.rm=TRUE)
  sr08<-sum(y08$rundvekt, na.rm=TRUE)
  mm08=kr08/sr08
  return(mm08)
}

##
boot_fit08<-boot(y08, meanfun.data08, R = 1000)

bq08<-quantile(boot_fit08$t,probs = c(0.025,0.5,0.975))
###
y209<-which(MainDataSet$year==2009)
y09 <- MainDataSet[y209,]
##
kr09<-y09$ykoord*y09$rundvekt
sr09<-sum(y09$rundvekt, na.rm=TRUE)
##
meanfun.data09 <- function(y09, indices){
  y09 <- y09[indices,]
  kr09<-sum(y09$ykoord*y09$rundvekt,na.rm=TRUE)
  sr09<-sum(y09$rundvekt, na.rm=TRUE)
  mm09=kr09/sr09
  return(mm09)
}

##
boot_fit09<-boot(y09, meanfun.data09, R = 1000)
```

```
bq09<-quantile(boot_fit09$t,probs = c(0.025,0.5,0.975))
####
y210<-which(MainDataSet$year==2010)
y10 <- MainDataSet[y210,]
##
kr10<-y10$ykoord*y10$rundvekt
sr10<-sum(y10$rundvekt, na.rm=TRUE)
##
meanfun.data10 <- function(y10, indices){
  y10 <- y10[indices,]
  kr10<-sum(y10$ykoord*y10$rundvekt,na.rm=TRUE)
  sr10<-sum(y10$rundvekt, na.rm=TRUE)
  mm10=kr10/sr10
  return(mm10)
}

##
boot_fit10<-boot(y10, meanfun.data10, R = 1000)


bq10<-quantile(boot_fit10$t,probs = c(0.025,0.5,0.975))
####
y211<-which(MainDataSet$year==2011)
y11 <- MainDataSet[y211,]
##
kr11<-y11$ykoord*y11$rundvekt
sr11<-sum(y11$rundvekt, na.rm=TRUE)
##
meanfun.data11 <- function(y11, indices){
  y11 <- y11[indices,]
  kr11<-sum(y11$ykoord*y11$rundvekt,na.rm=TRUE)
  sr11<-sum(y11$rundvekt, na.rm=TRUE)
  mm11=kr11/sr11
  return(mm11)
}

##
boot_fit11<-boot(y11, meanfun.data11, R = 1000)

bq11<-quantile(boot_fit11$t,probs = c(0.025,0.5,0.975))
####
y212<-which(MainDataSet$year==2012)
y12 <- MainDataSet[y212,]
##
kr12<-y12$ykoord*y12$rundvekt
sr12<-sum(y12$rundvekt, na.rm=TRUE)
##
meanfun.data12 <- function(y12, indices){
  y12 <- y12[indices,]
  kr12<-sum(y12$ykoord*y12$rundvekt,na.rm=TRUE)
  sr12<-sum(y12$rundvekt, na.rm=TRUE)
  mm12=kr12/sr12
  return(mm12)
}

##
boot_fit12<-boot(y12, meanfun.data12, R = 1000)

bq12<-quantile(boot_fit12$t,probs = c(0.025,0.5,0.975))
####
y213<-which(MainDataSet$year==2013)
y13 <- MainDataSet[y213,]
##
kr13<-y13$ykoord*y13$rundvekt
sr13<-sum(y13$rundvekt, na.rm=TRUE)
##
meanfun.data13 <- function(y13, indices){
  y13 <- y13[indices,]
  kr13<-sum(y13$ykoord*y13$rundvekt,na.rm=TRUE)
  sr13<-sum(y13$rundvekt, na.rm=TRUE)
  mm13=kr13/sr13
  return(mm13)
}

##
boot_fit13<-boot(y13, meanfun.data13, R = 1000)
```

```
bq13<-quantile(boot_fit13$t,probs = c(0.025,0.5,0.975))
####
y214<-which(MainDataSet$year==2014)
y14 <- MainDataSet[y214,]
##
kr14<-y14$ykoord*y14$rundvekt
sr14<-sum(y14$rundvekt, na.rm=TRUE)
##
meanfun.data14 <- function(y14, indices){
  y14 <- y14[indices,]
  kr14<-sum(y14$ykoord*y14$rundvekt,na.rm=TRUE)
  sr14<-sum(y14$rundvekt, na.rm=TRUE)
  mm14=kr14/sr14
  return(mm14)
}

##
boot_fit14<-boot(y14, meanfun.data14, R = 1000)
bq14<-quantile(boot_fit14$t,probs = c(0.025,0.5,0.975))
###
y215<-which(MainDataSet$year==2015)
y15 <- MainDataSet[y215,]
##
kr15<-y15$ykoord*y15$rundvekt
sr15<-sum(y15$rundvekt, na.rm=TRUE)
##
meanfun.data15 <- function(y15, indices){
  y15 <- y15[indices,]
  kr15<-sum(y15$ykoord*y15$rundvekt,na.rm=TRUE)
  sr15<-sum(y15$rundvekt, na.rm=TRUE)
  mm15=kr15/sr15
  return(mm15)
}

##
boot_fit15<-boot(y15, meanfun.data15, R = 1000)
bq15<-quantile(boot_fit15$t,probs = c(0.025,0.5,0.975))
####
y216<-which(MainDataSet$year==2016)
y16 <- MainDataSet[y216,]
##
kr16<-y16$ykoord*y16$rundvekt
sr16<-sum(y16$rundvekt, na.rm=TRUE)
##
meanfun.data16 <- function(y16, indices){
  y16 <- y16[indices,]
  kr16<-sum(y16$ykoord*y16$rundvekt,na.rm=TRUE)
  sr16<-sum(y16$rundvekt, na.rm=TRUE)
  mm16=kr16/sr16
  return(mm16)
}

##
boot_fit16<-boot(y16, meanfun.data16, R = 1000)
bq16<-quantile(boot_fit16$t,probs = c(0.025,0.5,0.975))
####
y217<-which(MainDataSet$year==2017)
y17 <- MainDataSet[y217,]
##
kr17<-y17$ykoord*y17$rundvekt
sr17<-sum(y17$rundvekt, na.rm=TRUE)
##
meanfun.data17 <- function(y17, indices){
  y17 <- y17[indices,]
  kr17<-sum(y17$ykoord*y17$rundvekt,na.rm=TRUE)
  sr17<-sum(y17$rundvekt, na.rm=TRUE)
  mm17=kr17/sr17
  return(mm17)
}
boot_fit17<-boot(y17, meanfun.data17, R = 1000)
bq17<-quantile(boot_fit17$t,probs = c(0.025,0.5,0.975))
####################################################################
##I then create two ned datasets, one with just the 50% percentile and one with all three
```

```
BootStrap<-
rbind(boot_fit00$t,boot_fit01$t,boot_fit02$t,boot_fit03$t,boot_fit04$t,boot_fit05$t,boot_fit06$t,boot_fit07$t,boot_fit08$t,boot_fit09$t,boot_
fit10$t,boot_fit11$t,boot_fit12$t,boot_fit13$t,boot_fit14$t,boot_fit15$t,boot_fit16$t,boot_fit17$t)
BootStrapPer<-rbind(bq00,bq01,bq02,bq03,bq04,bq05,bq06,bq07,bq08,bq09,bq10,bq11,bq12,bq13,bq14,bq15,bq16,bq17,deparse.level = 1)

## Write a new file
write.csv(BootStrapPer, "BootstrapPer.csv")
rm(list=ls())
##Loading in the new file
BOP<- read.table("BootstrapOriginal.csv", header = TRUE, sep = ",", dec = ".")
BOP$X <- NULL

##I give the columns new names so that they i am able to work with them
colnames(BOP) <- c("x","y","z")
##I create a dataset with years to match the bootsrap
Year <- c(2000,2001,2002,2003,2004,2005,2006,2007,2008,2009,2010,2011,2012,2013,2014,2015,2016,2017)
##Then i plot the bootstrap and the percentiles to look at the variability
plot(Year,BOP$y, type = "l",ylim=c(66.3,68.2), main = "Bootstrap with percentiles", ylab = "Mean lat for mean weight of spawners °N")
lines(Year,BOP$x, col = "3")
lines(Year,BOP$z, col = "2")

## I Will now calculate the mean weight of spawners using data from ICES
SWAG<-read.table("StockWeightAtAge.csv", header = TRUE, sep=";")
SAA<-read.table("stockAtAge.csv", header = TRUE, sep = ";")
PMAA<-read.table("ProportionMatureAtAge.csv", header = TRUE,sep = ";")
##I now remove the age groups 1 and 2 from "proportion ature at age" since they are all zero
PMAA$`1`<-NULL
PMAA$`2`<-NULL
##I give the columns names to make it easier to recognize
colnames(SWAG) <- c("Year","1","2","3","4","5","6","7","8","9","10","11","12","13+")
colnames(SAA) <- c("Year","3","4","5","6","7","8","9","10","11","12","13+")
colnames(PMAA) <- c("Year","1","2","3","4","5","6","7","8","9","10","11","12","13+")
##And i remove the first years from "Stock weight at age" as well since
##These are not included in the other data sets
SWAG2=SWAG[,c(1,4:14)]
## I create a place to put my uppcoming values
mw00<-c()
##I make a series of years
Age <- unique(SWAG$Year)
##And calculate the mean wheight of spawners using a for lopp to crate a datapoint
##For each induvidual year.
for (i in 1:length(Age)){
  mw00[i]<-sum(SWAG2[i,2:12]*SAA[i,2:12]*PMAA[i,2:12])/sum(SAA[i,2:12]*PMAA[i,2:12])
}
## a quick year dataset
write.csv(mw00,"MeanWeightOfSpawners.csv")
rm(list=ls())
mw00<-read.table("MeanWeightOfSpawners.csv", header = TRUE,sep = ",")
WheigtedLat <- read.table("WheightedLatYear.csv", header = TRUE, sep = ",", dec = ".")
Year <- c(2000,2001,2002,2003,2004,2005,2006,2007,2008,2009,2010,2011,2012,2013,2014,2015,2016,2017)
#Plotting mean weight of spawners by year
plot(Year,mw00$x,type = "o", xlab = "Year", ylab = "Mean weight of spawners, kg", pch = 20)
##Order the data to get a understandable graph
ordmw00<-order(mw00$x)
##Plotting Lattude against mean weight
plot(mw00$x[ordmw00],WheigtedLat$lat[ordmw00], type = "o", xlab = "Mean weight of spawners", ylab = "Weighted mean latitude°N")
## then i run a correlation test
cor(mw00$x,WheigtedLat$lat)
##this gives a value of 0.4201635, meaning that 17% of the variation can de explained by
##mean weight of spawners

rm(list=ls())
##I will now create a new dataset with mean latitude of landings
setwd("C:/Users/Even/OneDrive/Data")
MainDataSetUO<-read.table("MainDataSet.csv", header = TRUE, sep = ",", dec = ".")
##I reorder the dataset after fangstfeltkode so it will be easier to manage
orderFFK<-order(MainDataSetUO$fangstfeltkode)
MainDataSet<-MainDataSetUO[orderFFK,]
#I then devide the data into induvidual years
MainDataSet00<-MainDataSet[MainDataSet$year==2000,]
nb00<-c()
Area<-unique(MainDataSet$fangstfeltkode)
for(a in 1:length(Area)){
  nb00[a]<-nrow(MainDataSet00[MainDataSet00$fangstfeltkode==Area[a],])
  na.rm=TRUE
}
```

