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Investigating the long-term effects of climate on Norwegian Spring-Spawn Herring (*Clupea harengus)*

Chelsey Nieman
June 2014

Capstone Advisory Committee Final Capstone Project Signature Form

Investigating the long-term effects of climate on Norwegian Spring-Spawn Herring

Chelsey Nieman

June 2014
Masters of Advanced Studies
Marine Biodiversity and Conservation
Capstone Project

Capstone Advisory Committee

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“Climate change is happening, humans are causing it, and I think this is perhaps the most serious environmental issue facing us.”
- Bill Nye

"Undoubtedly we shall derive there from splendid discoveries of both practical and theoretical interest and these discoveries await the attention of International Fishery Research"
-Johan Hjort

A Praise to Herring
Jacob Westerbaen

Salted herring clean and fat,
Thick and long, without its head,
Cut with care along the spine,
Skinned and gutted, raw or fried
(Onions not to be forgotten),
Eaten by a hungry man
Ere the sun has gone to bed
In the evening late and sad,
With a mighty loaf of rye bread.
This is great cure, no theriac
Could be ever as praiseworthy.
Then a swig is most appropriate
Of good Breda or Harlem beer,
Or the Delft one, whichever ‘s nearer,
Which will make your throat again
Suitable and smooth and sleek,
So that you can better drink.
And if you are feeling awful,
Going ’round with your mouth open,
It can make you cheerful and fresh,
Cure from catarrhs coming from the head
That pass on to teeth and chest;
It helps also, if I may,
Timely shit and better pee;
It placates the inner winds
That requires food and drinks.
Can it really be otherwise?
He is healthy, he is wise
Who likes eating salted herring
Not the strange and sumptuous fare.

(Translated by M. Sazonov)

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Abstract

Climate change is causing unknown consequences to fisheries today and understanding these changes is key to better management for future generations. Norwegian Spring-Spawn Herring (NSSH) and sea surface temperature (SST) generally follow similar trends. Cooler temperatures tend to indicate low recruitment while warmer temperatures indicate moderate to high recruitment in the NSSH. The relationship between these two was analyzed in order to use temperature as a proxy variable in the analysis of stock biomass. A relationship was found between the two, and the variables were found to be cointegrated, which makes regressions between the two non-spurious regressions. Forecasts were made for the stock biomass for the next hundred years in 10 year intervals, and under differing climate change scenarios. It was found that increases in temperature are likely to cause a general increase in standing stock biomass for NSSH.

Introduction/Background

Climate change

One of the most pressing issues of the modern era is that of global climate change. The ultimate effects of climate change are only now becoming understood, and we are a long way out from knowing the consequences of these changes. However, as out understanding increases, this knowledge can be used to predict changes that will occur to the natural environment as a direct and immediate consequence of the climatic changes. It is important for us to understand the environmental impacts caused by climate change in order for us to manage our resources appropriately for the future. Adaptation may be our only choice, and so it is important to understand what is changing and how those changes are happening.

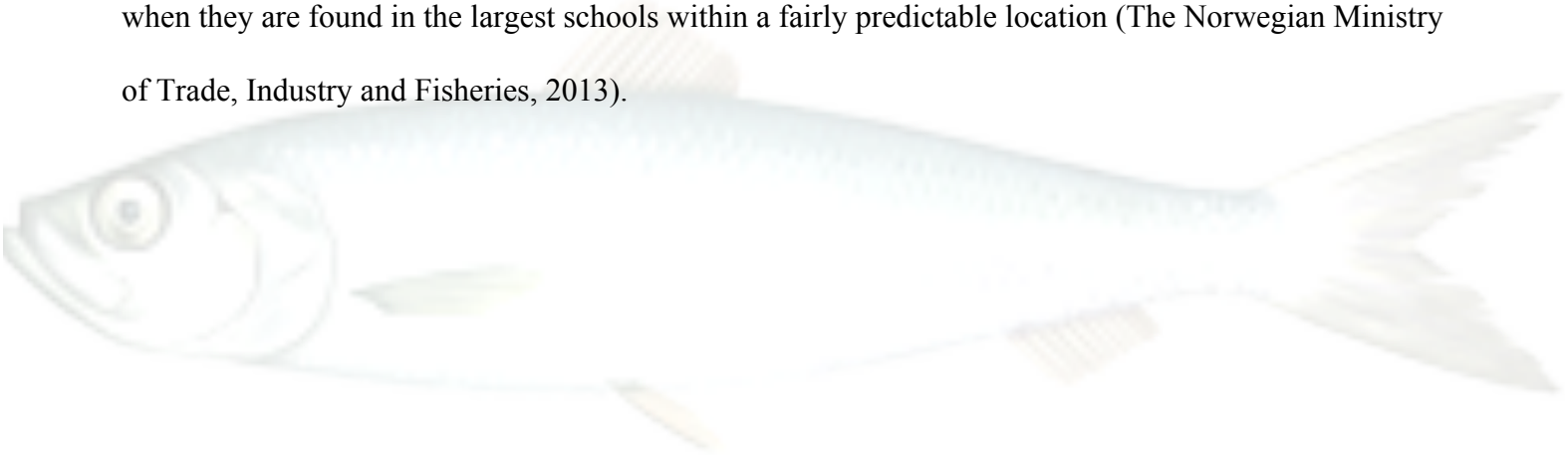
There is not a clear understanding of how climate change will affect fish communities. Reproductive success may decrease due to spawning timing becoming mismatched from optimal larval development times (Munday et al. 2008). Larvae is predicted to develop more quickly, but will have associated energy demand increases that may not facilitate increased survival (Green and Fisher 2004). Coral reef habitat is expected to be lost leading to extinctions in coral dependent species as well as decreases in species that rely on habitat complexity (Jones et al. 2004). Ranges of fishes are expected to shift towards higher latitudes. Fishes that reside in areas where habitat and temperature both play equal roles in productivity will see a contraction of their range (Munday et al. 2008). For fish that already reside at higher latitudes, the question arises of where are they to go, and what are the ultimate repercussions of this?

Fisheries are one of the last methods of food production that almost exclusively rely on wild harvest. As such, fisheries harvest is still highly dependent on environmental factors. This means that when managing fisheries, it makes sense to include environmental parameters in these assessments. However, current management practices include very few environmental parameters, and are usually based strictly on population models. There are other stocks that take the environment or ecosystem into account, however, these are limited, and are only used in a case by case basis. In fact, the only assessment that took temperature effects into account was the sardine fishery off the California Coast (Deyle at al 2013). The 3 year average Sea surface temperature (SST) from the end of the Scripps Institution of Oceanography Pier was found to correlate with reproductive success of sardines in this area. This parameter was subsequently included in management practices in order to improve the accuracy of stock assessments. However, a new analysis that added 17 years of data found the correlation to be statistically insignificant, and this strategy was abandoned (Lindegren and Checkley 2012). This does not mean that the relationship is insignificant. It does mean that the effects of temperature may be indirect, and may serve to affect the population dynamics in the California Current in as of yet unknown ways (Deyle at al 2013). However, sardines are not the only small pelagic fish that are affected by climate variability.

The uncertainties of climate change are innumerable, and as such, it is important to prepare for any and every uncertainty. This can be done through the modeling of marine systems. Modeling can give us insight into changes that may occur, and the subsequent consequences of such changes. This can also help managers to understand changes that are likely coming, and be able to adapt to these changes in the present, in order to sustain these ecosystems into the future.

Atlantic Herring (Clupea harengus)

There are three stocks of herring in the Norwegian Sea that are heavily fished. The largest and most commercially important of these is the Norwegian Spring Spawn Herring (NSSH). This stock has been consistently fished since the 1500s (Lorentzen and Hannesson 2006). The NSSH spawn on the benthos in the coastal fjords of Norway early in the year, in February and March. The larvae then drift north, into the Barents sea, where they stay while they develop until they mature at three years of age. The herring then spend their summers foraging for food onshore from April until August. In September, the fish contract into an offshore wintering ground, where they stay until it is time for them to migrate back to their spawning grounds. Most often they are fished during spawning or overwintering, as this is when they are found in the largest schools within a fairly predictable location (The Norwegian Ministry of Trade, Industry and Fisheries, 2013).



