ICES Journal of
Marine Science

ICES Journal of Marine Science (2020), doi:10.1093/icesjms/fsaa120

Evaluating acoustic-trawl survey strategies using an end-to-end ecosystem model

Arne Johannes Holmin, Erik A. Mousing, Solfrid S. Hjøllo, Morten D. Skogen, Geir Huse, and Nils Olav Handegard *

Marine Ecosystem Acoustic, Havforskningsinstituttet, Bergen, Norway

**Corresponding author: tel: +47 95854057; e-mail: nilsolav@hi.no.*

Holmin, A. J., Mousing, E. A., Hjøllo, S. S., Skogen, M. D., Huse, G., and Handegard, N. O. Evaluating acoustic-trawl survey strategies using an end-to-end ecosystem model. – ICES Journal of Marine Science, doi:10.1093/icesjms/fsaa120.

Received 30 March 2020; revised 16 June 2020; accepted 17 June 2020.

Fisheries independent surveys support science and fisheries assessments but are costly. Evaluating the efficacy of a survey before initiating it could save costs. We used the NORWECOM.E2E model to simulate Northeast Atlantic mackerel and Norwegian spring spawning herring distributions in the Norwegian Sea, and we ran vessel transects *in silico* to simulate acoustic-trawl surveys. The simulated data were processed using standard survey estimation software and compared to the stock abundances in the ecosystem model. Three existing real surveys were manipulated to demonstrate how the simulation framework can be used to investigate effects of changes in survey timing, direction, and coverage on survey estimates. The method picked up general sources of biases and variance, i.e. that surveys conducted during fish migrations are more vulnerable in terms of bias to timing and changes in survey direction than during more stationary situations and that increased effort reduced the sampling variance.

Keywords: fisheries independent surveys, NORWECOM.E2E, OSSE, simulating surveys, StoX, survey estimates

Introduction

A central part of a fisheries management system is monitoring programmes supporting the advice process (Hilborn and Walters, 2013). Depending on the fish stock, these programmes support assessments of a range of fish stocks, including full-fledged analytical age-based assessments. Regardless of the specific case, optimizing the available effort is a key challenge for any monitoring programme. Several measures exist to assess the efficacy of a monitoring programme in relation to the objectives, including sampling variance estimates, internal consistency between years, the goodness of fit to assessment models, etc. When several independent data series are available, the relative goodness of fit for these series to the assessment model is often used as an indication of performance (Hilborn and Walters, 2013; Berg and Nielsen, 2016). This provides valuable feedback to the agencies when prioritizing their effort, but there is an obvious caveat: The approach requires the data collection to be carried out for several years before any evaluation is possible, which is highly expensive. Also, there is often a reluctance to cancel a monitoring programme that has run for several years because the earlier effort will be lost, and, if the signal-to-noise ratio is low, the programme may still prove its worth when the duration of the time series is sufficient.

One approach to evaluate survey designs without prior data collection is to simulate the data. This requires a model that is fit for purpose and can be done on several scales, from small-scale features (Holmin *et al.*, 2012) to larger-scale distribution patterns (Gimona and Fernandes, 2003). Spatial distribution models or mechanistic ecosystem models can be used to simulate fish abundance and distribution, and this can be coupled with an observation model to simulate survey data (Handegard *et al.*, 2013). This is like an observation system simulation experiment (OSSE) used in physical oceanography (Lahoz *et al.*, 2005; Francis *et al.*, 2018). Questions on the sensitivity of monitoring programmes to shifts in time or coverage, or different designs, can be addressed, and methods where auxiliary information may be used can also be included.

For the simulation approach to be useful, the ecosystem model should be able to project plausible, spatiotemporally explicit distributions of fish abundance, biomass, and size for the near future (e.g. the following survey season). A more practical aspect is that building such a model for this specific purpose is expensive, and utilizing existing infrastructure is a requirement. In our case, the spatiotemporally explicit distributions of fish abundance are modelled using individual based models (IBMs) (Grimm and Railsback, 2005) coupled to an ocean circulation model. The NORWegian ECOlogical Modeling system End-to-End (NORWECOM.E2E) is a fully coupled 3-dimensional physical, chemical, and biological model system (Aksnes *et al.*, 1995; Skogen *et al.*, 1995; Skogen and Søiland, 1998) that contains several IBM modules, including Northeast Atlantic (NEA) mackerel (*Scomber scombrus*), Norwegian spring spawning (NSS) herring (*Clupea harengus*), blue whiting (*Micromesistius poutassou*), and *Calanus finmarchicus* (Huse and Fiksen, 2010; Hjøllo *et al.*, 2012; Utne *et al.*, 2012a). The NORWECOM.E2E model has previously been applied to model distributions of NSS herring, NEA mackerel, and blue whiting in the Norwegian Sea (Utne *et al.*, 2012b). The IBMs include the full life cycle of each species and provide information on, e.g. growth, mortality, reproduction, movement, and trophical interactions at a high spatial and temporal resolution.

Collecting survey data is costly, and if we could efficiently utilize other platforms, we could improve the data collection underpinning the management decisions.

The objectives of this article are (A) to present a framework where we (A1) use the NORWECOM.E2E model to simulate the spatially explicit NEA mackerel and NSS herring distributions in the Norwegian Sea, (A2) develop the method to run a trawl survey and acoustic-trawl survey *in silico* based on the NORWECOM.E2E model, (A3) estimate the abundance based on the simulated data using standard software (StoX), and (A4) develop a method to compare the estimates with that of the model state and (B) to test the framework by simulating three major pelagic surveys in the Norwegian Sea targeting NSS herring and NEA mackerel, estimating the effect of changes in timing and coverage.

Material and methods

The simulation framework (objective A)

The ecosystem model (objective A1)

We used the NORWECOM.E2E (Skogen *et al.*, 1995; Skogen and Søiland, 1998) ecosystem model to model the distributions of NSS herring (*C. harengus*) and NEA mackerel (*S. scombrus*). The model is composed of several modules and is built on a nutrients, phytoplankton, zooplankton, and detritus (NPZD) model. *Calanus finmarchicus*, a key stone species in the Norwegian Sea, is modelled separately using an IBM with 2-way coupling to the NPZD model (Hjøllo *et al.*, 2012; Huse *et al.*, 2018). A pelagic fish IBM (Utne *et al.*, 2012b) is used to predict fish distribution and abundance and is two-way coupled to the *C. finmarchicus* IBM and the NPZD model. The two-way coupling includes predator prey interactions, i.e. removal of zooplankton biomass by fish predation in both the NPZD model and the *C. finmarchicus* module. Increased zooplankton mortality also decreases grazing pressure on phytoplankton. Bottom-up processes impact biomass available at each trophic level. The NEA mackerel and NSS herring modules are run separately, and any interactions between these are not included. It has been hypothesized that predation by NEA mackerel on NSS herring larvae can be a significant mortality source for herring larvae (Skaret *et al.*, 2014), but although eggs and larvae are represented in the model, the eggs and larvae were not included in the zooplankton pool. This may affect the recruitment of NSS herring in multiyear runs, but it will have little impact in the context of evaluating survey design.