```
##transform the values from a single year into a data set
nb00<-data.frame(nb00)
##Remove any zeroes as these are not included in the latitudes
nb00<-nb00[-c(3, 8, 12, 25,28 ,35),]
##I then use the data set for that year to identify the area codes present
table(MainDataSet00$fangstfeltkode)
##Make a new set with these codes
Omr00<-c(3,406,410,411,412,417,422,501,502,507,508,509,512,
        513,514,518,519,520,522,523,524,529,530,535,705,706,
        719,731,1201,1207,1208,1209,80003,80004,80010,80044,80046,80047,80048,
        80049,80403,80404,80410,80411,80412,80413,80508,80509,80514,80519,80520,80523,
        80524,80525,80528,80529,80530,80535,80705,80706,80719,80731,80733)
##Create a for loop to extract the atitude from my data set and
##pair it with are code
h00<-data.frame(nb00,Omr00)
h00$ycord00<-NA
i=1

for(i in 1:nrow(h00)){
  h00$ycord00[i]<-unique(MainDataSet00[MainDataSet00$fangstfeltkode==h00$Omr00[i],]$ykoord)
}
h00
##Calculate (number of landings er area/latitude)/sum of number of landings
La00<-sum((h00$nb00*h00$ycord00)/(sum(h00$nb00)))
La00
## and repeat for each year
MainDataSet01<-MainDataSet[MainDataSet$year==2001,]
nb01<-c()
Area<-unique(MainDataSet$fangstfeltkode)
for(a in 1:length(Area)){
  nb01[a]<-nrow(MainDataSet01[MainDataSet01$fangstfeltkode==Area[a],])
  na.rm=TRUE
}

nb01<-data.frame(nb01)
nb01<-nb01[-c(4, 8, 10, 15,25 ,26),]
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet01$fangstfeltkode)

Omr01<-c(3,406,407,411,412,417,422,502,506,507,508,512,513,514,
        518,519,520,522,523,524,530,534,535,705,706,719,731,1201,
        1203,1207,1208,1209,80003,80004,80010,80044,80046,80047,80048,80049,80403,80404,
        80410,80411,80412,80413,80508,80509,80514,80519,80520,80523,80524,80525,80528,80529,
        80530,80535,80705,80706,80719,80731,80733)

h01<-data.frame(nb01,Omr01)
h01$ycord01<-NA
i=1

for(i in 1:nrow(h01)){
  h01$ycord01[i]<-unique(MainDataSet01[MainDataSet01$fangstfeltkode==h01$Omr01[i],]$ykoord)
}
h01

La01<-sum((h01$nb01*h01$ycord01)/(sum(h01$nb01)))
La01
##
MainDataSet02<-MainDataSet[MainDataSet$year==2002,]
nb02<-c()
Area02<-unique(MainDataSet02$fangstfeltkode)
for(a in 1:length(Area02)){
  nb02[a]<-nrow(MainDataSet02[MainDataSet02$fangstfeltkode==Area02[a],])
  na.rm=TRUE
}

nb02<-data.frame(nb02)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet02$fangstfeltkode)

Omr02<-c(3,406,407,412,417,418,422,502,507,508,509,512,
        513,514,518,519,520,523,524,528,529,530,534,535,705,706,
        719,731,1201,1207,1208,1209,80003,80004,80010,80044,80046,80047,80048,
        80049,80403,80404,80410,80411,80412,80413,80508,80509,80514,80519,80520,80523,
        80524,80525,80528,80529,80530,80535,80705,80706,80719,80731,80733)

h02<-data.frame(nb02,Omr02)
```

```
h02$ycord02<-NA
i=1

for(i in 1:nrow(h02)){
  h02$ycord02[i]<-unique(MainDataSet02[MainDataSet02$fangstfeltkode==h02$Omr02[i],]$ykoord)
}
h02

La02<-sum((h02$nb02*h02$ycord02)/(sum(h02$nb02)))
La02
##
MainDataSet03<-MainDataSet[MainDataSet$year==2003,]
nb03<-c()
Area03<-unique(MainDataSet03$fangstfeltkode)
for(a in 1:length(Area03)){
  nb03[a]<-nrow(MainDataSet03[MainDataSet03$fangstfeltkode==Area03[a],])
  na.rm=TRUE
}

nb03<-data.frame(nb03)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet03$fangstfeltkode)

Omr03<-c(3,406,407,410,411,412,417,422,501,502,507,508,509,512,
        513,514,518,519,523,524,528,529,530,534,535,705,706,
        719,731,1201,1208,80003,80004,80010,80044,80046,80047,80048,
        80049,80403,80404,80410,80411,80412,80413,80508,80509,80514,80519,80520,80523,
        80524,80525,80528,80529,80530,80535,80705,80706,80719,80731,80733)

h03<-data.frame(nb03,Omr03)
h03$ycord03<-NA
i=1

for(i in 1:nrow(h03)){
  h03$ycord03[i]<-unique(MainDataSet03[MainDataSet03$fangstfeltkode==h03$Omr03[i],]$ykoord)
}
h03

La03<-sum((h03$nb03*h03$ycord03)/(sum(h03$nb03)))
La03
##
MainDataSet04<-MainDataSet[MainDataSet$year==2004,]
nb04<-c()
Area04<-unique(MainDataSet04$fangstfeltkode)
for(a in 1:length(Area04)){
  nb04[a]<-nrow(MainDataSet04[MainDataSet04$fangstfeltkode==Area04[a],])
  na.rm=TRUE
}

nb04<-data.frame(nb04)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet04$fangstfeltkode)

Omr04<-c(3,406,407,410,411,412,417,418,422,502,506,507,508,509,512,
        513,514,518,519,520,522,523,524,528,529,530,535,705,706,
        719,731,1201,1207,1209,80003,80004,80010,80044,80046,80047,80048,
        80049,80403,80404,80410,80411,80412,80413,80508,80509,80514,80519,80520,80523,
        80524,80525,80528,80529,80530,80705,80706,80719,80731,80733)

h04<-data.frame(nb04,Omr04)
h04$ycord04<-NA
i=1

for(i in 1:nrow(h04)){
  h04$ycord04[i]<-unique(MainDataSet04[MainDataSet04$fangstfeltkode==h04$Omr04[i],]$ykoord)
}
h04

La04<-sum((h04$nb04*h04$ycord04)/(sum(h04$nb04)))
La04
##
MainDataSet05<-MainDataSet[MainDataSet$year==2005,]
nb05<-c()
Area05<-unique(MainDataSet05$fangstfeltkode)
for(a in 1:length(Area05)){
  nb05[a]<-nrow(MainDataSet05[MainDataSet05$fangstfeltkode==Area05[a],])
```

```
  na.rm=TRUE
}

nb05<-data.frame(nb05)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet05$fangstfeltkode)

Omr05<-c(3,406,407,410,411,412,417,418,422,502,506,507,508,509,
        512,513,514,518,519,520,522,523,524,528,529,530,534,535,
        705,706,719,1201,1203,1207,1208,80003,80004,80010,80044,80046,80047,80048,
        80049,80403,80404,80410,80411,80412,80413,80508,80509,80514,80519,80520,80523,80524,
        80525,80528,80529,80530,80535,80705,80706,80719,80731,80733)

h05<-data.frame(nb05,Omr05)
h05$ycord05<-NA
i=1

for(i in 1:nrow(h05)){
  h05$ycord05[i]<-unique(MainDataSet05[MainDataSet05$fangstfeltkode==h05$Omr05[i],]$ykoord)
}
h05

La05<-sum((h05$nb05*h05$ycord05)/(sum(h05$nb05)))
La05
##
MainDataSet06<-MainDataSet[MainDataSet$year==2006,]
nb06<-c()
Area06<-unique(MainDataSet06$fangstfeltkode)
for(a in 1:length(Area06)){
  nb06[a]<-nrow(MainDataSet06[MainDataSet06$fangstfeltkode==Area06[a],])
  na.rm=TRUE
}

nb06<-data.frame(nb06)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet06$fangstfeltkode)

Omr06<-c(3,406,407,410,411,412,417,418,422,501,502,506,507,508,
        509,512,513,514,518,519,522,523,524,528,530,534,535,706,
        719,731,1201,1203,1207,1208,80003,80004,80010,80044,80046,80047,80048,
        80049,80403,80404,80410,80411,80412,80413,80508,80509,80514,80519,80520,80523,80524,
        80525,80528,80529,80530,80535,80705,80706,80719,80731,80733)

h06<-data.frame(nb06,Omr06)
h06$ycord06<-NA
i=1

for(i in 1:nrow(h06)){
  h06$ycord06[i]<-unique(MainDataSet06[MainDataSet06$fangstfeltkode==h06$Omr06[i],]$ykoord)
}
h06

La06<-sum((h06$nb06*h06$ycord06)/(sum(h06$nb06)))
La06
##
MainDataSet07<-MainDataSet[MainDataSet$year==2007,]
nb07<-c()
Area07<-unique(MainDataSet07$fangstfeltkode)
for(a in 1:length(Area07)){
  nb07[a]<-nrow(MainDataSet07[MainDataSet07$fangstfeltkode==Area07[a],])
  na.rm=TRUE
}

nb07<-data.frame(nb07)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet07$fangstfeltkode)

Omr07<-c(3,406,407,410,411,412,417,418,422,501,502,506,507,508,
        509,512,513,514,518,519,520,522,523,524,528,529,530,534,
        535,705,706,719,731,1201,1203,1207,1208,80003,80004,80010,80044,80046,80047,80048,
        80049,80403,80404,80410,80411,80412,80413,80508,80509,80514,80519,80520,80523,80524,
        80525,80528,80529,80530,80535,80705,80706,80719,80731,80733)

h07<-data.frame(nb07,Omr07)
h07$ycord07<-NA
i=1
```

```
for(i in 1:nrow(h07)){
  h07$ycord07[i]<-unique(MainDataSet07[MainDataSet07$fangstfeltkode==h07$Omr07[i],]$ykoord)
}
h07

