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Special Collection:
Past and Future of Marine Ecosystems

Key Points:

- Develops a standardized protocol for detecting past ecosystem changes and simulating climate impacts by regional marine ecosystem models
- Details tools such as the Regional Climate Forcing Data Explorer Shiny application to access, visualize, and process climate forcing variables
- The protocol and tools are flexible and can be applied to the different marine ecosystem model types included in Fisheries and Marine Ecosystem Model Intercomparison Project

Supporting Information:

Supporting Information may be found in the online version of this article.

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An Integrated Global-To-Regional Scale Workflow for Simulating Climate Change Impacts on Marine Ecosystems

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Abstract As the urgency to evaluate the impacts of climate change on marine ecosystems increases, there is a need to develop robust projections and improve the uptake of ecosystem model outputs in policy and planning. Standardizing input and output data is a crucial step in evaluating and communicating results, but can be challenging when using models with diverse structures, assumptions, and outputs that address region-specific issues. We developed an implementation framework and workflow to standardize the climate and fishing forcings used by regional models contributing to the Fisheries and Marine Ecosystem Model Intercomparison Project (FishMIP) and to facilitate comparative analyses across models and a wide range of regions, in line with the FishMIP 3a protocol. We applied our workflow to three case study areas-models: the Baltic Sea Mizer, Hawai'i-based Longline fisheries therMizer, and the southern Benguela ecosystem Atlantis marine ecosystem models. We then selected the most challenging steps of the workflow and illustrated their implementation in different model types and regions. Our workflow is adaptable across a wide range of regional models, from non-spatially explicit to spatially explicit and fully-depth resolved models and models that include one or several fishing fleets. This workflow will facilitate the development of regional marine ecosystem model ensembles and enhance future research on marine ecosystem model development and applications, model evaluation and benchmarking, and global-to-regional model comparisons.

Plain Language Summary As the need to understand how climate change impacts marine ecosystems increases, it is crucial to develop reliable projections and improve how ecosystem model outputs are used in policy and planning. Standardizing data used in ecosystem models is essential for evaluating and communicating marine ecosystem model results. However, it can be difficult due to diverse model structures, assumptions, and outputs. We develop an implementation framework and workflow to standardize the climate and fishing data used by regional models participating in the Fisheries and Marine Ecosystem Model Intercomparison Project (FishMIP). We applied our framework to three case study models for the Baltic Sea, the Hawai'i-based Longline fisheries and the southern Benguela ecosystem. By focusing on the most challenging steps of the workflow, our study shows that our workflow is adaptable and how it can be implemented across a wide range of regions and types of ecosystem models. Our workflow will support the development of regional marine ecosystem model ensembles and promote future research on model evaluation and comparisons.

1. Introduction

Climate change is one of the key drivers drastically altering marine and terrestrial ecosystems at rates faster than ever previously recorded (Jaureguiberry et al., 2022; Pörtner et al., 2021). The impacts of climate change differ among regions of the world. Consequently, regionally focused models are needed to meet the needs of considering the effects of climate change at the scales necessary to address the system specific details. Currently, model-based studies project major marine biomass decreases in the tropics by the end of the century, while other areas, such as the Arctic, are expected to experience biomass increases or distribution shifts of economically important species (Cheung et al., 2010; Lotze et al., 2019; Palacios-Abrantes et al., 2022; Rogers et al., 2020; Tittensor et al., 2021). However, the high uncertainty related to these projections can preclude their uptake in decision-making and adaptation planning. Standardized model handling and reporting can help address this by facilitating multi-model comparisons, but also by creating a systematic and repeatable process for those interested in models or their outputs.

Model intercomparisons have been extensively used in climate science to quantify uncertainty in model estimates and projections (Wallach et al., 2016). Their use has been extended to agriculture (Rosenzweig et al., 2013), fisheries and marine ecosystems (Blanchard et al., 2024; Pethybridge et al., 2020; Tittensor et al., 2018), and other sectors (Frieler et al., 2024; IPCC, 2023; Rocklöv et al., 2021). The Fisheries and Marine Ecosystem Model Intercomparison Project (FishMIP) uses ensembles of marine ecosystem models to "better project the long-term impacts of climate change on fisheries and marine ecosystems and support policy development and long-term planning at the global and regional scales" (Novaglio, Bryndum-Buchholz, et al., 2024; Tittensor et al., 2018). As part of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP), FishMIP has developed several protocols (Blanchard et al., 2024; Tittensor et al., 2018) to provide a standardized, structured approach to comparisons of multiple Marine Ecosystem Models (MEMs) with the aim of offering more robust projections of changes in biomass and ecosystem structure globally (Bryndum-Buchholz et al., 2019; Lotze et al., 2019; Tittensor et al., 2021). FishMIP considers both global and regional MEMs, which have been calibrated against observations and are used to make medium- to long-term projections of ecosystem dynamics, structure and functioning under different emissions scenarios (Tittensor et al., 2018). To date, the focus of FishMIP has mostly been on global MEMs because of their similar spatial coverage, they have been developed to address climate impact issues by linking to Earth System Models (ESMs) and focus on very similar broad emergent issues in fisheries and ecology. A diverse set of regional modeling frameworks, including Atlantis, Ecopath with Ecosim, Mizer and OSMOSE, also participate in FishMIP (Audzijonyte et al., 2019; Christensen & Walters, 2004; Christensen et al., 2014; Shin & Cury, 2001). The geographical coverage of FishMIP regional MEMs is still limited (see Figure 1), with areas in Asia, Africa and Central and South America still poorly represented. Due to the patchy coverage of FishMIP regional MEMs and ensembles, regional extractions of global MEM outputs have often been used to inform climate impact assessments in data-limited areas (Blanchard & Novaglio, 2024; Cinner et al., 2022; Tittensor et al., 2018). While such extractions can fill in the knowledge gap, there remains uncertainty as to appropriate ranges of application in terms of system specific characteristics and spatial scale (Eddy et al., 2025).

Regional models were generally not designed to couple directly to ESMs and tend to be much more specific in terms of objectives, temporal and spatial scales, and have primarily focussed on fisheries issues. This and their

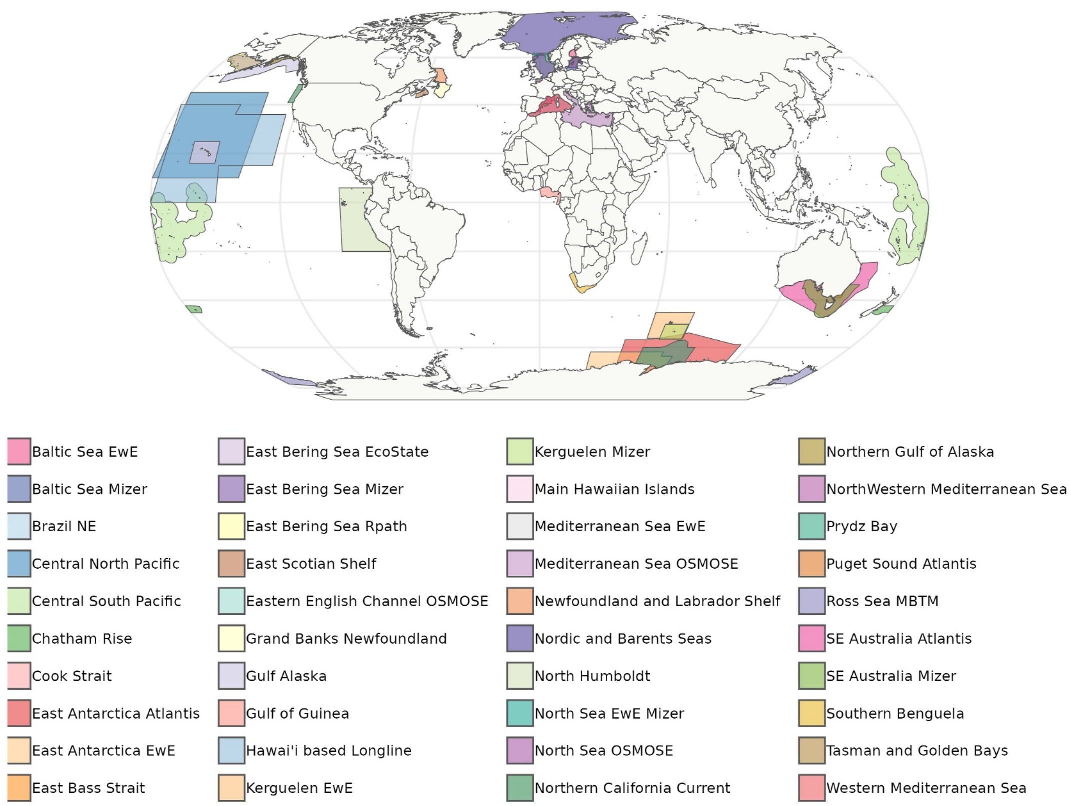

Figure 1. Regional marine ecosystem models participating in FishMIP.

more diverse representation of functional groups and ecosystem processes makes regional models much more heterogeneous in content and configuration, and harder to standardize and compare. Thus, there is a need to develop a framework tailored to implementing FishMIP simulation protocols by the different regional MEM types. In particular, the standardization of input and output data is a crucial step in model intercomparisons (Bahlburg et al., 2023; Tittensor et al., 2018) and this is a challenge for models with different structures, assumptions and outputs representing diverse ecosystems and fisheries worldwide. Here, we develop a framework and workflow that will guide and simplify the implementation of modeling experiments by regional MEMs, thus minimizing barriers to entry and thereby increasing the number of regional models performing simulations in a coordinated and standardized manner. Moreover, standardizing the climate and fishing effort forcings across regional and global models will facilitate comparisons of MEM outputs at different spatial scales, and evaluate the applicability of global models to predict future outcomes in data-poor regions (see Eddy et al., 2025).