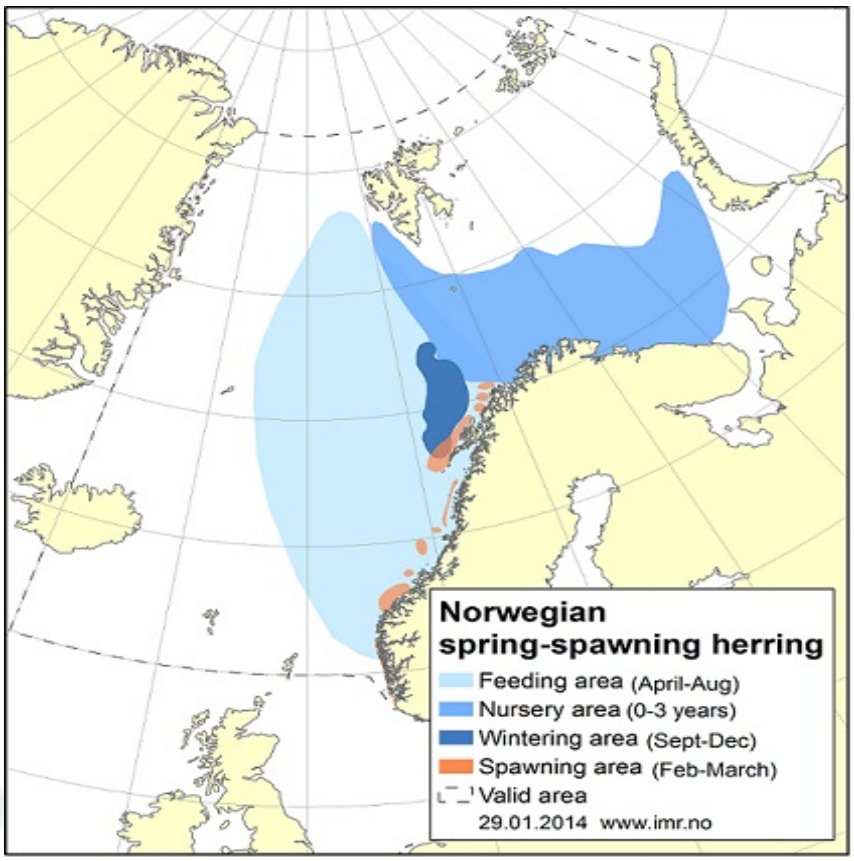


Figure 1. Norwegian spring-spawning herring are found off the western coast of Norway. They inhabit different areas during different seasons. They are fished during spawning season in their spawning aggregations as well as during winter when their habitat contracts. Figure from The Norwegian Ministry of Trade, Industry and Fisheries.

Herring being in an overall population decline as well as experiencing intense fishing pressure led to the commercial collapse of the fishery in 1968 (Lorentzen and Hannesson 2006). The stock did not recover until the early 1980s, assisted by a shift in environmental factors in their favor. Since the recovery, environmental conditions have been favorable, and herring recruitment has continued to be high even with intensive fishing pressure. Along with the improved environmental conditions favoring strong recruitment, a multi-national agreement was made in 2007 to sustainably manage the fishery. This agreement set up a quota system between Norway, Russia, Iceland, the EU, and the Faroe Islands. Under this agreement, Norway was allowed to fish 61% of the quota, Russia could fish 12.82%, Iceland could fish 14.51%, the EU could fish 6.51% and the Faroe Islands could fish a total of 5.61%.

Norway was given the largest share as they were historically the largest fishers of the stock, and most of the fishing grounds are located within their Exclusive Economic Zone. Also under this agreement, the other parties would be allowed to fish for NSSH inside Norway's Exclusive Economic Zone (The Norwegian Ministry of Trade, Industry, and Fisheries, 2013). In 2013, the Faroe Islands decided to withdraw from the agreement on the basis that the stock could be more heavily exploited and still remain at sustainable levels (The Norwegian Ministry of Trade, Industry and Fisheries, 2013). This led scientists and managers to reassess the status of the stock, and begin to ask more difficult questions about the future of the NSSH fishery.

Climactic factors

Like sardine in the California Current, Atlantic Herring are similarly influenced by climatic factors. However, the main climate oscillations in the North Atlantic Ocean are the North Atlantic Oscillation (NAO), which is long-term oscillation that can last up to thirty years, and the Atlantic Multidecadal Oscillation (AMO), which spans about twenty years (Knight et al 2006). These climatic forces play a major part in determining the makeup of the biological community off of the west coast of Norway. The AMO is mostly expressed through changes in average sea surface temperature (SST). When the AMO is in a positive flux, general SSTs are warmer, whereas when this flux is in a negative phase, SSTs are cooler. This causes drastic changes in not only the oceanography, but also in the aquatic biology as well as regional weather patterns and even terrestrial weather processes. For many years, the predominant interest in the AMO has been the use of the climate cycle to predict the likelihood and intensity of hurricanes in the Atlantic Ocean (Alheit et al 2013).

Another climatic force in play in this area is the North Atlantic Oscillation (NAO). This is part of the Arctic Oscillation, and contributes mainly to the frequency and intensity of storm tracks. The main

effects of the NAO are changes in wind patterns, as it is predominantly an atmospheric oscillation (Hurrell 1995). However, it has been suggested that prevailing wind patterns could play a role in recruitment of NSSH. When the NAO is in a positive state, it prevents Arctic air from being able to plunge southward, thereby causing warmer weather patterns, and contributes to warmer seas. This change in ocean temperatures has been known to reduce survival of fish larvae that are at the edge of their thermal tolerances (Knight et al 2006).

One of the consequences of the AMO for marine ecosystems is a shift is geographic range at the thermal extremities of marine resources. For fish in the North Atlantic, these minute changes in temperature can cause drastic range shifts for numerous species, including herring, cod and Atlantic sardine. Not only does this natural climate variability promote ecosystem shifts in fish species, but shifts in phyto- and zooplankton species has also been documented. The widely accepted hypothesis for the shift in planktonic resources is a shift in the critical thermal boundary to the north (Edwards et al 2013). For herring, it has been documented that temperature has a positive effect on growth as it supplies a sufficient amount of food (Fisken and Slotte, 2002). Juvenile herring survival heavily depends on a match between the first feeding of the larvae and abundance of planktonic prey items, which is highly dependent on environmental conditions (Fossum 1996). One of the main consequences of climatic variability for the NSSH is consistently low recruitment in cooler temperatures. However, warmer temperatures can result in either low or high recruitment (Alheit et al 2013). Another common consequence of climatic variability is the occurrence of regime shifts.

Regime shift

A regime shift is an abrupt change in the ecological makeup of an ecosystem. Usually they are influenced by environmental pressures, such as temperature changes, but can be exacerbated by

external pressures such as fishing and climate change. In the Baltic Sea, a regime shift has recently been documented, changing from a cod dominated ecosystem, to an ecosystem that is more conducive to herring and sprat. These regime shifts are enhanced by other stressors, including fishing mortality (Österblom et al. 2007). Various regime shifts have also been seen in the Norwegian Sea throughout the past hundred years. In the 1920s until the 1940s, a positive AMO shifted herring and mackerel assemblages to dominate the ecosystem, but a shift into the negative AMO in the 40s shifted Atlantic cod back into dominance (Drinkwater 2006). Cod assemblages dominated the ecosystem through the 80s. Cod remained dominant through a positive AMO flux in this time period, and it is likely that this occurred due to a fishery collapse in the Atlantic herring that occurred during this time period. The fishery collapse most likely occurred due to persistent low recruitment, coupled with overharvest of herring during this time period (Lorentzen and Hannesson 2006). Currently, the AMO has been in positive flux since the late 1980s, which supports the rebuilding of the stocks of Atlantic herring.