La07<-sum((h07$nb07*h07$ycord07)/(sum(h07$nb07)))
La07
##

MainDataSet08<-MainDataSet[MainDataSet$year==2008,]
nb08<-c()
Area08<-unique(MainDataSet08$fangstfeltkode)
for(a in 1:length(Area08)){
  nb08[a]<-nrow(MainDataSet08[MainDataSet08$fangstfeltkode==Area08[a],])
  na.rm=TRUE
}

nb08<-data.frame(nb08)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet08$fangstfeltkode)

Omr08<-c(3,406,407,410,411,412,417,418,422,501,502,506,507,508,
        509,512,513,514,518,519,520,522,523,524,528,529,530,534,
        535,705,706,719,731,1201,1207,1208,80003,80004,80010,80044,80046,80047,80048,
        80049,80403,80404,80410,80411,80412,80413,80508,80509,80514,80519,80520,80523,80524,
        80525,80528,80529,80530,80535,80705,80706,80719,80731,80733)

h08<-data.frame(nb08,Omr08)
h08$ycord08<-NA
i=1

for(i in 1:nrow(h08)){
  h08$ycord08[i]<-unique(MainDataSet08[MainDataSet08$fangstfeltkode==h08$Omr08[i],]$ykoord)
}
h08

La08<-sum((h08$nb08*h08$ycord08)/(sum(h08$nb08)))
La08
##
MainDataSet09<-MainDataSet[MainDataSet$year==2009,]
nb09<-c()
Area09<-unique(MainDataSet09$fangstfeltkode)
for(a in 1:length(Area09)){
  nb09[a]<-nrow(MainDataSet09[MainDataSet09$fangstfeltkode==Area09[a],])
  na.rm=TRUE
}

nb09<-data.frame(nb09)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet09$fangstfeltkode)

Omr09<-c(3,406,407,410,411,412,417,418,422,502,506,507,508,509,
        513,514,518,519,520,522,523,524,528,529,530,535,705,706,
        719,731,1201,1203,1207,1208,1209,80003,80004,80010,80044,80046,80047,80048,
        80049,80403,80404,80410,80411,80412,80413,80508,80509,80514,80519,80520,80523,80524,
        80525,80528,80529,80530,80535,80705,80706,80719,80731,80733)

h09<-data.frame(nb09,Omr09)
h09$ycord09<-NA
i=1

for(i in 1:nrow(h09)){
  h09$ycord09[i]<-unique(MainDataSet09[MainDataSet09$fangstfeltkode==h09$Omr09[i],]$ykoord)
}
h09

La09<-sum((h09$nb09*h09$ycord09)/(sum(h09$nb09)))
La09
##
MainDataSet10<-MainDataSet[MainDataSet$year==2010,]
nb10<-c()
Area10<-unique(MainDataSet10$fangstfeltkode)
for(a in 1:length(Area10)){
  nb10[a]<-nrow(MainDataSet10[MainDataSet10$fangstfeltkode==Area10[a],])
  na.rm=TRUE
```

```
}

nb10<-data.frame(nb10)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet10$fangstfeltkode)

Omr10<-c(3,406,407,410,411,412,417,418,422,502,506,507,508,509,
        512,513,514,518,519,520,522,523,524,528,529,530,534,535,
        705,706,719,731,1201,1207,1208,80003,80004,80010,80046,80047,80048,
        80049,80403,80404,80410,80411,80412,80413,80508,80509,80514,80519,80520,80523,80524,
        80525,80528,80529,80530,80705,80706,80719,80731,80733)

h10<-data.frame(nb10,Omr10)
h10$ycord10<-NA
i=1

for(i in 1:nrow(h10)){
  h10$ycord10[i]<-unique(MainDataSet10[MainDataSet10$fangstfeltkode==h10$Omr10[i],]$ykoord)
}
h10

La10<-sum((h10$nb10*h10$ycord10)/(sum(h10$nb10)))
La10
##
MainDataSet11<-MainDataSet[MainDataSet$year==2011,]
nb11<-c()
Area11<-unique(MainDataSet11$fangstfeltkode)
for(a in 1:length(Area11)){
  nb11[a]<-nrow(MainDataSet11[MainDataSet11$fangstfeltkode==Area11[a],])
  na.rm=TRUE
}

nb11<-data.frame(nb11)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet11$fangstfeltkode)

Omr11<-c(3,406,407,411,412,417,418,422,501,502,506,507,508,509,
        512,513,514,518,519,520,523,524,528,529,530,535,705,706,
        719,731,1201,1203,1207,1208,1209,80003,80004,80010,80044,80046,80047,80048,
        80049,80403,80404,80410,80411,80412,80413,80509,80514,80519,80520,80523,80524,80525,
        80528,80530,80705,80706,80719,80731,80733)

h11<-data.frame(nb11,Omr11)
h11$ycord11<-NA
i=1

for(i in 1:nrow(h11)){
  h11$ycord11[i]<-unique(MainDataSet11[MainDataSet11$fangstfeltkode==h11$Omr11[i],]$ykoord)
}
h11

La11<-sum((h11$nb11*h11$ycord11)/(sum(h11$nb11)))
La11
##
MainDataSet12<-MainDataSet[MainDataSet$year==2012,]
nb12<-c()
Area12<-unique(MainDataSet12$fangstfeltkode)
for(a in 1:length(Area12)){
  nb12[a]<-nrow(MainDataSet12[MainDataSet12$fangstfeltkode==Area12[a],])
  na.rm=TRUE
}

nb12<-data.frame(nb12)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet12$fangstfeltkode)

Omr12<-c(3,406,407,410,411,412,417,418,422,502,506,507,508,509,
        512,513,514,518,519,520,522,523,524,529,530,534,535,705,706,
        719,1201,1203,1207,1208,1209,80003,80004,80010,80044,80046,80047,80048,
        80049,80403,80404,80410,80411,80412,80413,80509,80514,80519,80520,80523,80524,80525,
        80528,80530,80535,80706,80719,80731,80733)

h12<-data.frame(nb12,Omr12)
h12$ycord12<-NA
i=1
```

```
for(i in 1:nrow(h12)){
  h12$ycord12[i]<-unique(MainDataSet12[MainDataSet12$fangstfeltkode==h12$Omr12[i],]$ykoord)
}
h12

La12<-sum((h12$nb12*h12$ycord12)/(sum(h12$nb12)))
La12
##
MainDataSet13<-MainDataSet[MainDataSet$year==2013,]
nb13<-c()
Area13<-unique(MainDataSet13$fangstfeltkode)
for(a in 1:length(Area13)){
  nb13[a]<-nrow(MainDataSet13[MainDataSet13$fangstfeltkode==Area13[a],])
  na.rm=TRUE
}

nb13<-data.frame(nb13)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet13$fangstfeltkode)

Omr13<-c(407,410,411,412,417,418,422,501,502,506,507,508,509,
        512,513,518,519,520,523,524,528,529,530,535,706,
        719,731,1207,1208,1209,80003,80004,80010,80044,80046,80047,80048,
        80049,80403,80404,80410,80411,80412,80413,80509,80514,80519,80520,80523,80524,80525,
        80528,80530,80706,80719,80731,80733)

h13<-data.frame(nb13,Omr13)
h13$ycord13<-NA
i=1

for(i in 1:nrow(h13)){
  h13$ycord13[i]<-unique(MainDataSet13[MainDataSet13$fangstfeltkode==h13$Omr13[i],]$ykoord)
}
h13

La13<-sum((h13$nb13*h13$ycord13)/(sum(h13$nb13)))
La13
##
MainDataSet14<-MainDataSet[MainDataSet$year==2014,]
nb14<-c()
Area14<-unique(MainDataSet14$fangstfeltkode)
for(a in 1:length(Area14)){
  nb14[a]<-nrow(MainDataSet14[MainDataSet14$fangstfeltkode==Area14[a],])
  na.rm=TRUE
}

nb14<-data.frame(nb14)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet14$fangstfeltkode)

Omr14<-c(3,407,410,411,412,417,422,501,502,506,507,508,509,512,
        513,514,518,519,520,522,523,524,528,529,530,535,706,719,
        1201,1203,1207,1208,1209,80003,80004,80010,80044,80046,80047,80048,80049,
        80403,80404,80410,80411,80412,80413,80509,80514,80519,80520,80523,80524,80525,80528,
        80530,80705,80706,80719,80731,80733)

h14<-data.frame(nb14,Omr14)
h14$ycord14<-NA
i=1

for(i in 1:nrow(h14)){
  h14$ycord14[i]<-unique(MainDataSet14[MainDataSet14$fangstfeltkode==h14$Omr14[i],]$ykoord)
}
h14

La14<-sum((h14$nb14*h14$ycord14)/(sum(h14$nb14)))
La14
##
MainDataSet15<-MainDataSet[MainDataSet$year==2015,]
nb15<-c()
Area15<-unique(MainDataSet15$fangstfeltkode)
for(a in 1:length(Area15)){
  nb15[a]<-nrow(MainDataSet15[MainDataSet15$fangstfeltkode==Area15[a],])
  na.rm=TRUE
}
```

```
nb15<-data.frame(nb15)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet15$fangstfeltkode)

Omr15<-c(3,410,411,412,417,418,422,501,502,506,507,508,509,512,
        513,514,518,519,520,522,523,524,529,530,535,705,706,719,
        1201,1207,1208,1209,80003,80004,80010,80046,80047,80048,
        80403,80404,80410,80411,80412,80413,80509,80514,80519,80520,80523,80524,80525,80528,
        80529,80530,80706,80719,80731,80733)

h15<-data.frame(nb15,Omr15)
h15$ycord15<-NA
i=1

for(i in 1:nrow(h15)){
  h15$ycord15[i]<-unique(MainDataSet15[MainDataSet15$fangstfeltkode==h15$Omr15[i],]$ykoord)
}
h15

La15<-sum((h15$nb15*h15$ycord15)/(sum(h15$nb15)))
La15
##
MainDataSet16<-MainDataSet[MainDataSet$year==2016,]
nb16<-c()
Area16<-unique(MainDataSet16$fangstfeltkode)
for(a in 1:length(Area16)){
  nb16[a]<-nrow(MainDataSet16[MainDataSet16$fangstfeltkode==Area16[a],])
  na.rm=TRUE
}

nb16<-data.frame(nb16)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet16$fangstfeltkode)