The NORWECOM.E2E model was run in offline mode using physical forcing (atmosphere and ocean) as inputs. The physical forcing used by the model is wind and short-wave radiation, ocean currents, salinity, temperature, water level, and sea ice, taken from a downscaling (10-km horizontal resolution using the ROMS model) of the Norwegian Earth System Model (NorESM1_ME) climate model under a rcp4.5 emission scenario (IPCC, 2013; Skogen *et al.*, 2018). The model domain covers the Norwegian Sea, the Barents Sea, and (parts of) the North Sea (Figure 1). The simulation period was 2010–2012, but only results from 2012, which were less influenced by the initial state, were used. The climate model represents the statistics of the climate in a period, and forcing is representative of present-day climate and not the specific year.

The IBM modules include the full life cycle including growth, mortality, reproduction, and movement for both *C. finmarchicus* and the pelagic fish. Fishing mortality is included for the pelagic fish where the official ICES harvest control rule is applied. The fishing mortality is applied evenly across the model domain, resulting in no spatiotemporal explicit fishery. The IBMs are implemented using super-individuals (Scheffer *et al.*, 1995) where each super-individual s has a unique position and represents N_s number of plankton or fish of a certain age and size. The model has been validated by comparison with field data in the Nordic and Barents Seas (Skogen *et al.*, 2007; Hjøllo *et al.*, 2012; Utne *et al.*, 2012b; Skaret *et al.*, 2014). The biogeochemical component is validated against observations of chlorophyll a at station M in the Norwegian Sea (Skogen *et al.*, 2007), and the *C. finmarchicus* IBM fields is compared to biomass, abundance, and the annual production in the Norwegian Sea (Hjøllo *et al.*, 2012). Movement and the resulting horizontal distribution of NSS herring and NEA mackerel are validated against observed distributions in the period 1995–2006 (Utne *et al.* 2012b). The horizontal fish distribution is constrained by temporal and spatial sampling, and in this study, the feeding migration for both species was driven by a generic migration routine based on temperature and food niches (see Supplementary material S1 for details and validation and Supplementary materials S2 and S3 for a visualization). The model was run for each fish IBM module separately, either NSS herring or NEA mackerel. In addition, the *C. finmarchicus* IBM was included in all simulations. The NEA mackerel migrates in and out of the model grid in the southern part of the model domain. This is modelled as a point source/sink within the model domain (north of the Shetland Islands) and may cause unrealistic distribution close to that singularity.

A challenge of the NORWECOM.E2E model that is particularly relevant for NEA mackerel is the implementation of the

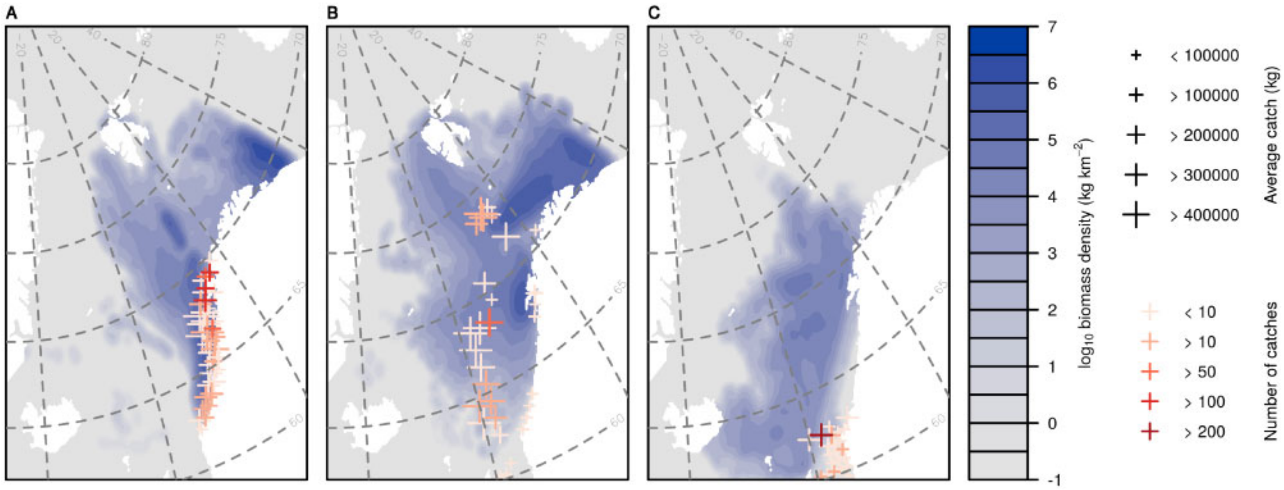

Figure 1. The model domain and the spatially resolved integrated biomass estimates from the NORWECOM.E2E model in blue for NSS herring in (a) January and (b) September–October and (c) for NEA mackerel in September. The red plus signs are the catches resolved in each sub-area given by the Norwegian commercial catch journal. The size of the sign indicates the mean catch within each grid cell whereas the intensity of the colour indicates the number of catches.

boundary conditions to the south and west. Since the mid-2000s, NEA mackerel has extended its range westwards along the south coast of Iceland towards the east coast of Greenland (Olafsdottir *et al*., 2019). However, the model domain only partially covers this area, and in the present study, the simulation of NEA mackerel is only representative of the part of the population that migrates into the Norwegian Sea and the area east of Iceland.

For both the NSS herring and NEA mackerel simulations, daily position, weight, length, and abundance of all super-individuals were stored. In addition, the super-individuals were interpolated on the model grid to produce area density for each day. In the following, we refer to the model simulations as the true abundance.

The in silico *survey (objective A2)*

The output from the NORWECOM.E2E model was used as input to an acoustic-trawl survey simulator, which generates acoustic and biotic data based on a specific survey design, such as parallel transect lines. The acoustic-trawl survey simulator assumes two inputs: the area density field providing the spatial distribution of abundance, which is used to simulate the acoustic data, and the set of super-individuals from which biological data (trawl data) are simulated.

The area density from the NORWECOM.E2E model was interpolated at the centre positions of log-distances of length 0.1 nautical miles along the simulated survey track, resulting in interpolated area density ρ_W in g m^{-2}. The area density was converted to nautical area scattering coefficient (NASC), which is the standard acoustic output from acoustic-trawl surveys (Maclennan *et al*., 2002). The associated trawl sampling was simulated by drawing a fixed number of fish with replacement from super-individuals inside a radius of 10 nautical miles around randomly selected log-distances. Eggs, larvae, and juveniles were excluded from the NORWECOM.E2E model to avoid artefacts of spawning and migration of juveniles in and out of survey region.

Simulation of NASC

In the conversion from area density to NASC, the first step is to convert to number density

$$\rho_N = \frac{\rho_W}{W_0},$$

where W_0 is a reference weight of the fish in g. The reference weight was modelled by a cubic length–weight relationship (Hile 1936) $W_0 = a\ L_0{}^b$, where a defines the weight of a fish of length 1 cm, b defines the growth, and L_0 is a reference length of the fish. When $b = 3$, there is an equal growth in all directions. The reference length L_0 was estimated from the super-individuals inside the survey region of each day by the square root of a weighted average of the square of fish length, i.e.

$$L_0 = \sqrt{\sum_s L_s{}^2 N_s / \sum_s N_s},$$

where L_s is the fish length and N_s is the number of individuals represented by each super-individual. In this estimate, the squared fish length was applied to reflect acoustical backscatter, which is proportional to cross-sectional area of the fish.

