

Exploring ecosystem effects of underwater noise in the nordic seas, using the NoBa-Atlantis E2E model

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Abstract

Underwater noise generated by human activities, such as shipping and seismic surveys, has emerged as a growing concern. Despite the mounting evidence that noise negatively impacts marine mammals, fish, and invertebrates, end-to-end ecosystem models often overlook noise as a stressor. This omission is due to the complexity of studying noise's influence on entire populations and ecosystems, making it difficult to gauge the potential total effects accurately. In this study, we implemented potential effects of underwater noise in the Atlantis ecosystem modelling framework. Noise effects on organisms were simulated through reduced growth and consumption rates, increased mortality and movement away from noisy areas. The noise module was tested by a Morris sensitivity analysis on most of the fish, mammal and invertebrate species in the model. The species were aggregated into 12 groups perturbed with six different noise levels, with the spatial dimension taken into account by repeating the analysis under varying spatial configurations. The results

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revealed substantial systemic effects from increased vulnerability to noise from zooplankton, while marine mammal noise vulnerability had relatively little impact, in line with earlier Atlantis studies. Additionally, the coastal area exhibited significantly higher biomass variability, indicating a need for more research in this region where noise is expected to increase the most. These results provide an initial estimation of the potential effects of noise at the ecosystem level in the Nordic and Barents Seas. However, for improved realism of the noise module in future studies, we emphasize the need to develop response functions for each species' sensitivity to noise. Understanding such species-specific sensitivities will be crucial in devising effective strategies to mitigate the detrimental consequences of underwater noise on marine ecosystems.

Keywords: Underwater noise, Atlantis, Sensitivity analysis, Ecosystem models, Noise pollution

1 **1. Introduction**

2 End-to-end models attempt to represent the dynamics of whole ecosys-
3 tems from primary producers to top predators, linked together through food-
4 web interactions, as well as the effects of the abiotic environment such as
5 temperature and sunlight, and human impacts (Travers et al., 2007). They
6 provide valuable insights into the potential responses of marine ecosystem
7 dynamics when exposed to stressors like fisheries and climate change (e.g.
8 Fulton et al., 2011; Geary et al., 2020). End-to-end ecosystem models find
9 frequent application in scenario projections and in exploring the effects of
10 multiple stressors (e.g. Ihde and Townsend, 2017; Olsen et al., 2018, 2019).

11 Underwater noise stemming from human activities such as shipping, seis-
12 mic surveys and underwater drilling, is rarely included in marine ecosystem
13 models. Human-induced noise significantly contributes to the ambient sound
14 of the ocean, particularly at low frequencies, where attenuation is minimal,
15 resulting in long-distance propagation (Hildebrand, 2009). There are indica-
16 tions of a substantial rise in ocean ambient noise levels since the 1950s, with
17 this trend persisting (Hildebrand, 2009; Frisk, 2012). In the Norwegian and
18 Barents Sea, ship traffic (sailed distance) is expected to increase by around
19 25-45% by 2040 from 2013 level, with the most notable growth in container
20 ship activity (DNV GL, 2018). Many marine species rely on sound for com-
21 munication and have good hearing, rendering them susceptible to elevated
22 noise levels in the ocean (Slabbekoorn et al., 2010; Cox et al., 2018; Erbe
23 et al., 2019; Popper and Hawkins, 2019; de Jong et al., 2020). There is high
24 confidence that anthropogenic noise detrimentally affects marine animals,
25 with strongest evidence for marine mammals and slightly less for fish and
26 invertebrates (Duarte et al., 2021).

27 Assessing the effects of underwater noise on ecosystems presents several
28 challenges. Firstly, the vulnerability of different species to this pressure is
29 highly uncertain, given that studies on noise effects are often ambiguous or
30 lacking (Popper and Hawkins, 2019). Moreover, even for species that exhibit
31 individual-level responses to noise, it is unclear whether these responses can
32 be generalized across individuals. Consequently, translating from individual
33 reactions to the population level is not straightforward (Kunc et al., 2016;
34 Popper et al., 2020). Although frameworks like the Population Consequences
35 of Acoustic Disturbance (PCAD; National Research Council, 2005) exist for

36 this purpose, their application necessitates copious empirical data or expert
37 input and have primarily been employed for marine mammals (Slabbekoorn
38 et al., 2019).

39 Secondly, underwater noise from different sources has different charac-
40 teristics, such as frequency and volume, which impact organisms differently.
41 Moreover, the propagation of noise in water depends on multiple factors such
42 as underwater topology, temperature and sea ice conditions (Farcas et al.,
43 2016; PAME, 2019). While in some places noise is quickly attenuated, it can
44 travel hundreds of kilometers in others (Halliday et al., 2017; Thode et al.,
45 2010). In essence, this implies that even when information on noise sources,
46 such as ship traffic and seismic survey data, is accessible, quantifying noise
47 levels in underwater habitats remains difficult.

48 Considering the above limitations and knowledge gaps, integrating noise
49 into marine ecosystem models is challenging. However, considering the rapid
50 industrialization of oceans, delaying action until the knowledge base is ex-
51 haustive is untenable (Williams et al., 2015). Given the multitude of affected
52 species and noise sources, the permutations to explore are extensive. In such
53 circumstances, modeling can serve as a beneficial approach, even if it cannot
54 substitute empirical data. Among the ecosystem models, to the best of our
55 knowledge, only Ecopath with Ecosim has to date incorporated the effects of
56 underwater noise (Stock et al., 2023a), wherein low-frequency noise impacts
57 the consumption rate of functional groups based on the distance from the
58 noise source and the sensitivity level of each functional group (Serpetti et al.,
59 2021; Steenbeek et al., 2020).

60 A reduction in growth and consumption rates is an expected result from

61 interrupted/reduced foraging or increased stress. These kinds of behavioural
62 changes due to noise exposure have been shown to different degrees in the
63 field (Ivanova et al., 2020; Rolland et al., 2012; Davidsen et al., 2019; Hawkins
64 et al., 2014) or in the laboratory (Sierra-Flores et al., 2015; Gendron et al.,
65 2020). For species that vocalize during foraging, the reduced communica-
66 tion range due to underwater noise will probably also lead to reduced for-
67 aging (Putland et al., 2018). It has been shown that underwater noise cuts
68 down the communication range or masks the signal for both fish and marine
69 mammals (Putland et al., 2018; Stanley et al., 2017; Dunlop, 2016). Di-
70 rect mortality resulting from noise exposure is rare, as it typically requires
71 noise sources to be sufficiently loud, such as those in close proximity to seis-
72 mic airguns (Popper et al., 2014; Popper and Hawkins, 2019; Fields et al.,
73 2019). However, there are also some accounts of increased mortality due to
74 less intense noise exposure, such as navigational failure in whales (Granger
75 et al., 2020), development failure in invertebrates (Nedelec et al., 2014) and
76 increased parasite burden in fish (Masud et al., 2020). Movement away from
77 areas with noise has been seen to greater or lesser extent in field studies on
78 both fish (Vabø et al., 2002; Jørgensen et al., 2004; Engås et al., 1996) and
79 marine mammals (Erbe et al., 2019, and references therein).