Omr16<-c(3,406,407,410,411,412,417,418,422,502,506,507,508,509,512,
        513,514,518,520,522,523,524,528,529,530,534,535,706,719,
        731,1201,1207,1208,1209,80003,80004,80010,80044,80046,80047,80048,80049,
        80403,80404,80410,80411,80412,80413,80509,80514,80519,80520,80523,80524,80525,80528,
        80529,80530,80705,80706,80719,80731,80733)

h16<-data.frame(nb16,Omr16)
h16$ycord16<-NA
i=1

for(i in 1:nrow(h16)){
  h16$ycord16[i]<-unique(MainDataSet16[MainDataSet16$fangstfeltkode==h16$Omr16[i],]$ykoord)
}
h16

La16<-sum((h16$nb16*h16$ycord16)/(sum(h16$nb16)))
La16
##
MainDataSet17<-MainDataSet[MainDataSet$year==2017,]
nb17<-c()
Area17<-unique(MainDataSet17$fangstfeltkode)
for(a in 1:length(Area17)){
  nb17[a]<-nrow(MainDataSet17[MainDataSet17$fangstfeltkode==Area17[a],])
  na.rm=TRUE
}

nb17<-data.frame(nb17)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet17$fangstfeltkode)

Omr17<-c(3,406,407,410,411,412,417,418,502,506,507,508,509,512,
        513,518,519,520,522,523,524,529,530,534,535,705,706,719,
        1201,1207,1208,1209,80003,80004,80010,80044,80046,80047,80048,80049,80403,80404,
        80410,80411,80412,80413,80509,80514,80519,80520,80523,80524,80525,80528,80529,80530,
        80535,80705,80706,80719,80731,80733)

h17<-data.frame(nb17,Omr17)
h17$ycord17<-NA
i=1

for(i in 1:nrow(h17)){
  h17$ycord17[i]<-unique(MainDataSet17[MainDataSet17$fangstfeltkode==h17$Omr17[i],]$ykoord)
```

```
}
h17

La17<-sum((h17$nb17*h17$ycord17)/(sum(h17$nb17)))
La17

##Gather all the data into one dataset and add year
WLL<-c(La00,La01,La02,La03,La04,La05,La06,La07,La08,La09,La10,La11,La12,La13,La14,La15,La16,La17)
Year <- c(2000,2001,2002,2003,2004,2005,2006,2007,2008,2009,2010,2011,2012,2013,2014,2015,2016,2017)
##Plot the mean latitude of landings and write a new file for easy acces
plot(Year,WLL,type = "o", xlab="Year", ylab="Latitude", main = "Mean latitude weighted by number of landings")
write.csv(WLL,"Landings.csv")

Landings <- read.table("Landings.csv", header = TRUE, sep = ",", dec = ".")
WheigtedLat <- read.table("WheightedLatYear.csv", header = TRUE, sep = ",", dec = ".")
cor(WheigtedLat$X,Landings)
##0.6137121=37%


##I will now run lm and AIC on my explanatory valuables.
rm(list=ls())
WheigtedLat <- read.table("WheightedLatYear.csv", header = TRUE, sep = ",", dec = ".")
## Load inn explanitory values
Lan<-read.table("Landings.csv",header = TRUE, sep = ",")
Landings<-as.numeric(Lan$x)
wei<-read.table("MeanWeightOfSpawners.csv",header = TRUE, sep = ",")
weight<-as.numeric(wei$x)
ICEST<-read.table("ICESdata.csv", header = TRUE)
ICES<-ICEST[-c(1, 2, 3, 4, 5, 6, 7, 8, 9, 10), ]
SSB<-ICES$SSB
pinro<-read.table("Pinro.csv", header = TRUE, fill = TRUE)
pinro<-pinro[-c(19), ]
pinro$Year <- NULL
Temperature<-rowMeans(pinro, na.rm = TRUE)
PinroS<-read.table("PinroSesong.csv",header = TRUE)
PinroS$Sesong=NULL
PinroSMean<-rowMeans(PinroS)


library(AICcmodvag)
##i now creade lm with my explanatory values.
## Models 1-3 and 9 are composits
## Models 4-8 are single parameters
Model1<-lm(WheigtedLat$lat~SSB+Temperature+weight+Landings)
Model2<-lm(WheigtedLat$lat~SSB+Temperature+weight)
Model3<-lm(WheigtedLat$lat~SSB+PinroSMean+weight+Landings)
Model4<-lm(WheigtedLat$lat~SSB)
Model5<-lm(WheigtedLat$lat~PinroSMean)
Model6<-lm(WheigtedLat$lat~weight)
Model7<-lm(WheigtedLat$lat~Landings)
Model8<-lm(WheigtedLat$lat~Temperature)
Model9<-lm(WheigtedLat$lat~SSB+PinroSMean)
##I then perform ann AICc modelt selection
AICc(Model1)
AICc(Model2)
AICc(Model3)
AICc(Model4)
AICc(Model5)
AICc(Model6)
AICc(Model7)
AICc(Model8)
AICc(Model9)
AICc(Model10)

##I use a stepwise model selction to select models based on the results
##from the AIC and use the summary function to examine the quality of explanatory valuables
mod1<-step(Model1)
summary(mod1)
mod3<-step(Model3)
summary(mod3)
summary(Model4)
summary(Model5)
mod9<-step(Model9)
summary(mod9)
```

```
##Now that i have created and examined all my varaibles i
##repeat much of the prosess for my data set containing only spg4
##For detailed explenations look to the process on the main data set.
rm(list=ls())

##Read inn the new dataset and remove unnessesary columns
setwd("~/Master/Oppgave/Data")
MainDataSet<-read.table("MainDataSet.csv", header = TRUE, sep = ",", dec = ".")

Only4 <-
which(MainDataSet$fangstfeltkode==502|MainDataSet$fangstfeltkode==501|MainDataSet$fangstfeltkode==507|MainDataSet$fangstfeltkode==506|MainDataSet$fangstfeltkode==512|MainDataSet$fangstfeltkode==513|MainDataSet$fangstfeltkode==80514|MainDataSet$fangstfeltkode==514|MainDataSet$fangstfeltkode==518|MainDataSet$fangstfeltkode==80519|MainDataSet$fangstfeltkode==519|MainDataSet$fangstfeltkode==80520|MainDataSet$fangstfeltkode==520|MainDataSet$fangstfeltkode==522|MainDataSet$fangstfeltkode==80523|MainDataSet$fangstfeltkode==523|MainDataSet$fangstfeltkode==80524|MainDataSet$fangstfeltkode==524|MainDataSet$fangstfeltkode==80525|MainDataSet$fangstfeltkode==528|MainDataSet$fangstfeltkode==80528|MainDataSet$fangstfeltkode==80529|MainDataSet$fangstfeltkode==529|MainDataSet$fangstfeltkode==80530|MainDataSet$fangstfeltkode==530|MainDataSet$fangstfeltkode==534|MainDataSet$fangstfeltkode==80535|MainDataSet$fangstfeltkode==535|MainDataSet$fangstfeltkode==406|MainDataSet$fangstfeltkode==407|MainDataSet$fangstfeltkode==417|MainDataSet$fangstfeltkode==418|MainDataSet$fangstfeltkode==1201|MainDataSet$fangstfeltkode==1203|MainDataSet$fangstfeltkode==1207|MainDataSet$fangstfeltkode==1208|MainDataSet$fangstfeltkode==1209)
SpawningGround4<- MainDataSet[Only4,]
write.csv(SpawningGround4, "SpawningGround4.csv")

SpawningGround4<-read.table("SpawningGround4.csv", header = TRUE, sep = ",", dec = ".")
SpawningGround4$X <- NULL
SpawningGround4$X.1<- NULL

##Converting rundvekt to a numeric
##Make a new column containing wheight times latitude
SpawningGround4$rundvekt<-as.numeric(SpawningGround4$rundvekt)
SpawningGround4$WL <- SpawningGround4$rundvekt * SpawningGround4$ykoord
## I now make a value for the wheight times latitude and the
##Dividing that by the wheight
##2000
vektlat2000<-sum(SpawningGround4[SpawningGround4$year==2000,]$WL,na.rm=TRUE)
vektet2000<-vektlat2000/sum(SpawningGround4[SpawningGround4$year==2000,]$rundvekt,na.rm=TRUE)
##2001
vektlat2001<-sum(SpawningGround4[SpawningGround4$year==2001,]$WL,na.rm=TRUE)
vektet2001<-vektlat2001/sum(SpawningGround4[SpawningGround4$year==2001,]$rundvekt,na.rm=TRUE)
##2002
vektlat2002<-sum(SpawningGround4[SpawningGround4$year==2002,]$WL,na.rm=TRUE)
vektet2002<-vektlat2002/sum(SpawningGround4[SpawningGround4$year==2002,]$rundvekt,na.rm=TRUE)
##2003
vektlat2003<-sum(SpawningGround4[SpawningGround4$year==2003,]$WL,na.rm=TRUE)
vektet2003<-vektlat2003/sum(SpawningGround4[SpawningGround4$year==2003,]$rundvekt,na.rm=TRUE)
##2004
vektlat2004<-sum(SpawningGround4[SpawningGround4$year==2004,]$WL,na.rm=TRUE)
vektet2004<-vektlat2004/sum(SpawningGround4[SpawningGround4$year==2004,]$rundvekt,na.rm=TRUE)
##2005
vektlat2005<-sum(SpawningGround4[SpawningGround4$year==2005,]$WL,na.rm=TRUE)
vektet2005<-vektlat2005/sum(SpawningGround4[SpawningGround4$year==2005,]$rundvekt,na.rm=TRUE)
##2006
vektlat2006<-sum(SpawningGround4[SpawningGround4$year==2006,]$WL,na.rm=TRUE)
vektet2006<-vektlat2006/sum(SpawningGround4[SpawningGround4$year==2006,]$rundvekt,na.rm=TRUE)
##2007
vektlat2007<-sum(SpawningGround4[SpawningGround4$year==2007,]$WL,na.rm=TRUE)
vektet2007<-vektlat2007/sum(SpawningGround4[SpawningGround4$year==2007,]$rundvekt,na.rm=TRUE)
##2008
vektlat2008<-sum(SpawningGround4[SpawningGround4$year==2008,]$WL,na.rm=TRUE)
vektet2008<-vektlat2008/sum(SpawningGround4[SpawningGround4$year==2008,]$rundvekt,na.rm=TRUE)
##2009
vektlat2009<-sum(SpawningGround4[SpawningGround4$year==2009,]$WL,na.rm=TRUE)
vektet2009<-vektlat2009/sum(SpawningGround4[SpawningGround4$year==2009,]$rundvekt,na.rm=TRUE)
##2010
vektlat2010<-sum(SpawningGround4[SpawningGround4$year==2010,]$WL,na.rm=TRUE)
vektet2010<-vektlat2010/sum(SpawningGround4[SpawningGround4$year==2010,]$rundvekt,na.rm=TRUE)
#2011
vektlat2011<-sum(SpawningGround4[SpawningGround4$year==2011,]$WL,na.rm=TRUE)
vektet2011<-vektlat2011/sum(SpawningGround4[SpawningGround4$year==2011,]$rundvekt,na.rm=TRUE)
##2012
vektlat2012<-sum(SpawningGround4[SpawningGround4$year==2012,]$WL,na.rm=TRUE)
vektet2012<-vektlat2012/sum(SpawningGround4[SpawningGround4$year==2012,]$rundvekt,na.rm=TRUE)
##2013
vektlat2013<-sum(SpawningGround4[SpawningGround4$year==2013,]$WL,na.rm=TRUE)
vektet2013<-vektlat2013/sum(SpawningGround4[SpawningGround4$year==2013,]$rundvekt,na.rm=TRUE)
##2014
```