The parameters a and b were fitted to the super-individuals inside the survey region of each day by a weighted log-linear regression

$$\log(W_s) = \log(a) + b\log(L_s),$$

weighted by N_s, where W_s is the weight of super-individual s.

The NASC is defined as $\mathrm{NASC} = 4\pi(1852)^2 s_a$ (Maclennan *et al*., 2002), where

$$s_a = \ \rho_N \sigma_{bs,0}, \tag{1}$$

given a reference backscattering cross-section $\sigma_{bs,0}$. The reference backscattering cross-section was calculated by applying the reference fish length to the standard target strength of herring (Foote, 1987) and mackerel (Misund and Beltestad, 1996),

$$\sigma_{bs} = \begin{cases} 10^{-7.19} L_0{}^2, & \text{for herring} \\ 10^{-8.65}\ L_0{}^2, & \text{for mackerel} \end{cases},$$

resulting in

$$\sigma_{bs,0} = \begin{cases} 4.71 \times 10^{-5}, & \text{for herring} \\ 1.29 \times 10^{-6}, & \text{for mackerel} \end{cases}.$$

Simulation of trawl samples

Acoustic trawl surveys typically rely on trawl sampling to estimate population parameters like age, maturity ogive, etc. Biotic data were simulated from the super-individuals by first drawing locations for trawl stations from the centre positions of the log-distances along the survey track. The probability of selecting a log-distance was a mixture of a constant probability for all log-distances and a probability proportional to the simulated NASC. These two probabilities were weighted equally, ensuring trawl stations also in areas with low densities of fish, as indicated by the simulated acoustic data, resembling procedures used on actual surveys. For each simulated trawl station z, a constant number $N_z = 100$ of fish were drawn with replacement from super-individuals inside a radius of 10 nautical miles, with probability proportional to the number of identical individuals of each super-individual. Age, length, weight, and gender were stored for each fish as input to the estimation.

Survey estimation (objective A3)

The simulated survey estimates were generated using the standard survey estimation tool StoX (Johnsen *et al.*, 2019), which is used for processing several Northern European pelagic and demersal fish surveys, including the surveys used as case studies in this article. For each simulated survey, a StoX project was generated, which (i) reads acoustic and biotic data (trawl stations), (ii) calculates the frequency distribution of fish in length intervals for each trawl station (length distribution), (iii) links the average length distribution in each stratum with the acoustic data, (iv) converts the acoustic data to fish density by dividing by the backscattering cross-section (1) for each length interval, (v) multiplies the fish density with the stratum area to obtain the survey abundance estimate, and (vi) estimates the variances of the survey estimates using a non-parametric bootstrap routine provided with StoX. In the bootstrap routine, biotic stations and acoustic transects are resampled with replacement in each stratum. This was repeated 100 times, and the 5% and 95% quantiles were used to estimate the 90% confidence interval of the survey estimates.

Comparison to the true biomass (objective A4)

The survey estimates with estimated 90% confidence intervals were divided by the true biomass to represent the ratio of observed vs. true biomass, referred to as relative estimates. The true biomass was calculated as the average of the total biomass $B(t)$ over all days $t_{\text{End}}, \ldots, t_{\text{Start}}$ of the survey,

$$B_{\text{TRUE}} = \frac{1}{t_{\text{End}} - t_{\text{Start}} + 1} \sum_{t_{\text{Start}}}^{t_{\text{End}}} B(t),$$

where $B(t)$ is the sum of the weights of all super-individuals inside the survey region. The weight of a super-individual was calculated as the product of the number N_s of individuals and the weight of each (identical) individual within the super-individual. Significant deviances from 1 in the survey estimate over true biomass would imply bias in the simulated survey. If $B(t)$ changes throughout the survey, e.g. due to migration in or out of the survey region, and the majority of the observations is made in a period when $B(t)$ differs markedly from B_{TRUE}, the relative estimate may be biased.

Application of the simulation framework (objective B)

An R (R Core Team, 2013) package (available at https://github.com/Sea2Data/pelfoss) was developed for the survey estimation described in objectives A2–A4, utilizing StoX and the associated R package Rstox (Johnsen *et al.*, 2019). The package defines three seed values controlling the random number generation of the simulator: (i) one for the starting point of the survey track, (ii) one for the random selection of trawl stations, and (iii) the seed value used by the bootstrapping performed by StoX to estimate the variance in the survey estimate.

Three surveys for NSS herring and NEA mackerel were used as test cases. These are the International Ecosystem Survey in the Nordic Seas (IESNS) in May (ICES, 2015) and the North Atlantic Spring Spawning Herring Survey (NASSHS) in February, primarily targeting NSS herring, and the International Ecosystem Summer Survey in the Nordic Seas (IESSNS) in July (ICES, 2015), primarily targeting NEA mackerel. Each of these surveys is conducted using multiple vessels, with contributions from multiple nations in the case of the IESNS and the IESSNS surveys. The corresponding simulated surveys were labelled Herring_IESNS, Herring_NASSHS, and Mackerel_IESSNS. An additional *in silico* survey-labelled Mackerel_IESSNS_sept was simulated by moving the Mackerel_IESSNS survey to September to coincide with the fishery. The IESSNS is a surface trawl survey, but here we have simulated it as a conventional acoustic-trawl survey. All simulated surveys are listed in Table 1.

To test how changes in coverage and survey timing affected the results, we shifted the timing for the test surveys by −30, 0, and +30 days (∼−1, 0, and +1 month) and ran the surveys in both directions, e.g. from south to north and north to south. Similar survey effort as in the actual surveys was used in the simulations. Each case was repeated twice, for two different seed values, referred to as seeds 1 and 2, where each seed was used to generate the survey track, the trawl stations and the variance estimate obtained by bootstrapping.

The simulated surveys were conducted using one vessel, contrary to the real surveys, where multiple vessels are used. To achieve comparable survey coverage as for the real surveys, a reference vessel speed of 7 knots was adjusted by factors corresponding to the number of vessels of the real surveys and rounded off to the vessel speeds 15, 20, and 30 knots (∼2, 3, and 4 vessels) for the IESNS, NASSHS, and IESSNS, respectively. The rationale for using only one vessel was to demonstrate the effects migration may have on the survey estimates more cleanly than with multiple vessels potentially moving in different directions relative to the migration. Using only one vessel may thus have exaggerated

Table 1. List of test case survey (left) and model runs (right).

Survey		Model run
Name	**Timing**	**Species**
Herring_IESNS	1/5–29/5	Herring
Herring_NASSHS	15/2–25/2[a]	Herring
Mackerel_IESSNS	1/7–29/7	Mackerel
Mackerel_IESSNS_sept	1/9–29/9	Mackerel

[a]The first year of this survey time series (1988–2008) was performed 2–3 weeks later.

effects of migration, but contrarily, the increased vessel speed will reduce the effects of migration.