80 Here we explore the effects of underwater noise on ecosystem components
81 using a simple representation of noise impacts in the Atlantis end-to-end
82 ecosystem model for the Norwegian and Barents Seas. Noise is introduced in
83 the model as a forced tracer. Organisms in the model are defined as sensitive
84 to noise at different levels (from insensitive to very sensitive). The nega-
85 tive effect of noise on sensitive organisms are simulated by (1) a reduction

86 in growth and consumption rates, (2) an increase in mortality not caused
87 by fisheries or predation, and (3) movements away from noisy areas. The
88 intention is to simulate the effects from noise exposure most commonly de-
89 scribed in the literature, and to explore ecosystem responses (both additive
90 and non-additive) to increased noise levels.

91 **2. Materials and methods**

92 *2.1. Area*

93 The Barents Sea is a shelf sea, with a mean depth of roughly 230 m, and
94 an area of about 1.4 million km² (Loeng and Drinkwater, 2007). The water
95 masses are dominated by warm, saline Atlantic water flowing in through the
96 Barents Sea opening in the south west, and the Arctic water masses in the
97 north, separated by the polar front. The Barents Sea has a strong seasonal
98 cycle, with polar night during winter, and 24 hours of light in summer. Given
99 its high-latitude location, the area has high productivity, and hosts the worlds
100 largest cod stock, the Northeast Arctic cod (*Gadus morhua*; hereafter cod).

101 To the southwest, the Barents Sea is connected to the Norwegian Sea. In
102 the Norwegian Sea, the warm, saline Northeast Atlantic slope current flows
103 northwards along the continental shelf, and the fresher coastal current flows
104 northwards along the Norwegian coast (Blindheim and Østhus, 2005). The
105 topography of the Norwegian Sea is very different from the shallow Barents
106 Sea, with a mean depth of over 1600 m. The area has two deep basins;
107 the Lofoten and the Norwegian Basins, which have depths of up to 4000 m.
108 Northeast Atlantic mackerel (*Scomber scombrus*; hereafter mackerel), blue
109 whiting (*Micromesistius poutassou*) and Norwegian spring spawning herring

110 (*Clupea harengus*; hereafter herring) all use the Norwegian Sea for feeding.
 111 A key prey zooplankton species is the copepod *Calanus finmarchicus*, with
 112 a total biomass of approximately 40 million tons (Fiskeridirektoratet, 2016).
 113 Whales, seals and seabirds are present year-long in the area.

114 *2.2. Model*

115 *2.2.1. NoBa Atlantis*

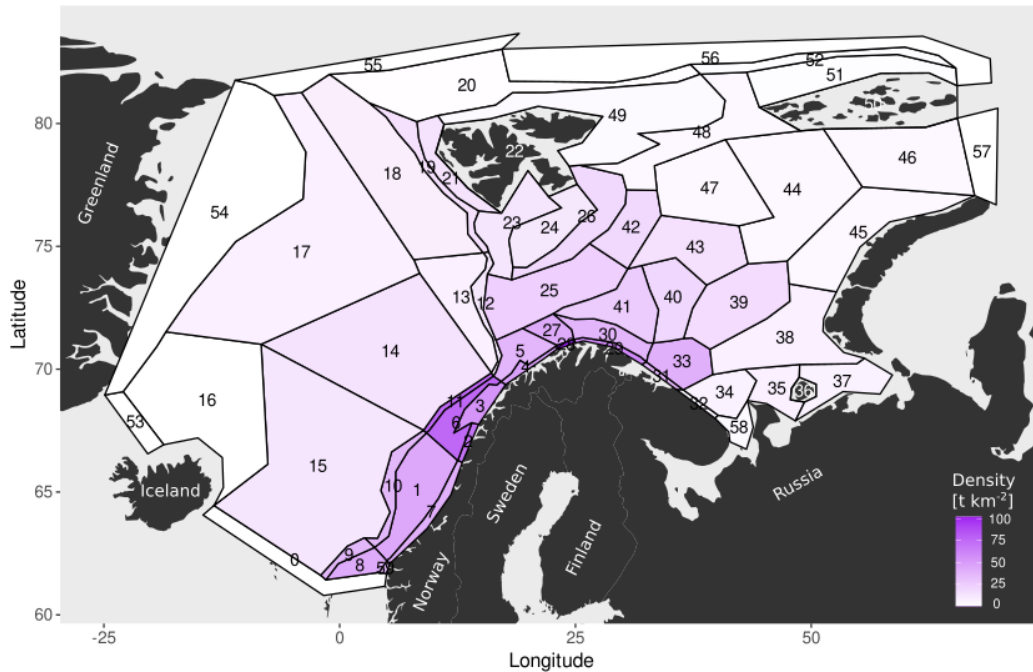


Figure 1: The NoBa Atlantis model domain where the color indicates vertebrate biomass density in each polygon (tonnes km⁻²) in the base run.

116 The Nordic and Barents Seas (NoBa) Atlantis model (Hansen et al., 2016,
 117 2019a) is an implementation of the Atlantis ecosystem model (Fulton et al.,
 118 2004; Audzijonyte et al., 2019) for the Nordic and Barents Seas (Figure 1).
 119 The NoBa area spans 4 million km², and is divided into 60 spatial poly-
 120 gons and 7 depth layers. The model ecosystem consists of 53 species and

121 functional groups (hereafter components), made up by 32 vertebrates, nine
122 invertebrates, seven plankton components and five components consisting of
123 bacteria (pelagic and benthic), carrion and detritus (labile and refractory).
124 Ten of the vertebrate components are marine mammals, two are seabirds,
125 one is snow crab (*Chionoecetes opilio*), whereas the rest are fish. All compo-
126 nents are connected through a partly flexible diet matrix, where the fraction
127 of prey available for the predator is parameterized. Additionally, prey eaten
128 depends on predator gape size and overlap between predator and prey in
129 time and space.

130 Physical forcing was taken from Nemo-NAA10 km model (Hordoir et al.,
131 2022), a modelling configuration based on the NEMO ocean engine (Gurvan
132 Madec and NEMO System Team, 2022). Nemo-NAA10 km is a regional
133 model that includes the Arctic and Atlantic Oceans north of 39°N, and which
134 has a horizontal resolution of about 10 km. In this study, the forcing was a
135 one-year cycle, with the projected year 2023 repeated throughout the entire
136 run. This year was chosen as it represents the median surface temperature
137 within the period from 1980 to 2100. The runtime was set to 75 years, where
138 the first 24 years constitute the spin-up of the model. Fisheries were kept
139 at estimated maximum sustainable yield levels for the commercial species
140 estimated within NoBa Atlantis (Hansen et al., 2019b). The model was
141 recalibrated to maintain a stable size at age for each component, and to
142 keep the biomass time series of each component within the limits of $\pm 50\%$
143 of initial biomass (Hansen et al., 2016) or to stabilize the biomass within a
144 higher baseline. Out of 53 components, 18 stayed within $\pm 50\%$ of initial
145 biomass after the spin-up period, and an additional 24 components stabilized

146 around a new biomass level. While the initial levels represented the biomass
147 of the components in the cold year of 1980, the year 2023 used in our study
148 was a much warmer year; therefore, a new ecosystem state was expected.