As the climate changes due to anthropogenic factors, regime shifts caused by natural climate variability are expected to become more pronounced, and in certain cases may become irreversible. Climatic oscillations that favor a particular assemblage of species may dominate (Brander 2010). As environmental conditions change in unpredictable ways, thresholds may be crossed and it may become more difficult to switch back into assemblages associated with cooler temperatures. In the North Atlantic, this may mean that the herring dominated ecosystem may prevail, without ever shifting back into a cod dominated assemblage. While this may mean a higher amount of stability in herring stocks, it might mean wide population shifts in cod stocks. Herring stocks tend to experience higher levels of recruitment when in a positive ecological regime, as well as experience higher recruitment when in warmer AMO positive sea surface conditions (Alheit et al 2005).

This project

This project looked at the relationship between SST and stock size of the NSSH. While the effects of temperature may be indirect, it has been found that there is a positive relationship between SST and spawning stock biomass. This allows temperature to work as an appropriate proxy variable, which can then be used to forecast fish stocks. While the exact relationship between SST and stock size is unknown, the relationship is close enough to where this type of analysis is appropriate. This project used the idea of the proxy variable to estimate the relationship between temperatures and stock size in order to forecast trends in stock size through changing climate scenarios. This project is not intended to estimate exact stock size for different temperatures, but instead focuses on the idea that if temperatures are known, general conclusions can be made about the consequential behavior of the stock. This can allow managers to prepare for long term trends of stock fluctuations as the climate of the planet becomes less predictable.

Currently, most fish stocks are managed on a year to year basis. However, this has lead to dire consequences in some fisheries as environmental conditions change, causing drastic decreases in the size of the fish stock. This can lead to over-harvest and even collapse. If the reactions of the stock to climatic influences is understood, then managers have a better chance of being able to adapt to these changes, thereby managing the fishery in a responsible way that will ensure conservation of the fishery for future generations. Careful management of fish stocks is important, especially in stocks that are data poor. This project looks at simple things that can be done by managers to estimate the generalized effects of temperature and, more importantly, changes in temperatures that are likely going to effect their fisheries in the near future.

It would be expected that SSTs in the early spring would have the greatest impact on the NSSH. This is

due to prey availability during their foraging months in the spring. The spring is also when juveniles have their first-feeding, which may be the time in their life history where they are most sensitive to changes in the water column, as this is the most temperature sensitive life stage. Warmer SSTs cause increased stratification in the water column, which leads to a greater availability of prey in the top 200 meters of the water column. It was also hypothesized that increases in temperature will cause increases in stock biomass in general, as warmer temperatures tend to influence increased recruitment.

The Models

Where did the data come from?

Fisheries Independent data was gathered from the International Council for the Exploration of the Seas (ICES). This is an intergovernmental organization with a focus on sustainability of the sea. Their main mission is to increase understanding of marine resources and provide this knowledge to the appropriate authorities (ICES 2014). Stock assessments have been done with a Virtual Population Analysis (VPA) since 1988 to the present through the ACOM/SCICOM Strategic Initiative on Stock Assessment Methods. These data sets incorporate data from fish trawls, acoustic surveys and larvae and egg capture trawls in order to estimate the total Standing Stock Biomass (SSB). This model is currently the model used by managers to set quotas for the fishery.

The temperature anomaly data was acquired from the Met Office, Hadley Centre for Climate Research in the UK. This data is from the HadISST climate model (HadISST, 2014). This data set included monthly temperature data for degree latitude blocks for the entirety of the ocean for 1870 through 2011. For the purposes of this analysis, a subset of temperatures was taken from 0.5 to 2.5 degrees East longitudinally, and 64.5 to 66.5 degrees north latitudinal. This region represents the area off the west coast of Norway that NSSH spend the dominant portion of their lives. This data was averaged over area, and then into an average annual temperature. It was then split into seasonal blocks dependent on the life history stage of the NSSH. Average spawning temperature represents the average temperatures from January through March. The average temperature for the onshore feeding time takes place over most of the summer from April to August. Offshore feeding temperatures make up the rest of the year, spanning from September to December.

Fisheries dependent data comes from work done by Toreson and Ostvedt (2000), in which they used catch per unit effort (CPUE) to determine SSB. This data set spans from 1907 until 1998. 1907 was the earliest that CPUE was measured consistently across the fishery. This data also includes the collapse from 1968 until 1982. Data was analyzed both with and without the collapse included. The collapse was excluded as it created a decoupling event that caused temperature to decouple from the stock size. In 1982, the collapse had fully 'recovered' and could be seen back in sync with historic stocks. Fisheries dependent data has many limitations, including the inability to account for hyperstability (Erisman et al 2011). That is, effort may not have been consistent throughout the entire time series. Another caveat to using fisheries dependent data is the proclivity of fishermen in this fishery to set their nets upon spawning aggregations, thereby pulling the majority of the stock out. This creates problems when managers assume that the entirety of the stock was not set upon, and can lead to overestimation of the stock size (Walters 2003).

10 -year-interval data was recreated from Biswas et al. (2008). This temperature data was from the CLIMBER-2 model (CLIMate-BioshpeRE model). Temperature differences are simulated SST anomalies from 2000 to 2100 taken from the aggregate average of the simulation. The simulation was developed by Petoukhov et al. (2000). The data is spatially segregated to include only the projected SST changes in the Northeastern Atlantic Ocean. High-resolution global climate model (GCM) prediction data was extracted from Lapp et al. 2011. This data focuses on 50 year projected changes in average SSTs. These projections are also not localized to the Northeastern Atlantic, but instead represent the entire North Atlantic. The GCM projections are an ensemble mean of multiple scenario runs from multiple models, which include CGCM3.1 (T47), CGCM3.1 (T63), ECHAM5/MPI-OM, GDFL-CM2.1, MIROC3.2 (hires), MIROC3.2 (medres), MRI-CGCM2.3.2, NCAR-CCSM3, NCAR-PCM, and UKMO-HadCM3 models.

Correlation analysis

To analyze correlations, a cross-correlation function was used to assess the maximum correlation between the two variables taking into account lag time between the two time series. Lag was included in the analysis as it would be likely that the effects of temperature may take a few years to be seen in the population. This helps to analyze the correlation over time, in order to see if there is a temporal lag between the two parameters. The equation used for the cross-correlation can be seen in Equation 1.

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{(n-1)s_x s_y} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}, \qquad \text{Equation 1}$$

Table 1. Results from the initial cross-correlation analysis show that stronger correlations can be seen with the fisheries independent stock assessment data, while the fisheries dependent data does not follow this trend. Greater lag was also seen among the fisheries independent data.

Fisheries data	Temperature	Correlation Coefficient	Lag
Fisheries Independent (1988-2012)	Annual	0.610086	0
	Spawning (Feb-March)	0.5297818	0
	Foraging (April-Aug)	0.4861769	-1
	Winter (Sep-Dec)	0.6820969	0
Fisheries Dependent (1907-1998)	Annual	0.2630142	9
	Spawning	0.1362396	14
	Foraging	0.2451375	9
	Winter	0.3673344	11
	Annual – No collapse	0.242322	13
	Spawning – No collapse	0.1779601	14
	Foraging – No Collapse	0.2232926	0
	Winter – No collapse	0.329063	11

The strongest correlation was seen between the fisheries independent data for the offshore wintering temperatures. There are stronger correlations with smaller lags with fisheries independent data than with the fisheries dependent data. Smaller lag time was also seen in the independent data than in the fisheries dependent data. A positive lag indicates that the stock size parameter lagged behind the temperature in year long increments. A negative lag indicates that the temperature parameter lagged behind stock size, and was only encountered once, in the onshore fisheries independent model. For the rest of the analysis, only annual temperatures and the fisheries independent data were used. These variables were used because it they showed a high correlation value with zero lag. Also, for future forecasting, annual average SST is a more easily accessed variable for managers. It seemed appropriate to use the model currently used by mangers in order to work through the relationships, as it is more

likely that managers will have access to these parameters.

