Developing a Southern Ocean Marine Ecosystem Model Ensemble To Assess Climate Risks and Uncertainties

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Key Points:

- Future responses of Southern Ocean primary production and animal biomass to climate change are uncertain in conservation and fishery areas.
- A key source of uncertainty is poorly resolved or missing sea-ice processes in climate forcings for ecological models.
- We propose a Southern Ocean Marine Ecosystem Model Ensemble to address key uncertainties in animal biomass response to climate change.

Abstract

Climate change could irreversibly modify Southern Ocean ecosystems. Marine ecosystem model (MEM) ensembles can assist policy making by projecting future changes and allowing the evaluation and assessment of alternative management approaches. However, projected changes in total consumer biomass from the Fisheries and Marine Ecosystem Model Intercomparison Project (FishMIP) global MEM ensemble highlight an uncertain future for the Southern Ocean, indicating the need for a region-specific ensemble. A large source of model uncertainty originates from the Earth system models (ESMs) used to force FishMIP models, particularly future changes to lower trophic level biomass and sea-ice coverage. To build confidence in regional MEMs as ecosystem-based management tools in a changing climate that can better account for uncertainty, we propose the development of a Southern Ocean Marine Ecosystem Model Ensemble (SOMEME) contributing to the FishMIP 2.0 regional model intercomparison initiative. One of the challenges hampering progress of regional MEM ensembles is achieving the balance of global standardised inputs with regional relevance. As a first step, we design a SOMEME simulation protocol, that builds on and extends the existing FishMIP framework, in stages that include: detailed skill assessment of climate forcing variables for Southern Ocean regions, extension of fishing forcing data to include whaling, and new simulations that assess ecological links to sea-ice processes in an ensemble of candidate regional MEMs. These extensions will help advance assessments of urgently needed climate change impacts on Southern Ocean ecosystems.

Plain Language Summary

Climate change poses a threat to the ecosystems of the Southern Ocean and the iconic species that live there. To address this, scientists use models to estimate how these ecosystems might change in the future. Ecosystem models can help inform decisions by evaluating different strategies for managing and protecting these vulnerable marine environments. Our research focuses on improving marine ecosystem model estimates by developing a group of specialised models for the Southern Ocean. This group of models, called the Southern Ocean Marine Ecosystem Model Ensemble (SOMEME), aims to reduce uncertainties by better representing regional characteristics, like sea ice, and marine life such as Antarctic krill and whales. Currently, our efforts are concentrated on making sure the group of models accurately reflects

the Southern Ocean's unique conditions. This involves refining how we simulate climate effects and fishing activities, including historical whaling impacts, and examining the interactions between marine life and sea ice. By improving these models, we hope to provide clearer guidance on the potential impacts of climate change on the Southern Ocean, helping to ensure its protection for future generations.

1 Introduction

Southern Ocean ecosystems are at risk of substantial and potentially irreversible climate-driven change, against a backdrop of expanding human activities, such as tourism, pollution, and fisheries (Constable et al., 2023; Meredith et al., 2019). Many species in the Southern Ocean are particularly vulnerable to climate change, especially those with life-histories dependent on sea-ice habitat (Gimeno et al., 2024; Trathan et al., 2020) or with limited capacity to adapt rapidly to novel biophysical conditions (Peck et al., 2004; Pecl et al., 2017). Importantly, the Southern Ocean also has a crucial feedback role in regulating the global climate system through its sheer size, and its links to physical, ecological, and biogeochemical processes in other ocean basins (Murphy et al., 2021). Consequently, the global implications of large-scale ecosystem responses to climate change exhibited in the Southern Ocean are profound, with Antarctic and Southern Ocean ecosystem services conservatively valued at US $180 billion annually (Stoeckl et al., 2024).

Risks associated with Southern Ocean ecological change are not limited to direct impacts on biomass and species populations, but also potential broader geopolitical and socio-economic knock-on implications (Pethybridge et al., 2020; Trebilco et al., 2020). For instance, changes in Southern Ocean ecosystems could lead to increased tensions over resources, as nations vie for fishery resources or seek new opportunities for natural resource use. In light of these challenges, there is an urgent need to provide modelling support to evaluate the consequences in the Southern Ocean of climate change and its risks to marine life, the services these ecosystems provide, and potential biogeochemical-climate feedbacks (Mallet et al., 2023; Meskhidze & Nenes, 2006). Providing mechanisms to strengthen existing management and forecasting frameworks and ensuring that they are fit-for-purpose will help ecosystem protection and management, given the rapid changes emerging.

Southern Ocean ecosystems are managed by the Commission for the Conservation of Antarctic Marine Living Resources (CCAMLR). Initially formed in 1982 to manage the increasing commercial interest in Antarctic krill, the jurisdiction extends to encompass all marine living resources and associated populations within ~36 million km^2 south of a line roughly delineating the Antarctic Polar Front (Figure 1). Its management objectives aim to conserve marine life, allowing rational use within that framework to meet societal needs for sustainably managed living and non-living resources. These objectives are pursued through a multifaceted approach that integrates international cooperation on scientific research, population and ecosystem monitoring, a precautionary approach to fisheries, including the setting of conservative catch limits, and the establishment of Marine Protected Areas (MPAs).

Building climate resilience into these management strategies is essential to account for short, medium, and long-term climate change. The recent Marine Ecosystem Assessment for the Southern Ocean (MEASO) highlighted the urgent need to further develop global policies focused on actions to mitigate impacts of climate change on Southern Ocean biodiversity and ecosystems (Constable et al., 2023). This work also stressed that advancing the suite of available climate-forced ecological models that can incorporate Earth system model (ESM) outputs will build confidence in marine ecosystem model (MEM) outputs (McCormack et al., 2021). Murphy et al. (2012) outlined three focus areas for improved modelling of Southern Ocean ecosystems:

1. Developing a fundamental understanding of food web dynamics.
2. Employing a range of mechanistic models to resolve ecological processes at different scales that consider physical and biogeochemical processes, as well as feedback.
3. Implementing robust methodologies for testing past and future change scenarios.

The wide range of regional MEMs developed across the Southern Ocean, the assessments of structure and function of marine food webs, and the improved understanding of ecosystem dynamics across spatiotemporal scales are a testament to the work carried out addressing focus areas one and two (Constable et al., 2023; Dahood et al., 2019; Hill et al., 2021; McCormack et al., 2021; Murphy et al., 2021). However, progress towards focus area three remains less advanced.

Global marine ecosystem model (MEM) ensembles have increasingly been used to assess medium to long-term potential future changes in marine animal biomass and ecosystem structure and function under various climate change scenarios (e.g., Lotze et al., 2019; Tittensor et al., 2021). These ensembles average outputs from multiple MEMs, driven by two ESMs. This approach allows consideration of diverse representations of marine ecosystems and the quantification of inter-model uncertainties, from MEMs and ESMs, in projected biomass for improved understanding of potential marine ecosystem states and of the confidence around such understanding. The Fisheries and Marine Ecosystem Intercomparison Project (FishMIP), which is part of the broader Inter-Sectoral Impact Model Intercomparison Project (ISIMIP), has demonstrated how model simulations can help evaluate the impacts of climate change on marine ecosystems at global and regional scales (Tittensor et al., 2018). This work has revealed potential declines in marine animal biomass with important consequences for fishery catches and the many socioeconomic benefits that marine ecosystems provide (Cinner et al., 2022; Lotze et al., 2019; Tittensor et al., 2021).

However, uncertainty in global FishMIP projections remains high, particularly in terms of spatial differences between models (Tittensor et al. 2021). For the Southern Ocean, a mix of climate-driven changes in marine animal biomass are expected, and areas with the highest projected increase in biomass also have the highest inter-model uncertainty (Figure 1). Current FishMIP work focuses on better understanding and addressing some of the most prominent sources of uncertainty, including ESM and socioeconomic forcing and MEM structure (Heneghan et al., 2021). This is particularly relevant at the regional scale, where FishMIP outputs could play a critical role in informing climate-resilient fisheries policy and management. To build confidence in projections, a new phase of the model intercomparison project, FishMIP 2.0, considers aspects such as the use of higher spatial resolution, reanalysis-forced ocean model outputs, and globally-standardised fishing effort forcing the development of a model ensemble skill assessment and evaluation framework for FishMIP 3a (Blanchard et al., 2024; Frieler et al., 2024), as well as integration of future climate and fishing scenarios (Maury et al., this issue, FishMIP 3b). FishMIP2.0 (Blanchard et al., 2024) also includes a detailed workflow to implement the regional MEM protocol (Ortega-Cisneros et al., this issue) to facilitate model intercomparison across scales and different parts of the world to help build regional modelling capacity, identify issues, and ultimately improve models.

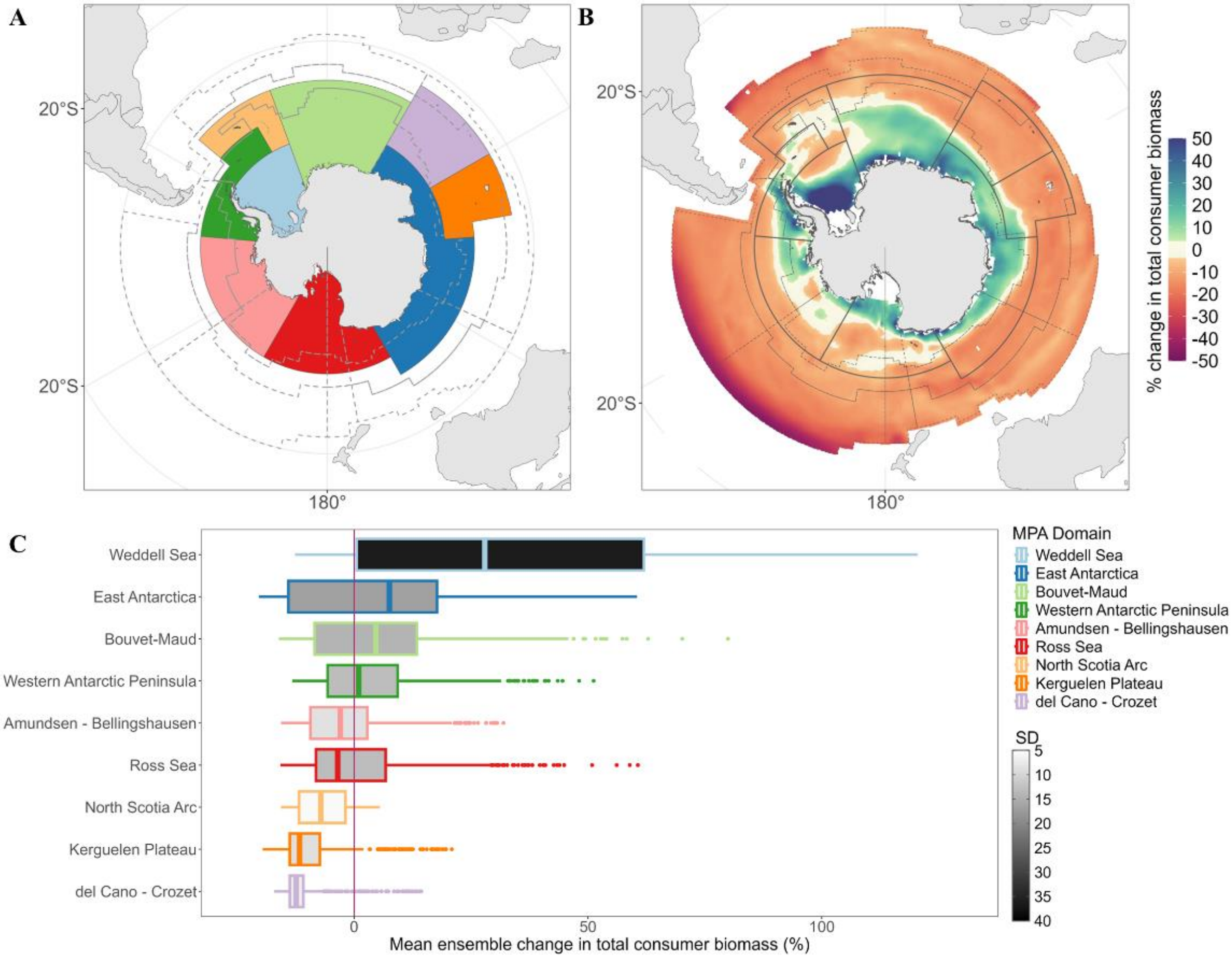

Figure 1. Future projections for % change in marine animal biomass for the Southern Ocean using global marine ecosystem model outputs recreated from Tittensor et al. (2021). A) CCAMLR Marine Protected Area (MPA) Planning domains (colour fill; source: CCAMLR GeoServer) overlaid onto the MEASO assessment areas (grey lines; source: measoshapes R package). B) FishMIP global ESM-MEM ensemble mean change in total consumer biomass (%) in the Southern Ocean by the end of the century (2091-2100) from the reference period (2005-2014) under the high emissions scenario (SSP5-8.5). Continuous grey lines represent the MPAs from (A) and dashed grey lines the MEASO regions. C) Box plots showing both the spatial variation (box and whiskers) in ensemble mean change and inter-model uncertainty (greyscale fill: SD) in total consumer biomass (%) by CCAMLR Marine Protected Areas Planning Domain by the end of the century (2091-2100) from the reference period (2005-2014) under SSP5-8.5, based on 6 members of the FishMIP global MEM ensemble. The red vertical line represents no change from the reference period. See Text S1 for notes on methodology to recreate these Southern Ocean-focused results from Tittensor et al. (2021) for panels B and C.