149 *2.2.2. The underwater noise module*

150 The code for noise pollution was released in Atlantis version 6594 (source
151 code published on <https://research.csiro.au/atlantis/home/links/>). For this
152 study, the noise code was reimplemented in code version 6357, which is the
153 code base used with multiple NoBa Atlantis studies (Hansen et al., 2019b;
154 Olsen et al., 2019; Nilsen et al., 2020). The noise module works by assigning
155 a number representing noise ($N_{i,j}$, in decibels) to each polygon i and depth-
156 layer j , and by assigning a scalar κ_x that represents the sensitivity of each
157 component, x , to noise. For each sensitive component which resides in a
158 noisy polygon and layer, a delta factor (δ_x) is computed by

$$\delta_x = \frac{\kappa_x}{N_{i,j}}. \quad (1)$$

159 The delta factor expresses the effect of $N_{i,j}$ on each component (x), and
160 δ_x takes values between 0 and 1. Parameters for growth (mum_x) and con-
161 sumption (C_x) are multiplied by the delta factor, and mortality parameters
162 (linear mortality, mL_x , and quadratic mortality, mQ_x , both of which are usu-
163 ally very small) are multiplied by the inverse. For species that move between
164 polygons, noisy polygons are made less suitable by the delta factor. $N_{i,j}$
165 is here assumed to have a negative impact, so for all polygons, layers and
166 components $\kappa_x \leq N_{i,j}$, to make sure that $\delta_x \leq 1$. When the delta factor is
167 equal to 1 parameter values are unchanged.

168 $N_{i,j}$ is implemented in the model as forcing. In this study noise was
169 turned on after the spin-up period, and kept constant for the rest of the run,
170 for areas and components as described below.

171 In the following sections a noise factor is used to represent noise pertur-
172 bation instead of the delta factor, defined as following:

$$\text{Noise factor} = (1 - \delta_x) \cdot 100 = \left(1 - \frac{\kappa_x}{N_{i,j}}\right) \cdot 100, \quad (2)$$

173 which is a percentage, where low numbers correspond to small amount of
174 perturbation and high numbers reflect high amount of perturbation.

175 *2.3. Sensitivity analysis*

176 *2.3.1. The Morris method*

177 We used the method of Morris for the sensitivity analysis, as it is feasi-
178 ble for models with large number of parameters (Morris, 1991; Campolongo
179 et al., 2007). This is a one-step-at-a-time method where only one input pa-
180 rameter is changed between consecutive simulations, however the set-up of
181 the simulations ensures a good exploration of the input factor space.

182 The method of Morris is based on *elementary effects* (EE), which are
183 estimates for the partial derivatives at each input parameter. After running
184 the simulations with input parameters perturbed according to the prescribed
185 set-up, the elementary effects are calculated as follows:

$$EE_i = \frac{B(i) - B(i - 1)}{\Delta}, \quad (3)$$

186 where $B(i)$ is the chosen model output of simulation number i and Δ is
187 the difference in noise perturbation between simulations i and $i - 1$. Each

188 elementary effect EE_i is assigned to the group that was perturbed, forming
189 a distribution of elementary effects for each group.

190 Three sensitivity measures are computed for each elementary effect dis-
191 tribution: the mean (μ), the mean of absolute values (μ^*) and the standard
192 deviation (σ) as follows,

$$\mu = \frac{1}{r} \sum_{i=1}^r EE_i \quad (4)$$

$$\mu^* = \frac{1}{r} \sum_{i=1}^r |EE_i| \quad (5)$$

$$\sigma = \sqrt{\sum_{i=1}^r (EE_i - \mu)^2} \quad (6)$$

193 The sensitivity measures yield estimates on how the model responds to
194 each of the input parameters: The mean (μ) quantifies the importance of the
195 input parameter on the output, while the standard deviation (σ) shows the
196 size of non-linear effects and/or effects due to interactions with other input
197 parameters. Morris (1991) outlined how to assess the group's contribution
198 to the overall result:

- 199 1. Negligible: For groups with both mean and standard deviation values
200 close to zero
- 201 2. Linear and additive: For groups with non-zero mean values and small
202 standard deviation
- 203 3. Nonlinear and/or dependent on other input parameters: For groups
204 with non-zero mean values and large standard deviation.

205 The mean of absolute values (μ^*) is a refined measure (Campolongo et al.,

206 2007). If the elementary effects are of opposite signs, μ might be low even if
 207 the effect is high, and this effect is found by using μ^* . If on the other hand
 208 $\mu^* = |\mu|$ the model is monotonic and no extra information is found from μ^* .

209 2.3.2. Species grouping

210 Each of the ecosystem components in NoBa Atlantis has a noise sensi-
 211 tivity parameter, κ_x . To reduce the number of simulations in the sensitivity
 212 analysis, we grouped the components into a total of 12 groups (table 1), in
 213 which all species were perturbed simultaneously and identically. Groups were
 214 formed based on taxonomy or functional role in the ecosystem. In addition,
 215 for species that are known to be sensitive to sound such as herring and cod
 216 (e.g. Popper et al., 2014), they were split into separate or smaller groups.
 217 Phytoplankton, detritus and bacteria were not included in any groups due to
 218 insufficient information regarding their susceptibility to noise effects. Polar
 219 bear (*Ursus maritimus*) and Arctic and boreal seabirds were also left out, as
 220 these components only spend parts of their time in and under water.

Table 1: NoBa Atlantis components included in each of the groups for the sensitivity analysis and their individual biomass in each polygon combination (in percent of total biomass for the given component) from the base run. For more details on the NoBa Atlantis components, refer to Hansen et al. (2016). SA1-SA3 refers to the three different area combinations applied in the sensitivity study (Figure 2). The three combinations together cover 33.7% of the total NoBa area.

SA-groups	NoBa Atlantis components	SA1 (%)	SA2 (%)	SA3 (%)
Zooplankton	Small zooplankton	37	14	19
	Medium zooplankton	20	15	7
	Large zooplankton	5	16	26
	Gelatineous zooplankton	4	13	9
Benthic	Predatory benthos	2	9	4
	Detrivore benthos	2	9	4

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Table 1 – *Continued from previous page*

SA-groups	NoBa Atlantis components	SA1 (%)	SA2 (%)	SA3 (%)
	Benthic filter feeders	18	20	29
	Red king crab	34	0	15
	Snow crab	0	7	20
	Sponges	32	11	26
	Corals	17	20	31
	Prawn	3	12	6
Elasmobranchs	Sharks, other	13	15	16
	Skates and rays	13	15	16
Mesopelagics	Mesopelagic fish	23	12	9
	Squid	3	12	5
Pelagics	Mackerel	5	0	1
	Capelin	22	29	31
	Blue whiting	22	15	9
	Polar cod	5	13	30
	Pelagic, large	25	7	11
	Pelagic, small	28	5	6
Herring	Herring	74	7	7
Flatfish	Greenland halibut	17	29	31
	Long rough dab	21	17	18
	Demersal, large	37	24	26
	Flatfish, other	22	16	27
DeepseaFish	Beaked redfish	100	0	0
	Golden redfish	47	29	19
GadoidsLarge	Cod	23	27	31
	Haddock	50	11	35
	Saithe	59	3	3
	Demersals, other	72	16	8
Seals	Bearded seal	0	17	24
	Harp seal	31	9	34
	Hooded seal	2	3	1
	Ringed seal	1	34	16
WhalesBaleen	Humpback whale	22	6	7
	Minke whale	22	8	11
	Fin whale	22	5	6
WhalesToothed	Killer whale	66	1	4
	Sperm whale	14	0	3

221 For the 12 SA-groups, noise sensitivity and polygon noise were set to give
222 a noise factor of 0, 10, 20, 30, 40 or 50%. As the confidence level on ecosystem
223 components' response to noise is generally very low (Hansen et al., 2022), we

224 decided to explore a large set of response levels. We expect a noise factor
225 of 50% to be on the extreme end of noise pollution effects, as this means
226 reducing growth and consumption rates by 50% for the affected species, as
227 well as higher mortality and effects of movement as explained above.