```
vektlat2014<-sum(SpawningGround4[SpawningGround4$year==2014,]$WL,na.rm=TRUE)
vektet2014<-vektlat2014/sum(SpawningGround4[SpawningGround4$year==2014,]$rundvekt,na.rm=TRUE)
#2015
vektlat2015<-sum(SpawningGround4[SpawningGround4$year==2015,]$WL,na.rm=TRUE)
vektet2015<-vektlat2015/sum(SpawningGround4[SpawningGround4$year==2015,]$rundvekt,na.rm=TRUE)
##2016
vektlat2016<-sum(SpawningGround4[SpawningGround4$year==2016,]$WL,na.rm=TRUE)
vektet2016<-vektlat2016/sum(SpawningGround4[SpawningGround4$year==2016,]$rundvekt,na.rm=TRUE)
##2017
vektlat2017<-sum(SpawningGround4[SpawningGround4$year==2017,]$WL,na.rm=TRUE)
vektet2017<-vektlat2017/sum(SpawningGround4[SpawningGround4$year==2017,]$rundvekt,na.rm=TRUE)
lat <-c(vektet2000,vektet2001,vektet2002,vektet2003,vektet2004,vektet2005,vektet2006,
vektet2007,vektet2008,vektet2009,vektet2010,vektet2011,vektet2012,vektet2013,vektet2014,vektet2015,vektet2016,vektet2017)
Year <- c(2000,2001,2002,2003,2004,2005,2006,2007,2008,2009,2010,2011,2012,2013,2014,2015,2016,2017)
vd4<- data.frame(lat, Year)
write.csv(vd4, "WheightedLatYear4.csv")
WheigtedLat4 <- read.table("WheightedLatYear4.csv", header = TRUE, sep = ",", dec = ".")
plot(WheigtedLat4$Year,WheigtedLat4$lat, type = "o", xlab = "Year", ylab = "Wheighted Latitude", main = "Main spawning ground")

pinro<-read.table("Pinro.csv", header = TRUE, fill = TRUE)
pinro$Year <- NULL
##Remove earlier years
pinro<-pinro[-c(1, 2, 3, 4, 5, 6, 7, 8, 9, 28), ]

##Calculate the means for each year
pinroMean<-rowMeans(pinro, na.rm = TRUE)
##Plot it to get a viusal
##Checking the correlation
cor(pinroMean,WheigtedLat4$lat)
#The correlation value is 0.4189595 meaning that 17% of  the variatio can be descrbed by the temp
orderPINRO<-order(pinroMean)
plot(pinroMean[orderPINRO],WheigtedLat4$lat[orderPINRO], type = "l",main = "Mean latitude by temperature", xlab="Average
temperature from PINRO", ylab = "Weighted Latitude")

##Now i check with the SSB
ICEST<-read.table("ICESdata.csv", header = TRUE)
ICES<-ICEST[-c(1, 2, 3, 4, 5, 6, 7, 8, 9, 10), ]
OrdSSB = order(ICES$SSB)
plot(ICES$SSB[OrdSSB], WheigtedLat4$lat[OrdSSB], type="l", xlab = "Spawning stock biomass", ylab = "Latitude", main = "Mean
latitude by SSB")
SSBmod<-cor(ICES$SSB, WheigtedLat4$lat)
##This gives me a value of 0.5325339 or about 28%

##Now that i have a wheighted mean latitude for 2000-2017 i can check it agains
##Temperature at PINRO and SSB

pinro<-read.table("Pinro.csv", header = TRUE, fill = TRUE)
pinro$Year <- NULL
##Remove earlier years
pinro<-pinro[-c(1, 2, 3, 4, 5, 6, 7, 8, 9, 28), ]

##Calculate the means for each year
pinroMean<-rowMeans(pinro, na.rm = TRUE)
##Plot it to get a viusal
plot(Year, pinroMean, type = "l", xlab = "Year", ylab = "Mean temperature")
##Checking the correlation
cor(pinroMean,WheigtedLat4$lat)
#The correlation value is 0.4189595 meaning that just under 20% of  the variatio can be descrbed by the temp
orderPINRO<-order(pinroMean)
plot(pinroMean[orderPINRO],WheigtedLat4$lat[orderPINRO], type = "l", xlab="Average temperature from PINRO", ylab = "Weighted
Latitude")

##Now i check with the SSB
ICEST<-read.table("ICESdata.csv", header = TRUE)
ICES<-ICEST[-c(1, 2, 3, 4, 5, 6, 7, 8, 9, 10), ]
OrdSSB = order(ICES$SSB)
plot(ICES$SSB[OrdSSB], WheigtedLat4$lat[OrdSSB], type="l", xlab = "Spawning stock biomass", ylab = "latitude")
cor(ICES$SSB, WheigtedLat4$lat)
##The corelation value is  0.5325339 meaning that 28% is explained by SSB

library(boot)
SpawningGround4$rundvekt<-as.numeric(SpawningGround4$rundvekt)

##Make a dataset with landings from just one year
y200<-which(SpawningGround4$year==2000)
y00 <- SpawningGround4[y200,]
```

```
##Make a boot function that will return the wheighted average for that year
meanfun.data00 <- function(y00, indices){
  y00 <- y00[indices,]
  kr00<-sum(y00$ykoord*y00$rundvekt, na.rm = TRUE)
  sr00<-sum(y00$rundvekt, na.rm=TRUE)
  mm00=kr00/sr00
  return(mm00)
}
## Run the bootstrap
boot_fit00<-boot(y00, meanfun.data00, R = 1000)
##And get the 0,25%,50% and 97,5% percentile
bq00<-quantile(boot_fit00$t,probs = c(0.025,0.5,0.975), na.rm = TRUE)
##And then i repeat this for each year
y201<-which(SpawningGround4$year==2001)
y01 <- SpawningGround4[y201,]
##
kr01<-y01$ykoord*y01$rundvekt
sr01<-sum(y01$rundvekt, na.rm=TRUE)
##
meanfun.data01 <- function(y01, indices){
  y01 <- y01[indices,]
  kr01<-sum(y01$ykoord*y01$rundvekt,na.rm=TRUE)
  sr01<-sum(y01$rundvekt, na.rm=TRUE)
  mm01=kr01/sr01
  return(mm01)
}

##
boot_fit01<-boot(y01, meanfun.data01, R = 1000)
boot_fit01$t


bq01<-quantile(boot_fit01$t,probs = c(0.025,0.5,0.975))
plot(boot_fit01$t)
######
y202<-which(SpawningGround4$year==2002)
y02 <- SpawningGround4[y202,]
##
kr02<-y02$ykoord*y02$rundvekt
sr02<-sum(y02$rundvekt, na.rm=TRUE)
##
meanfun.data02 <- function(y02, indices){
  y02 <- y02[indices,]
  kr02<-sum(y02$ykoord*y02$rundvekt,na.rm=TRUE)
  sr02<-sum(y02$rundvekt, na.rm=TRUE)
  mm02=kr02/sr02
  return(mm02)
}

##
boot_fit02<-boot(y02, meanfun.data02, R = 1000)
bq02<-quantile(boot_fit02$t,probs = c(0.025,0.5,0.975))

#####
y203<-which(SpawningGround4$year==2003)
y03 <- SpawningGround4[y203,]
##
kr03<-y03$ykoord*y03$rundvekt
sr03<-sum(y03$rundvekt, na.rm=TRUE)
##
meanfun.data03 <- function(y03, indices){
  y03 <- y03[indices,]
  kr03<-sum(y03$ykoord*y03$rundvekt,na.rm=TRUE)
  sr03<-sum(y03$rundvekt, na.rm=TRUE)
  mm03=kr03/sr03
  return(mm03)
}

##
boot_fit03<-boot(y03, meanfun.data03, R = 1000)
bq03<-quantile(boot_fit03$t,probs = c(0.025,0.5,0.975))
#####
y204<-which(SpawningGround4$year==2004)
y04 <- SpawningGround4[y204,]
##
kr04<-y04$ykoord*y04$rundvekt
```

```
sr04<-sum(y04$rundvekt, na.rm=TRUE)
##
meanfun.data04 <- function(y04, indices){
  y04 <- y04[indices,]
  kr04<-sum(y04$ykoord*y04$rundvekt,na.rm=TRUE)
  sr04<-sum(y04$rundvekt, na.rm=TRUE)
  mm04=kr04/sr04
  return(mm04)
}

##
boot_fit04<-boot(y04, meanfun.data04, R = 1000)
bq04<-quantile(boot_fit04$t,probs = c(0.025,0.5,0.975))
#####
y205<-which(SpawningGround4$year==2005)
y05 <- SpawningGround4[y205,]
##
kr05<-y05$ykoord*y05$rundvekt
sr05<-sum(y05$rundvekt, na.rm=TRUE)
##
meanfun.data05 <- function(y05, indices){
  y05 <- y05[indices,]
  kr05<-sum(y05$ykoord*y05$rundvekt,na.rm=TRUE)
  sr05<-sum(y05$rundvekt, na.rm=TRUE)
  mm05=kr05/sr05
  return(mm05)
}

##
boot_fit05<-boot(y05, meanfun.data05, R = 1000)


bq05<-quantile(boot_fit05$t,probs = c(0.025,0.5,0.975))
####
y206<-which(SpawningGround4$year==2006)
y06 <- SpawningGround4[y206,]
##
kr06<-y06$ykoord*y06$rundvekt
sr06<-sum(y06$rundvekt, na.rm=TRUE)
##
meanfun.data06 <- function(y06, indices){
  y06 <- y06[indices,]
  kr06<-sum(y06$ykoord*y06$rundvekt,na.rm=TRUE)
  sr06<-sum(y06$rundvekt, na.rm=TRUE)
  mm06=kr06/sr06
  return(mm06)
}

