BLUE ACTION

Case Study 4 "Marine Fisheries forecasts products"

Mackerel for sale in a Market. Photo by Samuel C. on Unsplash

About this document

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Summary for publication

This deliverable details work done on the development of Climate Services for use in the Marine Fisheries sector within Blue-Action Case Study (CS4). The work described here builds on the previous Blue-Action deliverable, D5.16 "Report on Marine Fisheries Climate Services Workshop" which identified a set of potentially valuable climate services based on interviews with stakeholders and potential users. This work focuses on developing the necessary knowledge to support these climate services and ecological forecasts, specifically by developing knowledge of the processes that link the variability of the physical environment to biological responses. Once complete, this knowledge can then be coupled to forecasts of the physical environment to yield marine ecological forecasts, and therefore marine ecological climate services.

The work performed was therefore focused on around 12 different strands of work, loosely grouped into three categories based on the biological response being forecast.

Three forecasts of the spatial distribution of species are being developed. For the spawning of **Blue Whiting** and the summer feeding distribution of **Mackerel,** solid links to the physical environment were identified. Previously published work looking at the factors controlling the distribution of **Bluefin Tuna** was updated and checked, and found to be still suitable.

Developing forecasts of the productivity (recruitment) of marine organisms required the most attention, as it is a relatively poorly established field. Two conceptual pieces of work, one looking at a conceptual framework for recruitment prediction and a second showing how to correct biases in fish stock assessments, provided an solid foundation. Work examining the recruitment of **Sandeel** in the North Sea showed the potential for developing forecasts, although these were driven primarily by non-environmental factors. Attempts to develop **herring** recruitment forecasts were so far unsuccessful, and did not outperform a persistence forecast, but there are data from the partner PFA to be integrated in the forecast in the upcoming months and this might change the outcome of this report. Work performed by WP2 in Blue-Action has also highlighted the potential for developing recruitment forecasts for **cod** in the Barents Sea.

The basis for **climate services forecasting the timing (phenology) of key events in the ocean** was also examined. A good basis for predicting the timing of sandeel spring-re-emergence, based on over winter temperature, was found. Similarly, there is a good base for predicting the migration of **garfish** and mackerel into Danish waters, for use by recreational fishers. However, attempts to investigate the timing of herring spawning in the English Channel did not prove successful.

The main results are summarised in the table below.

Proposed Climate Service	Source	Results of investigations	Operationalise?
Spawning distribution of blue whiting	Blue-Action CS4. Published in (Miesner and Payne, 2018)	Spawning distribution linked to deep-water salinity with species distribution model.	Yes
Summer feeding distribution of mackerel	Blue-Action CS4. Manuscript in preparation.	Feeding habitat linked to sea surface temperature with ecological niche model.	Yes
Summer feeding	Previously developed in FP7	Feeding habitat linked to sea	Yes

distribution of Bluefin Tuna	NACLIM project. Rechecked and updated in Blue-Action CS4. Published in (MacKenzie *et al.*, 2014)	surface temperatures greater than 11 degree C.	
Recruitment of sandeel in North Sea	Blue-Action CS4. Manuscript in preparation	Recruitment of four stocks linked to SST, demographic factors and year effects.	Yes
Recruitment of herring in the North Sea	Blue-Action CS4.	Recruitment predictions based on adult biomass and sea surface temperature tested but no significant predictive power.	No – no clear sign of predictive power (*)
Recruitment of cod in the Barents Sea	Blue-Action WP2. Published in (Årthun *et al.*, 2018b)	Total biomass and recruitment linked to sea surface temperature	Yes
Timing of sandeel re-emergence	Blue-Action CS4	Degree of re-emergence on 1st April linked to previous winter temperatures.	Yes
Timing of mackerel migration into Danish waters	Previously published (Jansen and Gislason, 2011)	Timing of migration linked to sea surface temperatures	Yes
Timing of garfish migration into Danish waters	Blue-Action CS4	Timing of migration linked to sea surface temperatures	Yes
Timing of herring spawning in English channel	Blue-Action CS4	Effect of temperatures on spawning phenology not significant	No (*)

(*) These are to be further explored in the upcoming months with data made available by PFA.

Based on these results, the systems where there is sufficient scientific support linking the physical environment with the biological response will next be developed in climate services. This will involve coupling the knowledge and models developed here to forecasts of the physical environment to produce ecological forecasts. The forecast skill of these predictive systems will be evaluated and their potential value to end-users estimated. Finally, these products will be operationalised and disseminated more generally.

Work carried out

General Approach

This deliverable represents the second of four deliverables within Case Study 4 of Blue-Action detailing the development of Climate Services for use in the Marine Fisheries sector. The work described here builds on Blue-Action D5.16 "Report on Marine Fisheries Climate Services Workshop" in which **stakeholders, both within and outside of the project consortium, were interviewed to identify potential climate services that could be of value in their decision-making processes**. Stakeholders included representatives from:

- the Commercial Fishing Industry (Danish Pelagic Producers Organisation, Marine Ingredients, Pelagic Freezer Trawler Association),
- Scientific Advisory and Monitoring Bodies (ICES HAWG and WGIPS workgrounds, ICCAT),
- the broader public (Recreational fishers).

One of the key results of this process was the **identification of potential climate services** that could be used by each of these end-users: these are summarized in Table 1.

Table 1 Overview of end-users and climate services identified in Deliverable D5.16

Co-designer / End-user	Category of the co-designer / end-user	Highest Priority Potential Climate Service(s)
Pelagic Freezer Trawler Association (PFA)	Commercial Fishing Industry	Timing of spawning in Downs herring
Danish Pelagic Producers Organisation (DPPO)	Commercial Fishing Industry	1) Productivity and 2) timing of Sandeel in the North Sea
Marine Ingredients	Commercial Fish Processing Industry	Productivity of the portfolio of small pelagic fish stocks in the North Sea
WKPELA2018	Scientific Advisory and Monitoring Body	Productivity of herring in the North Sea
WGIPS	Scientific Advisory and Monitoring Body	Spatial distribution of Blue whiting spawning
ICCAT	Scientific Advisory and Monitoring Body	Distribution of Atlantic Bluefin tuna in the North Atlantic
Recreational Fishers / *Fangstjournal*	Broader public and recreational fisheries	Timing and distribution of garfish migration

These proposed climate services can be classified into three general forms.

- The first type are those dealing with **future shifts in the spatial distribution of fish species and stocks i.e. where fish can be caught**: these are by far the most common form of existing marine ecological forecast products (Payne et al., 2017).
- There is also a strong interest from the stakeholder community in **forecasts of the productivity ("recruitment") of fish stocks (i.e. how many juvenile fish are produced in the future),** as this factor plays a key role in determining the future abundance and catch opportunities of the stock.
- Finally, the **timing of key events ("phenology"), such as migration into an area**, is also critical for many stakeholders who need to plan their activities accordingly.

The work performed within this case study touches on all three of these biological responses, and is grouped accordingly below.

In the development of these climate services, it is important to note that the scientific understanding of the dynamics of organisms in the ocean is often divided into two different schools of thought. In the "bottom-up" approach, variations in the physical environment drive variations in the biological response. On the other hand, in the "top-down" approach the effects of top-predators, competitors and humans (via fishing pressure) are responsible for biological variation. The "bottom-up" approach is clearly the most congruous with the work of Blue-Action, as it is focused on the links between the biological response and drivers of the physical environment, and is the approach taken in this case study.

Following this approach, the development of climate services in this case study has been split into two parts. In the first part, it is necessary to consider the links between the physical environment and biological response. For some of the proposed climate services, there is existing knowledge in the scientific literature that can be drawn upon. However, this is not true in all of the cases, meaning that such knowledge (to link the biological response to the physical driven) must first be developed: it is this development process that is described here (D5.17). Secondly, the physical-biological interaction model must then be coupled to a model (e.g. a seasonal or decadal prediction system from the rest of the Blue-Action project) that can deliver predictions of the physical environment. The coupled prediction system can then be used to generate future predictions of the biological response and its ability to forecast biological variables (rather than just physical variables) evaluated. Furthermore, the effects of improvements in the physical forecast system on biological predictability can also be evaluated, as can the value of the full climate service to the end-user. These types analyses will not be covered here, but will instead be detailed in the future Deliverable D5.18 "CS4 Report on the evaluation and valuation of Marine fisheries products". This deliverable will focus instead on the heart of the proposed climate services, the link between the linking biological responses in the ocean and their physical drivers.

Spatial distribution of migratory fish

Shifts in the spatial distribution of fish are expected to be amongst one of the most noticeable and important impacts of climate change in the future. One of the most visible impacts of climate change in the ocean are shifts in the distribution of marine species. Such shifts have been reported widely across all marine taxa, from the lower trophic levels to fish (Perry *et al.*, 2005) and top-predators, and are amongst the most commonly reported impacts of climate change on marine species reported in the literature (Poloczanska *et al.*, 2013). Shifts in marine species generally occur faster than terrestrial species (Poloczanska *et al.*, 2013) due to the relatively higher vulnerability of marine species to warming (Sunday *et al.*, 2012; Pinsky *et al.*, 2019). Temperature changes are widely recognised as playing a key role in these shifts and observed shifts are generally consistent with the local direction of climate change (Pinsky *et al.*, 2013; Hiddink *et al.*, 2015). Projections of future climate change indicate that this trend will continue (Cheung *et al.*, 2009, 2010), and that it will result in impacts on ocean dependent communities around the world (Allison *et al.*, 2009; Barange *et al.*, 2014; Blasiak *et al.*, 2017; Rogers *et al.*, 2019). Climate variability also has a key role to play in addition to climate change, and for highly responsive species, shifts in distributions can occur from one year to the next, driven by oceanographic variability (e.g. changes in the North Atlantic sub-polar gyre (Hátún et al., 2009), ENSO-driven shifts in the North Pacific).

Shifts in species distributions can be deeply problematic for dependent communities and nations. As traditionally fished species disappear and new (and often undesirable) species take their place, local communities and fishers are required to adapted their fishing techniques, infrastructure, markets and even local tastes to the new fishing opportunities. On the large scale, international conflicts over access rights to these new resources can arise as shifting fish stocks start to straddle international jurisdictions. An analysis of projected distribution shifts suggests a significant increase in such transboundary stocks over the coming century, to a point where as many as 40% of exclusive economic zones are impacted under extreme scenarios (Pinsky *et al.*, 2018). Examples of such conflicts are already being seen: the so-called North Atlantic "Mackerel war" (Dankel *et al.*, 2015; Spijkers and Boonstra, 2017), a dispute between the European Union, Norway, Iceland and the Faroe Islands over access to Mackerel (*Scomber scombrus*) has been described as the "most serious conflict between Scandinavian nations in 200 years" and is amongst the most notable, but other examples can also be found. The ability to foresee such shifts is therefore key to both avoiding conflict and adapting marine fisheries to a changing and variable climate.

Here we focus on developing climate services that can potentially forecast shifts in the distributions of marine species.

Blue Whiting Spawning Distribution

Blue whiting (*Micromesistius poutassou*) is a mesopelagic species that spawns in the Rockall region to the west of Great Britain and Ireland that at times has fuelled one of the world's largest fisheries (FAO, 2007). Regular shifts in the distribution of this (Figure 1) takes it between the Exclusive Economic Zones (EEZs) of Ireland, the United Kingdom and international waters, creating challenges for both fishers and scientists monitoring the stock, and is particularly problematic in the light of the United Kingdom's departure from the European Union. A climate service forecasting these distribution shifts would be of particular value to those assessing and monitoring the abundance of this stock.
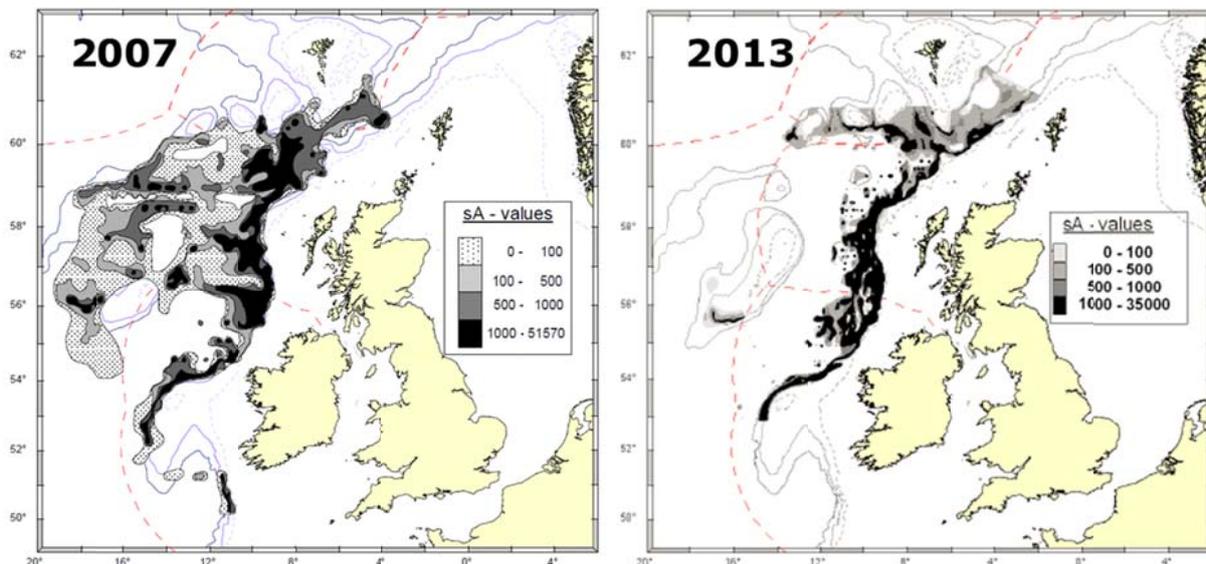

Figure 1 Distribution shifts in Blue whiting. The figures show the results of measurements of the abundance of blue whiting based on scientific surveys from 2007 (left panel) and 2013 (right panel). Abundance measurements are based on hydro acoustic surveys, where the target strength (sA) is directly proportional to the local biomass. Note the difference in distribution on western part of the range between the two years.

We have investigated the processes driving these distribution shifts, and shown that they have a strong linkage to oceanographic conditions. We examined these processes based on data from the Continuous Plankton Recorder, an opportunistic sampling programme that has been running for over 80 years, and that provides a broad coverage in space and time of the region of interest (Figure 2). Blue whiting larvae are amongst the most commonly reported fish species captured in this region, comprising more than 10% of all reported fish larvae (Corten and Lindley, 2003). Within the selected study region there were more than 34 000 observations available spanning from 1951-2005, with around 1100 of these being presences.
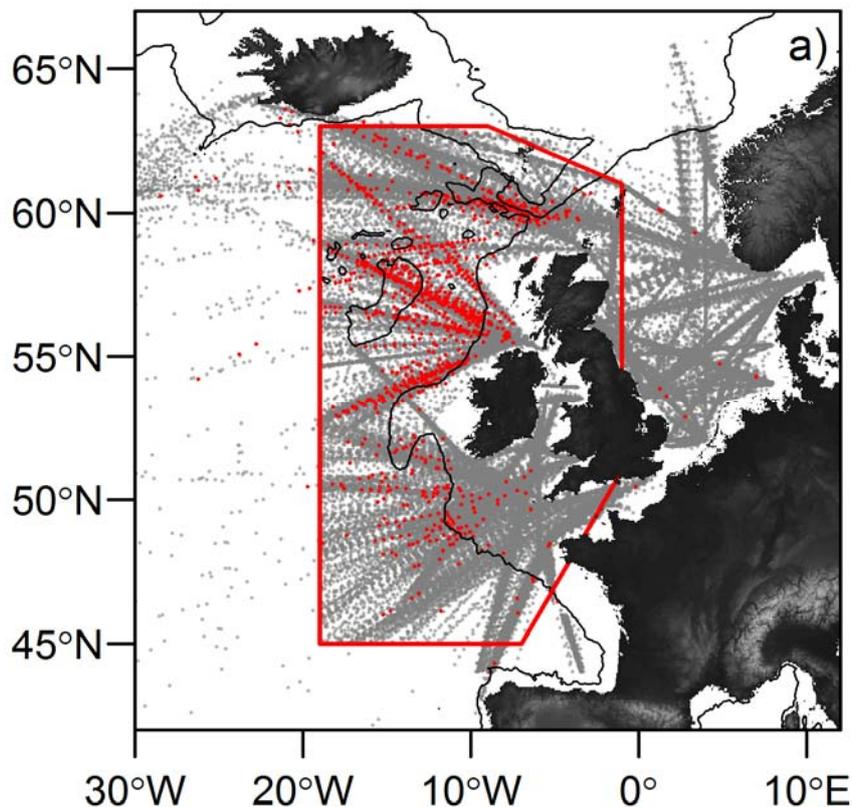

Figure 2 Distribution of samples from the CPR survey used in this analysis. Grey dots correspond to absences of blue whiting larvae, while red dots correspond to presences. The red box delineates the study region of interest.

We analysed these observations using a so-called species distribution model (or ecological niche model) to relate the likelihood of presence of absence of blue whiting larvae to environmental conditions. A large set of biologically relevant candidate explanatory variables were collected together into a generalized additive model (GAM), with a Bernoulli (presence/absence) observation error. Multiple model configurations were considered and the most parsimonious model was chosen based on the Aikaike Information Criteria. Model predictive skill was also assessed using 10 fold cross validation and used to inform model selection. The most important predictors identified were as follows:

- Day of year and latitude (used together to account for temporal and latitudinal variations in spawning activity)

- Bathymetry, to account for any preference for water depth. Blue whiting are a mesopelagic species found between 250 and 600m depth, and therefore generally tend to avoid coastal areas shallower than 200m
- Solar elevation angle. Blue whiting larvae perform vertical migrations in the water column at sunrise and sunset. As the CPR sampling device is towed at a 7-10m depth, the ability of this device to observe blue whiting larvae is correlated with the amount of light in the water column.
- Environmental conditions at the time and depth of spawning. The two key variables considered were temperature and salinity.

Of these variables, the first three are constant between years and therefore while they can constrain the distribution, they cannot drive interannual variability. Of the environmental factors, spawning salinity gave both the most statistically meaningful model, and also the most biologically reasonable, identifying a clear niche of optimal salinities in which blue whiting larvae appear to be spawned (Figure 3). It is thought that that this behaviour may represent the active selection of water masses to ensure that the spawned eggs are neutrally buoyant (*i.e.* do not sink before hatching) (Sundby and Kristiansen, 2015) or to ensure a match with suitable zooplankton prey for the larvae, which is also correlated with these water masses (Hátún *et al.*, 2009).
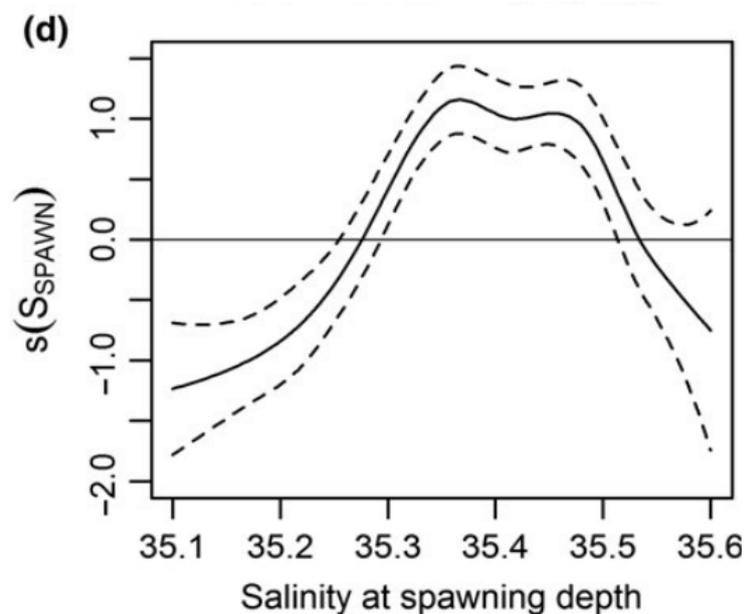

Figure 3 Optimal niche for spawning of blue whiting, as derived from a species distribution model of larval distribution. The dashed lines correspond to the 95% confidence interval, while the solid central line is the mean estimate. The vertical axis represents the salinity component of the Generalised Additive Model on the logit-transformed scale of the model.