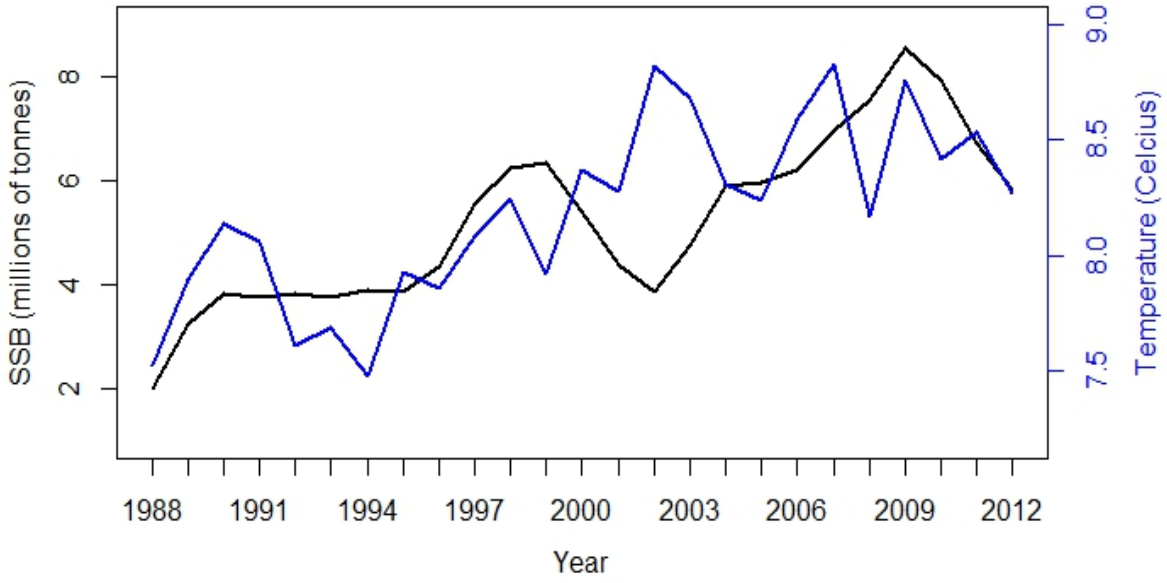


Figure 2. Fisheries independent data from ICES shows similar trends to the average annual SST for the same geographic regions. A correlation coefficient of 0.619986 with a 0 lag was found.

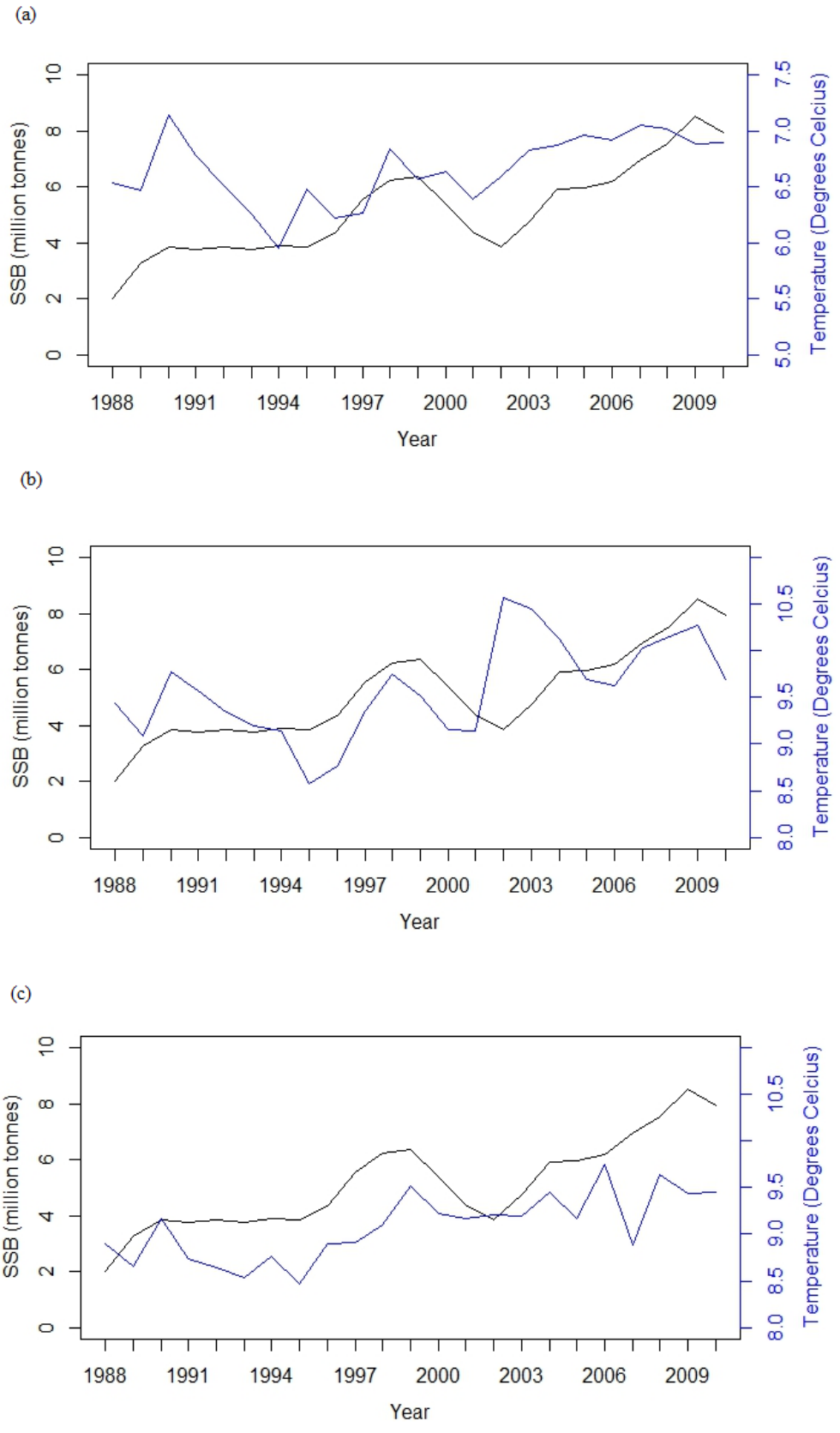


Figure3. A correlation was found between average fisheries independent stock biomass and temperatures during (a) spawnging (corr. coef. 0.5298), (b) foraging (corr. coef. 0.4862, -1 year lag) and (c) wintering (corr. coef. 0.6821).

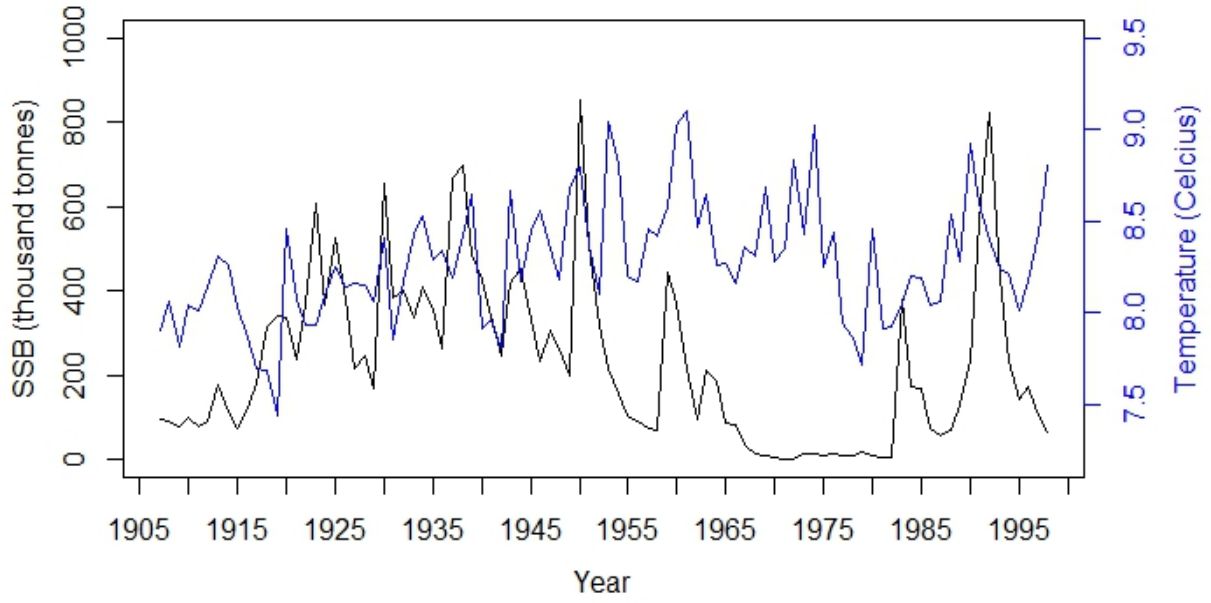


Figure 4. A correlation coefficient of 0.2630 with a 9 year lag was found between fisheries dependent data and average annual SST temperature for the area where NSSH occur.