228 *2.3.3. Spatial noise levels and repeated sensitivity analysis runs (SA1, SA2* 229 *& SA3)*

230 To explore the effect of polygon selection, we performed the sensitivity
231 analysis repeatedly on three combinations of polygons (Figure 2). The first
232 combination, SA1, spans the coastline of Norway, which is relatively noisy
233 due to the high density of vessels in the area (The European Marine Obser-
234 vation and Data Network; <https://emodnet.ec.europa.eu/en>). The two other
235 polygon combinations, SA2 and SA3, were found by picking arbitrary poly-
236 gons from the remaining area, with the condition that the total area of each
237 polygon combination should be of similar size as SA1. The combinations
238 used covered 10.2, 11.1 and 12.4% of the total NoBa area for SA1, SA2 and
239 SA3 respectively. We do not know the actual noise levels in the ocean, so
240 for simplicity equal levels of noise was applied to all polygons and layers in
241 a polygon combination.

242 *2.3.4. Choice of outputs*

243 Atlantis produces a range of output parameters. For this sensitivity anal-
244 ysis, we chose the following three outputs that were calculated for each model
245 simulation:

- 246 1. Total biomass [tonnes] of all components, except bacteria, detritus and
247 carrion, averaged over the last 10 years of the model simulation

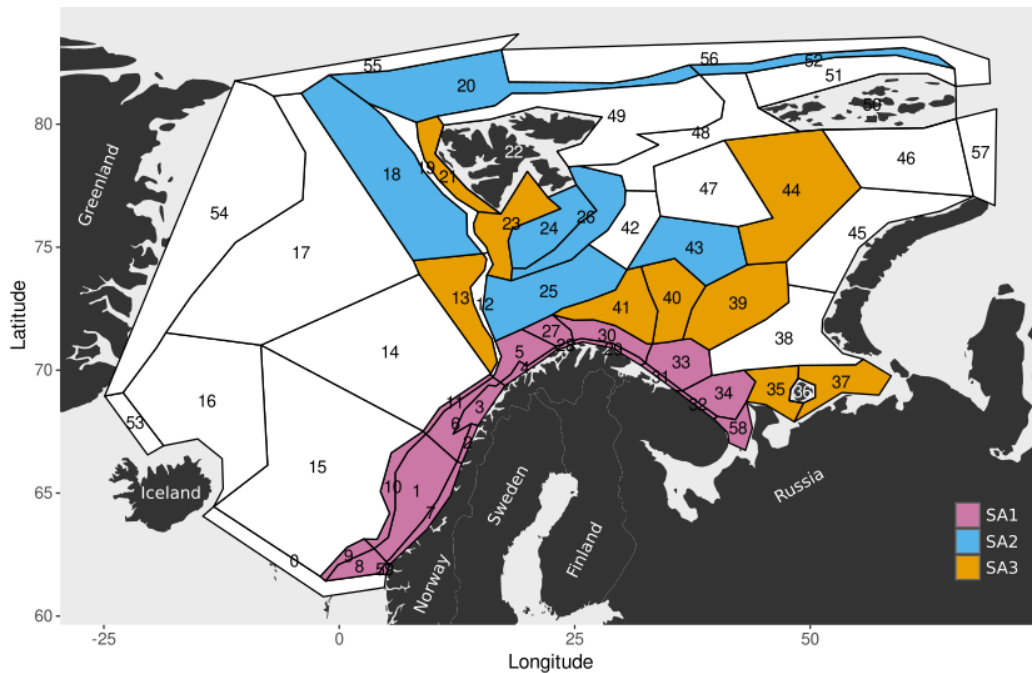


Figure 2: For each of the sensitivity analyses, only one of the shown colored areas are parameterized as noisy. The purple area is noisy in SA1, the blue is noisy in SA2 and the orange is noisy in SA3

- 248 2. Total biomass [tonnes] of vertebrate components, averaged over the last
 249 10 years of the model simulation
- 250 3. Change [km] between the center of gravity of all vertebrate components,
 251 averaged over the last 10 years of the model simulation

252 Because the two first outputs were dominated by a few components, we
 253 also looked at subsets of the total biomass and total vertebrate biomass
 254 outputs.

255 2.3.5. Sensitivity analysis setup

256 Atlantis models are computationally costly, and NoBa Atlantis requires
 257 14-18 hours run time for each of the 75-year long simulations. It is therefore

258 necessary to limit the number of simulations, at the same time as using a
259 well designed simulation plan. We used R (R Core Team, 2020) and the
260 *sensitivity* package (Iooss et al., 2023) with method *morris* to create the
261 plan for the sensitivity analyses. We chose the number of trajectories to be
262 $r = 30$. This also means that we get 30 elementary effects per SA-group.
263 With noise factor levels from 0 to 50%, we chose to use 6 levels to give the
264 noise factors 0, 10, 20, 30, 40 and 50%. Grid jump was set to 3, meaning that
265 the noise factor in consecutive runs could jump from 0 to 30%, from 10 to 40%
266 or from 20 to 50% (3 steps in noise factors). With 12 perturbed SA-groups
267 and 30 trajectories, we ended up with 390 runs in the sensitivity analysis
268 for each of the three polygon setups, resulting in 1170 runs in total. The
269 simulations were performed on resources provided by Sigma2 - the National
270 Infrastructure for High Performance Computing and Data Storage in Norway
271 and servers at the Institute of Marine Research (IMR) in Norway.

272 2.4. Analysis

273 To evaluate the sensitivity of the new parameters, the sensitivity mea-
274 sures, μ^* and σ described in section 2.3.1 are presented as scatter plots with
275 a point for each SA-group and polygon combination. The plots are supplied
276 with three lines showing $\sigma = \mu^*$ (solid), $\sigma = 0.5\mu^*$ (dashed) and $\sigma = 0.1\mu^*$
277 (dotted) to aid in identifying effects that are almost linear (below the lowest
278 line; $\frac{\sigma}{\mu} < 0.1$), monotonic ($0.1 < \frac{\sigma}{\mu} < 0.5$), almost monotonic ($0.5 < \frac{\sigma}{\mu} < 1$)
279 or non-monotonic and/or due to interactions with other SA-groups ($\frac{\sigma}{\mu} > 1$),
280 as outlined by Sanchez et al. (2014).

281 To evaluate effects on components, we constructed heatmap plots that
282 show μ for each component instead of for each SA-group. Prior to plotting,

283 mean values were normalized within each component by dividing each value
284 by the absolute maximum value of that component within each polygon
285 combination.