The final model therefore gives the ability to predict the spawning distribution of blue whiting with reasonable skill based on a set of environmental conditions. A comparison of the spawning distributions forecast from year to year by this model with independent observations from both scientific surveys and fisheries catches shows good agreement, indicating that the model is indicative of the adult distribution, as well as the larval distribution.

These results can therefore be used to form the basis of a climate service for predicting the distribution of Blue whiting. A manuscript detailing these results has been published (Miesner and Payne, 2018).

Mackerel Summer Feeding Distribution

The Northeast Atlantic stock of Mackerel supports the most valuable fishery in Europe. Recent shifts in the distribution of this species into Icelandic (Astthorsson et al., 2012) and Greenlandic (Jansen et al., 2016) have driven conflicts over fishing rights. This so-called North Atlantic "Mackerel war" (Dankel *et al.*, 2015; Spijkers and Boonstra, 2017), a dispute between the European Union, Norway, Iceland and the Farore Islands over access to Mackerel has been described as the "most serious conflict between Scandinavian nations in 200 years". There is little reason to think that such events are a "one-off" in this stock and the ability to forecast such distributional changes clearly of valuable to all stakeholders involved.

Previous attempts to understand the late 2000s shift in the summer feeding pattern of Mackerel have focused on modelling the distribution (ICES, 2013; van der Kooij et al., 2016; Nikolioudakis et al., 2018; Olafsdottir et al., 2018), as a way to understand the underlying processes. Typically, such approaches involve fitting a statistical model (a so-called species-distribution model, SDM) and analysing the explanatory variables to infer the mechanisms: modelled outputs represent the mean or expected density of fish for a given set of predictors. However, many factors contribute to the ultimate, realised distribution of a species in nature, including habitat availability, population abundance, competition, predation, and the need to close the life cycle. Distribution-oriented approaches conflate these factors, making the identification of causal factors challenging.

We focus here instead on a habitat-centric approach, via the use of a so-called ecological niche model (ENM). Such an approach is that it need not characterise all of the variables that control the distribution of a species: instead, the ENM approach can focus on a few key variables (such as temperature and productivity) that can limit the distribution of an organism. The advantage of such an approach is that it can be made insensitive to other factors (such as the abundance and type of prey) that are also important in determining distribution, but that cannot be observed. On the other hand, the model can only describe the potential habitat where a species might be found: it cannot say anything about whether that habitat will be occupied. Nevertheless, such an approach is extremely well suited to the development of physically-driven ecological forecasts, and therefore as the basis for novel climate services.

We parameterised our ENM using observations from the International Ecosystem Summer Survey (IESSNS) in the Nordic Seas (IESSNS). This scientific survey is coordinated through the International Council for the Exploration of the Seas (ICES) and covers the Norwegian Sea, and the waters around Iceland and Greenland. The survey was first performed in 2007 and then annually since 2010. While the main target species was originally Mackerel, the survey now provides an overview of the entire ecosystem in this region, from plankton to top-predators and sea birds. The survey uses a towed pelagic gear on a regular sampling grid with a spacing of between 30 and 80 nautical miles, and involves vessels from Norway, Greenland, the Faroe Islands and Iceland. Data was available in the form of biomass density of adult mackerel, together with geographical and temporal metadata, for the 2007 and 2010-2014 surveys.

These density estimates were matched up with observations of the oceans from remote sensing. Monthly averaged estimates of Sea Surface temperature (SST) were obtained from the HadISST data set (Rayner *et al.*, 2003) and while estimates of net primary production (NPP) were based on the Vertically Generalised Production Model (VGPM) (Behrenfeld and Falkowski, 1997).

In contrast to the aforementioned *species-distribution model* (SDM) oriented approaches, we apply an *ecological-niche model* (ENM) approach to characterise the relationship between the environment and the potential habitat of the species. Whereas SDMs attempt to model the resultant distribution, the use of an ENM approach characterises the regions of space where there is suitable habitat, even if it is not occupied: such an approach is therefore highly appropriate for characterising the changes in potential habitat, even if the habitat is not utilised.

We applied a quantile-regression approach (Cade and Noon, 2003) to the IESSNS survey data to parameterise the ecological niche of Mackerel with respect to key environmental conditions. Using this approach, we are able to estimate the maximum density of Mackerel that a given spatial region can support, which we interpret as a metric of habitat suitability. Predictors were chosen based on a combination of variables that are available, and that are thought to be ecologically relevant to this species, specifically sea-surface temperature and net primary production. The log10-transformed density of fish observed in a single haul was modelled as a function of these predictors using non-parametric spline smoothers to characterise the response: one-dimensional smoothers were used for single variables and two-dimensional tensor-product smoothers (Wood, 2006a, 2006b) to capture potential interactions between variables. The quantile-regression approach was implemented in a Bayesian framework by using an asymmetric-laplace observation model in the "Bayesian Regression Models using 'Stan'" (BRMS) package in R (Bürkner, 2017), with a asymmetry parameter of 0.9 (corresponding to the 90th percentile of the data). All priors on parameters and hyperparameters in the model were uninformative. Other percentiles (80th and 95th) were also examined and gave similar results. All potential combinations of explanatory parameters were examined and model selection performed using the "leave-one-out" (loo) approach to identify the best predictive model: loo information criteria were estimated using a combination of Pareto-Smoothed Importance Sampling and, where this was not appropriate, direct calculation (Vehtari *et al.*, 2017).

Table 2 Mackerel ENM model selection. Five models were fitted with varying explanation parameters (SST: sea surface temperature, NPP: Net primary production) and model configurations. The predictive skill of each model was assessed using the expected log-pointwise-predictive density (ELPD) metric and are expressed relative to the model with the largest ELPD. Standard errors are for the pairwise comparison of data points predicted from the model with the highest ELPD and the model of interest. The "Base" model corresponds to a simple constant intercept.

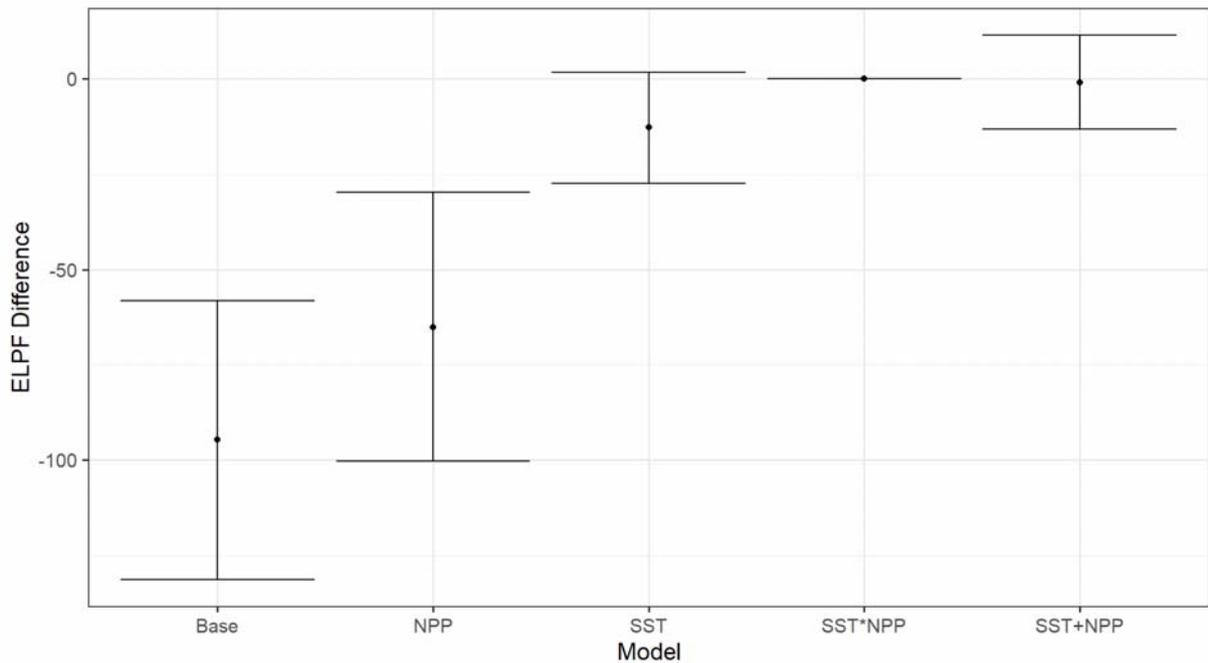| Model Name	SST	NPP	ELPD-ELPD$_{Max}$	Standard Error
SST*NPP	2d tensor product in SST & NPP		0.00	0.00
SST+NPP	Spline	Spline	-1.01	6.17
SST	Spline	-	-12.86	7.26
NPP	-	Spline	-65.05	17.65
Base	-	-	-94.66	18.29

Figure 4 Mackerel ENM model selection. Expected model predictive skill (ELPD) is plotted for each of the models in Table 2 relative to the model with the highest ELPD, with error bars for the pairwise comparison. See Table 2 for models details.

Model comparison shows that the best models include SST as a predictor (Table 2, Figure 4). While adding NPP, either in the form of a second independent smoother, or as a 2D tensor product smoother together with SST (thereby allowing interactions between the two parameters to be identified) improves the predictive performance of the model, although the effect is not statistically significant. We therefore conclude that there is little difference between these models. However, the addition of the NPP variable to the ENM does create a problem from the perspective of developing ecological forecasts and climate services, as forecasts of this variable are generally less skilful than sea surface temperature, and also less readily available. Furthermore, exploratory comparisons between models fitted with and without NPP show that while this variable may improve the model fit, it makes a relatively minor contribution to regulating the density of fish compared to SST (Figure 5). We therefore choose the SST-only ENM as the basis for futher analysis.
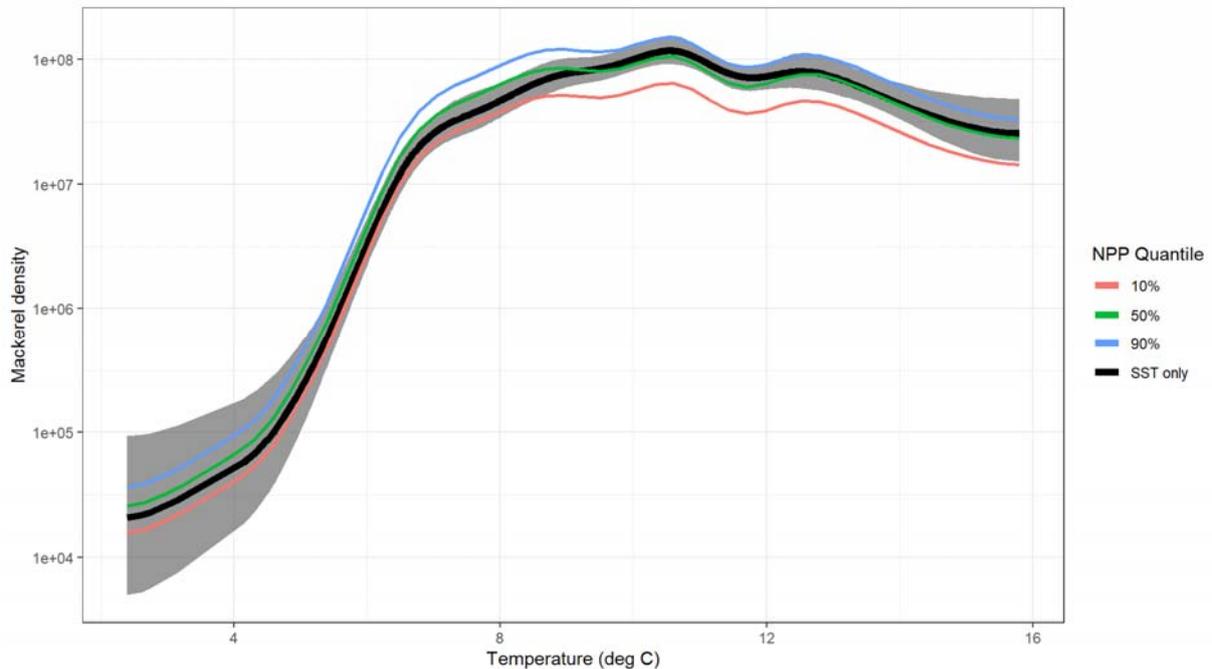
Figure 5 Mackerel Environmental Niche Model combining SST and NPP effects independently (SST+NPP). The model response is plotted as a function of Sea Surface Temperature for NPPs fixed at the 10th , 50th and 90th percentiles of observed values. For reference, the SST-only model (heavy black line), with associated uncertainty (grey filled area) is also plotted. Observations used to parameterise the model are also shown as points.

This model shows a clear temperature dependence of the local-density of mackerel on sea surface temperature (Figure 6). The density of mackerel declines with falling temperature from the peak value around 10-12 degrees, and falls off rapidly below 6-7 degrees. This suggests that temperature plays a clear limiting role, and that Mackerel habitat is generally limited to temperatures above 7 degrees. This results align closely with others published in the literature (Jansen *et al.*, 2016) based on a qualitative inspection of the relationship: the advantage of the approach taken here is that it is fully quantitative in nature and can be used to generate habitat metrics more generally.

A key illustration of the value of this approach can be seen when considering the mechanisms underpinning the distribution shifts. We applied the ENM across historical estimates of SST back to 1970, to calculate the suitability of these waters, and how they varied over time. We integrated this habitat suitability metric over a selection of areas, to generate a metric of the total amount of mackerel habitat in that region. In many of these cases, including in the Icelandic exclusive economic zone (EEZ) and both the eastern and western halves of the Greenlandic EEZ, a clear step change in the amount of habitat is present (Figure 7). However, the onset of this change is, crucially, in the late 1990s to early 2000s, significantly earlier than the first observation of Mackerel schools in Icelandic waters in 2007. This result suggests that environmental change preceded the shift in distribution of Mackerel, and therefore cannot be the proximate cause of the shift: other processes, such as the dynamics of migration, may have been more important. This result therefore represents a significant departure from the established paradigm around how these changes occurred, and highlight the value of the habitat-centric ENM approach.

The results shown here therefore provide an excellent basis for developing a forecast of the habitat of this species. Furthermore, forecasts of habitat can be converted into forecasts of distribution in cases where habitat is a limiting or controlling factor, such as when the amount of habitat decreases and

thereby compacts or constrains the distribution. Given the close linkage to the highly predictable sea surface temperature in this region, these results appear to be ideally suited to form the basis for ecological forecasts and for valuable climate services that can aid the management of this resource, and hopefully avoid further conflicts.
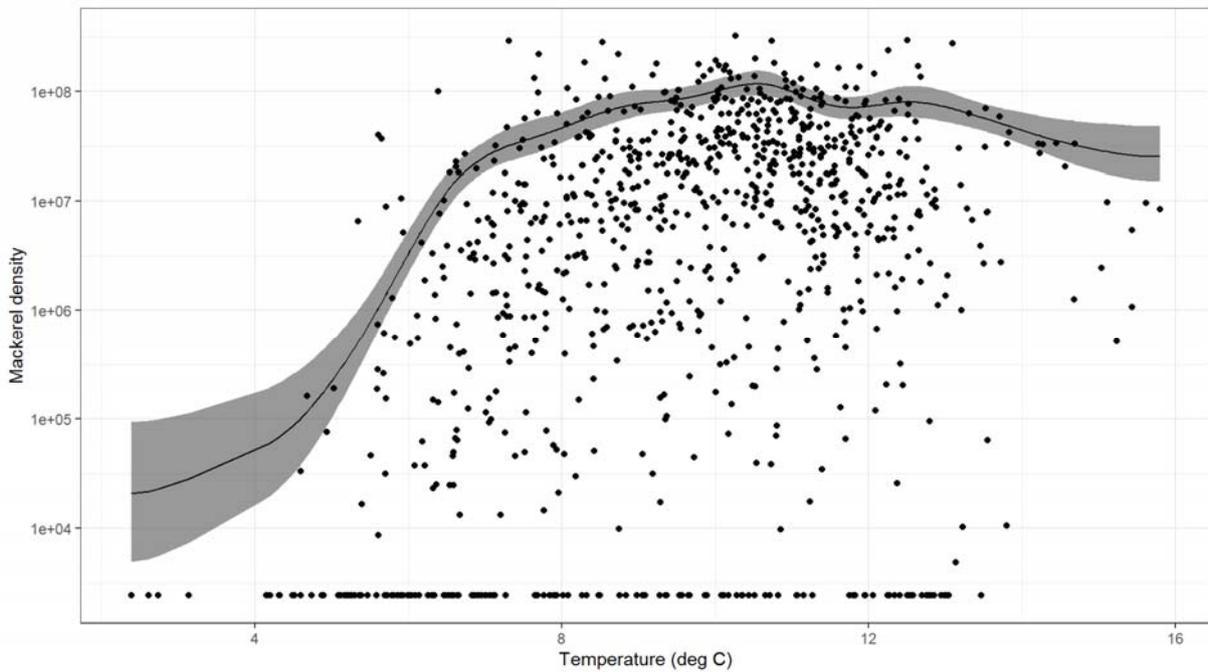

Figure 6 Mackerel Environmental Niche Model. The response of the SST-only model (black line) is plotted as a function of sea-surface temperature with associated uncertainty (grey filled area). Observations used to parameterise the model are also shown as points. As this is a quantile regression model, 90% of the points at a given temperature should fall below the line, and 10% above it.
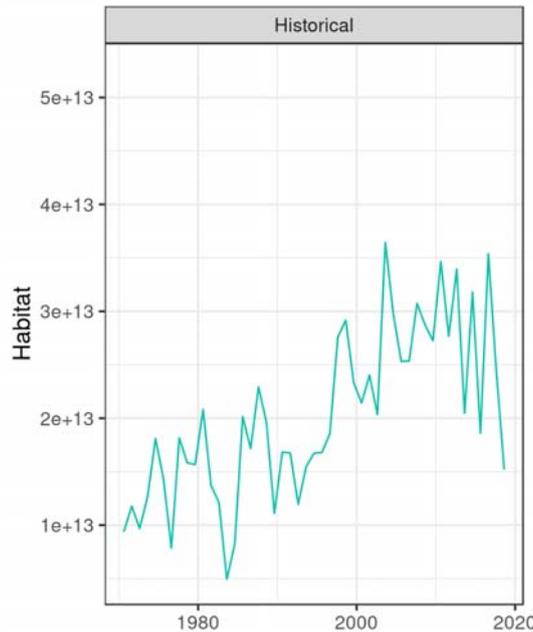
Figure 7 Timeseries of the amount of Mackerel habitat in the East Greenland EEZ, based on the SST-only ENM model.