This paper presents an overview of the approaches used by the different types of FishMIP regional MEMs in conducting climate-impact simulations, and describes an implementation framework to foster future intercomparisons of MEMs within and across a wide range of regions to ensure they produce assessments that can support policy. The ISIMIP 3a (Frieler et al., 2024) and FishMIP 3a (Blanchard et al., 2024) protocols are used to test the applicability of developing an implementation framework for FishMIP regional MEMs. FishMIP 3a is the first of the two tracks of the current simulation framework (FishMIP 2.0), which addresses the lack of standardized historical fishing data, and evaluates models against observations before carrying out future projections (Blanchard et al., 2024).

2. Materials and Methods

2.1. Marine Ecosystem Model Types in FishMIP

To date, FishMIP includes four regional marine ecosystem modeling frameworks: Atlantis, Ecopath with Ecosim (EwE), Mizer/therMizer and OSMOSE. EcoTran (Ruzicka et al., 2016) and Models of Intermediate Complexity for Ecosystem Assessments (Plagányi et al., 2014; Tulloch et al., 2019) have recently joined FishMIP. All of these modeling frameworks are vastly different in model type, representation of species and ecosystem processes, and inclusion and parameterization of physiological processes affected by climate variables and fishing, among other differences in model structure (Table 1, Tittensor et al., 2018). There is also great heterogeneity in terms of the input data requirements of each model (e.g., spatial and temporal resolution, variables required). Common key forcings used by all regional MEMs are sea water temperature and primary production/plankton biomass (Table 1, also see Tittensor et al., 2018; Eddy et al., 2025), and thus these are considered the standard environmental input forcings used by regional MEMs. However, some MEMs require additional forcings such as oxygen concentration and sea water pH, and even sea ice concentration. Within FishMIP, several EwE models only used Net Primary Production as climate forcing in the past and bias corrected the ESM forcings using the delta method described in Eddy et al. (2025).

Previous rounds of FishMIP simulations were conducted using outputs from the Coupled Model Intercomparison Project (CMIP) 5 and 6 (O'Neill et al., 2016; Taylor et al., 2012). Details can be found in Tittensor et al. (2018) and Blanchard et al. (2024). A major source of uncertainty when projecting climate impacts on marine ecosystems comes from differences in assumptions and structures about the implementation of temperature and other environmental effects among MEMs (Heneghan et al., 2021; Reum et al., 2024). Some differences between the regional MEMs in FishMIP include the number of species, functional groups, or size classes affected by temperature changes and the processes affected by temperature and primary production (Table 1). By designing this workflow, we standardize the climate and fishing effort forcings used by MEMs aiming to address some of the uncertainty sources mentioned above.

2.2. Simulation Workflow

The protocol 3a of ISIMIP (Frieler et al., 2024) and FishMIP 2.0 (Blanchard et al., 2024) focuses on evaluating how well marine ecosystems can recreate past/observed changes to marine ecosystems and fisheries (Blanchard et al., 2024). The workflow proposed here describes the implementation of protocol 3a at a regional scale. It also provides modelers with climate forcings needed to run their models, as well as detailed guidance on how to calibrate models to observed data, conduct simulations and contribute their model outputs to FishMIP and ISIMIP (Figure 2). The workflow was developed by the FishMIP regional modeling team through discussions at the regional modelers' online meetings and at two in-person meetings (The Fourth FishMIP workshop held in October 2022 and the joint National Oceanic and Atmospheric Administration and FishMIP workshop held in August 2023). The workflow follows best practices for multi-model comparison (e.g., den Boon et al., 2019), and incorporates the experience and knowledge of experts covering all regional model types included in FishMIP and across disciplines. The latest advancements and efforts conducted by FishMIP to further expand the geographical representation of regional models in FishMIP are also showcased.

Step 1: *Identify which climate model variables to use and how these are implemented*

For the FishMIP 3a protocol, climate forcing data is derived from the coupled physical and biogeochemical ocean models developed by the Geophysical Fluid Dynamics Laboratory (GFDL): Modular Ocean Model version 6 (MOM6) and Carbon, Ocean Biogeochemistry and Lower Trophics version 2 (COBALTv2). The GFDL-MOM6-COBALT2 model was forced by the Japanese 55-year atmospheric reanalysis JRA-55 (Tsujino et al., 2018) and it includes dynamic, time-varying river freshwater and nitrogen inputs that simulate the observed increase in nitrogen loading over the historical period (hereafter GFDL hindcast). This feature is especially important for coastal marine productivity and not regularly included in ESMs (Liu et al., 2021). The FishMIP 3a protocol also makes use of a parallel GFDL-MOM6-COBALT2 simulation without increasing nutrient loading, to test the sensitivity of the FishMIP models to this forcing (hereafter the control). GFDL-MOM6-COBALT2 outputs were regridded to a regular 0.25° horizontal resolution grid, while preserving vertical resolution. A complete list of oceanic climate-related variables available from GFDL-MOM6-COBALTv2 can be found in Frieler et al., 2024 (Table 8) and on the FishMIP 3a protocol.

Climate forcings are available from the German Climate Computation Center (DKRZ) server and the ISIMIP data repository in netCDF format. ISIMIP has developed tutorials and an Application Programme Interface (API) to access the climate forcings from the DKRZ server. FishMIP has also developed a tutorial on accessing the climate forcings from ISIMIP.

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Table 1
A Description of Climate Forcings Used by, and How Process Effects Are Represented in, the FishMIP Ecosystem Modeling Types

Ecosystem model name	Spatial and temporal scale and vertical resolutions	Key forcing variables used	Optional forcing variables used	Implementation of temperature effects/processes	Implementation of primary production/plankton biomass
Composite (hybrid) models—including multiple model formulations in system representation					
Atlantis	3-D spatial polygons matched to biophysical features; vertically resolved using "slab" layers (with finer layers and the surface and thicker at depth) Timestep is flexible, typically 6–24 hr	Sea Water Potential Temperature (thetao), Sea Water Salinity (so), Sea water X velocity (uo), Sea water Y velocity (vo)	Dissolved oxygen concentration (O_2), pH (pH), Mole Concentration of nutrients (NH, NO, Si and potentially micronutrients), Diatoms (phydiat), Diazotrophs (phydiaz), Picophytoplankton (phypico), Sea ice, irradiance, precipitation, river inflow, changes in sea level, eddy strength	Any model ecological process (e.g. metabolic rates, consumption, growth, mortality, movement/distribution, spawning) and the functional groups as defined by the modeler, as well as all modeled biogeochemical processes	Plankton mole concentration (in N m^{-3}) read in and forcing replaces the emergent phytoplankton biomass estimated for each model. Best done as a weighted average (somewhat similar to data assimilation), to minimize loss of mass conservation Delta method to correct primary production or plankton biomass can be applied as a relative anomaly to the phytoplankton growth rates (e.g., Rovellini et al., 2024)
Models of Intermediate Complexity (MICE)	Flexible, typically running in monthly or yearly time steps. Can be non-spatial or spatial. If spatial, applications are usually of coarse resolution. Spatially resolved in 2-D	Sea Water Potential Temperature (thetao)[a]	Chl-a, Primary Organic Carbon Production by All Types of Phytoplankton (intpp), Mole concentration of Diatoms (phydiat), Diazotrophs (phydiaz), Picophytoplankton (phypico), mesozooplankton (zmeso) and microzooplankton (zmicro), Rainfall, Sea ice	Different model ecological process (e.g. growth, mortality, movement/distribution, spawning) and the functional groups as defined by the modeler	Estimating multipliers for carrying capacity and predator-prey interactions (e.g., Tulloch et al., 2019)
OSMOSE	Flexible. Typically, resolution of 1/6° and a weekly time step. Spatially resolved in 2-D; the vertical distribution of species is handled through a matrix of accessibility	Sea Water Potential Temperature (thetao)[a], Primary Organic Carbon Production by All Types of Phytoplankton (intpp), Mole Concentration of Diatoms (phydiat), Diazotrophs (phydiaz), Picophytoplankton (phypico), mesozooplankton (zmeso) and microzooplankton (zmicro)	Sea Water Salinity (so), Dissolved oxygen concentration (O_2) (e.g., Morell et al., 2023; Moullec et al., 2019)	Species distributions, Maintenance rate, growth, fecundity, starvation mortality OSMOSE parameterization relies on species distribution model outputs. Climate forcings must be within the same range as the data used for parameterization of thermal preferences to avoid species collapses (e.g., out-of-range environmental conditions)	Statistical downscaling and bias correction to produce plankton biomass consistent with regional biogeochemical model (ROMS-PISCES) (e.g., Espinoza-Morriberon et al., 2016)