286 Because of the large variation in effects from different components and
287 SA-groups, we performed some extra simulations to uncover the reasons be-
288 hind the model behaviour in cases with extraordinary high response to noise.
289 We also calculated the Supportive Role to Fishery ecosystems (SURF) index
290 to explore connectivity and identify key prey species in the system (Plagányi
291 and Essington, 2014). This calculation was performed on the base run only.

292 Calculations on model output were performed in R and Python (Van Rossum
293 and Drake, 2009).

294 **3. Results**

295 *3.1. Biomass of components and SA-groups*

296 The heatmap (Figure 3) is a mosaic of positive and negative responses,
297 from which we can see that almost all components respond with less biomass
298 when their own SA-group is perturbed, seen as a red “staircase” from upper
299 left to lower right of each heatmap. The only exceptions are some zooplank-
300 ton components (see 3.2 Zooplankton perturbation). Some general patterns
301 can be found, such as a positive response of most benthic and pelagic com-
302 ponents to the large gadoid perturbation, likely attributable to predation
303 release.

304 For most components the strongest response is their own perturbation in
305 either SA1, SA2 or SA3. This is not the case for red king crab (*Paralith-*
306 *odes camtschaticus*), prawn (*Pandalus borealis*), squid (*Gonatus fabricii*) and

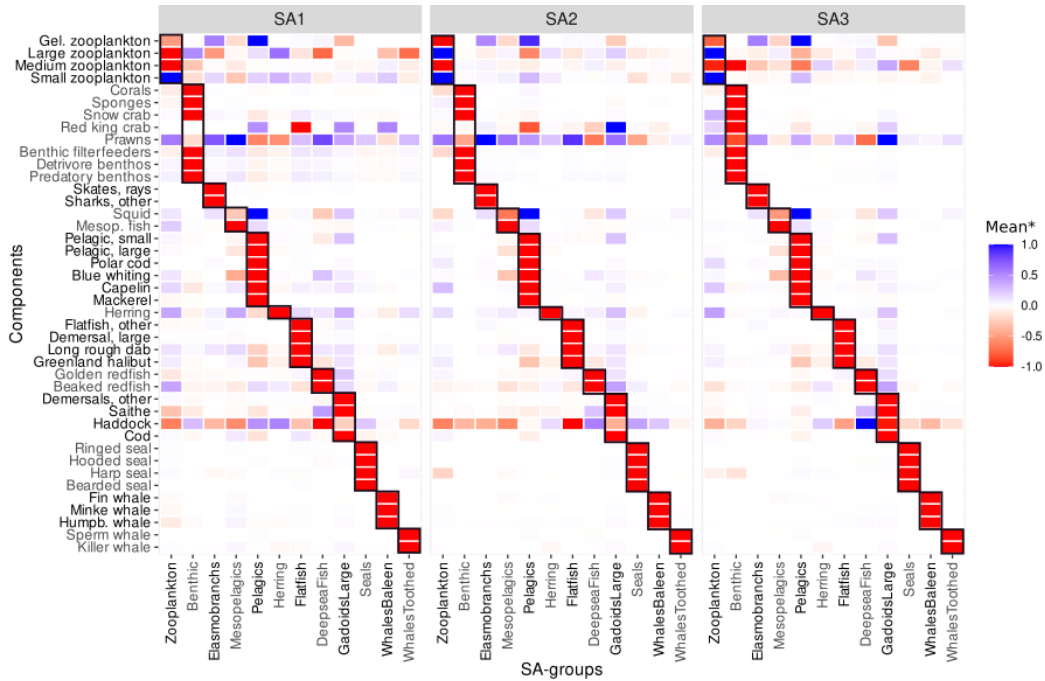


Figure 3: Heat map of normalized mean values of elementary effects with regard to total biomass, showing the effects on each component (y-axis) when the different SA-groups were perturbed (x-axis). The three panels show from left to right SA1, SA2 and SA3. The mostly red “staircase” going from the upper left to the lower right of each heat map is the effect of the perturbation of each SA-group on the components of that same SA-group. Mean* values μ have been normalized by dividing each value by the absolute maximum value for the component within each SA.

307 haddock (*Melogrammus aeglefinus*). Among these four, prawn and squid
 308 exhibit minimal response, regardless of the perturbed SA-group. In the case
 309 of haddock and red king crab, high responses result from unstable simula-
 310 tions where the component experience sudden peaks in biomass. Specifically,
 311 for red king crab, only three simulations are responsible for the strange pat-
 312 tern of this component in SA1, potentially considered outliers. In contrast,
 313 for haddock, the scenario is more intricate, with biomass peaks occurring
 314 in approximately 20% of all SA1 simulations, with much smaller peaks oc-

Table 2: The components with highest SURF indices (SUpportive Role to Fishery ecosystems, Plagányi and Essington (2014)) from the base run. The component arctic seabirds is not a typical prey species, and its presence on this list is a consequence of the current models inability to keep polar bears to its actual diet of (mainly) seals. In the model polar bears end up eating mostly arctic seabirds, making this component seem much more important as a prey species than it should be.

Component	SURF-index
Large zooplankton	0.019406
Medium zooplankton	0.010246
Labile detritus	0.007283
Squid	0.005934
Detrivore benthos	0.002434
Large phytoplankton	0.002256
Benthic bacteria	0.001981
Arctic seabirds	0.001385
Pelagic bacteria	0.001327
Herring	0.000895
Mesopelagic fish	0.000641
Small zooplankton	0.000541
Capelin	0.000399
Small phytoplankton	0.000365
Gelatineous zooplankton	0.000244

315 curring in SA2 and SA3. However, across the three polygon combination
 316 no discernible pattern is found regarding when the haddock biomass peaks
 317 occur.

318 Because figure 3 is normalized within each component, it does not de-
 319 pict which components exhibited the highest and lowest absolute responses.
 320 However, this is closely tied to each component's total biomass. Nevertheless,
 321 some components were observed to have higher responses than their biomass
 322 would suggest, such as haddock, beaked redbfish (*Sebastes mentella*) and her-
 323 ring, particularly in SA1. The underlying reason appears to be connected to
 324 zooplankton responses, as elucidated in the following section.

325 *3.2. Zooplankton perturbation*

326 Unlike the other SA-groups, zooplankton also exhibit a positive response
327 when subjected to simulated noise, as depicted by the dark blue tiles for
328 small and large zooplankton (Figure 3). A deeper investigation into this
329 unexpected outcome reveals the underlying mechanism: at the onset of the
330 simulation, shortly after the initiation of perturbation, there is a notable de-
331 crease in zooplankton biomass. Paralleling this, there is a substantial surge
332 in phytoplankton biomass due to the alleviation of grazing pressure. This, in
333 turn, results in an increased food supply for the zooplankton, causing some
334 zooplankton components to increase shortly thereafter. The heightened zoo-
335 plankton consumption generates greater quantities of detritus, serving as
336 a nutrient source for phytoplankton and for medium and gelatinous zoo-
337 plankton. By the end of the perturbed simulations, small zooplankton, in
338 particular, and to a lesser extent, large zooplankton, exhibit higher biomass
339 compared to the baseline run or the unperturbed simulations. Meanwhile,
340 medium and gelatinous zooplankton showcase smaller or similar biomass
341 compared to the unperturbed scenarios.