Bluefin tuna Summer Feeding Distribution

North Atlantic Bluefin Tuna (*Thunnus thynnus*) is a large and commercially valuable pelagic top-predator that has also, at times, been listed as "Endangered" by the IUCN. The species covers most of the North Atlantic, but recent years have seen a substantial shift of its northern range limit in response to warming waters, most notably into the Irminger Sea and Denmark Strait (MacKenzie et al., 2014), opening up potentially new fishing opportunities for Iceland and Greenland. The ability to foresee such distribution shifts is potentially useful in a management context, in a strategic planning role and in the execution of the fishery.

Shifts in the distribution of this species first came to the attention of the scientific community with the report of catches of Bluefin tuna in Denmark strait in a scientific fishing investigation in August 2012. This observation was repeated again in August 2014. These observations are extremely unusual, as the species is typically found much further to the south: it spawns, for example, in the western Mediterranean and in the Gulf of Mexico. An examination of historical records showed that this was the first documented observation of the species in the area for at least 370 years, and most likely ever. The mechanisms underpinning these shifts were investigated (MacKenzie *et al.*, 2014) in a previous project financed by the European Union 7th Framework Programme under grant agreement nos. 308299 (NACLIM), which participants in this case study were also involved with. The investigation found that the habitat of Bluefin tuna is constrained by the 11 degree isotherm. Tagging experiments published in the literature, for example, show that the species can temporarily move across fronts or dive below the thermocline into colder waters (down to freezing point) (Walli *et al.*, 2009) but always need to return to warmer water to warm up again. Based on this mechanism, it was possible to show that there has been a systematic expansion of habitat in this species since around 2000 (Figure 8).
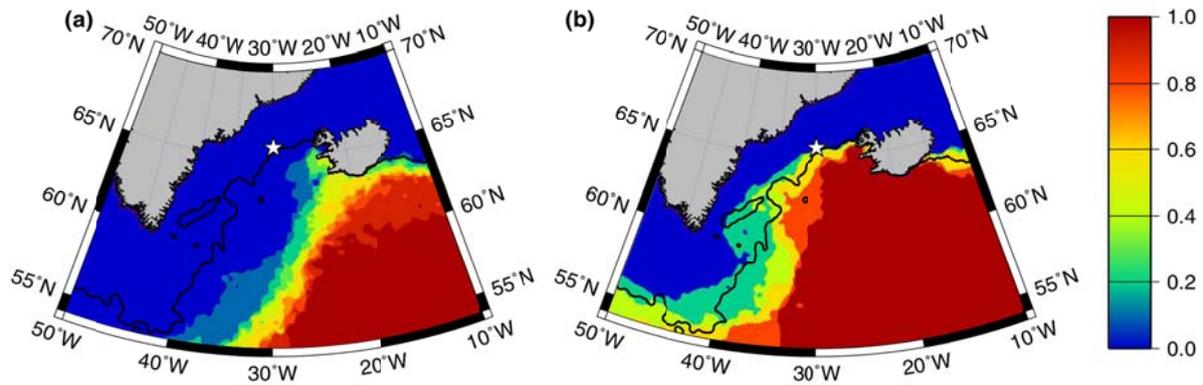
Figure 8 Proportion of years where Sea surface temperature (SST) >11 °C for (a) 1985–1994 (first decade of time series) and (b) 2007–2011 (5 years prior to capture). The contour line shows location of the 11 °C isotherm for 2012. The position of the haul that caught three bluefin tuna on August 22, 2012 is shown as a white star near 65°N, 30°W. (MacKenzie et al., 2014).

Such knowledge about the links between distribution and sea surface temperature can potentially form the basis for a climate service, particularly given the well-established predictability of temperature in this region (Matei *et al.*, 2012). We therefore updated the analysis performed by MacKenzie *et al.* (2014) based on the additional data available since the publication of this work (Figure 9). These results show clearly that the amount of habitat available in this region has fluctuated substantially since 2010. In some years, particularly in 2015 and 2018, the amount of habitat has been very low, comparable to the levels seen in the 1980s and 1990s. On the other hand, 2019 was the third largest amount of habitat. If anything, this highly degree of variability emphasizes the potential for ecological forecasting of the habitat to support the management and exploitation of this resource.
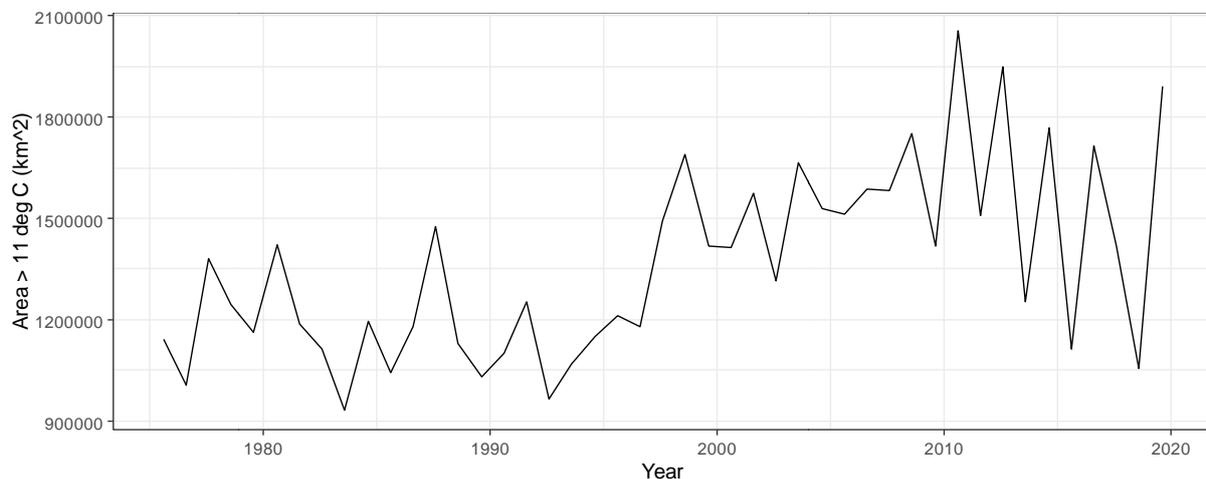

Figure 9 Area of potential bluefin tuna habitat (August SST > 11 deg C) in the Irminger Sea and Denmark Strait region.

We also performed a literature review to update the current state of knowledge about the processes controlling the distribution of Bluefin Tuna. In particular, we checked whether the distribution hypothesis proposed in MacKenzie et al (2014) still holds or whether it had been rejected by the scientific community. We found instead that this hypothesis has, if anything, been adopted by the community, and now supports other efforts to develop nowcasting systems for the distribution of this

species (Druon *et al.*, 2016). We also checked for new distribution models that could be used as alternative parameterisations: in particular, the work of Muhling et al (2017) in developing physiologically-based mechanistic models of Bluefin Tuna distribution (based on oxygen utilisation) is particularly relevant. However, this work also shows good agreement between the mechanistic approach developed there and empirical approaches (such as that of MacKenzie et al), further strengthening the proposed approach.

We therefore conclude that the scientific understanding of the processes controlling the distribution of Atlantic Bluefin Tuna has continued to improve in recent years. This ecological response therefore appears to be ideally suited to ecological forecasting and the development of associated climate services.

Productivity of marine organisms

A key characteristic of populations of marine organisms, and particularly of fish species, is their highly variable nature. Much of this variability arises from the reproductive process, where the number of individuals coming into the population (known as recruitment) varies substantially from year to year: in some cases by an order of magnitude or more. For example, the recruitment of Blue whiting in the North Atlantic suddenly increased by a factor of 5x during the mid-1990s, producing eight extraordinarily large year class in a row, before returning to "normal" again during the mid-2000s (Payne *et al.*, 2012). Such variability presents many problems for scientists trying to give advice, managers trying to set fishery limits and fishers trying to exploit the resource. It was therefore unsurprising that recruitment predictions were frequently identified as a desirable climate service in early stages of this Case Study and fisheries science has since its inception as a discipline dreamed of the ability to foresee such variability, albeit it with little success. However, advances in our ability to observe and forecast the ocean have opened the door to revisiting this problem and to develop unique and valuable climate services.

How to approach the recruitment forecasting challenge?

The dream of predicting recruitment is an old as fishery science itself. The work of Bjørn Helland-Hansen and Fridthof Nansen (1909) explicitly discussed the concept of predicting biological responses based on oceanographic observations for use in fisheries applications. Their work was closely followed by the discovery of "year-classes" in fish populations and their variability by Johan Hjort (1914, 1926), which set the field in motion ostensibly with the goal of foreseeing the future. The future fisheries science that these pioneers dreamed of was very much in the form of a predictive science.

Yet after 100 years of scientific endeavour, we as a field have little to show for it. Despite the early optimism, attempts to predict recruitment were met by failure after failure, and relations with the physical environment that, while initially seems robust, broke down after a few years. The definitive nail-in-the-coffin was the work of Myers (1998), who, revisiting previously published stock-recruitment relationships, found that just 1 out of 49 relationships had survived 10 years since publication. Today, there are few, if any, marine ecological forecasting systems predicting recruitment (Payne et al., 2017). Instead, good fisheries management is about identifying and managing the sources of uncertainty, rather than trying to foresee and adapt to future challenges .

However if ever there was a time in the history of fisheries science where it was going to be possible to make recruitment predictions, it would be now. Today we have the ability to observe the ocean in

unprecedented detail, based on the vast array of instruments that we have at hand e.g satellites, argo floats, moored observatories, gliders, and opportunistic sampling programmes such as the continuous plankton recorder and Ferry Boxes. Furthermore, we have long records of recruitment across many fish stocks covering 40-50 years or more (Ricard et al., 2012). The exponential increase in computational power has brought new tools into the grasp of the average researcher that were previously unthinkable, such as multi-model inference (Burnham and Anderson, 2002; Anderson, 2008), empirical dynamic models (Sugihara et al., 2012; Ye et al., 2015), Bayesian interference (Bürkner, 2017; Carpenter et al., 2017) and Generalised Additive Models ((Wood, 2006). And critically, we have developed the ability to reliably forecast the state of the ocean not just days or a weeks into the future but months, years and decades (Meehl et al., 2014; Payne et al., 2017; Tommasi et al., 2017).

Furthermore, despite openly expressed scepticism from the community (Planque, 2016), the recent decade has also shown that it is possible to make skilful and valuable marine ecological predictions. A recent review (Payne et al., 2017) highlighted around ten examples of such ecological forecast systems that were currently in operation and being used in decision making processes, and this number has continued to grow. The majority of these forecasts were of spatial distributions of species, which are being used to plan fishing activities (Eveson et al., 2015; Hobday et al., 2016), avoid bycatch of key species (Howell et al., 2008, 2015; Hazen et al., 2017) and even regulate exploitation (Hobday et al., 2011). Examples also exist of forecasts being used in the management of coral reef systems (Liu et al., 2018) and in forecasting the timing of key events (e.g. Mills et al., 2017). Recruitment forecasts, while notable by their current absence, are a logical extension of this long list of successes.

Revisiting the recruitment prediction problem therefore appears to be well-overdue. Within this Case Study, Blue-Action has therefore reviewed the broad literature around statistical forecasting, ecological forecasting and climate services, as well as recruitment forecasting, to gather a set of ideas about how to approach this problem systematically. These points are summarized as follows:

- "Users, users, users". The three most important aspects of any forecast are the user, the user, and the user. Ensuring that the goals of the recruitment forecast are matched to the needs of those that are actually going to be using it is essential to its success.
- "Define success". A recruitment forecast needs to have a clear goal in mind when being developed. What would be an acceptable degree of forecast accuracy for the use in mind?
- "Predict. Don't explain". The skill of a recruitment forecast needs to be evaluated in terms of the its predictive potential, rather than its ability to explain (Shmueli, 2009). While this is a subtle point, good explanatory power does not necessary correspond to good predictive power.
- "Choose wisely". The choice of explanatory variables in a statistical forecast model needs to be grounded in biological understanding of the important processes. Predictors should not be included simply because they are available.
- "Be uncertain". Forecasts should be expressed in probabilistic terms, rather than as an absolute number, to reflect the uncertainty associated with the model
- "Tell the world". Forecasts should be visible, transparent and publically available for all to see, discuss, and potentially use.
- "Check your results". Forecasts should be validated after the event and the results of these validations published with the forecast.
- "Embrace failure". Forecasts that fail need to be revisited in detail to try and understand what went wrong, and how they can be improved in the future, thereby adding the ability for the forecasting system and forecaster to learn

- "Patience you must have". A forecast system cannot be evaluated or rejected based on a single realization. Many realisations are required to prove, or disprove the real-world value of the system. In the meantime, retrospective forecasting experiments are the best guide to real-world performance.

These points can form the basis of a systematic approach to developing new recruitment forecasting systems. They represent in many ways a fundamental department from the traditional approach to the scientific endeavor, and are driven by the needs of society and users, rather than scientific curiosity. However, also have strong scientific foundations, being based on the principles of co-design, statistical forecasting and experience in meteorology. They therefore appear to be an appropriate way in which to revisit the forecasting problem.

A manuscript detailing this approach to recruitment forecasting is currently in preparation.

Bias Correction

Stock assessment is the process of estimating the current abundance and productivity of a fish stock, and forms the foundation of modern fisheries management. The process typically involves the development of a statistical model describing the current understanding of the system and the observations that are available of it: inputs into this process can include data from fisheries, scientific monitoring programmes and biological experiments. Assessments are typically updated on a yearly or multi-annual basis, where they are used as the basis for new scientific advice about future catch opportunities.

A well known but seldom appreciated aspect of these assessments is that they exhibit a systematic bias (Mohn, 1999; Hurtado-Ferro *et al.*, 2015). As an assessment is updated, the number of observations of a single cohort of fish increases. For example, an assessment performed in 2019 may only have a single observation of the 2018 year class: however, as time progresses, more and more data about the size of this year class become available, until it has finally passed all the way through the population and there are no more individuals alive. Unusually, the addition of this additional data causes changes in not just the precision of the estimate of year class strength but also in the estimated value as well: a systematic drift in the estimate is often seen. These drifts arise, for example, due to mismatches between some model parameters that are fixed of necessity (such as natural mortality) and the true value in the ocean. However, the exact mechanism underpinning this bias remains poorly understood and is the subject of active research within the field.

Such systematic biases can pose a substantial problem for both fisheries managers and scientists that are dependent on the results of stock assessments. Fisheries management systems, particularly in the form of harvest control rules, typically incorporate the presence of such biases into their design and evaluation procedures. Scientists using this data for research, on the other hand, often simply ignore this issue. However, particularly when trying to predict recruitment, the presence of such biases in the most recent years of a time series can create conceptual and practical problems for both the development and validation of such forecasts. Methods to both quantify the severity of the retrospective bias problem, and potentially for it, are therefore a needed but sorely lacking part of the recruitment forecasting toolbox.

We therefore attempted to resolve this issue before engaging on recruitment forecasting. In particular, we approached the problem from a statistical modelling perspective. We can consider the effect of retrospective bias in terms of a linear model, as follows:

$$\hat{X}_t = X_\infty + s(t)$$
$$X_t \sim N(\hat{X}_t, \sigma(t))$$

where $\hat{X}_t$ is the estimated value of some quantity X, observed after t assessments, X_∞ is the final "true" value of X that the model converges to after many assessments and $s(t)$ is the bias-correction function, represented here as a spline-smoother in t (although in principle any form could be considered). We then consider the assessed value, X_t, to follow a normal distribution with a mean (expected value) of $\hat{X}_t$ and standard deviation, σ. Normally, we would assume the standard deviation to be constant: however, in this case, we also model this variable as being dependent on the number of assessments i.e. $\sigma(t)$. This type of model is known as a distributional regression, where the parameters of the observational error model are also involved in the regression. These models are also typically very challenging to fit using standard statistical tools: however, the recent advent of user-friendly and powerful Bayesian samplers has made this type of analysis readily available to all. We solved this model system using the Bayesian Regression Modelling with Stan (BRMS) toolbox in R (Bürkner, 2017) to estimate the number-of-assessments-dependent terms for the bias $s(t)$ and precision $\sigma(t)$, together with the bias-corrected expected-converge value , X_∞ of each variable. The appropriateness of the model was checked using posterior-predictive checking (Gabry *et al.*, 2017).

The bias-correction approach was applied to the results of the assessment of Sandeel (*Ammodytes spp.*) in Sandeel management area 1r in the North Sea. The approach was applied to five key assessment characteristics: number of individuals at age 1 (N1), the number of new individuals (recruits) produced each year, the spawning stock biomass (SSB), the total stock biomass (TSB) and the total number of individuals (SumN). Model checking suggested that the model appeared to be an appropriate description of the data for all of these metrics. Substantial differences were seen, however, between the biases and precision estimates of the metrics, and as a function of time (Figure 10). Errors in some metrics, particularly N1 and the number of recruits tended to be dominated by exhibit a high degree of interannual variability, while others (SSB, SumN and TSB) are by dominated by more constant systematic biases. The presence of both biases and poor precision can contribute to a poor quality stock assessment, and we therefore combine these two metrics into a single metric, root mean square error (RMSE) as follows:

$$RMSE(t) = \sqrt{s(t)^2 + \sigma(t)^2}$$

This metric allows a more direct comparison between variables, and a clear visualization of the convergence process (Figure 11). In this case we can see that the spawning stock biomass (SSB) initially has the highest error term due to the large bias associated with this quantity (Figure 10). The error associated with all variables clearly decreases as more data points are added, and the model has essentially fully converged after 4-5 years. This matches well with the biology of the species, which typically live 4-5 years: after this point, no new observations are being added to the assessment.