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Table 1
Continued

Ecosystem model name	Spatial and temporal scale and vertical resolutions	Key forcing variables used	Optional forcing variables used	Implementation of temperature effects/processes	Implementation of primary production/plankton biomass
Trophodynamic models—structured based on species interactions and transfer of energy across trophic levels					
EcoTran (Coupled physical-trophic model)	2D and 3D implementations. Rectangular polygons of varying size, ~10–100s km, and 2–6 depth layers of varying thickness, ~10–100s m. Time-step typically 24 hr nearshore, but 3 hr in oceanic regions to simulate diel vertical migration	Temperatures within specific depth ranges. Horizontal water velocities. Nutrient (N) input rate or phytoplankton production rate (flexible phytoplankton group definitions)	User-defined changes to consumption rates of individual consumer groups or catch rates by individual fleets. User-defined changes to community composition and food web structure	Metabolic rate (Q_{10}). Feeding rate of poikilotherms is scaled via dome-shape response representing optimal and sub-optimal/lethal conditions	When driven via nitrate and ammonium input, primary production is estimated via Michaelis-Menten kinetics. Model may also be driven directly with phytoplankton biomass time-series output of a biogeochemical model (in cases where biomass is available but not production, a constant production/biomass ratio is typically assumed to estimate primary production rates)
EwE	Flexible, typically running in monthly time steps. Depth dimension is considered implicitly through food web interactions and habitat preference patterns for Ecopath and Ecosim. Ecospace is spatially resolved in 2-D; the vertical distribution of species is handled through the niche model (Christensen et al., 2014; de Mutsert et al., 2024)	Sea Water Potential Temperature (thetao)[a], Primary Organic Carbon Production by All Types of Phytoplankton (intpp)	Sea Water Salinity (so), Dissolved oxygen concentration (O_2)	Typically uses forcing and environmental response functions to model temperature effects through changes in assimilation efficiency, adjustment of consumption rates and mortality. In Ecospace, sea water temperature also affects species distributions	Primary production used as a forcing function influencing the production of plankton size classes. Primary production from ESMs is bias corrected using the delta method (Eddy et al., 2025). This method involves calculating relative values of primary production compared to the model base year EwE can also ingest primary producer biomass density distributions directly, overriding internal primary production growth dynamics (de Mutsert et al., 2024)
Size-based models—developed from food web, macroecological, and life history theory for exploration of community size spectra					
(ther)Mizer	Non-spatial. Mizer is a multi-species size-structured model, and therMizer allows climate and plankton forcing to be added to Mizer (Delius et al., 2024; Woodworth-Jefcoats et al., 2019)	Sea Water Potential Temperature (thetao)[a], Mole Concentration of Diatoms (phydiat), Diazotrophs (phydiaz), Picophytoplankton (phypico), mesozooplankton (zmeso) and microzooplankton (zmicro)		Individual metabolism, maximum consumption, search volume and predation mortality	Use the concentration of vertically integrated plankton size classes to estimate the plankton size spectrum via linear fit across these size classes

Note. The optional forcing column highlights variables that may be required by some implementations of the model type. The key forcings column represents those for which the climate input forcings described in the workflow are preferred over time series drawn from other sources or defined by default within the model. Adapted from Tittensor et al. (2018). [a]Averaged over specific depth ranges to represent the preferences of the different functional groups or species included in the model, thus indirectly capturing the 3D component; or at the surface, bottom of the water column.

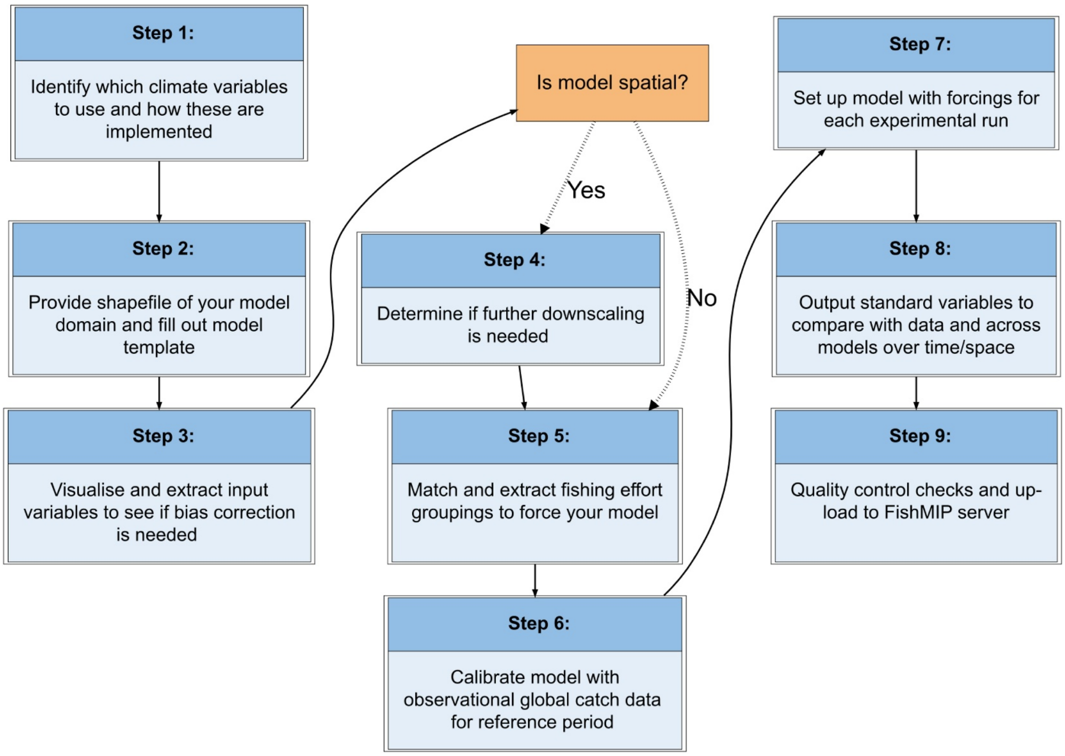

Figure 2. Regional simulation workflow that integrates standardized global forcings with required regional marine ecosystem model inputs. Steps are described in detail below.

Regional MEMs commonly use sea temperature, primary productivity and plankton biomass to force their models, but differ in the representation of sea temperature and primary production effects. Table 1 summarizes how temperature and primary production/plankton biomass forcings are implemented in the FishMIP regional MEMs.

Step 2: *Provide shapefile of your model domain and complete model template*

As per Step 1, modelers have the option to (a) access climate forcings directly from the DKRZ server or the ISIMIP repository or (b) provide model spatial boundaries (shapefile or bounding box) for the regional modeling team to extract all climate variables available in GFDL-MOM6-COBALTv2 (Table 8 of Frieler et al. (2024), FishMIP GitHub page). The creation of Python scripts to complete this step has streamlined the process into a standardized format for the 40 participating FishMIP regional models (Figure 1, as of December 2024). The Python scripts developed for regional data extraction are publicly available in the FishMIP GitHub repositories. Regional climate forcings are also publicly available at the University of Tasmania THREDDS server.

Modelers are required to document how the climate and fishing forcings were integrated into their models to ease the quantification of uncertainties due to differences in model structure and assumptions and the analysis of ensemble MEM projections (den Boon et al., 2019). The information required includes the environmental forcings equations used, and which ecological process are affected by each forcing, the fishing forcing set-up (e.g., fishing mortality rates, selectivity and catchability estimates, and how fishing gears and targeted functional groups were aggregated) as well as details on model calibration. Because models involved in FishMIP evolve through time, questionnaires with information about regional MEMs are stored in the FishMIP GitHub repository. Information on the model templates also feeds the model documentation on the ISIMIP website.

Step 3: *Visualize and extract input variables to see if bias correction is needed*

Validation of climate forcings (i.e., model variables used as input forcing of MEMs) from the GFDL hindcast against observations for the region of interest is necessary to determine whether bias correction is required. To

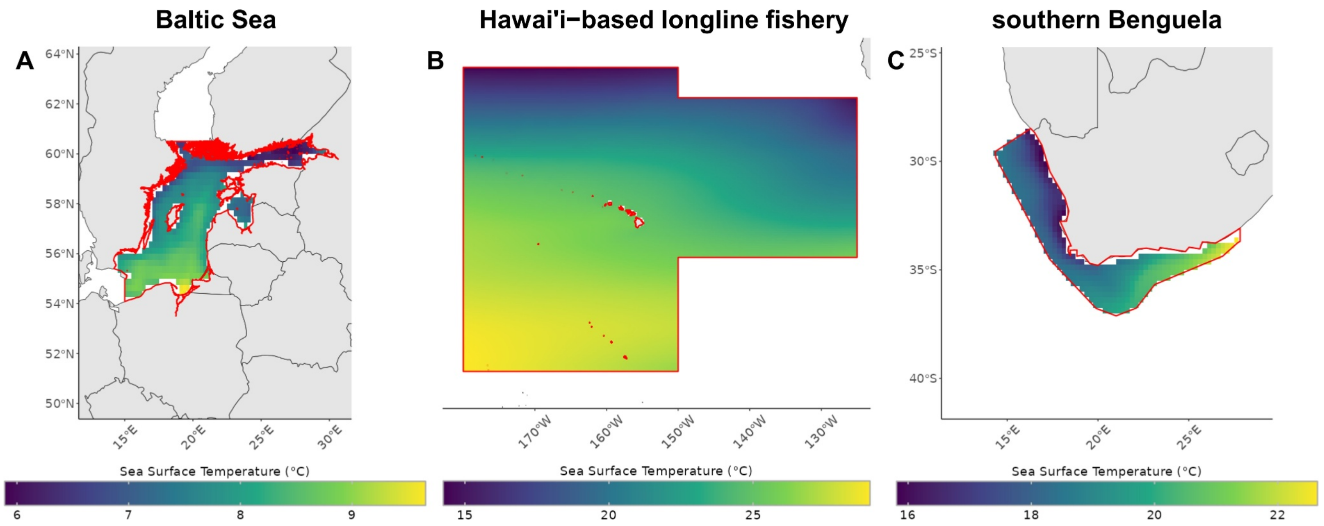

Figure 3. (a) Maps of area weighted sea surface temperature climatological means (1961–2010) calculated from the GFDL hindcast for the Baltic Sea Mizer, (b) Hawai'i-based longline fishing grounds, and (c) southern Benguela model domains.

improve the accessibility of climate data to different regional modeling teams and ease the processing of climate forcings, FishMIP developed the "Regional Climate Forcing Data Explorer" Shiny app (Figure 3). The Shiny app shows maps of climatological means for the historical period (1961–2010) of the 3a protocol, and time series of area weighted means for 37 climate variables available in GFDL hindcast for the regional models currently participating in FishMIP. These climate forcings can be downloaded for each model region for use as inputs by regional MEMs. However, some of these climate variables, particularly biogeochemical and ecological variables, cannot be validated against observations due to a lack of observational data (e.g., Bopp et al., 2013; Doney et al., 2009; Kwiatkowski et al., 2020).