To address the research gap of robustly testing scenarios of past and future change (focus area 3; Murphy et al. 2012), we propose the Southern Ocean Marine Ecosystem Model Ensemble (SOMEME; Figure 2) as a contribution to the FishMIP 2.0 regional model inter-comparison initiative. As a first step, we propose and develop a regionally relevant simulation experimental protocol that builds on the FishMIP two-track framework: 1) model evaluation and past change and 2) climate change projection that incorporates five stages of detailed assessment to determine its relevance for Southern Ocean regional marine ecosystems, along with identification of candidate marine ecosystem models, necessary extensions to simulation experiments, and challenges for future work. Evaluating the performance of ESMs and fisheries information provided to force MEMs will aid the understanding of uncertainty in marine animal biomass projections for this unique region and improve confidence in the use of such projections to inform policy and decision-making. This work will help address substantial uncertainties in our current understanding of marine ecosystem responses to future climate change, identified in the MEASO report as one of the main shortcomings in Southern Ocean modelling (Constable et al., 2023).

2 Materials and Methods

Protocol Development

Building on previous efforts to enhance regional MEM for the Southern Ocean (Constable et al., 2023; McCormack et al., 2021; Murphy et al., 2012), and facilitated by the FishMIP 2.0 protocol (Blanchard et al., 2024; Ortega-Cisneros et al., this issue) and the extensive FishMIP network, we first assembled and consulted a group of experts in ocean, biogeochemical, biological and socio-ecological modelling. We determined that a skill assessment of the ocean-biogeochemical model environmental forcing variables (sea surface temperature (SST), sea ice concentration, and phytoplankton biomass: Table S1; collectively referred to as climate forcings from hereon in) used in FishMIP 3a and required to drive MEMs was necessary to establish if they are fit-for-purpose in Southern Ocean regions. Carrying out this initial skill assessment would inform whether further regionally specific climate forcing extensions are necessary to capture key uncertainties and issues, relating to poor understanding and resolution of physical and biogeochemical processes, such as mixed-layer depth and sea ice dynamics (Constable et al., 2023; McCormack et al., 2021). By establishing standardised climate forcing for Southern Ocean regional MEMs, assembling a set of suitable MEMs and historical human activity forcing (fishing/whaling), as well as consolidating potential regional MEM outputs to inform an ensemble for ecosystem assessment, we propose the SOMEME protocol. Here, we step through the different stages of the proposed SOMEME protocol (Figure 2) to determine its suitability, potential applications, and possible future extensions.

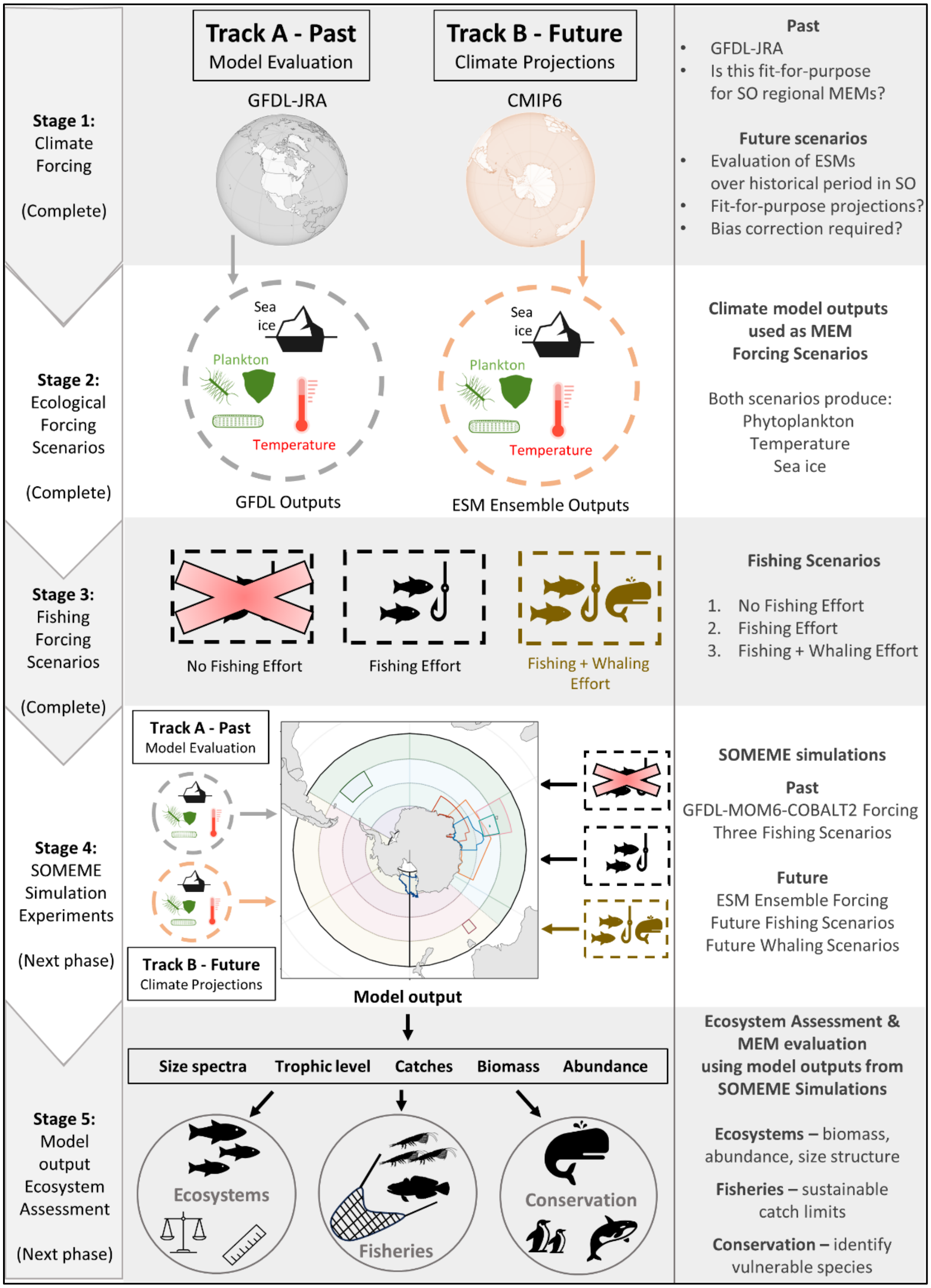

Figure 2: Schematic of proposed SOMEME protocol building upon ISIMIP3 and the FishMIP 2.0 protocols for Track A (model evaluation - past: FishMIP 3a) and Track B (projections - future: FishMIP 3b). The proposed protocol is composed of some stages that we complete and present here (i.e., Stage 1, 2, and 3), while others are future stages requiring further model development (Stage 4) and further consultation of the expert working group to reach a consensus (Stage 5).

Stage 1: Climate forcing

Track A - Observed drivers of past change

Total consumer biomass projections from Tittensor et al. (2021) were from global MEMs forced with non-bias adjusted (i.e., future projections are not corrected relative to observed current conditions) ESM outputs (GFDL-ESM4.1 and IPSL-CM6A-LR) and are therefore not necessarily expected to compare skilfully with observations, especially regionally. Therefore, FishMIP 2.0 includes a reanalysis-forced (JRA55-do: Tsujino et al., 2018) ocean-biogeochemical model (GFDL-MOM6-COBALT2: Adcroft et al., 2019; Stock et al., 2020) for Track A, focused on building confidence through MEM evaluation, detection, and attribution of past change to relative effects of drivers (e.g., climate and fishing). The reanalysis forcing, JRA55-do, is an observationally-constrained atmospheric model product for driving ocean model simulations and provides realistic forcing that captures historical climate variations, such as observed Southern Annular Mode variability. For most of the global ocean, it also includes temporally dynamic river freshwater and nitrogen inputs derived from long-term trends in land-use change (Liu et al., 2021), except Antarctica where riverine input and sea ice runoff are decoupled and constant with time (Tsujino et al., 2018). However, for FishMIP 2.0, sea ice concentration is the only climate forcing variable that is taken directly from JRA55-do rather than the reanalysis-forced ocean-biogeochemical model, GFDL-MOM6-COBALT2. The accuracy of sea-ice hindcasts from a suite of CMIP5 ESMs (Cavanagh et al., 2017), and more recently CMIP6 ESMs, have been previously assessed for the Southern Ocean (Casagrande et al., 2023). However, for FishMIP models these assessments have not been carried out in unison with an evaluation of other key forcing fields, such as phytoplankton biomass and temperature. To assess the ability of GFDL-MOM6-COBALT2 (GFDL-JRA from hereon in) to reproduce past environmental conditions for SST and phytoplankton biomass, as well as assessing the JRA55-do sea ice concentration, we compared the climate forcings to publicly available observational datasets.

Track B - Future scenarios and drivers

For historical simulations we intentionally choose environmental forcing variables that are not far removed from the observations (i.e., either a reanalysis forced ocean-biogeochemical model or the reanalysis products themselves). Using realistic environmental forcing variables over the historical period to drive MEM hindcast simulations means that observed disagreements in simulations of past fish biomass can be more reliably attributed to uncertainty in the MEM, rather than their environmental forcing. However, as observations do not exist for the future, we must also determine which free-running ESM are mechanistically best suited to force future projections with. The best way to do this is to compare the ESM forcing variables over the historical period to historical observations. The assumption then is that free-running ESMs that can recreate past observations best will simulate more reliable projections of the future. While choosing a single ocean forcing model simplifies comparisons across MEMs (i.e., Track A) for focused ecological research and reduces computational effort, it prevents the quantification of uncertainties in marine animal biomass projections due to differences in ESM structure. We thus carried out the same evaluation process as in Track A, but for a suite of CMIP6 models, to assess a broader range of ESMs for their suitability to force MEMs in the Southern Ocean. To align with best practices, we carefully considered the selected ESMs and climate forcing variables used to compare with observations to ensure we tested the key processes we are aiming to model (Schoeman et al., 2023). In doing so, we developed a proposed SOMEME protocol, which we outline in the following sections.

We considered 11 ESMs (Table S2) from CMIP6 (Eyring et al., 2016) which have diverse representations of the phytoplankton community, temperature effects, and sea ice dynamics. These models were specifically selected for their diverse and comprehensive representations of phytoplankton functional types, their varied approaches to modelling SST impacts on marine biogeochemical processes, and their capabilities in simulating sea-ice dynamics. Some of the selected models have been assessed for their representation of the Antarctic sea-ice seasonal cycle, area, and concentration, highlighting the advancements in CMIP6 over previous model iterations (Casagrande et al., 2023). By analysing these aspects concurrently, our study aims to provide a multi-faceted evaluation of ESM phytoplankton, temperature, and sea ice representation when compared to observational data.

Observational data

Observational datasets for comparisons with climate forcings included sea-ice concentration, sea surface temperature, and surface phytoplankton biomass. Monthly sea-ice concentration data came from the NOAA/NSIDC Climate Data Record of Passive Microwave Sea Ice Concentration, Version 4 (Meier et al., 2021) with a spatial resolution of 25 km x 25 km.

This dataset includes sea-ice concentration from 1982 until 2010. Sea surface temperature data was obtained from MODIS for the period 2002-2014 (O'Malley, 2015). Remote sensing surface phytoplankton biomass is inferred from empirical relationships between living phytoplankton biomass (Graff et al., 2015) and the particle backscattering coefficient derived from the water-leaving radiance spectrum measured by the MODIS satellite (Westberry et al., 2008) for the period 2002-2014.

ESM evaluation

To evaluate past model performance, we compared regional climatologies from the GFDL-JRA forcing variables and free-running CMIP6 ESMs against the remote sensing record. Temporally, climatologies were computed over the overlapping period between model simulation and satellite operation (1982-2010 for NOAA/NSIDC sea ice; 2002-2014 for MODIS SST and phytoplankton biomass). Regionally, climatologies were averaged over three domains, the Southern Ocean (30S-80S), Antarctic zone (60S-80S), and Weddell Sea (64.5S-83.5S; 20.5 W-83.5W).

Overall model performance is quantified as the centred-RMSE between the remote sensing climatology and each simulation (Text S3, Eq. 1). The cRMSE is the root mean square difference between simulated data and remote data across all points in space and time after removing the means of each data set. Additional metrics of model skill are included Taylor diagrams (Figures 4 & S7-S9) and the seasonal mean bias for austral summer (DJF) and winter (JJA) climatologies from GFDL-JRA and the CMIP6 ensemble relative to observations (Figures 4 & S7-S9).