342 Small zooplankton, along with certain prey species like dinoflagellates,
343 display a higher abundance in the SA1 area relative to the other two regions.
344 This likely accounts for the heightened variability in zooplankton within this
345 specific area. This pattern is similarly evident in medium and large zooplank-
346 ton, albeit to a lesser extent. This is attributed to their smaller growth values
347 when compared to those of small zooplankton, resulting in a less pronounced
348 alleviation of grazing pressure on phytoplankton.

349 The effect of increased zooplankton (and detritus) levels propagates through

350 the food web, resulting in higher biomass of numerous other components,
351 such as snow crab, prawn, detritivore and predatory benthos, mesopelagic fish,
352 pelagics large, polar cod (*Boreogadus saida*), blue whiting, capelin (*Mallotus*
353 *villosus*), herring, long rough dab (*Hippoglossoides platessoides*), Greenland
354 halibut (*Reinhardtius hippoglossoides*) and cod, as indicated by blue or pale
355 blue tiles in all three SA-versions (Figure 3). Direct predation is the likely
356 cause, as all of the above components feed on zooplankton (or detritus) as
357 part of their diet. For haddock, zooplankton perturbation triggers a negative
358 response (indicated by red tiles). However, in the SA1 area, where haddock
359 is more prevalent, the responses from haddock closely mirrors those of large
360 zooplankton. This can be partially attributed to the recruitment function of
361 haddock, which relies on the quantity of plankton biomass.

362 The significance of zooplankton as a primary prey species within the sys-
363 tem is further substantiated by the SURF index, which ranks large, medium,
364 small, and gelatinous zooplankton as the first, second, 12th, and 15th, re-
365 spectively (Table 2). Components that primarily feed on plankton, such as
366 squid, herring, capelin, and mesopelagic fish, also receive high rankings in
367 this index.

368 3.3. Polygon combinations

369 Through the division of the model domain into distinct polygon configu-
370 rations, parameterized with noise in separate sensitivity analyses (SA1-SA3),
371 it becomes evident that the spatial dimension significantly influences the out-
372 comes. The results reveal substantial variation across all output variables,
373 particularly pronounced in SA1. This disparity is illustrated in figure 4,
374 where the standard deviation (σ) of SA1 groups (depicted by pink dots) far

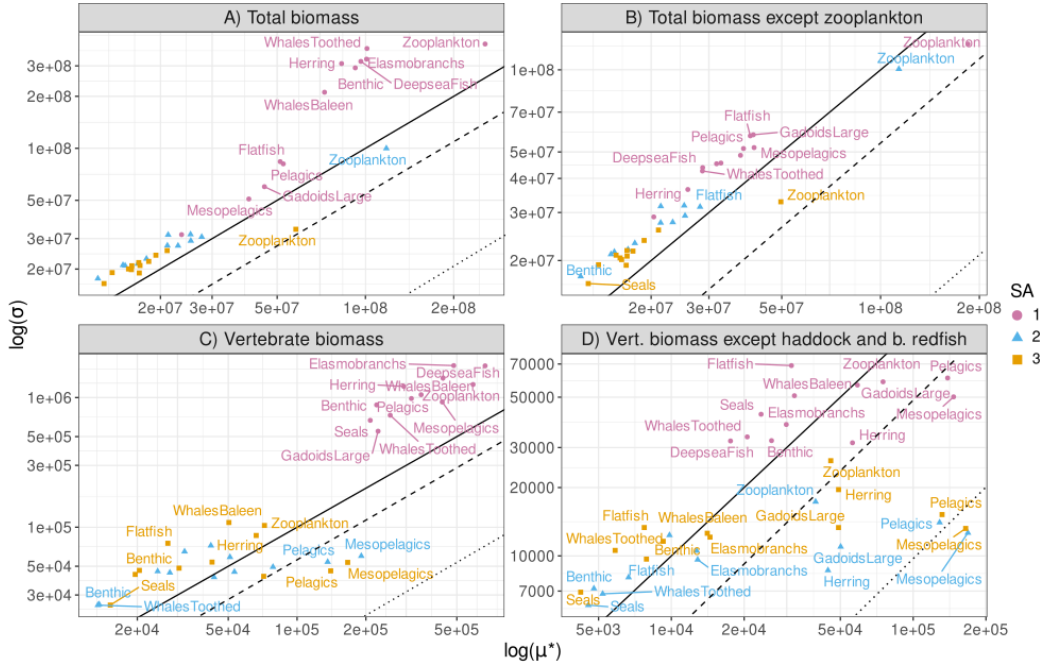


Figure 4: Plots of σ versus μ^* on a log-log scale calculated over four different output variables (A-D), where σ is the standard deviation and μ^* the mean of absolute values of the distributions of elementary effects. The colors indicate which polygon combinations were perturbed with simulated noise, called SA1, 2 and 3. The names on the plot indicate which SA-groups were perturbed. Lines correspond to $\sigma = \mu^*$ (solid), $\sigma = 0.5\mu^*$ (dashed) and $\sigma = 0.1\mu^*$ (dotted).

375 exceeds that of SA2 groups (depicted by blue triangles) and SA3 groups (de-
 376 picted by orange squares). The main effect, denoted as μ^* (representing the
 377 mean of absolute values of elementary effects), is also more pronounced in
 378 SA1 in contrast to the other regions, with only a few exceptions. This dis-
 379 tinction is evident as nearly all the SA1 points (pink dots) lie farther to the
 380 right along the x-axis compared to the corresponding points for SA2 and SA3
 381 areas. Hence, it is unequivocally established that the response to perturba-
 382 tion is intricately tied to the location of the noise. Specifically, the variation
 383 stemming from perturbation manifests prominently within the SA1 region.

384 The SA-group level responses observed in SA2 and SA3 bear similarity to
385 each other, with zooplankton's response serving as an exception (Figure 4 A
386 and B).

387 The high σ values observed, especially in the SA1 polygon combination,
388 point towards a considerable number of nonlinear responses and/or a high de-
389 gree of interdependence among components (Morris, 1991; Campolongo et al.,
390 2007). As elucidated earlier, certain zooplankton components (small zoo-
391 plankton mostly, large zooplankton to lesser extent) initiate a feedback loop
392 that triggers an increase in both phytoplankton and zooplankton biomass.
393 This phenomenon is particularly pronounced within the SA1 region, and it
394 likely constitutes one of the primary factors contributing to the very large
395 variation (σ) seen for all groups in SA1.

396 Furthermore, it is evident that when calculating elementary effects within
397 a narrower subset of components, the variation (σ) diminishes, while the main
398 effect (μ^*) becomes more accentuated. This trend becomes apparent when
399 comparing the total biomass plot in figure 4 A with subsequent plots (figures
400 B to D), each excluding specific components from the computations. Notably,
401 within plots C and D, the SA-groups with the most substantial main effect
402 across all three polygon configurations become discernible. These SA-groups
403 include mesopelagics, pelagics, herring, large gadoids, and zooplankton.