Herring_IESNS

The IESNS in May is a key acoustic-trawl survey for the assessment of NSS herring. It is a multinational survey coordinated through the Working Group of International Pelagic Surveys at the International Council for the Exploration of the Sea (ICES, 2015). The survey has participation from Norway, Faroe Islands, Iceland, Russia, and Denmark, and the strata system covers a large area of the Norwegian Sea (Figure 1a). The survey is conducted during the feeding season for NSS herring in the Norwegian Sea, and the fish is typically distributed over a large area. No significant fishery coincides in time with the IESNS survey, and we did not use the fisheries allocation method for this survey. The order of the strata (4, 3, 1, 2) was optimized for minimal transport between strata, with approximately south–north direction in all surveys except stratum 3, which was surveyed approximately north–south.

Herring_NASSHS

The NASSHS in February is a Norwegian acoustic-trawl survey that was initiated in 1988 and discontinued between 2008 and 2015. The latter period of the survey (2015 and onwards) has a different timing than the former period (see Table 1), and the effect of this is unknown. The survey is run during the spawning season along the Norwegian coast (Figure 1b). Timing of the survey is a challenge, since it coincides with the migration of NSS herring to and from the spawning grounds. In addition, the transects are shorter than for the IESNS and the distribution is patchier, which leads to higher sampling variance. The order of the strata (3, 2, 4, 5, 6, 7, 8, 17, 10, 9, 11, 13, 14) was optimized for minimal transport between strata, with approximately south–north direction in all strata except strata 3 and 10, which were surveyed approximately north–south, and stratum 8, which was surveyed approximately east–west.

Mackerel_IESSNS

The IESSNS is an international pelagic trawl survey with main objective to map the abundance and distribution of NEA mackerel in the Nordic Seas. The strata system covers a large part of the Norwegian Sea (Figure 2d). For the test case, the strata west of Iceland and one stratum along the Norwegian coast were removed from the analysis since the NORWECOM.E2E model did not extend to those regions. Otherwise the survey design was like the real survey, both in extent and timing. Although the IESSNS is a trawl survey, we simulated it as an acoustic trawl survey for consistency with the other simulated surveys. The order of the strata (3, 2, 1, 7, 9) was optimized for minimal transport between strata, with approximately south–north direction in strata 3, 1, and 7 and approximately north–south direction in strata 2 and 9.

Mackerel_IESSNS_sept

Based on the catch diary from 2012, 73% of the catches of NEA mackerel were registered in September. Since the fisheries did not coincide with the IESSNS survey, the second Mackerel_IESSNS survey, Mackerel_IESSNS_sept, was simulated by shifting the survey 2 months from July to September (Figure 2e). The Mackerel_IESSNS survey shifted by +30 days roughly coincides with the Mackerel_IESSNS_sept survey shifted by −30 days (August).

Results

The simulation framework was used to evaluate different survey designs, both in time and space. The effect of shifting a survey 1 month back or forth or changing the direction of a survey varies between surveys and stocks (NSS herring and NEA mackerel) depending on the stationarity of the stock and the areal extent of the survey. The relative estimates with 5 and 95 percentiles from the bootstrapping are presented for all six cases (Figure 3). Figure 3 also includes the coefficient of variance (*C.V.*) based on the bootstrapping of each run.

In general, changing the seed of the simulations had only a moderate effect on the relative estimates compared to the confidence intervals, with average absolute change in the estimate between seed 1 and seed 2 of 0.047.

Herring_IESNS

The IESNS occurs during the feeding season, when the distribution of NSS herring is spread across a large region of the Norwegian Sea (Figure 2a). The large extent of the distribution is expected to lead to a high variance in the survey estimates. This was verified by relatively wide 90% confidence intervals (Figure 3a) and the average *C.V.* of 0.18.

When the survey is shifted by +30 days, there is a slight increase in the estimated biomass for the normal survey direction compared to the surveys shifted by −30 or 0 days and, correspondingly, a slight decrease for the reversed survey direction (Figure 3a, values of blue triangles are larger than those of red and green triangles, and values of blue circles are smaller than those of red and green circles). A reason for these differences may be the north-eastward migration of NSS herring in the NORWECOM.E2E model starting in the middle of July (Supplementary materials S1 and S2). This migration coincides with the normal survey direction in strata 1 and 2, resulting in a longer time of exposure of the fish to the research vessel. For the survey shifted by +30 days in the reversed survey direction, fish are migrating out of strata 3 and 4 at the time when the research vessel observes the NSS herring in these strata, which may explain the lower relative estimate.

The differences between the different cases are generally within the 90% confidence intervals obtained by the bootstrapping, confirming the general notion that the fish has a wide, but fairly stationary distribution.

Herring_NASSHS

The NASSHS coincides in time with the migration and spawning of NSS herring south-westwards along the Norwegian coast. In the NORWECOM.E2E model, NSS herring migration is mimicked by a modified direction vector: westward migration starting around 20 March from the southern strata (strata 2–6) and north-eastward migration in July–August. Compared to the Herring_IESNS, the survey region of the Herring_NASSHS is smaller (Figure 2b vs. Figure 2a), implying higher effort and expected lower variance in the survey estimates, which is confirmed by the average *C.V.* of 0.07, which is markedly lower than that of the Herring_IESNS simulations (*C.V.* = 0.18).

The surveys conducted in the normal survey direction propagate opposite to the south-westward migration. Based on this, we should expect larger relative estimate in the reversed survey direction, since moving along the migration should lead to longer exposure to the research vessel. The relative estimate increases only slightly for the surveys shifted by −30 and 0 days (0.89–0.95 and 1.03–1.08, respectively) and decreases when shifted by +30 days (1.18–0.82). The decrease for the latter survey can be explained