Stage 2: Selecting Regional MEMs and links to climate forcing variables

To be considered in this round of MEM selection, we required regional modellers to be registered with FishMIP, submit shapefiles for their regional MEM and commit to running model simulations with the SOMEME protocol in the future. For models still in development, regional modellers had to establish a minimum requirement of incorporating climate forcing variables for temperature and primary production, with a sea ice concentration climate forcing encouraged. To date, the suite of existing MEM types, that could accommodate the minimum set of two climate forcing variables and fishing effort, includes Atlantis, mizer, Ecopath with Ecosim (EwE) and

Ecospace (McCormack et al., 2020; Subramaniam et al., 2020, 2022), a mass-balance Trophic Model, which has been adapted to an EwE model (Pinkerton & Bradford-Grieve, 2014; Pinkerton et al., 2010), a southern hemisphere model of intermediate complexity (MICE; Tulloch et al., 2018, 2019), and an Antarctic krill mechanistic spatial population model (KRILLPODYM; Green et al., 2023). This proposed MEM ensemble covers regions including Prydz Bay (5 models), the Kerguelen Plateau (4 models), East Antarctica (3 models), South Georgia (3 models), and the Ross Sea (3 models) (Figure 3). The proposed regional MEMs do not represent a traditional 'ensemble' as there are variations in the areas represented by each model type, although there are areas with overlap from multiple models for spatial comparisons. However, constructing a framework for standardised MEM outputs and assessments, as outlined in the Results and Discussion, sets up this proposed ensemble to better quantify model skill, understand uncertainties, and provide more comprehensive projections on the relative and combined effects of climate change and exploitation on changing Southern Ocean ecosystems.

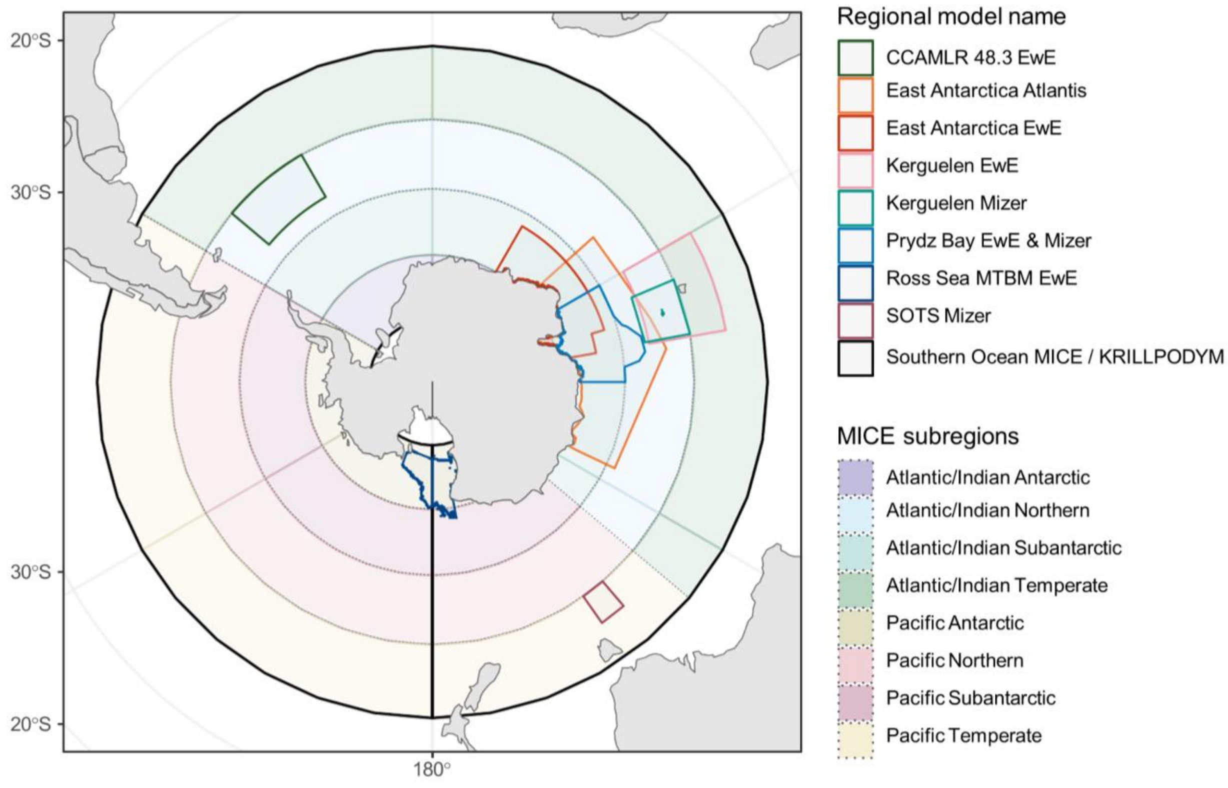

Figure 3. Regional ecosystem models currently proposed to form the initial Southern Ocean Marine Ecosystem Model Ensemble. Coloured lines show the spatial domain of each regional model. Note that Southern Ocean MICE and KRILLPODYM cover the same spatial extent. Coloured polygons represent the subregions included within the Southern Ocean MICE model.

Stage 3: Selecting standardised fishing forcings

To capture changes in fishing effort over time, we used the standardised FishMIP fishing inputs (Rousseau et al., 2024) from the Shiny app (Ortega-Cisneros et al., this issue) for fish species. The FishMIP effort does not include historical whaling, which is a dominant historical activity in this region. We therefore extend the fishing forcing for the Southern Ocean to include International Whaling Commission (IWC) whaling data (Allison, 2020), using the Prydz Bay region as an example. We aggregated the fishing and whaling effort to the functional group levels represented in the model. Mapping of fishing effort to species and functional groups is model-specific, but the workflow to implement this step is outlined in Ortega-Cisneros et al. (this issue). For regional MEMs that include whale species or functional groups, a similar method will be applied for the IWC effort data.

Stage 4: SOMEME Simulation experimental design

Building on the simulation experiments from the FishMIP 2.0 framework, we assessed whether simulation experiment extensions were needed to additionally capture regional relevance for SOMEME, with a focus on Track A. Given the importance of additional drivers (sea ice and whaling) that are not explicitly captured in the core FishMIP 3a attribution experiments, we developed a minimum set of additional simulation runs. First the outcome of the skill assessment of the climate forcings (Table S1) was needed to determine whether or not additional or different climate forcings were required for initial model evaluation simulations. We also visualised the historical fishing forcing data to assess coverage of key fish and crustacean groups and due to the importance of historical whaling in the region, compiled data from the IWC.

Stage 5: Model outputs and ecosystem assessment

To assess how well the regional MEM ensemble outputs capture past changes in ecosystem structure, function, and fisheries changes, we will need to draw on a range of existing databases to provide examples for model output evaluation for the Southern Ocean in alignment with the Southern Ocean-specific ecosystem Essential Ocean Variables (eEOVs; Constable et al., 2016) and Essential Biodiversity Variables (EBVs; Muller-Karger et al., 2018), which are biological and ecological variables established as key to aiding ecosystem understanding and assessment (Constable et al., 2016). We also propose an extended set of model outputs for SOMEME (Table 3) to work towards integrating ecosystem assessment with existing efforts, such as MEASO (Constable et al., 2023).

3 Results

Stage 1: Climate forcing - Track A & B

Skill assessment of the FishMIP 3a climate forcing, GFDL-JRA, for model evaluation (Track A) suggests that they are fit-for-purpose for regional MEMs in the Southern Ocean. We established this due to their relative performance when ranked against the 11 CMIP6 ESMs, with the ocean-biogeochemical model climate forcing for SST outperforming all CMIP6 ESMs at reproducing historical observations across the whole Southern Ocean (Table S5). Likewise, for sea ice concentration, the FishMIP 3a climate forcing, which is from JRA55-do, performed the best at reproducing observations across the Southern Ocean, when compared to the 11 CMIP6 ESMs (Table S5). However, for surface phytoplankton biomass, the FishMIP 3a climate forcing was ranked 9th when compared to the CMIP6 ESMs (Table S5), reflecting the large suite of contributing factors that can influence phytoplankton. Despite the lower performance of the FishMIP 3a climate forcing for surface phytoplankton biomass, we still deem the overall performance of the suite of climate forcing variables to be fit-for-purpose due to the peak performance of SST and sea ice concentration, and due to some uncertainty associated with remote sensing products to perform the surface phytoplankton comparison to observations (Moutier et al., 2019). As a result, we propose the SOMEME protocol to follow in accordance with the FishMIP 3a regional protocol (Ortega-Cisneros et al., this issue), using GFDL-JRA to force SST and phytoplankton biomass and JRA55-do to force sea ice concentration in regional MEMs, at 0.25° horizontal resolution. These forcings are also provided as both vertically resolved and vertically integrated to accommodate a range of regional MEM structural requirements.

Reanalysis-forced GFDL-JRA should be expected to perform better at capturing past conditions than fully-coupled ESMs. However, fully-coupled ESM are required for climate projections. As the new FishMIP 2.0 (Track B) climate and fishing forcing data are still under development, we compared the default FishMIP ESMs (GFDL and IPSL) as part of a broader suite of 11 CMIP6 ESMs. Overall, across the 11 CMIP6 ESMs, the inter-model variance was lowest and model skill at matching observations was highest for SST (Figure 4 A,D and Table S3). Sea ice concentration had higher inter-model variance and lower model skill when compared to SST (Figure 4 C,F and Table S3), but surface phytoplankton biomass had the highest inter-model variance and lowest model skill (Figure 4 B,E and Table S3), consistent with increasing levels of uncertainty in future projections of net primary production across models (Tagliabue et al., 2021). Also, it is noteworthy that there is an ESM, MIROCC-ES2L, that performs particularly poorly for sea ice concentration, so if this was removed this forcing variable would perform more favourably. Despite sea ice concentration having good model skill associated across the CMIP6 models at the scale of the Southern Ocean, with a more regional focus when assessed for the Weddell Sea, model skill reduces substantially, and inter-model variance increases substantially (Figures S7-S9; Tables S3-S5). This highlights the need for improved ESM climate forcing for sea ice and associated links to primary production to better represent regional scale dynamics.

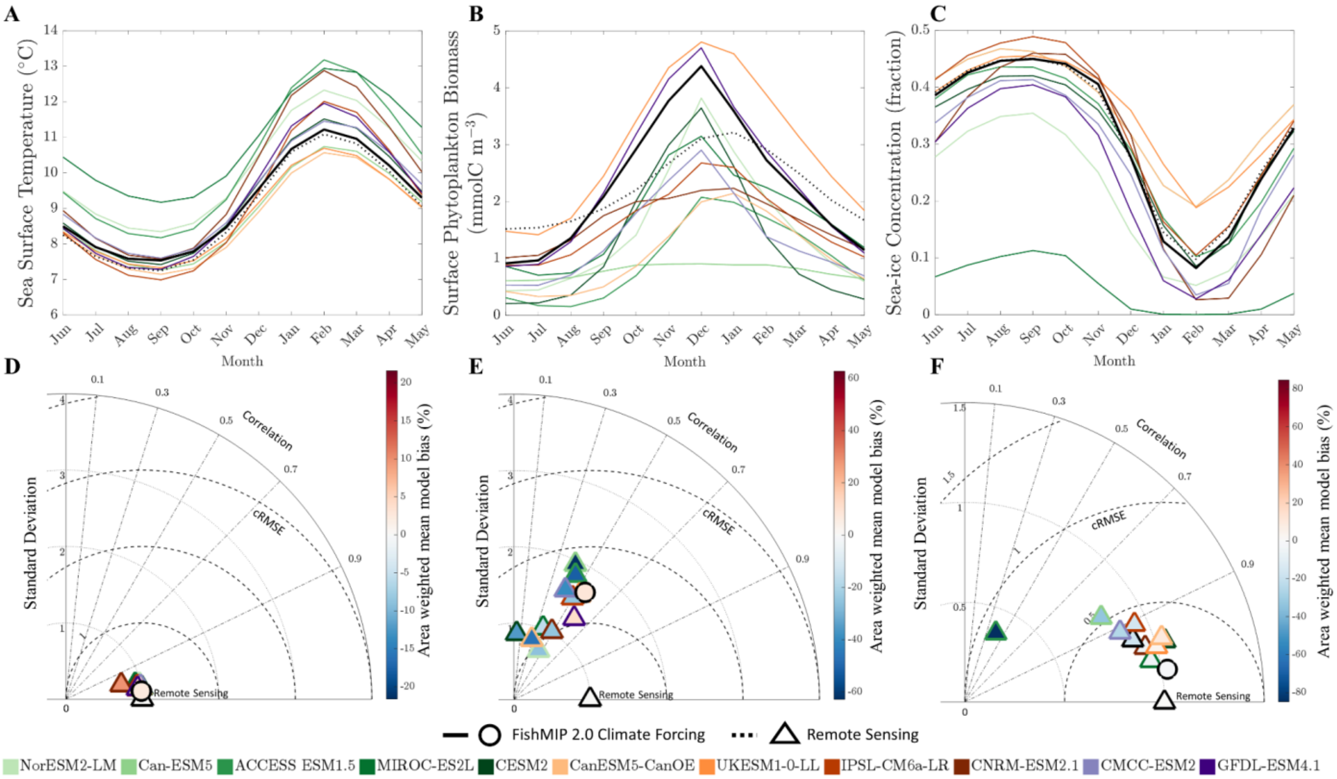

Figure 4: Evaluation of FishMIP historical climate forcing in the Southern Ocean. A) The FishMIP 3a climate forcing variables' climatology for A) SST (2002-2014), B) surface phytoplankton (2002-2014), and C) sea ice concentration (1981-2014) (solid black) are plotted with the remote sensing records (dashed black) and 11 fully-coupled ESMs over the historical period (solid coloured). Climatologies are spatially averaged across the entire Southern Ocean (30S-80S). Below, the corresponding Taylor diagrams illustrate the skill of the FishMIP 2.0 historical climate forcing (black circle) and fully-coupled ESMs (coloured triangles) against the remote sensing record (black triangle) over the same time period for D) SST, E) surface phytoplankton biomass, and F) sea ice concentration. Taylor statistics are computed across space and time (i.e., they are not spatially averaged) and are normalised by the standard deviation of the remote sensing record.