404 3.4. Movement

405 When considering the centre of gravity of vertebrate components and how
406 this centre moves as a result of noise perturbation (Figure 5), again the SA1
407 area has a very high variation (σ values) compared to the other areas. Across
408 the three polygon combinations the SA-groups with highest main effect (μ)

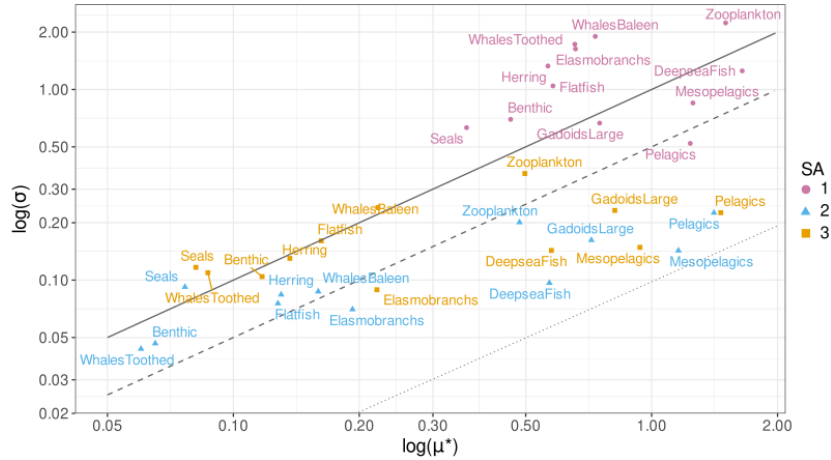


Figure 5: Scatter plot for vertebrate movement as output. The x-axis shows the mean, μ and the y-axis shows the standard deviation, σ , of the distributions of elementary effects on a log-log scale. Pink dots correspond to SA1, blue triangles to SA2 and orange squares to SA3. Names indicate simulations that include perturbations on the respective SA-group. Lines indicate $\sigma = \mu^*$ (solid), $\sigma = 0.5\mu^*$ (dashed) and $\sigma = 0.1\mu^*$ (dotted).

409 are the pelagics, mesopelagics and large gadoids. Deepsea fish has a high
 410 main effect in SA1, but not in the other areas, which is reflecting how this
 411 SA-group is distributed with most of its biomass in SA1 area. Overall the
 412 movement output has similar patterns to the biomass outputs.

413 4. Discussion

414 In this study, we presented a method for simulating the impacts of under-
 415 water noise on various ecosystem components within the Atlantis framework.
 416 The application of simulated noise resulted in reduced biomass for all fish
 417 and marine mammal components subjected to perturbation. Among the in-
 418 vertebrates, the effect was particularly pronounced for zooplankton, while
 419 other components showed comparatively minor responses, as discussed be-
 420 low. Additionally, the location of the simulated noise emerged as a crucial

421 factor.

422 *4.1. Biomass of components and SA-groups*

423 Most SA-groups and components decreased in biomass when perturbed
424 with simulated noise. Large biomass SA-groups and components had an over-
425 all stronger response, which is unsurprising given that elementary effects are
426 calculated based on biomass differentials. Nonetheless, there are certain com-
427 ponents that deviate from this pattern. Prawn and squid both respond very
428 little to perturbations, which is likely a consequence of their parametrization
429 into two cohorts, which is different from other invertebrates in the model
430 (Hansen et al., 2016). Their seemingly elevated overall response in figure
431 3 being a consequence of normalization, as all simulations feature similar
432 biomasses. On the other hand, haddock, beaked redfish and to some de-
433 gree herring exhibit greater susceptibility to perturbation compared to other
434 components with similar biomass levels. Previous NoBa Atlantis studies have
435 revealed haddock’s tendency for unstable behavior (Olsen et al., 2019; Hansen
436 et al., 2019a). This instability stems from the recruitment function chosen
437 for this component in the model, which incorporates plankton levels when
438 calculating the total spawned quantity. This approach aims to mimic the
439 naturally fluctuating recruitment rate of haddock (Johannesen et al., 2022).
440 However, it is likely that real-world survival rates are lower than those de-
441 picted in the NoBa Atlantis. In the case of beaked redfish, the reason for its
442 high biomass levels in SA1 is connected to zooplankton increases as well as
443 the fact that this component resides solely in the SA1 area.

444 *4.2. Zooplankton perturbation*

445 Zooplankton perturbation leads to a feedback loop of increased produc-
446 tion, which explains why this SA-group comes out as the most sensitive SA-
447 group in the sensitivity analysis. However, to what degree are these plankton
448 dynamics realistic? A recent study on Earth system models concluded that
449 zooplankton grazing is the largest source of uncertainty for marine carbon
450 cycling (Rohr et al., 2023). Previous Atlantis sensitivity analysis studies have
451 also found large systemic effects when perturbing zooplankton components;
452 Hansen et al. (2019a) found that the largest system responses in the NoBa
453 Atlantis model came from perturbed growth and consumption rates of zoo-
454 plankton. Similarly Bracis et al. (2020) found that growth rates of plankton
455 groups were one of the extremely sensitive parameters of the Eastern En-
456 glish Channel model. Also in the model of the southern Benguela upwelling
457 system Ortega-Cisneros et al. (2017) found marked effects when plankton
458 growth rates were perturbed, however in their study plankton were the only
459 components to be perturbed. From this, it is possible that extreme sensitivity
460 to zooplankton changes is an artefact of the implementation of the Atlantis
461 framework, which puts more emphasis on biogeochemical cycling than other
462 widely used ecosystem models (e.g Ecopath with Ecosim; Christensen and
463 Walters (2004)), but does not couple directly with the output of dedicated
464 plankton models, in contrast to models such as OSMOSE (Travers et al.,
465 2009).

466 The other SA-groups with consistently large effects when perturbed (high
467 μ and/or σ values) were those consisting of mainly plankton-feeding compo-
468 nents, such as pelagics, mesopelagics and herring. It is likely that the main

469 part of this effect is from an indirect perturbation of zooplankton due to
470 predator-prey interactions, which is again leading to a feedback loop of in-
471 creased production. Higher trophic level SA-groups such as seals and toothed
472 whales show very little effect, due to both small biomass and a trophic posi-
473 tion far from zooplankton, so buffered from cascading effects. Other studies
474 saw in part the same results. Hansen et al. (2019a) found that the response
475 from perturbation in fish was highest for pelagic fish such as capelin, polar
476 cod and herring. However, they also found a high response from killer whales
477 (*Orcinus orca*), which is not seen in this study. Also Bracis et al. (2020) saw
478 high effects of perturbation on cetaceans, although this was from perturbing
479 recruitment and mortality. In this study recruitment is not included in the
480 noise perturbation, and the change in mortality is likely too small to give
481 much influence at the population or system level.

482 By using the method described by Plagányi and Essington (2014) to iden-
483 tify key prey species from food web connections, called the SURF index, we
484 found components with high SURF index in our model coincided mainly to
485 the ones with large effects. In our model the highest SURF indices were
486 found in all zooplankton and phytoplankton components, squid, detrivore
487 benthos, herring, mesopelagic fish and capelin, when disregarding detritus
488 and bacterial components. Noting that the result for arctic seabirds is likely
489 a model artefact. This indicates that the SURF index is a reliable measure
490 of sensitive system components.