Climate model outputs are known to have systematic biases, which can preclude their direct use for regional climate-impact and vulnerability assessments (Casanueva et al., 2020). A number of bias correction methods of varying complexity have thus been developed to correct climate forcings using observations at regional scales (Casanueva et al., 2020 and references therein). The implications of bias correction include possible impacts on magnitudes, signals or trends (Oliveros-Ramos et al., 2023). For FishMIP 3a, regional modelers observed differences in sea temperature and primary production between the GFDL hindcast (1961–2010) and those derived from regional ocean models or observations (Figure 4, see Section 3.1 for an example of three case study areas). These temperature differences resulted in having species outside their thermal tolerance ranges causing some of them to collapse during pilot historical model runs. It was therefore decided to perform bias correction on the GFDL hindcast outputs for those MEMs and regions. The delta method for calibrating the mean (see Supporting Information S1) to observations was chosen due to its relative simplicity and applicability (Marshall et al., 2017; Pozo Buil et al., 2023).

The selection of the observational data set used to perform bias correction is of utmost importance, as previous studies found that bias correction methods strongly rely on the reference data set used for calibration (Gampe et al., 2019). We chose the Word Ocean Atlas 23 (WOA23) (Locarnini et al., 2023) because (a) this is a comprehensive, quality controlled data set based on ocean profiles data from 1981 to 2010, providing gridded climatological means for temperature, salinity, oxygen, among other variables, and (b) they have been extensively used for bias correction purposes (e.g., Séférian et al., 2013 (WOA09); W. Fu et al., 2022 (WOA18)). The Shiny app shows maps of climatological means (1981–2010), and area weighted monthly climatologies as time series, for sea water temperature and practical salinity from WOA23. The Shiny app also shows a map of the number of observations (1981–2010) for each grid cell and depth level used to calculate sea water temperature and salinity climatologies in WOA23. This metric indicates how well represented a given region is in the WOA23 data set. It must be noted that the number of available observations for a given variable decreases with increasing depth. Regions with limited available observations in WOA23 may need to use a different observational or reanalysis

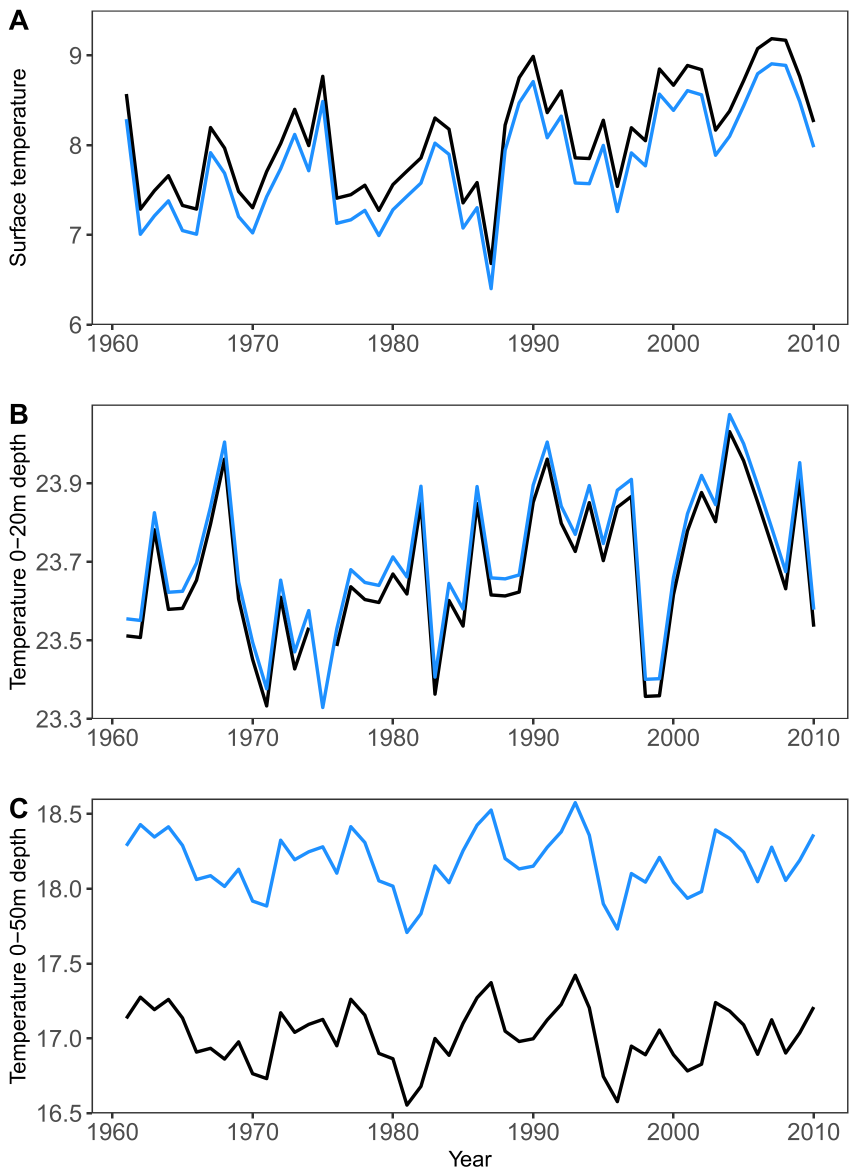

Figure 4. (a) Time series of bias corrected (black lines) and GFDL hindcast (light blue lines) sea temperature for the surface within the Baltic Sea Mizer model, (b) for the top 20 m within the Hawai'i-based longline fishing grounds, and (c) for the top 50 m of the southern Benguela. Time series show the spatially and annually averaged sea temperature (1961–2100) for each model region. The different depth intervals used to integrate sea temperature in panels (a–c) reflect the different input forcings used by each model (see Section 3.1 for more information). The bias corrected time series were calculated using the procedure detailed in Supporting Information S1.

data set to perform bias correction. For instance, the GLobal Ocean ReanalYses and Simulations (GLORYS, Lellouche et al., 2021) has been used to generate the ocean physical variables needed as input forcings for Atlantis models (Perryman et al., 2023). The choice of observational or reanalysis data set is to be determined at the discretion of the regional modeler, provided this information is supplied with their simulations.

Providing a temperature cutoff to determine if bias correction is necessary can be challenging due to the diverse species-specific responses to temperature, and the uncertainty associated with assumptions and structures about temperature effects in MEMs. Based on a literature review (e.g., Amaya et al., 2023; Castillo-Trujillo et al., 2023; de Souza et al., 2021; Russo et al., 2022), we suggest a bias correction should be applied if there is a difference of at least 1°C between the GFDL hindcast and sea temperature monthly climatologies at any given depth. A list of

Table 2
List of Gear and Functional Group Codes

Gear codes	
Dredges	Others_Support
Gillnets	Others_Unknown
Lift_Nets	Pots_and_Traps
Lines_Handlines_and_poles	Seine_Danish_and_Other
Lines_Longlines	Seine_Purse_Seine
Lines_Unspecified	Trawl_Midwater_or_Unsp
Others_Multiple_Gears	Trawl_Bottom
Others_Others	Falling_Gear
Functional groups	
Bathydemersal < 30 cm	Flatfish ≥ 90 cm
Bathydemersal 30–90 cm	Krill
Bathydemersal ≥ 90 cm	Lobsterscrab
Bathypelagic < 30 cm	Pelagic < 30 cm
Bathypelagic 30–90 cm	Pelagic 30–90 cm
Bathypelagic ≥ 90 cm	Pelagic ≥ 90 cm
Benthopelagic < 30 cm	Rays < 90 cm
Benthopelagic 30–90 cm	Rays ≥ 90 cm
Benthopelagic ≥ 90 cm	Reef-associated < 30 cm
Cephalopods	Reef-associated 30–90 cm
Demersal < 30 cm	Reef-associated ≥ 90 cm
Demersal 30–90 cm	Shark < 90 cm
Demersal ≥ 90 cm	Shark ≥ 90 cm
Demersalmollusc	Shrimp
Flatfish < 90 cm	

sequential steps to perform bias correction on sea water temperature can be found in Supporting Information S1. Those steps can also be used for variables such as salinity and oxygen.

Different approaches have been used to bias correct plankton biomass and primary productivity within FishMIP regional MEMs (Table 1). A common approach involves using the delta method to adjust ESM outputs and force primary production (Eddy et al., 2025) and the growth of plankton groups (Rovellini et al., 2024).

Step 4: *If spatial: determine if further downscaling is needed*

Major differences have been found between low-resolution ESM outputs and highly resolved downscaled projections at a regional scale (Melsom et al., 2009; Pozo Buil et al., 2023; Skogen et al., 2018). When forcing the Nordic and Barents Atlantis model with an ESM (1° resolution) and a regional ocean model (dynamically downscaled projections at 10 km resolution), a general agreement in future biomass trends and distribution patterns for some species at higher trophic levels was found. However, this was not the case for lower trophic level groups (e.g., plankton, mesopelagic fish and prawns), and for some higher trophic level species such as Northeast Arctic cod (*Gadus morhua*). These differences indicate that highly resolved forcings are needed in studies focused on coastal systems (as is the case for most regional MEMs) and/or representing finer-resolution processes. However, downscaled climate forcings, especially dynamically downscaled, are not available for most regions of the world, nor the full set of climate scenarios, and this represents a challenge for regional climate-impact assessments (Kristiansen et al., 2024; Pozo Buil et al., 2021).