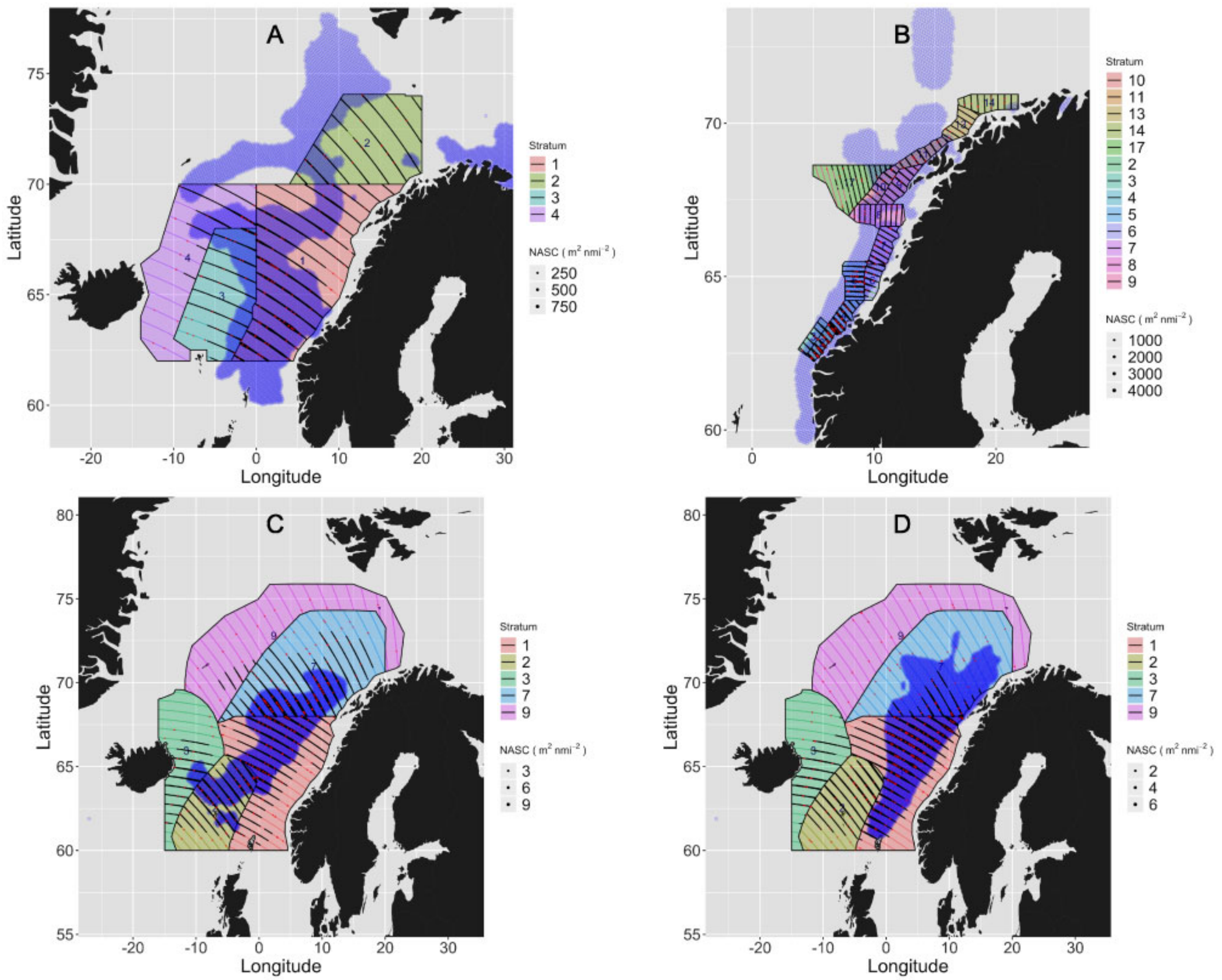

Figure 2. The strata systems, survey track lines, and modelled biomass distribution for the surveys listed in Table 1; (a) Herring_IESNS and (b) Herring_NASSHS for NSS herring and (c) Mackerel_IESSNS and (d) Mackerel_IESSNS_sept for NEA mackerel. The strata systems are shown as coloured patches and the distribution of modelled biomass is shown as blue dots for values >1 g m^{-2}. Survey lines are shown as red lines overlaid with black dots with size proportional to NASC, above a threshold of 10^{-3}. Locations of simulated trawl stations are shown as red stars.

by the westward migration starting half way through the survey, which leads to less fish present in the southern strata in the reversed survey direction (north-east to south-west) than in the normal survey direction when the vessel enters these strata before the westward migration.

Mackerel_IESSNS

The Mackerel_IESSNS covers a large area (Figure 2d), analogous to the Herring_IESNS (Figure 2a). The width of the estimated 90% confidence intervals are similar between these surveys, and all contain value 1 (Figure 3d vs. Figure 3a). The average *C.V.* of the estimates is 0.13, which is comparable to the Herring_IESNS ($C.V. = 0.18$).

Timing has only minor effects on the relative estimates. In contrast, all relative estimates for the reversed survey direction are lower than any of the estimates for the normal direction, with an average decrease of ∼17.5% (Figure 3d, triangles vs. circles of the same colour). This may be caused by the modelled northward migration of NEA mackerel during months June–August, which spans the three timings of the survey (Supplementary material S3). This migration is particularly strong in strata 1 and 7, where the normal survey direction is northward, along the migration. This leads to more exposure and consequently larger relative estimates for the normal vs. the reversed survey direction.

Mackerel_IESSNS_sept

The Mackerel_IESSNS_sept is shifted 2 months in time relative to the Mackerel_IESSNS. The timing of the Mackerel_IESSNS_sept coincides with the migration of NEA mackerel in the NORWECOM.E2E model from a wide distribution to a concentrated distribution in the southern part of stratum 1, starting at the beginning of September. The two simulated IESSNS surveys overlap largely in time for the month August, resulting in similar relative estimates (blue symbols in Figure 3d vs. red symbols in Figure 3e). The correspondence is not exact since adding 30 days to July is not identical to subtracting 30 days from September.

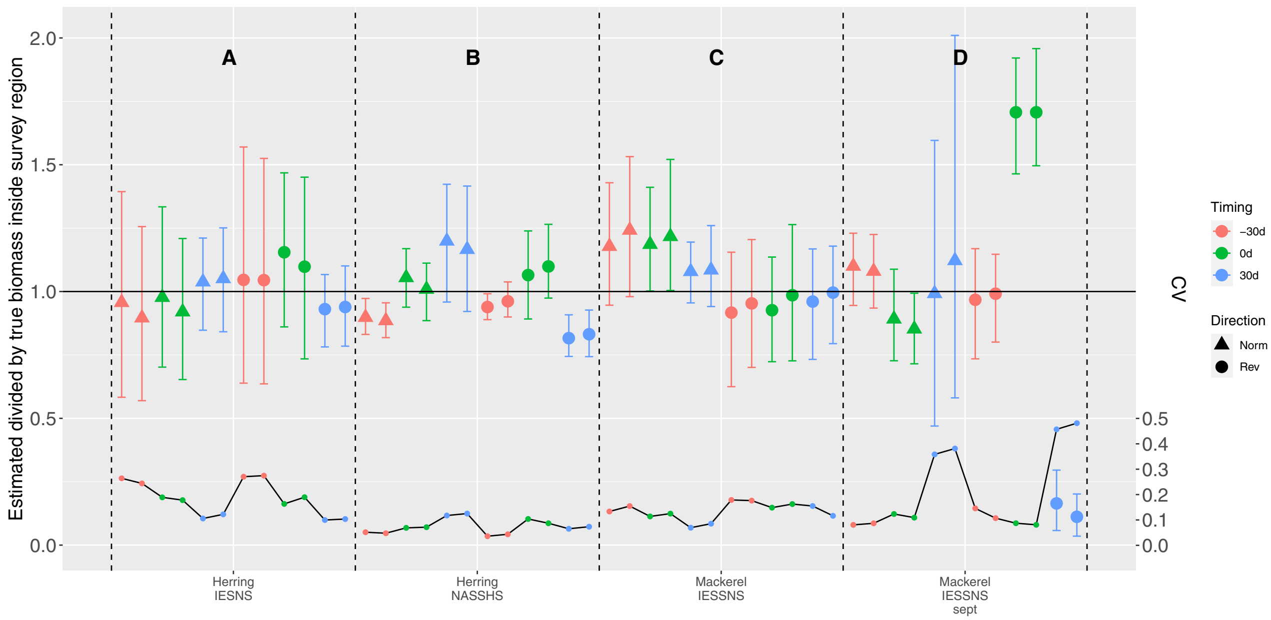

Figure 3. Estimated abundance divided by the true abundance (relative estimate) within the survey area for each simulation case (a–d, Table 1). The surveys are separated by vertically dotted lines. Each case is run using two different seeds in the individual based migration model and plotted adjacent to one another with the same colour and symbol. The colours (red, green, and blue) indicate shifting the survey by −30, 0 and +30 days, respectively, and the triangles and closed circles represent the normal and reversed survey direction, respectively. The error bars are the 5 and 95 percentiles of relative estimates made from 100 bootstrap replicates of the simulated survey using StoX. The coefficient of variation (*C.V.*, standard deviation divided by average) is plotted below as points connected by black lines, c.f. axis in the lower right corner.