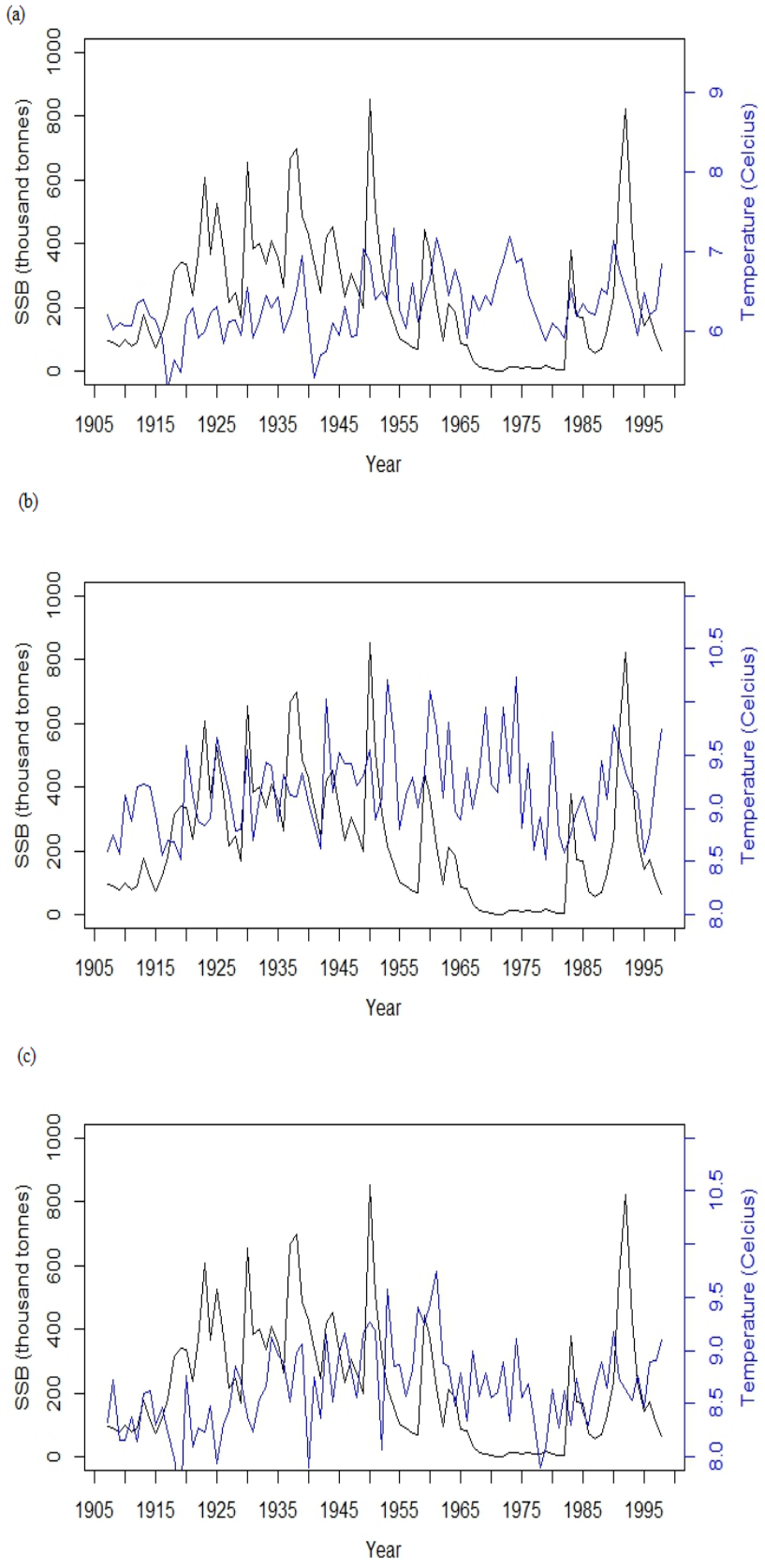


Figure 5. The corrleation between the average fisheries dependent SSB (thousand tonnes) and temepratures was found for (a) spawning (corr. coef. 0.1362, lag 14 years), (b) foraging (corr. coef. 0.2451, lag 9 years), and (c) wintering (corr. coef. 0.3673, lag 11 years).

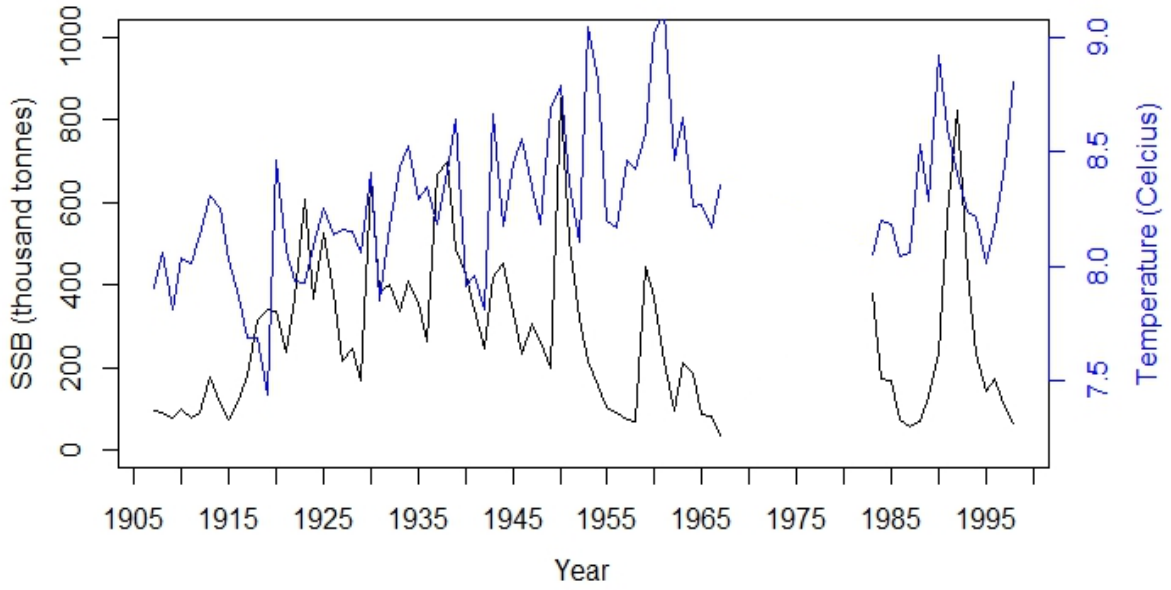


Figure 6. A correlation coefficient of 0.2233 with a 13 year lag was found between the annual SST data and the fisheries dependent stock with the removal of the years where collapse decoupled the data sets.