Stage 2: Regional MEMs and linking climate forcing variables

Through our assessment of selected MEMs that can contribute model simulation results to SOMEME, we evaluated the way that environmental forcing is incorporated into the different regional model types. Below we provide a description of the regional MEM types proposed for

SOMEME, and the way in which climate forcings have been incorporated into model processes, as well as potential areas that novel climate forcings could be included.

Table 1. A selection of regional marine ecosystem models (MEMs), including published and MEMs in development that would be ready to implement the proposed SOMEME protocol. Climate forcings are differentiated as ready for climate forcing (*italic*), and possible with model development (underlined).

MEM	**Region**	**Functional groups modelled**	**Climate forcing**	**Stage**
Atlantis	East Antarctica	Phytoplankton, zooplankton, krill, fish, sea birds, marine mammals	*Temperature* *Phytoplankton* *Sea ice concentration*	In development
EwE + Ecospace	Kerguelen Plateau	Zooplankton, fish, marine mammals	*Temperature* *Phytoplankton (chl* a*)* *Sea ice concentration*	Subramaniam et al. (2020, 2022)
EwE	East Antarctica: CCAMLR 58.4.2	Phytoplankton zooplankton, fish, marine mammals	*Temperature* *Phytoplankton* *Sea ice concentration*	In development
EwE	Prydz Bay	Zooplankton, fish, marine mammals	*Temperature* *Phytoplankton (chl* a*)* *Sea ice concentration*	McCormack et al. (2020)
Ecopath (EwE)	South Georgia (CCAMLR subarea 48.3)	Zooplankton, fish, marine mammals	*Temperature* *Phytoplankton* *Sea ice concentration*	Hill et al. (2012) In development
KRILLPODYM (SOMEME compatibility)	Circumpolar	Antarctic krill	*Temperature* *Phytoplankton (chl* a*)* *Sea ice concentration*	Green et al. (2023) In development
Mass balance Trophic Model	Ross Sea	Zooplankton, fish, marine mammals	*Temperature* *Phytoplankton (chl* a*)* *Sea ice concentration*	Pinkerton & Bradford-Grieve, 2014; Pinkerton et al. (2010)
MICE	Circumpolar (entire southern	Zooplankton, Antarctic krill,	*Temperature*	Tulloch et al.

	hemisphere)	baleen whales	*Phytoplankton (chl* a*)* *Sea ice concentration*	(2018, 2019)
mizer/therMizer	Heard Island and McDonald Islands	Fish	*Temperature* *Phytoplankton (biomass)* Sea ice concentration	In development
mizer/therMizer	Prydz Bay	Zooplankton, fish, marine mammals, sea birds	*Temperature* *Phytoplankton (biomass)* Sea ice concentration	In development
mizer/therMizer	SOTS	Zooplankton, fish	*Temperature* *Phytoplankton (biomass)* Sea ice concentration	In development

Atlantis

Atlantis is an end-to-end ecosystem model that extensively represents the food web and associated ecological processes (Audzijonyte et al., 2017a). It also contains fishing, management and economic sub-models that can be activated to represent human dimensions of ecosystem interactions (Audzijonyte et al., 2017b). The ecosystem represented in Atlantis is an environmentally influenced representation of physiological and ecological processes. Many environmental variables can be incorporated, but temperature is the most used and typically the best understood. Processes include temperature-forcing conditions, physiological rate processes, the nutritional content of lower-level ecosystem species, and the timing and magnitude of environmentally mediated events (such as spawning) for relevant consumer groups. Atlantis implementations in the Antarctic have a simple but representative ecological sea ice forcing, with the state and extent of the sea ice influencing the growth and survivorship of sea-ice dependent species groups. Atlantis does not typically use primary production forcing, relying instead on its explicit biogeochemical sub-model to dynamically model these components. However, a comparison with remote sensing and ESMs outputs is undertaken to check for consistency. In extreme cases, where there is strong disagreement between the two approaches and modellers wish to resemble ESM distributions of primary production (especially nearshore) more closely, a hybrid approach is taken that uses a weighted average of the external forcing values for primary production and the explicit Atlantis sub-model variables. Modellers determine the weighting, and it is typically tuned such that the best fit to observations is achieved.

Ecopath with Ecosim (EwE)

In brief, EwE models can use forcing functions that can influence predator-prey interactions or production rates for primary producers. The Ecopath module sets up the initial conditions for the temporal within Ecosim and the spatio-temporal dynamics within Ecospace (Bentley et al., 2024). In Ecosim, trends in primary productivity can be used to evaluate ecosystem response to environmental change. For consumers in the model, response curves can be used to represent environmental influences on the biological parameters of a functional group or on predator-prey interactions (Stock et al., 2023). Ecospace inherits these response curves and simulates environmental influences using reference time series maps depicting spatial distribution and magnitude (de Mutsert et al., 2024). Environmental parameters such as temperature, salinity and oxygen concentration have been used to model climate impacts on ecosystems (Stock et al., 2023) and recently, Antarctic models have begun representing sea-ice dynamics to further understand climate impacts on Southern Ocean ecosystems (Dahood et al., 2019).

KRILLPODYM

KRILLPODYM integrates environmental forcings to compute krill habitat quality indices and the advection of biomass (Green et al., 2023). Temperature and primary production are used in the calculation of both spawning habitat (Green et al., 2021), a multiplier on recruitment, and life-stage habitats, which scale mortality rates of krill age classes. Sea ice concentration is also used to calculate the habitat for key life stages, modulating survival of both late summer and overwintering larvae. The spatial dynamics of krill biomass are forced through a combination of ocean current and sea ice advection.

MICE

Models of Intermediate Complexity for Ecosystem Assessments (MICE) extend stock assessment approaches to represent multiple species and stressors in an ecosystem. In contrast to more complex whole-of-ecosystem models, MICE focus on key species, ecological processes, interactions, and data-driven model fitting while managing uncertainties (Plagányi et al., 2014). These models integrate physical models to evaluate effects of environmental forces and interactions between species and stressors, such as climate change impacts. In the Southern Ocean, MICE models have been developed to hindcast (1890-2012) and predict future abundance to 2100 of five baleen whales and krill under climate change Representative Concentration Pathways (RCP) 8.5 (Tulloch et al., 2018, 2019). This MEM links krill and whale population dynamics to sea-surface temperature, phytoplankton, and sea-ice extent outputs from an early version of the Australian ESM (ACCESS), which included a Nutrient-Phytoplankton-Zooplankton-Detritus model (NPZD) forced by a General Circulation Model that included ocean and atmosphere dynamics (Law et al., 2017; Ziehn et al., 2017). Environmental forcing was included in the krill dynamics through a statistical climate-growth parameter (Atkinson et al., 2006) that relates experimentally-validated increases in Antarctic krill length (mm.d^{-1}) to sea surface temperature (*SST*, °C), and food availability indicated by chlorophyll-*a* concentration (*CHL*, mg.m^{-3}). The model also included the relative favourability of environmental conditions encountered by whales based on sea-ice concentration (mean sea-ice mass (kg.m−2)) outputs of the coupled climate-NPZD model.

mizer

Size spectrum models developed using *mizer* (Scott et al., 2014) can incorporate temperature effects using the *therMizer* extension (Woodworth-Jefcoats et al., 2019), which includes temperature scalars on metabolism and search rates. Plankton forcing can be included by constructing size spectra time series for the resource spectrum that forces the dynamic food web component of the models, usually derived from biomass of phytoplankton and zooplankton (Woodworth-Jefcoats et al., 2019). There are also options to include additional primary producer resource spectra, through the addition of modified resource spectra (Audzijonyte et al., 2023), similar to a bespoke sea-ice algae primary production included in a Ross Sea food web model (Pinkerton et al., 2010). Links between sea-ice concentration and a habitat suitability index for growth and mortality are not currently represented in *mizer*, but it could be included through a size-based mortality term, similar to other novel uses of adapted fishing mortality terms that can provide a flexible forcing functionality (Houle et al., 2016).

Additional marine ecosystem model types

The regional MEMs proposed for the initial round of SOMEME best represent east Antarctic ecosystems, but due to the open nature of FishMIP and the larger number of published MEMs that have potential to be incorporated in future rounds (Figure S10, Table S6), we anticipate improved region representation. Additionally, this proposed MEM ensemble contains some model types not currently contributing to FishMIP. In advancing the SOMEME protocol, one of the critical discussion points in the expert working groups was assessing the kinds of extensions to the FishMIP 2.0 protocol that are needed to better represent Southern Ocean regional processes and uncertainties. One key extension is the assessment of model capacity to resolve dominant energy pathways. This is particularly important for Antarctic krill, given its dominance in many regions, as well as it being the target of the largest Southern Ocean fishery, which is predicted to grow substantially (Trathan, 2023). With the range of regional MEMs available, a valuable step in model assessment would be comparing krill biomass projections among food web models that resolve trophic linkages (e.g. mizer, EwE and Atlantis) versus krill-specific models that better resolve life-history and habitats (e.g., KRILLPODYM (Green et al., 2023) and MICE (Tulloch et al., 2018)). As a result, we are proposing the inclusion of additional models to address this important area, while future addition of species-specific model frameworks remains open.

Stage 3: Fishing and whaling forcing - Prydz Bay case study

For the proposed SOMEME protocol, we suggested three fishing and whaling scenarios (Stage 3, Figure 2):

1. No fishing or whaling effort forcing
2. Fishing effort forcing
3. Fishing and whaling effort forcing

Implementing these scenarios will allow for standardised comparisons of fishing and no fishing between regional MEMs and global MEMs across the shared region, as well as accounting for the inclusion of whaling effort in SOMEME.

The two effort time series for whaling and fishing in Prydz Bay (Figure 5) demonstrate the long-term historical human forcing in the region and are both important to include in ecosystem model evaluation, detection, and attribution studies that include systematic comparison of climate and fishing effects.

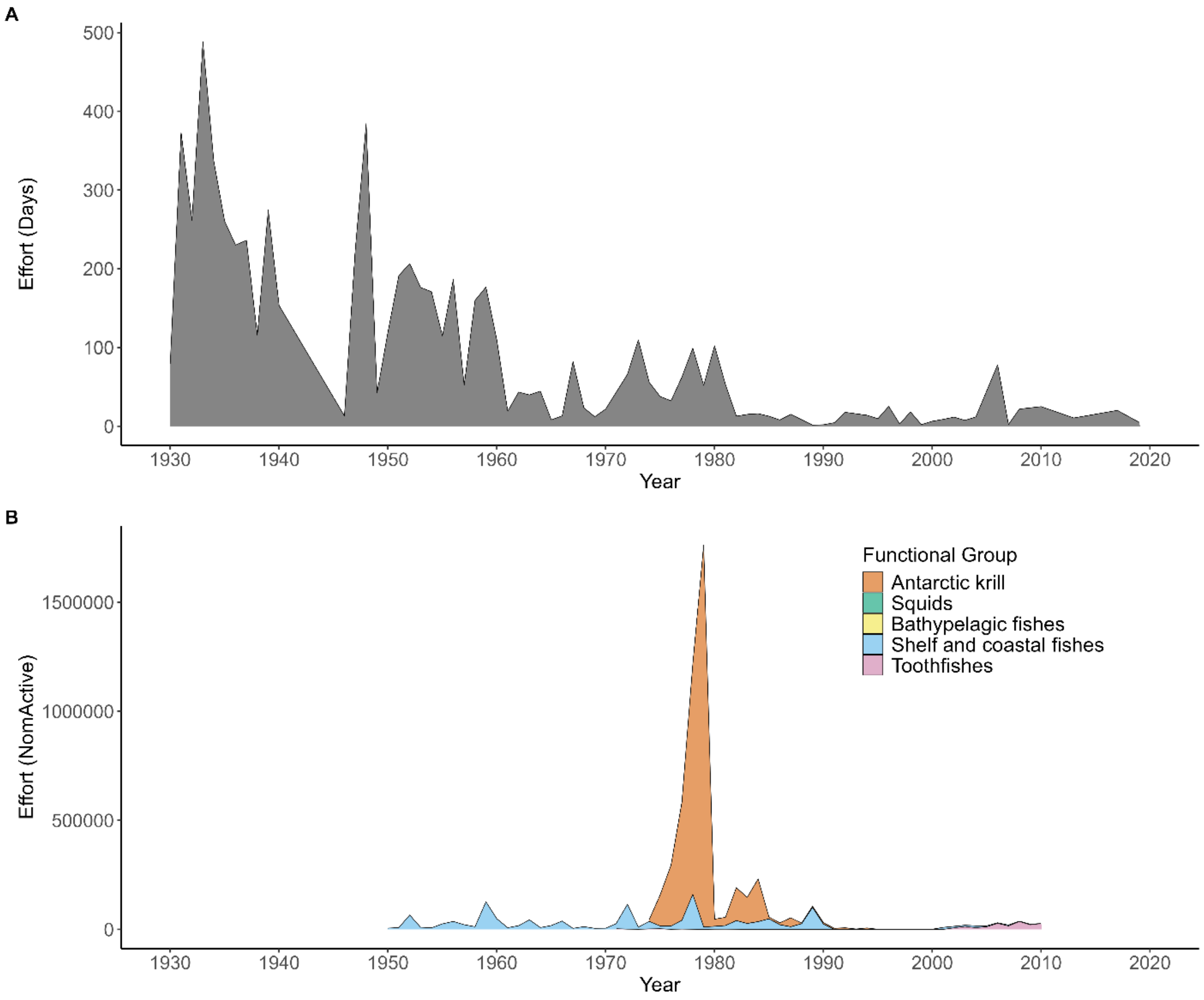

Figure 5. A) Total whaling effort and B) fishing effort in the 20th and early 21st centuries for the Prydz Bay region. Whaling effort is presented as days at sea aggregated for all species from the International Whaling Commission (IWC) database version 7.1 (Allison, 2020), and fishing effort is the nominal effort of the active fleet (NomActive).