The *C.V.* varies markedly from ∼0.1 for the surveys shifted by −30 or 0 days (August or September) to ∼0.45 when shifted by +30 days (October). The large *C.V.* in the latter case is related to the concentrated distribution of NEA mackerel of the model, which induces skewness in the estimated abundance per transect and, consequently, high variability when transects are bootstrapped to estimate the *C.V.*

The Mackerel_IESSNS_sept displays a large effect of reversing survey direction. For the normal timing, the relative estimates averaged across seeds increased from 0.87 to 1.71 when reversing direction (Figure 3e, green triangles vs. circles). This discrepancy can be explained by the southward migration of NEA mackerel in the NORWECOM.E2E model coinciding in time and space with the southward survey direction in stratum 1 for the simulated survey in the reversed direction, thus leading to longer exposure of the NEA mackerel to the research vessel. For the surveys conducted in October, reversing direction leads to a decrease from 1.06 to 0.14 (Figure 3e, blue triangles vs. circles). This decrease can be explained by the NEA mackerel migrating out of the survey region. When reversing survey direction, the survey reaches the concentrated distribution at a later time than for the normal direction, and more NEA mackerel has had time to exit the survey region.

Discussion

The objectives of this study were to develop a framework to simulate pelagic fish surveys using an ecosystem model (A) and apply the framework on surveys supporting the management of NSS herring and NEA mackerel (B). With the study, we have developed a link between the ecosystem model and the conventional survey estimation methods facilitating, e.g. the prediction of the outcome of a survey and the evaluation of different survey strategies and designs. Furthermore, we have built the system on top of already established models and methods, thus utilizing the effort that has already been invested. When there is an existing survey, the sampling variance in the survey can be analysed to get an idea whether you oversample or not. However, considerations like this cannot be done for new surveys or if the sampling needs to shift in time, and this is the major advantage of the OSSE.

The simulation framework

Quality of observations is largely affected by two components: the data quality assurance and the sampling scheme. OSSEs have already been used to optimize monitoring programmes and design observational networks in both coastal (De Mey-Frémaux *et al.*, 2019) and open oceans (Fu *et al.*, 2011; Majkut *et al.*, 2014; Charria *et al.*, 2016; García-García *et al.*, 2019), to analyse the impact on forecasts by including or excluding assimilation of virtual observations (Oke and O'Kane, 2011), and to reconstruct observations to give a synoptic map by correcting the station positions for advection by adding the mean flow from a circulation model . The present OSSE was developed using the NORWECOM.E2E model to produce spatially varying NEA mackerel and NSS herring distributions in the Norwegian Sea and thereafter run vessel transects *in silico* to simulate acoustic-trawl surveys. The simulated data were run through the standard software for survey estimation, and the estimates were compared to the true stock abundances from the ecosystem model. Several factors should be considered when developing and applying OSSEs.

First, any OSSE will depend on the model skill of the underlying model. However, the diversity of ecosystem models highlights that there is not any universally appropriate, or intrinsically superior model, but rather a diversity of models with strengths and weaknesses (Spence *et al.*, 2018). In this study, the migration model was parameterized based on available survey and environmental information and using primarily reactive mechanisms under a relatively simple framework. The exact mechanisms driving fish migration and distribution are however poorly understood and include both reactive and predictive mechanisms (Neill, 1984), probably with multiple impacts by several environmental factors (Secor, 2015; Huse, 2016).

Consequently, there is a need to identify the appropriate model tailored to the actual question to aid decision-making as the results depend on how the migration is parameterized. It is worth noting that the generating model does not have to cover all the parameters and processes governing the migration and distribution but should provide realistic distributions similar to those of the real populations. If one wish to use the framework presented in this study to predict the outcome of a real survey, e.g. for implementation into survey design practices, the validity of the ecosystem model is crucial. On the other hand, surveys are very expensive and it takes many years to establish a time series. Therefore, an OSSE with a good simulation ability could be a natural component in all survey planning, especially in the establishment of new monitoring systems as the design of an optimal observational network requires some existing knowledge, which in turn will rely on data from other networks or models. Therefore, survey design is a two-way and reciprocal problem.

Second, the migration model predicts a smooth fish distribution, but pelagic fish may form dense schools that will cause a patchy distribution of acoustic values (see, e.g. Gimona and Fernandes, 2003). When patchiness is not accounted for in the simulation, sampling variance may be underestimated. To address this, the observation model could be further developed to simulate the fish school distributions based on the correlation structures in real data superimposed on the smooth model fields. This would potentially lead to more realistic simulated data for the estimation step.

Third, there are several causes of biases in acoustic-trawl surveys (Løland *et al.*, 2007). These include, e.g. larger-scale biases like coverage of the stock, smaller scale processes like bottom and surface blind zones (Totland *et al.*, 2009), avoidance (De Robertis and Handegard, 2013), and depth-dependent target strength (Ona, 2003). In our simulation, we chose to look only at the fish from the model domain that were inside our survey area assuming that coverage was perfect. We did this since the migration model was not explicitly validated on the borders. This is particularly relevant for the NEA mackerel migration west of Iceland. However, we did assume that the model allowed us to compare different designs within the strata system. We also used the same target strength for both the simulation and the estimation steps, which removed any potential biases in applying erroneous target strength. In the model, the fish is vertically distributed, but the distribution is randomized and based on observations. Therefore, the model does not predict the depth distribution and no depth-dependent target strength was included. This ignores biases related to the depth-dependent target strength for, e.g. herring (Ona, 2003), but, unless the vertical distribution changes between years, this is less of a concern since the estimates are used as relative indices in the assessment models. Biases that vary between years are not addressed in this implementation. To do this, multiyear simulations are needed and the model must be able to predict realistic between-year variability in distribution patterns. This is an important next step in the development.

Application of the framework

The study illustrates how abundance estimates vary when surveys are shifted in time and/or direction and how the design also has an impact on the variance and estimated error. Of the simulated cases (Figure 3), three (A, B, and D) are already existing trawl surveys used in stock assessment, while the other (C) is a theoretical survey, designed to coincide with the fisheries. Focusing on the precision of the estimates, the existing cruises were robust with a small sensitivity to a shift in time and direction. Except for the forward shift in timing for Herring_NASSHS (B), the true abundance was within the 5 and 95 percentiles. For case A, the NSS herring IESNS survey, there is wide confidence intervals and high coefficient of variation for especially the early surveys, due to wide distribution of the NSS herring during feeding season.