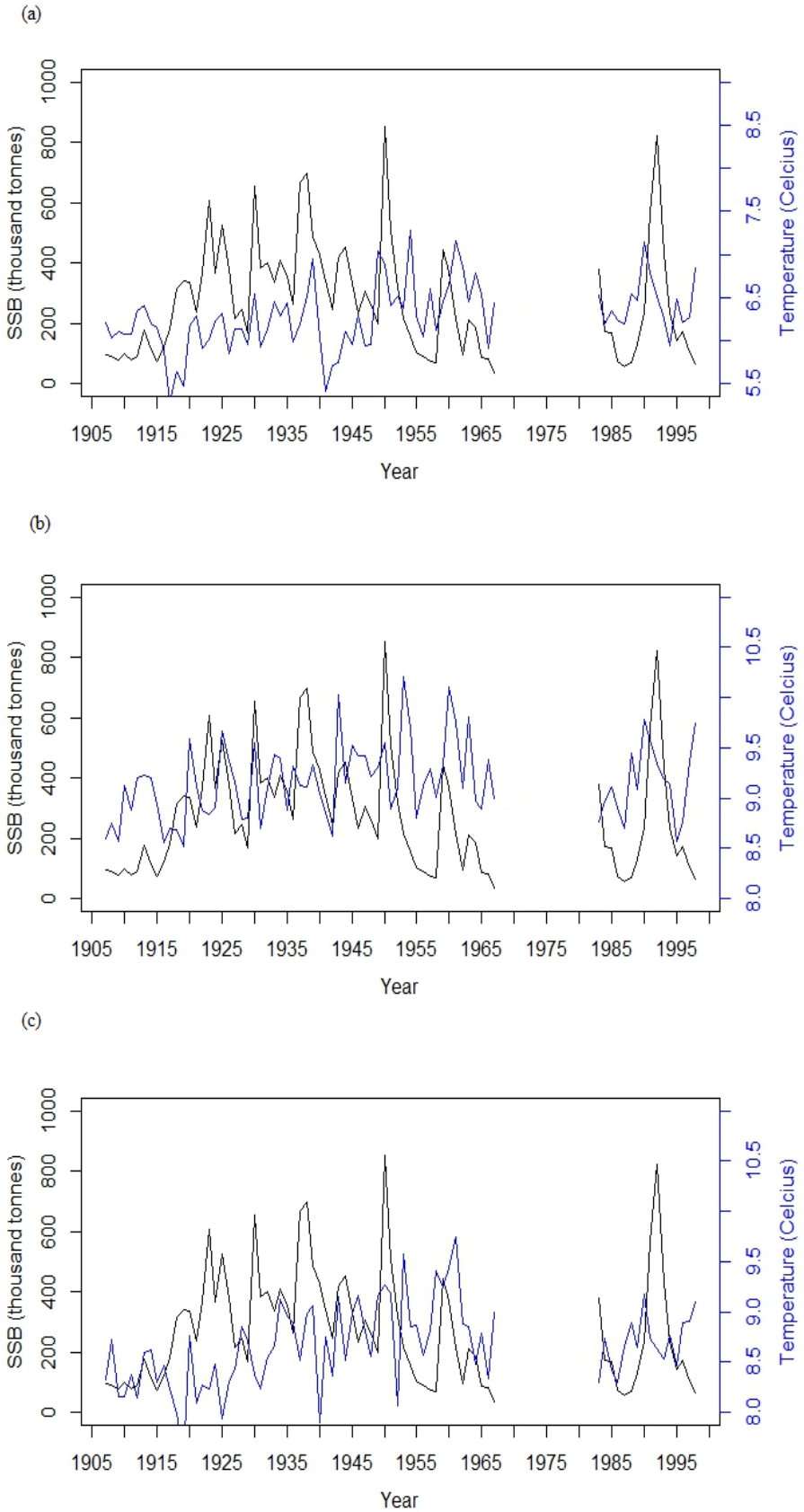


Figure 7. The correlation between the average fisheries dependent DDB (thousand tonnes) and SST was found with the removal of the years where the fisheries collapse caused decoupling was found for (a) spawing (corr. coef. 0.1779, 14 year lag), (b) foraging (corr. coef. 0.2232), and (c) wintering (corr. coef. 0.3291, 11 year lag).

Ricker models and the Stock-Recruitment Relationship

The next logical step would be to incorporate the effects of temperature into stock assessment models, so that the fishery is managed in real time with respect to this environmental variable. The most likely place for temperature to play a role in these stock assessment models would be in the stock-recruitment curve. Variations in the stock-recruitment relationship may be explained by changes in temperature. This would increase the precision of the model, and could then be used to make more precise measurements of stock abundance. The Ricker model, as seen in equation 2, is one such stock-recruitment curve, that shows the logistic relationship between the stock size this year and recruitment next year.

$$N_{t+1} = N_t e^{r_0\left(1-\frac{N_t}{K}\right)} \qquad \text{Equation 2}$$

The issues with using this type of analysis are that there is a need for a lot of information on the fishery, including time series information. This information is hard to acquire, and in many data poor fisheries this may not be a logical option. In the NSSH fishery, this has been done by Fiksen and Slotte (2002). They worked a temperature parameter into the Ricker stock-recruitment recruitment relationship, showing how temperature relates to the recruitment of young herring into the fishery. They found that the inclusion of SST into the model generally increased the precision of the model, as well as removed a great deal of autocorrelation from the residual variability (Fiksen and Slotte 2002). In this model, temperature no longer serves as a proxy variable, but is instead an adjustment variable. This adjustment variable then serves the purpose of making the stock-recruitment, and therefore the stock assessment, a more precise value. This is the next logical step for this work, as it would directly feed into management practices.

Cointegration and Causality

The Augmented Dickey Fuller test was used to test the cointegration of the data. This tests for the stationary nature of the residuals of a data set. Cointegration is the test of whether the two variables have similar stochastic trends. This test transforms the data into a stationary time series and then tests the residuals to see if the trending of the residuals, or unit roots, are similar. If they are similar, the two time series are known to be cointegrated. This test is necessary, because correlation does not imply causation. However, if the data sets are cointegrated, then any regressions done with the data will not be spurious. It was found that the temperature and the biomass of the stock are non-stationary. This was found with a ADF statistic of -2.0309 and a p-value of 0.5606. When the data was log transformed (using the natural log), a ADF statistic of -3.4108 was found, with a p-value of 0.07628, which is significant to a 90% confidence. This shows that the log transformed data is non-stationary, and any regressions done with this data are not spurious. The rest of the analysis done were completed with both the raw data as well as the transformed data. This non-stationarity means that the data are cointegrated. That is, they share similar long-term relationships. This means that the analysis can continue without worry of spurious correlations.

A Granger test was done to determine causality. This test, which is widely used in the field of economics, is a way to determine mathematically whether one parameter relies on the other, or is caused by the other. The equation for this analysis can be seen in Equation 3. However, for this data set, there were no significant values for the Granger test, which means that we cannot conclude that temperature determines stock size. This would be expected, as there are many other parameters that play a major role in the size of the stock. This does not rule out the ability to use temperature as a proxy variable. This model takes lag into account up to a 5 year lag. For all models, including the log

transformed model, all data was found to be statistically insignificant for causality. However, this does not mean the regressions are spurious. This simply implies that there are other factors at work here, and that the relationship between temperature and SSB are not direct.

$$x_n = \sum_{k=1}^{\infty} a_{x,k} x_{n-k} + \sum_{k=1}^{\infty} b_{x,k} y_{n-k} + \xi_n,$$
$$y_n = \sum_{k=1}^{\infty} a_{y,k} y_{n-k} + \sum_{k=1}^{\infty} b_{y,k} x_{n-k} + \psi_n,$$

Equation 3

Ordinary Linear Regressions

In order to build a model for forecasting, a regression was done with the fisheries independent annual model. The regression model is shown in equation 4. The R^2 was 0.3722 with an adjusted R^2 of 0.3423, with a p-value of 0.001994. This means that the temperature model explains 34.23% of the variation in the fish stock. While this is not a high number, we must remember that there are many other factors that are contributing to stock size and recruitment, and temperature is just a proxy variable to give an idea of the relationship between climate and fish stocks. Figure 8 illustrates this relationship. However, time series data has a high likelihood to be serially correlated, which will make the regression less accurate.

$$2.0867\,T - 19.2381 = S$$

Where T = average annual SST (in degrees Celcius)
and S = Standing stock biomass (in millions of tonnes)