Stage 4: SOMEME Simulations

Establishing that for Track A the FishMIP 3a GFDL-JRA climate forcings are fit-for-purpose provides confidence that we can use those climate forcings. The simulations for Track A SOMEME will therefore include the core set from FishMIP, and an extended set of additional simulations to account for historical whaling activity (Table 2). The SOMEME protocol is a living document, with detailed protocol guidelines, code, and community development hosted on a GitHub repository, while continuity of resources will be assured using Zenodo releases.

Table 2: Model simulations for Track A of the SOMEME protocol, an extension of Track A of FishMIP 2.0, which contributes to FishMIP 3a. Climate forcing spatial resolution is 0.25° for all simulations.

Climate forcing (x 2)	Emission Scenario	Time period	Socio-economic scenario (x 3)	No. of runs	Track (ISIMIP)
GFDL-JRA (SST, phyto biomass) + JRA55-do sea ice concentration GFDL-JRA (SST, phyto biomass) - JRA55-do sea ice concentration	historical (obsclim)	1961-2010	- No fishing (nat) - Fishing: time-varying effort (histsoc) - Fishing + whaling (histsoc + IWC)	6	A - model evaluation (FishMIP 3a)

As the climate forcings for FishMIP 2.0 (Track B) are not yet publicly accessible, the corresponding and potentially additional Southern Ocean ESM forcings are yet to be decided. To support the development of future simulation rounds we propose a structured quantitative assessment to determine whether SOMEME requires an extended climate forcing, in addition to FishMIP 2.0 core runs. The same procedure is recommended, along with stakeholder discussions, to develop applicable regional extensions for implementing future fishing scenarios (Maury et al., this issue).

Stage 5: Model outputs and ecosystem assessment

To enhance ecosystem assessments in the face of climate change, it is imperative to standardise key ecological outputs across MEM protocols for model evaluation and future scenario testing. As a preliminary step, we propose that all regional MEMs produce mandatory outputs as specified in the FishMIP 2.0 protocol (Table 9, FishMIP 2.0 protocol), enabling comprehensive inclusion in FishMIP 2.0. These outputs, which can be provided as spatial data or aggregated by region, include a variety of biomass and fisheries catch metrics, especially for pelagic and demersal groups, along with broader community measures such as total consumer biomass. While the optional outputs in Table 9 focus on refining size structure among model outputs, they do not primarily address Southern Ocean research questions. Therefore, we recommend expanding the output set for all regional MEMs participating in the SOMEME protocol (Table 3) to cover essential aspects such as biomass of key functional groups, species distribution, phenology, range shifts, and trophic interactions, all crucial for understanding marine ecosystem structure and function.

By mapping model outputs to established ecosystem assessment frameworks, we can leverage existing observational data to refine model evaluations and augment current research efforts via resources like the Antarctic bioDiVersity dAta iNfrastruCture (ADVANCE). Long-standing data collection and ecosystem monitoring has been carried out by CCAMLR Ecosystem Monitoring Program (CEMP). For key indicator species CEMP have collected annual population, diet and life-history parameter observations of (predominantly seabirds and seals) at sites across the Southern Ocean since 1989. Incorporating eEOVs into MEM evaluations (Table 3) enhances predictive capabilities, supports strategic planning, and strengthens conservation efforts. This holistic approach underscores the importance of structured, data-driven decision-making in managing marine ecosystems. Comparisons between eEOVs and a standardised regional MEM ensemble should include data on abundance at varying ecological levels, from individual species to community metrics. Noteworthy data resources include the Ocean Biodiversity Information System (OBIS, https://www.obis.org/) and the Global Biodiversity Information Facility (GBIF, https://www.gbif.org), for which Southern Ocean EOVs/EBVs have been assessed for suitability in MEASO ecosystem assessment (Bonnet-Lebrun et al., 2023). Additional landmark databases include COPEPOD and KRILLBASE (Atkinson et al., 2017) for zooplankton, Myctobase (Woods et al., 2022) for fish, and the Pelagic Size Structure database (PSSdb) (Dugenne et al., 2023) for abundance, biomass, and size structure data.

Table 3: Model outputs proposed to contribute to the FishMIP 2.0 protocol extension, SOMEME. Each model output has an associated category of Essential Biodiversity Variable (EBV), Essential Ocean Variable (EOV) or evaluation variable and some examples of data sources to carry out model evaluation.

Model output	EBV/EOV/Evaluation	Example data sources
Antarctic krill abundance/biomass	Species abundance/biomass	OBIS-GBIF COPEPOD (COPEPOD, 2019) KRILLBASE (Atkinson et al., 2017)

Antarctic krill catches	Species catches	FishMIP reconstructed catch CCAMLR KRILLBASE (Atkinson et al., 2017)
Plankton size spectra	Total community spectrum	Pelagic Size Structure database (PSSdb) (Dugenne et al., 2023)
Mesopelagic fish biomass	Total, functional group, and species biomass	Myctobase (Woods et al., 2022)
Demersal fish abundance and biomass	Total & species abundance/biomass	OBIS-GBIF Survey data (Duhamel et al., 2019)
Demersal fish catches	Total & species catch	FishMIP reconstructed catch CCAMLR: https://fisheryreports.ccamlr.org/
Penguin/seal/other seabird abundance	Total, functional group, and species abundance	CCAMLR Ecosystem Monitoring Program (CEMP)
Whale abundance	Total, functional group, and species abundance	OBIS-GBIF
Whale biomass	Total, functional group, and species biomass	OBIS-GBIF
Whale catch	Total, functional group, and species	IWC catch
Trophic structure	Diet, trophic level	SCAR Southern Ocean Diet and Energetics Database (SCAR, 2018)

Fisheries dependent and independent survey data, such as those conducted in the Kerguelen region (Duhamel et al., 2019), are essential for parameterizing and calibrating MEMs (Subramaniam et al., 2022). It is crucial to avoid duplication in the data used for parameterizing and testing models (McCormack et al., 2021). Additionally, integrating reconstructed catch data that FishMIP has provided for modellers to use in model evaluation is vital, and a comparable product exists for the Sea Around Us fish catch data set (Pauly et al., 2020). Regional fisheries catches are publicly available from CCAMLR (https://fisheryreports.ccamlr.org/). Whaling catch data are available from the IWC (https://iwc.int/scientific-research/data-availability) upon request.

4 Discussion

Our results show that the FishMIP 3a model evaluation protocol is suitable, albeit with extensions, for the initial phase of SOMEME to conduct model evaluation for regional MEMs in the Southern Ocean. Extensions include historical whaling activity while establishing a baseline for sea ice processes in ecosystems, allowing for attribution of past change. To this end, we provide a framework for simulation experiments, climate forcing and fishing and whaling effort on a regional MEM basis, as well as recommending observational data for use in model evaluation. The FishMIP 3b climate projection protocol, that combines both climate and future fishing scenarios, is still under development for Track B (Maury et al. this issue) and will require a similar assessment to determine what extensions are needed to ensure relevance for Southern Ocean, and other regions. As a preliminary step, our comparison of a broader suite of 11 CMIP6 ESMs alongside the default two CMIP6 ESMs used in FishMIP 3b future projections without fishing (Tittensor et al., 2021), show that to adequately capture uncertainties in higher trophic level and sea ice variables, other ESMs should be considered for the Southern Ocean, alongside a common standard applied globally. We also identify future model development priorities and data requirements, including physical, lower trophic level, and higher trophic level data to be able to assess implications of climate change and support fisheries policy relevant scenarios (MEASO) in the Southern Ocean.

4.1 Climate forcing

We set out to address whether using a global forced-ocean-biogeochemistry model with high resolution for a regional focus (i.e., GFDL-JRA) was fit-for-purpose to carry out FishMIP 3a, model evaluation through detection and attribution of past ecosystem change in Southern Ocean regions. The comparisons of forcing fields for SST, surface phytoplankton biomass and sea ice from JRA55-do to observational data suggests they are broadly fit-for-purpose within the protocol for regional MEMs in the Southern Ocean. There are many benefits in using this standardised ocean model forcing that aligns with FishMIP 3a. If we intend on future polar cross comparisons, Arctic and Antarctic MEMs would need to be forced by the same ocean model forcing fields, and as such we need standard inputs. However, there is still notable uncertainty in phytoplankton biomass (Figure S5 & S8), which additionally is not directly linked to the JRA55-do sea ice concentration MEM forcing variable. While we do not view this as a major issue for initial MEM evaluation hindcast simulations, other reanalysis forced ocean-biogeochemical models or state estimates could be considered in the future, especially those run at high resolution and with prognostic sea-ice variables saved. ACCESS-OM2-01 is a high-resolution global ocean-sea ice coupled model (Kiss et al., 2020) forced with the JRA-55 atmospheric reanalysis product (Tsujino et al., 2018) and presents another, potentially higher spatial resolution product. But it currently lacks the level of complexity in lower trophic levels required for FishMIP MEMs, with only one phytoplankton and one zooplankton group (Rohr et al., 2023). However, ongoing developments of ACCESS-OM2-01 suggest this is likely to change in the near future.

To carry out future climate scenario projections, climate forcings that are based on fully-coupled ESMs are required to capture climate dynamics and long-term variability. Despite advances in sea-ice representation from CMIP5 to CMIP6, ESMs are still lacking in their capacity to represent sea-ice dynamics at a regional scale (Casagrande et al., 2023). Our case-study evaluating 11 ESMs highlights high levels of uncertainty in climate forcing in the historical period for the Southern Ocean, with inter-model variability increasing and model skill reducing as the spatial comparison became more regionalised (Figures S7-S9, Tables S3-S5). We face significant challenges in accurately predicting changes in marine ecosystems due to these highlighted uncertainties. This uncertainty at the ESM level can propagate to MEMs, affecting our ability to project changes in important marine biogeochemical processes such as net primary productivity, zooplankton grazing, mesozooplankton biomass, and carbon export (Henson et al., 2022; Petrik et al., 2022; Rohr et al., 2023; Tagliabue et al., 2021). For example, variations in phytoplankton biomass due to different rates of grazing by zooplankton can substantially alter estimates of carbon transfer through marine food webs, impacting predictions of carbon export to deeper ocean layers, a process crucial for long-term carbon sequestration. In addition, MEM-ESM two-way coupling is an important future direction to incorporate key biogeochemical and ecological feedback related to climate change (Rohr et al., 2023), and is necessary to incorporate potential ocean-climate feedbacks independent of carbon cycling. Phytoplankton and zooplankton are known to release cloud-forming aerosols, which can lead to substantial modification to earth's radiative budget, especially in the Southern Ocean (Mallet et al., 2023; Meskhidze & Nenes, 2006). Thus, improving phytoplankton cycling through to higher trophic level coupling could have a profound effect on our ability to accurately simulate Southern Ocean climate. Further complexity is added by the regional variability in these processes. For instance, uncertainties in how phytoplankton respond to nutrient availability directly impact the predictions of regional net primary productivity. There are hints of increasing iron limitation associated with the changing light field in the Southern Ocean (Ryan-Keogh et al., 2023) that, if continued, potentially herald losses in future primary production. Yet, almost all ESMs as part of CMIP6 project exhibit increasing rates of primary production and standing stocks of phytoplankton biomass (Kwiatkowski et al., 2020). These uncertainties underscore the need to further assess key nutrient cycling processes (Boyd et al., 2024), and the requirement for refined observational data and model inter-comparisons to improve the predictive capabilities of both ESMs and MEMs regarding these important oceanic functions. By carrying out a regional assessment of ESMs and establishing a standardised protocol via SOMEME, we aim to highlight areas in particular need for refined ESM forcings. We envision following a similar staged assessment of climate forcing for Track B to fulfil a crucial step in building confidence in future projections for the Southern Ocean by enabling us to assess ESM and MEM-side uncertainty. This also suggests a potential requirement to assess higher resolution ocean-sea ice models for our protocol extension for Track B, future scenarios. This could also include considering ESM climate forcings that use reanalysis-based products for bias-adjustment, provided the inputs are assessed and the resolution is appropriate for regional-scale marine ecosystem models.