Several platforms are today capable of carrying acoustic sensors, including vessels of opportunity, fishing vessels (Fassler *et al.*, 2016), autonomous surface vehicles (Mordy *et al.*, 2017), autonomous underwater vehicles (Fernandes *et al.*, 2003; Patel *et al.*, 2004), etc. It remains, however, an open question how to optimally use these platforms. As an example, for operations using fishing vessels, they typically operate in a smaller area with higher effort (c.f. Figure 1) than the more dispersed effort from the research vessel-based surveys. The OSSE can be used to simulate surveys associated in time and space with the fishing operations. To address the skew sampling, the fishing vessels could deploy unmanned surface vehiclesto run random transects in the vicinity of the fishing operation and the catch data could be used to obtain the biological parameters. Initial simulations indicate that a concentrated survey strategy might be worth considering for populations that are known to migrate through a specific region and also illustrate that survey designs based on the fishing fleet have a large bias due to the limited regional coverage of the stock. Our OSSE could be further developed to include the costs associated with the different platforms, allowing us to search for more cost-efficient approaches to survey the various components of marine ecosystem.

Concluding remarks

An OSSE combining an ecosystem model with conventional survey estimation methods has been used to illustrate how such a system can be used to investigate the sensitivity of monitoring programmes to shifts in time or coverage. In addition, this approach would also allow us to optimize surveys in time and space, provided that the model simulations are realistic. The model exercise has been done through an estimation of the abundance of NSS herring and NEA mackerel from simulated acoustic trawl surveys using different survey designs. The realism of the simulated survey data depends largely on the skill of the migration model. As the model skill of the migration model is further improved, we could more reliably use the model framework to allocate survey effort. The next steps in this process are to explore multiyear ecosystem model runs, further expand the observation model to support swept area trawl surveys, including an improved catch-sample simulator (to adequately address the NEA mackerel surveys), allow for more boats in the survey design, and model the along track distributions to mimic the high-resolution variability along the track. The goal is to have a better tool to reduce the uncertainty in fish stock assessments by optimizing survey effort.

Supplementary data

Supplementary material is available at the *ICESJMS* online version of the manuscript.

Acknowledgements

This study was supported by The Norwegian Seafood Research Fund (FHF) through the PELFOSS (PELagic Fish Observation System Simulator) project (grant number 901319). EAM, SSH, and MDS acknowledge support from the European Union's Horizon 2020 Research and Innovation programme under grant agreement no. 677038 (ClimeFish) and the Research Council of Norway through the sustainable multi-species harvest from the Norwegian Sea and adjacent ecosystems (grant number 299554). NOH and AJH acknowledge support from the REDUS project funded by the Norwegian Ministry of Trade, Industry and Fisheries.

Data availability statement

The data underlying this article are available in Zenodo at https://dx.doi.org/10.5281/zenodo.3367349 under Creative commons 4.0 licence.

References

Aksnes, D. L., Ulvestad, K. B., Baliño, B. M., Berntsen, J., Egge, J. K., and Svendsen, E. 1995. Ecological modelling in coastal waters: towards predictive physical-chemical-biological simulation models. Ophelia, 41: 5–36.

Berg, C. W., and Nielsen, A. 2016. Accounting for correlated observations in an age-based state-space stock assessment model. ICES Journal of Marine Science, 73: 1788–1797.

Charria, G., Lamouroux, J., and De Mey, P. 2016. Optimizing observational networks combining gliders, moored buoys and FerryBox in the Bay of Biscay and English Channel. Journal of Marine Systems, 162: 112–125.

De Mey-Frémaux, P., Ayoub, N., Barth, A., Brewin, R., Charria, G., Campuzano, F., Ciavatta, S., *et al.* 2019. Model-observations synergy in the coastal ocean. Frontiers in Marine Science, 6: 436.

De Robertis, A., and Handegard, N. O. 2013. Fish avoidance of research vessels and the efficacy of noise-reduced vessels: a review. ICES Journal of Marine Science, 70: 34–45.

Fassler, S. M. M., Brunel, T., Gastauer, S., and Burggraaf, D. 2016. Acoustic data collected on pelagic fishing vessels throughout an annual cycle: operational framework, interpretation of observations, and future perspectives. Fisheries Research, 178: 39–46.

Fernandes, P. G., Stevenson, P., Brierley, A. S., Armstrong, F., and Simmonds, E. J. 2003. Autonomous underwater vehicles: future platforms for fisheries acoustics. ICES Journal of Marine Science: Journal du Conseil, 60: 684–691.

Foote, K. G. 1987. Fish target strengths for use in echo integrator surveys. Journal of the Acoustical Society of America, 82: 981–987.

Francis, O., Panteleev, G., Yaremchuk, M., Luchin, V., Stroh, J., Posey, P., and Hebert, D. 2018. Observing system simulation experiments and adjoint sensitivity analysis: methods for observational programs in the Arctic Ocean. Arctic, 71: 1–14.

Fu, W., Høyer, J. L., and She, J. 2011. Assessment of the three dimensional temperature and salinity observational networks in the Baltic Sea and North Sea. Ocean Science, 7: 75–90.

García-García, L. M., Sivyer, D., Devlin, M., Painting, S., Collingridge, K., and van der Molen, J. 2019. Optimizing monitoring programs: a case study based on the OSPAR eutrophication assessment for UK waters. Frontiers in Marine Science, 5: 503.

Gimona, A., and Fernandes, P. G. 2003. A conditional simulation of acoustic survey data: advantages and potential pitfalls. Aquatic Living Resources, 16: 123–129.

Grimm, V., and Railsback, S. F. 2005. Individual-Based Modeling and Ecology: Princeton University Press, NJ, USA. 448 pp.

Handegard, N. O., du Buisson, L., Brehmer, P., Chalmers, S. J., De Robertis, A., Huse, G., Kloser, R., *et al.* 2013. Towards an acoustic-based coupled observation and modelling system for monitoring and predicting ecosystem dynamics of the open ocean. Fish and Fisheries, 14: 605–615.

Hilborn, R., and Walters, C. J. 2013. Quantitative Fisheries Stock Assessment: Choice, Dynamics and Uncertainty. Springer Science & Business Media, Dordrecht, Netherlands. 575 pp.

Hjøllo, S. S., Huse, G., Skogen, M. D., and Melle, W. 2012. Modelling secondary production in the Norwegian Sea with a fully coupled physical/primary production/individual-based *Calanus finmarchicus* model system. Marine Biology Research, 8: 508–526.

Holmin, A. J., Handegard, N. O., Korneliussen, R. J., and Tjostheim, D. 2012. Simulations of multi-beam sonar echos from schooling individual fish in a quiet environment. The Journal of the Acoustical Society of America, 132: 3720–3734.

Huse, G. 2016. A spatial approach to understanding herring population dynamics. Canadian Journal of Fisheries and Aquatic Sciences, 73: 177–188.