These results show that there are clear signs of significant retrospective bias in this stock for all years in which a cohort is present in the population. This has significant implications for both the way that we model recruitment and for the way in which we evaluate the validity of our forecasts. These results will therefore be used in all subsequent work to perform a pre-modelling bias correction of the data. The code to perform these analyses is currently being incorporated into a software package in the language R to enable these corrections to be applied more generally. Once a corresponding scientific manuscript has been completed, the package will be released to the scientific community to enable the general adoption of this methodology.
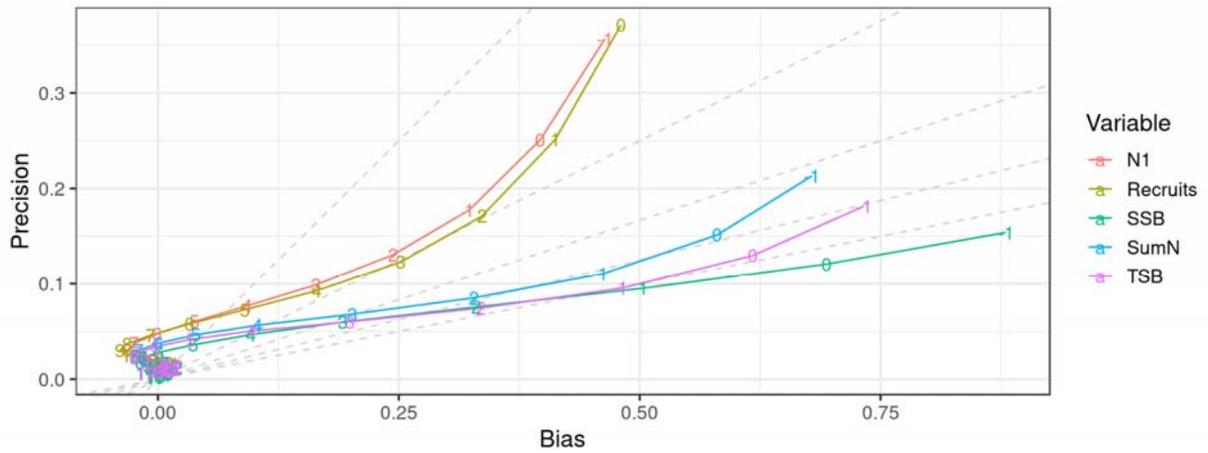
Figure 10 Estimates of retrospective bias and precision for the Sandeel assessment in Management Area 1r. The smoothed estimates of bias s(t) and precision (t) are plotted against each other for the same number of assessments, t (indicated by the labels). Note that these variables were log-transformed prior to modelling, and both the biases and precision estimates are therefore on a log scale.
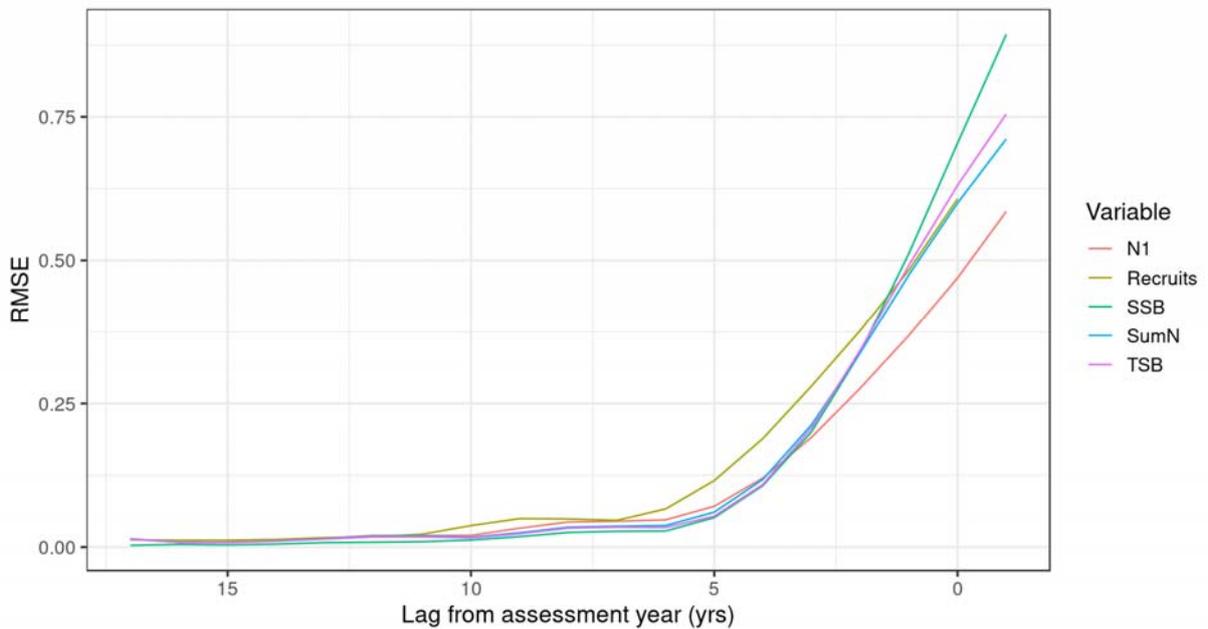

Figure 11 Estimated root-mean-squared error in the assessment of Sandeel in management area 1r due to the retrospective bias problem for each of five key variables. Note that the variables have been log-transformed prior to modelling, so that the RMSE error is therefore the error on a log scale.

Recruitment of Sandeel in the North Sea

The lesser sandeel (*Ammodytes marinus*), is a pelagic species of the *Ammodytidea* family and is one of the most common sandeel found in the North Sea. Adult lesser sandeel habitats are found in most of the North Sea, generally distributed across the shallow sandy banks (van Deurs *et al.*, 2009). Sandeel is seen as one of the main links between primary production and the higher trophic levels in the North Sea, observed for both larger piscivorous fish (e.g. cod and haddock) and seabirds (Eliasen et al., 2011). The lesser sandeel has historically supported a large fishery, which has seen a large decline in recent years (Dickey-Collas et al., 2014).
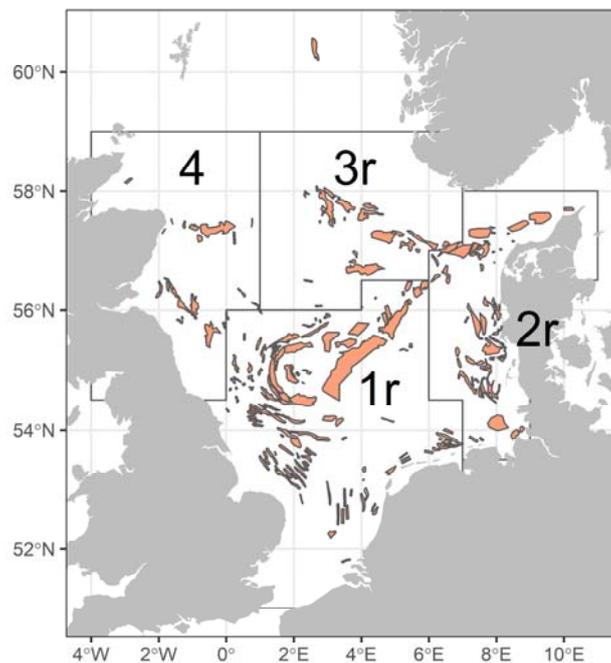
Management of the species in the North Sea based on the definition of multiple sub-units ("stocks") of the total population. Although the adult sandeel are highly spatially constrained, larval sandeel are found throughout the water column and drift between banks on oceanic currents (Christensen *et al.*, 2008). Particle-tracking studies (Christensen *et al.*, 2008; Pedersen *et al.*, 2019) suggest the division of the species' range into 7 different individually managed stocks. Analytical stock assessments are performed in management areas 1r, 2r, 3r and 4 (**Error! Reference source not found.**), while the remaining three stocks are considered "data poor" by ICES.

Annual recruitment to each of these stocks is a key controlling factor in the size of the fishery, and has been studied closely. Recruitment in the south-western part of the North Sea (i.e. management area 1r) is negatively correlated with temperature, while the main prey, *Calanus Finmarchus*, abundance has a positive influence (Arnott and Ruxton, 2002; Lindegren *et al.*, 2018). Density dependence has been found to be a large driver in recruitment, where competition between young adults and juveniles has a large negative effect on recruitment (van Deurs *et al.*, 2009). Adult sandeel show cannibalistic behaviour, feeding on late stage larvae and juveniles (Eigaard *et al.*, 2014).

However, while there is a good knowledge base underpinning the variability of recruitment in this stock, previous work has not been performed in a predictive setting. Here we reevaluate existing knowledge

from a forecast perspective in management areas 1r-4, with a view to potentially developing operational forecast products and climate services.

Recruitment was modelled based on a range of environmental and ecological predictors that could be potentially used in forecast system. We limited the analysis to variables that would realistically be available at the time when a forecast is needed, or could be readily predicted: some variables, such as the abundance of zooplankton, have been shown to be significant explanatory variables (Lindegren *et al.*, 2018) but the data availability can be delayed by 1-2 years, making them impractical for forecasting applications. For the purposes of this initial analysis, we focused on the known values of these variables: the recruitment forecast skill therefore represents the maximum forecast skill that can be expected. In a real setting some of these variables will need to be predicted themselves leading to an inevitable reduction of the real skill below the potential skill: this aspect of the climate service will be addressed in a future Blue-Action deliverable (D5.18) if relevant. The predictors considered can be broken down as follows:

- Sea surface temperatures (SST)
  - P3 - Jul-Sep temperatures experienced by the adults prior to spawning
  - P4 - Oct-Dec temperatures experienced by the adults prior to / during spawning
  - Q1 - Jan-Mar temperature experienced during egg development
  - Q2 - Apr-Jun temperature experienced by larvae during pelagic drift phase
  - Q3 - Jul-Sep temperature experienced by post-settlement juveniles
  - Q4 - Oct-Dec temperature experienced by post-settlement juveniles
- Demographic parameters (as of 1 Jan)
  - logN1 - log of the numbers of juveniles (age 1)
  - logSumN - log of the total number of individuals in the population of Age 1 or greater
  - logTSB - log of the total stock biomass
  - logSSB - log of the spawnign stock biomass
- Other variables
  - Year - Cohort year, included to allow time-variation in the mean productivity of the stock due to systematic shifts in other unquantified variables

The forecast model is parameterised based on these explanatory variables by first fitting all models that can be created by including / excluding the set of 11 explanatory variables. To avoid collinearity, models are restricted to include one environmental and one additional demographic variable in addition to logSSB. The small-sample corrected Akaike Information Criteria (AICc) for each model over the calibration period is converted to an Akaike weight within the ensemble and then used to weight the individual predictions from each model when operating in forecast mode. Log recruitment is used as the response variable, with an additive structure for each explanatory term. The logSSB and Year variables are represented by spline smoothers, with the maximum degrees of freedom associated with each spline constrained to be three or less. The models are fit using the mgcv and MuMIn packages in R.

Aggregated recruitment values and forecasts across the entire North Sea were produced by a simple arithmetic sum of the corresponding values from each of the four stocks. The forecast models for each stock were fitted independently, and then summed to produce the value for the entire "Portfolio".

Probabilistic forecasts were generated by based on the predictive distributions generated by the fitted models. Continuous values of log-recruitment were converted to terciles (high, medium and low) based on the distribution of recruitment over the full historical time series for each stock and for the

"Portfolio" of stocks. Categorical forecasts were made by choosing the most likely value of the three terciles.

Forecast skill was assessed in a situation that directly mimics the operational usage of this forecast system. The available data was first truncated at a cut-off year (e.g. 2006) and the empirical model described above was parameterised using all data up to and including this year (calibration period). The predictors available in the remaining part of the time series (validation period) were then used to make predictions for each year class. The process was then repeated for cut-off years from 2006 to 2018. Forecast skill was then evaluated by comparing the predicted values with the true recruitment values.

We examined the skill of the prediction system for all management areas at a lead of 1 cohort, mimicking potential operational usage. In all management areas the mean forecast error is on-par or better (i.e. lower RMSE) than the geometric mean recruitment forecasts used in official sandeel stock assessment (Figure 12a,b) for management area 1r and 2r: area 3r and 4 not shown). Information rich stocks show highest predictability and accuracy (i.e. area 1r and 2r), while the two areas with the shorter time series shows overall less accuracy (Figure 12c). The portfolio forecast has the highest overall accuracy, indicating the aggregation of predictions can improve the forecast, even in cases where some stocks are poorly forecast.
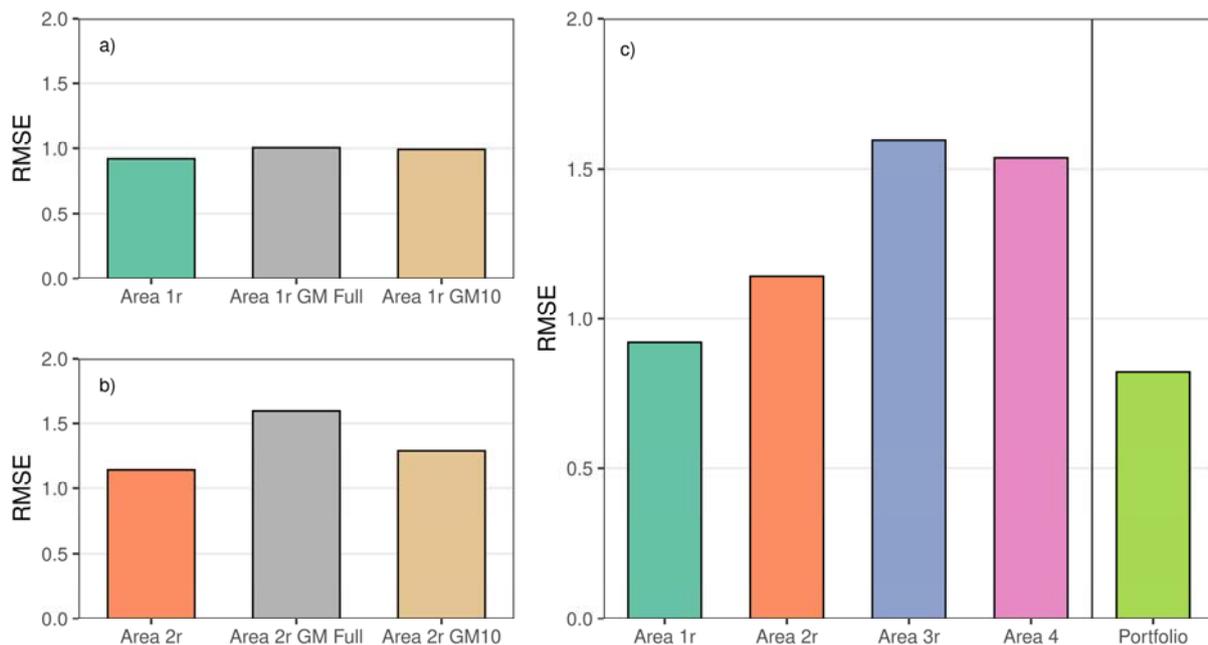

Figure 12 Root-mean-squared error of the different management areas and reference forecasts at lead 1. Lower RMSE indicates higher model accuracy. a) Management area 1r ensemble forecast and geometric mean reference forecasts. Here the ensemble forecast shows some improvement in accuracy compared to the reference forecasts. b) Same but with area 2r c) RMSE of all management areas and the portfolio forecasts. Area 1r and area 2r shows highest accuracy of individual forecasts, while the portfolio is the overall most accurate.

For categorical forecasts, hit rate metrics clearly show that longer time series are associated with better predictability, as the only two forecasts consistently outperforming random guessing are management area 1r and 2r at a 66% and 54% proportion correct (Figure 13). A large drop off in hit rate is seen in the less predictable areas (respectively at 50% and 25% hit rate for area 3r and 4), where performance is not

significantly different to random guessing. Here the large forecast uncertainties are heavily influencing the portfolio forecast, leading to a poor hit rate of 25% correct forecasts.
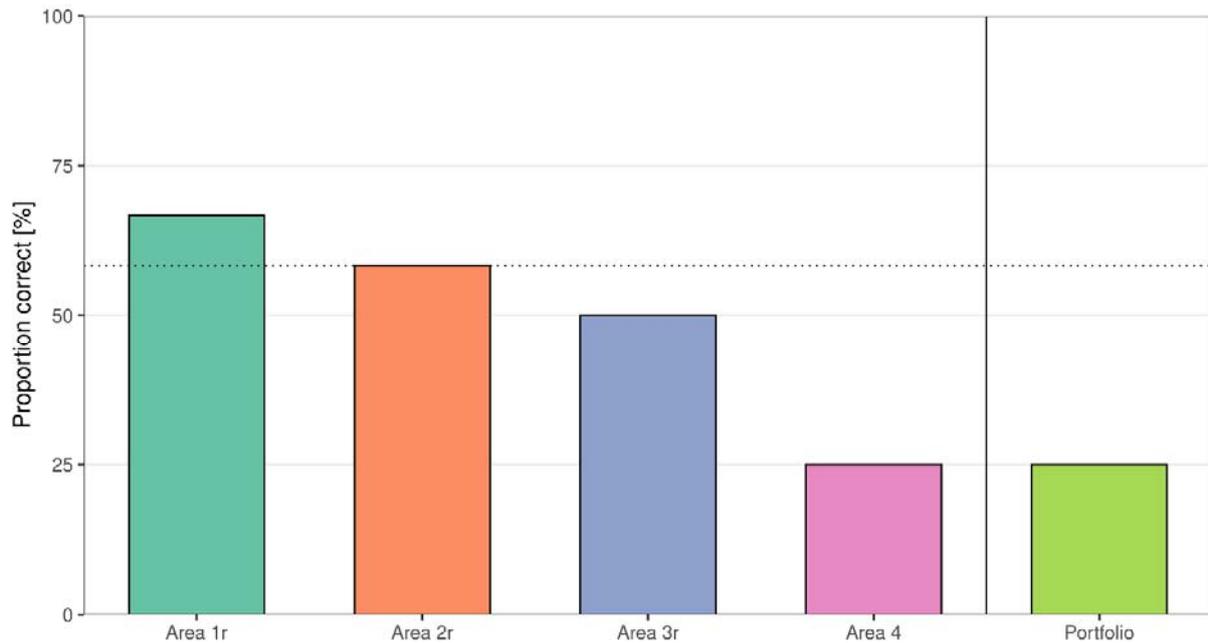
Figure 13 Hit rate of the different management areas indicating the percentage of correct retrospective forecasts at lead 1. Dashed line indicates the upper 95th percentile of hits expected by a random guessing reference forecast (on average correct 33% of the time). Area 1r and 2r are the only management areas where the system is significantly better than random guessing, with the less predictable areas only reaching 25% (i.e. area 4 and the portfolio forecast).

The true-skill score (TSS) statistic indicates area 1r being the only management area where the model can correctly differentiate all the different categories (Figure 14), outperforming the reference forecast of random guessing consistently. Most other areas shows inability to differentiate, either due to no model predictions or events of a given category or perverse forecasts predicting a category wrongly. This is seen in forecasts for areas 2r, which has a TSS scores not significantly-different from zero, indicating that they do not have the ability to outperform random guessing even with a high hit rate. This result arises in part due to the relatively low recruitment seen in these stocks in recent years, affecting the ability of the TSS metric to quantify the forecast skill. Area 3r and 4 have negative skill scores, which shows a consistent pattern of the model forecasting the wrong category. This is likely due to large uncertainties propagating into the forecast, resulting in a wide prediction distribution, where properly distinguishing between categories is difficult. Overall the low recruitment category shows the highest TSS, while correctly distinguishing between a high and not-high recruitment year shows mostly negative skill scores (Figure 14b). The portfolio forecast is once again heavily affected by the low scoring areas, where the large uncertainties of area 3r and 4 has a negative effect on the ability to correctly distinguish between categories. Here the same effect is seen, where the aggregation of the wide prediction distributions results in lower predictability. RMSE, hit rate and TSS shows similar patterns, with the longer time series significantly improving predictability. This is noteworthy, as this could potentially be a criterion for selecting suitable species and stocks for forecasting. Creating a categorical portfolio forecast seems to rely on the selected stocks showing some predictability individually, to not be negatively influenced by large uncertainties.
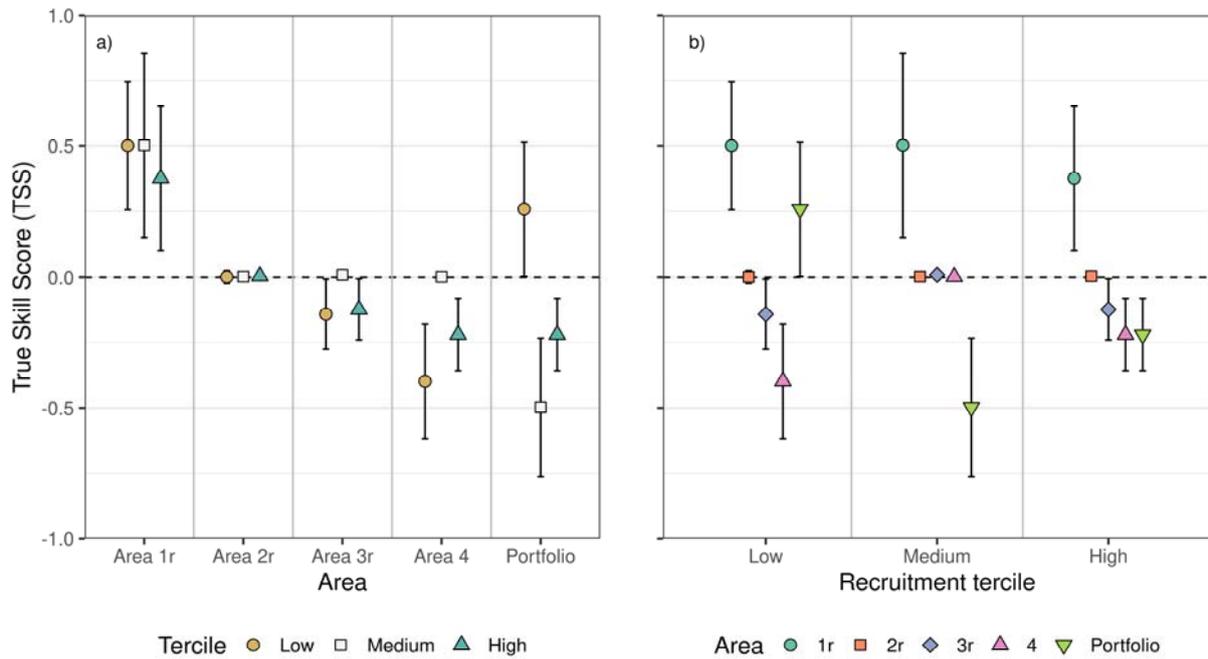
Figure 14 a) The skill of the recruitment forecast system in predicting each of high, medium, and low recruitments is shown for all individual areas and the portfolio forecast at lead 1. (b) The skill shown according to recruitment terciles is shown. Model skill is represented as the True (Peirce) Skill Score (TSS), which ranges between +1 and -1, and has a value of 1 for perfect skill, and 0 for random guessing (black dashed line). The 95% confidence interval for the estimated skill score are shown as error bars on each of the points.