OSMOSE-Humboldt is the only FishMIP regional model that has performed statistical downscaling (Oliveros-Ramos et al., 2017). Oliveros-Ramos et al. (2023) evaluated 19 nested statistical downscaling models describing the relationship between empirical distributions of historical modeled and observed sea surface temperature (SST). These authors concluded that no single statistical downscaling model performed better than all others across regions, indicating that these approaches should be evaluated on a case-by-case basis. The "Gridded time series analysis" R package implements the statistical downscaling models described in Oliveros-Ramos et al. (2023). This is one approach currently being evaluated for future use within FishMIP.

Given the complexity of downscaling approaches and the need to evaluate their performance on a regional basis, we have not yet standardized a statistical downscaling approach to be used in this implementation framework (other than performing bias correction). ISIMIP has a bias correction and statistical downscaling protocol, which has been applied to atmospheric climate data and it is likely not directly transferable to oceanic variables (Lange, 2019). If downscaling needs to be carried out by regional modelers, we advise ecosystem modelers to choose a statistical downscaling approach that performs best for their region, and use the best observational data set available (WOA23 was selected for this workflow) and the time periods specified in step 3 (Supporting Information S1) to perform downscaling to ensure consistency with this implementation framework. We acknowledge that standardizing the choice of a statistical downscaling method is an area that warrants further attention within FishMIP.

Step 5: *Match and extract fishing effort groupings to force your model*

For FishMIP protocol 3a, global fishing effort time series (hereafter called global effort data) were made available to FishMIP modelers (Blanchard et al., 2024), and future scenarios are being developed for Phase 3b (Maury et al., 2024). Global effort data was derived from Rousseau et al. (2024) and consists of 16 gears or fleets and a total of 29 functional groups (Table 2). These data allowed global modelers to represent historical fishing impacts, which many global MEMs were not able to include before. Regional models did include fishing effort or mortality, and in most cases, used statistics from government agencies or regional advisory organizations, which are generally considered to be more accurate. Several discussions were held to find the best way to use global effort data developed for protocol 3a to standardize fishing forcing between global and regional MEMs and improve the comparability of their outputs.

Fishing effort data used to force regional models and fishery catch data (Watson & Tidd, 2018) used for model calibration were processed and extracted for each regional MEM by the FishMIP coordination team and are publicly available in the FishMIP THREDDS server. More details on the regional extractions of catch and effort data can be found in Blanchard et al. (2024).

Most regional models include at least some of their ecological components at the species level, or at least at taxonomic resolutions finer than reported in aggregated global statistics. Consequently, it was necessary to make some assumptions on how to split the global effort and catch data by fleet and functional group to match the taxonomic resolution of the regional model considered. Regional effort and catch time series (where available) are to be used in combination with the global data to inform the processing assumptions (e.g., disaggregation of effort by functional groups into species). Careful consideration and a preliminary analysis of the global effort data for some model regions highlighted important inconsistencies with effort data from regional management authorities and other local sources commonly used by regional modelers (see Section 3.2). Inconsistencies were mostly due to the nature of the global data, which is global in coverage but less detailed and reliable at the regional scale. To address this issue, three sensitivity tests are proposed for the implementation of the global data:

1. Global effort data only: If there is a good agreement between the historical trends and magnitude of the global and regional effort data (correlation coefficient $\geq$0.5), modelers implement the global effort data into their regional MEMs following the procedure described in Supporting Information S1.
2. Bias correction of the global effort using regional data: If there are differences between the historical trends and magnitude of the global and regional effort data for some fleets, modelers can use the global effort data for those fleets showing reasonable historical trends and use their regional effort/mortality to correct the global effort forcing for those that do not.
3. Regional effort data only: If there is little agreement (correlation coefficient $<$0.5) between the historical trends and magnitude of the global and regional effort data. Modelers should use their regional effort/mortality to perform simulations as per their baseline models. Modelers are requested to describe the differences between these data sets to justify the use of regional data and to ensure improvements are made in future. This will also allow us to evaluate the influence of global versus regional effort forcings on historical model outputs.

   Modelers are required to submit their fishing effort/mortality time series with their simulations. We acknowledge that regional effort and catch time series are often not publicly available as they belong to national government agencies. In those cases, we ask modelers to submit their forcings as relative values if this does not contravene the access conditions under which the data was granted. The sequential steps involved in processing the global effort and catch data to obtain a time series of fishing effort and total catch split by fleet and functional groups can be found in Supporting Information S1. Code will be provided in the FishMIP Github repository for worked examples that illustrate this step.

Step 6: *Calibrate MEM outputs with observational global catch data for reference period*

Calibrating MEM outputs to observational data is a computationally- and time-intensive process. For some models (EwE, Mizer), it may be feasible to recalibrate models with all climate and fishing forcings since specific protocols exist (Bentley et al., 2024; Delius et al., 2024). We have provided catch data extracted for each regional shapefile to facilitate this step in cases where no other data are available (step 5) or where experimental design necessitates. Even though the 3a experiments extend to 2010, the catch time series extends up to and including 2004. Later years (2005–2010) must not be used in calibration because we have retained the last 6 years of the catch data for predictive skill assessment across models.

In cases where recalibration cannot be carried out, we still encourage modelers to submit their runs and compare them to the outputs of their baseline calibrated runs, including inputs. In this case, we ask modelers to submit the

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results of their baseline model runs. It may, in some cases, be appropriate to carry out a statistical post-hoc adjustment of simulations based on the discrepancy of the two runs. Another possibility is simply to provide the non-calibrated runs with a clear indication in the model template that recalibration was not carried out. In these cases, an analysis of relative changes may still be performed, keeping in mind that the non-calibrated model may have limited performance when capturing observed historical changes for the system in question.

In all cases, we expect modelers to carry out "sanity checks" of their models. This is step 0 of the Hipsey et al. (2020) framework. This involves ensuring that processes and rates in each MEM are plausible and sensible. We then suggest using a subset of the model skill metrics to assess how well the MEMs forced with the global effort data compared to the original MEM calibrated with regional effort/mortality data. A minimum set of suggested metrics and plots include bias and correlation of time series of catches and, if observations are available, biomasses for key functional groups and species in the model. We ask modelers to submit the data and all data sources (when those are publicly available) used in this step if different to what has been provided and detailed in steps 3 and 5. When this is not feasible, possibly due to permissions, relative time series and summary statistics should be provided.

A toolbox is being developed to analyze and compare spatial model outputs within an integrated and standardized workflow and calculate a number of skill metrics (i.e., MapCompR). MapCompR provide functions to (a) compare spatial maps from different species, (b) compare spatial maps of the same species obtained with different methods, and (c) analyze model predictions (Ouled-Cheikh et al., 2024).

Step 7: *Set up MEMs with forcings for each experimental run*

The FishMIP protocol 3a consists of four model experiments and eight scenarios, with different combinations of climate and human forcings (see Table 1 of the FishMIP 3a protocol). A model experiment is a set of model simulations with a particular goal (e.g., model evaluation), while a scenario is a particular setting for climate and human forcing drivers (e.g., fishing). The two core experimental runs aim to evaluate the impacts of climate with time-varying river input forcing at 0.25° resolution (step 3), with and without fishing (step 5). Two optional but preferred runs were set up to estimate the sensitivity of model outputs to riverine influx (control, input forcings held at 1955 values throughout the simulations). This model experiment is also run with and without fishing.

Two additional experiments were also set up in the FishMIP 3a protocol, aiming to understand the impacts of resolution on model outputs, and use climate forcings at a 1° resolution with exactly the same set-up listed above for the core and preferred runs. In translating the FishMIP 3a protocol to a regional context, we decided to focus on the experiments using 0.25° resolution forcings (i.e., the core runs) due to the finer resolution needed to force regional models.

Step 8: *Output standard variables to compare with data and across models over time/space*

The FishMIP protocol 3a lists all the mandatory and optional model outputs to be provided by modelers (Table 9, FishMIP protocol 3a), including the variable specifiers. We request that modelers report what species and species groups were allocated to the different output variables (Table 9, FishMIP protocol 3a) in the model templates (step 2). Regional modelers should submit their spatial outputs as NetCDF files, while outputs from non-spatial regional MEMs can be saved as .csv files.

The optional outputs include indicators such as the biomass and catch of different size classes of pelagic and demersal fish. These outputs are highly relevant at the regional scale as they can be directly linked to system specific species of ecological and economic importance. The mandatory and optional outputs will also allow the estimation of ecosystem indicators (Coll et al., 2016; Shin, Bundy, et al., 2010; Shin, Shannon, et al., 2010), which are regularly calculated in regional modeling studies in a number of regions and allow for a further point of comparison. These include species-based, size-based and trophodynamic indicators that have already been compared across regional MEMs and ecosystems in the frame of the IndiSeas working group (C. Fu et al., 2019; Ortega-Cisneros, Shannon, et al., 2018; Reed et al., 2016; Shin et al., 2018). Depending on the scenarios and forcings considered, a subset of indicators could be used that are the most sensitive, responsive and specific to

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changes in drivers. For example, Shin et al. (2018) showed that among the IndiSeas indicators tested, mean fish length had the more specific response to changes in plankton biomass, while total catch/biomass ratio was more specific to changes in fishing pressure. Recent sensitivity and uncertainty analyses can be used to identify the indicators that are more robust to uncertainties (Luján et al., 2024). A standardized protocol could be developed in the future for the FishMIP MEMs to identify a common set of indicators that are robust to uncertainties in model parameterization.