Equation 4

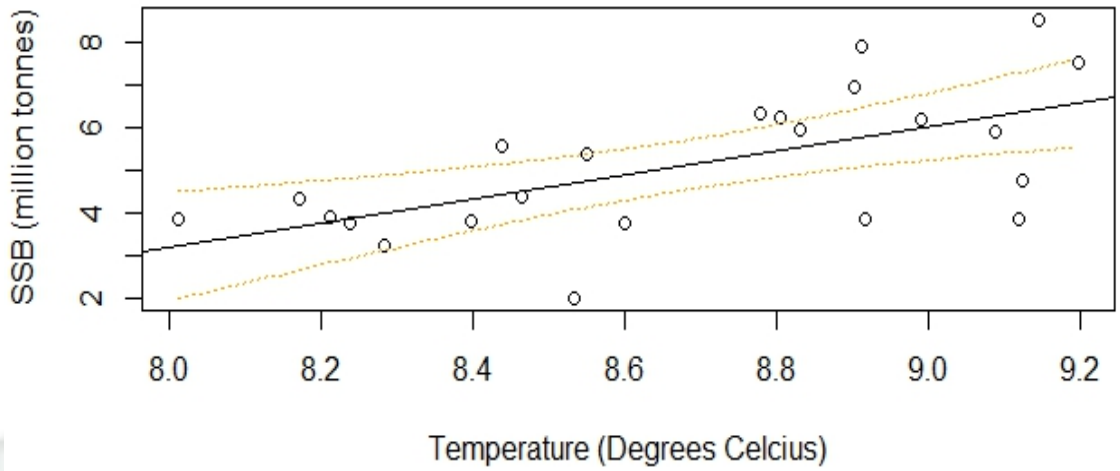


Figure 8. A ordinary linear regresssion was completed using the Newey West Estimator resulting in a regression equation of 2.0867T-19.2381=S, where T= avereage annual temperature and S=standing stock biomass. The orange lines represent the confidence intervals for the equation. (R^2= 0.3722, adjusted R^2 = 0.3423, p-value = 0.001994).

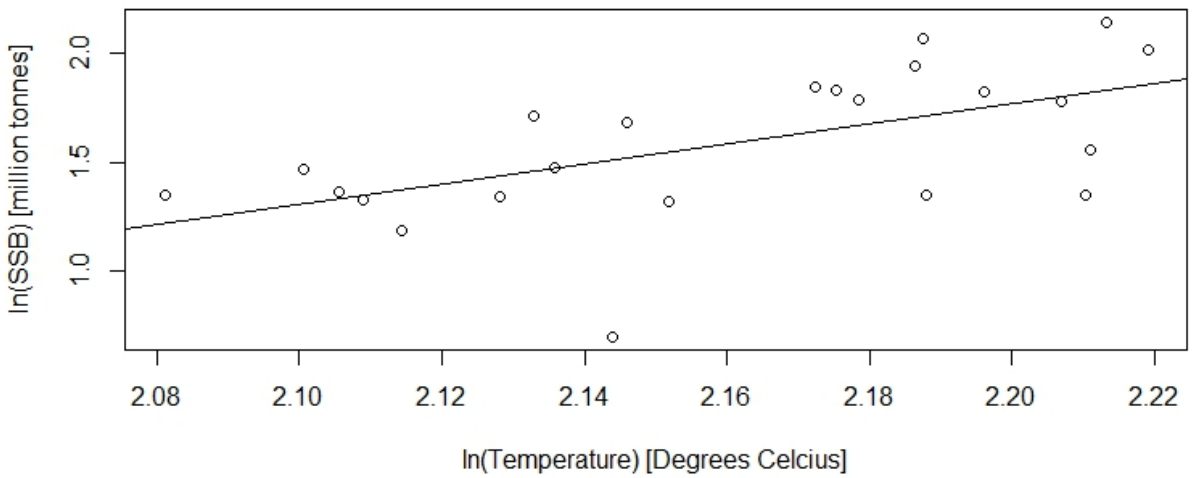


Figure 9. An ordinary linear regression was completed with the ln transformed data using the Newey West Estimator resulting in a linear equation of 4.6397(ln(T))-8.4412=ln(S), where T=average annual SST and S= standing stock biomass (R^2= 0.3233, adjusted R^2= 0.291, p-value = 0.004644).

To deal with the issues from serial correlation, a Durbin-Watson Test for serial correlation was preformed. It was found that there was a level one serial correlation (d=0.4987, p-value=1.367e-06). This means that there a first order serial correlation in the analysis. In order to remove the serial correlation, regressions were done with the Newey West Test. This test uses an ordinary least squares model while also correcting for heteroscedasticity as well as autocorrelation in the time series. When the Newey West test was done, the same regression model was returned. This means that while autocorrelation is present, the equation 2.8067T-19.2381=S (Equation 4) (R^2= 0.3722, adjusted R^2 = 0.3423, p-value = 0.001994), where T= average annual SST and S= standing stock biomass, is the most accurate model both with and without the autocorrelation. However, while the overall regression is significant, the p-value for the intercept was 0.11818 (t-value = -1.6292, SE= 11.8082) and the p-value for the relationship between the temperature and the SSB was 0.06072 (t-value= 1.9819, SE=1.4161). Statistically speaking neither of these values are significant.

$$2.0867\,T - 19.2381 = S$$

Where T = average annual SST (in degrees Celcius)
and S = Standing stock biomass (in millions of tonnes)

Equation 4

A regression was also done for the ln transformed data. The Newey West test was used for this linear regression also in order to control for heteroscedasticity and autocorrelation. The output for this regression was also significant, with an equation of 4.6397(ln(T))-8.4412=ln(S) (Equation 5) (R^2= 0.3233, adjusted R^2= 0.291, p-value = 0.004644), where T= average annual SST and S= standing stock biomass. The transformed nature of this data makes it difficult to find confidence intervals for error. Transforming data with natural logs helps to deal with outliers as well as gives a better fit to the data. For the transformed data, the intercept was found to be significant with a p-value of 0.05990 (t-value = -1.9889, SE = 4.2442). The slope (the relationship between temperature and SSB) was also found to be significant with a p-value of 0.03006 (t-value = 2.3268, SE= 1.994).

$$4.6397(\ln(T)) - 8.4412 = \ln(S)$$

Where T = average annual SST (in degrees Celcius)
and S = Standing stock biomass (in millions of tonnes)

Equation 5

Forecasting

Forecasting was done with the linear regression model for the raw data. This was chosen for forecasting as the raw data is easily available and can give us simple clear results. The logarithmically

transformed data could also be used for this analysis, however, converting between logarithmic values and raw data would be necessary. This means that conclusions would have to be reverted from logarithmic data in order to make conclusions. Because of this, the raw data regressions were used. Equation 4 was used for this analysis. The limitations of the regression are essential to recognize when using it for predictions. While the models do explain about 34% of the variance in the data, this does not explain all the variation in the data. Using the predicted increases in SST, forecasts of stock biomass can be made using the regressions found for this relationship. Two different models were used for predictions. These forecasts can be seen in figures 10 and 11. The GCM predictions show fifty and one hundred year projections for the North Atlantic Ocean, while the CLIMBER-2 model shows average temperature in ten year intervals for the Northeastern Atlantic Ocean. The GCM models show the likelihood of changes for differing climate scenarios, including B1, A1B, and A2 scenarios.

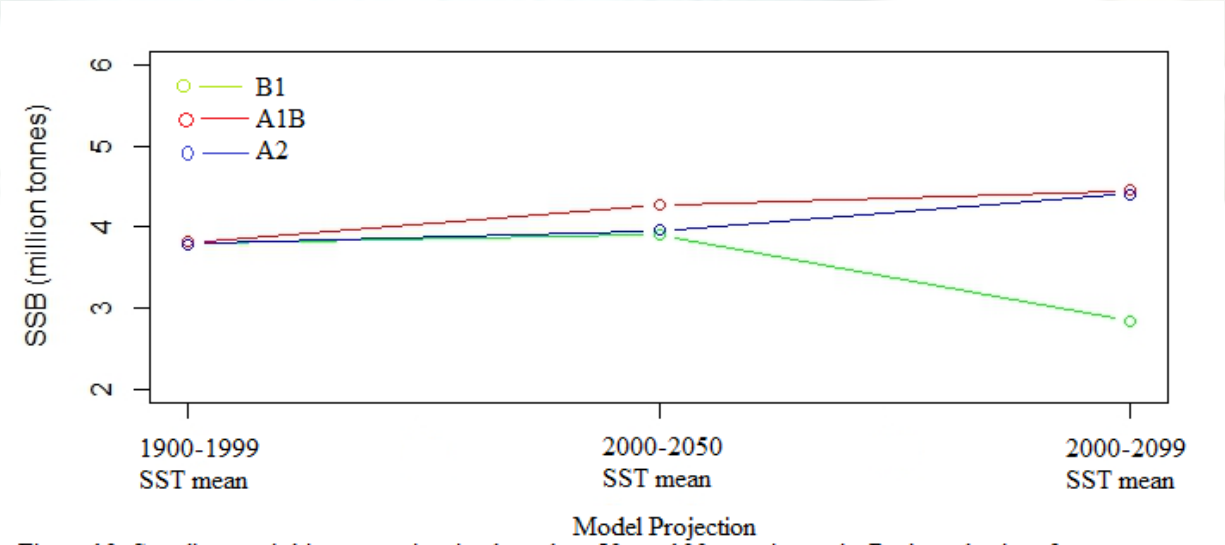


Figure 10. Standing stock biomass estimation based on 50- to 100-year intervals. Projected values for sea surface temperatures are from GCM models for the North Atlantic Ocean. The forecast for the stock biomass is based on the regression equation 2.8067T-19.2381=S, where T= sea surface temperatures in degrees Celcius and S = standing stock biomass in millions of tonnes. The green line represents B1 scenarios, the red line represents an A1B scenario, and the blue line represents an A2 scenario.