The importance of the individual predictors can be assessed by applying the relative variable importance (RVI) approach (Burnham and Anderson, 2004). While overall predictability of the system is somewhat limited by the length of the time series, more interestingly, the ensemble RVI shows very different dynamics than usually assumed. All areas show similar results, where stock-recruitment relationship seems more driven by temperature, demography and time variation compared to the spawning stock biomass (Figure 15). The pattern is seen throughout retrospective forecasts, where SSB consistently is among the lowest RVIs to a given model ensemble. This could indicate sandeel recruitment is not driven by a large spawning stock, but rather effects experienced by juveniles, such as density dependence or temperature driven effects (e.g. metabolic requirements). RVI has been observed to change throughout the evaluated time period, where especially the time varying cohort effect shows large variation, indicating that the system is non-stationary.
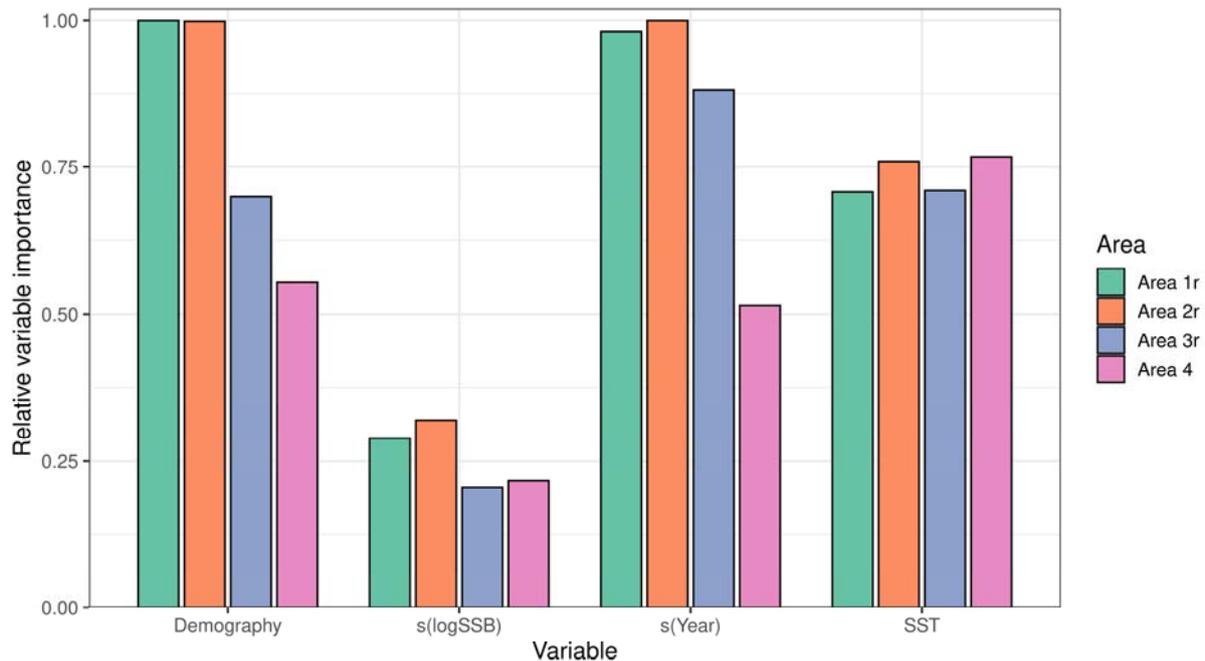
Figure 15 The relative variable importance (defined on a scale between 0 and 1 of each group of explanatory variables) is shown for the model ensemble incorporating all data e.g. 1983-2018. These terms are however not constant, and can and do change over time. Terms fitted with a spline smoother are denoted by the s() term - all other terms are linear. The RVIs for the demographic and SST groups are lumped together and represent the sum of the RVIs for the members of these groups. Interesting to note is the low importance of logSSB, while the time-variation in productivity is highly important across all management areas.

In conclusion, the results presented here clearly show that in some cases it is possible to develop skillful forecasts of sandeel recruitment (e.g. categorical forecasts in management area 1r, and continuous forecasts for the aggregated recruitment across the North Sea). These results can therefore form the basis for an ecological forecast forecast system. However, there seems to be little to be gained by coupling this model to a seasonal-forecast system and making forecasts in this manner: the predictability of the stock is generally derived from demographic effects (e.g. competition with older siblings) and unquantified year-effects, rather than temperature variations. While there is clearly the basis for a valuable forecast product here, future work will focus on quantifying the value of this forecast based on near-real time observations and auxiliary data, rather than on near-term climate predictions.

Recruitment of Herring in the North Sea

Herring (*Clupea harengus*) in the North Sea for the basis for one of the largest herring fisheries in Europe. The size and productivity of this stock has varied greatly over time, ranging from a post-WWII high of nearly 5 million tonnes to the mid-1970s low of less than 50 000 tonnes: today the stock has recovered to an adult biomass of around 2 million tonnes. While these changes in abundance have been primarily by overexploitation of the stock, variations in the baseline productivity (recruitment) of the stock have also been observed, most notably in the late 1970s and in the period after 2000 (Payne *et al.*, 2008). While there have been many hypotheses over the years about the role of the environment in these changes, there is still a limited consensus around the precise mechanisms involved. Nevertheless, the knowledge available suggests that it may be possible to predict recruitment to this stock, and such a forecast product has been identified by stakeholders as a potentially valuable climate service.

We investigated the ability to forecast this stock using the same approaches described above. Based on published literature (Payne *et al.*, 2008, 2013) highlighting a link between recruitment to this stock and water temperature, we extracted appropriate time series of water temperature at the time of spawning (Aug-Dec) from the HadISST data set. We then applied the same retrospective forecasting approach described above for Sandeel and for the generic approach to recruitment forecasting to this dataset. However, to maintain consistency with existing management structures, we implemented a non-stationary version with environmental covariates of the standard Ricker stock-recruitment model (Minto *et al.*, 2014) ie:

$$R_y = \alpha_y S_y exp(-\beta S_y + \gamma T_y)$$

where R_y is the recruitment, S_y is the spawning stock biomass and T_y is the temperature anomaly, all in a given year, y. The constants β and γ are time-invariant constants, but α_y is time-varying, represented by a first order random walk. The model was written and fitted in a Bayesian framework using non-informative priors, with sampling performed using the Stan software in R (Carpenter *et al.*, 2017).
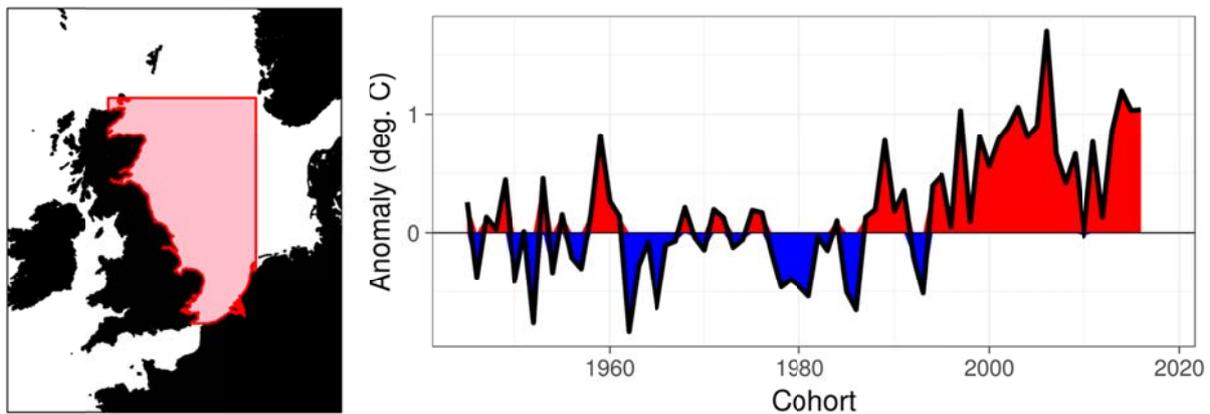

Figure 16 Temperatures used for modelling North Sea herring recruitment. left) Spatial domain over which temperature was averaged. right panel) Time series of temperature anomalies relative to 1960-2000 baseline

A series of different configurations of this model, using both stationary and non-stationary parameterizations were trialed and their predictive skill compared (Figure 17). All models showed a significant fall off in performance when they moved from the calibration period (leads <= 0) to the forecast validation period (lead > 1). At a lead of 1 cohort, the lead of greatest management relevance, the GM10 model performed the best. This model, using simply the geometric mean of the last 10 years, is the equivalent of a persistence forecast and is the current procedure used in this stock for making forecasts for evaluating catch opportunities.

The inability of the forecast systems to outperform this most basic of models is a strongly negative result, and suggests that there is little hope for producing skillful ecological forecasts and valuable climate services for this particular stock at the current time.

Nevertheless, one useful side effect of this work came from the use of the non-stationary Ricker model. The time-series of α parameter estimates for this stock can be used to generate a time series of F_{MSY}, the fishing mortality at maximum sustainable yield (Figure 18). This value is a key reference point in determining whether a fishery is fished sustainably or not, and is typically assumed to be constant in time. This result therefore represents the first time that we are aware of where a time-series of this value has been produced, and clearly shows substantial variation in the value of this reference point.

The applications and implications of this valuable result in a fisheries-management context are currently being explored.
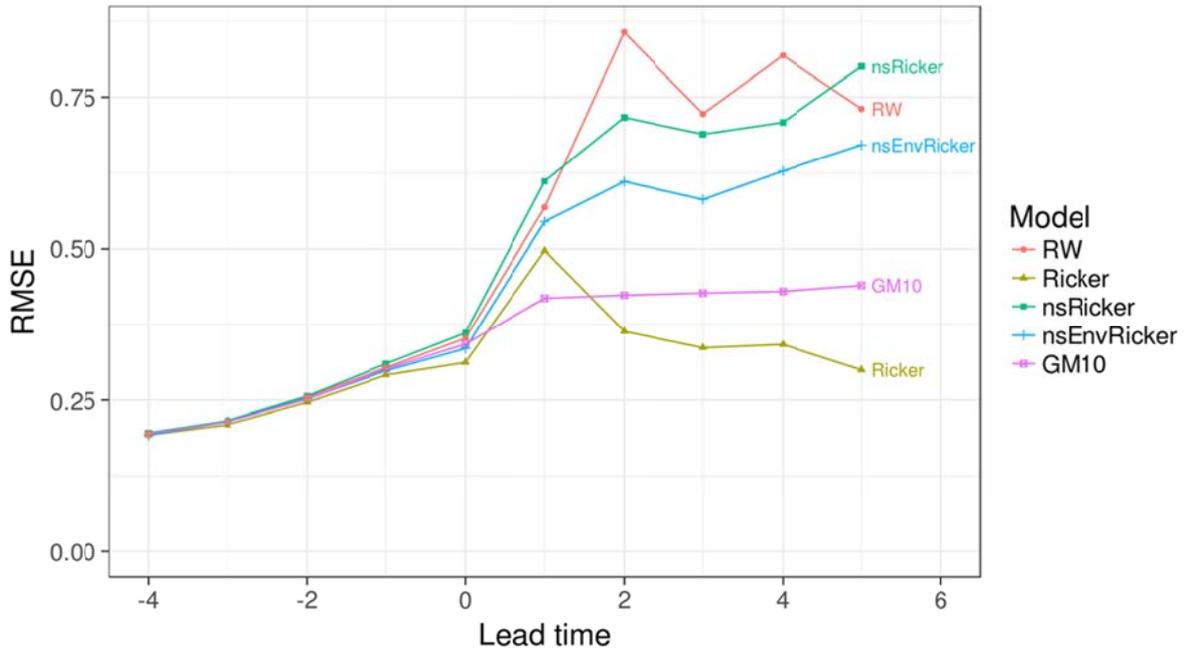

Figure 17 Forecast skill of various models for North Sea herring recruitment. The root-mean squared error (RMSE) between the forecast and observed recruitment is plotted as a function of lead time (in years): lead zero corresponds to the most recent cohort in the assessment, negative leads to previous cohorts and positive leads to future cohorts. Models shown here are a simple first-order random walk (RW), a stationary ricker model (Ricker), a non-stationary Ricker (nsRicker), a nonstationary ricker with a temperature environmental covariate (nsEnvRicker) and a 10-year running geometric mean (GM10).
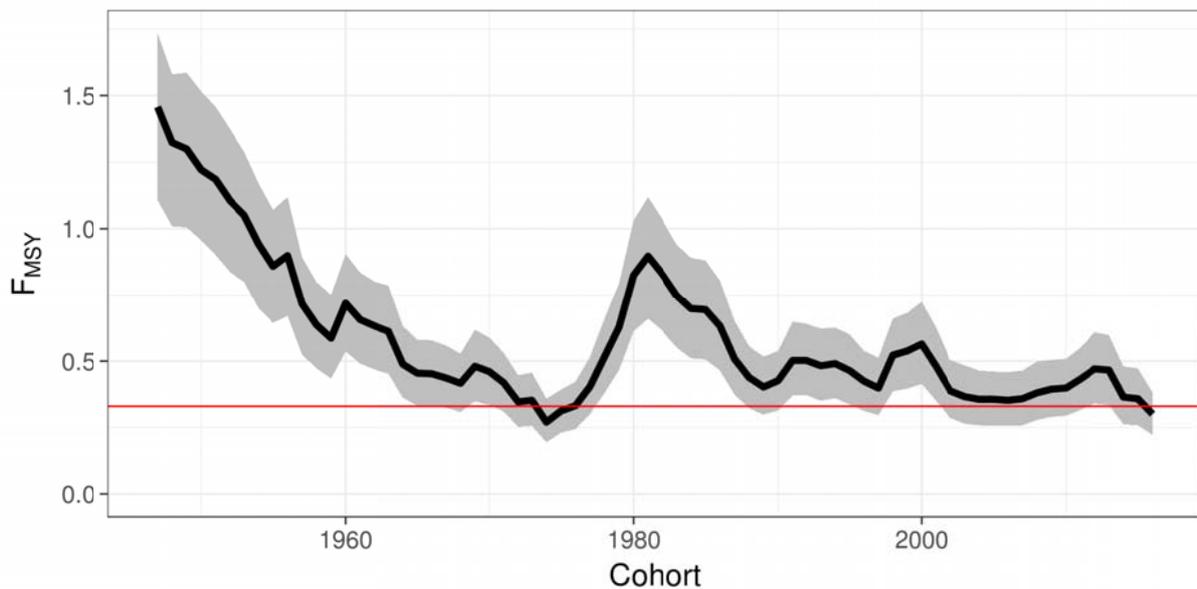

Figure 18 Time-series of FMSY for North Sea herring. FMSY is the fishing mortality at maximum sustainable yield, a commonly used reference point used in the management of this stock. The heavy black link shows the estimated value as a function of time, while the grey area is the 95% confidence interval. The horizontal red line corresponds to FMSY = 0.33, the current reference point for this stock.

Recruitment of Cod in the Barents Sea

The Barents sea population of cod is currently the worlds largest and most productive cod population. A combination of good management practices together with clear benefits from a warming climate have driven this population to the highest levels observed thus far.

Work performed in Work Package 2 of Blue-Action has demonstrated that the productivity of this stock is closely linked to the inflow of water from the North Atlantic into the Barents Sea (Årthun *et al.*, 2018a). Furthermore, as this water originates in the form of anomalies from the North Atlantic sub-polar gyre region, it is possible to make observationally-derived forecasts of the state of the Barents Sea, and therefore of the productivity of the Barents Sea cod stock with 6-8 years of lead time (Figure 19). Such forecasts could be potentially of great value to the management of fisheries in this region.

Case Study 4 therefore intends to collaborate with WP2 to build on top of this knowledge to develop and operationalize a climate service for Barents Sea cod. Full details of these reports have been previously reported in the manuscript Årthun et al. (2018a) and in "D2.5 - Assessment of Oceanic anomalies of predictive potential".
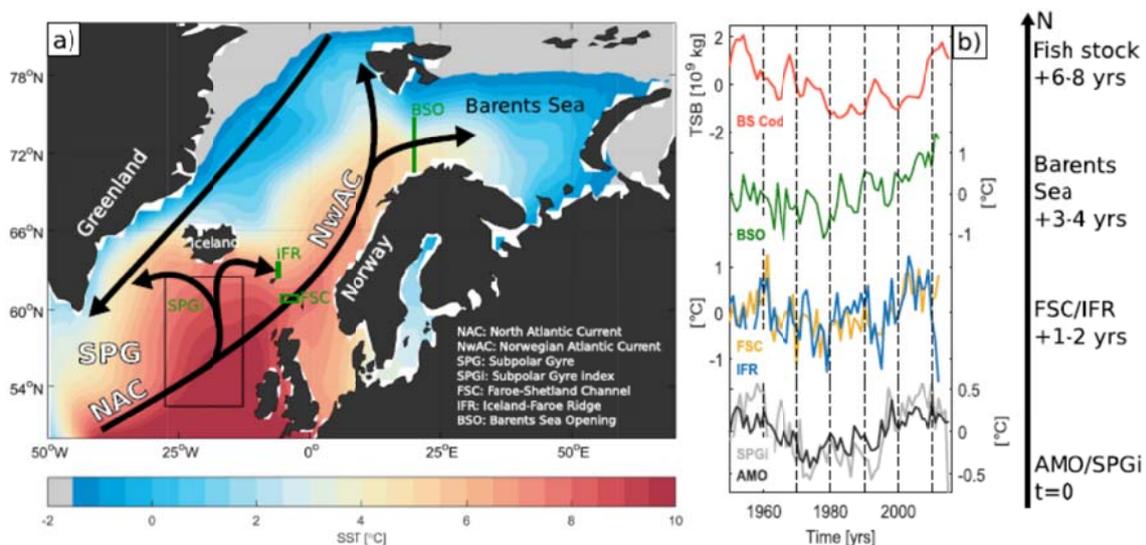

Figure 19 Barents Sea cod stock and upstream hydrography. (a) Winter sea surface temperature [28] and schematic of the major ocean currents in and between the subpolar North Atlantic Ocean and the Nordic Seas. Abbreviations are defined in the inset legend. (b) Time series of observed Barents Sea cod stock (total stock biomass; TSB) and temperature anomalies from the Nordic Seas Atlas [29] along the Atlantic water pathways used as upstream hydrographic predictors. The AMO and SPG indexes are defined in Material and methods. All anomalies are relative to 1950–2012. The average travel times of observed hydrographic anomalies from the subpolar North Atlantic (represented by AMO/SPGi) to the Nordic Seas (FSC/IFR) and to the Barents Sea, and their lagged influence on the cod stock, are indicated. From (Årthun et al., 2018a)

Phenology (timing) of key events

Phenology is the study of the timing of key events in the life-cycle of organisms. Phenological responses of marine organisms to climate change are commonly reported (Chambers *et al.*, 2013; Poloczanska *et al.*, 2013): warming of the oceans has led to the advancement of many key biological processes. Such a result is unsurprising and in line with expectations (Burrows *et al.*, 2011). Most marine organisms, for example, are cold-blooded (endothermic) and their body temperature and metabolic rates are therefore determined by the environment: increases in temperature therefore lead to an increase in metabolism

and can lead to changes in key parts of the lifecycle. For those that are dependent on the ocean, knowning when an event (such as a migration) will occur, can be as important as knowing, for example, how many fish there will be, and there are already several examples of phenology-oriented marine ecological forecast products (Mills *et al.*, 2017). The close coupling between the physical environment and the biological response, together with the needs of users, make this ideally suited to developing a climate service.