4.2 Linking ESM forcing to regional MEM ecological processes

Ecological processes that are critical in determining the response of marine life to climate change are often poorly understood, with an associated lack of information and data for testing or are fundamentally difficult to represent in ecological models (Murphy et al., 2016). Links between sea-ice habitat and life history and mortality are lacking or not well resolved in many models, resulting in large associated uncertainty. Given the high uncertainty of change in total consumer biomass in key areas (Figure 1 B,C), the impact of sea-ice habitat loss could be an additional source of uncertainty in ecosystem resilience to current and future changes that are not well covered by current projections for animal biomass. Given the already bleak outlook projected for some iconic species, such as the emperor penguin (*Aptenodytes forsteri*; Fretwell & Trathan, 2019; Trathan et al., 2020), and the consequences of sea-ice habitat loss already occurring such as mass mortality of emperor penguin chicks (Fretwell et al., 2023), improved representation of these processes is vital for ecosystem modelling in the Southern Ocean.

Representing sea-ice related ecological processes in marine ecosystem models (MEMs) remains an area of significant uncertainty, particularly in the context of ecological links that are critical for both regional and global assessments (Dahood et al., 2019). Marine ecosystem projections for the Arctic Ocean face parallel challenges with uncertainty around sea ice and associated ecological processes propagating from ESMs to MEMs (Mason et al., this issue), so lessons learned from model integration and improvement in the Southern Ocean could help improve science-based decision-making for both polar regions. Therefore, the model evaluation and socioeconomic scenarios used in SOMEME could also be applied to research and planning for future fisheries management and marine ecosystem change in the Arctic.

4.3 Ecosystem assessment using SOMEME

To summarise information about ecosystem structure and function across models and to quantify uncertainties, outputs from the diverse set of MEMs are combined into an ensemble. A recent assessment of Ecopath models from four regions in the Southern Ocean highlights a number of ways to assess outputs across regional MEMs robustly (Hill et al., 2021). Hill et al. (2021) identified several effective methodologies to account for the inherent variations caused by distinct approaches used in each regional MEM, which they refer to as "model personality". Firstly, converting all models to a common currency, such as from wet mass to organic carbon, is essential for standardising comparisons and ensuring that outputs are evaluated on a consistent basis. Furthermore, aggregating species into common functional groups across different models can significantly reduce discrepancies arising from varied classification systems, thereby harmonising the representation of ecosystem components. Another critical step involves the standardisation of energetic parameters, such as consumption to biomass and production to biomass ratios, across models. This standardisation helps to neutralise differences due to arbitrary parameter choices and focuses the comparison on structural differences in the ecosystems.

Employing robust model metrics that are insensitive to absolute biomass values, such as connectivity and network analysis indices, also provides a clearer insight into ecosystem dynamics, independent of their scale. Additionally, carefully evaluating regional differences in biomass and feeding relationships, while controlling for structural uncertainty in MEMs is crucial (Reum et al., 2024). This approach not only helps in distinguishing genuine ecological differences across regions but also enhances our understanding of how regional characteristics influence ecosystem dynamics. Finally, reconciling and balancing different model outputs by adjusting known biases ensures the reliability and consistency of comparisons, thus providing a robust framework for evaluating and understanding MEMs. This comprehensive approach is essential for isolating true ecological insights from artefacts introduced by differing model constructions. All MEMs should be subjected to systematic validation and uncertainty assessments when the tools to do so have become sufficiently mature (Rynne et al., this issue; Steenbeek et al., 2024).

Moreover, projecting the impacts of climate change on fisheries with confidence is vital. Ecosystem models should provide projected catches for key species such as Antarctic krill and toothfishes, which are essential for managing sustainable fisheries. These projections help in understanding potential shifts in species abundance and distribution, allowing for adaptive management strategies in fisheries to mitigate the impacts of climate change. Standardising these ecological and fishery-related outputs across ecosystem models facilitates comprehensive analyses, aiding conservation efforts and informed policymaking in response to climate challenges. To ensure outputs include those that are comparable for detection of past ecosystem changes, we must also consider the availability of observational data and whether it is fit for purpose for model intercomparison in the Southern Ocean regional model domains.

4.4 Enhancing species-specific processes and regional MEM representation

Future work will benefit from assessment of biomass projections among food web models that resolve trophic linkages versus species-specific models that better resolve life-history and habitats. The application of this approach would be useful for key species that present nuanced relationships with their biophysical environment, such as Antarctic krill. The environmental drivers that influence krill population success are highly dependent on life-history stage, which for krill is complex and thought to be synchronised with seasonal cycles of sea ice and primary production (Kawaguchi et al., 2007; Nicol, 2006). In particular, the autumn-winter environment likely exerts a strong control on the recruitment of larvae into the post-larval population the following spring (Meyer, 2012; Murphy et al., 2007). Larval krill were initially viewed as sea ice-obligate over winter, their survival and recruitment being determined by the availability of sea ice (Atkinson et al., 2004; Siegel & Loeb, 1995). However, in certain environments, alternate mechanisms may enable larvae to overwinter without sea ice, making the relationship with sea-ice more facultative (Jia et al., 2016; Reiss et al., 2017; Walsh et al., 2020). While these conceptual models are all plausible, the mechanisms remain challenging to empirically validate in the field due to the large spatio-temporal scales over which these processes integrate (Kohlbach et al., 2017; Veytia et al., 2021). A species-specific framework complimenting the MEM could provide a robust approach for hypothesis testing, explicitly examining how empirical knowledge gaps contribute to uncertainty in future projections.

Numerous MEMs exist across the Southern Ocean that were unable to be considered for the candidate set proposed in this iteration of SOMEME (Figure S10, Table S6), due to limited ability to continue model development and carry out simulations. As the capacity to incorporate additional MEMs increases, the SOMEME protocol and data assimilation and integration frameworks will ease the incorporation of a more comprehensive regional MEM coverage for the Southern Ocean. We expect an increase in capacity due to an expanding network of collaborators, as well as advances in climate and ecological model development (Christin et al., 2019; Nguyen et al., 2023) and the integration of artificial intelligence tools with ecosystem modelling approaches. Given the highly regional nature of current projections, this will build confidence in incorporating information from SOMEME into management and policy decision making.

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Data

Scripts, and associated data, detailing the complete workflow for this manuscript are available in R and Python under an open licence in: GitHub [https://github.com/fish-MIP/SOMEME/]; and Zenodo [https://doi.org/10.5281/zenodo.11089934].

References

Adcroft, A., Anderson, W., Balaji, V., Blanton, C., Bushuk, M., Dufour, C. O., et al. (2019). The GFDL Global Ocean and Sea Ice Model OM4.0: Model Description and Simulation Features. *Journal of Advances in Modeling Earth Systems*, *11*(10), 3167–3211. https://doi.org/10.1029/2019MS001726

Allison, C. (2020). IWC individual catch database (Version 7.1 released 23 December 2020) [Data set]. 135 Station Road, Impington, Cambridge, CB24 9NP UK: International Whaling Commission.

Atkinson, A., Siegel, V., Pakhomov, E., & Rothery, P. (2004). Long-term decline in krill stock and increase in salps within the Southern Ocean. *Nature*, *432*(7013), 100–103. https://doi.org/10.1038/nature02996

Atkinson, A., Shreeve, R. S., Hirst, A. G., Rothery, P., Tarling, G. A., Pond, D. W., et al. (2006). Natural growth rates in Antarctic krill (*Euphausia superba*): II. Predictive models based on food, temperature, body length, sex, and maturity stage. *Limnology and Oceanography*, *51*(2), 973–987. https://doi.org/10.4319/lo.2006.51.2.0973

Atkinson, A., Hill, S. L., Pakhomov, E. A., Siegel, V., Anadon, R., Chiba, S., et al. (2017). KRILLBASE: a circumpolar database of Antarctic krill and salp numerical densities, 1926–2016. *Earth System Science Data*, *9*(1), 193–210. https://doi.org/10.5194/essd-9-193-2017

Audzijonyte, A., Gorton, R., Kaplan, I., & Fulton, E. A. (2017a). *Atlantis User's Guide Part I: General Overview, Physics and Ecology* (report). University of Tasmania. Retrieved from https://figshare.utas.edu.au/articles/report/Atlantis_User_s_Guide_Part_I_General_Overview_Physics_and_Ecology/23199212/1

Audzijonyte, A., Gorton, R., Kaplan, I., & Fulton, E. A. (2017b). *Atlantis User's Guide Part II: Socio-Economics* (report). University of Tasmania. Retrieved from https://figshare.utas.edu.au/articles/report/Atlantis_User_s_Guide_Part_II_Socio-Economics/23199215/1

Audzijonyte, A., Delius, G. W., Stuart-Smith, R. D., Novaglio, C., Edgar, G. J., Barrett, N. S., & Blanchard, J. L. (2023). Changes in sea floor productivity are crucial to understanding the impact of climate change in temperate coastal ecosystems according to a new size-based model. *PLOS Biology*, *21*(12), e3002392. https://doi.org/10.1371/journal.pbio.3002392

Bentley, J. W., Chagaris, D., Coll, M., Heymans, J. J., Serpetti, N., Walters, C. J., & Christensen, V. (2024). Calibrating ecosystem models to support ecosystem-based management of marine systems. *ICES Journal of Marine Science*, *81*(2), 260–275. https://doi.org/10.1093/icesjms/fsad213

Blanchard, J. L., Novaglio, C., Maury, O., Harrison, C. S., Petrik, C. M., Arcos, L. D. F., et al. (2024, January 22). Detecting, attributing, and projecting global marine ecosystem and fisheries change: FishMIP 2.0. https://doi.org/10.22541/essoar.170594183.33534487/v1

Bonnet-Lebrun, A.-S., Sweetlove, M., Griffiths, H. J., Sumner, M., Provoost, P., Raymond, B., et al. (2023). Opportunities and limitations of large open biodiversity occurrence databases in the context of a Marine Ecosystem Assessment of the Southern Ocean. *Frontiers in Marine Science*, *10*. https://doi.org/10.3389/fmars.2023.1150603

Boyd, P. W., Arrigo, K. R., Ardyna, M., Halfter, S., Huckstadt, L., Kuhn, A. M., et al. (2024). The role of biota in the Southern Ocean carbon cycle. *Nature Reviews Earth & Environment*, 1–19. https://doi.org/10.1038/s43017-024-00531-3

Casagrande, F., Stachelski, L., & de Souza, R. B. (2023). Assessment of Antarctic sea ice area and concentration in Coupled Model Intercomparison Project Phase 5 and Phase 6 models. *International Journal of Climatology*, *43*(3), 1314–1332. https://doi.org/10.1002/joc.7916

Cavanagh, R. D., Murphy, E. J., Bracegirdle, T. J., Turner, J., Knowland, C. A., Corney, S. P., et al. (2017). A Synergistic Approach for Evaluating Climate Model Output for Ecological Applications. *Frontiers in Marine Science*, *4*. https://doi.org/10.3389/fmars.2017.00308

Christin, S., Hervet, É., & Lecomte, N. (2019). Applications for deep learning in ecology. *Methods in Ecology and Evolution*, *10*(10), 1632–1644. https://doi.org/10.1111/2041-210X.13256

Cinner, J. E., Caldwell, I. R., Thiault, L., Ben, J., Blanchard, J. L., Coll, M., et al. (2022). Potential impacts of climate change on agriculture and fisheries production in 72 tropical coastal communities. *Nature Communications*, *13*(1), 3530. https://doi.org/10.1038/s41467-022-30991-4

Constable, A. J., Melbourne-Thomas, J., Muelbert, M. M. C., McCormack, S., Brasier, M., Caccavo, J. A., et al. (2023). *Marine Ecosystem Assessment for the Southern Ocean: Summary for Policymakers*. Integrated Climate and Ecosystem Dynamics in the Southern Ocean, Scientific Committee on Antarctic Research, Scientific Committee on Oceanic Research, Integrated Marine Biosphere Research. https://doi.org/10.5281/zenodo.8359585

Constable, A. J., Costa, D. P., Schofield, O., Newman, L., Urban, E. R., Fulton, E. A., et al. (2016). Developing priority variables ("ecosystem Essential Ocean Variables" — eEOVs) for observing dynamics and change in Southern Ocean ecosystems. *Journal of Marine Systems*, *161*, 26–41. https://doi.org/10.1016/j.jmarsys.2016.05.003

COPEPOD. (2019). The global plankton database [NOAA Tech. Memo. NMFS-F/ST-37]. Retrieved April 28, 2024, from https://www.st.nfms.noaa.gov/copepod

Dahood, A., Watters, G. M., & Mutsert, K. de. (2019). Using sea-ice to calibrate a dynamic trophic model for the Western Antarctic Peninsula. *PLOS ONE*, *14*(4), e0214814. https://doi.org/10.1371/journal.pone.0214814

Dugenne, M., Corrales-Ugalde, M., Luo, J., Kiko, R., O'Brien, T., Irisson, J.-O., et al. (2023). First release of the Pelagic Size Structure database: Global datasets of marine size spectra obtained from plankton imaging devices. *Earth System Science Data Discussions*, 1–41. https://doi.org/10.5194/essd-2023-479

Duhamel, G., Péron, C., Sinègre, R., Chazeau, C., Gasco, N., Hautecoeur, M., et al. (2019). Important readjustments in the biomass and distribution of groundfish species in the northern part of the Kerguelen Plateau and Skiff Bank. In D. C. Welsford, J. Dell, & G. Duhamel (Eds.), *Proceedings of the Second Symposium on The Kerguelen Plateau: Marine Ecosystem and Fisheries* (pp. 135–184). Hobart: CCAMLR.

Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., & Taylor, K. E. (2016). Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geoscientific Model Development*, *9*(5), 1937–1958. https://doi.org/10.5194/gmd-9-1937-2016

Fretwell, P. T., & Trathan, P. N. (2019). Emperors on thin ice: three years of breeding failure at Halley Bay. *Antarctic Science*, *31*(3), 133–138. https://doi.org/10.1017/S0954102019000099

Fretwell, P. T., Boutet, A., & Ratcliffe, N. (2023). Record low 2022 Antarctic sea ice led to catastrophic breeding failure of emperor penguins. *Communications Earth &*

Environment, *4*(1), 1–6. https://doi.org/10.1038/s43247-023-00927-x

Frieler, K., Volkholz, J., Lange, S., Schewe, J., Mengel, M., del Rocío Rivas López, M., et al. (2024). Scenario setup and forcing data for impact model evaluation and impact attribution within the third round of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP3a). *Geoscientific Model Development*, *17*(1), 1–51. https://doi.org/10.5194/gmd-17-1-2024

Gimeno, M., Giménez, J., Chiaradia, A., Davis, L. S., Seddon, P. J., Ropert-Coudert, Y., et al. (2024). Climate and human stressors on global penguin hotspots: Current assessments for future conservation. *Global Change Biology*, *30*(1), e17143. https://doi.org/10.1111/gcb.17143

Graff, J. R., Westberry, T. K., Milligan, A. J., Brown, M. B., Dall'Olmo, G., Dongen-Vogels, V. van, et al. (2015). Analytical phytoplankton carbon measurements spanning diverse ecosystems. *Deep Sea Research Part I: Oceanographic Research Papers*, *102*, 16–25. https://doi.org/10.1016/j.dsr.2015.04.006

Green, D. B., Bestley, S., Corney, S. P., Trebilco, R., Lehodey, P., & Hindell, M. A. (2021). Modeling Antarctic Krill Circumpolar Spawning Habitat Quality to Identify Regions With Potential to Support High Larval Production. *Geophysical Research Letters*, *48*(12), e2020GL091206. https://doi.org/10.1029/2020GL091206

Green, D. B., Titaud, O., Bestley, S., Corney, S. P., Hindell, M. A., Trebilco, R., et al. (2023). KRILLPODYM: a mechanistic, spatially resolved model of Antarctic krill distribution and abundance. *Frontiers in Marine Science*, *10*. Retrieved from https://www.frontiersin.org/articles/10.3389/fmars.2023.1218003

Heneghan, R. F., Galbraith, E., Blanchard, J. L., Harrison, C., Barrier, N., Bulman, C., et al.

(2021). Disentangling diverse responses to climate change among global marine ecosystem models. *Progress in Oceanography*, *198*, 102659. https://doi.org/10.1016/j.pocean.2021.102659

Henson, S. A., Laufkötter, C., Leung, S., Giering, S. L. C., Palevsky, H. I., & Cavan, E. L. (2022). Uncertain response of ocean biological carbon export in a changing world. *Nature Geoscience*, *15*(4), 248–254. https://doi.org/10.1038/s41561-022-00927-0

Hill, S. L., Pinkerton, M. H., Ballerini, T., Cavan, E. L., Gurney, L. J., Martins, I., & Xavier, J. C. (2021). Robust model-based indicators of regional differences in food-web structure in the Southern Ocean. *Journal of Marine Systems*, *220*, 103556. https://doi.org/10.1016/j.jmarsys.2021.103556

Hill, S. L., Keeble, K., Atkinson, A., & Murphy, E. J. (2012). A foodweb model to explore uncertainties in the South Georgia shelf pelagic ecosystem. *Deep Sea Research Part II: Topical Studies in Oceanography*, *59–60*, 237–252. https://doi.org/10.1016/j.dsr2.2011.09.001

Houle, J. E., de Castro, F., Cronin, M. A., Farnsworth, K. D., Gosch, M., & Reid, D. G. (2016). Effects of seal predation on a modelled marine fish community and consequences for a commercial fishery. *Journal of Applied Ecology*, *53*(1), 54–63. https://doi.org/10.1111/1365-2664.12548

Jia, Z., Swadling, K. M., Meiners, K. M., Kawaguchi, S., & Virtue, P. (2016). The zooplankton food web under East Antarctic pack ice – A stable isotope study. *Deep Sea Research Part II: Topical Studies in Oceanography*, *131*, 189–202. https://doi.org/10.1016/j.dsr2.2015.10.010

Kawaguchi, S., Yoshida, T., Finley, L., Cramp, P., & Nicol, S. (2007). The krill maturity cycle: a conceptual model of the seasonal cycle in Antarctic krill. *Polar Biology*, *30*(6), 689–698. https://doi.org/10.1007/s00300-006-0226-2

Kiss, A. E., Hogg, A. M., Hannah, N., Boeira Dias, F., Brassington, G. B., Chamberlain, M. A., et al. (2020). ACCESS-OM2 v1.0: a global ocean–sea ice model at three resolutions. *Geoscientific Model Development*, *13*(2), 401–442. https://doi.org/10.5194/gmd-13-401-2020

Kohlbach, D., Lange, B. A., Schaafsma, F. L., David, C., Vortkamp, M., Graeve, M., et al. (2017). Ice Algae-Produced Carbon Is Critical for Overwintering of Antarctic Krill Euphausia superba. *Frontiers in Marine Science*, *4*. https://doi.org/10.3389/fmars.2017.00310

Kwiatkowski, L., Torres, O., Bopp, L., Aumont, O., Chamberlain, M., Christian, J. R., et al. (2020). Twenty-first century ocean warming, acidification, deoxygenation, and upper-ocean nutrient and primary production decline from CMIP6 model projections. *Biogeosciences*, *17*(13), 3439–3470. https://doi.org/10.5194/bg-17-3439-2020

Law, R. M., Ziehn, T., Matear, R. J., Lenton, A., Chamberlain, M. A., Stevens, L. E., et al. (2017). The carbon cycle in the Australian Community Climate and Earth System Simulator (ACCESS-ESM1)–Part 1: Model description and pre-industrial simulation. *Geoscientific Model Development*, *10*(7), 2567–2590.

Liu, X., Stock, C. A., Dunne, J. P., Lee, M., Shevliakova, E., Malyshev, S., & Milly, P. C. D. (2021). Simulated Global Coastal Ecosystem Responses to a Half-Century Increase in River Nitrogen Loads. *Geophysical Research Letters*, *48*(17), e2021GL094367. https://doi.org/10.1029/2021GL094367

Lotze, H. K., Tittensor, D. P., Bryndum-Buchholz, A., Eddy, T. D., Cheung, W. W. L., Galbraith, E. D., et al. (2019). Global ensemble projections reveal trophic amplification of ocean biomass declines with climate change. *Proceedings of the National Academy of Sciences*, *116*(26), 12907–12912. https://doi.org/10.1073/pnas.1900194116

Mallet, M. D., Humphries, R. S., Fiddes, S. L., Alexander, S. P., Altieri, K., Angot, H., et al. (2023). Untangling the influence of Antarctic and Southern Ocean life on clouds. *Elementa: Science of the Anthropocene*, *11*(1), 00130. https://doi.org/10.1525/elementa.2022.00130

Mason, J. G., Bryndum-Buchholz, A., Palacios-Abrantes, J., Badhe, R., Morgante, I., et al. (this issue). Key Uncertainties and Modeling Needs for Managing Living Marine Resources in the Future Arctic Ocean. *Earth's Future*.

Maury, O., Tittensor, D. P., Eddy, T. D., Allison, E. H., Bahri, N., Barrier, N., et al. (this issue). The Ocean System Pathways (OSPs): a new scenario and simulation framework to investigate the future of the world fisheries.

McCormack, S. A., Melbourne-Thomas, J., Trebilco, R., Blanchard, J. L., & Constable, A. (2020). Alternative energy pathways in Southern Ocean food webs: Insights from a balanced model of Prydz Bay, Antarctica. *Deep Sea Research Part II: Topical Studies in Oceanography*, *174*, 104613. https://doi.org/10.1016/j.dsr2.2019.07.001

McCormack, S. A., Melbourne-Thomas, J., Trebilco, R., Griffith, G., Hill, S. L., Hoover, C., et al. (2021). Southern Ocean Food Web Modelling: Progress, Prognoses, and Future Priorities for Research and Policy Makers. *Frontiers in Ecology and Evolution*, *9*. Retrieved from https://www.frontiersin.org/articles/10.3389/fevo.2021.624763

Meier, W. N., Fetterer, F., Windnagel, K., & Stewart, J. S. (2021). NOAA/NSIDC Climate Data Record of Passive Microwave Sea Ice Concentration (Version 4) [Data set]. Boulder, Colorado USA: National Snow and Ice Data Center. https://doi.org/10.7265/efmz-2t65

Meredith, M. P., Sommerkorn, M., Cassotta, S., Derksen, C., Ekaykin, A. A., Hollowed, A. B., et al. (2019). Polar Regions. In *The Ocean and Cryosphere in a Changing Climate: Summary for Policymakers* (H.-O. Pörtner, D.C. Roberts, V. MassonDelmotte, P. Zhai, M. Tignor, E. Poloczanska, K. Mintenbeck, A. Alegría, M. Nicolai, A. Okem, J. Petzold, B. Rama, N.M. Weyer (eds.), pp. 203–320). Cambridge University Press, Cambridge, UK and New York, NY, USA: Intergovernmental Panel on Climate Change. Retrieved from https://doi.org/10.1017/9781009157964.005.

Meskhidze, N., & Nenes, A. (2006). Phytoplankton and Cloudiness in the Southern Ocean. *Science, 314*(5804), 1419–1423. https://doi.org/10.1126/science.1131779

Meyer, B. (2012). The overwintering of Antarctic krill, Euphausia superba, from an ecophysiological perspective. *Polar Biology*, *35*(1), 15–37. https://doi.org/10.1007/s00300-011-1120-0

Moutier, W., Thomalla, S. J., Bernard, S., Wind, G., Ryan-Keogh, T. J., & Smith, M. E. (2019). Evaluation of Chlorophyll-a and POC MODIS Aqua Products in the Southern Ocean. *Remote Sensing*, *11*(15), 1793. https://doi.org/10.3390/rs11151793

Muller-Karger, F. E., Miloslavich, P., Bax, N. J., Simmons, S., Costello, M. J., Sousa Pinto, I., et al. (2018). Advancing Marine Biological Observations and Data Requirements of the Complementary Essential Ocean Variables (EOVs) and Essential Biodiversity Variables (EBVs) Frameworks. *Frontiers in Marine Science*, *5*. https://doi.org/10.3389/fmars.2018.00211

Murphy, E. J., Cavanagh, R. D., Hofmann, E. E., Hill, S. L., Constable, A. J., Costa, D. P., et al. (2012). Developing integrated models of Southern Ocean food webs: Including ecological complexity, accounting for uncertainty and the importance of scale. *Progress in Oceanography*, *102*, 74–92. https://doi.org/10.1016/j.pocean.2012.03.006

Murphy, E. J., Cavanagh, R. D., Drinkwater, K. F., Grant, S. M., Heymans, J. J., Hofmann, E. E., et al. (2016). Understanding the structure and functioning of polar pelagic ecosystems to predict the impacts of change. *Proceedings of the Royal Society B: Biological Sciences*, *283*(1844), 20161646. https://doi.org/10.1098/rspb.2016.1646

Murphy, E. J., Trathan, P. N., Watkins, J. L., Reid, K., Meredith, M. P., Forcada, J., et al. (2007). Climatically driven fluctuations in Southern Ocean ecosystems. *Proceedings of the Royal Society B: Biological Sciences*, *274*(1629), 3057–3067. https://doi.org/10.1098/rspb.2007.1180

Murphy, E. J., Johnston, N. M., Hofmann, E. E., Phillips, R. A., Jackson, J. A., Constable, A. J., et al. (2021). Global Connectivity of Southern Ocean Ecosystems. *Frontiers in Ecology and Evolution*, *9*. https://doi.org/10.3389/fevo.2021.624451

de Mutsert, K., Coll, M., Steenbeek, J., Ainsworth, C., Buszowski, J., Chagaris, D., et al. (2024). 5.7 - Advances in spatial-temporal coastal and marine ecosystem modeling using Ecospace. In D. Baird & M. Elliott (Eds.), *Treatise on Estuarine and Coastal Science (Second Edition)* (pp. 122–169). Oxford: Academic Press. https://doi.org/10.1016/B978-0-323-90798-9.00035-4

Nguyen, T., Brandstetter, J., Kapoor, A., Gupta, J. K., & Grover, A. (2023, December 18). ClimaX: A foundation model for weather and climate. arXiv. https://doi.org/10.48550/arXiv.2301.10343

Nicol, S. (2006). Krill, Currents, and Sea Ice: Euphausia superba and Its Changing Environment. *BioScience*, *56*(2), 111–120. https://doi.org/10.1641/0006-

3568(2006)056[0111:KCASIE]2.0.CO;2

O'Malley, R. (2015). Oregon state university ocean productivity [Data set]. https://sites.science.oregonstate.edu/ocean.productivity/.