##
boot_fit06<-boot(y06, meanfun.data06, R = 1000)
bq06<-quantile(boot_fit06$t,probs = c(0.025,0.5,0.975))
####
y207<-which(SpawningGround4$year==2007)
y07 <- SpawningGround4[y207,]
##
kr07<-y07$ykoord*y07$rundvekt
sr07<-sum(y07$rundvekt, na.rm=TRUE)
##
meanfun.data07 <- function(y07, indices){
  y07 <- y07[indices,]
  kr07<-sum(y07$ykoord*y07$rundvekt,na.rm=TRUE)
  sr07<-sum(y07$rundvekt, na.rm=TRUE)
  mm07=kr07/sr07
  return(mm07)
}

##
boot_fit07<-boot(y07, meanfun.data07, R = 1000)
bq07<-quantile(boot_fit07$t,probs = c(0.025,0.5,0.975))
####
y208<-which(SpawningGround4$year==2008)
y08 <- SpawningGround4[y208,]
##
kr08<-y08$ykoord*y08$rundvekt
sr08<-sum(y08$rundvekt, na.rm=TRUE)
```

```
##
meanfun.data08 <- function(y08, indices){
  y08 <- y08[indices,]
  kr08<-sum(y08$ykoord*y08$rundvekt,na.rm=TRUE)
  sr08<-sum(y08$rundvekt, na.rm=TRUE)
  mm08=kr08/sr08
  return(mm08)
}

##
boot_fit08<-boot(y08, meanfun.data08, R = 1000)
bq08<-quantile(boot_fit08$t,probs = c(0.025,0.5,0.975))
###
y209<-which(SpawningGround4$year==2009)
y09 <- SpawningGround4[y209,]
##
kr09<-y09$ykoord*y09$rundvekt
sr09<-sum(y09$rundvekt, na.rm=TRUE)
##
meanfun.data09 <- function(y09, indices){
  y09 <- y09[indices,]
  kr09<-sum(y09$ykoord*y09$rundvekt,na.rm=TRUE)
  sr09<-sum(y09$rundvekt, na.rm=TRUE)
  mm09=kr09/sr09
  return(mm09)
}

##
boot_fit09<-boot(y09, meanfun.data09, R = 1000)
bq09<-quantile(boot_fit09$t,probs = c(0.025,0.5,0.975))
####
y210<-which(SpawningGround4$year==2010)
y10 <- SpawningGround4[y210,]
##
kr10<-y10$ykoord*y10$rundvekt
sr10<-sum(y10$rundvekt, na.rm=TRUE)
##
meanfun.data10 <- function(y10, indices){
  y10 <- y10[indices,]
  kr10<-sum(y10$ykoord*y10$rundvekt,na.rm=TRUE)
  sr10<-sum(y10$rundvekt, na.rm=TRUE)
  mm10=kr10/sr10
  return(mm10)
}

##
boot_fit10<-boot(y10, meanfun.data10, R = 1000)
bq10<-quantile(boot_fit10$t,probs = c(0.025,0.5,0.975))
####
y211<-which(SpawningGround4$year==2011)
y11 <- SpawningGround4[y211,]
##
kr11<-y11$ykoord*y11$rundvekt
sr11<-sum(y11$rundvekt, na.rm=TRUE)
##
meanfun.data11 <- function(y11, indices){
  y11 <- y11[indices,]
  kr11<-sum(y11$ykoord*y11$rundvekt,na.rm=TRUE)
  sr11<-sum(y11$rundvekt, na.rm=TRUE)
  mm11=kr11/sr11
  return(mm11)
}

##
boot_fit11<-boot(y11, meanfun.data11, R = 1000)
bq11<-quantile(boot_fit11$t,probs = c(0.025,0.5,0.975))
####
y212<-which(SpawningGround4$year==2012)
y12 <- SpawningGround4[y212,]
##
kr12<-y12$ykoord*y12$rundvekt
sr12<-sum(y12$rundvekt, na.rm=TRUE)
##
meanfun.data12 <- function(y12, indices){
  y12 <- y12[indices,]
  kr12<-sum(y12$ykoord*y12$rundvekt,na.rm=TRUE)
```

```
  sr12<-sum(y12$rundvekt, na.rm=TRUE)
  mm12=kr12/sr12
  return(mm12)
}

##
boot_fit12<-boot(y12, meanfun.data12, R = 1000)
bq12<-quantile(boot_fit12$t,probs = c(0.025,0.5,0.975))
####
y213<-which(SpawningGround4$year==2013)
y13 <- SpawningGround4[y213,]
##
kr13<-y13$ykoord*y13$rundvekt
sr13<-sum(y13$rundvekt, na.rm=TRUE)
##
meanfun.data13 <- function(y13, indices){
  y13 <- y13[indices,]
  kr13<-sum(y13$ykoord*y13$rundvekt,na.rm=TRUE)
  sr13<-sum(y13$rundvekt, na.rm=TRUE)
  mm13=kr13/sr13
  return(mm13)
}

##
boot_fit13<-boot(y13, meanfun.data13, R = 1000)
bq13<-quantile(boot_fit13$t,probs = c(0.025,0.5,0.975))
####
y214<-which(SpawningGround4$year==2014)
y14 <- SpawningGround4[y214,]
##
kr14<-y14$ykoord*y14$rundvekt
sr14<-sum(y14$rundvekt, na.rm=TRUE)
##
meanfun.data14 <- function(y14, indices){
  y14 <- y14[indices,]
  kr14<-sum(y14$ykoord*y14$rundvekt,na.rm=TRUE)
  sr14<-sum(y14$rundvekt, na.rm=TRUE)
  mm14=kr14/sr14
  return(mm14)
}

##
boot_fit14<-boot(y14, meanfun.data14, R = 1000)
bq14<-quantile(boot_fit14$t,probs = c(0.025,0.5,0.975))
###
y215<-which(SpawningGround4$year==2015)
y15 <- SpawningGround4[y215,]
##
kr15<-y15$ykoord*y15$rundvekt
sr15<-sum(y15$rundvekt, na.rm=TRUE)
##
meanfun.data15 <- function(y15, indices){
  y15 <- y15[indices,]
  kr15<-sum(y15$ykoord*y15$rundvekt,na.rm=TRUE)
  sr15<-sum(y15$rundvekt, na.rm=TRUE)
  mm15=kr15/sr15
  return(mm15)
}

##
boot_fit15<-boot(y15, meanfun.data15, R = 1000)
bq15<-quantile(boot_fit15$t,probs = c(0.025,0.5,0.975))
####
y216<-which(SpawningGround4$year==2016)
y16 <- SpawningGround4[y216,]
##
kr16<-y16$ykoord*y16$rundvekt
sr16<-sum(y16$rundvekt, na.rm=TRUE)
##
meanfun.data16 <- function(y16, indices){
  y16 <- y16[indices,]
  kr16<-sum(y16$ykoord*y16$rundvekt,na.rm=TRUE)
  sr16<-sum(y16$rundvekt, na.rm=TRUE)
  mm16=kr16/sr16
  return(mm16)
}
```

```
##
boot_fit16<-boot(y16, meanfun.data16, R = 1000)
bq16<-quantile(boot_fit16$t,probs = c(0.025,0.5,0.975))
####
y217<-which(SpawningGround4$year==2017)
y17 <- SpawningGround4[y217,]
##
kr17<-y17$ykoord*y17$rundvekt
sr17<-sum(y17$rundvekt, na.rm=TRUE)
##
meanfun.data17 <- function(y17, indices){
  y17 <- y17[indices,]
  kr17<-sum(y17$ykoord*y17$rundvekt,na.rm=TRUE)
  sr17<-sum(y17$rundvekt, na.rm=TRUE)
  mm17=kr17/sr17
  return(mm17)
}
boot_fit17<-boot(y17, meanfun.data17, R = 1000)
bq17<-quantile(boot_fit17$t,probs = c(0.025,0.5,0.975))

##I then create two ned datasets, one with just the 50% percentile and one with all three
BootStrap4<-
rbind(boot_fit00$t,boot_fit01$t,boot_fit02$t,boot_fit03$t,boot_fit04$t,boot_fit05$t,boot_fit06$t,boot_fit07$t,boot_fit08$t,boot_fit09$t,boot_
fit10$t,boot_fit11$t,boot_fit12$t,boot_fit13$t,boot_fit14$t,boot_fit15$t,boot_fit16$t,boot_fit17$t)
BootStrapPer4<-rbind(bq00,bq01,bq02,bq03,bq04,bq05,bq06,bq07,bq08,bq09,bq10,bq11,bq12,bq13,bq14,bq15,bq16,bq17,deparse.level =
1)

## Write a new file
write.csv(BootStrapPer4, "BootstrapPer4.csv")
rm(list=ls())
##Loading in the new file
BOP4<- read.table("BootstrapPer4.csv", header = TRUE, sep = ",", dec = ".")
BOP4$X <- NULL

##I give the columns new names so that they i am able to work with them
colnames(BOP4) <- c("x","y","z")
##I create a dataset with the years to match the bootsrap
Year <- c(2000,2001,2002,2003,2004,2005,2006,2007,2008,2009,2010,2011,2012,2013,2014,2015,2016,2017)
##Then i plot the bootstrap and the percentiles to look at the variability
plot(Year,BOP4$y, type = "l",ylim=c(64.3,69.2), main = "Bootstrap of SG4", ylab = "Weighted latitude°N")
lines(Year,BOP4$x, col = "3")
lines(Year,BOP4$z, col = "2")

plot(mw00[ordermw00],WheigtedLat4$lat[ordermw00], type = "o")
cor(mw00,WheigtedLat4$lat)

rm(list=ls())
setwd("C:/Users/Even/OneDrive/Data")
##To avoid redoing the entire dataset, i simply substitute the wole data serr
##with just SPG4 without changing the name
MainDataSetUO<-read.table("SpawningGround4.csv", header = TRUE, sep = ",", dec = ".")
##I reorder the dataset after fangstfeltkode so it will be easier to manage
orderFFK<-order(MainDataSetUO$fangstfeltkode)
MainDataSet<-MainDataSetUO[orderFFK,]
#I then devide the data into induvidual years
MainDataSet00<-MainDataSet[MainDataSet$year==2000,]
nb00<-c()
Area<-unique(MainDataSet$fangstfeltkode)
for(a in 1:length(Area)){
  nb00[a]<-nrow(MainDataSet00[MainDataSet00$fangstfeltkode==Area[a],])
  na.rm=TRUE
}

nb00<-data.frame(nb00)
nb00<-nb00[-c(2,4,7,18,21,24),]
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet00$fangstfeltkode)