Step 9: *Quality control checks and upload MEM outputs to FishMIP server*

There are strict specifications on how to prepare and name MEM outputs for submission to FishMIP. File names consist of a series of identifiers including the regional MEM type, climate forcing, the climate, socioeconomic and sensitivity scenario identifiers, and the variable identifier, region and timesteps. Specific guidelines and instructions can be found on the ISIMIP website and the FishMIP protocol 3a repository.

This is a seemingly trivial but extremely important step to ensure ensemble consistency and expedite analysis. It is crucial that modelers follow closely the formatting guidelines for reporting model outputs to facilitate their analysis within the ISIMIP framework. Regional modelers should use the quality control tool developed by ISIMIP, which allows modelers to check their outputs against the definitions and conventions of ISIMIP protocol before submission. Regional modelers should contact the FishMIP regional modeling team if they have questions about how to format their MEM outputs. Once model outputs are ready for submission, modelers must save them on the upload area (a folder is available for each model region and type) of the DKRZ server.

2.2.1. Applying the Framework

The workflow described here (Figure 2) has been applied to three case study areas-models: the Baltic Sea Mizer, the Hawai'i-based Longline therMizer and the southern Benguela ecosystem Atlantis regional models. Details on these models (e.g., functional groups, fleets, calibration and skill assessment) can be found in the FishMIP GitHub repository. The results represent a subset of the steps described in the workflow and were selected to illustrate the implementation of the most challenging steps of the workflow and how they can be applied to different MEM types and model regions to illustrate the applicability and flexibility of the workflow.

3. Results

3.1. Case Study 1: Climate Forcing Intermodel Comparison

In step 3 of our workflow, our Shiny app can be used to visualize and download climate forcings at 0.25° resolution within a regional model boundary. The app also compares the GFDL hindcast to the WOA23 data set so ecosystem modelers can determine if bias correction is required for physical ocean variables for their model region (see Figure 3 for sea temperature).

3.1.1. Baltic Sea Mizer Model

The Baltic Sea Mizer model uses SST as model input, averaged over the whole model domain (Lindmark et al., 2022). A time series of monthly SST was acquired from the GFDL hindcast, spanning from January 1961 to December 2010 (Figure 4a). The bias corrected time series (Figure 4a), obtained following the sequential steps described in Supporting Information S1, was compared to the GFDL hindcast to determine if bias correction was needed for this model. The absolute difference between these time series (annual means) was 0.28°C, and suggested that bias correction may be needed for this model if this difference is higher for the monthly averages at any given depth for deeper depths.

3.1.2. Hawai'i-Based Longline therMizer Model

The Hawai'i-based longline therMizer model uses temperature averaged over 18 depth ranges as model input. This model captures species' vertical behavior and exposure to different depths, and includes temperature at depth ranges from 0 to 20 m up to 400–1200 m depth (see FishMIP Github Repository for an explanation of the approach). Eighteen temperature time series (January 1961 to December 2010) were acquired for this model from the GFDL hindcast. Each time series corresponds to the 18 preferred depth ranges for the model species (see

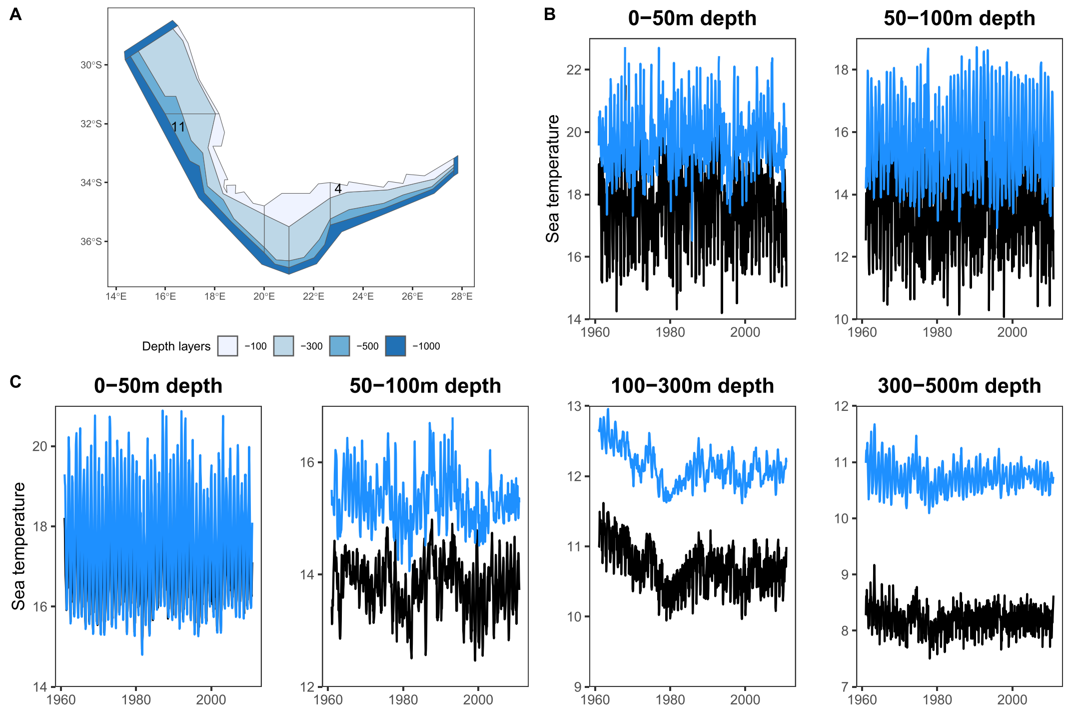

Figure 5. (a) Model geometry of the southern Benguela Atlantis model showing model polygons and depth layers. (b) Time series of bias corrected (black) and GFDL hindcast (light blue) monthly temperatures at different depth ranges for model polygons 4 (18 boxes × 2 depth layers) and (c) 11 (18 boxes × 4 depth layers).

Figure 4b for an illustration of average temperature at 0–20 m depth). The comparison between the GFDL hindcast and the bias corrected time series of annual means indicates small absolute differences in temperature (0.04°C) for the 0–20 m depth range. While the bias was negligible for the 0–20 m depth layer for this model, the bias was higher for deeper depths, and simulations (results not shown here) using the GFDL hindcast without bias correction resulted in some species going extinct during the simulations because the GFDL hindcast temperatures fell outside observed temperatures. This highlights the importance of the bias correction step for some models, specifically those including functional groups with narrow thermal preferences.

3.1.3. Southern Benguela Ecosystem Atlantis Model

The southern Benguela ecosystem Atlantis model is a spatially explicit model, for which the model area is divided into 18 polygons (Ortega-Cisneros et al., 2017). The model extends to a maximum depth of 500 m, with two depth layers near the coast and two additional ones offshore (Figure 5) and an assumption of an open boundary layer underlying the offshore boxes (1000 m depth). The procedure detailed in step 3 (Supporting Information S1) was followed as was the case for the Baltic Sea Mizer and Hawai‘i-based longline therMizer models. For the southern Benguela Atlantis model, this procedure resulted in 59 time series of sea water temperature (1961–2010) from the GFDL hindcast because it was necessary to aggregate the gridded inputs into the 18 spatial polygons used as the spatial configuration for this regional model (instead of one for the whole model area), and then to calculate average temperature for the different depth layers used in this model (Figure 5). For illustrative purposes, the bias corrected and GFDL hindcast time series (monthly means) for two model polygons of the southern Benguela ecosystem Atlantis model are shown in Figure 5. The absolute difference between these data sets at the 0–50 m depth layer ranges from 0.63 to 4.21°C for box 4 (Figure 4b) and 0.04–1.73°C for box 11 (Figure 4c). For the 300–500 m depth layer of box 11, the difference between the time series varied from 2.11 to 2.94°C. It is therefore expected that using the GFDL hindcast without bias correction would likely result in several modeled species going extinct during model simulations.

For other spatially explicit models (case-dependent, step 4), comparing them with gridded observed climatologies can help indicate whether further statistical downscaling may also be needed (e.g., Oliveros-Ramos et al., 2023). For this, we recommend following the guidelines provided in step 4.

3.2. Case Study 2: Fishing Effort Forcing Intermodel Comparison

All regional MEMs in FishMIP include fishing impacts. However, they vary in their representation of those impacts, such as the use of fishing effort or mortality, the number of fleets, and the number of functional groups impacted by fishing. Here, we provide an overview of how the global fishing effort was used for our three regional MEMs, including one to several fleets.

All fisheries models are based on the premise that fishing mortality is the product of selectivity × catchability × effort. Only effort was varied in the construction of the fishing forcing, with selectivity and catchability unchanged from the way in which the respective models typically deal with these parameters. In the Baltic Sea Mizer and Hawai'i therMizer selectivity and catchability were set to 1 throughout for both. For the southern Benguela ecosystem Atlantis, catchability is set to 1, and constant age selectivity is used with fishing mortality. For anchovy, age selectivity applies to fish older than 6 months and for sardine older than 1 year.