Timing of sandeel spring re-emergence

Adult sandeel (Ammodytes marinus) have a unique life cycle have which can be divided into two main seasonal phases; feeding and overwintering. Due to high site fidelity for post-settled sandeel, these phases are expected to be linked to a patchwork of sand banks with little exchange between them. The overwintering period includes a specialized behaviour comprising a strategy that involves burying in sandy sediment surviving on energy reserves obtained during the feeding season. The exact time-window of overwintering is not well-described, but based on decreasing catches within the fishery, it is thought to last between August and April, interrupted only by spawning around December/January. During spring, they emerge from the sand and begin the foraging season, which involves diel behaviour alternating between the upper pelagic zone forming large schools during daylight to feed on zooplankton and burying in the sediment during night.

The phenology of this specialised seasonal behaviour is not well understood, and in particular the trigger for sandeel "waking up" from their overwintering "sleep" has not been studied in detail. However, it has clear implications for both the fishery and for the ecology of this species. Sandeel are one of the largest fisheries in the North Sea region (by landigns) and are a particularly important commercial species in Denmark. The sandeel are caught using pelagic gear while they are feeding in the water column, and are therefore only accessible to the fishery during this part of their life cycle. Phenological variation in the timing of the fishery can be problematic for vessels that sail out expecting catch, only to find that the species has year to emerge from over-wintering. Furthermore, changes in the phenology of re-emergence will also influence the interaction of the sandeel with the rest of the ecosystem, both as predator and prey: the match, or mismatch, of sandeel phenology with that of other species can be key to determining the strength of these interactions, with both positive and negative effects possible. Here, we investigate the transition from overwintering to foraging in sandeel and examine at the parameters that might determine the variation in its timing.

As the basis for this analysis, we use standardised estimates of catch rate (CPUE) from the North Sea from 1993 to 2018. This data is resolved at the trip-level based on reports from vessel log-books, and is standardised based on the size and power of the vessel. We assume that the above dataset is representative of sandeel abundance in the water column after overwintering: it is, in any case, representative of the fishery. We assume that catch rates from the fishery mirror the availability of sandeel, which might explain when they start their feeding period after overwintering and furthermore also when the whole population of sandeel are fully emerged and we might expect that the overwintering period is over. We make use of the typical dome-shaped distribution of the fishery data, where one might expect that fishery catch rates are low in the start of the season when first sandeel are emerging, increases to a certain point when the whole population have emerged and then decreases again as sandeel are starting to bury as a result of their overwintering behaviour. Generalised additive models were fitted to the catch rates with the aim of smoothing the otherwise noisy data (Figure 20), an approach shown to greatly improve the determination of phenological metrics (Ferreira *et al.*, 2014).

The calculation and definition of phenological metrics, however, was used in a non-standard manner. Management restrictions introduced in 2005 limited the fishing season to a 1st April start date, meaning that for approximately half of the time series there are no observations prior to 1st April: this is problematic for our analysis, as it makes it impossible to define phenology metrics in cases where the sandeel has already "woken up" prior to 1st April. We therefore choose to invert this problem and, rather than look at, for example, the date when the catch rate passes a given threshold (a standard phenological metric), we look at the catch rate on a given date (1st April). By comparing the estimated 1st April catch rate to the maximum catch rate (which varies from year to year, based on the biomass of the stock) (Figure 20), we can then calculate a metric of whether the species has fully or only-partially emerged from over-wintering.
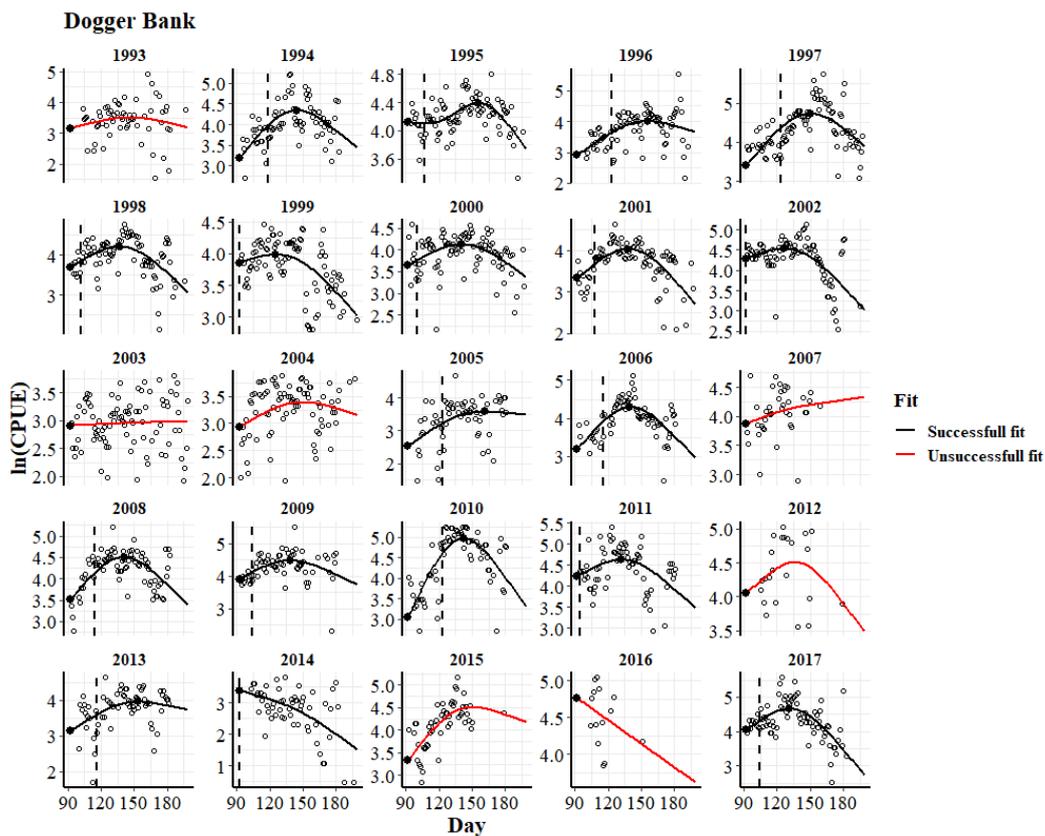

Figure 20 Sandeel catch rates for the Dogger bank area. GAM models were fitted to the daily CPUE values in order to smooth the data and estimate ln(CPUE) on April 1st and peak ln(CPUE). A set of criteria involving the goodness of the fit and the position of the breakpoint from a fitted hockey stick regression (vertical dashed line) was used to identify 1993, 2003, 2004, 2007, 2012, 2015, and 2016 as unsuited for the analysis (i.e. very poorly estimated peak ln(CPUE).

Phenology metrics were then compared to a suite of environmental conditions leading up to the emergence from over-wintering. Model comparison and selection procedures showed that the emergence of sandeel from the sand after overwintering was found to be related to the temperature experienced by the sandeel near the bottom. It was found that in cold years a relatively small proportion (compared to warm years) of the population has awaken by 1st of April (Figure 21).
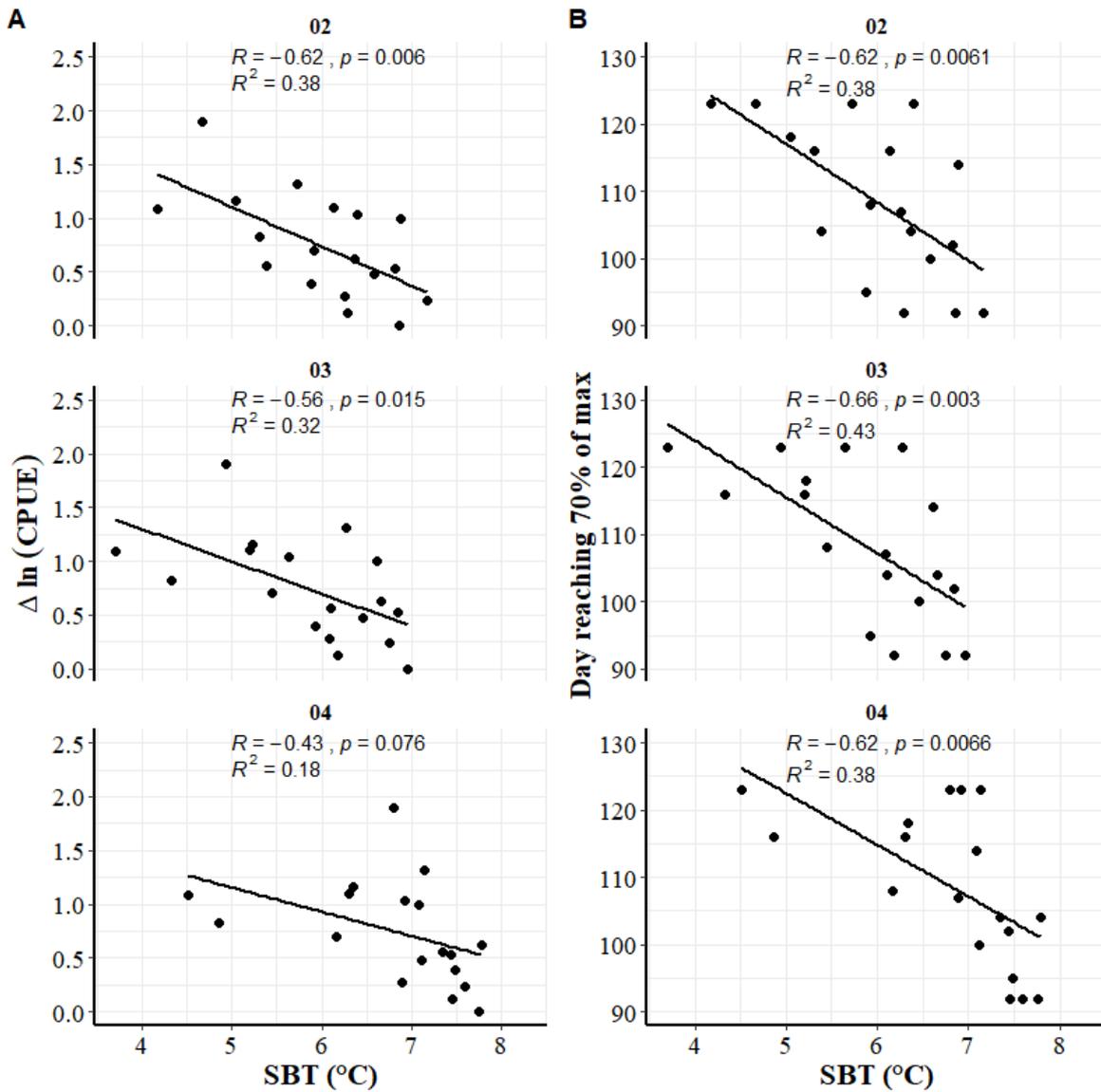
Figure 21 Correlation of sandeel phenology with environmental conditions for the Dogger Bank area. The difference (Δ) in ln(CPUE) between the 1st April and the maximum catch rates (A) and estimated day reaching 70% of maximum CPUE for each year (B) as a function of sea bottom temperature (SBT) for February (02), March (03) and April (04). The coefficient of determination (R2), Pearson's correlation coefficient and associated p-value are shown.

Mechanisms underpinning these correlations were examined using a simple bioenergetics model. We hypothesise that warm winters lead to a higher metabolism and thereby a higher rate of consumption of reserves stored during the previous summer. Increased depletion of reserves therefore creates an elevated "starvation pressure" that drives the sandeel to move into the water column to start foraging for food. We therefore employed a bioenergetics model describing the consumption of fat stores over the winter to model this process. We found good agreement between the state of reserve anomaly on 1st April and 1st April phenological metric Figure 22, supporting this hypothesis.
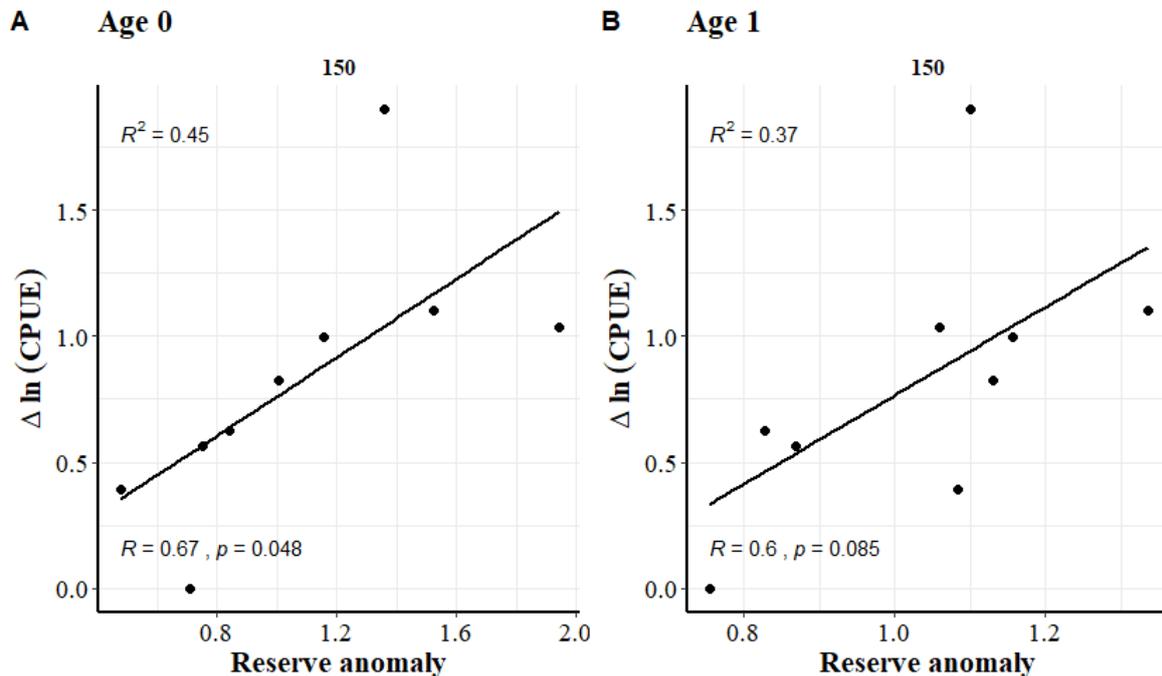
Figure 22 Correlation of sandeel phenology with physiological reserves. The difference (Δ) in catch rates on the 1st of April to the maximum catch rate are plotted as a function of energy reserves used by day 90 for Age 0 (A) and Age 1 (B). Energy reserves were calculated as a function of daily temperatures from November 1 to April 1 and initial fish length observed during the sandeel survey running in Nov/Dec each year, using the bioenergetics model from van Deurs et al. (2011) (Marine biology, 158(12), 2755-2764). On the graphs reserves are presented as anomaly deviation from the mean. The coefficient of determination (R2), Pearson's correlation coefficient and associated p-value are shown.

We therefore conclude that there is good evidence for substantial environmentally-driven variation in the phenology of sandeel emergence from overwintering. Furthermore, these results are not just based on correlations with environmental conditions, but are also supported by mechanistically-based bioenergetics models. We therefore conclude that there is a good basis for developing a climate service around these results.

Timing of migration of Garfish and Mackerel into Danish waters

Garfish (*Belone belone* DA: *hornfisk*) and Mackerel (*Scomber scombrus*) are two species that migrate into the coastal waters around Denmark every summer from their main habitat in the North Atlantic. Garfish pass Denmark on their way further into the Baltic Sea, where they spawn, while Mackerel are primarly on a feeding migration. Both species are the targets of popular recreational fisheries, and the arrival of Garfish in particular is eagerly anticipated in Denmark. Based on our previous interviews with recreational fishers in Denmark (Blue-Action deliverable D5.16) we identified an interest in forecasts of the arrival of these two species.

The migration of both species can be monitored in near-real time based on results obtained from recreational fisheries. The citizen-science app "Fangstjournalen" has been established in Denmark for more than five years now and gives fishers the ability to record their fishing trips in the form of a electronic logbook, including the location, time of day, gear used, target species, and the catches (number and size). Importantly the duration of the fishing activities is also reported, allowing estimates of the catch per hour of fishing, which is typically assumed to be related to the local density of fish.

Blue-Action Case Study 4 has developed an interface to this database that allows the extraction and processing of this data in near-real time. The data is first extracted and quality checks applied, including the removal of obviously erroneous entries (e.g. one fisher reported catching 40 garfish in under 75 minutes on a single rod – a rate of one every second minute!). The data is then smoothed through the use of a generalised additive model, plots produced and uploaded to the internet for public dissemination (see e.g. Figure 23). These results form one cornerstone of the envisaged climate service, i.e. the summary and direct dissemination of results from the citizen science app.
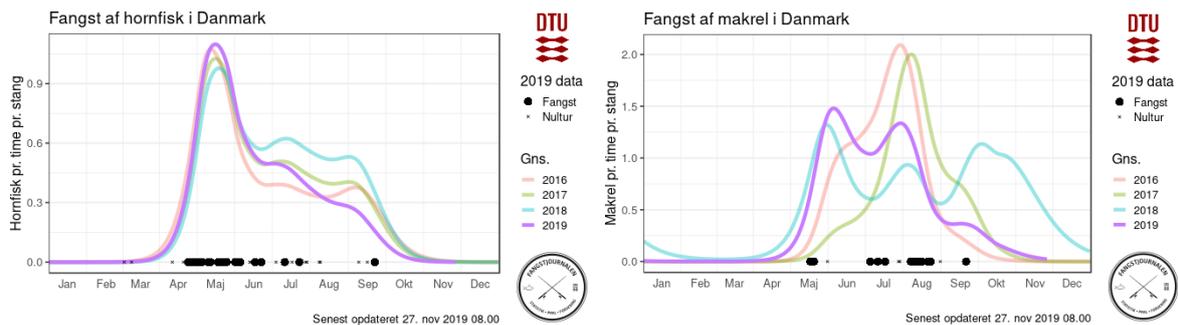
Figure 23 Near-real time monitoring of (left) Garfish and (right) Mackerel migrations into Danish waters. Data is based on catches reported by recreational anglers using the "Fangstjournalen" app, and processed using a statistical model to smooth the data. The figures are updated daily and are available via the website http://fishforecasts.dtu.dk

The second aspect of the forecast is the development of forecasts of the arrival of both species. There is a good scientific basis for forecasts of the migration of Mackerel into Danish waters. Work published previously in the literature (Jansen and Gislason, 2011) linked the timing of both arrival and departure of Mackerel to sea surface temperatures in the region. This work therefore forms a clear basis for developing an ecological forecast and climate service.