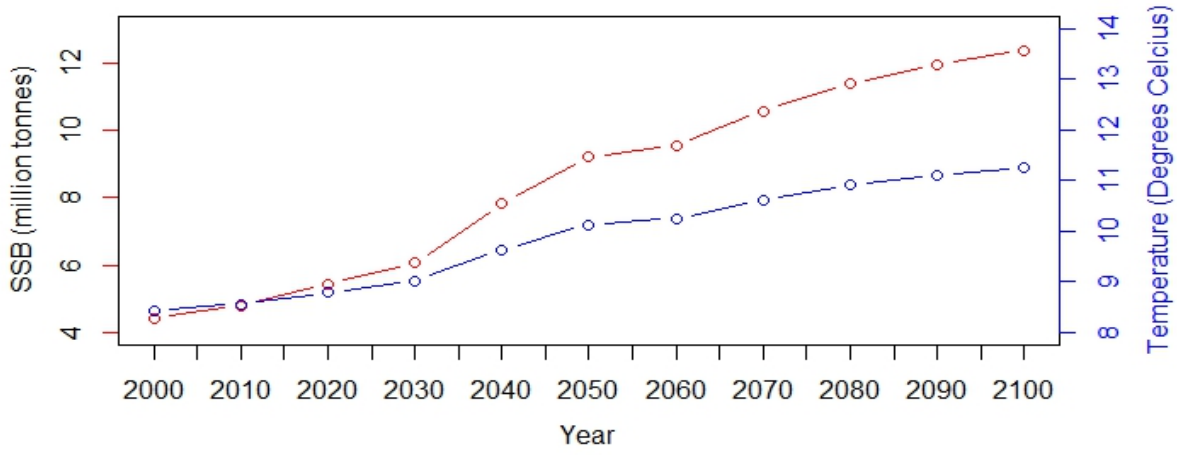


Figure 11. Standing stock biomass estimation for ten year intervals based on estimated sea surface temperatures. Temperatures are from the average aggregate from the CLIMBER-2 model for the northeastern Atlantic Ocean. The model for this forecast is 2.8067T-19.2381=S, where T= average sea surface temperature in degrees Celcius and S= standing stock biomass in million of tonnes.

Discussion

How the models work and don't work

While it is important to understand changes that may happen in the fishery, there are many caveats to this type of modeling. Data for this type of modeling is hard to come by, and sometimes may be inaccurate. For example, fisheries dependent models may be inaccurate due to hyperstability and a non-consistent definition of CPUE. The forecasting data, while the aggregate average of model predictions, is still a projections, and may not accurately represent actual changes seen in the environment. It is also important to remember the unknown of the exact relationship between temperature and stock biomass. It must also be understood that temperature may have different effects on the stock at different stages in the life history of the herring. This could mean that the relationship is much more complex than currently understood. There could also be other environmental factors that play a major role in the size of the herring stocks, which could outweigh the effects of temperature.

Biological

This modeling may give us a better understanding of how the environment plays more of a role in fisheries than managers have taken into account. With increasing average SSTs, there may be a shift in the carrying capacity of the ecosystem, or permanent shifts in the ecosystem composition. The regime shift between small pelagic fishes and Cod in the Northeastern Atlantic may become more pronounced, which may eventually lead to a threshold event. This may mean that a shift back to a cod dominated assemblage may be less and lees likely to occur.

There may be other effects of climate change that are important to consider. These are things such as shifts in weather and wind patterns, which may cause changes in SST. Increased stratification in the

oceans, as well as ocean acidification are also likely to play a role in the shifting sizes of the stock biomass. The shifting in the AMO may also exhibit unpredictable patterns. However, it is likely that herring stocks will increase in size with an increase in the temperature of the average SST anomaly. While the exact effects are not understood, the general trend may give managers an idea of the generalized future of the stock. This can then give a basic understanding of the changes which can shape the decisions made in the future on how to adapt to changes in the climate.

The use of different climate scenarios can also give some insight on possible changes in the future that are dependent on choices made by policymakers today. In the GCM models, the A2 scenario is the business as usual scenario that includes the increase in greenhouse gas emissions, while the B1 scenarios incorporates a reduction in emissions. In this forecast, the B1 scenario is the only scenario that shows a reduction in the average biomass of NSSH. This scenario also predicts a lesser amount of GHG warming, which may coincide with cooler SST, leading to poor recruitment years, and poor age-classes of NSSH.

Management

This fishery has been an established multi-nationally managed fishery for many years. However, as changes in the stock occur, changes must also be made in the management of the stock. Changes in the stock have already been seen by various nations, leading to the withdrawal of the Faroe Islands from the agreement. This was based on science from the Faroe Islands noting an increase in NSSH in the EEZ of the Faroe Islands. This was mainly due to changes in the spatial distribution of the stock as well as changes in overall size of the stock (The Norwegian Ministry of Trade, Industry, and Fisheries, 2013). Changes are already being felt in the stock, and more are likely to follow. The response of managers to the withdrawal of the Faroe Islands was to set aside their allotment of the total allowable

catch (TAC), and carry on with the distribution of the rest of the TAC to the interested parties. However, this is not a strategy that will last for long. Managers can not rely on historical numbers to manage fisheries anymore. Because of the changes in the environment, it is essential for managers to be able to adapt to changes also.

These forecasts show an overall trend of increasing standing stock biomass in the NSSH. It is essential that managers take this into account when setting TACs for each year, and also should be taken into consideration when working with stock assessments. While these analysis can only show general stock trends, these trends are important to take into account. That being said, this does not mean that managers should be more liberal with their allotments. It means that these sorts of analyses should be conducted on more species that show the same general trends in order to have a basic idea of changes that may occur in the ecosystem.

Conclusions

While this study is not exhaustive, it does highlight some essential changes that may be occurring in the ecosystem. Temperature can be used as a proxy variable to understand in a basic way, how the environment affects the stock. This is an important step on the way to ecosystem-based management. While this type of management is a long way off for most fisheries, as the climate becomes less predictable, it is important to try and incorporate as many of the changes as possible. This includes environmental components that previously have not been considered.

Future steps in this research should include finding ways to incorporate temperature effects into the stock assessment models. As is shown above, a relationship has been found between the stock-recruitment relationship and temperature. The VPA models that are currently used for assessment of this stock should have environmental components incorporated, and the first of such might be temperature. The only way to stay ahead of the consequences of climate change is to try and forecast the possible changes that may occur. By figuring out the exact relationship between the stock and temperatures, it may be possible to stay ahead of climate change by working to discover the effects now, and subsequently, working them into management as quickly as possible.

There is no one size fits all climate scenario for fisheries. Effects of climate change are compounded by other stressors in the environment including ocean acidification, anthropogenic nutrient inputs, overharvesting and coral bleaching. The effects of these processes are more likely to be seen on shorter time scales that the direct effects of climate change. However, the increased stress is likely to create threshold events that eventually may lead to regime shifts, or even collapse. Understanding the effects of climate change now may ensure that the world's fisheries may be protected for tomorrow.

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