3.2.1. Baltic Sea Mizer Model

The Baltic Sea Mizer model required an alternative approach to how fishing was incorporated. This Mizer model consists of three fish species: Atlantic cod (*Gadus morhua*), Atlantic herring (*Clupea harengus*) and European sprat (*Sprattus sprattus*). The original model (Lindmark et al., 2022) was calibrated to stock-level fishing mortalities and did not explicitly include different fleets. The majority of landings of cod stem from the bottom trawl fleet (“Trawl_Bottom”), and the majority of sprat and herring by pelagic trawl fleet (“Trawl_Midwater_or_Unsp”) (verified using logbook data and assessment reports from the regional advisory organization ICES). Therefore, these gears were selected in the initial processing of the global effort data. The effort (“NomActive”) was next summed by year and functional group, where cod belongs to “demersal 30–90 cm” and sprat and herring belong to “pelagic < 30 cm.” A time series of relative global fishing effort was made by dividing the effort by the maximum in the time window 1992–2004. This deviation from the workflow (scaling to maximum rather than mean) was made because the bottom trawl effort was characterized by a few large spikes in effort (two years with fishing efforts larger than 5 standard deviations above the mean). To go from relative fishing effort to fishing mortality in the Baltic Mizer model, the mean difference between the fishing mortality derived from stock assessments and that of the relative effort time series over the time period 1961–2010 was added to the relative time series to correct the global effort forcing. The time series of assessment-derived fishing mortalities and global fishing effort are shown in Figures 6a–6c. The validation compared these time series for cod, herring and sprat through a correlation; the Pearson's correlation coefficient r was -0.203 ($p = 0.156$), 0.497 ($p < 0.0001$) and 0.6 ($p < 0.0001$) for cod, herring and sprat respectively. The model predicted average spawning stock biomass (SSB) (forced with global climate and fishing data) was compared to the average SSB from the assessment in the calibration time window (1992–2004), as in the original publication (Lindmark et al., 2022). The model returns a comparable SSB as the original model for cod and herring (77 vs. 56 tonnes, and 600 vs. 532 tonnes for the original model and the one forced with global data, respectively), while sprat SSB is nearly half in the simulation with global forcings. This is partly explained by sprat having higher fishing mortality in the global data (mortalities are on average +0.25 higher than the assessment fishing mortalities) in the calibration time window.

3.2.2. Hawaiʻi-Based Longline (ther)Mizer Model

The Hawaiʻi-based longline model (Woodworth-Jefcoats et al., 2019) includes the longline fleet (“Lines_Longlines”), hence this fleet was selected in the initial processing of the global effort data. The modeled Hawaiʻi-based longline fleet catches 12 model species included in three pelagic (“pelagic < 30 cm,” “pelagic 30–90 cm,” “pelagic ≥ 90 cm”) and two shark (“shark < 90 cm,” “shark ≥ 90 cm”) functional groups. The effort (“NomActive”) across these five functional groups was aggregated to estimate the total effort of the longline fleet per year, under the assumption that a single longline fleet is catching these functional groups. This assumption is based on the characteristics of the Hawaiʻi-based longline fleet.

The Hawaiʻi-based longline model starts in 1995, and thus, a baseline average effort was calculated using the time period 1995–2004. The time series of global effort (“NomActive”) for the longline fleet was then divided by the

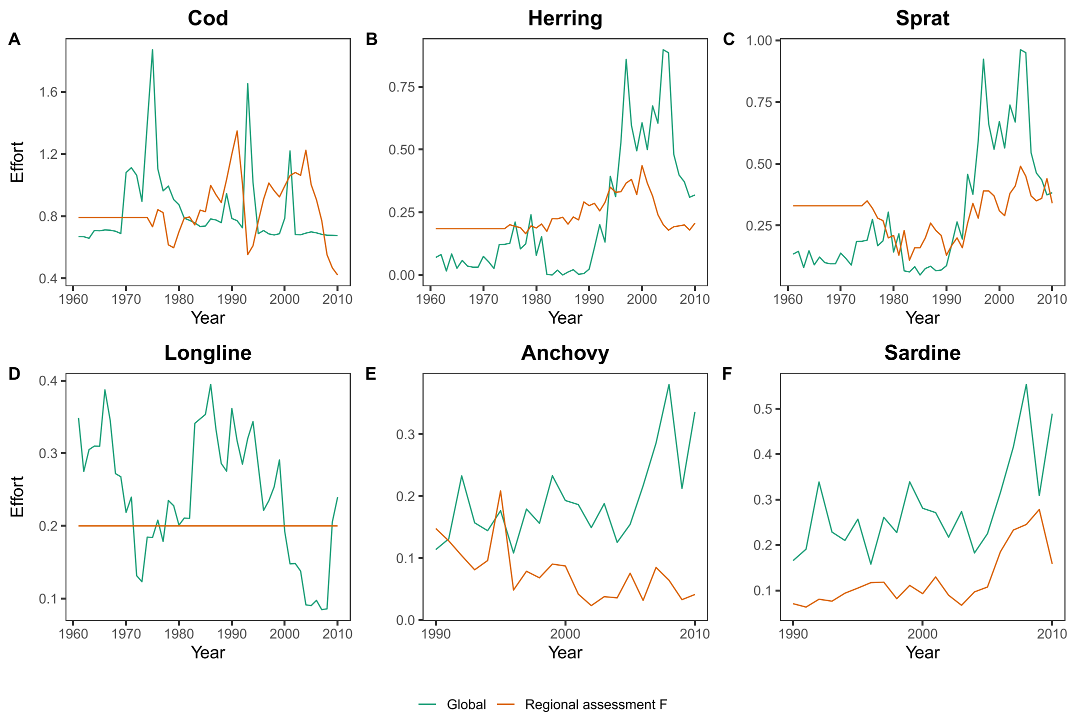

Figure 6. (a–c) Annual global fishing effort time series for key functional groups compared with regional inputs for the Baltic Sea Mizer, (d) Hawai'i-based longline therMizer, and (e–f) southern Benguela ecosystem Atlantis regional models. Global fishing effort refers to the effort time series calculated using the effort provided by FishMIP and the regional assessment refers to the fishing mortality or harvest proportions derived from stock assessments (see Section 3.2).

baseline average effort to estimate the relative global fishing effort. The global relative fishing effort was multiplied by 0.2, which is the fishing mortality ($F = 0.2$) used to calibrate the Hawai'i-based longline therMizer model (Woodworth-Jefcoats et al., 2019), to arrive at a time series of fishing mortality values (Figure 6d). Fishing mortality $F = 0.2$ was used in this model because a fishing mortality close to 0.2 has been estimated for those species with available stock assessments (Woodworth-Jefcoats et al., 2019 and references therein).

The Hawai'i-based longline therMizer model applied the global fishing effort to the functional groups caught by the longline fleet. A validation run was performed using constant fishing mortality ($F = 0.2$) as per the original model (Woodworth-Jefcoats et al., 2019). The validation used a correlation test to compare observed and modeled catch at size for the 12 species targeted in the model. All correlations were significant (max p-value = 0.0028), while the Pearson's correlation coefficient r ranged from 0.296 to 0.922, with a mean of 0.65 and a median of 0.684.

3.2.3. Southern Benguela Atlantis Model

The southern Benguela Atlantis model followed the approach detailed in step 5 (Supporting Information S1), as described for the Hawai'i-based longline therMizer model. The southern Benguela Atlantis model (Ortega-Cisneros, Cochrane, et al., 2018; Ortega-Cisneros et al., 2017) includes purse seine, inshore and offshore demersal trawl, mid-water trawl, line and jig fisheries targeting a number of functional groups within the model. The original model was calibrated against biomass and catch time series for key functional groups (Ortega-Cisneros et al., 2017).

The purse-seine fishery, targeting small pelagics, is the largest fishery in terms of landings in South Africa (DFFE, 2023). Therefore, this fleet was selected for the initial processing of the global effort data. First, the effort ("NomActive") for the purse seine fleet ("Seine_Purse_Seine") was filtered. This fleet targets anchovy (*Engraulis encrasicolus*) and sardine (*Sardinops sagax*), and also round herring (*Etrumeus whiteheadi*) in recent years; these species belong to the "pelagic < 30 cm" functional group in the global effort data. A relative time series of global effort for the purse seine fleet and the "pelagic < 30 cm" functional group was then estimated using the baseline effort calculated from 1990 to 2004 (this model starts in 1990). The conversion from relative fishing effort to fishing mortality was achieved by multiplying the relative effort time series by the annual baseline fishing mortality for anchovy and sardine in this model (Figures 6e and 6f). The correlation between the global effort data for the purse seine fleet and the harvest proportion for anchovy and sardine derived from the stock assessment for these species (de Moor, 2021) was estimated as a form of validation. A high and significant correlation was found for sardine ($r = 0.668$, $p < 0.0001$) but not for anchovy ($r = -0.171$, $p = 0.459$).

4. Discussion

Here we described an implementation framework for regional MEMs to participate in comparative analyses as part of FishMIP, across models and a wide range of regions worldwide. Our workflow for setting up regional MEMs for climate hindcasts or projections is flexible enough to apply to a range of MEM types. The case study intercomparison applications of our workflow show that each specific model-region combination has unique requirements that can be accommodated by the extraction tools we have designed. We envisage this workflow will facilitate future research on MEM ensemble development and applications in at least the following ways: (a) regional MEM ensembles, (b) model evaluation and benchmarking (across multiple models/regions), (c) global-regional model intercomparison for regions.