Huse, G., and Fiksen, Ø. 2010. Modelling encounter rates and distribution of mobile predators and prey. Progress in Oceanography, 84: 93–104.

Huse, G., Melle, W., Skogen, M. D., Hjøllo, S. S., Svendsen, E., and Budgell, W. P. 2018. Modeling emergent life histories of copepods. Frontiers in Ecology and Evolution, 6: 23.

ICES. 2015. Manual for International Pelagic Surveys (IPS). Series of ICES Survey Protocols SISP 9—IPS. 92 pp.

IPCC. 2013. Annex II: climate system scenario tables. *In* Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Chan, pp. 1395–1445. Ed. by Prather M., Flato G., Friedlingstein P., Jones C., Lamarque J.-F., Liao H., and Rasch P. Cambridge University Press, Cambridge, UK/New York, NY, USA.

Johnsen, E., Totland, A., Skålevik, Å., Holmin, A. J., Dingsør, G. E., Fuglebakk, E., and Handegard, N. O. 2019. StoX: an open source software for marine survey analyses. Methods in Ecology and Evolution, 10: 1523–1528.

Lahoz, W. A., Brugge, R., Jackson, D. R., Migliorini, S., Swinbank, R., Lary, D., and Lee, A. 2005. An observing system simulation experiment to evaluate the scientific merit of wind and ozone measurements from the future SWIFT instrument. Quarterly Journal of the Royal Meteorological Society, 131: 503–523.

Løland, A., Aldrin, M., Ona, E., Hjellvik, V., and Holst, J. C. 2007. Estimating and decomposing total uncertainty for survey-based abundance estimates of Norwegian spring-spawning herring. ICES Journal of Marine Science, 64: 1302–1312.

Maclennan, D. N., Fernandes, P. G., and Dalen, J. 2002. A consistent approach to definitions and symbols in fisheries acoustics. ICES Journal of Marine Science, 59: 365–369.

Majkut, J. D., Carter, B. R., Frölicher, T. L., Dufour, C. O., Rodgers, K. B., and Sarmiento, J. L. 2014. An observing system simulation for Southern Ocean carbon dioxide uptake. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 372: 20130046.

Misund, O. A., and Beltestad, A. K. 1996. Target-strength estimates of schooling herring and mackerel using the comparison method. ICES Journal of Marine Science, 53: 281–284.

Mordy, C. W., Cokelet, E. D., De Robertis, A., Jenkins, R., Kuhn, C. E., Lawrence-Slavas, N., Berchok, C. L., *et al.*; Joint Institute for the Study of the Atmosphere and Ocean, University of Washington (JISAO-UW), and National Oceanic and

Atmospheric Administration (NOAA) Pacific Marine Environmental Laboratory. 2017. Advances in ecosystem research: saildrone surveys of oceanography, fish, and marine mammals in the Bering Sea. Oceanography, 30: 113–115.

Neill, W. H. 1984. Behavioral enviroregulation's role in fish migration. *In* Mechanisms of Migration in Fishes, pp. 61–66. Ed. by J. D. McCleave, G. P. Arnold, J. J. Dodson, and W. H. Neill. Springer US, Boston, MA. https://doi.org/10.1007/978-1-4613-2763-9_4 (last accessed 3 May 2019).

Oke, P. R., and O'Kane, T. J. 2011. Observing system design and assessment. *In* Operational Oceanography in the 21st Century, pp. 123–151. Ed. by A. Schiller and G. B. Brassington. Springer, Netherlands.

Olafsdottir, A. H., Utne, K. R., Jacobsen, J. A., Jansen, T., Óskarsson, G. J., Nøttestad, L., Elvarsson, B. Þ., *et al.* 2019. Geographical expansion of Northeast Atlantic mackerel (*Scomber scombrus*) in the Nordic Seas from 2007 to 2016 was primarily driven by stock size and constrained by low temperatures. Deep Sea Research Part II: Topical Studies in Oceanography, 159: 152–168.

Ona, E. 2003. An expanded target-strength relationship for herring. ICES Journal of Marine Science, 60: 493–499.

Patel, R., Handegard, N. O., and Godø, O. R. 2004. Behaviour of herring (*Clupea harengus* L.) towards an approaching autonomous underwater vehicle. ICES Journal of Marine Science, 61: 1044–1049.

R Core Team. 2013. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. http://www.R-project.org/ (last accessed 7 July 2020).

Scheffer, M., Baveco, J. M., DeAngelis, D. L., Rose, K. A., and van Nes, E. H. 1995. Super-individuals a simple solution for modelling large populations on an individual basis. Ecological Modelling, 80: 161–170.

Secor, D. H. 2015. Migration Ecology of Marine Fishes. Johns Hopkins University Press, Baltimore, USA. 304 pp.

Skaret, G., Dalpadado, P., Hjøllo, S. S., Skogen, M. D., and Strand, E. 2014. *Calanus finmarchicus* abundance, production and population dynamics in the Barents Sea in a future climate. Progress in Oceanography, 125: 26–39.

Skogen, M. D., Budgell, W. P., and Rey, F. 2007. Interannual variability in Nordic seas primary production. ICES Journal of Marine Science, 64: 889–898.

Skogen, M. D., Hjøllo, S. S., Sandø, A. B., and Tjiputra, J. 2018. Future ecosystem changes in the Northeast Atlantic: a comparison between a global and a regional model system. ICES Journal of Marine Science, 75: 2355–2369.

Skogen, M. D., and Søiland, H. 1998. A User's Guide to NORVECOM V2.0. The Norwegian Ecological Model System, 42: s. https://brage.bibsys.no/xmlui/handle/11250/113623 (last accessed 13 December 2018).

Skogen, M. D., Svendsen, E., Berntsen, J., Aksnes, D., and Ulvestad, K. B. 1995. Modelling the primary production in the North Sea using a coupled three-dimensional physical-chemical-biological ocean model. Estuarine, Coastal and Shelf Science, 41: 545–565.

Spence, M. A., Blanchard, J. L., Rossberg, A. G., Heath, M. R., Heymans, J. J., Mackinson, S., Serpetti, N., *et al.* 2018. A general framework for combining ecosystem models. Fish and Fisheries, 19: 1031–1042.

Totland, A., Johansen, G. O., Godo, O. R., Ona, E., and Torkelsen, T. 2009. Quantifying and reducing the surface blind zone and the seabed dead zone using new technology. ICES Journal of Marine Science, 66: 1370–1376.

Utne, K. R., Hjøllo, S. S., Huse, G., and Skogen, M. 2012a. Estimating the consumption of *Calanus finmarchicus* by planktivorous fish in the Norwegian Sea using a fully coupled 3D model system. Marine Biology Research, 8: 527–547.

Utne, K. R., Huse, G., Ottersen, G., Holst, J. C., Zabavnikov, V., Jacobsen, J. A., Óskarsson, G. J., *et al.* 2012b. Horizontal distribution and overlap of planktivorous fish stocks in the Norwegian Sea during summers 1995–2006. Marine Biology Research, 8: 420–441.

Handling editor: David Demer