Omr00<-c(406,417,501,502,507,512,513,514,518,519,520,522,523,
        524,529,530,535,1201,1207,1208,1209,80514,80519,80520,80523,80524,
        80525,80528,80529,80530,80535)

h00<-data.frame(nb00,Omr00)
h00$ycord00<-NA
i=1
```

```
for(i in 1:nrow(h00)){
  h00$ycord00[i]<-unique(MainDataSet00[MainDataSet00$fangstfeltkode==h00$Omr00[i],]$ykoord)
}
h00

La00<-sum((h00$nb00*h00$ycord00)/(sum(h00$nb00)))
La00
##
MainDataSet01<-MainDataSet[MainDataSet$year==2001,]
nb01<-c()
Area<-unique(MainDataSet$fangstfeltkode)
for(a in 1:length(Area)){
  nb01[a]<-nrow(MainDataSet01[MainDataSet01$fangstfeltkode==Area[a],])
  na.rm=TRUE
}

nb01<-data.frame(nb01)
nb01<-nb01[-c(4, 5, 18, 19),]
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet01$fangstfeltkode)

Omr01<-c(406,407,417,502,506,507,512,513,514,518,519,520,522,
        523,524,530,534,535,1201,1203,1207,1208,1209,80514,80519,80520,
        80523,80524,80525,80528,80529,80530,80535)

h01<-data.frame(nb01,Omr01)
h01$ycord01<-NA
i=1

for(i in 1:nrow(h01)){
  h01$ycord01[i]<-unique(MainDataSet01[MainDataSet01$fangstfeltkode==h01$Omr01[i],]$ykoord)
}
h01

La01<-sum((h01$nb01*h01$ycord01)/(sum(h01$nb01)))
La01
##
MainDataSet02<-MainDataSet[MainDataSet$year==2002,]
nb02<-c()
Area02<-unique(MainDataSet02$fangstfeltkode)
for(a in 1:length(Area02)){
  nb02[a]<-nrow(MainDataSet02[MainDataSet02$fangstfeltkode==Area02[a],])
  na.rm=TRUE
}

nb02<-data.frame(nb02)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet02$fangstfeltkode)

Omr02<-c(406,407,417,418,502,507,512,513,514,518,519,520,
        523,524,528,529,530,534,535,1201,1207,1208,1209,80514,80519,80520,
        80523,80524,80525,80528,80529,80530,80535)

h02<-data.frame(nb02,Omr02)
h02$ycord02<-NA
i=1

for(i in 1:nrow(h02)){
  h02$ycord02[i]<-unique(MainDataSet02[MainDataSet02$fangstfeltkode==h02$Omr02[i],]$ykoord)
}
h02

La02<-sum((h02$nb02*h02$ycord02)/(sum(h02$nb02)))
La02
##
MainDataSet03<-MainDataSet[MainDataSet$year==2003,]
nb03<-c()
Area03<-unique(MainDataSet03$fangstfeltkode)
for(a in 1:length(Area03)){
  nb03[a]<-nrow(MainDataSet03[MainDataSet03$fangstfeltkode==Area03[a],])
  na.rm=TRUE
}

nb03<-data.frame(nb03)
##finne ykoordinat for hver fangstfeltskode
```

```
table(MainDataSet03$fangstfeltkode)

Omr03<-c(406,407,417,501,502,507,512,513,514,518,519,523,524,
        528,529,530,534,535,1201,1208,80514,80519,80520,
        80523,80524,80525,80528,80529,80530,80535)

h03<-data.frame(nb03,Omr03)
h03$ycord03<-NA
i=1

for(i in 1:nrow(h03)){
  h03$ycord03[i]<-unique(MainDataSet03[MainDataSet03$fangstfeltkode==h03$Omr03[i],]$ykoord)
}
h03

La03<-sum((h03$nb03*h03$ycord03)/(sum(h03$nb03)))
La03
##
MainDataSet04<-MainDataSet[MainDataSet$year==2004,]
nb04<-c()
Area04<-unique(MainDataSet04$fangstfeltkode)
for(a in 1:length(Area04)){
  nb04[a]<-nrow(MainDataSet04[MainDataSet04$fangstfeltkode==Area04[a],])
  na.rm=TRUE
}

nb04<-data.frame(nb04)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet04$fangstfeltkode)

Omr04<-c(406,407,417,418,502,506,507,512,513,514,518,519,520,522,
        523,524,528,529,530,535,1201,1207,1209,80514,80519,80520,
        80523,80524,80525,80528,80529,80530)

h04<-data.frame(nb04,Omr04)
h04$ycord04<-NA
i=1

for(i in 1:nrow(h04)){
  h04$ycord04[i]<-unique(MainDataSet04[MainDataSet04$fangstfeltkode==h04$Omr04[i],]$ykoord)
}
h04

La04<-sum((h04$nb04*h04$ycord04)/(sum(h04$nb04)))
La04
##
MainDataSet05<-MainDataSet[MainDataSet$year==2005,]
nb05<-c()
Area05<-unique(MainDataSet05$fangstfeltkode)
for(a in 1:length(Area05)){
  nb05[a]<-nrow(MainDataSet05[MainDataSet05$fangstfeltkode==Area05[a],])
  na.rm=TRUE
}

nb05<-data.frame(nb05)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet05$fangstfeltkode)

Omr05<-c(406,407,417,418,502,506,507,512,513,514,518,519,520,522,
        523,524,528,529,530,534,535,1201,1203,1207,1208,80514,80519,80520,
        80523,80524,80525,80528,80529,80530,80535)

h05<-data.frame(nb05,Omr05)
h05$ycord05<-NA
i=1

for(i in 1:nrow(h05)){
  h05$ycord05[i]<-unique(MainDataSet05[MainDataSet05$fangstfeltkode==h05$Omr05[i],]$ykoord)
}
h05

La05<-sum((h05$nb05*h05$ycord05)/(sum(h05$nb05)))
La05
##
MainDataSet06<-MainDataSet[MainDataSet$year==2006,]
nb06<-c()
```

```
Area06<-unique(MainDataSet06$fangstfeltkode)
for(a in 1:length(Area06)){
  nb06[a]<-nrow(MainDataSet06[MainDataSet06$fangstfeltkode==Area06[a],])
  na.rm=TRUE
}

nb06<-data.frame(nb06)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet06$fangstfeltkode)

Omr06<-c(406,407,417,418,501,502,506,507,512,513,514,518,519,522,
        523,524,528,530,534,535,1201,1203,1207,1208,80514,80519,80520,
        80523,80524,80525,80528,80529,80530,80535)

h06<-data.frame(nb06,Omr06)
h06$ycord06<-NA
i=1

for(i in 1:nrow(h06)){
  h06$ycord06[i]<-unique(MainDataSet06[MainDataSet06$fangstfeltkode==h06$Omr06[i],]$ykoord)
}
h06

La06<-sum((h06$nb06*h06$ycord06)/(sum(h06$nb06)))
La06
##
MainDataSet07<-MainDataSet[MainDataSet$year==2007,]
nb07<-c()
Area07<-unique(MainDataSet07$fangstfeltkode)
for(a in 1:length(Area07)){
  nb07[a]<-nrow(MainDataSet07[MainDataSet07$fangstfeltkode==Area07[a],])
  na.rm=TRUE
}

nb07<-data.frame(nb07)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet07$fangstfeltkode)

Omr07<-c(406,407,417,418,501,502,506,507,512,513,514,518,519,520,522,
        523,524,528,529,530,534,535,1201,1203,1207,1208,80514,80519,80520,
        80523,80524,80525,80528,80529,80530,80535)

h07<-data.frame(nb07,Omr07)
h07$ycord07<-NA
i=1

for(i in 1:nrow(h07)){
  h07$ycord07[i]<-unique(MainDataSet07[MainDataSet07$fangstfeltkode==h07$Omr07[i],]$ykoord)
}
h07

La07<-sum((h07$nb07*h07$ycord07)/(sum(h07$nb07)))
La07
##

MainDataSet08<-MainDataSet[MainDataSet$year==2008,]
nb08<-c()
Area08<-unique(MainDataSet08$fangstfeltkode)
for(a in 1:length(Area08)){
  nb08[a]<-nrow(MainDataSet08[MainDataSet08$fangstfeltkode==Area08[a],])
  na.rm=TRUE
}

nb08<-data.frame(nb08)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet08$fangstfeltkode)

Omr08<-c(406,407,417,418,501,502,506,507,512,513,514,518,519,520,522,
        523,524,528,529,530,534,535,1201,1207,1208,80514,80519,80520,
        80523,80524,80525,80528,80529,80530,80535)

h08<-data.frame(nb08,Omr08)
h08$ycord08<-NA
i=1

for(i in 1:nrow(h08)){
```

```
  h08$ycord08[i]<-unique(MainDataSet08[MainDataSet08$fangstfeltkode==h08$Omr08[i],]$ykoord)
}
h08

La08<-sum((h08$nb08*h08$ycord08)/(sum(h08$nb08)))
La08
##
MainDataSet09<-MainDataSet[MainDataSet$year==2009,]
nb09<-c()
Area09<-unique(MainDataSet09$fangstfeltkode)
for(a in 1:length(Area09)){
  nb09[a]<-nrow(MainDataSet09[MainDataSet09$fangstfeltkode==Area09[a],])
  na.rm=TRUE
}

nb09<-data.frame(nb09)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet09$fangstfeltkode)

Omr09<-c(406,407,417,418,502,506,507,513,514,518,519,520,522,
         523,524,528,529,530,535,1201,1203,1207,1208,1209,80514,80519,80520,
         80523,80524,80525,80528,80529,80530,80535)

h09<-data.frame(nb09,Omr09)
h09$ycord09<-NA
i=1

for(i in 1:nrow(h09)){
  h09$ycord09[i]<-unique(MainDataSet09[MainDataSet09$fangstfeltkode==h09$Omr09[i],]$ykoord)
}
h09

La09<-sum((h09$nb09*h09$ycord09)/(sum(h09$nb09)))
La09
##
MainDataSet10<-MainDataSet[MainDataSet$year==2010,]
nb10<-c()
Area10<-unique(MainDataSet10$fangstfeltkode)
for(a in 1:length(Area10)){
  nb10[a]<-nrow(MainDataSet10[MainDataSet10$fangstfeltkode==Area10[a],])
  na.rm=TRUE
}

nb10<-data.frame(nb10)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet10$fangstfeltkode)