However, the current understanding of Garfish migration is less well developed, and in general, this species is poorly studied. Previous work has indicated a relationship between temperature and the arrival of Garfish: however, this analysis was based on relatively short time series (up to 2006) and simple analyses. We therefore updated this analysis with an additional 12 years of data, to both check that its validity still holds, and to allow our own parameterisation.

We based the analysis of Garfish migration on bycatch data from Danish commercial fisheries. While this species has little or no targeted commercial fishery, it is regularly caught as bycatch. We therefore analysed daily sales records from more than 130 ports around Denmark, aggregating the data into predefined regions (Figure 24). Catches in each of these regions could then be visualised and phenology metrics calculated (Figure 25). Substantial work was put into finding phenology metrics that were robust to the noise apparent in the data, while at the same time retaining the inherent variability. Metrics of the cumulative proportion of landings were general found to perform the best, and agreed most closely with visual interpretation.
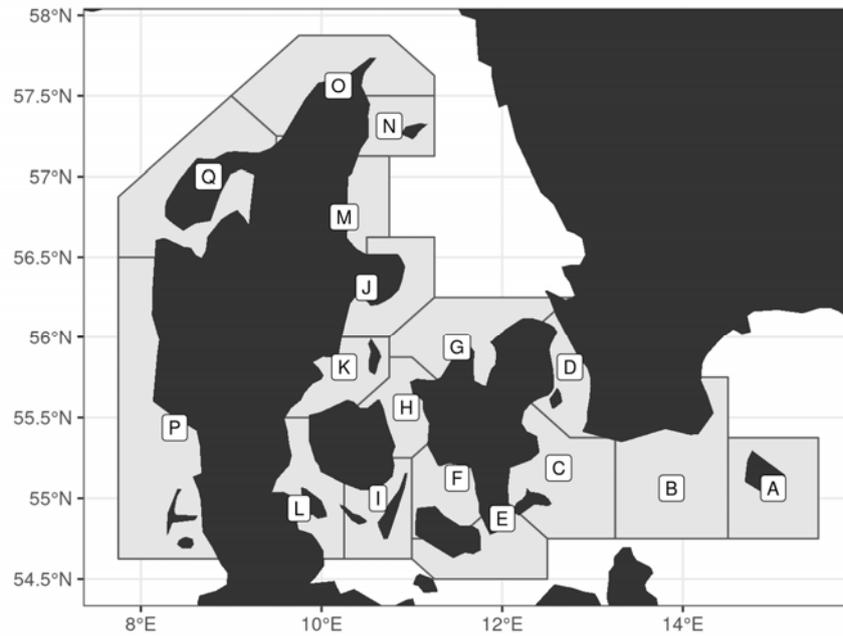
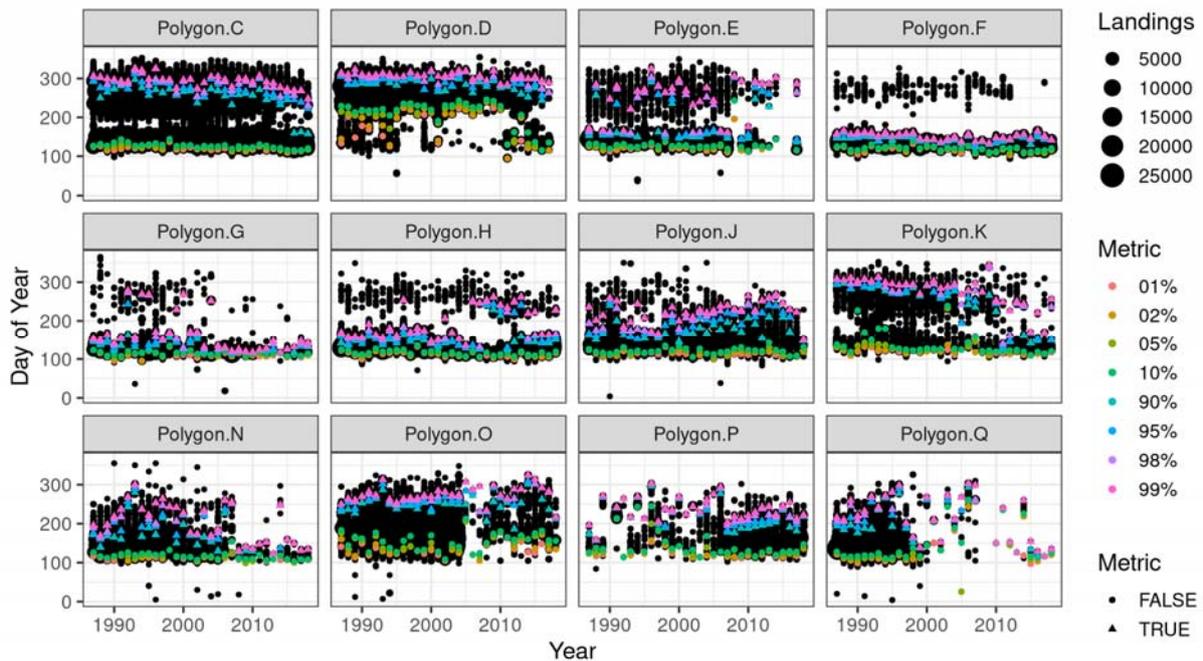**Figure 24 Aggregation polygons used for the analysis of Garfish data**

Figure 25 Landings of Garfish in Denmark, divided up by region. Landings are plotted as points, with the size of the point proportional to the size of the landings (in kg), and plotted according to year and the day of year of the landing. Phenology metrics, based on the cumulative proportion of landings, are over plotted as coloured points. The difference between inward and outward migrations is clear in many regions , particularly Polygons C, E, and F. Only landings in the 12 largest regions are shown.

Changes in the phenology of migration could thereafter be identified. There were clear and significant trends to in the phenology metrics for the arrival (5%) and departure (95%) of Garfish in Danish waters. Garfish are now arriving in Denmark approximately 9 days earlier than they were thirty years ago, while they are leaving nearly a month earlier.
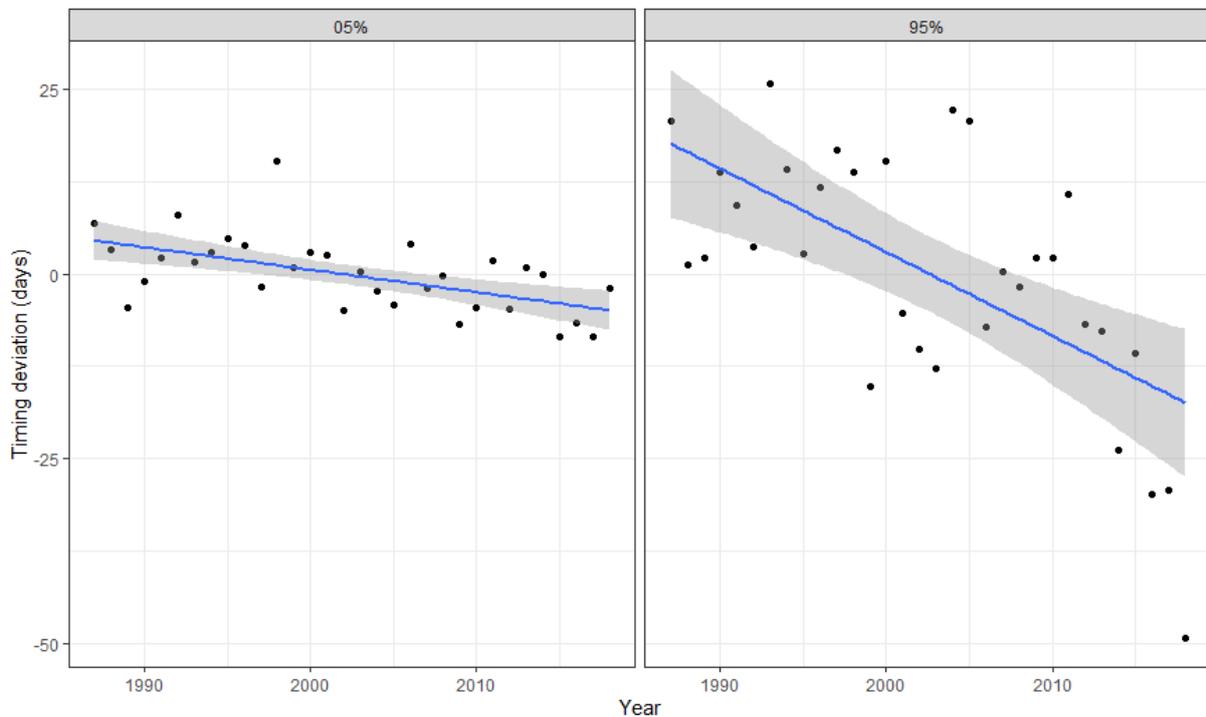

Figure 26 Phenology of Garfish migration in Danish waters. Temporal anomalies in the arrival (5%) and departure (95%) of garfish averaged across all regions are plotted as a function of time, with a linear regression (blue line) and confidence intervals (grey area).

However, both arrival and departure metrics exhibit appreciable variability that can potentially be explained by environmental conditions, such temperature. We therefore extracted temperature anomalies in each polygon from satellite observations and compared them with the local anomaly in timing. A significant negative correlation was found for both metrics, indicating that warmer temperatures lead to earlier arrivals and departures (Figure 27).
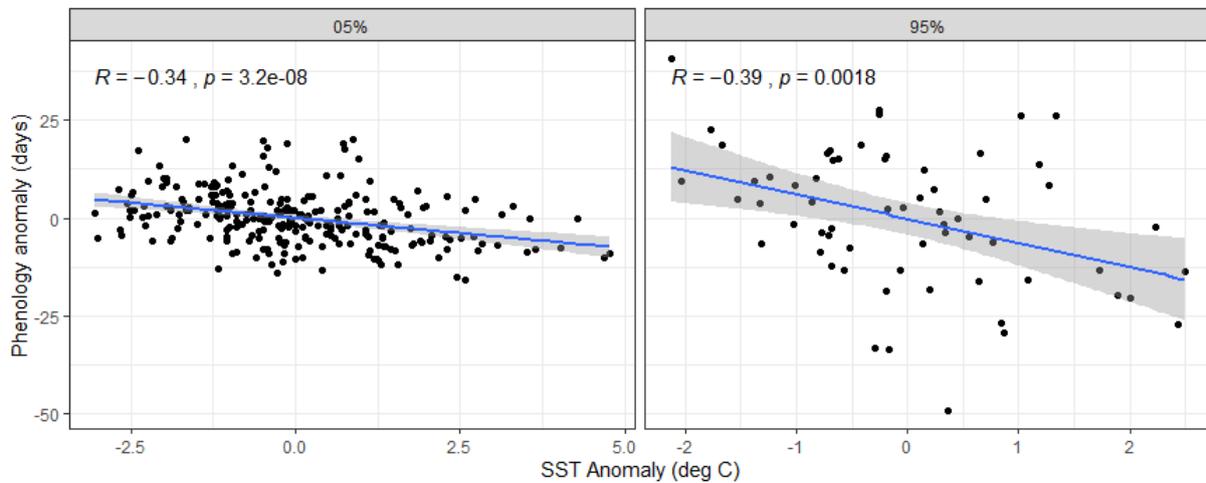
Figure 27 Environmental determinates of Garfish migration phenology. Correlation between the local phenology anomaly (in a polygon in a year) and the local temperature anomaly. Pearson correlation coefficients (R) and significant levels (p) are also shown, together with a linear-regression line and confidence intervals.

We therefore conclude that the migration of both garfish and mackerel into Danish waters is correlated with the local water temperatures. This knowledge can potentially therefore be used to predict the arrival and departure of these species, and thereby support a potential climate service.

Timing of spawning of herring in the English Channel

Herring (*Clupea harengus*) in the North Sea spawn on a collection of gravel banks along the east coast of Great Britain. The species shows a high degree of homing behaviour to these banks, with adults returning to spawn on the same bank. As result, the North Sea herring stock can be viewed as a series of at least four sub-populations that, while following the dynamics of the general population, also have their own dynamics. The largest of these components in recent years is that spawning in the English Channel, also known as the Downs component, although its contribution to the total stock has varied substantially over time (Payne, 2010).

Fisheries on the Downs component target the herring for their flesh for human consumption, but also for their roe (eggs), which are processed and sold to markets primarily in Asia. A key aspect of this fishery is ensuring that the fish are harvested shortly prior to the eggs being spawned, to ensure the highest quality. However, interannual variation in the timing of spawning means can lead to fluctuating roe quality. In our interviews with stakeholders in this fishing industry, and particularly with the Pelagic Fisheries Association, the ability to forecast the timing of spawing and the quality of the roe was seen as a potentially valuable climate service.

We therefore investigated the factors determining the timing of the spawning in this component. We used data from the International Herring Larval Survey (IHLS), an internationally coordinated survey that covers all of the spawning components with the aim of quantifying both their relative abundance and the total abundance of the stock. The Downs component is covered by three surveys with codes E6 (16-31 Dec), E7 (1 -15 Jan) and E8 (16-31 Jan), and generates a spatially resolved snapshot of the density of larvae between 5 and 24mm in length in these time windows.

Initial attempts at working with this data focused on using the length distributions directly. The goal of this analysis was to take advantage of the full dimensionality of the dataset, based on the spatially-resolved length distributions and accounting for correlations between nearly observations and neighbouring length classes. Data was processed one survey at a time using a space-length model fitted using the Integrated Nested Laplace Approximation (INLA) with Poisson and Negative Binomial observation errors. However, while the individual models appeared to fit the individual surveys well, there was a general lack of coherence between the fits: in particular the hyperparameters of the fits tended to vary wildly, indicating differing degrees of smoothing. Ideally all of the surveys would be fit in a single model: however, this did not prove to be computationally feasible and were ultimately forced to abandon this approach entirely. We therefore took a simpler approach, based on estimates of the abundance of the very smallest herring larvae between 8 and 11mm, the so-called larval abundance index, LAI.

We first compared the individual LAI values against each other as a way to detect trends in the relative proportions of the component occurring in each of the surveys. For example, if the spawning distribution were to be later than average, we would expect to see a general increase in the proportion of the stock in the last survey, and a relative decrease in the first survey. We therefore first examined the relative values of these surveys with respect to each other (Figure 28). There is in general a high degree of variability present in these ratios, at least some of which is attributable to noise in the observations. However, trends are also apparent, particularly when comparing the E8 survey, indicating that this survey period may be increasing systematically. However, in the presence of such a high degree of noise, it is difficult to interpret these results more fully.
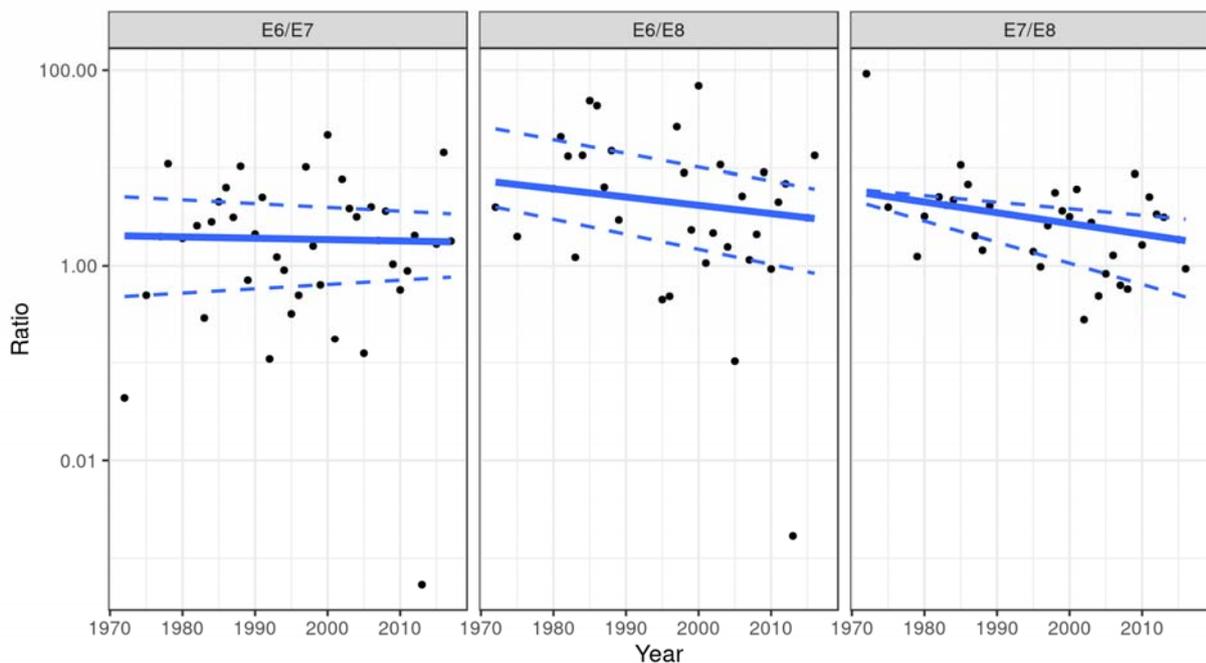
Figure 28 Ratio of herring LAI survey values in the southern North Sea. E6: 16-31 Dec. E7: 1-15 Jan, E8: 16-31 Jan. Note the logarithmic y scale. Lines correspond to a quantile regression for the 25%, 50% and 75% percentiles

We therefore develop a statistical model to interpret this data in a more appropriate manner. As inspiration we used a model that we had published previously (Payne, 2010) to process this data, the spawning-component abundance index model (SCAI). This model is a state-space model, treating the

underlying abundance of the component as a first-order random walk in log-space (thereby allowing for exponential growth and decay of the population to arise naturally in the model). Observations, in the form of LAI indices, are then modelled via an observation model. This approach has proved to be a key advance in understanding the results of the IHLS survey, and dealing with this type of data. We therefore reimplemented the model using modern software approaches (specifically using a Bayesian approach with the Stan software package in R). We furthermore extended the observation model to allow the relationship between the underlying state and the observations in a survey to be temperature dependent, as would be expected in the case of the temperature-moderated changes in the spawning phenology. In addition, we also extended the original SCAI model to allow a student t distribution observation error (in contrast to the original Guassian observation error) to account for outliers and to give the model the characteristics of a robust regression. Model checking was performed using posterior-predictive checking. All models appeared to be appropriate for the data at hand, although there were also clear outliers that require further investigation, and potentially compensation for within the modelling framework.