Ortega-Cisneros, K., Fierro-Arcos, D., Lindmark, M., Novaglio, C., Woodworth-Jefcoats, P. A., Eddy, T. D., et al. (this issue). An Integrated Global-to-Regional Scale Workflow for Simulating Climate Change Impacts on Marine Ecosystems. *Earth's Future*.

Pauly, D., Zeller, D., & Palomares, M. L. D. (2020). Sea Around Us Concepts, Design and Data [Data set]. seaaroundus.org.

Peck, L. S., Webb, K. E., & Bailey, D. M. (2004). Extreme sensitivity of biological function to temperature in Antarctic marine species. *Functional Ecology*, *18*(5), 625–630. https://doi.org/10.1111/j.0269-8463.2004.00903.x

Pecl, G. T., Araujo, M. B., Bell, J. D., Blanchard, J., Bonebrake, T. C., Chen, I. C., et al. (2017). Biodiversity redistribution under climate change: impacts on ecosystems and human well-being. *Science*.

Pethybridge, H. R., Fulton, E. A., Hobday, A. J., Blanchard, J., Bulman, C. M., Butler, I. R., et al. (2020). Contrasting Futures for Australia's Fisheries Stocks Under IPCC RCP8.5 Emissions – A Multi-Ecosystem Model Approach. *Frontiers in Marine Science*, *7*. Retrieved from https://www.frontiersin.org/articles/10.3389/fmars.2020.577964

Petrik, C. M., Luo, J. Y., Heneghan, R. F., Everett, J. D., Harrison, C. S., & Richardson, A. J. (2022). Assessment and Constraint of Mesozooplankton in CMIP6 Earth System Models. *Global Biogeochemical Cycles*, *36*(11), e2022GB007367. https://doi.org/10.1029/2022GB007367

Pinkerton, M. H., & Bradford-Grieve, J. M. (2014). Characterizing foodweb structure to identify potential ecosystem effects of fishing in the Ross Sea, Antarctica. *ICES Journal of Marine Science*, *71*(7), 1542–1553. https://doi.org/10.1093/icesjms/fst230

Pinkerton, M.H., Bradford-Grieve, J. M., & Hanchet, S. M. (2010). A balanced model of the food web of the Ross Sea, Antarctica. *CCAMLR Science*, *17*, 1–31.

Plagányi, É. E., Punt, A. E., Hillary, R., Morello, E. B., Thébaud, O., Hutton, T., et al. (2014). Multispecies fisheries management and conservation: tactical applications using models of intermediate complexity. *Fish and Fisheries*, *15*(1), 1–22. https://doi.org/10.1111/j.1467-2979.2012.00488.x

Reiss, C. S., Cossio, A., Santora, J. A., Dietrich, K. S., Murray, A., Mitchell, B. G., et al. (2017). Overwinter habitat selection by Antarctic krill under varying sea-ice conditions: implications for top predators and fishery management. *Marine Ecology Progress Series*, *568*, 1–16. https://doi.org/10.3354/meps12099

Reum, J. C. P., Woodworth-Jefcoats, P., Novaglio, C., Forestier, R., Audzijonyte, A., Gårdmark, A., et al. (2024). Temperature-Dependence Assumptions Drive Projected Responses of Diverse Size-Based Food Webs to Warming. *Earth’s Future*, *12*(3), e2023EF003852. https://doi.org/10.1029/2023EF003852

Rohr, T., Richardson, A. J., Lenton, A., Chamberlain, M. A., & Shadwick, E. H. (2023). Zooplankton grazing is the largest source of uncertainty for marine carbon cycling in CMIP6 models. *Communications Earth & Environment*, *4*(1), 1–22. https://doi.org/10.1038/s43247-023-00871-w

Rousseau, Y., Blanchard, J. L., Novaglio, C., Pinnell, K. A., Tittensor, D. P., Watson, R. A., & Ye, Y. (2024). A database of mapped global fishing activity 1950–2017. *Scientific Data*, *11*(1), 48. https://doi.org/10.1038/s41597-023-02824-6

Ryan-Keogh, T. J., Thomalla, S. J., Monteiro, P. M. S., & Tagliabue, A. (2023). Multidecadal trend of increasing iron stress in Southern Ocean phytoplankton. *Science*, *379*(6634), 834–840. https://doi.org/10.1126/science.abl5237

Rynne, N., Novaglio, C., Blanchard, J. L., Bianchi, D., Christensen, V., Coll, M., et al. (this issue). Skill assessment framework for the Fisheries and Marine Ecosystem Model Intercomparison Project. *Earth's Future*.

Schoeman, D. S., Gupta, A. S., Harrison, C. S., Everett, J. D., Brito-Morales, I., Hannah, L., et al. (2023). Demystifying global climate models for use in the life sciences. *Trends in Ecology & Evolution*, *38*(9), 843–858. https://doi.org/10.1016/j.tree.2023.04.005

Scientific Committee on Antarctic Research. (2018). SCAR Southern Ocean Diet and Energetics Database (Version 3) [Data set]. Australian Antarctic Data Centre. Retrieved from doi:10.26179/5d1aec22f41d5

Scott, F., Blanchard, J. L., & Andersen, K. H. (2014). mizer: an R package for multispecies, trait-based and community size spectrum ecological modelling. *Methods in Ecology and Evolution*, *5*(10), 1121–1125. https://doi.org/10.1111/2041-210X.12256

Siegel, V., & Loeb, V. (1995). Recruitment of Antarctic krill Euphausia superba and possible causes for its variability. *Marine Ecology Progress Series*, *123*, 45–56. https://doi.org/10.3354/meps123045

Steenbeek, J., Ortega, P., Bernardello, R., Christensen, V., Coll, M., Exarchou, E., et al. (2024). Making Ecosystem Modeling Operational–A Novel Distributed Execution Framework to Systematically Explore Ecological Responses to Divergent Climate Trajectories. *Earth's Future*, *12*(3), e2023EF004295. https://doi.org/10.1029/2023EF004295

Stock, A., Murray, C. C., Gregr, E. J., Steenbeek, J., Woodburn, E., Micheli, F., et al. (2023).

Exploring multiple stressor effects with Ecopath, Ecosim, and Ecospace: Research designs, modeling techniques, and future directions. *Science of The Total Environment*, *869*, 161719. https://doi.org/10.1016/j.scitotenv.2023.161719

Stock, C. A., Dunne, J. P., Fan, S., Ginoux, P., John, J., Krasting, J. P., et al. (2020). Ocean Biogeochemistry in GFDL's Earth System Model 4.1 and Its Response to Increasing Atmospheric CO2. *Journal of Advances in Modeling Earth Systems*, *12*(10), e2019MS002043. https://doi.org/10.1029/2019MS002043

Stoeckl, N., Adams, V., Baird, R., Boothroyd, A., Costanza, R., Hatton MacDonald, D., et al. (2024). The value of Antarctic and Southern Ocean ecosystem services. *Nature Reviews Earth & Environment*, *5*(3), 153–155. https://doi.org/10.1038/s43017-024-00523-3

Subramaniam, R. C., Corney, S. P., Swadling, K. M., & Melbourne-Thomas, J. (2020). Exploring ecosystem structure and function of the northern Kerguelen Plateau using a mass-balanced food web model. *Deep Sea Research Part II: Topical Studies in Oceanography*, *174*, 104787. https://doi.org/10.1016/j.dsr2.2020.104787

Subramaniam, R. C., Corney, S. P., Melbourne-Thomas, J., Péron, C., Ziegler, P., & Swadling, K. M. (2022). Spatially explicit food web modelling to consider fisheries impacts and ecosystem representation within Marine Protected Areas on the Kerguelen Plateau. *ICES Journal of Marine Science*, *79*(4), 1327–1339. https://doi.org/10.1093/icesjms/fsac056

Tagliabue, A., Kwiatkowski, L., Bopp, L., Butenschön, M., Cheung, W., Lengaigne, M., & Vialard, J. (2021). Persistent Uncertainties in Ocean Net Primary Production Climate Change Projections at Regional Scales Raise Challenges for Assessing Impacts on Ecosystem Services. *Frontiers in Climate*, *3*. https://doi.org/10.3389/fclim.2021.738224

Tittensor, D. P., Eddy, T. D., Lotze, H. K., Galbraith, E. D., Cheung, W., Barange, M., et al.

(2018). A protocol for the intercomparison of marine fishery and ecosystem models: Fish-MIP v1.0. *Geoscientific Model Development*, *11*(4), 1421–1442. https://doi.org/10.5194/gmd-11-1421-2018

Tittensor, D. P., Novaglio, C., Harrison, C. S., Heneghan, R. F., Barrier, N., Bianchi, D., et al. (2021). Next-generation ensemble projections reveal higher climate risks for marine ecosystems. *Nature Climate Change*, *11*(11), 973–981. https://doi.org/10.1038/s41558-021-01173-9

Trathan, P. N. (2023). What is needed to implement a sustainable expansion of the Antarctic krill fishery in the Southern Ocean? *Marine Policy*, *155*, 105770. https://doi.org/10.1016/j.marpol.2023.105770

Trathan, P. N., Wienecke, B., Barbraud, C., Jenouvrier, S., Kooyman, G., Le Bohec, C., et al. (2020). The emperor penguin - Vulnerable to projected rates of warming and sea ice loss. *Biological Conservation*, *241*, 108216. https://doi.org/10.1016/j.biocon.2019.108216

Trebilco, R., Melbourne-Thomas, J., & Constable, A. J. (2020). The policy relevance of Southern Ocean food web structure: Implications of food web change for fisheries, conservation and carbon sequestration. *Marine Policy*, *115*, 103832. https://doi.org/10.1016/j.marpol.2020.103832

Tsujino, H., Urakawa, S., Nakano, H., Small, R. J., Kim, W. M., Yeager, S. G., et al. (2018). JRA-55 based surface dataset for driving ocean–sea-ice models (JRA55-do). *Ocean Modelling*, *130*, 79–139. https://doi.org/10.1016/j.ocemod.2018.07.002

Tulloch, V. J. D., Plagányi, É. E., Matear, R., Brown, C. J., & Richardson, A. J. (2018). Ecosystem modelling to quantify the impact of historical whaling on Southern Hemisphere baleen whales. *Fish and Fisheries*, *19*(1), 117–137.

https://doi.org/10.1111/faf.12241

Tulloch, V. J. D., Plagányi, É. E., Brown, C., Richardson, A. J., & Matear, R. (2019). Future recovery of baleen whales is imperiled by climate change. *Global Change Biology, 25*(4), 1263–1281. https://doi.org/10.1111/gcb.14573

Veytia, D., Bestley, S., Kawaguchi, S., Meiners, K. M., Murphy, E. J., Fraser, A. D., et al. (2021). Overwinter sea-ice characteristics important for Antarctic krill recruitment in the southwest Atlantic. *Ecological Indicators*, *129*, 107934. https://doi.org/10.1016/j.ecolind.2021.107934

Walsh, J., Reiss, C. S., & Watters, G. M. (2020). Flexibility in Antarctic krill Euphausia superba decouples diet and recruitment from overwinter sea-ice conditions in the northern Antarctic Peninsula. *Marine Ecology Progress Series*, *642*, 1–19. https://doi.org/10.3354/meps13325

Westberry, T., Behrenfeld, M. J., Siegel, D. A., & Boss, E. (2008). Carbon-based primary productivity modeling with vertically resolved photoacclimation. *Global Biogeochemical Cycles*, *22*(2). https://doi.org/10.1029/2007GB003078

Woods, B., Trebilco, R., Walters, A., Hindell, M., Duhamel, G., Flores, H., et al. (2022). Myctobase, a circumpolar database of mesopelagic fishes for new insights into deep pelagic prey fields. *Scientific Data*, *9*(1), 404. https://doi.org/10.1038/s41597-022-01496-y

Woodworth-Jefcoats, P. A., Blanchard, J. L., & Drazen, J. C. (2019). Relative Impacts of Simultaneous Stressors on a Pelagic Marine Ecosystem. *Frontiers in Marine Science, 6*. https://doi.org/10.3389/fmars.2019.00383

Ziehn, T., Lenton, A., Law, R. M., Matear, R. J., & Chamberlain, M. A. (2017). The carbon cycle in the Australian Community Climate and Earth System Simulator (ACCESS-ESM1)–Part 2: Historical simulations. *Geoscientific Model Development*, *10*(7), 2591–2614.