491 *4.3. Polygon combinations*

492 Although the three polygon combinations were similar in geographic size,
493 the results showed that the variation due to perturbation was much higher

494 for the SA-groups in SA1. This trend was consistent across all considered
495 output variables. Much of this heightened variability can be attributed to the
496 zooplankton-phytoplankton feedback loop detailed earlier, as the main driver
497 behind this process, small zooplankton, has much higher biomass in SA1
498 than in SA2 and SA3. When outputs with fewer components are considered
499 (Figure 4 panels B to D), the effect of the heightened production from the
500 feedback loop is still discernible due to the increased biomass of the remaining
501 components.

502 Nonetheless, other factors also contribute to the disparities observed among
503 the three areas. While SA2 and SA3 are both located in the vicinity of the
504 Barents Sea, SA1 is coastal. SA1 encompasses spawning and nursery grounds
505 for numerous organisms, resulting in high yearly fluctuations in biomass. It
506 is therefore not unlikely that this area experiences larger variations between
507 the different perturbations, making conditions especially favorable or unfa-
508 vorable for some organisms. Furthermore, SA1 is positioned further south
509 than the other two polygon combinations, leading to higher temperatures,
510 which enhances the production boost that this area can accommodate.

511 *4.4. Linear and synergistic responses*

512 This sensitivity analysis suggested large synergistic effects in the system,
513 particularly for the total biomass output. When we examine the other out-
514 put variables, it becomes apparent that they exhibit diminishing synergism
515 and increasing linearity as we progressively remove components from the cal-
516 culations. This trend is attributed to the components that were excluded,
517 as they were responsible for triggering feedback effects and/or instability in
518 the system — examples being zooplankton components, haddock, and beaked

519 redfish. This underscores the point that the outcomes of a sensitivity analysis
520 can markedly differ based on the chosen output variables. Bracis et al. (2020)
521 similarly found that a majority of the perturbed parameters in their analysis
522 yielded synergistic responses for the total biomass output. While Hansen
523 et al. (2019a) and Nye et al. (2013) identified synergistic effects within At-
524 lantis, they employed a different approach to sensitivity analysis, involving
525 fewer combinations and consequently resulting in fewer potential synergistic
526 responses being identified.

527 *4.5. Uncertainties*

528 The noise module attempts to simulate how noise impacts organisms in
529 real life, by reduced feeding rates (lower growth and consumption rates), a
530 slight increase in mortality, and it prompts organisms to leave noisy areas
531 if possible. All of these effects have been found in studies on noise effects
532 (as detailed in the introduction). This approach is comparable to how noise
533 consequences are estimated in energy budget modelling approaches (Soudijn
534 et al., 2020). Notably, the recent incorporation of underwater noise as a
535 potential stressor in the Ecopath with Ecosim ecosystem model follows a
536 similar pattern, involving reduced consumption for affected species and three
537 sensitivity levels (Stock et al., 2023b).

538 However, certain aspects of noise effects are omitted from the module,
539 such as the possible direct adverse impacts of noise on species' reproduction
540 and early life stages. Studies have indicated reduced survival (De Soto et al.,
541 2013; Nedelec et al., 2014) and feeding (Gendron et al., 2020) of marine larvae
542 exposed to ship noise. Since larvae are carried by currents and cannot escape
543 noise sources, they are particularly vulnerable to potential harm. Moreover,

544 noise can detrimentally affect other reproduction stages (de Jong et al., 2020).
545 Therefore, a future version of the noise module should ideally encompass
546 reproductive stages' effects. Nonetheless, additional knowledge is required to
547 determine the extent of species vulnerability during reproduction and early
548 life stages.

549 Furthermore, the model did not discriminate between different frequen-
550 cies, as only one source of noise can be defined for each area. Additionally,
551 noise cannot be located to smaller areas than the size of each polygon and
552 layer. Consequently, representing both low-frequency noise (typically from
553 ship traffic or seismic surveys) and high-frequency noise (usually from mili-
554 tary sonars and recreational vessels) was unfeasible in this instance. Different
555 sources of noise possess distinct physical attributes, with low-frequency noise
556 traveling much farther and impacting organisms differently due to varying
557 hearing ranges. Given the concurrent activity of numerous sectors in Nor-
558 wegian waters (Hansen et al., 2022), this extension would be valuable. Nev-
559 ertheless, focusing on the effects of ship noise, which dominates underwater
560 noise at low frequencies Hildebrand (2009), the current model should work
561 well when sensitivity is specified solely for low-frequency noise. Because low-
562 frequency noise experiences minimal attenuation, assuming nearly uniform
563 effects across the NoBa Atlantis polygons is reasonable.

564 Advancing the representation of underwater noise in ecosystem models
565 requires response functions for each species, connecting modeled noise and
566 sensitivity levels with actual underwater noise and species sensitivity. This
567 challenge is underscored by Serpetti et al. (2021) and Stock et al. (2023b) in
568 the context of the Ecopath with Ecosim model. Achieving this could involve

569 expert assessments of species biomass reduction at predefined noise levels or
570 designing studies that can be compared across species. For marine mam-
571 mals, response functions could potentially be derived from studies utilizing
572 the Population Consequences of Acoustic Disturbance approach (King et al.,
573 2015; Popper and Hawkins, 2019) or similar methodologies. This means that
574 the most concerning aspect is the paucity of data regarding many species in
575 the area. While some information exists on marine mammals' noise response
576 (e.g. National Research Council, 2005; Southall et al., 2021) and select stud-
577 ies cover vital fish species like cod (Nedelec et al., 2015; Sierra-Flores et al.,
578 2015), herring (Vabø et al., 2002; Doksæter et al., 2009; Handegard et al.,
579 2015; Sivle et al., 2015), capelin (Jørgensen et al., 2004), mackerel (Hawkins
580 et al., 2014) and polar cod (Ivanova et al., 2020), few studies focus on non-
581 commercial fish and invertebrates. Additionally, these studies are challenging
582 to compare due to a lack of standardization (Hawkins et al., 2020). This dis-
583 parity makes validating and calibrating noise sensitivities for various model
584 components difficult. Consequently, the module should be regarded as a
585 hypothesis.

586 **5. Conclusions and further work**

587 Given that evaluations of noise effects on ecosystems are currently lack-
588 ing from the Norwegian and Barents Sea, exploring possible outcomes using
589 end-to-end ecosystem models is one of very few options. The range of ecosys-
590 tem effects, in particular the synergistic effects, identifies the need for more
591 knowledge on the topic.

592 Regardless of how realistic the noise module is, this study demonstrated

593 that the area along the Norwegian coast (SA1) is more sensitive to pertur-
594 bations than the areas in the open sea (SA2 and SA3). Because the coastal
595 area is also where most noisy or potentially disturbing activities take place
596 (shipping, fisheries, oil and gas) it is worthwhile to look into the mechanisms
597 of the variations to find out how to avoid such large fluctuations and instabil-
598 ity in the ecosystems of this area. Furthermore, as the shipping in this area
599 is expected to increase, while ecosystem effects of underwater noise is still
600 poorly understood, it is all the more reason to take a precautionary approach
601 and limit the amount of noise by activity restrictions or low-noise vessels at
602 least until more information is available to make informed decisions.

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611 During the preparation of this work the authors used AI tool ChatGPT
612 in order to improve grammar and sentence structure of the text. After using
613 this tool, the authors reviewed and edited the content as needed and take
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