Good agreement was found between the SCAI model results published previously, and our reimplementation of the algorithm here (Figure 29). Specifically, the "Const. Normal" model in this figure is directly comparable with the previously published results: the minor differences can attributed to the length of the time series and fitting methods (Bayesian sampling vs. optimisation via automatic differentiation of the likelihood) and are well within the uncertainties. We can also see that the different model configurations generally agree with each other and previous results.
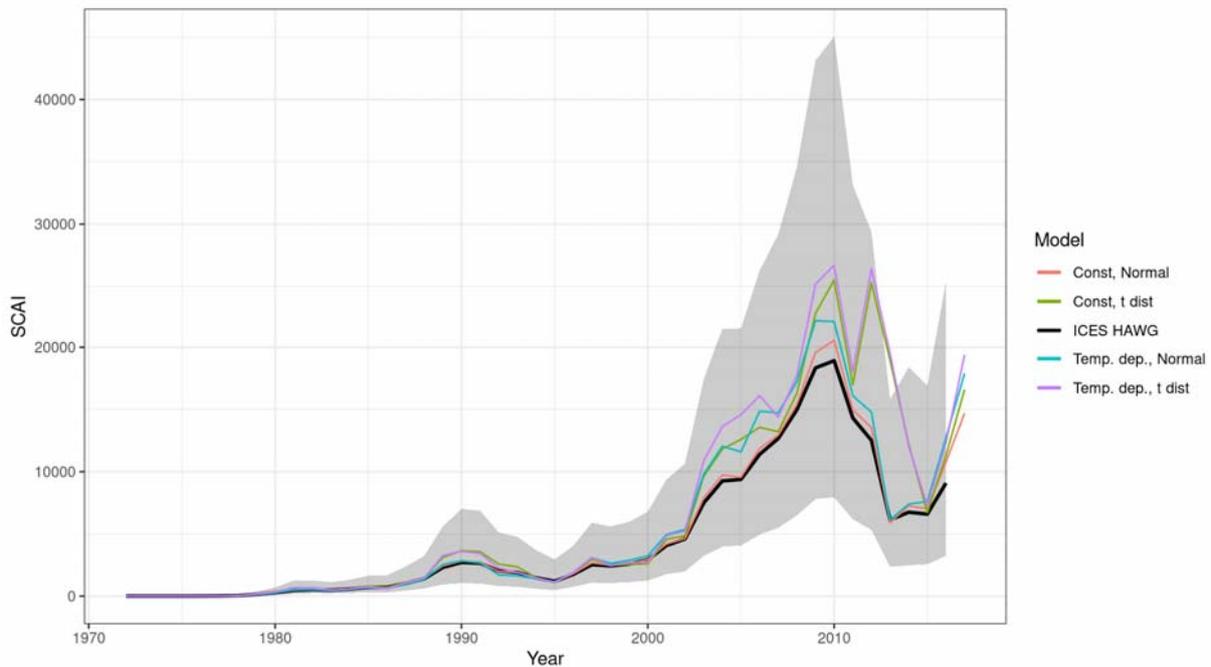
Figure 29 Comparison of SCAI indices for the Downs component for different model configurations. Four models are shown in total, two with either constant (Const.) or temperature dependent (Temp. dep.) observation structures and with two variations on the observation error model (Normal or student t distribution). For reference, the most recent SCAI index calculated by the ICES HAWG stock assessment group based on the method of Payne (2010) is shown as a black line, with the grey area representing the uncertainties in this estimate.

The temperature dependent models showed a clear response of the relative proportions to the temperature in the region (Figure 30). The last survey, E8, increased its relative proportion with warming temperatures, while the other two (E6 and E7) showed clear decreases. This is a challenging result to understand, and is counterintuitive to initial expectations: warming temperatures would give earlier spawning, decreasing the last surveys and potentially increasing the first. However, we note that the confidence intervals around the catchability parameters are very large.
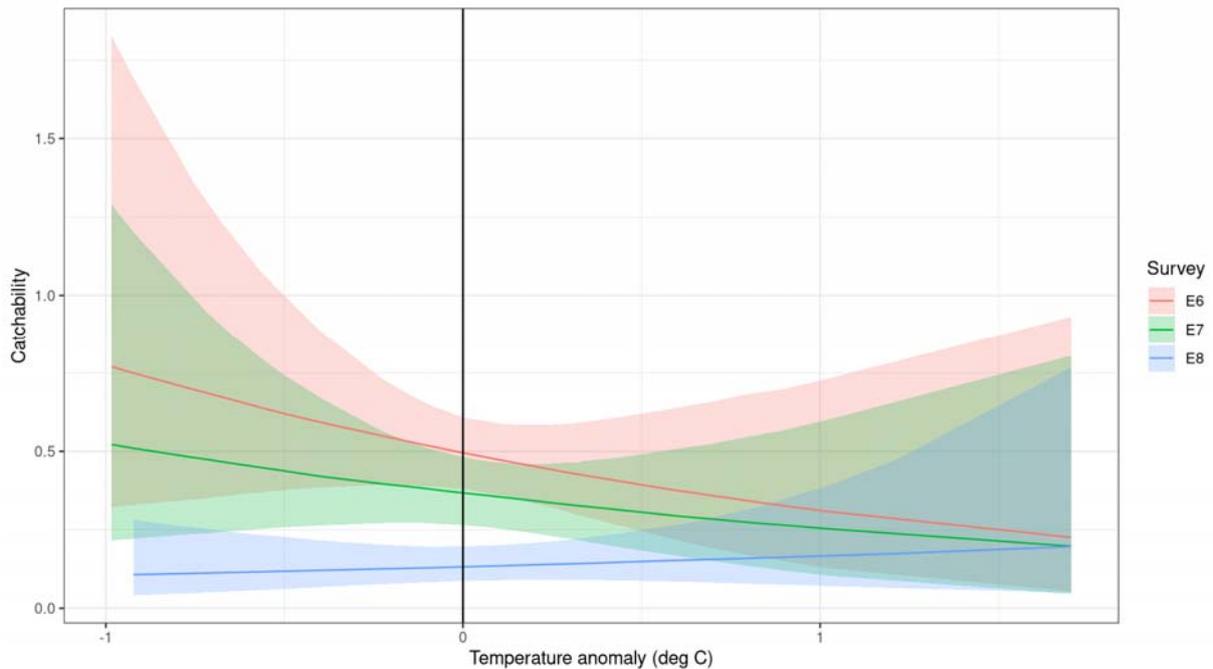

Figure 30 Effect of temperature on the relative proportions (catchability) of each survey. Colours correspond to the different surveys, while filled areas cover the 95% confidence interval.

Model selection was performed using the "leave-one-out" (loo) approach to identify the best predictive model. Loo information criteria were estimated using a combination of Pareto-Smoothed Importance Sampling and, where this was not appropriate, direct calculation (Vehtari et al., 2017). The results of this analysis show that the best model is actually that without temperature dependence but incorporating a student t observation error (Figure 31). However, there is little difference between any of these models in terms of their predictive power, and adding temperature as a covariate does not seem to improve the quality of the model.
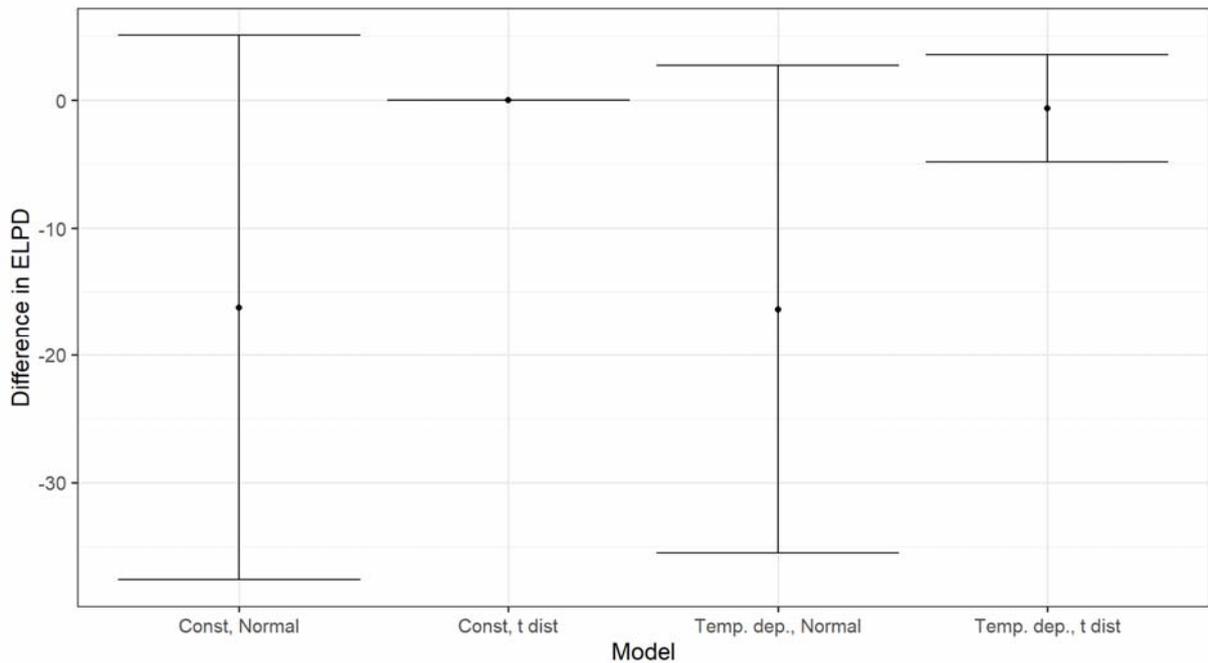
Figure 31 Model comparison. The estimated log predictive density (ELPD) of each model relative to the model with the highest ELPD, with error bars for the pairwise comparison.

We therefore conclude that there is little evidence to support the effect of sea surface temperature on variations in spawning phenology observed in this component. Further data may shed light on this issue, but the IHLS data does not appear to be of sufficient quality to resolve these issues. We therefore conclude that there is little scientific basis to support a climate service here.

Main results achieved

The main results achieved are summarised in the table below:

Proposed Climate Service	Source	Results of investigations	Operationalise?
Spawning distribution of blue whiting	Blue-Action CS4. Published in (Miesner and Payne, 2018)	Spawning distribution linked to deep-water salinity with species distribution model.	Yes
Summer feeding distribution of mackerel	Blue-Action CS4. Manuscript in preparation.	Feeding habitat linked to sea surface temperature with ecological niche model.	Yes
Summer feeding distribution of Bluefin Tuna	Previously developed in FP7 NACLIM project. Rechecked and updated in Blue-Action CS4. Published in (MacKenzie *et al.*, 2014)	Feeding habitat linked to sea surface temperatures greater than 11 degree C.	Yes

Recruitment of sandeel in North Sea	Blue-Action CS4. Manuscript in preparation	Recruitment of four stocks linked to SST, demographic factors and year effects.	Yes
Recruitment of herring in the North Sea	Blue-Action CS4.	Recruitment predictions based on adult biomass and sea surface temperature tested but no significant predictive power.	No – no clear sign of predictive power (*)
Recruitment of cod in the Barents Sea	Blue-Action WP2. Published in (Årthun *et al.*, 2018b)	Total biomass and recruitment linked to sea surface temperature	Yes.
Timing of sandeel re-emergence	Blue-Action CS4	Degree of re-emergence on 1st April linked to previous winter temperatures.	Yes
Timing of mackerel migration into Danish waters	Previously published (Jansen and Gislason, 2011)	Timing of migration linked to sea surface temperatures	Yes
Timing of garfish migration into Danish waters	Blue-Action CS4	Timing of migration linked to sea surface temperatures	Yes
Timing of herring spawning in English channel	Blue-Action CS4	Effect of temperatures on spawning phenology not significant	No (*)

(*) These are to be further explored in the upcoming months with data made available by PFA.

Generally we have found that the majority of the proposed climate services have a solid scientific basis to support them. While we found evidence of environment influences for the recruitment of herring and the timing of herring spawning in the English channel, the statistical tests performed indicated that they did not have sufficient predictive power to outperform a reference forecast (i.e. of persistence or of no change respectively). However, the majority of the proposed climate services appeared to have some support and cover three major types of biological response: shifts in spatial distribution, recruitment and phenology.

Progress beyond the state of the art

The results described here represent a significant progression beyond the state of the art: **each of the new physical-biological relationships described here has not been reported before in the literature, and therefore represents a new discover**y.

- The most important of these is the **identification of potential predictability in the recruitment to sandeel and cod stocks.** As noted above, recruitment is generally viewed within marine science as being unpredictable, and to even attempt to develop predictions of this variable involves a high risk of failure by conventional wisdom. However, the development of a framework within which to approach recruitment prediction has proved to be a significant advance, and now allows us to approach this problem in a rigorous and systematic manner. Furthermore, the results obtained show clear evidence of predictability, and therefore represent a significant break with the dominant paradigm.
- A second major step beyond the state of the art is the d**evelopment of new understanding around the processes driving the shifts in the distribution of mackerel**. The identification of a lag between the expansion of habitat and the shift in distribution is novel, and, when published, will require a significant rethink of this issue within the community.

Impact

How has this work contributed to the expected impacts of Blue-Action?
The work performed here has contributed to the expected impacts of the Blue-Action project as follows:

Improve the capacity to respond to the impact of climatic change on the environment and human activities in the Arctic, both in the short and longer term

By further developing the previously identified climate services, Blue-Action has paved the way to improve the capacity of end-users and stakeholders to respond to climate change and climate variability.

Improve the uptake of measurements from satellites by making use of new Earth observation assets

The work performed here has developed key climate services that need to be developed to aid end-users in their day-to-day decisions. Many of these climate services rely on existing and new Earth observation assets and technologies to drive the forecast models. The new climate services that will be developed based on this work will take these products up directly and demonstrate their value to the wider community.

Improve stakeholders' capacity to adapt to climate change

The development of these climate services in this case study is very much motivated by the needs of stakeholders to responds to changes in the marine living resources that they are dependent upon. These organisms are in turn strongly influenced by the vagaries of a variable and changing marine climate. Identification and development of potential climate services therefore paves the way for adapting to this variability in the future.

Contribute to better servicing the economic sectors that rely on improved forecasting capacity

The development of climate services that could be utilised by end-users aids in servicing of these sectors by developing new forecasting capacity and providing a basis for better decision making.

Improving innovation capacity and the integration of new knowledge

As our previous review of the current state-of-the-art in marine ecological forecasting has shown (D5.16, Payne et al. (2017), there is relatively little uptake of the new-found forecast skill developed in the climate sciences. This work contributes to integrating this new knowledge into the management and utilisation of marine living resources by first identifying where it could be of use and now developing the necessary climate services.

Strengthening the competitiveness and growth of companies by developing innovations meeting the needs of European and global markets; and, where relevant, by delivering such innovations to the markets

The work performed this far, and the potential climate services that we are developing, will strengthen the competitiveness and growth of the companies using them by reducing key uncertainties associated with their businesses.

Impact on the business sector

As detailed above, the work performed here paves the way for having a positive impact on the business sector and for fuelling Blue Growth. By identifying where there is a need for marine ecological climate service information, it becomes possible to focus our research efforts in the areas where they will have the most important. The work performed here is now starting to fill these gaps and once operational, these climate services can be expected to have a positive impact on the business sector.

Lessons learned and Links built

- The key lesson learnt during this work relates to the ambition of the scale study. In retrospective it is now clear that we have initially been too optimistic about the amount of work required to develop climate services. The number of climate services that we have decided to develop, based on D5.16, is rather large, meaning that we are essentially trying to develop too many climate services at the same time, with limited resources and workforce. Focusing on a smaller number of climate services instead would have given more space for close interaction with the stakeholders involved, allowing for multiple interactions and a much higher degree of detail.

- Furthermore, it would have been better to base the identified climate services on already published relationships between the physical environment and the biological response: instead, many of the climate services targeted here require the additional development of knowledge beyond that in the scientific literature. An alternative approach could have been to focus solely on potential climate services based on already published knowledge, and focus instead on operationalising that knowledge and tailoring it to the end-user. However, the climate services also reflect the needs of stakeholders for information to support their decision making processes: such needs exist irrespective of the state of scientific knowledge. Developing climate services where there is also a need to develop appropriate knowledge first should therefore, in principle, produce better quality and more targeted climate services, even if it is also the more demanding route.

- The work performed has also continued to build **links both within and outside of the project. In particular, the link formed with the work of WP2 around observationally-based predictions of cod biomass in the Barents Sea** was an unexpected but extremely positive development that we now expect will lead to an additional new climate service.

Contribution to the top level objectives of Blue-Action

This deliverable contributes to the achievement of the following objectives and specific goals indicated in the Description of the Action, part B, Section 1.1: http://blue-action.eu/index.php?id=4019

Objective 7 Fostering the capacity of key stakeholders to adapt and respond to climate change and boosting their economic growth by identifying and meeting their needs for marine ecological climate services that can be used to both foresee and thereby adapt to changes in the marine living resources that they are dependent upon.

Objective 8 Transferring knowledge to a wide range of interested key stakeholders by identifying how climate predictions generated in climatology and oceanography can be used to develop forecasts of marine living resources that are relevant to end-users in their everyday decision making and developing appropriate products.

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Dissemination and exploitation of Blue-Action results

Dissemination activities

Type of dissemination activity	Name of the scientist (institution), title of the presentation, event	Place and date of the event	Type of Audience	Estimated number of persons reached	Link to Zenodo upload
Participation to a event other than a conference or workshop	Mark Payne (DTU), Title: Marine Ecological Climate Services	Silver Spring, MD (US), 5 June 2018	Scientific Community (higher education, Research)	24	https://doi.org/10.5281/zenodo.3556838
Participation to a conference	Mark Payne (DTU), Title: Future distributions of Atlantic Bluefin Tuna :seasonal, decadal and centennial scales	Washington DC (US), 7 June 2018	Scientific Community (higher education, Research)	80	https://doi.org/10.5281/zenodo.3556844
Participation to a workshop	Mark Payne (DTU), Title: Blue Whiting Spawning Habitat Forecast 2019	Online 16 Jan 2019	Scientific Community (higher education, Research)	20	https://doi.org/10.5281/zenodo.3556848
Participation in activities organised jointly with	Mark Payne (DTU) Developing and	Online presentation,	Scientific Community (higher	100	https://doi.org/10.5281/zenodo.3556850

other H2020 project(s)	Valuing Climate Services	28 Jan 2019	education, Research)		
Participation to a workshop	Mark Payne (DTU) 2019 Sandeel Recruitment Forecast	Copenhagen (DK), 29 Jan 2019	Scientific Community (higher education, Research)	15	https://doi.org/10.5281/zenodo.3556852
Participation to a workshop	Mark Payne (DTU) Fishforecasts -User-driven Forecasts of Life in the Ocean	Copenhagen (DK), 25 June 2019	Scientific Community (higher education, Research) Industry	50	https://doi.org/10.5281/zenodo.3556858
Participation to a workshop	Mark Payne (DTU) North Sea Sandeel Recruitment Forecast 2019/20	Copenhagen (DK), 20 Sep 2019	Industry	10	https://doi.org/10.5281/zenodo.3556862

Peer reviewed articles

Title	Authors	Publication	DOI	Is Blue-Action correctly acknowledged?	Open Access granted
Lessons from the First Generation of Marine Ecological Forecast Products	Payne, M.R. *et. al*	Frontiers in Marine Science	10.3389/fmars.2017.00289	YES	Yes
Oceanographic variability shapes the spawning distribution of blue whiting (Micromesistius poutassou).	Miesner, A. K. & Payne, M. R	Fisheries Oceanography	10.1111/fog.12382 https://backend.orbit.dtu.dk/ws/files/157011564/Post_Print.docx	YES	Yes

Uptake by the targeted audiences

As indicated in the Description of the Action, the audience for this deliverable is the general public (PU) is and is made available to the world via CORDIS.

This is how we are going to ensure the uptake of the deliverables by the targeted audiences:

We will continue to disseminate and engage with the scientific community at conferences and meetings targeting this audience, such as those listed above.

For engaging with the business sector, we will continue engaging with the following in working groups and in ad hoc meetings:

- the Commercial Fishing Industry (Danish Pelagic Producers Organisation, Marine Ingredients, Pelagic Freezer Trawler Association),
- Scientific Advisory and Monitoring Bodies (ICES HAWG and WGIPS workgrounds, ICCAT).