4.1. Regional Marine Ecosystem Model Ensembles

The framework presented here provides modelers with a workflow that allows them to process climate and fishing forcings in line with their model requirements and the resources of the modeling team to perform the simulations. Our protocol proved flexible in accommodating MEMs with one fleet (Hawai'i-based longline therMizer model) or several fleets targeting different functional groups (southern Benguela ecosystem Atlantis models). Notably, the availability of the global fishing effort also represents an important step for regions where local fishing effort and mortality are unknown or where records are incomplete, as this will allow regional modelers to represent the impacts of fishing on their MEMs. In addition, the global effort data can be used to represent artisanal fisheries, for which there is limited available data worldwide (Cisneros-Montemayor et al., 2020). It is, however, recommended that the limitations of such an approach (see Section 4.4) be clearly communicated to any end-user of such projections (e.g., decision makers) and that global effort data be combined with any available regional information or knowledge from local experts to improve the implementation of the global data into regional MEMs.

We hope the development of this workflow will accelerate and foster comparisons of MEMs across and within regions. For instance, MEM ensembles can be used to conduct experiments and test scenarios in a standardized manner or to perform in-depth evaluations of uncertainty sources in climate projections (e.g., Murphy et al., 2024). The latter is particularly important given the increasing need for MEM outputs to support policy and decision-making, for which regional models should be particularly suited.

4.2. Model Benchmarking

Benchmarking is necessary to improve the uptake of MEM outputs and to make them policy-relevant (Frieler et al., 2024). There are several different approaches to benchmarking, ranging from quantifying error to fully conducting uncertainty assessments (Luo et al., 2012; Mackinson et al., 2018; Ogunro et al., 2018). One of the main issues related to improving the reliability and robustness of projections by MEMs is their limited cross-ecosystem validation against historical data (Heneghan et al., 2021; Novaglio, Bryndum-Buchholz, et al., 2024), which is true at both global and regional levels. One of the reasons is the limited observational data available at the global scale. For instance, the data sets available to FishMIP are mostly derived from global catch reconstructions (Watson & Tidd, 2018). Recently, a fisheries-independent data set of biomass from bottom trawl surveys became available, but it only covers coastal regions in the Northern Hemisphere, and authors suggest that biomass cannot be compared across regions (Maureaud et al., 2024). At the regional scale, in several instances, there is enough data to conduct calibration, but the availability of appropriate optimization routines can constrain the application of systematic calibration of regional MEMs (Oliveros-Ramos & Shin, 2025). To address these issues, FishMIP aims to develop standardized data sets to evaluate historical model simulations (Blanchard et al., 2024), standardized methodological frameworks for model skill evaluation (Rynne et al., 2024), novel approaches to exploring how best to constrain projections, and novel lightweight approaches to systematically execute and assess MEMs (Steenbeek et al., 2024). These actions will support the development of model benchmarks and tools (Collier et al., 2018; W. Fu et al., 2022) and ultimately lead to improved ecosystem models. This implementation framework represents one of these actions by standardizing model forcings and observational data sets and ultimately reducing model parameterization uncertainty (Blanchard et al., 2024).

4.3. Global-Regional Model Intercomparison

The FishMIP 3a protocol permits the use of standardized fishing effort for global and regional models. While regional ecosystem modelers may find the global effort forcing less precise for their regions compared to local data due to factors such as the taxonomic resolution of the forcing (functional groups instead of species) and system specific variation in catch or effort reporting not captured in the global reconstructions, the standardized fishing effort allows modelers to conduct systematic comparisons between global and regional MEMs. This is a priority area for future work, as it will enable us to determine if the projections from regional MEMs are similar or different to those from global MEMs and the likely causes for these differences (Eddy et al., 2025; Novaglio, Bryndum-Buchholz, et al., 2024). Fostering these comparisons is especially important for regional impact assessments in data-limited areas, as they will provide insights into whether projections from global MEMs can be used for regional purposes.

4.4. Insights From Using the Global Fishing Effort on Regional MEMs

Poor agreement was found between the historical trends of the global and regional fishing efforts for some species, for example, cod in the Baltic Sea and anchovy in the southern Benguela ecosystem models. This is likely explained by the functional group resolution of global effort data, compared to regional resolution, which was to the species level. Thus, in several instances, one fleet can target different species within the same functional group. For example, both anchovy and sardine were included in the "pelagic < 30 cm" functional group targeted by the purse seine fleet in the southern Benguela model. Similarly, in the Baltic Sea model, two species were included in the same functional group and fleet. The level of taxonomic resolution (e.g., functional group), therefore, results in the same temporal variability in effort being applied to the different species within a functional group and gear. This is, however, not always the case for species targeted under the same fleet. The global effort data can thus be less representative for some species within the same functional group, and this could explain why anchovy harvest proportions showed a poor correlation with the global effort estimates, while an acceptable correlation was observed for sardine for the southern Benguela model.

The protocol thus advises modelers to first evaluate how regional observations compare to global data, and the applicability of the latter for a particular region. For instance, the sensitivity analysis presented in step 5 will allow us to determine the impacts of using global versus regional forcings on regional MEM outputs and whether the differences between the effort time series are sufficiently large to impact model outputs and the extent of the impact. We acknowledge that if the differences in trends and magnitudes between the data sets are considerable, it may not be productive for regional modelers to recalibrate their MEMs to the global fishing effort, which are considered less appropriate than the regional ones. If recalibration cannot be carried out, we still hope modelers will submit their runs and compare them to the outputs of their baseline calibrated runs and regional observations. The latter will help identify areas for improvement and refinement of both global and regional MEMs, and global data sets (e.g., effort data) that are regularly used for other reasons in fisheries and anthropogenic impact assessments. Moreover, it will ultimately contribute to the improvements of MEMs within FishMIP (Heneghan et al., 2021), which are often also used for other purposes, the rigor of which would also benefit from any MEM improvements. Lastly, it will also contribute to efforts by the FishMIP community to include an evaluation approach into the MEM protocol (Blanchard et al., 2024) that could also be used regionally. All of these advances move the entire MEM community more clearly toward best practice standards that could be applied to any MEM at any scale in all project work (Planque et al., 2022; Steenbeek et al., 2021).

4.5. Next Steps

Given the large amounts of climate and fishing effort data used for this protocol, the Regional Climate Forcing Data Explorer Shiny app is a significant step forward in simplifying the processing of these forcings as it performs some of the common steps (e.g., extraction and subsetting) followed in data processing. Moreover, several R and Python scripts that supplement the data processing and analyses performed in this study are publicly available in the FishMIP GitHub repository to ensure the replicability of the process. In the near future, the Shiny app will also integrate the global effort data for the participating regional MEMs to further simplify the analysis of forcings and foster the application of this workflow for comparisons across regions and global-regional comparisons.

Another area that requires further attention is the use of a harmonized downscaling approach. While this was an area that needed attention for only specific models in the past, it has become one of the focus areas for future work in FishMIP due to the importance of using highly resolved projections for regional climate-impact assessment and other management applications (Pozo Buil et al., 2021).

5. Conclusions

To date, a range of different methods have been used to process and implement climate forcings in regional MEMs participating in FishMIP, with the decision on the methods used lying with the ecosystem modelers. The diversity of approaches to implementing climate impacts on MEMs can limit the ability of researchers to replicate the process and compare and analyze MEM ensemble outputs. To address this concern, we developed a workflow that standardizes the analysis of climate and fishing forcings, with a focus on global-regional and regional model intercomparisons. The development of this framework is particularly timely, given the increasing number of regional modelers joining FishMIP and the need to systematically evaluate the impacts of climate change worldwide.

While this workflow is designed for model intercomparisons under FishMIP, it may also be adapted to other climate model-MEM linkages. This is particularly important given that projections under climate change are becoming standard expectations in many jurisdictions as the influence of climate change on marine ecosystems matches or exceeds that of fishing (e.g., Fulton et al., 2024). The steps identified in Figure 2 can be generalized to:

1. Identify climate variables needed for the MEM
2. Develop shapefiles of MEM region to extract variables from climate models
3. Aggregate climate variables for non-spatial models
4. Apply downscaling, if needed, for spatial models
5. Apply appropriate fishing effort
6. Calibrate MEM
7. Set up MEM experimental or scenario runs
8. Perform quality checks

If a regional modeler has an application that requires use of different forcing data sets (e.g., use of more regionally specific fishing effort data than what is available in the global fishing data set), then the user can apply those data as needed. However, as a check to their climate-MEM set-up, they can use the FishMIP forcing data sets and perform the FishMIP quality check as a first pass. The inclusion of these regional simulations in FishMIP will facilitate a broader intercomparison and wider understanding of climate impacts on fishing ecosystems globally. The user could then apply their local forcing data for their final application. Substituting forcing data sets enables the user to test the sensitivity of their climate-MEM to different drivers.

The workflow presented here provides a flexible approach to setting up regional MEMs for hindcasts or projections under different climate and fishing scenarios. This workflow is adaptable to different types of regional MEMs, including those that are aspatial or spatial and fully-depth resolved, and those that include one or several fishing fleets. Despite some limitations in the global effort data, the results shown here support its use in regional MEMs, especially for areas with limited fishing information. It is expected that regional models conduct the simulations as described in this protocol to evaluate differences in MEM outputs when using global versus regional sources, provide recommendations for improving global-regional comparisons, and detect drivers of past change in a standardized manner.

Data Availability Statement

Climate and effort forcings are available from Liu et al. (2022) and Novaglio, Rousseau, et al. (2024). The Regional Climate Forcing Data Explorer (Fierro Arcos et al., 2024) for marine ecosystem modelers and end-users can be found here: https://rstudio.global-ecosystem-model.cloud.edu.au/shiny/FishMIP_Input_Explorer/. Further documentation associated with this implementation workflow is available here: http://portal.sf.utas.edu.au/thredds/catalog/gem/fishmip/catalog.html, https://github.com/Fish-MIP/Regional_MEM_Model_Templates, https://github.com/Fish-MIP/FishMIP_Input_Explorer/tree/main/scripts.

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