Omr10<-c(406,407,417,418,502,506,507,512,513,514,518,519,520,
         522,523,524,528,529,530,534,535,1201,1207,1208,80514,80519,
         80520,80523,80524,80525,80528,80529,80530)

h10<-data.frame(nb10,Omr10)
h10$ycord10<-NA
i=1

for(i in 1:nrow(h10)){
  h10$ycord10[i]<-unique(MainDataSet10[MainDataSet10$fangstfeltkode==h10$Omr10[i],]$ykoord)
}
h10

La10<-sum((h10$nb10*h10$ycord10)/(sum(h10$nb10)))
La10
##
MainDataSet11<-MainDataSet[MainDataSet$year==2011,]
nb11<-c()
Area11<-unique(MainDataSet11$fangstfeltkode)
for(a in 1:length(Area11)){
  nb11[a]<-nrow(MainDataSet11[MainDataSet11$fangstfeltkode==Area11[a],])
  na.rm=TRUE
}

nb11<-data.frame(nb11)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet11$fangstfeltkode)

Omr11<-c(406,407,417,418,501,502,506,507,512,513,514,518,519,520,
```

```
        523,524,528,529,530,535,1201,1203,1207,1208,1209,80514,80519,80520,
        80523,80524,80525,80528,80530)

h11<-data.frame(nb11,Omr11)
h11$ycord11<-NA
i=1

for(i in 1:nrow(h11)){
  h11$ycord11[i]<-unique(MainDataSet11[MainDataSet11$fangstfeltkode==h11$Omr11[i],]$ykoord)
}
h11

La11<-sum((h11$nb11*h11$ycord11)/(sum(h11$nb11)))
La11
##
MainDataSet12<-MainDataSet[MainDataSet$year==2012,]
nb12<-c()
Area12<-unique(MainDataSet12$fangstfeltkode)
for(a in 1:length(Area12)){
  nb12[a]<-nrow(MainDataSet12[MainDataSet12$fangstfeltkode==Area12[a],])
  na.rm=TRUE
}

nb12<-data.frame(nb12)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet12$fangstfeltkode)

Omr12<-c(406,407,417,418,502,506,507,512,513,514,518,519,520,522,
        523,524,529,530,534,535,1201,1203,1207,1208,1209,80514,80519,80520,
        80523,80524,80525,80528,80530,80535)

h12<-data.frame(nb12,Omr12)
h12$ycord12<-NA
i=1

for(i in 1:nrow(h12)){
  h12$ycord12[i]<-unique(MainDataSet12[MainDataSet12$fangstfeltkode==h12$Omr12[i],]$ykoord)
}
h12

La12<-sum((h12$nb12*h12$ycord12)/(sum(h12$nb12)))
La12
##
MainDataSet13<-MainDataSet[MainDataSet$year==2013,]
nb13<-c()
Area13<-unique(MainDataSet13$fangstfeltkode)
for(a in 1:length(Area13)){
  nb13[a]<-nrow(MainDataSet13[MainDataSet13$fangstfeltkode==Area13[a],])
  na.rm=TRUE
}

nb13<-data.frame(nb13)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet13$fangstfeltkode)

Omr13<-c(407,417,418,501,502,506,507,512,513,518,519,520,523,
        524,528,529,530,535,1207,1208,1209,80514,80519,80520,80523,80524,
        80525,80528,80530)

h13<-data.frame(nb13,Omr13)
h13$ycord13<-NA
i=1

for(i in 1:nrow(h13)){
  h13$ycord13[i]<-unique(MainDataSet13[MainDataSet13$fangstfeltkode==h13$Omr13[i],]$ykoord)
}
h13

La13<-sum((h13$nb13*h13$ycord13)/(sum(h13$nb13)))
La13
##
MainDataSet14<-MainDataSet[MainDataSet$year==2014,]
nb14<-c()
Area14<-unique(MainDataSet14$fangstfeltkode)
for(a in 1:length(Area14)){
  nb14[a]<-nrow(MainDataSet14[MainDataSet14$fangstfeltkode==Area14[a],])
```

```
  na.rm=TRUE
}

nb14<-data.frame(nb14)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet14$fangstfeltkode)

Omr14<-c(407,417,501,502,506,507,512,513,514,518,519,520,522,
         523,524,528,529,530,535,1201,1203,1207,1208,1209,80514,80519,80520,
         80523,80524,80525,80528,80530)

h14<-data.frame(nb14,Omr14)
h14$ycord14<-NA
i=1

for(i in 1:nrow(h14)){
  h14$ycord14[i]<-unique(MainDataSet14[MainDataSet14$fangstfeltkode==h14$Omr14[i],]$ykoord)
}
h14

La14<-sum((h14$nb14*h14$ycord14)/(sum(h14$nb14)))
La14
##
MainDataSet15<-MainDataSet[MainDataSet$year==2015,]
nb15<-c()
Area15<-unique(MainDataSet15$fangstfeltkode)
for(a in 1:length(Area15)){
  nb15[a]<-nrow(MainDataSet15[MainDataSet15$fangstfeltkode==Area15[a],])
  na.rm=TRUE
}

nb15<-data.frame(nb15)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet15$fangstfeltkode)

Omr15<-c(417,418,501,502,506,507,512,513,514,518,519,520,522,
         523,524,529,530,535,1201,1207,1208,1209,80514,80519,80520,
         80523,80524,80525,80528,80529,80530)

h15<-data.frame(nb15,Omr15)
h15$ycord15<-NA
i=1

for(i in 1:nrow(h15)){
  h15$ycord15[i]<-unique(MainDataSet15[MainDataSet15$fangstfeltkode==h15$Omr15[i],]$ykoord)
}
h15

La15<-sum((h15$nb15*h15$ycord15)/(sum(h15$nb15)))
La15
##
MainDataSet16<-MainDataSet[MainDataSet$year==2016,]
nb16<-c()
Area16<-unique(MainDataSet16$fangstfeltkode)
for(a in 1:length(Area16)){
  nb16[a]<-nrow(MainDataSet16[MainDataSet16$fangstfeltkode==Area16[a],])
  na.rm=TRUE
}

nb16<-data.frame(nb16)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet16$fangstfeltkode)

Omr16<-c(406,407,417,418,502,506,507,512,513,514,518,520,522,
         523,524,528,529,530,534,535,1201,1207,1208,1209,80514,80519,80520,
         80523,80524,80525,80528,80529,80530)

h16<-data.frame(nb16,Omr16)
h16$ycord16<-NA
i=1

for(i in 1:nrow(h16)){
  h16$ycord16[i]<-unique(MainDataSet16[MainDataSet16$fangstfeltkode==h16$Omr16[i],]$ykoord)
}
h16
```

```
La16<-sum((h16$nb16*h16$ycord16)/(sum(h16$nb16)))
La16
##
MainDataSet17<-MainDataSet[MainDataSet$year==2017,]
nb17<-c()
Area17<-unique(MainDataSet17$fangstfeltkode)
for(a in 1:length(Area17)){
  nb17[a]<-nrow(MainDataSet17[MainDataSet17$fangstfeltkode==Area17[a],])
  na.rm=TRUE
}

nb17<-data.frame(nb17)
##finne ykoordinat for hver fangstfeltskode
table(MainDataSet17$fangstfeltkode)

Omr17<-c(406,407,417,418,502,506,507,512,513,518,519,520,522,
        523,524,529,530,534,535,1201,1207,1208,1209,80514,80519,80520,
        80523,80524,80525,80528,80529,80530,80535)

h17<-data.frame(nb17,Omr17)
h17$ycord17<-NA
i=1

for(i in 1:nrow(h17)){
  h17$ycord17[i]<-unique(MainDataSet17[MainDataSet17$fangstfeltkode==h17$Omr17[i],]$ykoord)
}
h17

La17<-sum((h17$nb17*h17$ycord17)/(sum(h17$nb17)))
La17

WLL4<-c(La00,La01,La02,La03,La04,La05,La06,La07,La08,La09,La10,La11,La12,La13,La14,La15,La16,La17)
Year <- c(2000,2001,2002,2003,2004,2005,2006,2007,2008,2009,2010,2011,2012,2013,2014,2015,2016,2017)
plot(Year,WLL4,type = "o", xlab="Year", ylab="Latitude", main = "Mean latitude weighted by number of landings")
write.csv(WLL4,"Landings4.csv")

rm(list=ls())
WheigtedLat4 <- read.table("WheightedLatYear4.csv", header = TRUE, sep = ",", dec = ".")
## Load inn explanitory values
Lan<-read.table("Landings4.csv",header = TRUE, sep = ",")
Landings<-as.numeric(Lan$x)
wei<-read.table("MeanWeightOfSpawners.csv",header = TRUE, sep = ",")
weight<-as.numeric(wei$x)
ICEST<-read.table("ICESdata.csv", header = TRUE)
ICES<-ICEST[-c(1, 2, 3, 4, 5, 6, 7, 8, 9, 10), ]
SSB<-ICES$SSB
pinro<-read.table("Pinro.csv", header = TRUE, fill = TRUE)
pinro<-pinro[-c(19), ]
pinro$Year <- NULL
Temperature<-rowMeans(pinro, na.rm = TRUE)
PinroS<-read.table("PinroSesong.csv",header = TRUE)
PinroS$Sesong=NULL
PinroSMean<-rowMeans(PinroS)

Model41<-lm(WheigtedLat4$lat~SSB+Temperature+weight+Landings)
Model42<-lm(WheigtedLat4$lat~SSB+Temperature+weight)
Model43<-lm(WheigtedLat4$lat~SSB+PinroSMean+weight+Landings)
Model44<-lm(WheigtedLat4$lat~SSB)
Model45<-lm(WheigtedLat4$lat~PinroSMean)
Model46<-lm(WheigtedLat4$lat~weight)
Model47<-lm(WheigtedLat4$lat~Landings)
Model48<-lm(WheigtedLat4$lat~Temperature)
Model49<-lm(WheigtedLat4$lat~SSB+PinroSMean)
AICc(Model41)
AICc(Model42)
AICc(Model43)
AICc(Model44)
AICc(Model45)
AICc(Model46)
AICc(Model46)
AICc(Model47)
AICc(Model48)
AICc(Model49)
AICc(Model40)
```

```
mod41<-step(Model41)
summary(mod41)
summary(Model44)
mod49<-step(Model49)
summary(mod49)

##A script for all spawning grounds exept møre was also made
##It is almost identical with nly a few differneces in which area codes included
```